# Technology Differentiation, Product Market Rivalry and M&A Transactions

Sam Arts
Department of management, strategy and innovation
Faculty of economics and business
KU Leuven
sam.arts@kuleuven.be

Bruno Cassiman
Department of management, strategy and innovation
Faculty of economics and business
KU Leuven

Jianan Hou
Department of management, strategy and innovation
faculty of economics and business
KU Leuven
jianan.hou@kuleuven.be

## ABSTRACT

Prior work has mostly studied the relation between product market competition and M&A deals. In this paper, we study how competition and differentiation in technology space relates to M&A transactions. Relying on a new text-based method to map each firm's competitive position in technology space and to measure the differentiation of a firm's technology portfolio relative to all other firms, we find that firms with unique and differentiated technology are typical targets while firms with less differentiated technology are more likely to become acquirers. Moreover, firms with unique technology are particularly targeted by close competitors in the product market and receive a higher acquisition price, particularly in case of M&As with close product market firms. Our findings illustrate that a unique and differentiated technology portfolio is an important resource traded in the market for corporate control and a key driver of M&A deals, particularly between close competitors in the product market.

## 1. Introduction

According to the resource-based view, a firm's competitive advantage and superior performance relies on resources that are unique and difficult to imitate and substitute, such as unique and proprietary firm technology (Wernerfelt, 1984; Peteraf, 1993; Mowery et al., 1998). Besides conducting internal R&D to push the technology frontier and develop a unique technology portfolio, firms might also acquire these resources through M&As with other firms that successfully innovate (Barney, 1986; Phillips and Zhadanov, 2013). In fact, anecdotal evidence suggests that acquiring unique technology is a key driver for firms to engage in M&As, particularly when product market rivals pioneer new technologies (Holmström and Roberts, 1998).[1] To give one example, Overture Services was the first company to develop and patent cost-per-click technology in 2003, i.e. the internet advertising technology currently used by Google and Facebook, before being acquired by Yahoo! in the same year.[2]

Prior work has extensively studied the role of R&D investments and the size of technology portfolios – measured by patents – as driver of M&A deals and acquisition price (e.g. Bena and Li, 2014; Grimpe and Hussinger, 2014; Yu et al. 2016). In this paper, we theoretically contribute to the M&A literature by studying how the uniqueness and differentiation of a firm's technology portfolio influences M&A transaction incidence and acquisition price. Empirically, we develop a new text-based method to map each firm's competitive position in technology space and to measure the uniqueness or differentiation of a firm's technology portfolio relative to all other firms.[3] In line with the resource-based view, we treat a unique and differentiated technology portfolio as a key resource for a firm's competitive advantage and superior performance (Barney 1991; Peteraf, 1993; Mowery et al., 1998; Arts et al 2021). We further build on Barney (1986) and interpret M&As as resource acquisitions on strategic factor markets. Because firms' resource endowments – including the uniqueness and differentiation of their technology portfolio – varies, these resources might explain why certain firms become targets, which firms acquire those targets, and the eventual acquisition price paid for the targets (Adegbesan, 2009; Grimpe and Hussinger, 2014).

Collecting an economy wide dataset of all M&A transactions involving US public firms between 1984 and 2006, we match each target (acquirer) firm to a group of pseudo target (acquirer) firms based on industry, size, and market value, and match each real M&A deal (real target-acquirer pair) to multiple pseudo deals (e.g. Bena and Li, 2014). Controlling for amongst others R&D investments and the size of the technology portfolio (number of citation-weighted patents) which have been show to trigger M&As (e.g. Wagner and Cockburn, 2010; Phillips and Zhadanov, 2013; Bena

[1] See for instance https://www2.deloitte.com/content/dam/Deloitte/us/Documents/mergers-acqisitions/us-mergers-acquisitions-2018-trends-report.pdf

[2] Overture Services filed a patent (US6907566) in 2003 for a "method and system for optimum placement of advertisements on a webpage", the first patent in history pioneering the keyword "cost-per-click". The patent received more than 900 patent citations, including from the PageRank patent (US6285999), invented by Larry Page and exclusively licensed to Google.

[3] Although not all technologies are patented (e.g. Hall et al., 2014), we will use firm patent portfolios, firm technology or firm technology portfolios interchangeably in this paper. Similarly, we will use the terms uniqueness and differentiation interchangeably.

and Li, 2014; Grimpe and Hussinger, 2014), we find that firms with unique and differentiated technology are more likely to become targets and are associated with a higher acquisition price. An increase in technology differentiation from the 25th to the 75th percentile increases the odds of being a target with 34% and the acquisition price with 8%. By contrast, firms with less unique technology are more likely to become acquirers. Increasing technology differentiation from the 25th to the 75th percentile corresponds with a decrease in the odds of becoming an acquirer with 56%. These findings suggest that technology pioneering firms – with more differentiated technology – are more likely to become targets while firms with less differentiated technology are more likely to become acquirers (Phillips and Zhadanov, 2013). Notably, the differentiation of a firm's technology portfolio is statistically and economically a more important driver of both M&A transaction incidence and acquisition price than the size of a firm's technology portfolio as measured by the number of citation-weighted patents.

Furthermore, controlling for amongst others the technology similarity between acquirers and targets which has been shown to drive M&As (Ahuja and Katila 2001; Cassiman et al, 2005; Bena and Li, 2014), interaction effects at the deal level illustrate that firms with unique technology are particularly targeted by close competitors in the product market as measured by the overlap in the 10-K product descriptions of firms (Hoberg and Phillips, 2016). For close product market rivals (75th percentile of product market overlap), the odds of M&A transaction incidence are 4 times higher for targets with unique technology versus targets with less differentiated technology (75th versus 25th percentile of technology differentiation). For distant product market firms (25th percentile of product market overlap), the odds of M&A transaction incidence are only 2 times higher for targets with a high versus low degree of technology differentiation. Likewise, the differentiation of the target's technology portfolio has a stronger effect on the acquisition price paid by close product market firms. The acquisition price paid by close product market firms is 28% higher for targets with a high versus low degree of technology differentiation. By contrast, the acquisition price paid by distant product market firms is only 17% higher for targets with a high versus low degree of technology differentiation.

Our paper makes different contributions to the literature studying the relationship between M&As and innovation (e.g. Valentini, 2012; Guadalupe et al., 2012; Seru 2014), and particularly to the stream of research studying R&D and innovation as drivers of M&A transaction incidence and acquisition price (e.g., Bena and Li, 2014; Grimpe and Hussinger, 2014; Chen et al. 2020). First, whereas prior work mostly studied the relation between product market competition and M&A deals (e.g. Phillips and Zhadanov, 2013; Cunningham et al., 2021), we study how competition and differentiation in technology space relates to M&A transactions. Second, we introduce a new text-based method to measure a firm's competitive position and differentiation in technology space relative to all other firms based on the semantic content of patent portfolio. Third, collecting an economy wide dataset of all M&A transactions involving US public firms between 1984 and 2006, our findings illustrate that a unique and differentiated technology portfolio is a key resource traded in the market for corporate control and a key driver of M&A transaction incidence and acquisition price, particularly between close competitors in the product market (Barney 1986).

