Technology Development and Corporate Mergers*

Danqing Mei†

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ABSTRACT

I examine the motives as well as consequences of merger-and-acquisition (M&A) transactions between companies with varying degrees of technological overlap. High-overlap deals, with more collaboration between inventors from the merging companies, produce more patents and go deeper in the existing fields. In contrast, low-overlap deals, with a higher percentage of new inventors, experience larger technology shifts and develop patents in unexplored areas with higher commercial value. Importantly, M&A completion facilitates technology transformation to a greater degree than the two companies, especially pairs with low overlap, could have accomplished on their own. Overall, the direction of innovation is an important motive for technology-driven acquisitions.

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†Danqing Mei is a PhD student in Finance at the Columbia Business School. He can be reached at `dmei19@gsb.columbia.edu`

Where does innovation come from? Albert Einstein suggested that "Combinatory play seems to be the essential feature in productive thought." In the world of business, we can naturally examine the role of "combinatory play" in shaping innovation through the lens of mergers and acquisitions (M&As), transactions through which two companies combine their knowledge bases and research resources. Indeed, the first iPhone, which was a combination of a cell phone, a touch screen, and an operating system, represents a good example of this phenomenon.[1] M&A played an important role in iPhone's development process. In 2005—two years before the iPhone was first brought to the market—Apple acquired FingerWorks, a company specializing in touch screen technology.

Importantly, in addition to financial and product concerns, today many M&As are driven by the desire to acquire innovation capabilities and technology development.[2] Interestingly, many innovation-driven deals feature a pair of merging companies with relatively low technological overlap, such as Amazon and Whole Foods. Ranking highly among the most surprising and interesting M&As of 2017,[3] the deal caught the attention of the public exactly because Amazon and Whole Foods are related to each other so remotely with respect to their technological features. Differing from most existing studies on M&As, which tend to evaluate a deal's synergy creation by focusing on product or technological overlap, deals like the one in which Amazon acquired Whole Foods apparently serve a new role as they might facilitate a firm's technology shift and exploration of fresh new areas.[4]

To understand how technology is developed through M&A deals, especially those with low technological overlap, I propose that the direction of innovation is an important dimension for characterizing a firm's innovation activity. A firm's technology direction is captured by using a vector representation for the technology space based on the firm's patent portfolio.

[1] On the theory side, Weitzman (1998) provides a model in which new ideas are generated from a combination of old ideas.

[2] "Innovation is at the core of most M&A transactions." See `www.financierworldwide.com/innovation-driven-ma-explorers-enablers-and-expanders`.

[3] See `www.factumltd.com/blog/17-surprising-industry-mergers-2017/` or `www.securedocs.com/blog/top-ma-deals-of-2017` as examples.

[4] One recent article, "Why Companies Are Using M&A to Transform Themselves, Not Just to Grow", on *Harvard Business Review* discusses how technology interacts with M&A in today's economy.

To construct these vectors, in addition to the method proposed by Jaffe (1986) that utilizes the information on technology classifications assigned by the patent office, I also explore raw texts from patent filings. In detail, each element in such a vector represents the intensity of the corresponding technology classification or technology term within a firm's patent portfolio, measuring the weight a firm allocates to the technology field. As a new dimension of the firm's innovation activity, the direction of innovation complements the quantity of innovation, which is measured by aggregating the total number of patents within the firm (see Lerner and Seru (2017) for the most recent survey paper). Focusing on both the quantity and direction of innovation, I examine the motives as well as the consequences of M&As between companies with varying degrees of technological overlap through the following three tests.

First, I analyze the ex-post innovation activities of successful M&As and document a tradeoff between deals with high and those with low technological overlap. I find that merging companies with high technological overlap tend to produce more patents after deal completion, indicating economies of scale and reconfirming the conventional wisdom that the presence of high overlap is a benefit for M&A deals. However, companies with low technological overlap achieve larger technology shifts and develop patents in unexplored areas. Therefore, the tradeoff between high- and low-overlap deals can be translated into a tradeoff between the quantity and direction of innovation. Furthermore, information on patent inventors sheds light on the underlying mechanism behind this tradeoff. By combining inventor data with M&A data, I find that high-overlap deals are associated with more collaboration between the original inventors from merging companies. Low-overlap deals are, however, associated with a higher percentage of new inventors. These patterns suggest that the structures of research teams differ in high- and low-overlap deals, indicating that human capital provides one channel through which to explain the tradeoff.

Following my analysis of the ex-post consequences, I run a predictive regression for the technological overlap between merging companies, to discover which factors ex ante motivate high- or low-overlap deals. The results reveal that high-overlap deals are usually made between R&D-intensive firm pairs where the target companies are financially distressed by low return-on-assets (ROA). On the other hand, low-overlap deals feature a stale acquirer buying a profitable target from another industry. The findings suggest that high-overlap M&As are driven by technology concerns – the acquirer values the target's innovation potential despite its poor financial performance. In contrast, low-overlap M&As are motivated by profitability concerns – the acquirer aims to transform itself into new and profitable areas of technology. To support these arguments, I further utilize the distinction between a patent's scientific value and its commercial value (Kogan et al., 2017). I find that, consistent with the technology motive, high-overlap merging companies produce patents of higher scientific value, and that, consistent with the profitability motive, low-overlap companies produce patents with higher commercial value.

The two above-mentioned tests show the importance of innovation direction to understand how technology is developed from combinations of merging companies, especially a pair with low technological overlap. The acquirer's interest in a low-overlap target, however, implies that the acquirer could have shifted its technology in the absence of the transaction. Therefore, in the last test, I aim to address this endogeneity problem and identify the causal effects of an M&A on a firm's innovation direction. Like Seru (2014) and Bena and Li (2014), I conduct a quasi-experiment that compares completed deals as the treatment group with a sample of "exogenously" withdrawn deals as the control group. The control group is constructed from M&As that fail for reasons exogenous to innovation. I find that the merging companies in successful deals achieve a technology shift that is more pronounced than anything they could have accomplished on their own, which contrasts with what occurs following failed deals. Moreover, this effect is especially pronounced in deals between technologically low-overlap firms.

In summary, I discover an interesting pattern for the process of technology development in the context of M&As – a low-overlap pair promote new fields of technology while a high-overlap pair produces more innovation output. This finding represents a new piece of firm-level evidence that a diversity of backgrounds and knowledge bases promotes innovation and new ideas. At the individual level, recent papers such as Freeman and Huang (2015) and Bernstein et al. (2018) examine the coordination patterns in co-authoring academic papers or co-inventing utility patents. Instead, my paper highlights the role of "combinatory play" in M&As at the firm level in facilitating technology shift and development, which to the best of my knowledge has not been documented in the literature.

The paper contributes to the literature along three dimensions. First, it documents a new tradeoff between technologically high and low overlap in the M&A literature. Inspired by theoretical work on the relationship between asset complementarity and deal synergy (Rhodes-Kropf and Robinson, 2008), most empirical studies in this literature focus on relatedness between merging companies as a criterion for evaluating a deal's synergy creation.[5] For example, Hoberg and Phillips (2010) find that merging two firms that are positioned closely in the product market creates more value, while Bena and Li (2014) document that large technological overlap between two firms ex ante predicts merger pairing and ex post improves the combined firm's innovation capability (in terms of quantity). Differing from these studies, I focus more sharply on deals between technologically low-overlap firms and highlight the direction of innovation as another important dimension of the firm's innovation activity. I find that, though high overlap between firm pairs implies a larger quantity of innovation, which is consistent with the conventional wisdom of previous studies, low overlap in the technology space promotes more development into unexplored areas.

Second, there is a growing body of literature that studies the relationship between innovation and M&As as companies are increasingly choosing to acquire innovation and technology instead of pursuing in-house development (Sevilir and Tian, 2012; Phillips and Zhdanov, 2013; Bena and Li, 2014). It belongs to a broader stream of the literature that studies how new ideas are generated or spread in an economy (Jovanovic and MacDonald, 1994; Lucas

[5] Some studies, such as Fan and Goyal (2006) and Ahern and Harford (2014), explicitly study the value of vertical mergers by focusing on relatedness between vertical industries.

and Moll, 2014; Akcigit et al., 2016). While the work here often emphasizes the importance of complementarity (as captured by high overlap), my paper directly evaluates the value of low overlap in the technology space and links it to a firm's technology transformation by shifting the focus from the quantity of innovation to the direction of innovation. In addition, Cunningham et al. (2018) studies incentives in M&As to kill innovation and preempt future competition, which contributes to the current debate over how the antitrust authority should govern the heated M&A market for high-tech companies. My paper adds to the discussion that deals between seemingly unrelated parties, which can operate off the radar of the antitrust authority, facilitate the acquirer to shift its technology and explore areas with higher commercial value.

Third, my paper is among the first few attempts to design a granular vector representation for the technology space by exploring raw text data from patent filings (Younge and Kuhn, 2016; Kelly et al., 2018; Bowen et al., 2019).[6] Beginning with Jaffe (1986), researchers have been using technology classifications or patent citations to capture *between-firm* technology distance, complementarity, and spillover. Recent examples include Serrano (2010), Bloom et al. (2013), Bena and Li (2014), and Akcigit et al. (2016). My paper takes this approach one step further and utilizes these vectors to infer *within-firm* technology shift and transformation. In addition, using text data in this context gives us much richer information than we have when relying solely on technology classifications or patent citations. It is also not subject to a patent examiner's personal bias, as is shown in several papers that study the drawbacks of conventional measures based on classifications and citations (Jaffe et al., 2000; Roach and Cohen, 2013; Younge and Kuhn, 2016).

The rest of the paper proceeds as follows. In Section I, I describe the data sources for M&As and patents. I also develop measures of technological overlap and technology shift. In Section II, I examine the ex-post innovation activities after deal completion, focusing in

[6]Beyond the use of text data, I also construct a comprehensive dataset that matches both public and private target companies to the patent database by adopting the state-of-the-art approach from Autor et al. (2019). Details on the data project can be found at `https://github.com/danielm-github/patentsmatch_bingsearchapproach`.

particular on the relationship between ex-ante technological overlap and ex-post technology development in terms of quantity and direction. In Section III, I investigate incentives behind high- and low-overlap deals. In Section IV, I identify the role of M&As in shaping a firm's innovation direction via a quasi-experiment. Section V concludes.

I. Data Sources and Sample Overview

A. Merger and Acquisition

This study's M&A sample consists of all U.S. deals announced between January 1, 1985 and December 31, 2017 from the Securities Data Company ("SDC") database. It starts in 1985 because SDC data are less reliable before 1985 and it ends in 2017 because of the restriction of patent data, which will be discussed in detail in Section I.B.1. Following the prior M&A literature (Hsieh and Walkling, 2005; Gaspar et al., 2005), I apply the following filters: (1) the acquirer is a public company that is covered by Compustat/CRSP before the deal announcement; (2) the acquirer owns less than 50% of the target's stock before the acquisition and more than 50% after the acquisition; (3) the form of deal is coded by the SDC as a merger, an acquisition of majority interest, or an acquisition of assets; and (4) the transaction is not classified by the SDC as a divestiture, spin-off, or repurchase. These criteria yield an initial sample of 46,029 completed deals and 2,552 withdrawn deals. If I restrict the sample to M&As between public acquirers and public targets, I obtain 5,037 completed deals and 1,138 withdrawn deals. Firm characteristics and stock prices/returns are collected from Compustat and CRSP. The actual sample size varies across my analyses, depending on the availability of required additional information.

B. Patents

B.1. Matching Patent Data with SDC and Compustat

One of the most difficult challenges that faces researchers using patent data is that the U.S. Patent and Trademark Office (USPTO) does not record the names of patent assignees systematically. Therefore, it is difficult for researchers to link these data with well-established databases like CRSP, Compustat, or the SDC. For a long time, fuzzy name matching was the common practice in the literature when researchers sought to match patents of public firms to Compustat and CRSP. The latest systematic effort following this approach is Kogan et al. (2017), who create a link between patent data and CRSP data from 1926 through 2010.

Recently, Autor et al. (2019) proposes a new name-matching algorithm that can improve accuracy and efficiency with the help of a search engine.[7] If the top pages that pop up after searching several entries are similar, these searches are likely to be pointing to the same firm. In addition to applying this algorithm to the universe of public firms in Compustat, I also apply it to the universe of private target firms in the SDC, which to the best of my knowledge is the first attempt in the literature to match patent assignees to private firms using a web search engine.

For each patent, I obtain its patent number, the dates of application, grant, and publication, its technology classification code, and the text description from about 6 million patent filings covering 1976-2017 from PatentsView (`www.patentsview.org`), which is a data service company that helps the USPTO parse and organize patent filings.[8] Relying on the dataset from PatentsView and my own matching procedure, I characterize a firm's inno-

[7] Their detailed codes and data can be found on `http://www.pian-shu.com/`. My initial project started before they published their paper and procedure. There are, then, a few differences between our procedures, as detailed in my GitHub page `https://github.com/danielm-github/patentsmatch_bingsearchapproach`. I further extend their sample period from 2013 to 2017.

[8] Note that the company also applies the state-of-the-art disambiguation algorithm to the universe of patent inventors. Like patent assignees, patent inventors are not organized by the USPTO using unique identifiers. At the current stage, I use the inventor database from the Harvard Dataverse, `https://dataverse.harvard.edu/dataverse/patent`, which disambiguates inventors from 1975 through 2010. In 2015, the USPTO hosted an Inventor Disambiguation Workshop and the new algorithm has been integrated into PatentsView. I plan to update the paper with this new inventor data soon.

vation activity based on two dimensions, the direction of innovation and the quantity of innovation.

B.2. Innovation Vector - Direction of Innovation

To measure the direction of innovation, I construct an ***Innovation Vector*** for any patent or patent portfolio by utilizing either the technology classification coded by the patent examiner or the text description from the patent filings, which are denoted as a class-based innovation vector (CIV) and a text-based innovation vector (TIV), respectively.

1. *Class-based Innovation Vector*

Following Jaffe (1986), I form a ***class-based innovation vector*** with a length of 422 elements. Each element represents one technology classification and there are in total 422 technology classifications now coded by the USPTO. For each patent p, the class-based innovation vector (CIV_p) is simply a vector of one in its corresponding technology class and zeros otherwise. Adding all patents in a firm f gives us the class-based innovation vector of its patent portfolio (CIV_f), which can be a proxy for firm f's innovation direction.

