Strategic similarity in mergers and acquisitions

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Abstract

Using textual analysis and the firm life-cycle theory to proxy for a company's competitive strategy, this paper empirically examines the strategic similarity theory. The findings show that merger and acquisition transactions are more likely between firms with the same strategy. Moreover, when the acquirer and the target firm compete on the basis of one strategy, the deal yields higher stock returns and stronger future asset growth. Overall, the results reveal that synergies obtained from the similar strategy constitute an important determinant of the boundaries of the firm.

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1 Introduction

Companies design diverse strategies to adapt themselves to their relevant external environments and to achieve competitive advantage. For example, firms pursuing low cost strategies focus on lowering the levels of operational expenditure (Porter, 1980), and firms geared towards product innovation invest more in research and development (R&D). The strategic similarity theory posits that if a company competing on the basis of one strategy were to merge with another organization with a similar strategy, the resultant firm would be better positioned to fully realize the synergistic benefits of combining similar skills (Lubatkin, 1987; Ramaswamy, 1997). In principle, the same strategy members are likely to respond in the same way to disturbances (Caves and Porter, 1977), while the management teams of the target and bidder of different strategic approaches would find it difficult to reach consensus on critical aspects of operations that are crucial for the realization of synergies (Ramaswamy, 1997). The literature has provided supportive evidence for the theory in the banking industry (Ramaswamy, 1997; Altunbaş and Marqués, 2008). However, banks significantly differ from the rest of the companies, which hampered the researchers to generalize the findings. This paper examines whether strategic similarity benefits public mergers and acquisitions (M&A) in a large sample of industries, and lends strong support for the predictions of the strategic similarity theory.

The analysis builds on the firm life-cycle theory, which contends that firm life-phases and companies' strategies are inherently related; firms behave like living organisms, they pass through stages of growth, and their strategies correspond to the stage of the life-cycle (Lippitt and Schmidt, 1967; Quinn and Cameron, 1983). The two most common approaches for measuring firm life-cycle in the literature center on the characteristics of firms that vary among the stages. The first approach hinges on selecting one of those characteristics (Klein and Marquardt, 2006; DeAngelo et al., 2010; Arikan and Stulz, 2016). These univariate proxies emphasize firm's particular aspects (for example, age), and they do not address other features that also adjust when a company traverses the phases, nor the differences between the industries. The second approach incorporates few univariate measures into one proxy, to reflect that many attributes of a firm adapt with the stages (e.g. Antony and Ramesh (1992), Dickinson (2011)). Nevertheless, it overlooks the importance of industries, which diverge significantly in the given aspects (software production differs from furniture manufacturing).

Therefore, I develop a relative measure of the firm life-cycle, exploiting the textual analysis of 10-K financial statements. The new measure leans on the notion that firm-level life-cycle is a composite of many overlapping, but distinct product life-cycle stages (Dickinson 2011). It divides companies into stages depending on the life-phases of all the products in the firm and their ranking among other companies within the industry. The ranking represents the relative aspect of the measure and a novelty to the literature because it determines the life-stage of a company in relation to the similar firms.

The first component of the relative measure consists of firms' product life-cycles. To calculate them, I adopt the proxy by Hoberg and Maksimovic (2019), which 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 company's products pertaining to a particular stage. The second essential component defines a firm life-cycle by averaging the product life-cycle vectors of three consecutive years, and identifying the product life-cycle that obtains the highest ranking among the companies in the matching industry. This step embeds the relative aspect of the proxy: firm life-cycle (and correspondingly firm strategy) is measured in relation only to the similar firms. As a result, firms are flagged as innovative, cost-minimizing, stable, or old companies. Innovative companies compete on the basis of innovative products, cost-minimizing companies lower their operational expenses, firms in the mature phase target stable product characteristics and stable relationship with suppliers and customers, and old companies gradually terminate obsolete models.

In line with the economic theory, companies oriented towards innovative strategy are the youngest, grow the fastest, and allocate the biggest part of their sales to R&D; while companies in the last phase are the oldest, have the smallest growth rate and the smallest market-to-book (MB) ratio. The combination of traditional life-cycle proxies (asset size, age of the company, retained earnings over assets) explains 0.29 of the variation in the new proxy. This result suggests that the new measure carries additional information not absorbed by the classic proxies, that can bolster our understanding of the companies' strategies.

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 an 2017, target and acquirer firms spread through all the strategic groups, yet innovative and old companies realize the highest probability of becoming targets, while companies in the mature and innovative group are associated with the highest probability of becoming acquirers. Second, the odds of transaction for companies with the same strategic traits are more than twice as large as the odds for companies that belong to dissimilar strategies. This acquirer-target pair analysis reveals that firms value the synergies between their and the target firm's competitive posture in public deals. Third, deals with strategy overlap earn, on average, 72 basis points higher combined announcement returns, and that the acquiror's size increases significantly after the acquisition compared with the companies that bought a target with a different strategy. In summary, consistent with the strategic similarity theory, this paper shows that the synergies between acquirers' and target firms' strategies constitute a focal determinant of M&A decisions.

The rest of the paper is organized as follows. Section 2 briefly describes the related literature. Section 3 discloses the data. Section 4 introduces the relative firm life-cycle measure. Section 5 tests the hypothesis. Section 6 offers additional tests, and Section 7 concludes.

2 Related literature

This paper speaks primarily to the literature studying asset complementarities and synergies in M&A. The property rights theory (Grossman and Hart, 1986; Hart and Moore, 1990) outlines that complementary assets should be bounded together under common ownership to reduce the incomplete contracting problems. As a natural step, Rhodes-Kropf and Robinson (2008) broaden the theory to M&A, and they formulate the assortative matching concept: 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 exploit 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) show that human capital relatedness contributes to both the likelihood and benefits of mergers. I document that synergies arising from the strategic similarity constitute a strong determinant of M&A decisions.