## 2. Theory and hypotheses

According to the resource-based view, a firm's competitive advantage and performance relies on resources that are unique and difficult to imitate and substitute, such as unique and proprietary firm technology (Wernerfelt, 1984; Peteraf, 1993; Mowery et al., 1998). To quantify the value of firm technology, prior work shows how R&D investments and the size of a firm's technology portfolio – as measured by patents – positively relate to firm performance (e.g., Hall et al., 2005). More recent work illustrates that the value of a firm's technology portfolio to a large extent also depends on its uniqueness and differentiation relative to the technology portfolio all other firms (Arts et al., 2021).[4]

Besides conducting internal R&D to push the technology frontier and develop a unique and differentiated technology portfolio, firms can also buy these resources through the market for technology or the market for corporate control (Arora & Gambardella, 1990; Arora et al., 2001). In line with prior work, we conceptualize M&As as resource acquisitions in strategic factor markets, and specifically focus on the acquisition of firm technology portfolios as measured by patents (Barney, 1986; Ahuja and Katila 2001; Grimpe and Hussinger, 2014; Bena and Li, 2014). A large survey of M&A executives pointed out that acquiring technology is the most important strategic driver for firms to engage in M&A deals.[5] Prior academic studies found mixed results and showed that firms with a higher R&D intensity, smaller patent portfolio, slower growth in patenting, but more heavily cited patents are more likely to be acquired or receive a higher acquisition price, while firms with a lower R&D intensity but a larger patent portfolio are more likely to be acquirers (Wagner and Cockburn, 2010; Bena and Li, 2014; Grimpe and Hussinger, 2008; Grimpe and Hussinger, 2014).

So far, the M&A literature studied R&D investments and patenting of acquiring and target firms in isolation and did not consider each firm's competitive position in the entire technology space including all other firms not involved in the M&A deal. However, to get a better understanding of how the boundaries of the firm and M&A transactions are drawn, one should transcend simple two-party relationships between acquirers and targets and take competitive interactions between all firms into account (Holmström and Roberts, 1998). A firm's competitive position in technology space, and the uniqueness or differentiation of its technology portfolio relative to all other firms, is arguably an important driver of M&A transactions overlooked in prior empirical studies.

[4] Using a panel of all US public firms from 1989-2015, and controlling for amongst others R&D investments and the number of citation-weighted patents in the portfolio, they illustrate that technology differentiation – the uniqueness of a patent portfolio relative to all other firms – has a strong positive and long-lasting relation with firm performance (ROA, Tobin's Q).
[5] See https://www2.deloitte.com/content/dam/Deloitte/us/Documents/mergers-acqisitions/us-mergers-acquisitions-2018-trends-report.pdf

Despite the lack of largescale empirical evidence, descriptive and anecdotal evidence suggest that acquiring a unique technology portfolio might play a key role in M&A decisions. For instance, a report from Deloitte in 2018 showed that nearly a third of the 1,200 S&P companies engaged in M&A deals with the primary purpose of acquiring unique and pioneering technologies in fields such as Artificial Intelligence, robotics and cyber security.[6] Even R&D intensive and technology pioneering firms such as Alphabet, Intel or Cisco engage in M&As to acquire unique and proprietary technology from other firms.[7] For instance, in 2017 Intel acquired Mobileye for 15.3 billion US dollars, a firm which pioneered and patented chip-based camera systems that power advanced driver assistance and self-driving cars.[8] Besides the motivation of acquirers to engage in M&As to get their hands on unique technology owned by other firms, potential target firms themselves may also have an incentive to invest in R&D and push the technology frontier in order to become an attractive acquisition target and exit through strategic sales (Phillips and Zhadanov, 2013). Given the importance of unique proprietary technology for firm performance (Arts et al. 2021), we hypothesize that firms with a high degree of technology differentiation, i.e. having a unique and differentiated technology portfolio, are more likely to become targets compared to otherwise very similar firms with a low degree of technology differentiation.

*Hypothesis 1: Firms with a unique and differentiated technology portfolio are more likely to become targets.*

The price of firm resources in strategic factor markets is determined by other firms' expectations of the value of these resources (Barney, 1986). If resources are perceived as valuable by multiple other firms, a bidding competition might drive up the price of acquiring the resources. In case of M&As, the transaction price reflects the expected value of the resources of the target firm for the bidding firm (Grimpe & Hussinger, 2014; Arora et al., 2018). Given that unique and differentiated firm technology is an important resource for long-term firm performance (Arts et al. 2021), we hypothesize that target firms with a high degree of technology differentiation, i.e. having a unique and differentiated technology portfolio, should be associated with a higher acquisition price relative to target firms with a low degree of technology differentiation.

*Hypothesis 2: Target firms with a unique and differentiated technology portfolio are associated with a higher acquisition price.*

Firms with unique technology should be particularly attractive targets for close competitors in the product market. By engaging in an M&A with a close competitor that has a unique technology portfolio, firms can both strengthen their competitive advantage by integrating the acquired technology into their own product business, and avoid current or future product market rivalry with the technologically differentiated target firm (Baker & Bresnahan 1985; Cunningham et al., 2021). To

[6] See https://www2.deloitte.com/ch/en/pages/financial-advisory/articles/future-of-the-deal.html
[7] See for instance: Bloomberg, February 29, 2008, "Innovation through Acquisition" and Forbes, November 8, 2005, "Does Innovation Through Acquisition Work?"
[8] https://www.wsj.com/articles/what-is-mobileye-1489412782

give one example, Google bought three search engine companies (Outride, Orion, and Kaltrix) for their unique technology and patents.[9] For instance, Kaltrix, one of the acquired companies, pioneered and patented proprietary technology to dramatically speed up the calculations of Google's own PageRank algorithm.[10] These acquisitions allowed Google to directly incorporate the acquired unique technology and search engine features into its own online search tool and thereby strengthen its existing competitive advantage. At the same time, the acquisitions allowed Google to avoid current or future product market competition with these technology pioneering firms. As the example of Google and the acquisition of Overture Services by Yahoo! discussed in the introduction illustrate, a potential target firm's unique technology is presumably perceived as a more valuable resource in strategic factor markets by close competitors in the product market. Therefore, we hypothesize that firms with a high degree of technology differentiation, i.e. having a unique and differentiated technology portfolio, are particularly targeted by close competitors in the product market.

*Hypothesis 3: Firms with a unique and differentiated technology portfolio are particularly attractive targets for close competitors in the product market.*

Besides increasing M&A transaction incidence, the higher valuation of a target firm's technology by close product market rivals should also be reflected in the acquisition price, which captures the expected value of the resources of the target firm for the bidding firm (Barney, 1986). Because a unique and differentiated technology portfolio is presumably perceived as a more valuable resource by close product market rivals, we hypothesize that a target firm's technology differentiation should have a stronger effect on the acquisition price paid by close product market rivals versus the acquisition price paid by more distant product market firms.

*Hypothesis 4: The uniqueness and differentiation of a target firm's technology portfolio should particularly relate to a higher acquisition price if the acquirer is a close product market rival.*

## 3. Methodology

### *3.1 Data and sample*

We combine data on all US public firms linked to patents from Arora et al. (2021), firm financial information from Compustat, data on product market overlap between firms from Hoberg and Philips (2016), data on stock market returns from the CRSP US stock database, and data on M&A deals involving US public firms from Thomson Reuters SDC.

[9] See http://googlepress.blogspot.com/2001/09/google-acquires-technology-assets-of.html and http://googlesystem.blogspot.com/2006/04/google-acquires-orion-referential.html
[10] https://en.wikipedia.org/wiki/Kaltix

To construct firm patent portfolios, we use the DISCERN patent database which matches all US public firms to patents from the USPTO for the period 1980-2015 (Arora et al., 2021).[11] In order to construct the patent portfolio of firm *i* in year *t*, we sample all granted patents linked to firm *i* with filing year between year *t-5* and year *t-1* (e.g., Ahuja and Katila 2001, Rothaermel and Deeds 2004, Hirshleifer et al. 2018).[12] The dataset includes 4,866 US public firms and 57,772 firm-year level patent portfolios for the years 1980 to 2015.