2. *Text-based Innovation Vector*

In addition to accessing the technology classification code, I explore more information from the text descriptions of patent filings via textual analysis (Younge and Kuhn, 2016; Kelly et al., 2018; Bowen et al., 2019). This approach is very similar to that applied in Hoberg and Phillips (2010, 2016), in which the authors convert a firm's 10K filing into a bag-of-words representation and use it as a proxy for the firm's position in the product market. Similarly, each patent can be written as a word vector and a firm's patent portfolio is then a combination of all these word vectors. Figure 1 displays an intuitive comparison between the ***class-based*** measure and the ***text-based*** measure.

[Insert Figure 1 here.]

To construct the ***text-based innovation vector***, I start with technical descriptions from patent filings in the USPTO. From each patent's original filings, PatentsView parses and organizes the texts into a ***brief summary***. As shown by the example presented in Appendix A, the brief summary starts from the beginning of the section labeled "description" and ends with "detailed description," typically right before the list of figures and/or drawings. I then calculate the weight of each word using the "term frequency inverse document frequency" (TF-IDF) approach. The details regarding the approach can be found in Appendix B. This approach ensures that the weight of a word is high when the word frequently appears in one patent filing but does not appear in most other filings.

3. *Technological Overlap*

With the ***class-based innovation vector*** CIV_p, I estimate a score of technological overlap for any pair of two firms (or patent portfolios) i, j as the "cosine similarity" between CIV_i and CIV_j (Jaffe 1986):

$$CCS_{ij} = \frac{CIV_i \cdot CIV_j}{||CIV_i|| \cdot ||CIV_j||}, \tag{1}$$

where CCS_{ij} denotes class-based cosine similarity between firm i and firm j. Because TIV embeds richer information from text data, I estimate a text-based cosine similarity (TCS) between a pair of either two patents or two patent portfolios, as follows:

$$TCS_{ij} = \frac{\sum_{p\in i} W_p TIV_p \cdot \sum_{q\in j} W_q TIV_q}{|| \sum_{p\in i} W_p TIV_p|| \cdot || \sum_{q\in j} W_q TIV_q||}, \tag{2}$$

where W_p (W_q) provides additional freedom for assigning a weight to each patent p (q) to reflect the relative importance of any patent.[9] In this paper, I use an equal-weighting scheme consistently.

In fact, "cosine similarity" aims to capture the degree of overlap between any two vectors. It is widely used in studies of textual analysis and information processing (Sebastiani, 2002;

[9]For example, I can weigh patents by economic value using the approach introduced by Kogan et al. (2017).

Hoberg and Phillips, 2016). It is called "cosine similarity" because it is equivalent to the cosine of the angle between two vectors. Therefore, it equals one when the two vectors point in the same direction and zero when the two vectors have no overlap and are thus orthogonal to each other.

In addition to capturing overlap, I can also apply the same method to measure the technology shift within one firm over two time periods, t_1 and t_2. Denoting a firm's patent portfolio during time period t_1 (t_2) as p_{t_1} (p_{t_2}), a large technology shift can be then captured by a small $CCS^f_{p_{t_1}p_{t_2}}$ or $TCS^f_{p_{t_1}p_{t_2}}$.[10] As the score is bounded between zero and one, I calculate class-based (text-based) ***Tech Shift*** as $1 - CCS^f_{p_{t_1}p_{t_2}}$ ($1 - TCS^f_{p_{t_1}p_{t_2}}$), to illustrate the point more clearly.

B.3. Patent Count - Quantity of Innovation

Both CIV and TIV are indicators of a firm's direction of innovation in the technology space, but neither of the two measures reflects a firm's quantity of innovation. Relevant studies often count the number of patent grants by reference to the date of a patent application as a measure of innovation quantity. To mitigate bias from the truncation problem or patenting trends (Lerner and Seru, 2017), I also adopt a normalization method following Bena and Li (2014) and Lerner and Seru (2017). I explain details regarding the method in Section II.A. In short, I normalize each patent by considering the fact of clustering over patenting time and technology classifications.

C. Sample Overview

A firm is defined as ***innovative at year t*** if the firm is active in patenting during the three-year period of $[t-3, t-1]$. After combining the M&A sample with the patent database, I focus on M&As that involve innovative firms if both the target and the acquirer are innovative

[10]The superscript f in the notation implies that the corresponding cosine similarity measures the degree of technology shift within the same firm f. This helps to distinguish this within-firm measure from the original measure of technological overlap between two entities.

in the year of a deal announcement (because otherwise the technological overlap between the target and the acquirer is mechanically zero). Figure 2 Panel A (B) plots the number of public (private) M&As and the share of deals involving innovative firms over the sample period running from 1985 through 2017.[11]

[Insert Figure 2 here.]

Overall, the percentage of deals involving innovative firms begins rising in 2000 and stabilizes in recent years. In summary, among all public M&As, 1,178 deals (or 19%) involve innovative acquirers and innovative targets. Among M&As with public acquirers and private targets, 4,997 deals (or 11%) involve innovative merging companies.

For each target and acquirer pair in an M&A deal in year t, I can measure their technological overlap by calculating CCS or TCS between the patent portfolios of each firm during the period $[t-3, t-1]$. Figure 2 Panel C plots the average class-based and text-based technological overlaps for all deals involving innovative firms over the sample period. Technological overlap between acquirers and targets is almost stable over the sample period. Note that the sharp drop in 2017, which is the end of the sample period, is probably not economically meaningful because it can reflect the truncation problem in the patent data. In Section II, the test sample will end in 2014 to mitigate such bias.

Table I shows summary statistics for deal and firm characteristics to compare M&As that involve innovative firms with other M&As. Panel A is based on public M&As while Panel B is based on private M&As. In both panels, the two groups can be seen to differ along many dimensions. The results reported in Panel A (B) indicate that deals involving innovative firms are much larger than those involving other non-innovative firms by 129% (142%) in terms of deal value. For public M&As, deals involving innovative firms are less likely to be friendly or stock deals. The merging companies are less likely to operate in the

[11]A public deal occurs when a public acquirer buys a public target while a private deal occurs when a public acquirer buys a private target.

same industry by 3-7 percentage points if they are both innovative firms.[12] The difference is statistically significant. Unconditionally, the average probability that the target and the acquirer operate in the same industry is 66.6% for public M&As and 54.1% for private M&As. This finding indicates that M&As involving innovative firms may play a stronger role in catalyzing technology shift and transformation because the acquirer and the target are more likely to operate in different industries.

[Insert Table I here.]

On the firm's side, both the innovative target and the innovative acquirer are significantly larger and have lower book-to-market ratios. The innovative target and the acquirer in a public deal are 132% and 255% larger than their non-innovative counterparts, respectively, when firm size is measured as market capitalization before the deal announcement. The book-to-market ratio of innovative target or acquirer is lower by 10-20 percentage points. These statistics indicate that in either public or private M&As involving innovative firms, the target and the acquirer tend to be larger firms embedded with higher growth options. Last but not least, the innovative target's ROA is lower by five percentage points while the innovative acquirer's ROA is higher by three to five percentage points. The differences are statistically significant at 1%. Table I also reports the innovation characteristics of the target and the acquirer. In an average public (private) deal involving innovative firms, the target owns 33.5 (9.4) patents while the acquirer owns 331.6 (371.1) patents.

II. Technology Development after M&A

In this section, I analyze ex-post innovation activity, in both quantity and direction, and examine whether there is any tradeoff between M&As with high and those with low

[12]Hoberg and Phillips (2016) proposes a novel measure to identify a public company's product market based on its 10-K filings. They establish that their measure is superior to the conventional industry classification codes. The main results reported in Tables II, III, and IV still hold when I replace the same-industry dummy with their new measure.

technological overlap. Conditional on successful M&As that involve innovative merging companies, I conduct a cross-sectional analysis by regressing ex-post innovation performance on ex-ante technological overlap plus deal, innovation, and firm characteristics, as follows:

$$
\begin{aligned}
InnovationPerformance_{d;T_{t_a};A_{t_a}} = {} & \alpha_t + \beta_1 CCS_{T_{t_b};A_{t_b}} (\text{or } \beta_1 TCS_{T_{t_b};A_{t_b}}) \\
& + \beta_2 Deal_{d;t_b} + \beta_3 Innovation_{T_{t_b};A_{t_b}} \\
& + \beta_4 Firm_{T_{t_b};A_{t_b}} + \epsilon_{d;T;A}. \qquad (3)
\end{aligned}
$$

In equation (3), α_t stands for the year fixed effects, d stands for deal, T and A denotes Target and Acquirer, and t_b and t_a denotes the three-year window before the deal announcement and after deal completion. *Deal* characteristics include deal size, toehold, type of deal consideration, and deal attitude. *Innovation* characteristics include the target and the acquirer's R&D expenses and patent counts before the M&A. *Firm* characteristics include firm size, return on assets (ROA), and the book-to-market ratio. Variables from the target side will not be included when I run this regression with the sample of all M&As that include private targets.[13] The firm's post-deal innovation will be evaluated by three measures: level of patent output, shift of innovation, and development of new technology. The first measure corresponds to the firm's innovation quantity while the second and third measures correspond to the firm's innovation direction.

A. Level of Patent Output

I use the conventional patent count as the first measure of post-deal innovation performance in equation (3). In addition to the simple count of patents, I also calculate a normalized patent count by adjusting the number based on each patent's application year and technology classification to mitigate bias introduced by the truncation problem, patent office policy, or technological trends (Seru, 2014; Bena and Li, 2014; Lerner and Seru, 2017).

[13] Deal value is not included in this specification because many private deals do not disclose their deal values.

In particular, I first calculate the median number of patents across the innovative firms in each technology class k in year t. Then each patent count is scaled by its corresponding median value from the first step. The scaled number is then aggregated to the firm level with a time window (t_a) of three years after deal completion ($[y_c+1, y_c+3]$ where y_c denotes the year of deal completion). I report the regression results in Table II.

[Insert Table II here.]

To obtain the results reported in Table II columns (1) and (2) (or (3) and (4)), I use simple and normalized patent counts over the time window t_a as the dependent variables. Panel A results are based on all M&As including public and private deals, while Panel B results are based on only public deals. I first report the regression results in Panel A. The patent output level is positively correlated with the ex ante technological overlap, which indicates an economy of scale between high-overlap firms in the technology space. The coefficient on $CCS_{T_{t_b};A_{t_b}}$ ($TCS_{T_{t_b};A_{t_b}}$) ranges from 0.39 to 0.65 (1.09 to 1.85), which is statistically significant at 1%.[14] A one-standard-deviation increase in $CCS_{T_{t_b};A_{t_b}}$ ($TCS_{T_{t_b};A_{t_b}}$) implies the granting of 12.9%-21.4% (20.3%-34.4%) more patents after deal completion, which equals around 50-132 new patents. Panel B results display the same pattern. When the test sample is restricted to public M&As, the sample size decreases but I can include firm characteristics on the target side as control variables. These results reconfirm the conventional wisdom of synergy creation from high-overlap deals.

Among the other variables, the acquirer's pre-deal innovation capabilities positively predict its post-deal patent count at 1% statistical significance, as can be seen in both panels. In terms of economic magnitude, a 10% increase in the acquirer's pre-deal patent count implies the granting of 19%-24% more patents after deal completion. In addition, the acquirer's size and ROA are also positively correlated with the post-deal quantity of innovation. A

[14]Here, the ex-ante technological overlap between the target and the acquirer is denoted as $CCS_{T_{t_b};A_{t_b}}$ or $TCS_{T_{t_b};A_{t_b}}$. It represents the class-based or text-based cosine similarity between Target and Acquirer before an M&A.

10% increase in the acquirer's market capitalization (of approximately \$2 million on average) implies the granting of 1% more patents while a one-standard-deviation increase in the acquirer's ROA implies the granting of 11.1%-16.4% more patents for all M&As and 16.4%-24.9% more for public deals. These coefficients are intuitive, as a large and innovative acquirer is expected to achieve a higher patent output level after an M&A.

B. Innovation Shifts

In addition to the conventional measure of patent count, I focus on the direction of innovation by first evaluating ex-post technology shifts following completed deals. As mentioned in Section I.B.2, I can measure a firm f's degree of technology shift by calculating the cosine similarity between f's patent portfolios across time periods. Denote y_a as the year of the deal announcement and y_r as the year of deal resolution (when the deal is either completed or withdrawn). Then A_{t_b} represents the acquirer's patent portfolio within a three-year window prior to y_a, i.e. $[y_a - 3, y_a - 1]$, and A_{t_a} represents the new patent portfolio within a three-year window after y_r, i.e. $[y_r + 1, y_r + 3]$.[15] The acquirer's technology shift is thus negatively captured by the class-based (text-based) within-firm cosine similarity, $CCS^f_{A_{t_b};A_{t_a}}$ ($TCS^f_{A_{t_b};A_{t_a}}$).[16] Because cosine similarity is bounded between zero and one, I use $1 - CCS^f$ or $1 - TCS^f$ as the measure for the acquirer's ***Tech Shift***.

[Insert Figure 3 here.]

As illustrated in Figure 3, however, the acquirer's technology can undergo a "mechanical" shift if the M&A implies nothing more than what the two companies could have accomplished on their own. Therefore, it is economically meaningful to introduce a second measure of ***Tech***

[15]In the case of a successful M&A, this variable denotes the new patents of the merged company (target + acquirer) after deal completion while in the case of a failed M&A, it denotes the new patents of the acquirer alone. Distinguishing between successful and failed deals will be relevant to the analysis presented in Section IV.

[16]In the notation $CCS^f_{A_{t_b};A_{t_a}}$ ($TCS^f_{A_{t_b};A_{t_a}}$), the superscript f indicates that the variable measures the cosine similarity within one firm. The subscript A_{t_b} (A_{t_a}) denotes the Acquirer's patent portfolio before (after) the M&A.

Shift for the combined firm instead of the acquirer alone. This new measure is calculated by comparing the acquirer's post-deal patent portfolio against a pre-deal benchmark that combines the merging pair's patent portfolios. It is denoted as $1 - CCS^{f}_{(A+T)_{t_b};A_{t_a}}$ or $1 - TCS^{f}_{(A+T)_{t_b};A_{t_a}}$.

Table III investigates the key factors that affect technology shifting in either the acquirer or the combined firm through a cross-sectional regression, conditional on successful deals. In particular, I'm interested in how the ex-ante technological overlap between the merging companies is associated with the ex-post technology shift.