The paper also adds to the literature on the importance of strategy and firm life-cycle in financial decisions. O'Brien (2003) focuses on how a competitive strategy based on being an industry innovator impacts the capital structure. The paper maintains that the appropriate proxy for the strategic importance of the innovativness to the firm 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 company's decisions also depend on the strategy (life-cycle) of related companies.

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. (2020) provide evidence that firms with more exposure to the mature life-cycle stage disclose substantially more details, while firms in the early stage of the life-cycle strongly favor secrecy, consistent with inward-focused organic investment and mitigating competitive threats. I propose a relative firm life-cycle measure, based on textual analysis of 10-K financial statements, which offers new 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 U.S. 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, 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 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, because their balance sheets are very different from other firms, or to the utilities sector, since they are heavily regulated.
5. Date effective, percentage of shares owned after transaction, and percentage of shares acquired are nonmissing.
6. A company did not acquire another firm 120 days before the announcement day.

After I merge M&A data with company-year observations, both for the acquirers and for the targets, the procedure leaves me with 3,104 M&A 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 a large number in the second half of 1990s. Subsidiary acquisitions are more common than the acquisitions of the entire public companies, and cash only deals are dominating over stock only deals, with the average of 40% of the total number of transactions.

Table 1: 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	0.35	0.10	0.55
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

Following existing literature, the other variables used throughout the paper are constructed as follows. Assets is defined as a natural logarithm of book assets (Computat item AT). Age is the natural logarithm of firm's age, measured as number of years in Compustat database. Debt is 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 firm's profitability (EBITDA/AT). MB is market-to-book ratio, calculated as price of the stock at the fiscal year-end multiplied by the number of shares outstanding and divided by common capital (PRCC_F*CSHO/CEQ).

Table 2 presents descriptive statistics for acquirers and targets in the sample. Both type of companies are large US firms, with the 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.

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.

Variable	mean	std	min	25%	50%	75%	max
assets_acq	6.98	2.00	0.79	5.60	6.99	8.42	10.47
age_acq	10.98	6.01	1.00	7.00	9.00	15.00	28.00
debt_acq	0.20	0.20	0.00	0.03	0.17	0.31	1.71
RD_acq	0.12	0.86	0.00	0.00	0.01	0.08	17.98
EBITDA_acq	0.12	0.15	-2.13	0.09	0.14	0.19	0.43
MB_acq	2.30	2.30	0.54	1.32	1.73	2.51	58.04
firmLC_acq	2.34	0.99	1.00	1.00	2.00	3.00	4.00
assets_tar	6.73	2.27	0.54	4.98	6.65	8.53	10.47
age_tar	11.36	5.79	1.00	7.00	10.00	15.00	28.00
debt_tar	0.20	0.21	0.00	0.02	0.17	0.31	1.71
RD_tar	0.20	1.23	-2.35	0.00	0.02	0.10	17.98
EBITDA_tar	0.07	0.23	-3.57	0.05	0.11	0.17	0.43
MB_tar	2.01	1.92	0.54	1.18	1.54	2.21	39.12
firmLC_tar	2.40	1.06	1.00	1.00	2.00	3.00	4.00

4 The strategy measure

To verify the strategic similarity theory in the banking industry, Ramaswamy (1997) and Altunbaş and Marqués (2008) use five areas to proxy for a bank's strategy: market coverage, marketing posture, risk propensity, operational efficiency, and client mix. Yet, this set of characteristics is not equally relevant in all the industries. To find an attribute representing the firm's strategy applicable to the wider range of companies, I apply the firm life-cycle theory, which hypothesizes that all firms pass through stages of growth and that their strategies correspond to the stage of the life-cycle.

The literature acknowledges that capturing life-cycle at the firm level is notoriously challenging because the life-cycle depends on a set of internal and external factors of a company (Dickinson, 2011). It uses two approaches to draw conclusion about the firm life-cycle from companies financial statements, which diverge in their techniques. The first approach identifies firms' characteristics that are distinctive among the stages and employs one of those characteristics as the proxy. So far: dividend changes (Grullon et al., 2002), earned to contributed capital ratio (DeAngelo et al., 2006), firm age (Arikan and Stulz, 2016), size (Klein and Marquardt, 2006), among others, have been implemented. While these variables indicate a firm's phase, they do not comprehensively define it, because they focus on the specific aspects of the life-cycle. Dividend changes and earned to contributed capital ratio build on the life-cycle theory of dividends, which states that dividends tend to be payed by mature, established firms. The age proxy partitions the firms in young, middle, or mature life-cycle conditional on the years listed as publicly traded firms. Young firms exist less than four years from their IPO, middle-aged firms between four and nine years, and mature firms trade more than nine years as public companies. Table 3 exhibits the discrepancies between the mentioned proxies using Microsoft. According to the age proxy, the firm remains in the mature phase from the start of the sample in 1995. Nonetheless, the average earned-to-contributed capital ratio varies over years: from 1995 to 2004 attains 0.34, between 2005 and 2011 amounts to -0.26, and from 2012 to 2017 about 0.05; and the firm begins to distribute dividends as of 2003.

Table 3: Univariate life-cycle proxies for Microsoft from 1995 to 2018

The table reports age and three life-cycle proxies for Microsoft. Column 1 shows age of the company as number of years from the company's IPO. Column 2 provides the life-cycle proxy by Arikan and Stulz (2016). Column 3 shows the ratio of retained earnings over assets, the life-cycle proxy by DeAngelo et al (2006). The last column exhibits dividend indicator by Grullon et al. (2002).