To collect information on M&A deals between US public firms, we follow Bena and Li (2014) and use the Thomson Reuters SDC Platinum domestic M&A database, and restrict the sample to completed deals announced between January 1 1984 and December 31 2006. All deals where the form was coded as a merger, an acquisition of majority interests, or an acquisition of assets remain in the dataset. We exclude deals whose acquirer or target firm is from the financial sector (primary SIC between 6000 and 6999). A deal is retained only in case the acquirer owns less than 50% of the target firm at announcement,[13] is seeking to own more than 50% of the target firm, and owns more than 90% of the target firm after the deal completion. In order to eliminate small and economically insignificant deals, we require that both acquirer's and target's total assets be valued at more than 1 million (acquirer/target firm total assets last 12 months prior to the deal) or that the transaction value is at least 1 million (all in 1984 constant dollars). Next, we examine how many deal participants are covered by Compustat (with information on historical industry classification[14] and financial characteristics) and the CRSP US stock database (with information on stock returns). To do so, we match each deal participant to Compustat by 6-digit CUSIP number and retrieve firm characteristics at the end of the fiscal year before deal announcement.[15] The stock return of deal participant from 14 months to 3 months prior to the deal announcement is retrieved from CRSP by 6-digit CUSIP number. Finally, we find 12,506 deals where all information on acquirers is available, 3,609 deals where information on target firms is available, and 1,665 deals where information on both acquirer and target firms is available.

[11] DISCERN database is available from: https://zenodo.org/record/3709084. We start from a sample of 1,345,945 US patents granted between 1980 and 2015 and their disambiguated patent assignees at the time of patent grant. This sample of patents are assigned to either publicly listed US firms or one of their subsidiaries. We dynamically match each patent to its ultimate owner based on the matching dataset provided by DISCERN .

[12] We require that the first active year of firm *i* should be no later than year *t* and the last active year should be no earlier than year *t-1*. Following Arora et al. (2021), we define an active record as the year with positive common shares traded and available sales. We set the last active year no earlier than year *t-1* instead of year *t* in order to include those firms which were acquired or dissolved in year *t* in the sample. When constructing the patent portfolio, we do not only include patents invented by itself but also patents acquired through M&A or other ownership change activities.

[13] As the share owned by acquirer at announcement is not available for 98% of deals from SDC, we deduct the acquired share from share owned by acquirer after transaction to obtain the share owned by acquirer at announcement.

[14] We download 256,636 "gvkey-fiscal year" level observations from Compustat. However, the historical SIC information of 78,300 observations is not available. We fill in the missing values in two steps. First, if the historical SIC of the same firm in later years is available, we replace the missing SIC in earlier years with the first available historical SIC. Second, if the historical SIC information is unavailable for the company during the whole sample period (1983 to 2006), we replace the historical SIC with current SIC.

[15] For a deal announced in year t, if the fiscal year end date of the acquirer (target) firm is earlier than the deal announcement date, we collect firm characteristics of the acquirer (target) firm at the end of fiscal year t. Otherwise, we collect firm characteristics at the end of fiscal year t-1.

To construct a matched control sample of pseudo targets and acquirers, we match each target (acquirer) firm to at most five pseudo target (acquirer) firms based on industry, size (assets), and market valuation (book-to-market value). For a target (acquirer) firm of a deal announced in year *t*, we first select all firms from the same industry (SIC code)[16] which were not involved in any M&A deal in the three-year period prior to year *t*. Among all control firms from the same industry, we select for each target (acquirer) firm up to five of the most similar control firms based on size (*total assets*) and market value (*B/M*, book-to-market value) as pseudo targets (acquirers) by means of propensity score matching (Bena and Li, 2014). As such, we have for each acquirer up to five pseudo acquirers, for each target up to five pseudo targets, and for each deal (acquirer-target pair) up to ten pseudo deals consisting of real acquirers matched to pseudo targets and real targets matched to pseudo acquirers. In the analysis, we restrict the sample to firms with at least one patent in their portfolio (between year *t-5* and year *t-1*). The final sample includes 4,415 actual acquirers and 13,212 pseudo acquirers, 903 targets and 2,726 pseudo targets, and 379 actual deals (acquirer-target pairs) and 2,388 pseudo deals. Table A.1 in Appendix shows the number of acquirer/target firms and M&A deals over time.

### *3.2 Measuring firms' competitive position and differentiation in technology space*

Whereas prior work predominantly relied on patent classes to characterize firm technology portfolios (e.g., Puranam et al., 2009; Ornaghi, 2009; Makri et al., 2010; Phene et al. 2012; Bena & Li, 2014; Aharonson & Schilling 2016), we exploit the fact that firms have to provide a fully written disclosure of their technology in exchange for legal patent protection,[17] and harness the processed, cleaned, and stemmed technical keywords extracted from the titles, abstracts, and claims of all US patents (Arts et al., 2021).[18] Compared to patent classes, patent text provides a more detailed insight in a firm's technology portfolio (Thompson and Fox-Kean, 2005; Arts et al. 2018), and particularly in a firm's competitive position and differentiation in technology space relative to other firms (Arts et al. 2021b). Moreover, patent text outperforms in the identification of pioneering technologies which is important to assess whether a firm is pushing the technology frontier relative to other firms (Arts et al. 2021a).

First, we use the DISCERN data to construct the patent portfolio of each US public firm *i* in year *t* by collecting all of its patents filed between year *t-5* and *t-1.* To characterize a firm's technology

[16] In line with Bena and Li (2014), we start from 4-digit SIC codes. If there are no more than 5 control firms in the same 4-digit SIC as the actual acquirer (target), we will move to 3-digit SIC codes. Likewise, if there are no more than 5 control firms in the same 3-digit SIC group, we will move to 2-digit SIC codes.

[17] According to U.S. law, a patent must "contain a written description of the invention … in such full, clear, concise, and exact terms as to enable any person skilled in the art … to make and use the same, and shall set forth the best mode contemplated by the inventor or joint inventor of carrying out the invention." See 35 U.S. Code § 112, available from https://www.law.cornell.edu/uscode/text/35/112

[18] For each patent, they concatenate title, abstract, and claims, lowercase the text, and tokenize it to words using the following regular expression: [a-z0-9][a-z0-9-]*[a-z0-9]+|[a-z0-9]. They consider a word as a sequence of letters and numbers that could be separated by hyphens ("-"). Next, they remove words composed only by numbers, one-character words, stop words from the Natural Language Toolkit (NLTK) in the Python library, and words appearing in only one patent. In addition to natural stop words, they remove a manually compiled list of 32,255 very common non-technical keywords. Finally, They apply stemming to each word using the SnowBall method.

portfolio, we represent the patent portfolio of firm *i* in year *t* as a vector of 1,030,335 dimensions where each dimension corresponds to one stemmed technical keyword from the entire vocabulary, and its value captures the share of patents from firm's *i* patent portfolio in year *t* which contain the particular keyword. To illustrate our approach, Figure 1 displays word clouds based on the 100 most frequent stemmed technical keywords in the patent portfolio of two different companies. For First Solar, manufacturer of thin film cadmium telluride photovoltaic panels, the most common stemmed technical keywords include *photovolta*, *film, cadmium, tellurid,* and *semiconductor.* For Infinera Corporation, manufacturer of wavelength division multiplexing-based packet optical transmission equipment, the most common stemmed technical keywords include *wavelength*, *multiplex*, *optic*, *signal,* and *transmiss.*[19]

'Insert Figure 1'