[Insert Table III here.]

For Table III, the dependent variable is the acquirer's or the combined firm's *Tech Shift*. The independent variables are class-based or text-based technological overlap, plus deal, innovation, and firm characteristics as controls. The results reported in Panel A are based on all M&As of public and private deals while those reported in Panel B are based only on public deals. For both panels, the key variable of interest, ex-ante technological overlap between the merging companies, has a negative and significant coefficient in all specifications. The result indicates that, when the ex-ante technological overlap is low, the ex-post degree of technology shift is high. Furthermore, by combining the merging companies' pre-deal patent portfolios as the benchmark, the coefficients reported in columns (3) and (4) show that a low-overlap pair of merging companies undergoes a larger technology shift that takes their innovation direction beyond what they could have accomplished on their own. A one-standard-deviation decrease in $CCS_{T_{t_b};A_{t_b}}$ ($TCS_{T_{t_b};A_{t_b}}$) boosts class-based (text-based) *Tech Shift* by 8.6-9.1 (8.0-8.1) percentage points, which accounts for around 21% of the average *Tech Shift* for the combined firm across the sample.

To better understand the economic magnitude of these results, I compare two deals from 2007 as an example in Appendix D. The first deal, between Philips and Color Kinetics, involves two firms with low technological overlap, which facilitates Philips's technology shift into LED.[17] The second deal, between Pfizer and Coley Pharmaceutical, is another conventional deal in the healthcare industry, and thus features a high-overlap acquirer and target. The difference in technological overlap is 1.2 standard deviations and Pfizer achieves a smaller technology shift than Philips by 36.6%.

With respect to deal, innovation, and firm characteristics, several variables are also significantly correlated with technology shift. The acquirer's R&D expense and its patent stock predict a smaller technology shift. A 10% decrease in the acquirer's patent count (of around 30 patents) boosts the dependent variable by 1.5-2.5 percentage points. This result is intuitive because it would be easier for a less innovative acquirer to achieve a larger technology shift. The acquirer's ROA also has negative and significant coefficients, as can be seen in both panels. This indicates that an ex-ante less profitable acquirer can undergo a larger technology shift ex post, which provides supportive evidence for destructive creation.

C. Development of New Technology

In the previous section, I constructed the pre-deal benchmark as a naive combination of the target and the acquirer. In reality, however, it is difficult to know exactly the extent to which developing new technology depends on the pre-deal knowledge bases of the target and the acquirer. In this section, I propose a new measure for the development of new technology based on the idea of orthogonality, which allows freedom of varying weights that the new technology can assign to the merging companies' existing knowledge bases.

[Insert Figure 4 here.]

[17] In 2000, researchers were focusing on improving the efficiency of LED to make it an option for general lighting. The U.S. Department of Energy wanted to partner with private industry to develop an ultra-efficient design for an LED and launched a competition, the L Prize, in 2008. During the same period of time, Philips began shifting its business and technology from semiconductors and televisions to healthcare and lighting. In the lighting business, the company also invested heavily in the research and development of LEDification. From 2005 to 2007, Philips acquired Lumileds, TIR Systems, and Color Kinetics to develop and strengthen its LED portfolio in the lighting industry. Through the M&As, Philips established a leading global R&D center for LED devices, headquartered in Boston. In late 2009, Philips took part in the L Prize and won the first one granted by the energy department, in 2011.

In technology-driven acquisitions, the acquirer often hopes to break new ground by combining the target's knowledge base with its own. Therefore, the new variable measures the freshness of technology development after deal completion by comparing the combined firm's post-deal innovation vector with the linear span of the two firms' pre-deal innovation vectors. In particular, I take the length of the orthogonal residual by projecting the post-deal innovation vector on the two pre-deal vectors from the target and the acquirer.[18] The top panel of Figure 4 provides the illustration of how I calculate this variable, $OrthogonalNorm$. The bottom panel is designed to facilitate a better understanding of $OrthogonalNorm$ through the example of Apple and iPhone. If we are able to create a vector representation for iPhones, touch screens, and cell phones as illustrated in the figure, the $OrthogonalNorm$ will capture the significance of the iPhone as an invention, which cannot be explained by a simple combination of a cell phone and a touch screen. With this new measure, I want to test the relationship of this combination with the ex-ante technological overlap as well as the other deal and firm characteristics.[19]

To obtain the results reported in Table IV, I conduct a similar cross-sectional test to regress $OrthogonalNorm$ on the ex-ante technological overlap between the acquirer and the target, plus deal, innovation, and firm characteristics. The Panel A results are based on both public and private deals while those reported in Panel B are based only on public deals. The coefficients on $CCS_{T_{t_b};A_{t_b}}$ or $TCS_{T_{t_b};A_{t_b}}$, in both panels, are negative and significant, indicating that when the target and the acquirer have low overlap in the technology space the combined firm will achieve more advanced development of fresh new technology after the M&A. A one-standard-deviation decrease in the ex-ante technological overlap boosts the development of new technology by 3.5-7.3 percentage points, which accounts for 5.9%-15.5% of the average $OrthogonalNorm$ across the M&A sample.[20] These results suggest that the

[18] I first normalize these vectors to unit length to focus on innovation direction instead of quantity.

[19] Beyond the measures developed from the class-based or text-based innovation vectors, I also follow the literature to calculate (1) the score of originality and generality and (2) the percentage of exploitative and exploratory patents for the combined firm's patent portfolio after deal completion. The regression results are reported in Appendix G Table XIII.

[20] Note that we need not worry about the mechanical relationship between $OrthogonalNorm$ and the ex-

combination of a low-overlap acquirer and target pair is more likely to give birth to fresh innovation that goes beyond what they could accomplish with a simple combination of their existing knowledge bases.[21] Again, the example provided in Appendix D can give us a better understanding of the economic magnitude of these effects. With higher technological overlap of 1.2 standard deviations, Pfizer's technology exploration is lower than Philips by 46.3%.

[Insert Table IV here.]

With respect to the other variables, the acquirer's patent stock is negatively correlated with the development of new technology, a result that is statistically significant at 1%. In terms of the economic magnitude, a 10% increase in the acquirer's patent count (of around 30 patents) reduces the development of new technology by 0.9-2.1 percentage points, which accounts for 1.5%-5.7% of the average $OrthogonalNorm$ across the M&A sample. This result is intuitive because, when the acquirer is highly innovative before the M&A, it becomes more difficult for the firm to develop an original patent or patent portfolio that is ***orthogonal*** to its pre-deal knowledge base.

D. Human Capital Mechanism

The analysis of ex-post innovation performance coresponding to the previous three tables presents a tradeoff between M&As with high and low technological overlap. High-overlap deals perform better in terms of innovation quantity while low-overlap deals perform better

ante technological overlap. If there is any, it will work against my regression results. As shown in Appendix E, higher technological overlap (or a smaller angle between CIV_T and CIV_A) is more likely to trigger a case of non-negative projection (as in the bottom panel) and thus generate a larger $OrthogonalNorm$ than in the normal case (as in the top panel), by geometry.

[21]One might be concerned about repeated M&As by large acquirers because the associated technology shift and exploration can be driven by a series of M&As while the regression here treats each deal separately. To alleviate this concern, I adopt three strategies. First, I run the same regressions in Tables II, III, and IV with acquirers of small market capitalizations – these small acquirers are much less likely to be involved in repeated M&As. The results still hold. Second, I shorten the estimation window for the firm's patent portfolio to two years and pool any subsequent M&As from the same acquirer within one year and treat them as one large deal. While the strategy does not entirely rule out all the repeated M&As, it mitigates the concern as the main results still hold. Third, I construct the post-deal innovation vector by only considering the patents that involve at least one target inventor to make sure that the target company is part of the innovation process after deal completion. The results still hold.

in terms of innovation direction. As I can utilize the detailed inventor-level information for each patent, I study the underlying mechanism from the human capital perspective.

Following Bernstein (2015) and Brav et al. (2018), I classify each inventor of the new patents after deal completion into three categories – 1) the target inventor, who works originally for the target company before the M&A, 2) the acquirer inventor, who works for the acquirer before M&A, and 3) the new inventor, who starts working for the combined firm after the M&A.[22] Based on these three categories, I develop two measures, *Collaboration* and *Freshness*, which correspond to the structure of the research team after deal completion.

On the patent level, I define *Collaboration* as the fraction of new patents that involves at least one target inventor and one acquirer inventor. This variable measures how much of the ex-post technology development can be attributed to communication between the merging companies' original research teams. On the inventor level, I define *Freshness* as the fraction of new inventors associated with the combined firm's patent portfolio after deal completion. This variable indicates the extent to which the combined firm invests in human capital to develop new technology. A simple illustration of these two measures can be found in Appendix F. To obtain the results reported in Table V, I regress these two variables on the ex-ante technological overlap plus the other deal, innovation, and firm characteristics.

[Insert Table V here.]

The results reported in columns (1) and (2) of Table V show that the ex-post *Collaboration* is positively associated with the ex-ante technological overlap. This result indicates that, when the merging companies are technologically high-overlap, there is more communication between their original research teams after they merge, which serves as a channel for the economy of scale that I observe in section II.A. On the other hand, the results reported in columns (3) and (4) show that *Freshness* in the combined firm's research team is negatively

[22] The drawback to this approach is that we can observe an inventor-company link only when the inventor files a successful patent grant with the company. In addition, due to the restriction on the current inventor data from Harvard, I have to restrict the sample to 1985-2010. The results will be updated with the newly collected high-quality inventor data from PatentsView.

associated with the merging companies' technological overlap. Consistent with my findings in sections II.B and II.C, low-overlap companies hire new inventors to achieve technology shifting and to explore fresh new areas.

III. Incentives for M&As in the Innovation Process

In this section, I study the ex-ante incentives behind an innovation-driven deal with high or low overlap, in two steps. In the first step, I use a predictive regression to identify the ex-ante determinants of a deal's technological overlap. Based on these determinants, I summarize the ex-ante motivations for deals between technologically high-overlap firms and deals between technologically low-overlap firms. In the second step, I present supportive evidence by drawing a distinction between a patent's scientific value and its commercial value.

A. Predicting a Deal's Technological Overlap

I first predict the technological overlap of each deal using various innovation and firm characteristics of the the acquirer and the target. For Table VI, the dependent variable is either $CCS_{T_{t_b};A_{t_b}}$ or $TCS_{T_{t_b};A_{t_b}}$ and the independent variables consist of all the firm and innovation characteristics presented in Table I.

[Insert Table VI here.]

For private deals, as can be seen in columns (1) and (2), the acquirer's R&D expense positively predicts technological overlap. A high-overlap pair of firms merge when the acquirer is investing heavily in innovation activities. One might worry that this relationship is mechanical because more innovative acquirers are supposed to be more likely to overlap with targets in certain technology fields. Nevertheless, the coefficients on the patent count of the acquirer and the target are neither positive nor significant, a result that can mitigate this concern. Interestingly, the acquirer's market capitalization negatively predicts technological overlap. This finding appears to be consistent with anecdotal evidence that large, stale companies seeking technology shifting through low-overlap acquisitions.

For public deals, as can be seen in columns (3) and (4), the target's R&D expense positively predicts the deal's technological overlap while the target's ROA negatively predicts the overlap. On the one hand, high-overlap M&As are more likely to involve innovative targets. On the other hand, low-overlap M&As are more likely to involve high-profitability targets. In all four specifications, the same industry dummy has a positive and significant coefficient.

Based on these results, Table VI can be interpreted as a two-sided story. On the one hand, if I focus on what predicts a deal with low technological overlap, I find that a low-overlap merger happens more frequently between merging companies from different industries, especially when the target is profitable and enjoys a high ROA. This result suggests that low-overlap M&As are motivated by profitability concerns - the acquirer aims to transform itself by moving into new and profitable areas. On the other hand, a high-overlap merger is more likely to be associated with two R&D-intensive companies in which the target is financially distressed. This is apparently a motive related to technology concerns – the acquirer values the target's innovation potential despite its poor financial performance.

The partnership between ARM and Apple formed in the 1990s offers a good example of the technology-driven motivation. At the time, ARM was struggling financially although its chip design (which was completely different from Intel's and required much less space and energy consumption) was extremely advanced and valuable.[23] In hindsight, many commentators today argue that if Apple had not saved ARM's technology in the 1990s, we would not have been able to enjoy smartphones or other mobile devices that rely heavily on ARM.

[23] The example is not perfect because it was not a standard M&A. Apple invested in an approximately 40% stake in ARM.

B. Scientific Value vs. Economic Value

To support the above arguments regarding technology concerns and profitability motives, I further utilize the distinction between a patent's scientific value and its commercial (or economic) value and examine how these two measures interact with the technological overlap between the merging companies.

While a patent's scientific value is usually measured by counting future citations, Kogan et al. (2017) propose a novel way to capture a patent's commercial value by measuring the firm's stock market reaction around the patent grant date. After I match my data with their measures, I use two dependent variables to obtain the results reported in Table VII, the per-patent scientific value and the per-patent commercial value of the combined firm's new patents after deal completion, and regress them on the ex-ante technological overlap, plus deal, innovation, and firm characteristics as controls. To avoid truncation bias, I also apply the same normalization method used in section II.A to obtain the results reported in columns (3) and (4).

[Insert Table VII here.]

Kogan et al. (2017) show that the scientific value of a patent is positively correlated with its commercial value in the universe of all patents. In Table VII Panel A, however, I report coefficients with signs opposite to those reported in Panel B. The (three out of four) positive and significant coefficients in Panel A indicate that high technological overlap is associated with patents of higher average scientific value, a finding that seems to be consistent with the technology concerns – high-overlap merging companies delve more deeply into their previous technology fields. Alternatively, the (two out of four) negative and significant coefficients in Panel B indicate that low technological overlap is associated with patents of higher average commercial value, a finding that is consistent with profitability motives – low-overlap merging companies explore new technology fields with higher commercial potential.

IV. Identifying the Effects of M&As

In this section, I identify the effects of an M&A on a firm's innovation process by comparing completed deals with "exogenously" withdrawn deals. The previous conditional analyses of successful deals establish the importance of innovation direction for understanding the process of technology development before and after M&As, especially those between firms with low technological overlap. The acquirer's interest in a low-overlap target, however, implies that the acquirer could have shifted its technology in the absence of an M&A. Therefore, to address this endogeneity concern, this section focuses in particular on the role of an M&A in causally shaping a firm's innovation from the perspective of technology shift and transformation.