Year	(1) age	(2) age proxy	(3) retained earnings	(4) dividend indicator
1995	11	mature	0.46	no
1996	12	mature	0.39	no
1997	13	mature	0.37	no
1998	14	mature	0.34	no
1999	15	mature	0.37	no
2000	16	mature	0.35	no
2001	17	mature	0.32	no
2002	18	mature	0.30	no
2003	19	mature	0.32	yes
2004	20	mature	0.20	yes
2005	21	mature	-0.17	yes
2006	22	mature	-0.27	yes
2007	23	mature	-0.47	yes
2008	24	mature	-0.36	yes
2009	25	mature	-0.29	yes
2010	26	mature	-0.19	yes
2011	27	mature	-0.05	yes
2012	28	mature	0.00	yes
2013	29	mature	0.08	yes
2014	30	mature	0.12	yes
2015	31	mature	0.07	yes
2016	32	mature	0.02	yes
2017	33	mature	0.01	yes

The second approach recognizes the challenges of the univariate measures, given the evidence that a range of factors specifies a firm's life-stage, and it combines multiple parameters in a single proxy. Anthony and Ramesh (1992) use four variables: age, sales growth, dividend yield, and capital expenditures; and Dickinson (2011) encompasses the information from the operating, financing, and investment cash-flows. Yet, these proxies neglect industries, which differ on many aspects. In 2017, two-digit NAICS industry *Educational services* averaged 12.2 years, while *Manufacturing* reached 27 years. Likewise, Fama and French (2001) and Denis and Osobov (2008) report the changing characteristics of the US publicly traded companies, with the significantly lower proportion of dividend payers. Also, many industries include particular types of product life-cycles, which affect differently sales revenue over time, and correspondingly, distinctly impact cash flow and sales growth of the companies (Rink and Swan, 1979).

4.1 Firm life-cycle measure based on company's products

On account of these challenges, I build on a recent approach in the finance literature which relies on textual analysis of firms' financial statements (Hoberg and Maksimovic, 2019; Chen et al., 2020), and I propose a relative firm life-cycle proxy. The proxy emanates from the concept that company's attributes (such as sales, capital expenditure, dividends, marketing etc.) depend crucially on the company's products. Since a company owns a portfolio of various products, the combination of product life-cycles governs the life-cycle of the entire firm. The novelty of the proxy lies in the relative component- a company's life-cycle, and consequently a company's strategy, is determined with respect to the similar firms, and not to the whole population of firms.

I initiate by calculating the product life-cycle by Hoberg and Maksimovic (2019), which implements textual analysis on 10-K financial statements.* Unlike the other proposed measures, this methodology reflects that companies contain multiple products in different life-cycle stages. 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 fillings that appear as "10-K","10-K405","10KSB", "10KSB40", or "10-KT". Then I implement anchor-phrase methods to extract paragraphs from 10-K fillings that relate to a specific life-cycle of a company. Ap-

*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.

pendix A describes the procedure in details. I deviate from the exact Hoberg and Maksimovic (2019) procedure in two ways: first, I delete the names of the cities in the U.S. 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". With the four individual paragraph counts, I normalize the product life-cycle exposure vector 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 direct statements 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 life-cycle, I calculate for each company-year the percentile ranking of every product life-cycle within industry[†] in a three-year period. The product life-cycle with the highest ranking denotes the firm life-cycle. 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.[‡]

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. Its corresponding percentiles for 2008, based on its average, within its industry are [95 28 0 0], and it is assigned to the innovative group. In the same way, a company fits the cost minimization phase if the highest percentile accompanies the second product phase. Whenever the dominant product life-cycle percentile of a firm is in the third or the forth phase, I sort the firm as a stable or an old company, respectively. Thereby, the new firm life-cycle measure indicates the company's highest product life-cycle percentile within it's industry in a three-year period, and it designates companies to innovative, cost minimizing, stable, or old life-cycle.

[†]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 also by identifying the nearest rivals as in Hoberg and Phillips (2016).

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

These phases shape companies' strategic orientation: initially, for every product, the firm invests on design and development. Afterwards, attention turns to process innovation, which lowers firm's average cost of production. The incentive for process innovation grows as the firm produces more units over which costs can be spread. Subsequently, the firm value in the mature phase arises from stable product characteristics and stable relationships with suppliers and customers. Finally, in the product discontinuation stage, the focus is on supporting products still in service and phasing out obsolete models. Since the firm life-cycle measure serves as a proxy for the company's strategy, I use the terms firm life-cycle and company's strategy interchangeably.

Table 4 summarizes average firms' characteristics in each strategy group. In line with the economic theory, innovative 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.[§]. Cost-minimizing companies hold the highest debt percentage and are slightly older than stable firms. Consistent with the findings of Kogan et al. (2017) that large firms tend to file more patents, stable firms obtain the highest number of patents per year. Old firms are the oldest, have the smallest growth rate and the smallest MB ratio. In addition, product life-cycle phases demonstrate that, on average, firms combine strategies in all phases, but innovative firms produce the highest percentage of innovative products, cost-minimizing companies focus on lowering cost of production, while stable companies load predominantly on the third product life-cycle stage. The product life-cycle vector for old firms supports the idea that the new proxy identifies firm life-phase relative to the other companies in the same industry; even though old firms have the highest percentage of obsolete products among all firms, they stack more on minimizing the costs in absolute terms.

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

Table 4: 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.

firm LC	age	growth	MB	R&D	debt	$pat	#pat	Life1	Life2	Life3	Life4
innovative	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
stable	10.65	1.22	2.45	0.14	0.22	0.01	8.47	0.22	0.34	0.39	0.04
old	13.37	1.13	2.00	0.15	0.23	0.01	6.55	0.16	0.36	0.20	0.27

4.2 Dynamics of life-cycle

Figure 1 depicts the ratio of firm strategies over years for the entire sample of firms, including acquirers, targets, and firms that did not transact. The proportion of innovative 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. In the same period, cost minimizing corporations comprise between 26% and 37%, and stable firms vary between 25% and 31%. Old public companies are the least represented category, with the peak of 20% after the financial crisis.