Next, we compute the technology similarity between two firms in a given year by means of cosine similarities (Jaffe 1989). We use TF-IDF weights which increase with the share of patents in a particular firm-year level patent portfolio which contain a particular keyword and decrease by the total number of firm patent portfolios from the entire population in the same year which contain the particular keyword.[20] TF-IDF weights help to adjust for the fact that certain keywords are more representative of a firm's patent portfolio in a given year (e.g., *photovolta* or *cadmium* for First Solar, or *wavelength* and *multiplex* for Infinera) and for the fact that some keywords appear very frequently across the patent portfolios of many firms and are therefore less representative for any given firm (e.g., *electr, tool, apparatus, or drug*). We compute for each year *tech similarity* for every pair of US public firms. Our data covers the years 1980-2015 and includes 4,832 firms, 57,772 firm-year observations,[21] and 98,279,118 pairwise *tech similarities*. Importantly, the correlation between *tech similarity* and *prod similarity* from Hoberg and Philips (2021) is only 0.25, illustrating that firms which are close competitors in the product market often rely on different technologies and vice versa.[22]

To measure the uniqueness and differentiation of firm *i*'s technology portfolio in year *t*, we calculate $tech\ differentiation_{it} = 1 - \frac{1}{n-1}\sum_{j=1, j\neq i}^{n} tech\ similarity\ _{ijt}$ , with *n* equal to all firms active in year *t* and $tech\ similarity_{ijt}$ equal to the technology similarity between firm *i* and firm *j* in year *t*. Because of TF-IDF, new or recent keywords which capture pioneering technologies receive a higher weight in the calculation of technology differentiation while older and more established

[19] We retrieved 1,671 unique and stemmed keywords from 135 First Solar patents filed between 2003 and 2014, and 2,247 words from 295 Infinera patents filed between 2000 and 2014.

[20] The TF-IDF adjustment is conducted as follows. First, we construct a vector for each firm where the value of each dimension captures the term frequency (TF), namely the share of patents using the given word. Second, for each word we count its document frequency (DF), namely the number of firms using this given word. Due to the high skewness of DF, we take the logarithm for it with base 10. Finally, we divide TF by the logarithm of DF to get the adjusted value.

[21] A firm-year observation is only included in case the firm has at least one patent in its portfolio (i.e. in years t-5 to t-1).

[22] We downloaded pairwise business description/product similarity scores between 1988 and 2014 from the TNIC database (Hoberg and Philips 2021). The similarity is only available for firm-years whose 10K filings are available and are covered by Compustat. Financial firms (SIC 6000-6999) and firm-years with nonpositive sales or with assets less than 1 million are excluded...

keywords which are common across the portfolio of many companies receive a lower weight. Therefore, firms pioneering new technologies increase the uniqueness and differentiation of their technology portfolio relative to other firms.[23] For instance, Overture Services filed a patent in 2003 for a "method and system for optimum placement of advertisements on a webpage", the first patent pioneering the keyword "*cost-per-click"*, i.e. the internet advertising technology used by Google and Facebook amongst others. Pioneering cost-per-click technology increased the uniqueness and differentiation of Overture Services' technology portfolio. Interestingly, the company was acquired by Yahoo! in the same year. As another example, in 1988 the biotech firm Immunex discovered and patented "Interleukin-7", the first patent introducing the keyword "*il-7",* a protein which affects the invasion and growth of tumor cells. Immunex merged with American Cyanamid in 1992 and later was acquired by Amgen in 2002. As a final example, in 1992 Applied Immune Sciences pioneered and patented "the production of recombinant adeno-associated virus vectors", the first patent in history using the keyword "raav". rAAV was a major breakthrough in genome engineering and therapy enabling the insertion, deletion or substitution of DNA sequences into the genomes of live mammalian cells. The company was acquired 3 years later by Rhone-Poulenc Rorer. These examples illustrate how firms pioneering new technologies increase the uniqueness and differentiation of their technology portfolio and often become an attractive acquisition target.

To compare our new measure with the traditional characterization of firm technology portfolios, we also calculate *tech differentiation (class)*, *tech differentiation (subclass)*, and *tech differentiation (citation)* in the exact same way except for using patent classes, subclasses, or backward patent citations from the firm's patents instead of keywords (e.g. Jaffe, 1989). Table A.2 in appendix provides a detail description of how each measure is constructed. Interestingly, our new text-based *tech differentiation* measure only weakly correlates with *tech differentiation (class)* (corr=0.109), *tech differentiation (subclass)* (corr=0.013), and *tech differentiation (citation)* (corr=-0.074). These correlations illustrate how the semantic content of patent portfolios provides a different characterization of firm technology and a firm's competitive position and differentiation in technology space compared to the conventional approach based on patent classifications or citations.

'Insert Figure 2'

Our open access dataset of *tech similarity* for all pairs of US public firms and each year can be used to map and visualize a company's competitive position and differentiation in technology space relative to all or a selection of other firms. As an illustration, Figure 2 shows the network of all firms in the medical equipment industry in 1998. Each node represents one firm, the size of the node is proportional to the size of the firm's patent portfolio in 1998 (based on patents from 1993-1997), two nodes are connected by an edge in case the *tech similarity* between the firms is above 0.35, and the

[23] The correlation between differentiation of firm i in year t and the number of new keywords pioneered by firm i in the period t-5 to t-1 (scaled by the total number of patents in t-5 to t-1) is 0.18 (significant at 1% level), illustrating how companies pioneering new technologies increase their technology differentiation.

thickness of the edge is proportional to *tech similarity* between the firms (thicker edge means higher *tech similarity*). Node colors represent different product market clusters based on the *prod similarity* between firms, i.e. the overlap in the 10-K product descriptions of firms, available from Hoberg and Philips (2016). The figure illustrates that firms with a unique and differentiated technology portfolio, i.e. isolated nodes with few links to other firms, are often acquired, particularly by product market rivals (firms from the same product market cluster). For example, in 1998 Guidant acquired Incontrol. Incontrol's technology for treating heart arrhythmia complemented Guidant's products for minimally invasive cardiac treatment.[24]

### *3.3 Other variables*

In line with prior work, we include *total assets*, *sales change*, *ROA*, *leverage*, *cash*, *stock return*, and *B/M* to control for firms' financial characteristics (Bena and Li, 2014; Hirshleifer et al. 2018). Besides *tech differentiation*, we include other firm innovation characteristics: *R&D intensity*, *citation-weighted patents*, and *tech specialization.* We winsorize all financial characteristics from Compustat/CRSP at the 1% and 99% levels (e.g. Bena and Li 2014, Hirshleifer et al. 2018, Belenzon et al. 2016, Humphery-Jenner 2014, Custódio et al. 2019). At the (pseudo) deal level, we include both *tech similarity* and *prod similarity* between (pseudo) acquirers and (pseudo) targets because technology and product market similarity are important drivers of M&A deals (Bena & Li, 2014; Hoberg & Philips, 2010; Yu et al., 2016; Ornaghi, 2009). Finally, we control for the fact whether (pseudo) acquirers and (pseudo) targets are from the *same state.* All variables are defined in Table A.2 in appendix.

## 4. Results

### *4.1 Firm likelihood to engage in M&As*

In this section, we investigate how technology differentiation relates to a firm's likelihood to be a target or acquirer. Table 1 presents descriptive statistics for targets versus industry, size, and B/M matched pseudo targets (Panel A), acquirers versus industry, size, and B/M matched pseudo acquirers (Panel B), and actual deals (acquirer-target pairs) versus pseudo deals (pseudo acquirer-target pairs) (Panel C).