One major challenge that arises when identifying the impact of M&A on innovation is the endogenous selection issue. Firms can be self-selected into the treatment group (i.e. participating in M&As) as a result of technology concerns. Therefore, comparing the average innovation activities of merged firms with those of the rest could lead to biased estimates. To mitigate this selection issue, Seru (2014) first proposes constructing a control sample of bids that fail for reasons exogenous to innovation. In this way, the assignment of M&A deals into the treatment and control groups should be orthogonal to innovation, which is the outcome variable in which we are interested.[24]

[Insert Table VIII here.]

I start with the sample of withdrawn deals and find 172 failed public M&As with innovative targets and innovative acquirers from 1985 through 2014. I end the sample period in 2014 to mitigate truncation bias in the post-merger analysis as it usually takes about three years for the USPTO to approve or reject a patent application. For each deal, I search for news and filings that report the reasons for failure via Factiva, Google, and Edgar. I then

[24]Bena and Li (2014) conduct a similar exercise to study the effects of M&As on the number of new patent grants. Bernstein (2015) utilizes a sample of withdrawn IPOs to examine the impact of IPO on innovation.

classify the reasons for failure into eight categories. Table VIII provides a detailed breakdown on how the 172 deals fall into these categories. Competing bids, objections raised by regulatory bodies, and adverse market conditions are the three reasons for failure that I deem exogenous to innovation. I further require that the acquirer have at least one patent during a three-year window t_a after deal resolution, that is, $[y_w+1, y_w+3]$, where y_w denotes the year a deal is withdrawn, because it requires a post-deal patent portfolio to estimate the innovation direction for the failed deals. These criteria yield a control sample of 60 deals.[25]

To facilitate the quasi-experiment, I need a treatment sample built from friendly completed deals. For each deal in the control sample, I select the candidates for the treatment sample by requiring that (i) both members of the merger pair be innovative, (ii) the deal is completed before 2014, (iii) the industries of both the target and the acquirer match those in the control sample, and (iv) the deal is announced during the period $[y_a-1, y_a+1]$, where y_a denotes the announcement year of the deal in the control sample. After completing this step, 15 deals in the control sample cannot be matched with the same industry pair and required event window. This approach ensures that the candidate deals for the treatment sample are matched with the control sample with regards to industry composition and time series of an M&A wave, which are important factors in the M&A literature (Roberts and Whited, 2013). Among these candidates, I choose the one that is closest to the control sample in terms of ex-ante technological overlap between the merging companies. In this way, ex ante the treated deal and the control deal agree on industry composition, announcement date and technological overlap. Insofar as the reason for failure is exogenous to innovation, ex post the difference in innovation direction between the treatment group and the control sample can be attributed to the completion of M&As, which solves the identification challenge.[26]

[25]Note that a withdrawn deal is not equivalent to an unsold target. Especially among the withdrawn deals in the control sample, 77% fail because of competing bids. Often these target firms are successfully merged into a different acquirer shortly after the date of deal withdrawal. In fact, SDC usually codes the deal completion date of the competing bid as the deal withdrawal date of the failed bid. If the target merges with a new acquirer, it either disappears from the dataset or its post-merger patents cannot be separated from the new acquirer. Therefore, it is better to avoid estimating the target side after deal failure if one wants to investigate post-merger innovation activities.

[26]For a sanity check, I also regress an indicator of a successful deal on technological overlap and all the

More importantly, as pointed out in section II.B, the acquirer will have a "mechanical" shift if the two companies naively merge after deal completion. Therefore, I use two measures as dependent variables in the quasi-experiment. The first is the combined firm's technology shift, which is also used for columns (3) and (4) in Table III. The second is $OrthogonalNorm$, which is used for Table IV. The quasi-experiment essentially tests whether M&A completion facilitates technology shift to a greated extent than what the merging companies could have accomplished on their own.

A. Technology Shift in a Quasi-Experiment

In this section, I use the combined firm's *Tech Shift* as the dependent variable, as defined in section II.B. For completed deals, I compare the post-deal innovation vector with a pre-deal benchmark that is constructed from a naive combination of the target's and the acquirer's pre-deal patent portfolios. For failed deals, the pre-deal benchmark is constructed by the patent portfolio of the acquirer alone. I denote this variable as $1 - CCS^{f}_{(A+T)_{t_b};A_{t_a}}$ or $1 - TCS^{f}_{(A+T)_{t_b};A_{t_a}}$. Because the deals in the control sample are withdrawn for reasons that are exogenous to innovation, I can establish that an M&A successfully facilitates technology shift if the combined firm's *Tech Shift* is larger in the treatment sample than in the control sample.

In Table IX Panel A (B), I report the results of regressions in which the dependent variable is the class-based (text-based) *Tech Shift* for the combined firm. In both panels, for column (1) I regress the dependent variable on a dummy variable "*Completed*" that equals one if the deal is completed and zero otherwise; for column (2) I additionally control for the ex-ante technological overlap between the merging companies; for column (3) I control for both technological overlap and its interaction with the dummy variable "*Completed*."

[Insert Table IX here.]

other control variables within the test sample. Only the target's ROA can predict deal completion with a statistically significant coefficient.

As can be seen in column (1), I find that deal completion has a positive and significant effect on the combined firm's ***Tech Shift***. The mean and standard deviation of the class-based (text-based) ***Tech Shift*** are 0.47 (0.46) and 0.32 (0.27) if I compute ***Tech shift*** in the same way for all deals involving innovative firms, whether completed or withdrawn.[27] The results reported in Panel A (B) show that deal completion implies an increase of 0.4-0.6 (0.6-1.3) standard deviations in the class-based (text-based) ***Tech Shift***, which is significant both statistically and economically. To obtain the results reported in column (3), I control for ex-ante technological overlap and its interaction with "*Completed*." The negative and significant coefficient on the interaction term indicates that the effect of M&A completion on the combined firm's technology shift is pronounced for low-overlap merging companies, which is consistent with the findings I report in section II.B. More importantly, if we compare this coefficient with the corresponding coefficients of CCS or TCS in Table III, the quasi-experiment yields a coefficient of larger magnitude. This result is intuitive because the acquirer and the target are never randomly paired – the acquirer will probably experience some pre-shifting in its technology before it finds the right target. The shift observed before and after deal completion will then be downward-biased if we do not control for the acquirer's pre-shift. Therefore, I find a coefficient of larger magnitude in Table IX after the quasi-experiment eliminates this bias by comparing two companies both of which intend to acquire a target.

B. Orthogonal Norm in a Quasi-Experiment

In this section, I replace the dependent variable used for Table IX with $OrthogonalNorm$, which is defined in Table IV. I examine whether an M&A leads to development of fresh new technology that cannot be explained by the knowledge bases of the merging companies. Similarly, the key independent variables include a dummy variable "*Completed*" that equals one if the deal is completed and zero otherwise, the ex-ante technological overlap between

[27]The correlation between the class-based measure and the text-based measure is 0.59.

the merging companies, and an interaction term for the above two variables. In Table X I report the regression results.

[Insert Table X here.]

In almost all of the specifications, the coefficients of the *Completed* dummy are positive and significant at 5%-10%. This finding implies that successful M&As promote the development of fresh technology to a greated extent than failed deals. The standard deviation for either class-based or text-based $OrthogonalNorm$ is around 0.3. The results reported in column (3) indicate that deal completion implies an increase of 0.3-0.5 standard deviations. As can be seen in Panel A, for which the regression is based on technology classifications, I also find a negative and significant coefficient for the interaction term. The corresponding coefficient reported in Panel B is negative and insignificant. Combining the results reported in Tables IX and X, I conclude that M&A completion facilitates the firm's technology shift and transformation to a greater extent than the merging companies could have accomplished on their own.

V. Conclusion

This paper studies the relationship between a firm's innovation process and M&A. I first document an interesting relationship between the ex-ante technological overlap of the merger pair and the combined firm's ex-post technology development. Technologically low-overlap companies achieve larger technology shifts and, moreover, they are more likely to dive into new technology fields that are "orthogonal" to their previous research areas. In contrast, technologically high-overlap companies produce more innovation in the quantitative sense. Evidence from inventor data suggests that more collaboration between researchers from merging companies occurs in high-overlap deals and that there is a higher percentage of new inventors in low-overlap deals. I then summarize the drivers of low-overlap deals as profitability motives and the drivers of high-overlap deals as technology concerns. These findings are supported by a comparative analysis of the commercial value and the scientific value of new patents after deal completion. Using a quasi-experiment, I show that a successful merger will facilitate a firm's technology transformation to a greater extent than the merging companies could have accomplished on their own.

The research fits into a broader framework that studies the tradeoff between "proximity" and "distance" in many economic activities. Proximity usually implies more frequent incidence (quantity) while distance often implies larger change or impact (quality). Similar patterns are found regarding home bias in the asset management literature (Lewis, 1999), the comparison of hard and soft information in the banking literature (Liberti and Petersen, 2019), and the pattern of coauthoring networks in the labor economics literature (Freeman and Huang, 2015).[28] In this paper, I investigate the tradeoff faced by firms in the M&A market between choosing a distant or proximate partner in the technology space.

Investigating technology development through the M&A lens, my paper sheds light on how "combinatory play" gives birth to fresh research and new ideas. With the availability of high-quality data on patents and inventors, we can focus directly on the collaboration pattern at the inventor level. Guided by theoretical work on organizational economics, empirical questions such as what drives inventor networks within firms and the consequences of certain network structures for collaboration represent interesting directions for future research.

[28] It is interesting that the relationship is found to be opposite in the banking literature. Local banks have high-quality information about local populations (through soft information) and thus manage better portfolios of local loans, while nonnative banks have standardized hard information and thus manage larger portfolios.

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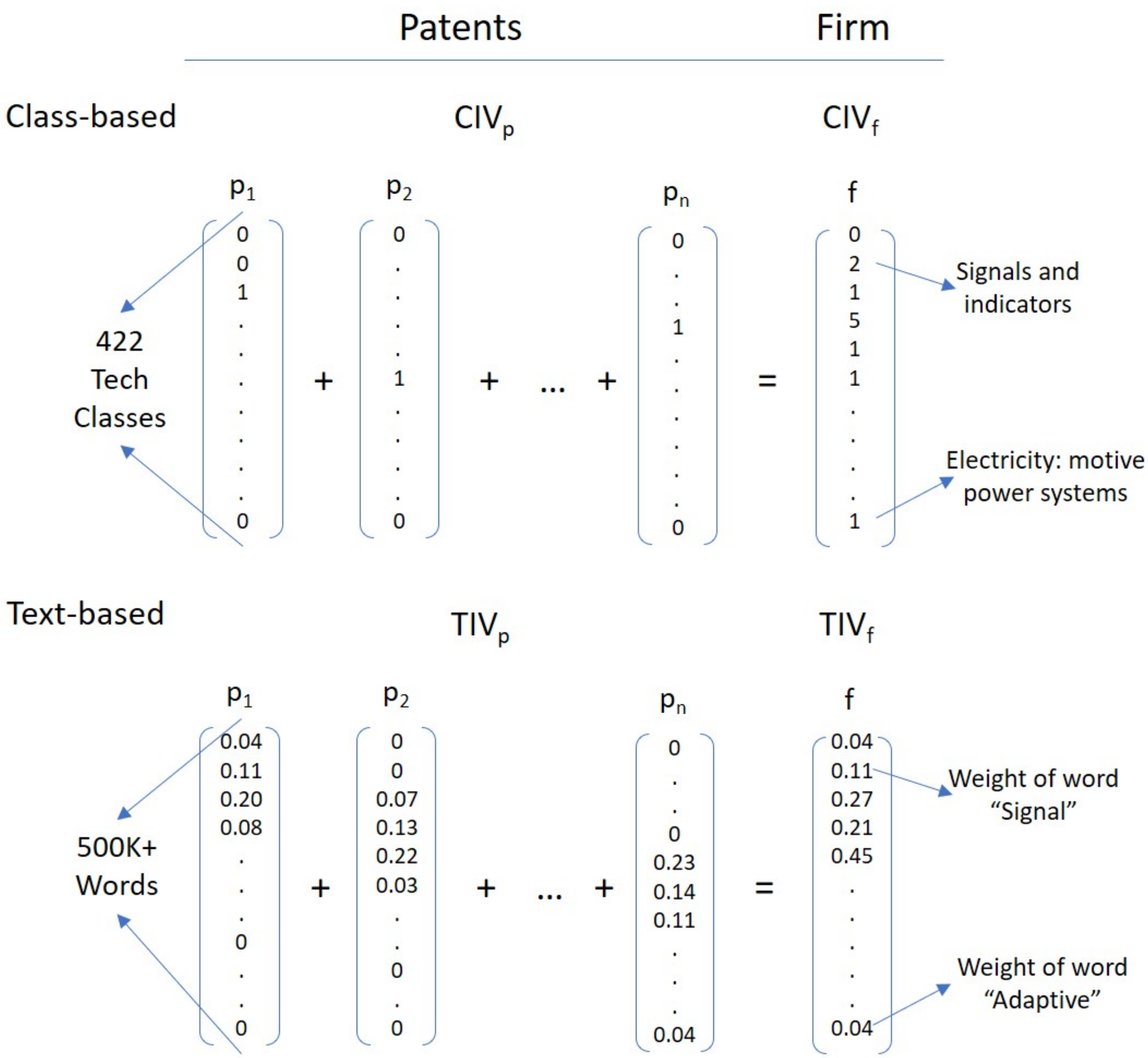


Figure 1. Comparison of CIV and TIV. This figure illustrates how I construct CIV_f and TIV_f based on technology classifications and patent filing texts, respectively.