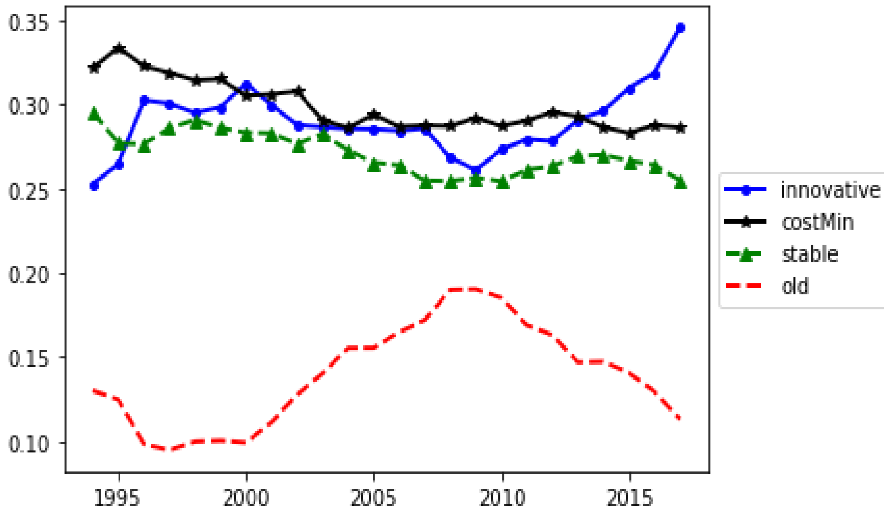
Table 5 discloses the other type of dynamics: the mobility between the phases in one year horizon.[‖] It outlines that firms primarily remain with the same life-cycle, but the lack of zero loadings in all the transition matrices confirms that companies may progress from the current to any of the three remaining stages, similar to Miller and Friesen (1984). With this

[¶] 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 applied also in Brown et al. (2009)

[‖] 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 innovative firms and 5% of the old firms delisted in the following year for those reasons.

Figure 1: Firm strategies over years

The figure shows the fractions of US firms strategies, between 1994 and 2017. The purple part represents firms in the first life-cycle phase, the yellow fraction shows the second life-cycle phase, and the blue and red sections stand for the third and forth phase, 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 life-cycles is described in Section 4 and Appendix A.



feature, the proxy departs from the traditional view that the stages are sequential and that hierarchical progression cannot be easily reversed (as in Quinn and Cameron (1983)), which has been repudiated by evidence of successful strategies to rejuvenate and extend life cycles (Lambkin and Day, 1989). One of the leading examples is Apple 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 most valuable companies in the world.

The extreme changes within one year, the movement from the innovative to the old phase, and vice versa, form the smallest fraction of transitions, and they mostly occur as a consequence of firm restructuring and selling the least profitable segments. As an example, before 1999, the management team of Ultrak company (CIK:318259) emphasized acquisitions as a way to obtain new products, integrated systems, experienced personnel, channels of distribution, and new geographic territories. However, in 2000, Ultrak replaced the management

Table 5: Transition matrix of firm life-cycle in one year horizon.

The table reports the transition matrix of firm life-cycle for US public firms during the period 1994-2017. The calculation of firm life-cycle is given in Section 2.

	Firm life-cycle in the following year			
Firm life cycle	innovative	costMin	stable	old
innovative	83%	6%	8%	3%
costMin	5%	84%	6%	4%
stable	7%	8%	81%	4%
old	4%	8%	6%	81%

team and referred to the transformation from a distributorship to a technology-based company as challenging, generating losses and resulting in down-sizing the work force. This short description elucidates why, accounting for other industry participants in the same year, Ultrak company is labeled as an innovative firm in 1999, while in 2000 and until 2004, it is flagged as an old company.

4.3 Comparison with other life-cycle proxies

In this section, I compare the new life-cycle proxy with the proxies adopted in the finance literature so far: age by Arikan and Stulz (2016), dividend increases by Grullon et al. (2002)), earned to contributed capital ratio by DeAngelo et al. (2006)), and additionally, the product life-cycle measure by Hoberg and Maksimovic (2019). In unreported results, I run the ordered logistic regression, with the firm life-cycle proxy as the dependent variable, and other life-cycle measures as independent variables. The pseudo R2 for the regression is 0.29, which implies that the majority of the variation in the measure if left unexplained by the current proxies. Age and dividend increase exhibit positive and statistically significant coefficients, while earned-to-contributed capital ratio weakly correlates with the firm life-cycle proxy. Due to the specification, the last product life-cycle positively relates to the firm life-cycle. Hence, the new life-cycle proxy provides additional information not incorporated in the current proxies.

To gain the intuition about the divergence between the new firm life-cycle proxy and the three proxies already employed in the literature, Table 6 presents the example of Amazon 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 old 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 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 afterwards, linking Amazon to different stages. Lastly, the relative textual-based proxy marks Amazon as an innovative or a stable company in that period.

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 dividend life-cycle hypothesis, and they can separate only between mature and non mature companies. Conversely, the new measure can distinguish between the four states, and movement among them is not bound only to one phase. For instance, Amazon repositions from an innovative (first phase) to a stable company (third phase) and vice versa. According to the transition matrices in Table 5, a company can preserve the same position, or it can evolve to one of the three remaining stages in any period.

To mitigate concerns that Amazon and Microsoft might be two companies with rear discrepancies, I calculate the percentage of classifications that diverge between the age proxy and the new proxy on the entire sample of companies. As the number of stages differs among the two proxies (3 vs 4), I use two diverse, but conservative estimates. The first estimate perceives a difference between the two proxies only if: 1) the new proxy groups a firm into an innovative, while age proxy detects the firm as mature; 2) the new proxy labels a firm as stable or old, 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

Table 6: Differences between different life-cycle proxies for Amazon

The table shows different variables of the life-cycle proxies for Amazon between 1997 and 2018. The calculation of firm life-cycle is given in Section 2. Age is number of years since the IPO. Re/at is earned to contributed capital ratio, calculated as retained earnings over assets. Div are dividends payed.