'Insert Table 1'

As shown in Panel A of Table 1, targets are not significantly different from pseudo targets in terms of *R&D intensity*, *citation-weighted patents*, or *tech differentiation*. As shown in Panel B, acquirers are less R&D intensive and have a lower degree of *tech differentiation* compared to pseudo acquirers, but have more *citation-weighted patents* and a lower degree of *tech specialization*. These statistics suggest that having a low R&D intensity and missing a differentiated technology portfolio might trigger companies to become an acquirer. Comparing acquirers with targets, we find that

[24] https://www.bizjournals.com/sanjose/stories/1998/08/10/daily8.html

acquirers on average have much more *citation-weighted patents* compared to targets, but targets are more R&D intensive, have a higher degree of *tech differentiation* and *tech specialization*. In terms of financial characteristics, acquirers own larger *assets* and *cash* holdings, achieve higher *ROA* and *stock return*, and have lower *B/M* compared to targets. Finally, in Panel C of Table 2, we see that actual acquirer-target pairs have both a higher *tech similarity* and *prod similarity* compared to pseudo acquirer-target pairs, and are more likely to locate in the *same state*.

In line with Bena and Li (2014), we run the following conditional logit model to estimate the likelihood of being a target:

$$Target_{imt} = \alpha + \beta_1 * tech\ differentiation_{it} + \beta_2 * innovation\ characteristics_{it-1} + \beta_3 * financial\ characteristics_{it-1} + dealFE_m + \varepsilon_{imt}$$

$Target_{imt}$ equals one if firm *i* is the actual target in deal *m* in year *t*, and equals zero in case of an industry, size, and B/M matched pseudo target. We control for firm *i's* financial characteristics (i.e. *total assets*, *stock return, sales change, leverage, cash, ROA,* and *B/M*) and innovation characteristics (i.e. *R&D intensity*, *citation-weighted patents*, and *tech specialization*) in year *t-1*. Notice that $tech\ differentiation_{it}$ is calculated based on firm *i's* patents from years *t-5 to t-1*. $DealFE_m$ refers to deal fixed effects for target and matched pseudo targets involved in deal *m*. The same specification is applied to the sample of (pseudo) acquirer firms to distinguish acquirers from industry, size, and B/M matched pseudo acquirers. In line with Alcacer and Chung (2014), we calculate the marginal effect as odds ratio change caused by one standard deviation increase of the corresponding variable.

'Insert Table 2'

Table 2 displays the results of the conditional logit models with binary indictors for target (columns 1-4) and acquirer (columns 5-8) as outcomes. In line with Hypothesis 1, R&D intensive firms with a more unique and differentiated technology portfolio are more likely to become targets. A one standard deviation increase in *R&D intensity* and *tech differentiation* increase the odds ratio of being acquired with respectively 44.1% and 25.2% (column 1). *Citation-weighted patents* and *tech specialization* have no significant effect on the likelihood of becoming a target. As shown in column 5, firms with a lower *R&D intensity*, fewer *citation-weighted patents*, and a less differentiated technology portfolio are more likely to be acquirers. A one standard deviation increase in *R&D intensity*, *citation-weighted patents,* and *tech differentiation* decreases the odds ratio of being an acquirer with respectively 15.2%, 14.1% and 37.0%. Interestingly, the effect of *tech differentiation* measured by means of patent classes, subclasses or citations is mostly insignificant and much smaller compared to *tech differentiation* based on patent text. This result illustrates how patent text provides a different characterization of a firm's competitive position and differentiation in technology space compared to the traditional approach based on patent classification and citations (e.g., Jaffe 1989).

### *4.2 M&A transaction pairing*

To study M&A transaction likelihood between (pseudo) acquirers and (pseudo) targets, we run the following deal-level conditional logit model.

$$AcquirerTarget_{ijmt} = \alpha + \beta_1 * target\ tech\ differentiation_{it} + \beta_2 * acquirer\ tech\ differentiation_{jt} + \beta_3 * tech\ similarity_{ijt} + \beta_4 * prod\ similarity_{ijt} + \beta_5 * target\ tech\ differentiation_{it} * prod\ similarity_{ijt} + \beta_6 * innovation\ characteristics_{it-1} + \beta_7 * financial\ chacteristics_{it-1} + \beta_8 * innovation\ characteristics_{jt-1} + \beta_9 * financial\ chacteristics_{jt-1} + \beta_{10} * same\ state_{ijt} + dealFE_m + \varepsilon_{ijmt}$$

$AcquirerTarget_{ijmt}$ equals one if firm *i* and firm *j* are the actual acquirer-target pair for deal *m* in year *t*, and zero in case of industry, size, and B/M matched pseudo acquirer-target pairs. We control for the financial and innovation characteristics of both firm *i* and firm *j* in year *t-1*, and capture the effect of geographic location on M&A transactions by including $same\ state_{ijt}$ equal to one in case firm *i* and *j* are located in the same state in year *t*. Next, $tech\ similarity_{ijt}$ and $prod\ similarity_{ijt}$ capture the technology and product market similarity between firms *i* and *j* in year *t*. Finally, $DealFE_m$ capture deal fixed effects. Due to data availability, we restrict the analysis to 2,186 deals of which 311 real deals and 1,875 matched pseudo deals[25]. In particular, we can only include deals for which both (pseudo) acquirers and (pseudo) targets have at least one patent (to measure *tech similarity*). To improve readability, we will refer in the tables and discussion of the results to acquirers for the group of firms including both acquires and matched pseudo acquirers, and to targets for the group of firms including both targets and matched pseudo targets.

'Insert Table 3'

As shown in column 2 of Table 3, technology and product market similarity between acquirers and targets are both important drivers of M&A transactions. A one standard deviation increase in *tech similarity* and *prod similarity* multiply the odds of an M&A deal with respectively 2.6 and 3.3. This finding is consistent with prior studies emphasizing the important role of technology and product market synergies for M&As (e.g. Ahuja and Katila 2001, Hagedoorn and Duysters 2002, Hoberg and Philips 2010, Makri et al. 2010, Sears and Hoetker 2014, Bena and Li 2014, Yu et al. 2016). In line with our previous findings in Table 2 and Hypothesis 1, a one standard deviation increase in *target tech differentiation* increases the odds of a deal with 191% while a standard deviation increase in *acquirer tech differentiation* decreases the odds of a deal by 96% (column 3). In column 3, we include the interaction between *target tech differentiation* and *prod similarity* which is significant at p=0.069. In line with Hypothesis 3, the differentiation of a target's technology portfolio particularly increases M&A transaction likelihood with acquirers that are close competitors in the product market. For close product market rivals (75th percentile of *prod similarity*), the odds of M&A transaction incidence are 4 times higher for target's with unique and differentiated technology versus targets with less

[25] Prod market similarities are not available for all deals announced before 1989, given Hoberg and Philips (2021) restrict to firm-years whose 10K filings are available and are covered by Compustat. Furthermore, financial firms (SIC 6000-6999) and firm-years with nonpositive sales or with assets less than 1 million are excluded.

differentiated technology (75th versus 25th percentile of *target tech differentiation*). For more distant product market firms (25th percentile of *prod similarity*), the odds of M&A transaction incidence are only 2 times higher for target's with a high versus low degree of technology differentiation.