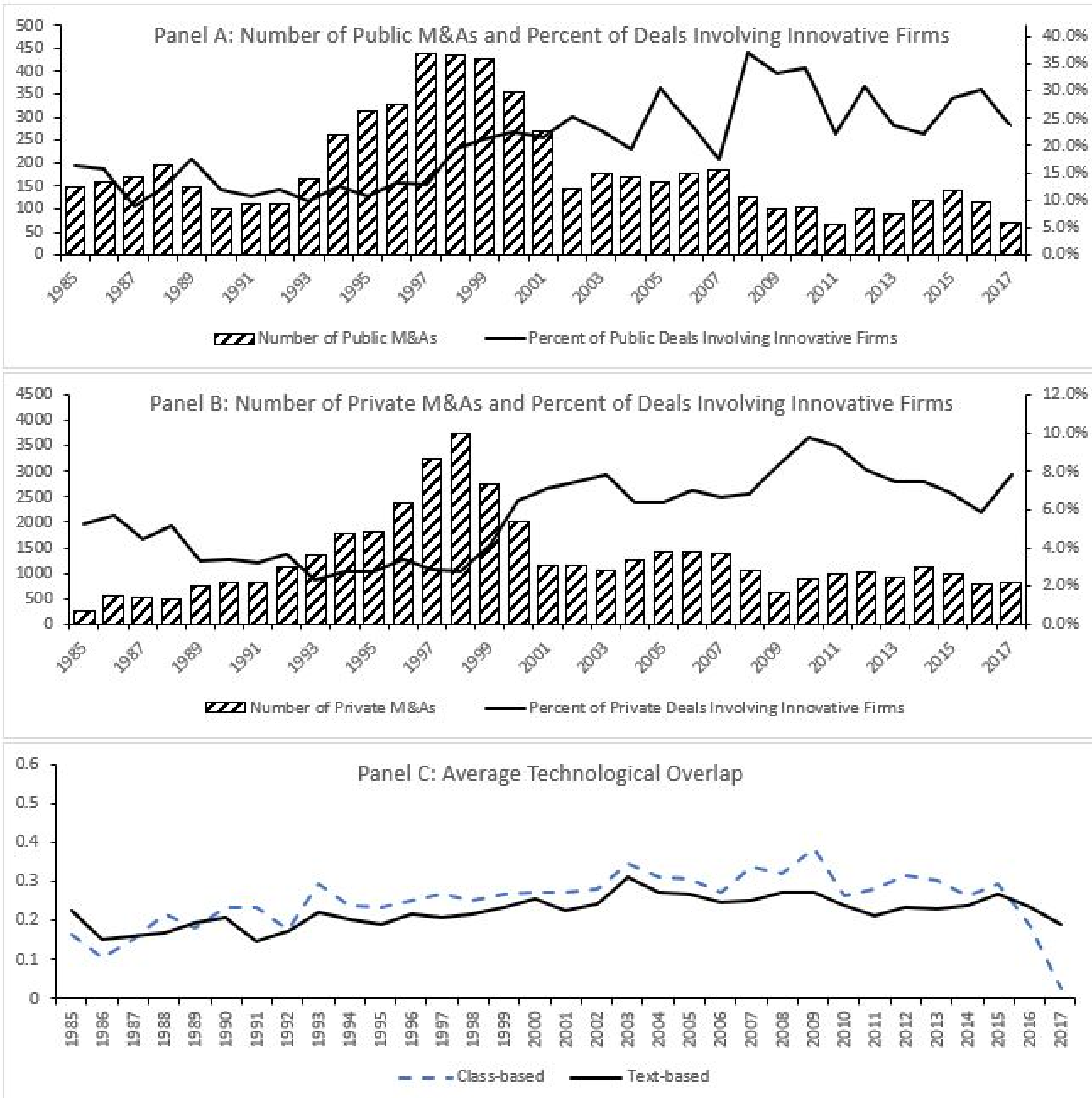


Figure 2. M&A Trends Involving Innovative Firms. This figure shows trends in public and private M&As involving innovative firms from 1985 through 2017. Public M&As are deals between public acquirers and public targets while private M&As are deals between public acquirers and private targets. Panel A plots the number of completed public M&As (on the left axis) and the percentage of public deals that involve innovative firms (on the right axis). Panel B plots the number of completed private M&As (on the left axis) and the percentage of private deals that involve innovative firms (on the right axis). Panel C plots the average technological overlap for deals that involve innovative firms from 1985 through 2017.

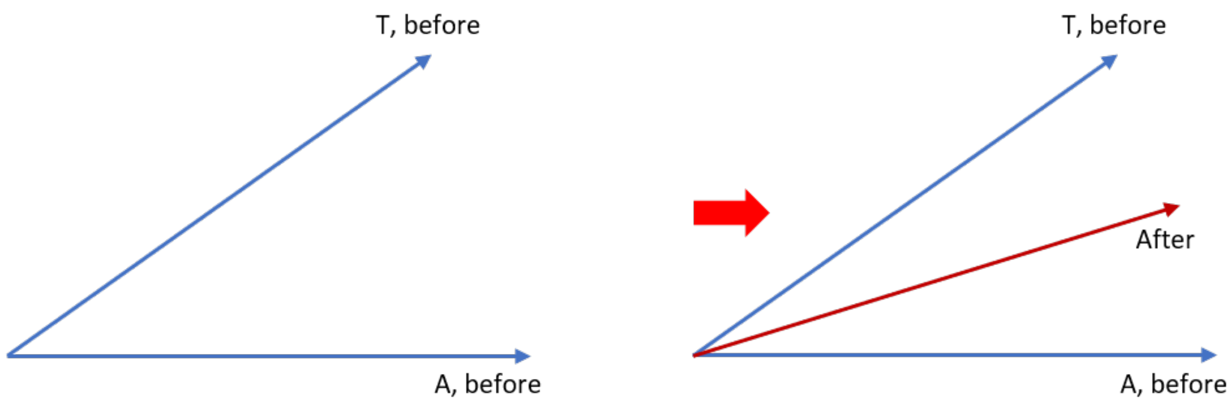


Figure 3. A Naive Combination. This figure illustrates the acquirer's "mechanical" technology shift that is implied by what the merging companies could have accomplished on their own.

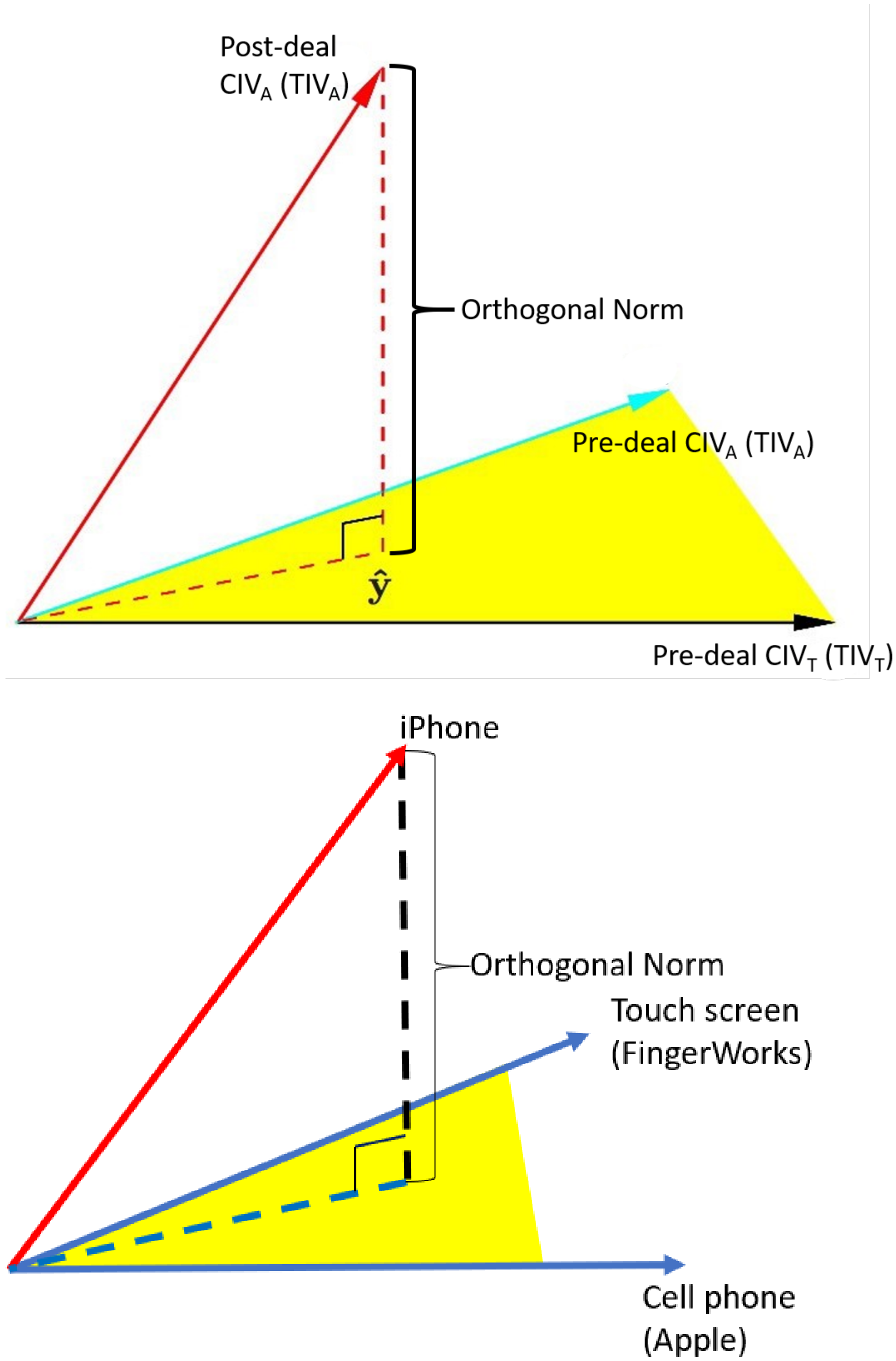


Figure 4. Illustration of $\boldsymbol{OrthogonalNorm}$**.** The top panel illustrates how I construct the $OrthogonalNorm$ variable from innovation vectors before and after deal completion. The bottom panel illustrates an example in which the significance of the iPhone can be measured by combining cell phones and touch screens (from FingerWorks).

Table I

Summary Statistics

In this table I compare innovative deals with all other deals in a universe of completed M&As from 1985 through 2017 with reference to deal and firm characteristics. All variables are defined in Appendix C. In Panel A I report the summary statistics for all public M&As between public acquirers and public targets. In Panel B I report the summary statistics for all private M&As between public acquirers and private targets. In columns (1) and (2) I report the mean and standard deviation of each variables for innovative and non-innovative deals. In column (3) I report the average difference between (1) and (2) and its corresponding t-statistics. In addition, I also report the innovation characteristics for innovative deals.

Panel A:	(1)		(2)		(3)	
Public M&As	Innovative Deals		Non-innovative Deals			
	N = 994		N = 4,043			
	Mean	S.D.	Mean	S.D.	Diff	t-stat
Deal Characteristics:						
Deal Value in M	3,011.13	8,794.90	1,313.87	4,824.91	1,697.26	8.19
Toehold	0.01	0.04	0.01	0.05	-0.00	-2.21
Friendly	0.97	0.17	0.98	0.14	-0.01	-1.95
Stock Deal	0.29	0.45	0.37	0.48	-0.09	-5.07
Same Industry	0.61	0.49	0.68	0.47	-0.07	-4.44
Target's Firm Characteristics:						
Market Cap in M	2,210.59	6,807.17	952.00	3,589.36	1,258.59	8.05
Book-to-Market	0.49	0.52	0.70	0.64	-0.20	-9.26
ROA	0.02	0.26	0.06	0.20	-0.05	-6.04
Acquirer's Firm Characteristics:						
Market Cap in M	28,454.00	56,860.98	8,007.36	25,437.07	20,446.64	16.97
Book-to-Market	0.37	0.31	0.54	0.41	-0.17	-12.01
ROA	0.15	0.15	0.10	0.17	0.05	8.60
Target's Innovation:						
R&D Expense in M	47.51	90.66				
Patent	33.46	118.46				
Normalized Patent	8.82	25.77				
Acquirer's Innovation:						
R&D Expense in M	198.70	186.70				
Patent	331.60	1,190.57				
Normalized Patent	67.12	186.66				

Panel B: Private M&As	(1) Innovative Deals N = 2,131		(2) Non-innovative Deals N = 38,861		(3)	
	Mean	S.D.	Mean	S.D.	Diff	t-stat
Deal Characteristics:						
Deal Value in M	210.53	753.49	87.07	456.04	123.46	8.75
Toehold	0.00	0.03	0.00	0.03	0.00	3.08
Friendly	0.99	0.09	0.99	0.09	-0.00	-0.19
Stock Deal	0.11	0.32	0.12	0.33	-0.01	-0.83
Same Industry	0.51	0.50	0.54	0.50	-0.03	-2.53
Acquirer's Firm Characteristics:						
Market Cap in M	21,085.91	57,828.52	5,615.49	27,609.83	15,470.42	23.21
Book-to-Market	0.40	0.31	0.50	0.44	-0.10	-10.53
ROA	0.12	0.20	0.09	0.43	0.03	3.14
Target's Innovation:						
Patent	9.39	122.53				
Normalized Patent	2.44	19.00				
Acquirer's Innovation:						
R&D Expense in M	152.99	179.87				
Patent	371.09	1,700.29				
Normalized Patent	53.21	179.03				

Table II

Level of Patent Output after M&A

This table is based on the sample of completed deals with innovative targets and acquirers from 1985 through 2014. Panel A covers all public and private M&As while Panel B covers public M&As. The dependent variable for columns (1) and (3) is the logarithm of patent count after M&As while the dependent variable for columns (2) and (4) is the logarithm of normalized patent count (Bena and Li, 2014; Lerner and Seru, 2017). I use a time window of three years after deal completion, i.e. $[y_c + 1, y_c + 3]$. $CCS_{T_{t_b};A_{t_b}}$ or $TCS_{T_{t_b};A_{t_b}}$ denotes the technological overlap between target and acquirer before an M&A. The remaining variables are defined in Appendix C. In each column, we report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Public and Private M&As