Year	firm life-cycle	age	re/at	div
1997	1	1	-.226	0
1998	1	2	-.247	0
1999	1	3	-.358	0
2000	1	4	-1.075	0
2001	1	5	-1.769	0
2002	1	6	-1.507	0
2003	1	7	-1.358	0
2004	3	8	-.725	0
2005	3	9	-.547	0
2006	3	10	-.421	0
2007	3	11	-.211	0
2008	3	12	-.103	0
2009	3	13	.008	0
2010	3	14	.060	0
2011	3	15	.065	0
2012	1	16	.051	0
2013	1	17	.050	0
2014	1	18	.026	0
2015	3	19	.028	0
2016	3	20	.047	0
2017	3	21	.062	0

groups and the total number of observations in the sample. One can observe that 18% of the company-year observations are binned to the opposite stages. The second estimate appends two additional categories: innovative and old firms by the new proxy that correspond to the middle group in age proxy. It divulges that 32% of the firms do not belong to the similar phase according to the two proxies. Overall, the new measure proffers a different standpoint on the firm life-cycle, not fully embodied by the traditional firm life-cycle proxies.

5 Results

The strategic similarity theory maintains that merger and acquisition deals in which the acquirer and the target firm embrace the same strategy perform better compared to other deals. One of the reasons why different strategies lead to worse performance could be the difficulty to reach a consensus between the management teams of the target and bidder on critical aspects of operations that are crucial to foster synergies. The results in line with this theory should pinpoint that acquirers opt for targets with the same strategy, and that those deals yield higher synergies. On this ground, I study the target firms' and the acquirer firms' strategies, the acquirers and the target strategic pairs, and the deal performance.

5.1 Target firms' strategies

The paper is articulated around the idea that acquirers take into account the target's competitive strategy in their M&A decisions. To test this hypothesis, Figure 2 plots the fraction of the target firms in distinct strategic groups over years. Targets are located in all the groups, but compared with all the companies in Figure 1, old and innovative 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).

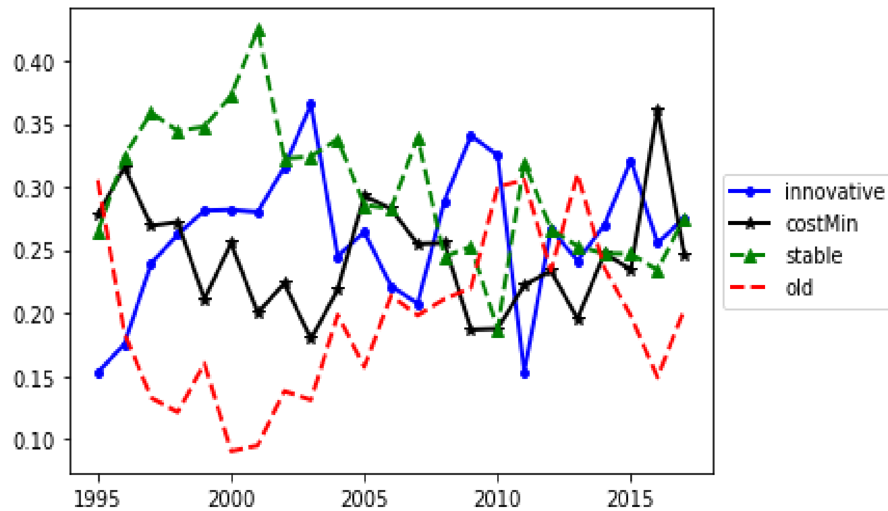
For a direct test, I run a conditional logistic regression, following Bena and Li (2014):

$$\begin{split} TargetFirm_{jm,t} = \alpha + \beta 1 innovative_{j,t-1} + \beta 2 stable_{j,t-1} + \beta 3 old_{j,t-1} + \\ \beta 4 X_{j,t-1} + DealFE_m + \epsilon_{jm,t} \end{split} \tag{1}$$

where the dependent variable 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. Since a company fits only one of the four stages, the cost-minimizing group acts as the reference category 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, and R&D costs, which have been shown in previous studies to predict the probability of becoming a target or an acquirer firm. DealFE are the fixed effects for each target firm and its control firms. YearFE are the year fixed effects. All variables are measured at the fiscal year-end immediately prior

Figure 2: Target firms' strategies over years

The figure shows the fractions of US target firms' strategies, between 1995 and 2017. The purple part represents firms in the first life-cycle phase, the yellow fraction shows the second life-cycle phase, and the blue and red sections stand for the third and forth phase, respectively. The sample consists of 3,104 targets. 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.



to acquisition announcement date. Column 1 includes only the indicator variables for the innovative, stable, and old firms, whereas Column 2 incorporates also the control variables.

For each deal, there is one observation for the target firm, and multiple observations for the control target group. To form the control group, for each target 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 3 years, and have the most similar propensity-matching score based on assets, age, debt, MB ratio, and R&D costs.

Table 7 records coefficient estimates from the conditional logit regression. Across specifications, old and innovative companies are associated with a higher probability of becoming targets, significant at 1% level. For the innovative (old) companies, the odds of becoming a target are 1.60 (1.43) times as large as the odds for companies pursuing cost-minimizing strategy. The results support the hypothesis that target firm's strategy shapes the M&A decision of the acquiring firm. Compared with the closest firms by the propensity score, smaller

Table 7: 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 a target (acquirer) in a given year and zero otherwise. Cost-minimizing groups serves as a reference category in all the columns. The independent variables are measured at the fiscal year-end immediately prior to acquisition announcement date. The detailed explanation for the control sample is given in Section 5.3. T-statistics is given in parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	target	target	acquirer	acquirer
inn	1.143***	0.471***	0.462***	0.335***
	(19.32)	(6.18)	(8.64)	(4.40)
stable	0.257***	0.159***	0.0844*	0.376***
	(4.81)	(2.71)	(1.72)	(6.70)
old	0.417***	0.356***	0.209***	0.240***
	(6.17)	(4.71)	(3.04)	(3.31)
assets		-0.646***		-0.403***
		(-30.17)		(-22.83)
debt		-2.638***		-1.648***
		(-17.92)		(-12.31)
ebitda		0.966***		-10.98***
		(9.21)		(-19.88)
R&D		0.487***		2.708***
		(2.69)		(4.79)
MB		0.000602		-0.00915***
		(0.19)		(-3.33)
Deal FE	Yes	Yes	Yes	Yes
Pseudo R2	0.04	0.36	0.02	0.28
N	18621	18604	18620	18620