### *4.3 Acquisition price*

To examine the relation between the technology differentiation of a target firm and the acquisition price, we estimate the following model by ordinary least squares (OLS):

$$\begin{aligned} Acquisition\ price_{imt} &= \alpha + \gamma_i + \delta_t + \beta_1 * target\ tech\ differentiation_{it} + \beta_2 * tech\ similarity_{ijt} \\ &+ \beta_3 * prod\ similarity_{ijt} + \beta_4 * target\ tech\ differentiation_{it} \\ &* prod\ similarity_{ijt} + \beta_5 * innovation\ characteristics_{it-1} + \beta_6 \\ &* financial\ characteristics_{it-1} + \varepsilon_{imt} \end{aligned}$$

$Acquisition\ price_{imt}$ equals the logarithmic transformation of the price paid for target *i* for deal *m* in year *t*. We control for target firm *i*'s financial characteristics (i.e. *total assets, stock return, sales change, leverage, cash, ROA,* and *B/M*) and innovation characteristics (i.e. *R&D intensity, citation-weighted patents,* and *tech specialization*) in year *t-1* and include transaction announcement year ($\delta_t$) and industry fixed effects ($\delta_t$)[26]. As before, $tech\ similarity_{ijt}$ and $prod\ similarity_{ijt}$ capture the technology and product market similarity between target firm *i* and acquirer firm *j* in year *t*. We restrict the sample to a cross section of 902 actual targets whose acquisition price is available in SDC. In contrast to estimating the likelihood of being a target/acquirer and M&A transaction incidence, we cannot include matched (pseudo) acquirers/targets and deal fixed effects.

'Insert Table 4'

Table 4 summarizes the results. The number of observations varies across columns due to data availability. In particular, *tech similarity* is only available in case both the target and acquirer have at least one patent. In line with Hypothesis 2, we find that target firms with a more unique and differentiated technology portfolio are associated with a higher acquisition price. A one standard deviation increase in *tech differentiation* relates to an increase in acquisition price between 7% and 17%. In terms of other innovation characteristics, we find that more R&D intensive firms and firms with more citation-weighted patents also receive a higher acquisition price. A standard deviation increase in *target R&D intensity* relates to a increase in transaction price with 14%-34% and a standard deviation increase in *citation-weighted patents raises* transaction price by 10%-17%. In columns 3-4, we include *tech similarity* and *prod similarity* between target and acquirer and the interaction between *target tech differentiation* and *prod similarity*. The effect of *citation-weighted patents* becomes insignificant after including *tech similarity* and *prod similarity*. In contrast to Grimpe

[26] Year dummies are generated based on transaction announcement year. Industry dummies are generated based on the first digit of firm's SIC code.

and Hussinger (2014), we fail to find a significant relation between *tech similarity* and *acquisition price*. In line with Alperovych at al. (2021), we find that acquirers pay a higher price for targets which are more distant in the product market than for targets that are close product market rivals. This result is also consistent with Custódio and Metzger (2013) who show that CEOs of acquiring firms with prior experience in the target's product industry can negotiate a better deal and pay a lower premium for the target. Nevertheless, the interaction between *target tech differentiation* and *prod similarity* is positive and significant at p=0.086. The acquisition price paid by close product market firms (75$^{th}$ percentile of *prod similarity*) is 28% higher for targets with unique and differentiated technology versus targets with less differentiated technology (75$^{th}$ versus 25$^{th}$ percentile of *tech differentiation*). By contrast, the acquisition price paid by distant product market firms (25$^{th}$ percentile of *prod similarity*) is only 17% higher for targets with a high versus low degree of technology differentiation. This finding supports Hypothesis 4 that a unique and differentiated technology portfolio is particularly valuable for close product market rivals.

## 5. Discussion and conclusion

Whereas prior work predominantly focused on the relation between product market competition and M&A deals, we study how firm competition and differentiation in technology space relates to M&A transactions. Collecting an economy wide dataset of all M&A transactions involving US public firms between 1984 and 2006, and developing a new text-based method to map each firm's competitive position in technology space and to measure the uniqueness and differentiation of a firm's technology portfolio relative to all other firms, we show that technology pioneering firms – with a high R&D intensity and a differentiated technology portfolio – are more likely to become targets while less strong innovating firms – with a lower R&D intensity and a smaller and less differentiated technology portfolio – are more likely to be acquirers. In addition, we illustrate that firms with unique and differentiated technology are particularly targeted by close competitors in the product market and receive a higher acquisition price, particularly in case of M&As with close product market firms. Together, our findings illustrate that a firm's competitive position and differentiation in technology space is a key driver of M&A transaction incidence and transaction value, especially for close competitors in the product market.

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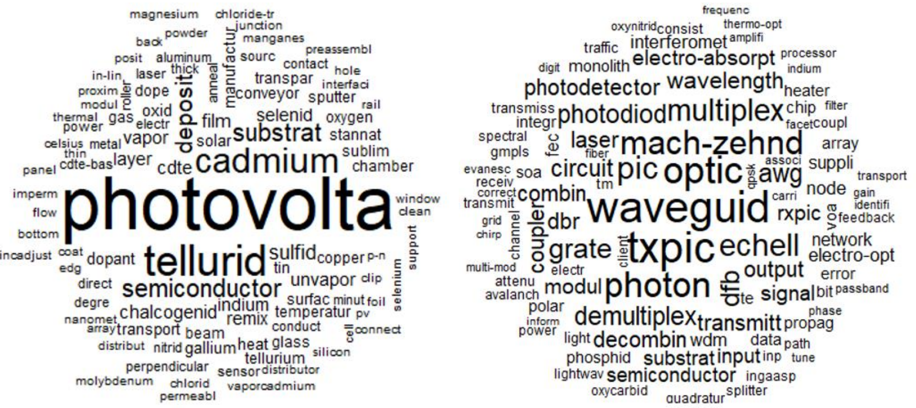
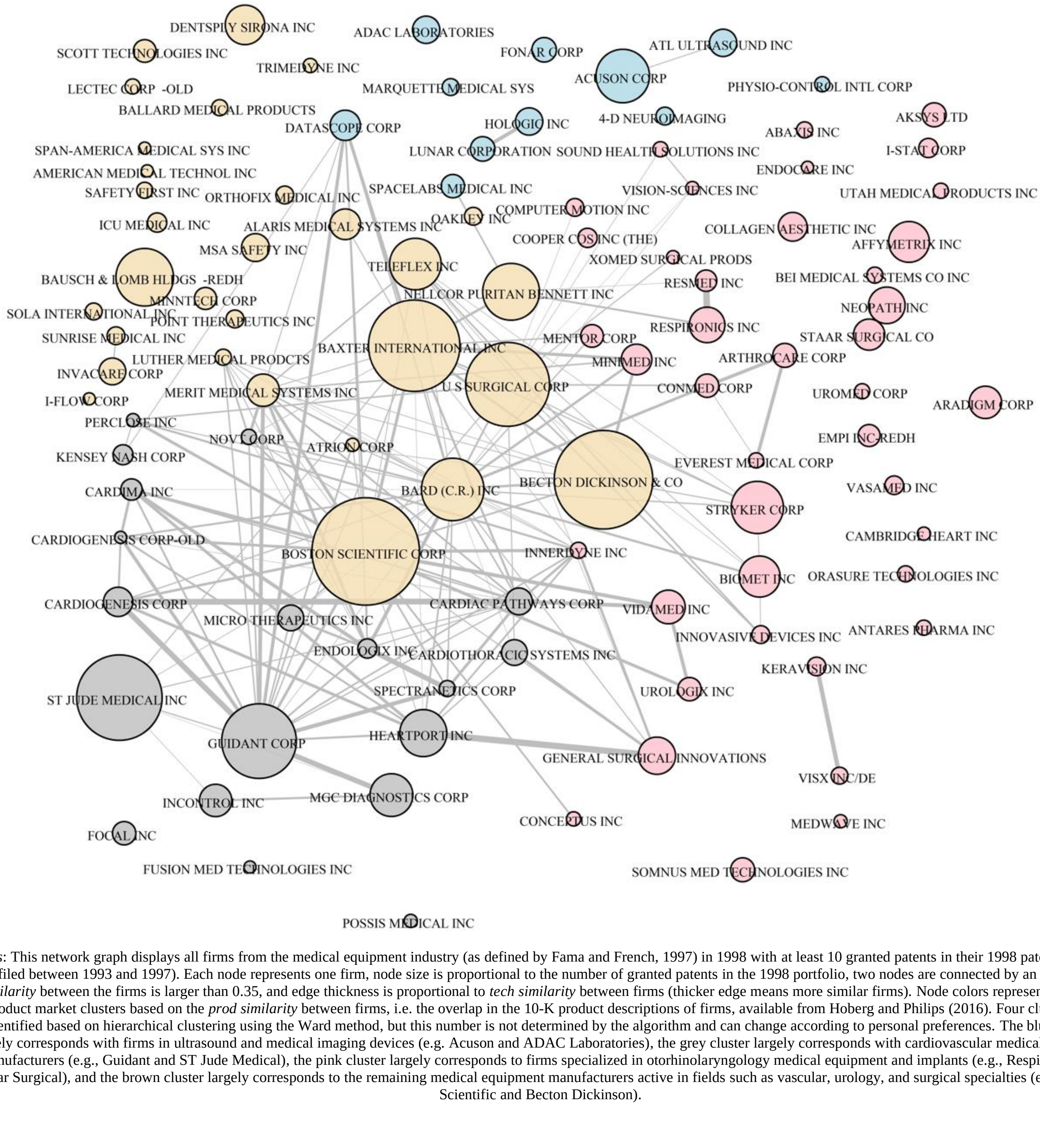
## Figure 1. Word cloud firm patent portfolios