Log of	(1) Patent Count	(2) Normalized Patent Count	(3) Patent Count	(4) Normalized Patent Count
$CCS_{T_{t_b};A_{t_b}}$	0.652***	0.393***		
	(8.04)	(6.07)		
$TCS_{T_{t_b};A_{t_b}}$			1.846***	1.087***
			(12.24)	(9.02)
Toehold	0.576	1.154**	0.518	1.126**
	(1.22)	(2.27)	(1.10)	(2.22)
Stock Deal	0.203***	0.027	0.159**	0.002
	(2.80)	(0.45)	(2.21)	(0.04)
Friendly	-0.250	-0.229	-0.154	-0.174
	(-1.30)	(-1.24)	(-0.81)	(-0.96)
Log(Acquirer's R&D Expense)	0.327***	0.191***	0.311***	0.181***
	(17.74)	(12.82)	(16.96)	(12.16)
Log(Acquirer's Patent)	2.461***	2.087***	2.361***	2.029***
	(37.58)	(28.91)	(37.31)	(28.51)
Log(Acquirer's Market Cap)	0.103***	0.093***	0.114***	0.100***
	(5.62)	(6.44)	(6.32)	(6.91)
Acquirer's Book-to-Market	-0.226***	-0.156**	-0.217**	-0.150**
	(-2.60)	(-2.19)	(-2.52)	(-2.09)
Acquirer's ROA	0.886***	0.627***	0.849***	0.604***
	(5.12)	(4.72)	(4.97)	(4.58)
Same Industry (SIC-2)	0.027	-0.032	-0.019	-0.057
	(0.51)	(-0.75)	(-0.36)	(-1.33)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	2815	2815	2815	2815
Adjusted R^2	0.63	0.64	0.65	0.64

Panel B: Public M&As

Log of	(1) Patent Count	(2) Normalized Patent Count	(3) Patent Count	(4) Normalized Patent Count
$CCS_{T_{t_b};A_{t_b}}$	0.948***	0.541***		
	(6.95)	(4.74)		
$TCS_{T_{t_b};A_{t_b}}$			1.929***	1.005***
			(8.12)	(4.85)
Log(Deal value)	-0.041	0.040	-0.062	0.030
	(-0.28)	(0.35)	(-0.41)	(0.26)
Toehold	1.209	1.814**	1.345	1.899**
	(1.38)	(2.35)	(1.48)	(2.36)
Stock Deal	0.040	-0.034	0.043	-0.029
	(0.36)	(-0.36)	(0.40)	(-0.31)
Friendly	-0.191	-0.204	-0.209	-0.215
	(-0.83)	(-1.02)	(-0.89)	(-1.08)
Log(Target's R&D Expense)	0.081*	0.015	0.061	0.006
	(1.82)	(0.38)	(1.34)	(0.16)
Log(Target's Patent)	0.589	0.985**	0.219	0.790*
	(1.22)	(2.17)	(0.47)	(1.79)
Log(Acquirer's R&D Expense)	0.244***	0.172***	0.238***	0.169***
	(6.84)	(5.72)	(6.64)	(5.57)
Log(Acquirer's Patent)	2.351***	1.974***	2.201***	1.897***
	(20.93)	(18.99)	(19.81)	(18.00)
Log(Target's Market Cap)	0.070	-0.012	0.067	-0.013
	(0.50)	(-0.11)	(0.46)	(-0.12)
Target's Book-to-Market	-0.032	-0.024	-0.066	-0.045
	(-0.42)	(-0.36)	(-0.88)	(-0.65)
Target's ROA	0.058	-0.125	0.001	-0.165
	(0.28)	(-0.74)	(0.00)	(-1.00)
Log(Acquirer's Market Cap)	0.103***	0.099***	0.124***	0.110***
	(2.98)	(3.63)	(3.64)	(3.99)
Acquirer's Book-to-Market	-0.024	-0.116	-0.056	-0.133
	(-0.17)	(-0.95)	(-0.39)	(-1.08)
Acquirer's ROA	1.585***	1.152***	1.344***	1.020***
	(4.86)	(4.46)	(4.15)	(3.95)
Same Industry (SIC-2)	-0.003	0.012	-0.022	0.007
	(-0.03)	(0.14)	(-0.23)	(0.09)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	883	883	883	883
Adjusted R^2	0.64	0.64	0.65	0.65

Table III

Technology Shift after M&A

This table is based on the sample of completed deals with innovative targets and acquirers from 1985 through 2014. Panel A covers all public and private M&As while Panel B covers public M&As. Columns (1) and (3) are based on technology classifications while columns (2) and (4) are based on patent texts. The dependent variable for columns (1) and (2) (columns (3) and (4)) is the *Tech Shift* for the acquirer (combined firm), calculated as one minus the cosine similarity between the combined firm's post-deal patent portfolio and the acquirer's (combined firm's) pre-deal patent portfolio. $CCS_{T_{t_b};A_{t_b}}$ or $TCS_{T_{t_b};A_{t_b}}$ denotes the ex-ante technological overlap between the target and the acquirer. The remaining independent variables are defined in Appendix C. In each column, I report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Public and Private M&As

	(1) One minus $CCS^f_{A_{t_b};A_{t_a}}$	(2) One minus $TCS^f_{A_{t_b};A_{t_a}}$	(3) One minus $CCS^f_{(A+T)_{t_b};A_{t_a}}$	(4) One minus $TCS^f_{(A+T)_{t_b};A_{t_a}}$
$CCS_{T_{t_b};A_{t_b}}$	-0.329***		-0.262***	
	(-17.89)		(-14.54)	
$TCS_{T_{t_b};A_{t_b}}$		-0.529***		-0.434***
		(-18.55)		(-15.81)
Toehold	-0.150	-0.093	-0.033	-0.061
	(-0.94)	(-0.64)	(-0.26)	(-0.65)
Stock Deal	-0.039**	-0.017	-0.027*	-0.015
	(-2.42)	(-1.34)	(-1.77)	(-1.26)
Friendly	-0.074**	-0.094***	-0.010	-0.015
	(-2.08)	(-3.15)	(-0.27)	(-0.45)
Log(Acquirer's R&D Expense)	-0.046***	-0.043***	-0.043***	-0.041***
	(-11.21)	(-11.97)	(-10.72)	(-11.83)
Log(Acquirer's Patent)	-0.201***	-0.239***	-0.154***	-0.187***
	(-15.00)	(-19.93)	(-13.49)	(-18.56)
Log(Acquirer's Market Cap)	-0.002	0.004	-0.007*	-0.003
	(-0.49)	(1.27)	(-1.91)	(-0.82)
Acquirer's Book-to-Market	0.079***	0.055***	0.050**	0.033**
	(3.74)	(3.28)	(2.29)	(1.97)
Acquirer's ROA	-0.094**	-0.119***	-0.081*	-0.106***
	(-2.08)	(-3.35)	(-1.87)	(-3.12)
Same Industry (SIC-2)	-0.014	-0.003	-0.021*	-0.008
	(-1.15)	(-0.36)	(-1.82)	(-0.91)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	2815	2815	2815	2815
Adjusted R^2	0.38	0.43	0.37	0.40

Panel B: Public M&As

	(1) One minus $CCS^f_{A_{t_b};A_{t_a}}$	(2) One minus $TCS^f_{A_{t_b};A_{t_a}}$	(3) One minus $CCS^f_{(A+T)_{t_b};A_{t_a}}$	(4) One minus $TCS^f_{(A+T)_{t_b};A_{t_a}}$
$CCS_{T_{t_b};A_{t_b}}$	-0.384***		-0.276***	
	(-12.55)		(-9.61)	
$TCS_{T_{t_b};A_{t_b}}$		-0.620***		-0.435***
		(-14.30)		(-10.66)
Log(Deal value)	0.012	0.007	0.032	0.017
	(0.37)	(0.21)	(1.01)	(0.56)
Toehold	-0.161	-0.036	-0.294	-0.236
	(-0.81)	(-0.26)	(-1.63)	(-1.53)
Stock Deal	-0.045*	-0.026	-0.013	-0.012
	(-1.93)	(-1.33)	(-0.63)	(-0.68)
Friendly	-0.060	-0.035	-0.022	0.020
	(-1.24)	(-0.85)	(-0.44)	(0.48)
Log(Target's R&D Expense)	0.000	0.006	-0.012	-0.010
	(0.04)	(0.86)	(-1.51)	(-1.36)
Log(Target's Patent)	0.055	0.166***	-0.016	-0.008
	(0.89)	(3.69)	(-0.25)	(-0.13)
Log(Acquirer's R&D Expense)	-0.030***	-0.032***	-0.022***	-0.026***
	(-3.86)	(-4.78)	(-2.95)	(-4.02)
Log(Acquirer's Patent)	-0.226***	-0.253***	-0.149***	-0.173***
	(-10.43)	(-12.34)	(-8.50)	(-10.32)
Log(Target's Market Cap)	0.001	0.005	-0.028	-0.008
	(0.02)	(0.15)	(-0.90)	(-0.26)
Target's Book-to-Market	0.033*	0.017	0.003	0.027*
	(1.73)	(1.25)	(0.15)	(1.72)
Target's ROA	0.072*	0.041	0.075*	0.004
	(1.67)	(1.15)	(1.87)	(0.13)
Log(Acquirer's Market Cap)	-0.006	-0.003	-0.015**	-0.009
	(-0.71)	(-0.40)	(-2.16)	(-1.54)
Acquirer's Book-to-Market	0.052	0.026	0.024	0.016
	(1.49)	(1.08)	(0.62)	(0.56)
Acquirer's ROA	-0.357***	-0.191***	-0.248***	-0.180***
	(-4.32)	(-2.90)	(-2.84)	(-2.76)
Same Industry (SIC-2)	-0.017	-0.025	-0.014	-0.006
	(-0.81)	(-1.44)	(-0.70)	(-0.38)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	883	883	883	883
Adjusted R^2	0.40	0.47	0.36	0.41

Table IV

Development of New Technology after M&A

This table is based on the sample of completed deals with innovative targets and acquirers. Panel A covers all public and private M&As while Panel B covers public M&As. Columns (1) and (2) are based on technology classifications and patent texts, respectively. The dependent variable is $OrthogonalNorm$, which is taken from the norm of the orthogonal part after I project the post-deal innovation vector on the pre-deal innovation vectors of the merger pair. $CCS_{T_{t_b};A_{t_b}}$ or $TCS_{T_{t_b};A_{t_b}}$ denotes the ex-ante technological overlap between the target and the acquirer. The remaining independent variables are defined in Appendix C. In each column, I report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Public and Private M&As

Dependent Variable: $OrthogonalNorm$	(1) Class-based	(2) Text-based
$CCS_{T_{t_b};A_{t_b}}$	-0.190***	
	(-10.77)	
$TCS_{T_{t_b};A_{t_b}}$		-0.185***
		(-6.80)
Toehold	-0.225	-0.168
	(-1.39)	(-1.26)
Stock Deal	-0.050***	-0.045***
	(-3.22)	(-3.29)
Friendly	-0.039	-0.024
	(-1.00)	(-0.80)
Log(Acquirer's R&D Expense)	-0.010**	-0.004
	(-2.38)	(-0.96)
Log(Acquirer's Patent)	-0.085***	-0.205***
	(-8.11)	(-24.52)
Log(Acquirer's Market Cap)	0.009**	0.006
	(2.15)	(1.63)
Acquirer's Book-to-Market	0.047**	0.033
	(2.07)	(1.62)
Acquirer's ROA	0.054	0.083**
	(1.32)	(2.13)
Same Industry (SIC-2)	-0.022*	-0.012
	(-1.89)	(-1.20)
Year Fixed Effects	Yes	Yes
Observations	2815	2815
Adjusted R^2	0.18	0.18

Panel B: Public M&As

Dependent Variable: *OrthogonalNorm*	(1) Class-based	(2) Text-based
$CCS_{T_{t_b};A_{t_b}}$	-0.213***	
	(-7.12)	
$TCS_{T_{t_b};A_{t_b}}$		-0.237***
		(-5.58)
Log(Deal value)	-0.042	-0.048**
	(-1.50)	(-1.99)
Toehold	-0.476**	-0.208
	(-2.22)	(-1.15)
Stock Deal	-0.065***	-0.069***
	(-2.95)	(-3.73)
Friendly	-0.024	0.028
	(-0.49)	(0.70)
Log(Target's R&D Expense)	0.003	-0.000
	(0.35)	(-0.04)
Log(Target's Patent)	-0.062	-0.052
	(-1.16)	(-1.01)
Log(Acquirer's R&D Expense)	0.007	0.001
	(0.96)	(0.21)
Log(Acquirer's Patent)	-0.094***	-0.191***
	(-5.29)	(-13.26)
Log(Target's Market Cap)	0.052*	0.060**
	(1.91)	(2.55)
Target's Book-to-Market	-0.028	-0.012
	(-1.26)	(-0.72)
Target's ROA	0.070	-0.036
	(1.55)	(-1.04)
Log(Acquirer's Market Cap)	-0.005	-0.003
	(-0.64)	(-0.49)
Acquirer's Book-to-Market	0.068*	0.064**
	(1.79)	(2.06)
Acquirer's ROA	-0.062	0.125
	(-0.63)	(1.46)
Same Industry (SIC-2)	-0.009	-0.002
	(-0.46)	(-0.12)
Year Fixed Effects	Yes	Yes
Observations	883	883
Adjusted R^2	0.15	0.23

Table V

Inventor Analysis

This table is based on the sample of completed public deals with innovative targets and acquirers from 1985 to 2010. Columns (1) and (3) are based on technology classifications while columns (2) and (4) are based on patent texts. The dependent variable for columns (1) and (2) is the percentage of new patents that involve at least one target inventor and one acquirer inventor. The dependent variable for columns (3) and (4) is the percentage of new inventors for the combined firm after deal completion. $CCS_{T_{t_b};A_{t_b}}$ or $TCS_{T_{t_b};A_{t_b}}$ denotes the ex-ante technological overlap between the target and the acquirer. In each column, I report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Collaboration	*Collaboration*	*Freshness*	*Freshness*
$CCS_{T_{t_b};A_{t_b}}$	0.003		-0.044**	
	(0.60)		(-2.05)	
$TCS_{T_{t_b};A_{t_b}}$		0.025**		-0.072**
		(2.13)		(-2.03)
Deal Controls	Yes	Yes	Yes	Yes
Innovation Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	696	696	696	696
Adjusted R^2	0.08	0.09	0.31	0.31