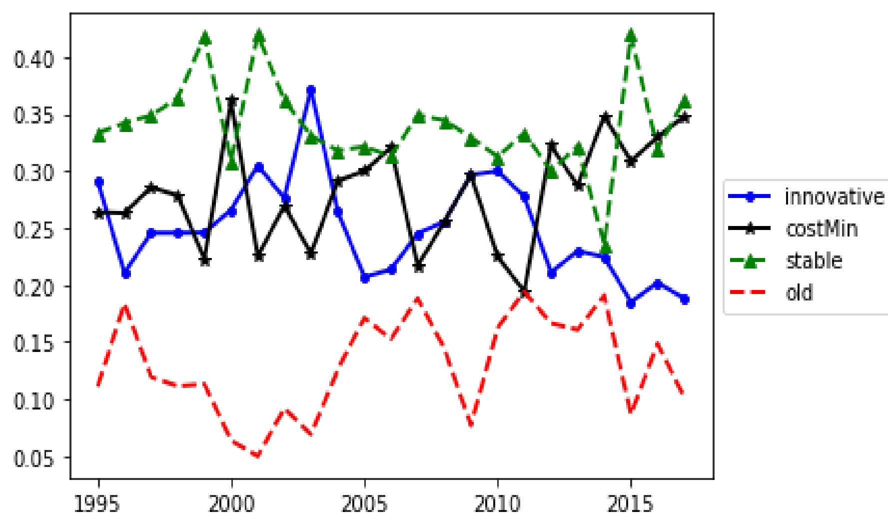
size, higher profitability, and bigger R&D expenses are positively related to the probability of becoming a target, while higher debt ratio decreases the probability of being acquired.

5.2 Acquirer's life-cycle

In order to verify the strategic synergies, I need to study the match between acquirers and targets. I begin by inspecting the acquirers' strategic traits. Figure 3 illustrates the ratio of acquirers' strategies over years. Acquirers do not cluster in one stage, but they spread through all the phases. Compared to all the companies in Figure 1, stable companies seize higher percentage.

Figure 3: Acquirer strategies over years

The figure shows the fractions of US acquirers' strategies, between 1995 and 2017. The purple part represents firms in the first life-cycle phase, the yellow fraction shows the second life-cycle phase, and the blue and red sections stand for the third and forth phase, respectively. The sample consists of 3,104 acquirers. 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.



In the next step, I repeat the conditional logistic regression in Equation 1:

$$\begin{aligned} AcquirorFirm_{im,t} = \alpha + \beta 1 innovative_{i,t-1} + \beta 2 stable_{i,t-1} + \beta 3 old_{i,t-1} + \\ \beta 4 X_{i,t-1} + DealFE_m + \epsilon_{im,t}, \end{aligned} \tag{2}$$

where the dependent variable is an indicator variable equal to one if the firm acquired another public company or a subsidiary in a given year, and zero otherwise. Table 7 Columns 3 and 4 report the coefficient estimates. Cost-minimizing companies again serve as a reference category, and all other variables remain specified as in Equation 1. The columns imply that cost-minimizing companies have the lowest probability of becoming acquirers. After considering other explanatory variables in Column 4, stable and innovative phases are associated with the highest probability of becoming acquirers. For the innovative (stable) companies, the odds of becoming an acquirer are 1.53 (1.51) times as large as the odds for cost-minimizing companies. Smaller size, lower debt ratio, lower profitability, and higher R&D compared with the closest companies by propensity matching score, positively affect the likelihood of becoming an acquirer. In summary, this section substantiates that acquirers diverge in their competitive position, which hints that they should also aim for different target firms.

5.3 Life-cycle pairs

After demonstrating that both acquirers' and targets' strategies matter in M&A deals, the next step analyses the acquirer-target pairs. Table 8 partitions the deals on the acquirer and target strategy groups. It establishes that acquirers and targets cover all the groups, but one patterns stands out in the table: companies mostly acquire firms with the same strategy; the percentage varies from 30% for old firms to 48% for innovative firms. As the number of companies in different strategies does not have to equate, I investigate this pattern in a more formal setting.

Table 8: 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	innovative	costMin	stable	old	Total
innovative	374	110	205	98	787
costMin	141	348	212	161	862
stable	238	203	474	162	1,077
old	69	100	94	115	378
Total	822	761	985	536	3,104

Table 9 shows coefficient estimates from the conditional logit regression:

$$\begin{aligned} realPair_{ijm,t} = \alpha + \beta sameStrategy_{ijm,t-1} + \gamma_1 innovativeAcq_{im,t-1} + \gamma_2 stableAcq_{im,t-1} \\ + \gamma_3 oldAcq_{im,t-1} + \gamma_4 innovativeTar_{jm,t-1} + \gamma_5 stableTar_{jm,t-1} + \gamma_6 oldTar_{jm,t-1} + \\ \delta 1 Xacquiror_{im,t-1} + \delta 2 Xtarget_{jm,t-1} + DealFE_m + \epsilon_{ijm,t}, \end{aligned} \tag{3}$$

where the independent 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). I select the control sample based on the propensity-matching score within the same industry and the same year, as in Table 7. The coefficient of interest is related to the variable *sameStrategy*, which is a dummy variable equal to one if a company-pair overlaps in the strategy, and zero otherwise. Table 9 Column 1 includes the variable *sameStrategy*, and three strategies for both acquirers and targets: innovative, stable, and old firms. Column 2 saturates the model with control variables. For both acquirers and targets, cost-minimizing group serves as a reference category.

In both columns, *sameStrategy* exhibits positive and significant coefficient at 1% level, indicating the same strategy leads to merger pairing. For the companies that pursue the same strategy, the odds of transaction are 2.12 (2.07) times as large as the odds for companies that belong to different groups. Strategy variables point out that cost-minimizing companies have the lowest probability of participating in mergers. The other control variables show predictable signs. The findings are also in line with Chen et al. (2020). 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.

To summarize, I present a large body of evidence and tests in favor of the strategic similarity hypothesis; target firm's strategy forms an important factor in M&A decisions because of the strategic synergies in M&A deals. But what are the benefits of acquiring a company with the same strategy?