(a) First Solar Inc. (b) Infinera Corporation




*Notes*: This figure illustrates the word clouds of two companies, namely First Solar Inc. (panel a) and Infinera Corporation (panel b). For each firm, we plot its top 100 most frequently used stemmed technical keywords identified from its patents granted between 1980 and 2015. Size of a word is proportional to the TF-IDF weight.

## Figure 2. Network of firms in medical equipment industry in 1998




*Notes*: This network graph displays all firms from the medical equipment industry (as defined by Fama and French, 1997) in 1998 with at least 10 granted patents in their 1998 patent portfolio (i.e. filed between 1993 and 1997). Each node represents one firm, node size is proportional to the number of granted patents in the 1998 portfolio, two nodes are connected by an edge if *tech similarity* between the firms is larger than 0.35, and edge thickness is proportional to *tech similarity* between firms (thicker edge means more similar firms). Node colors represent different product market clusters based on the *prod similarity* between firms, i.e. the overlap in the 10-K product descriptions of firms, available from Hoberg and Philips (2016). Four clusters are identified based on hierarchical clustering using the Ward method, but this number is not determined by the algorithm and can change according to personal preferences. The blue cluster largely corresponds with firms in ultrasound and medical imaging devices (e.g. Acuson and ADAC Laboratories), the grey cluster largely corresponds with cardiovascular medical equipment manufacturers (e.g., Guidant and ST Jude Medical), the pink cluster largely corresponds to firms specialized in otorhinolaryngology medical equipment and implants (e.g., Respironics and Staar Surgical), and the brown cluster largely corresponds to the remaining medical equipment manufacturers active in fields such as vascular, urology, and surgical specialties (e.g. Boston Scientific and Becton Dickinson).

# Table 1: Descriptive statistics

| | Mean | S.D. | Mean | S.D. | T test | |
|---|---|---|---|---|---|---|
| Panel A | Targets | | Pseudo Targets | | *t* | Pr(\|T\| > \|t\|) |
| Tech differentiation | 0.946 | 0.030 | 0.945 | 0.028 | -1.374 | 0.1697 |
| Tech differentiation (class) | 0.960 | 0.025 | 0.958 | 0.026 | -2.027 | 0.0427 |
| Tech differentiation (subclass) | 0.996 | 0.005 | 0.996 | 0.006 | -1.940 | 0.0525 |
| Tech differentiation (citation) | 0.996 | 0.058 | 0.998 | 0.038 | 1.094 | 0.2743 |
| R&D intensity | 11.741 | 12.686 | 11.527 | 11.962 | -0.459 | 0.6462 |
| Citation-weighted patents | 171.543 | 711.158 | 150.177 | 456.635 | -1.047 | 0.2951 |
| Tech specialization | 0.486 | 0.320 | 0.466 | 0.302 | -1.667 | 0.0956 |
| Total assets | 784.532 | 1,793.906 | 525.560 | 1,329.872 | -4.623 | 0.0000 |
| Sales change | 15.882 | 63.533 | 30.595 | 101.713 | 4.090 | 0.0000 |
| ROA | 2.265 | 25.357 | 1.521 | 24.509 | -0.784 | 0.4330 |
| Leverage | 17.739 | 18.941 | 15.779 | 19.524 | -2.634 | 0.0085 |
| Cash | 24.831 | 23.378 | 29.964 | 26.544 | 5.184 | 0.0000 |
| B/M | 0.560 | 0.504 | 0.516 | 0.492 | -2.299 | 0.0215 |
| Stock return | -5.939 | 61.022 | 2.939 | 72.043 | 3.328 | 0.0009 |
| Panel B | Acquirers | | Pseudo Acquirers | | *t* | Pr(\|T\| > \|t\|) |
| Tech differentiation | 0.924 | 0.042 | 0.932 | 0.034 | 12.664 | 0.0000 |
| Tech differentiation (class) | 0.953 | 0.027 | 0.956 | 0.027 | 6.689 | 0.0000 |
| Tech differentiation (subclass) | 0.994 | 0.008 | 0.995 | 0.011 | 4.124 | 0.0000 |
| Tech differentiation (citation) | 0.999 | 0.021 | 0.998 | 0.041 | -1.645 | 0.0999 |
| R&D intensity | 7.919 | 7.725 | 9.074 | 8.410 | 8.063 | 0.0000 |
| Citation-weighted patents | 1,587.857 | 6,074.662 | 482.209 | 1,976.231 | -18.233 | 0.0000 |
| Tech specialization | 0.361 | 0.304 | 0.384 | 0.291 | 4.495 | 0.0000 |
| Total assets | 3,324.345 | 7,015.476 | 1,395.928 | 3,767.917 | -23.148 | 0.0000 |
| Sales change | 32.842 | 84.815 | 24.132 | 79.406 | -6.202 | 0.0000 |
| ROA | 11.744 | 15.016 | 8.369 | 16.794 | -11.862 | 0.0000 |
| Leverage | 15.259 | 16.339 | 16.576 | 18.342 | 4.243 | 0.0000 |
| Cash | 25.121 | 22.909 | 26.747 | 23.925 | 3.953 | 0.0001 |
| B/M | 0.417 | 0.337 | 0.482 | 0.429 | 9.274 | 0.0000 |
| Stock return | 25.614 | 84.113 | 11.056 | 77.854 | -10.539 | 0.0000 |
| Panel C | Acquirer-Target Pairs | | Pseudo Acquirer-Target Pairs | | *t* | Pr(\|T\| > \|t\|) |
| Tech similarity | 0.259 | 0.173 | 0.170 | 0.151 | -9.432 | 0.0000 |
| Prod similarity | 0.141 | 0.091 | 0.094 | 0.064 | -10.987 | 0.0000 |
| Same state | 0.280 | 0.450 | 0.170 | 0.375 | -4.651 | 0.0000 |

*Notes:* This table reports the descriptive statistics of actual acquirers and target firms as well as pseudo firms. We only include the deal if both acquirer and target are covered by Compustat/CRSP and filed at least one patent in the five-year window before the announcement of the deal. *ROA*, *R&D intensity*, *Sales change*, *Leverage*, *Cash*, and *Stock return* are measured as percentages. *ROA*, *Sales change*, *R&D intensity*, *Total assets*, *Leverage*, *Cash*, *B/M*, and *Stock return* are winsorized at levels of 1% and 99%. *Prod similarity* is only available for observations after 1989 (inclusively). Hence, statistics reported in Panel C are based on deals whose *prod similarity* measures of acquirer-target pairs and at least one pseudo acquirer-target pairs are available. Definitions of variables are in Table A.2 in Appendix. Patent data are collected from DISCERN patent database. *, **, and *** indicates significance at the 10%, 5%, and 1% level, respectively.