Table VI

Determinants of Technological Overlap

This table is based on the sample of completed deals with innovative targets and acquirers. Columns (1) and (2) are based on public and private M&As while columns (3) and (4) are only based on public M&As. The dependent variable is either the class-based or text-based technological overlap between the merging companies. The independent variables are defined in Appendix C. In each column, I report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Public and Private M&As		Public M&As	
	(1)	(2)	(3)	(4)
	$CCS_{T_{t_b};A_{t_b}}$	$TCS_{T_{t_b};A_{t_b}}$	$CCS_{T_{t_b};A_{t_b}}$	$TCS_{T_{t_b};A_{t_b}}$
Log(Acquirer's R&D Expense)	0.015***	0.014***	-0.000	0.002
	(2.79)	(4.94)	(-0.05)	(0.49)
Log(Acquirer's Patent)	-0.025*	0.028***	0.026	0.091***
	(-1.82)	(3.67)	(1.21)	(7.37)
Log(Target's R&D Expense)			0.036***	0.028***
			(3.55)	(4.65)
Log(Target's Patent)	-0.218***	0.006	-0.044	0.170***
	(-3.90)	(0.17)	(-0.75)	(3.60)
Log(Acquirer's Market Cap)	-0.013**	-0.013***	-0.016*	-0.019***
	(-2.33)	(-4.51)	(-1.91)	(-3.92)
Acquirer's Book-to-Market	-0.012	-0.029*	-0.007	0.013
	(-0.42)	(-1.78)	(-0.20)	(0.54)
Acquirer's ROA	0.058	0.019	-0.172*	0.040
	(1.23)	(0.74)	(-1.77)	(0.81)
Log(Target's Market Cap)			0.013	0.018***
			(1.37)	(3.11)
Target's Book-to-Market			-0.064***	-0.014
			(-2.83)	(-1.05)
Target's ROA			-0.232***	-0.083***
			(-4.45)	(-2.82)
Same Industry (SIC-2)	0.086***	0.044***	0.113***	0.066***
	(5.79)	(5.56)	(5.04)	(5.23)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	1921	1921	884	884
Adjusted R^2	0.03	0.06	0.12	0.22

Table VII

Scientific Value vs Economic Value

This table is based on the sample of completed public deals with innovative targets and acquirers from 1985 through 2010. The dependent variable for Panel A (B) is the logarithm of per patent citations (economic value from Kogan et al. (2017)) in columns (1) and (2) and normalized citations (economic value) in columns (3) and (4). Columns (1) and (3) are based on technology classifications while columns (2) and (4) are based on patent texts. In each column, I report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A	(1)	(2)	(3)	(4)
Log of	Scientific	Scientific	Normalized	Normalized
(Per Patent)	Value	Value	Scientific Value	Scientific Value
$CCS_{T_{t_b};A_{t_b}}$	0.182*		0.046	
	(1.84)		(0.60)	
$TCS_{T_{t_b};A_{t_b}}$		0.460***		0.269**
		(3.02)		(2.47)
Deal Controls	Yes	Yes	Yes	Yes
Innovation Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	667	667	667	667
Adjusted R^2	0.75	0.76	0.37	0.38
Panel B	(1)	(2)	(3)	(4)
Log of	Economic	Economic	Normalized	Normalized
(Per Patent)	Value	Value	Economic Value	Economic Value
$CCS_{T_{t_b};A_{t_b}}$	-0.103		-0.051	
	(-0.92)		(-0.45)	
$TCS_{T_{t_b};A_{t_b}}$		-0.581***		-0.370**
		(-3.17)		(-2.06)
Deal Controls	Yes	Yes	Yes	Yes
Innovation Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	667	667	667	667
Adjusted R^2	0.64	0.65	0.68	0.68

Table VIII

Reasons for Withdrawn Deals

This table reports the breakdown of reasons for withdrawn deals. For each deal, I search news sources around the deal withdrawal date via Factiva, Google, and Edgar. I then organize the reasons for deal failure into 8 categories. Five are related to innovation while the other three are exogenous to innovation.

Withdrawn Deals Involving Innovative Firms		172
Reasons exogenous to innovation:		
Blocked by regulatory bodies	12	
Competing bid	56	
Market condition	5	
Total		73
Reasons related to innovation:		
Disagreement over growth strategy	8	
Disagreement over restructuring	11	
Disagreement over valuation	24	
Negative news/unexpected legal actions	23	
Not enough information/expected to fail	33	
Total		99

Table IX

Technology Shift in Quasi-experiment

This table applies to the control sample of deals withdrawn for reasons exogenous to innovation and the treatment sample of completed deals that are carefully matched with the control sample. The dependent variable for Panel A (B) is one minus the class-based (text-based) cosine similarity between the patent portfolios of the acquirer after the M&A and a benchmark before the M&A. The benchmark is constructed from a naive combination of the target's and acquirer's pre-deal patent portfolios. *Completed* equals one if the deal belongs to the treatment sample and zero otherwise. $CCS_{T_{t_b};A_{t_b}}$ or $TCS_{T_{t_b};A_{t_b}}$ denotes the ex-ante technological overlap between the target and the acquirer. *Interaction* denotes the interaction term for the above two variables. *Friendly* is excluded from the deal controls because all deals in this test are friendly deals. In each column, I report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: $1 - CCS_{(A+T)_{t_b};A_{t_a}}$	(1)	(2)	(3)
Completed	0.169**	0.164**	0.278***
	(2.45)	(2.36)	(3.12)
$CCS_{T_{t_b};A_{t_b}}$		-0.235**	0.004
		(-2.01)	(0.02)
Interaction			-0.441*
			(-1.99)
Deal Controls	Yes	Yes	Yes
Innovation Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Observations	82	82	82
Adjusted R^2	0.06	0.11	0.13
Panel B: $1 - TCS_{(A+T)_{t_b};A_{t_a}}$	(1)	(2)	(3)
Completed	0.149***	0.182***	0.350***
	(2.85)	(3.41)	(3.56)
$TCS_{T_{t_b};A_{t_b}}$		-0.439***	-0.004
		(-2.72)	(-0.02)
Interaction			-0.678**
			(-2.05)
Deal Controls	Yes	Yes	Yes
Innovation Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Observations	90	90	90
Adjusted R^2	0.24	0.32	0.34

Table X

Orthogonal Norm in Quasi-experiment

This table applies to control sample of deals withdrawn for reasons exogenous to innovation and the treatment sample of completed deals that are carefully matched with the control sample. The dependent variable for Panel A (B) is class-based (text-based) $OrthogonalNorm$, which is defined in Table IV. *Completed* equals one if the deal belongs to the treatment sample and zero otherwise. $CCS_{\mathsf{T}_{t_b};\mathsf{A}_{t_b}}$ or $TCS_{\mathsf{T}_{t_b};\mathsf{A}_{t_b}}$ denotes the ex-ante technological overlap between the target and the acquirer. *Interaction* denotes the interaction term for the above two variables. *Friendly* is excluded from the deal controls because all deals in this test are friendly deals. In each column, I report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Class-based $OrthogonalNorm$	(1)	(2)	(3)
Completed	0.139**	0.018	0.114*
	(2.39)	(0.32)	(1.78)
$CCS_{\mathsf{T}_{t_b};\mathsf{A}_{t_b}}$		-0.504***	-0.274**
		(-4.62)	(-2.37)
Interaction			-0.412**
			(-2.20)
Deal Controls	Yes	Yes	Yes
Innovation Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Observations	82	82	82
Adjusted R^2	0.06	0.28	0.33

Panel B: Text-based $OrthogonalNorm$	(1)	(2)	(3)
Completed	0.073*	0.091**	0.150*
	(1.74)	(2.08)	(1.87)
$TCS_{\mathsf{T}_{t_b};\mathsf{A}_{t_b}}$		-0.221	-0.063
		(-1.62)	(-0.26)
Interaction			-0.244
			(-0.89)
Deal Controls	Yes	Yes	Yes
Innovation Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Observations	90	90	90
Adjusted R^2	0.34	0.35	0.36

Appendix A. An Illustration of a Brief Summary

Patent Number: 7,431,596 **Title:** Connector assembly with mold removal hole
Abstract: A connector has a first housing (1) and a second housing (2) with a receptacle (4) for receiving the first housing (1)……
Inventor, Assignee, Date, etc.
Description: BACKGROUND OF THE INVENTION Description of the Related Art **Brief Summary** SUMMARY OF THE INVENTION BRIEF DESCRIPTION OF THE DRAWINGS DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

Appendix B. Text-based Innovation Vector

I first build a dictionary from the set of unique words that patent applicants use in brief summaries in patent filings with the USPTO. I choose brief summaries simply because the size of the text is fairly manageable, at around 15 gigabytes, which reduces the time and effort involved in data processing and computation.[29] I first eliminate stop words.[30] In addition, I filter out words that appear extremely infrequently (fewer than 5 times in all the patent filings) or extremely frequently (in more than 90% of the patent filings), and stem the remaining words (i.e. removing suffixes) to improve the signal-to-noise ratio (Gentzkow et al., 2019). These filters reduce the size of the dictionary from 2,106,582 words to 529,354 words.

After building the dictionary, I convert all the text descriptions into a corpus matrix, denoted as C. Each row of C corresponds to a patent description while each column of C corresponds to a word in the dictionary. Therefore, the dimensions of C are $5,937,953 \times 529,354$ (number of patent filings in the PatentsView database $\times$ number of unique words in the dictionary). Each element of C, denoted as $c_{p;w}$, counts the number of times a given word (w) in the dictionary appears in a given patent description (p).

The key consideration in constructing the ***text-based innovation vector*** depends on how each word is weighted by its importance. In textual analysis, the "term frequency inverse document frequency" (TF-IDF) approach is effective for emphasizing words that are more informative about the topic of a document. The transformation is as follows:

$$TFIDF_{pw} \equiv TF_{pw} \times IDF_{w}. \tag{B1}$$

The first component TF_{pw} denotes term frequency and is defined as:

$$TF_{pw} \equiv \frac{c_{pw}}{\Sigma_k c_{pk}}, \tag{B2}$$

[29]The size of the detailed description for my patent data is approximately 150 gigabytes.
[30]I use the stop-word list complied by NLTK, `https://www.nltk.org/book/ch02.html`

which means that the term frequency of word w in patent p equals the word count of w divided by the total number of words in p. The second component in equation (B1), IDF_w, denotes inverse document frequency and is defined as:

$$IDF_w \equiv \log\left(\frac{\text{Number of patents}}{\text{Number of patents containing word } w}\right). \tag{B3}$$

IDF_w under-weighs the word w if it appears in many patents because such a common word should contain less information about the topic of a patent.

The product of these two components, $TFIDF_{pw}$, measures the relative importance of word w in patent p. $TFIDF_{pw}$ is high when word w appears frequently in patent p but it does not appear in many other patents. With this TF-IDF transformation, the innovation vector of each patent p is constructed as a vector of the same length as the dictionary (529,345 elements) where each element equals $TFIDF_{pw}$ for the corresponding word w. Note that the text-based innovation vector is a sparse vector, as the typical length of brief summary for a patent after text cleaning ranges from 100 to 400 unique words. For any word w that does not appear in patent p, $TFIDF_{pw} = 0$. To eliminate the impact of text length, I normalize the vector to a unit norm and define it as the text-based innovation vector (TIV_p) for patent p. Following the same logic as I followed for the class-based measure, the text-based innovation vector (TIV_f) for firm f's patent portfolio is calculated as $\Sigma_p TIV_p$ for each patent p that belongs to firm f.

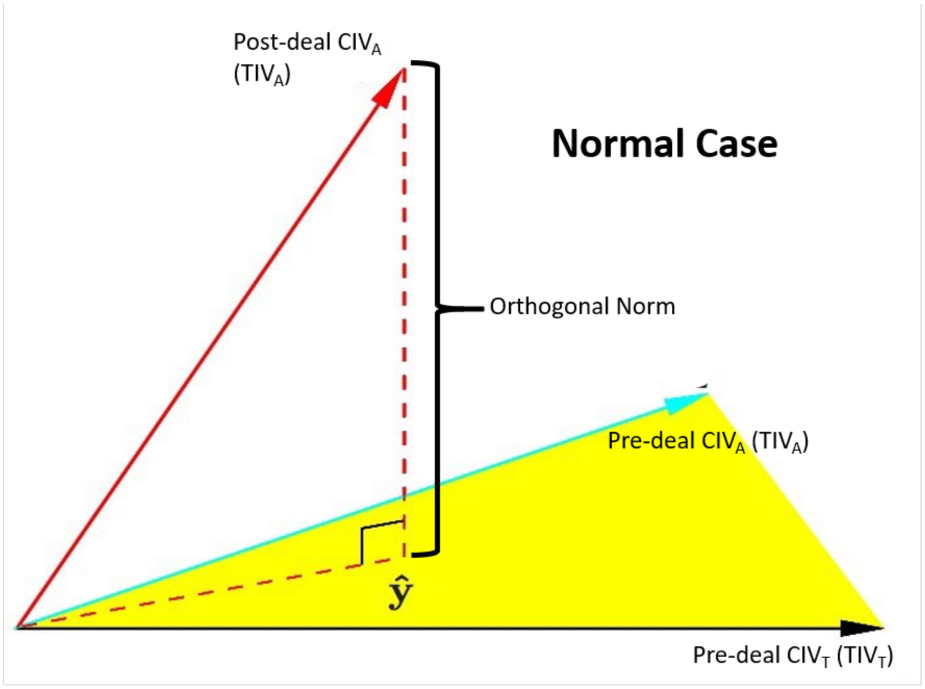
Appendix C. Variable Definitions

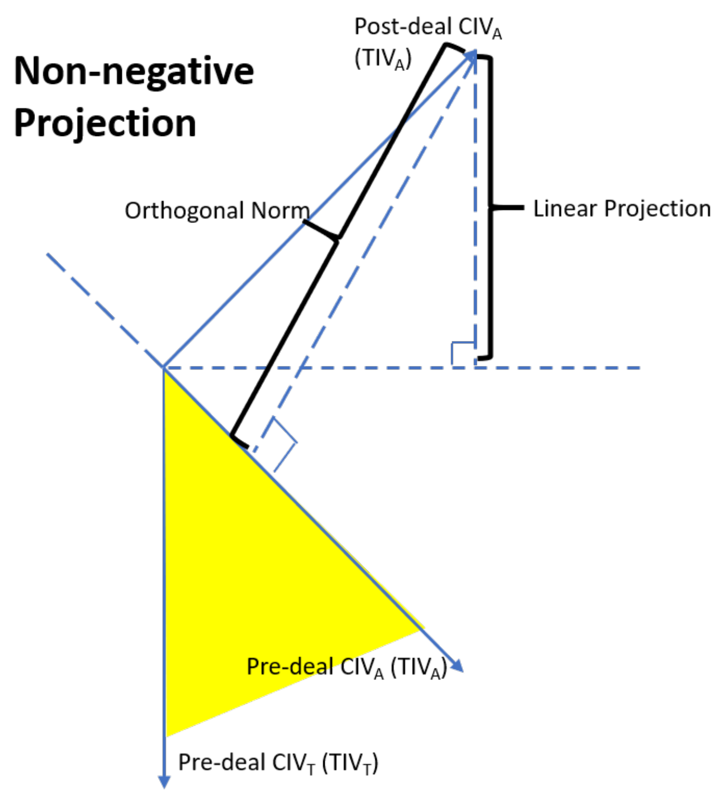
Variables	Definition
Deal Characteristics:	
Deal value in M	The total value of consideration paid by an acquirer, excluding fees and expenses, in millions.
Toehold	The percentage of target shares held by an acquirer prior to an announcement.
Friendly	A dummy variable that equals zero if a target company resists or receives an unsolicited offer, as reported in the SDC and one otherwise.
Stock deal	A dummy variable that equals one if a deal is a pure stock offer and zero otherwise.
Same industry	A dummy variable that equals one if a target and an acquirer are in the same two-digit SIC industry and zero otherwise.
Firm Characteristics:	
Market Cap in M	The value of a firm's market capitalization before a deal announcement, in millions.
Book-to-Market	A firm's book-to-market ratio, calculated at the fiscal year end before a deal announcement.
ROA	The ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) scaled by lagged assets, calculated at the fiscal year end before a deal announcement.
Innovation Characteristics:	
R&D Expense in M	A firm's research and development expense at the fiscal year end before a deal announcement, in millions.
Patent	The number of granted patents whose application years fall into $[y_a - 3, y_a - 1]$, where y_a denotes the year of a deal announcement.
Normalized Patent	First, I calculate the median number of patent counts across all the innovative firms in each technology class k in year y. Second, each patent count is scaled by its corresponding median value from the first step. Third, the scaled number is then aggregated at the firm level with a time window (t_b) of three years before a deal announcement ($[y_a - 3, y_a - 1]$, where y_a denotes the year of a deal announcement).