Table 9: Acquirer-target firm pairing

The table shows the coefficient estimates form conditional logit model, where the independent 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. T-statistics is given in parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
	realPair	realPair
sameStrategy	0.752***	0.728***
	(18.05)	(14.22)
inn	0.400***	0.332***
	(9.36)	(3.82)
innT	0.883***	0.604***
	(19.49)	(7.66)
stable	0.0441	0.390***
	(1.12)	(5.79)
stableT	0.154***	0.219***
	(3.72)	(3.37)
old	0.228***	0.311***
	(4.25)	(3.24)
oldT	0.460***	0.461***
	(9.10)	(5.42)
Control variables	No	Yes
Deal FE	Yes	Yes
Pseudo R2	0.04	0.11
N	37241	37241

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:

$$
\begin{aligned}
combinedReturn_{ijm} = \alpha + \beta 1 * sameStrategy_m + \gamma 1 * DealCharateristics_m \\
+\gamma 2 * Xi + \gamma 3 * Xj + IndFE + YearFE,
\end{aligned}
\tag{4}
$$

where Deal Characteristics integrate: a public target indicator, as the long-standing literature attests different CAR based on public status of the target (see for example Andrade et al. (2001)), stockOnly and cashOnly dummy, to control for acquisitions of targets paid only with stocks or cash (Travlos, 1987); relative deal size, since larger deals are subject to smaller announcement returns (Alexandridis et al., 2013); industry relatedness (diffInd) of the acquisition, to capture that diversifying acquisitions have been found to destroy value (Morck et al., 1990).

I implement 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 days 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

Table 10: Combined announcement returns

This table reports OLS regression results for the combined abnormal returns, CAR(-1,1), measured using Carhart four-factor model returns. The detailed explanation of the firm synergy measures is given in Section 4. T-statistics is given in parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors account for heteroscedasticity and within-industry clustering.

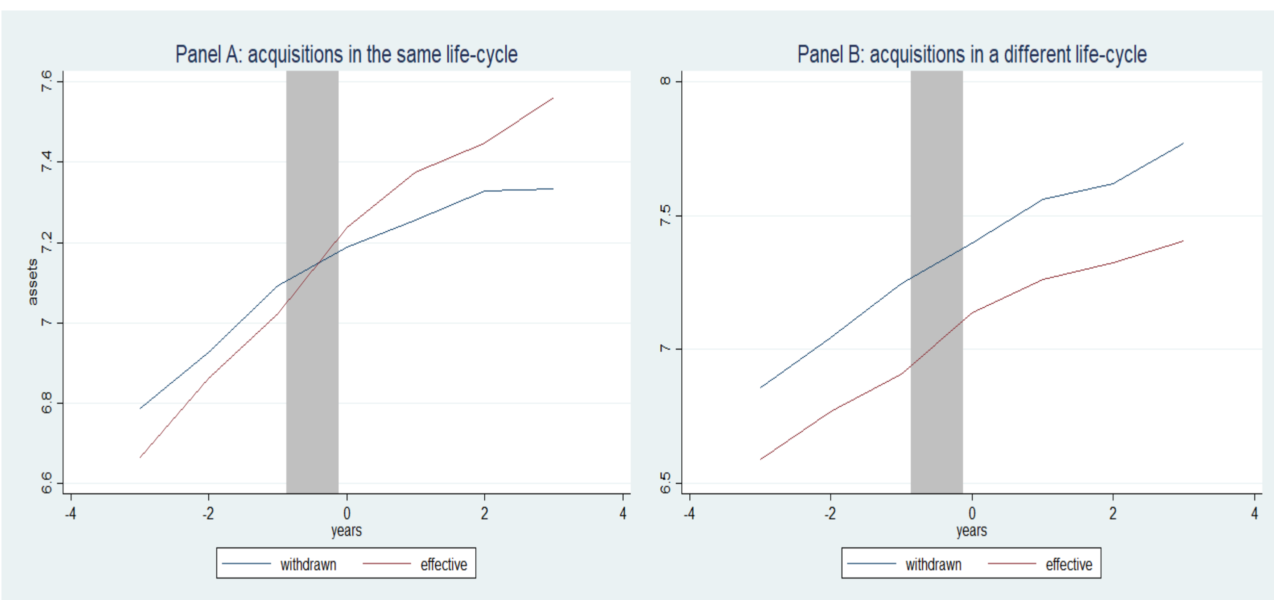
	(1)	(2)
	combinedReturn	combinedReturn
sameStrategy	0.725**	0.720***
	(2.67)	(2.99)
relativeSize		-0.000
		(-1.30)
cash		1.507***
		(4.53)
stockOnly		-2.676***
		(-3.94)
diffInd		-0.782**
		(-2.57)
subsidiary		-2.576***
		(-6.27)
Control variables	No	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Constant	-0.749	4.528**
	(-0.46)	(2.38)
R2	0.02	0.06
N	3104	3104

significant at the 1% level, suggesting that deals where the acquirer and the target belong to the same strategic group yield, on average, 72 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 a real post-acquisition gains, in particular asset growth. The challenge is that asset 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 acquired a target company with the same (different) strategy with the withdrawn acquisitions of companies in the same (different) strategy. The withdrawn acquisitions occur during the same year as the matched effective acquisitions, and acquirers of the two acquisitions have the same age.** An additional condition for the control group is that the companies did not buy another public company or a subsidiary of a public company three years before the acquisition attempt. I adopt the three year period 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: 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 deal in which the acquirer and the target are with the same strategy, while Panel B displays the deals with acquirer and the target with different strategies. Year 0 is the year of the announcement.



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

Figure 11 verifies the parallel trend assumption. Panel A plots the average asset size for the treatment and control 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 mechanical (A+B>A); however, the analysis concentrates on the time 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 compared with their control sample, while companies that acquired a target with a different strategy do not materialize such growth. I conclude that the two samples satisfy the parallel trend assumption necessary for the DiD analysis.