Appendix D. An Example: Comparing Two Deals

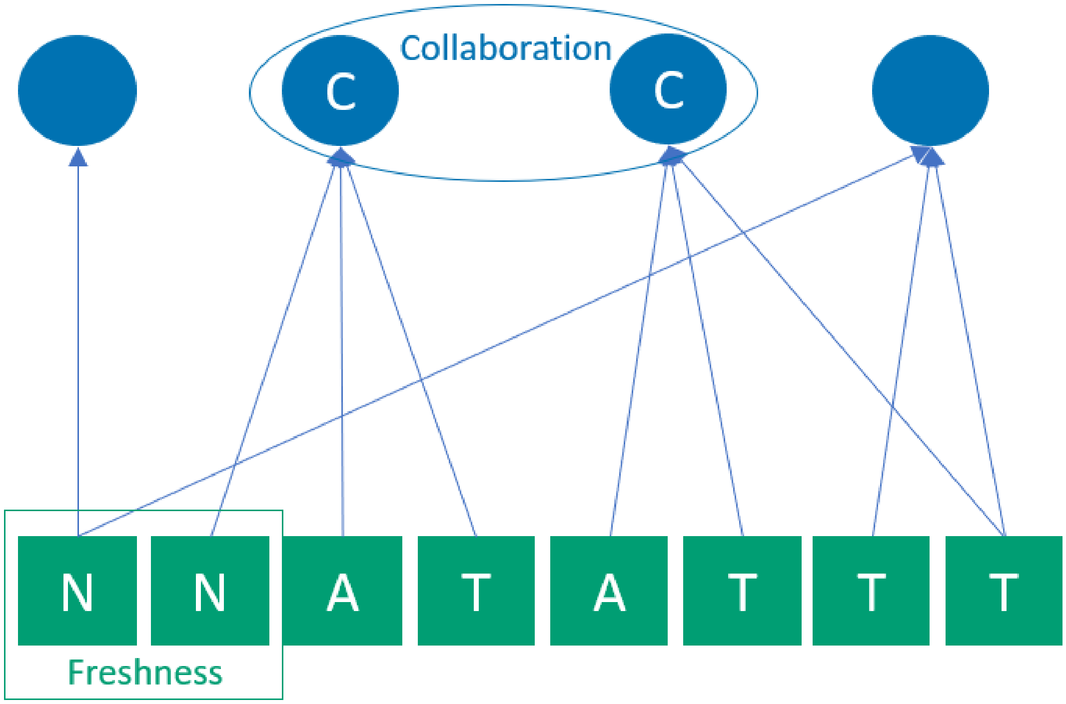
Philips	$\Longleftrightarrow$	Pfizer
Color Kinetics		Coley Pharmaceutical
Low-overlap	1.2 std ↑	High-overlap
Fewer patents		More patents
14	71.4% ↑	24
Larger shift		Smaller shift
0.41	36.6% ↓	0.26
Larger exploration		Smaller exploration
0.80	46.3% ↓	0.43

Appendix E. More about *Orthogonal Norm*





Appendix F. Measures from Inventor Data



Appendix G. Appendix Tables

Table XI

Acquirer's Announcement Return

In this table I compare high-overlap deals with low-overlap deals from 1985 through 2017 with reference to the acquirer's return around the deal announcement date. In Panel A I report the summary statistics for the acquirer's raw return and cumulative abnormal return ("CAR") in a time window of [-2, +1] around the deal announcement date. In columns (1) and (2) I report the mean and standard deviation. In column (3) I report the average difference between (2) and (1) and its corresponding t-statistics. In Panel B I regress the acquirer's announcement return on the technological overlap between the merging companies. The dependent variable for columns (1) and (2) (columns (3) and (4)) is the acquirer's raw return (CAR) around the deal announcement date. Columns (1) and (3) and based on technology classifications while columns (2) and (4) are based on patent texts. The control variables are all defined in Appendix C. In each column, I report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A:	(1)		(2)		(3)	
	High-overlap		Low-overlap			
Acquirer's	Mean	S.D.	Mean	S.D.	Diff	t-stat
Raw Return [-1, +2]	-0.04%	9.20%	0.53%	7.19%	0.57%	1.49
CAR [-1, +2]	-0.49%	9.13%	0.32%	7.54%	0.81%	2.10

Panel B:	(1)	(2)	(3)	(4)
Acquirer's	RET [-1, +2]	RET [-1, +2]	CAR [-1, +2]	CAR [-1, +2]
$CCS_{T_{t_b};A_{t_b}}$	-0.005		-0.006	
	(-1.03)		(-1.16)	
$TCS_{T_{t_b};A_{t_b}}$		-0.016*		-0.019**
		(-1.78)		(-2.10)
Deal Controls	Yes	Yes	Yes	Yes
Innovation Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	2811	2811	2811	2811
Adjusted R^2	0.00	0.01	0.01	0.01

Table XII

Deal Failure Rate

This table is based on the sample of completed deals with innovative targets and acquirers. It covers all public M&As. Columns (1) and (2) are based on technology classifications and patent texts, respectively. The dependent variable is a dummy variable that equals one if the deal is withdrawn and zero otherwise. $CCS_{\mathsf{T}_{t_b};\mathsf{A}_{t_b}}$ or $TCS_{\mathsf{T}_{t_b};\mathsf{A}_{t_b}}$ denotes the ex-ante technological overlap between the target and the acquirer. The remaining independent variables are defined in Appendix C. In each column, I report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	(1) Deal Failure	(2) Deal Failure
$CCS_{\mathsf{T}_{t_b};\mathsf{A}_{t_b}}$	-0.046*	
	(-1.65)	
$TCS_{\mathsf{T}_{t_b};\mathsf{A}_{t_b}}$		-0.023
		(-0.46)
Log(Deal value)	-0.013	-0.013
	(-0.46)	(-0.49)
Toehold	0.274	0.263
	(1.23)	(1.18)
Stock Deal	0.040*	0.038
	(1.68)	(1.59)
Friendly	-0.576***	-0.577***
	(-11.61)	(-11.63)
Log(Target's R&D Expense)	0.000	-0.000
	(0.06)	(-0.01)
Log(Target's Patent)	0.066	0.069
	(0.70)	(0.74)
Log(Acquirer's R&D Expense)	-0.000	-0.000
	(-0.02)	(-0.00)
Log(Acquirer's Patent)	-0.020	-0.019
	(-0.98)	(-0.91)
Log(Target's Market Cap)	0.021	0.021
	(0.77)	(0.78)
Target's Book-to-Market	0.001	0.003
	(0.04)	(0.18)
Target's ROA	0.063	0.071*
	(1.55)	(1.77)
Log(Acquirer's Market Cap)	-0.018***	-0.018***
	(-2.68)	(-2.61)
Acquirer's Book-to-Market	-0.023	-0.022
	(-0.65)	(-0.62)
Acquirer's ROA	-0.156*	-0.150*
	(-1.78)	(-1.69)
Same Industry (SIC-2)	0.000	-0.002
	(0.02)	(-0.10)
Year Fixed Effects	Yes	Yes
Observations	1104	1104
Adjusted R^2	0.25	0.25

Table XIII

Innovation Strategy

This table is based on the sample of completed deals with innovative targets and acquirers from 1985 through 2014. The dependent variable for Panel A is the originality and generality of the combined firm's patent portfolio after deal completion. Originality is calculated as one minus the Herfindahl Index of the number of cited patents across 3-digit technology classifications. Generality is calculated as one minus the Herfindahl Index of the number of patents across 3-digit technology classifications which cite the specific patents. The dependent variable for Panel B is the percentage of exploratory and exploitative patents after deal completion. A patent is considered exploitative if at least 80% of its citations are based on the existing knowledge of the firm, whereas a patent is exploratory if at least 80% of its citations are based on new knowledge. Columns (1) and (3) are based on technology classifications while columns (2) and (4) are based on patent texts. In each column, I report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A	(1) Originality	(2) Originality	(3) Generality	(4) Generality
$CCS_{T_{t_b};A_{t_b}}$	-0.058*		0.009	
	(-1.84)		(0.30)	
$TCS_{T_{t_b};A_{t_b}}$		-1.075*		-0.020
		(-1.88)		(-0.43)
Deal Controls	Yes	Yes	Yes	Yes
Innovation Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	2815	2815	2815	2815
Adjusted R^2	0.51	0.53	0.42	0.42
Panel B	(1) Exploitative	(2) Exploitative	(3) Exploratory	(4) Exploratory
$CCS_{T_{t_b};A_{t_b}}$	0.094		-0.061**	
	(0.67)		(-2.11)	
$TCS_{T_{t_b};A_{t_b}}$		0.108		-0.167**
		(0.90)		(-2.36)
Deal Controls	Yes	Yes	Yes	Yes
Innovation Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	2815	2815	2815	2815
Adjusted R^2	0.54	0.55	0.58	0.58

Table XIV

Development of New Technology after M&A – Small Acquirers

This table is based on the sample of completed deals with innovative targets and acquirers. It covers all public and private M&As with the acquirer's market capitalization smaller than 2.5 billion. Columns (1) and (2) are based on technology classifications and patent texts, respectively. The dependent variable is $OrthogonalNorm$, which is taken from the norm of the orthogonal part after I project the post-deal innovation vector on the pre-deal innovation vectors of the merger pair. $CCS_{T_{t_b};A_{t_b}}$ or $TCS_{T_{t_b};A_{t_b}}$ denotes the ex-ante technological overlap between the target and the acquirer. The remaining independent variables are defined in Appendix C. In each column, I report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: $OrthogonalNorm$	(1) Class-based	(2) Text-based
$CCS_{T_{t_b};A_{t_b}}$	-0.172***	
	(-6.30)	
$TCS_{T_{t_b};A_{t_b}}$		-0.164***
		(-3.87)
Toehold	-0.300	-0.329
	(-1.16)	(-1.21)
Stock Deal	-0.028	-0.049**
	(-1.20)	(-2.31)
Friendly	-0.059	-0.065*
	(-1.02)	(-1.92)
Log(Acquirer's R&D Expense)	-0.001	0.004
	(-0.16)	(0.61)
Log(Acquirer's Patent)	-0.116***	-0.284***
	(-3.10)	(-7.87)
Log(Acquirer's Market Cap)	0.011	0.007
	(1.30)	(0.89)
Acquirer's Book-to-Market	0.002	0.002
	(0.06)	(0.10)
Acquirer's ROA	0.123**	0.163***
	(2.55)	(3.50)
Same Industry (SIC-2)	-0.026	0.001
	(-1.45)	(0.08)
Year Fixed Effects	Yes	Yes
Observations	1373	1373
Adjusted R^2	0.15	0.09

Table XV

Development of New Technology after M&A – Target Inventors

This table is based on the sample of completed deals with innovative targets and acquirers. It covers all public and private M&As with the acquirer's market capitalization smaller than 2.5 billion. Columns (1) and (2) are based on technology classifications and patent texts, respectively. The dependent variable is $OrthogonalNorm$, which is taken from the norm of the orthogonal part after I project the post-deal innovation vector on the pre-deal innovation vectors of the merger pair. Here, I only consider the patents that involve at least one target inventor. $CCS_{T_{t_b};A_{t_b}}$ or $TCS_{T_{t_b};A_{t_b}}$ denotes the ex-ante technological overlap between the target and the acquirer. The remaining independent variables are defined in Appendix C. In each column, I report coefficient estimates and their heteroskedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: $OrthogonalNorm$	(1) Class-based	(2) Text-based
$CCS_{T_{t_b};A_{t_b}}$	-0.115***	
	(-8.74)	
$TCS_{T_{t_b};A_{t_b}}$		-0.114***
		(-5.35)
Toehold	-0.199*	-0.054
	(-1.95)	(-0.51)
Stock Deal	-0.045***	-0.034***
	(-3.80)	(-3.06)
Friendly	-0.026	-0.016
	(-0.81)	(-0.56)
Log(Acquirer's R&D Expense)	-0.008**	-0.005*
	(-2.45)	(-1.70)
Log(Acquirer's Patent)	-0.058***	-0.133***
	(-6.94)	(-18.78)
Log(Acquirer's Market Cap)	0.006*	0.007***
	(1.80)	(2.59)
Acquirer's Book-to-Market	0.027	0.030*
	(1.42)	(1.85)
Acquirer's ROA	0.030	0.067**
	(1.00)	(2.44)
Same Industry (SIC-2)	-0.010	-0.005
	(-1.09)	(-0.64)
Year Fixed Effects	Yes	Yes
Observations	2815	2815
Adjusted R^2	0.13	0.13