In DiD analysis, I estimate the following regression using a panel data set three years prior to bid announcement to three years after the deal announcement:

$$\begin{aligned} Assets_{mt} = \alpha + \beta 1 after_{mt} + \beta 2 after_{mt} * effective_m + \beta 3 sameStrategy_m * after_{mt} \\ + \beta 4 sameStrategy_m * after_{mt} * effective_m + DealFE_m + YearFE_t + \epsilon_{mt}. \end{aligned} \tag{5}$$

The dependent variable, $Assets_{ijt}$, is the acquiror'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 dummy variable *sameStrategy* equals one for the deals in which the acquirer and the target have the same strategy, and zero otherwise. 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. The coefficient of interest is $\beta 4$ for the interaction term between *sameStrategy*, *after*, and *effective*, which detects the effect on asset size after acquiring a target with the same strategy.

Table 11 Column A presents coefficient estimates from the OLS regression in equation (1). 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

Table 11: Long-term assets of acquirers

The table presents the coefficient estimates of difference-in-differences regression, where the dependent variable is asset size. Column 1 includes the real DiD, while Column 2 is the placebo test, where it is falsely assumed that the acquirers acquired a company three years before the actual acquisition.

	(1)	(2)
	assets	assets
after	0.394**	-0.00758
	(2.25)	(-0.04)
after x effective	-0.213**	-0.242**
	(-2.51)	(-2.55)
sameStrategy x after	-0.208**	-0.00989
	(-2.53)	(-0.11)
sameStrategy x after x effective	0.340***	0.153
	(3.47)	(1.42)
_cons	6.717***	6.836***
	(189.38)	(161.76)
Adjusted R2	0.61	0.57
N	9645	7718

positive and significant at the 1% level. The findings establish that the strategic synergies deliver real post-acquisition gains, supporting the strategic similarity hypothesis.

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 B 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 results in this section highlight that companies consider target firm's strategy as an important factor in M&A deals because of the potential financial and real benefits emerging from the strategic synergies.

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 that are more broadly similar to all firms in the economy (asset complementarity effect) because those firms have more opportunities for pairings that can generate synergies; and 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 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 *sameStrategy* 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. Broad similarity is defined as the average similarity between firm i and all other firms j in the sample. Product similarity is the average pairwise similarity between firm i and its ten most similar rivals j. The closest rivals are the ten firms with the highest local similarity to i. These measures use 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 turns insignificant after the inclusion of the same strategy variable and the similarity score between the acquirer and the target. These results support the theory of Gimeno and Woo (1996), that companies can be strategically similar with little market overlap, but also strategically different with substantial market overlap.

Table 12: Firm pairs with synergy variables

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 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. twoCompScore is the similarity score between the companies. broadSimilarityTar is the broad similarity of target firms. productSimilarityTar is the product similarity of target firms. techProx is the technological proximity of the given firm pair. culturalDis is the cultural distance between the firm-pair. T-statistics is given in parenthesis. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	realPair	realPair	realPair	realPair	realPair
sameStrategy	0.720***	0.756***	0.700***	0.705***	0.652***
	(15.45)	(15.42)	(15.97)	(14.29)	(8.45)
twoCompScore	0.141***	0.220***		0.218***	
	(28.49)	(32.65)		(32.33)	
broadSimilarityTar		-0.0524		-0.0414	
		(-1.00)		(-0.77)	
productSimilarityTar		-0.144***		-0.147***	
		(-21.64)		(-21.74)	
techProx			2.323***	2.114***	
			(19.22)	(14.47)	
culturalDis					-0.545***
					(-10.36)
inn	0.335***	0.359***	0.330***	0.355***	0.301***
	(5.58)	(5.20)	(5.66)	(5.07)	(2.95)
innT	0.646***	0.822***	0.594***	0.815***	0.574***
	(9.97)	(11.01)	(10.32)	(10.85)	(5.13)
stable	0.116**	0.141**	0.108**	0.121**	0.107
	(2.39)	(2.52)	(2.35)	(2.13)	(1.25)
stableT	0.0419	0.197***	0.0718	0.165***	0.226**
	(0.80)	(3.51)	(1.54)	(2.91)	(2.48)
old	0.212***	0.246***	0.167***	0.206***	0.159
	(3.38)	(3.37)	(2.82)	(2.80)	(1.60)
oldT	0.366***	0.540***	0.350***	0.499***	0.657***
	(5.71)	(7.89)	(6.14)	(7.23)	(7.11)
Control variables	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes

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 12 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 significance of the strategy variable continues to persists after the inclusion of both product market and technology variables.

Finally, this section explores whether corporate culture can explain the main strategy findings. 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 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 compared to the first four columns because the culture variables data begin in 2001. Coefficient on the same strategy dummy are positive and statistically significant at 1% level in both columns, suggesting that corporate culture does not fully explain the strategy variable. The coefficient on corporate culture distance is negative and statistically significant at 1% level, confirming the results of Li et al. (2020). Taken as a whole, this paper uncovers that strategic synergies are a strong impetus of M&A deals.

7 Conclusion

Mergers and acquisitions are one of the largest and most readily observable forms of corporate investment (Masulis et al., 2007) that generate substantial reallocation of capital (Bonaime et al., 2018). According to the strategic similarity theory, companies benefit more from those deals if they acquire a target firm pursuing the same competitive strategy. This paper is the first to provide large scale evidence in support of the theory. Therefore, the paper underscores a new dimension of asset complementarities in public M&A deals by documenting that acquirers consider target firm's strategic orientation. Purchasing a company with the same strategy yields synergies, which are visible through financial and real ex-post benefits.

The second contribution of the paper relates to the methodology. I propose a relative proxy to estimate the firm strategy, which relies on the firm life-cycle theory and the textual analysis of corporate 10-K financial statements. The new measure indicates which life-cycle group of products ranks the highest within the industry in which a company operates. 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. I look forward to extending the analysis to other related questions, like the strategy of the serial acquirers and their targets.

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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 intro-

duction 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