# Table 2: Likelihood of being a target or acquirer

| | Target | | | | Acquirer | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Tech differentiation | 7.856** | | | | -8.658*** | | | |
| | (3.123) | | | | (1.278) | | | |
| Tech differentiation (class) | | 0.159 | | | | -4.304** | | |
| | | (2.666) | | | | (1.985) | | |
| Tech differentiation (subclass) | | | 11.094 | | | | -0.587 | |
| | | | (10.578) | | | | (1.566) | |
| Tech differentiation (citation) | | | | -0.654 | | | | 1.822*** |
| | | | | (0.690) | | | | (0.508) |
| R&D intensity | 3.007*** | 3.109*** | 3.118*** | 3.092*** | -1.715*** | -1.829*** | -1.690*** | -1.683*** |
| | (0.605) | (0.606) | (0.606) | (0.606) | (0.368) | (0.375) | (0.369) | (0.368) |
| Citation-weighted patents | -0.049 | -0.124*** | -0.116*** | -0.123*** | -0.066*** | 0.014 | 0.019 | 0.017 |
| | (0.048) | (0.038) | (0.039) | (0.038) | (0.022) | (0.019) | (0.018) | (0.018) |
| Tech specialization | 0.094 | 0.233 | 0.218 | 0.234 | 0.148 | 0.041 | -0.082 | -0.075 |
| | (0.183) | (0.190) | (0.177) | (0.176) | (0.101) | (0.109) | (0.095) | (0.095) |
| Deal fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 3,629 | 3,629 | 3,629 | 3,629 | 17,627 | 17,627 | 17,627 | 17,627 |
| Number of actual acquirers/targets | 903 | 903 | 903 | 903 | 4,415 | 4,415 | 4,415 | 4,415 |
| Number of pseudo acquirers/targets | 2,726 | 2,726 | 2,726 | 2,726 | 13,212 | 13,212 | 13,212 | 13,212 |
| ll | -1110 | -1113 | -1113 | -1113 | -4644 | -4661 | -4667 | -4664 |
| pseudo r2 | 0.079 | 0.077 | 0.077 | 0.077 | 0.209 | 0.206 | 0.205 | 0.205 |
| | *Marginal effects (%)* | | | | | | | |
| Tech differentiation | 25.159 | | | | -37.031 | | | |
| Tech differentiation (class) | | 0.413 | | | | -12.284 | | |
| Tech differentiation (subclass) | | | 6.457 | | | | -0.620 | |
| Tech differentiation (citation) | | | | -2.912 | | | | 6.948 |
| R&D intensity | 44.079 | 45.872 | 46.039. | 45.577 | -15.219 | -16.307 | -14.980 | -14.908 |
| Citation-weighted patents | -8.309 | -22.200 | -20.603 | -21.985 | -14.098 | 2.834 | 3.826 | 3.569 |
| Tech specialization | 2.922 | 7.404 | 6.909 | 7.425 | 4.470 | 1.213 | -2.443 | -2.239 |

*Notes*: The upper panel of the table reports coefficient estimates from conditional logit regression. An target (acquirer) can enter the sample if both itself and its pseudo firms are covered by Compustat/CRSP and filed at least one patent in the five-year period prior to the deal announcement. The dependent variable is equal to one for the actual acquiring firms (target firms), and zero for the pseudo firms. Control variables include *Total assets, Stock return, Sales change, Leverage, Cash, ROA, and B/M*. Variables *Total assets* and *Citation weighted patents* are in natural logarithms. *ROA*, *Sales change*, *R&D intensity*, *Total assets*, *Leverage*, *Cash*, *B/M*, and *Stock return* are winsorized at levels of 1% and 99%. Definitions of variables are provided in the Appendix. Robust standard errors (clustered at the deal level) are reported in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively. The bottom panel of the table reports the marginal effects which equals the odds ratio change caused by one standard deviation increase of the corresponding variables.

## Table 3: Likelihood of M&A transaction pairing

| | (1) | (2) | (3) |
|---|---|---|---|
| *Target characteristics* | | | |
| Target tech differentiation | 14.043*** | 36.943*** | 38.031*** |
| | (4.702) | (7.593) | (7.716) |
| Target R&D intensity | 2.134*** | 1.974* | 2.100** |
| | (0.767) | (1.049) | (1.054) |
| Target citation-weighted patents | -0.009 | -0.183* | -0.170* |
| | (0.071) | (0.094) | (0.094) |
| Target tech specialization | -0.254 | -0.130 | -0.106 |
| | (0.294) | (0.384) | (0.384) |
| *Acquirer characteristics* | | | |
| Acquirer tech differentiation | -16.219*** | -15.921*** | -15.687*** |
| | (4.001) | (5.952) | (6.055) |
| Acquirer R&D intensity | 2.688** | 1.547 | 1.444 |
| | (1.206) | (1.626) | (1.670) |
| Acquirer citation-weighted patents | -0.102 | -0.299*** | -0.300*** |
| | (0.075) | (0.112) | (0.114) |
| Acquirer tech specialization | 0.059 | -0.125 | -0.108 |
| | (0.411) | (0.517) | (0.526) |
| *Acquirer-target pair characteristics* | | | |
| Tech similarity | | 8.127*** | 8.265*** |
| | | (1.152) | (1.172) |
| Prod similarity | | 20.606*** | 20.270*** |
| | | (1.950) | (1.999) |
| Target tech differentiation * Prod similarity | | | 95.754* |
| | | | (52.572) |
| Deal fixed effects | Yes | Yes | Yes |
| Number of observations | 2,186 | 2,186 | 2,186 |
| Number of actual deals | 311 | 311 | 311 |
| Number of control deals | 1,875 | 1,875 | 1,875 |
| ll | -486.2 | -333.4 | -332.0 |
| pseudo r2 | 0.178 | 0.437 | 0.439 |
| | *Marginal effects (%)* | | |
| *Target characteristics* | | | |
| Target tech differentiation | 49.735 | 189.230 | 191.772 |
| Target R&D intensity | 33.548 | 30.672 | 32.925 |
| Target citation-weighted patents | -1.422 | -34.920 | -32.090 |
| Target tech specialization | -7.897 | -3.952 | -3.225 |
| *Acquirer characteristics* | | | |
| Acquirer tech differentiation | -100.641 | -98.086 | -96.107 |
| Acquirer R&D intensity | 24.918 | 13.661 | 12.694 |
| Acquirer citation-weighted patents | -26.667 | -99.648 | -100.061 |
| Acquirer tech specialization | 1.476 | -3.130 | -2.684 |
| *Acquirer-target pair characteristics* | | | |
| Tech similarity | | 259.373 | 267.225 |
| Prod similarity | | 329.243 | 334.17 |

*Notes:* The table reports coefficient estimates from conditional logit regression. A deal can enter the sample if the M&A deal was announced after 1989 (inclusively) and both the acquirer and the target and their respective pseudo firms own at least one patent in the five-year period prior to the deal announcement. The dependent variable is equal to one for the actual acquirer-target firm pair, and zero for the pseudo pairs. In case of collinearity, independent variables are centered before constructing the interaction term. Control variables include *Total assets, Stock return, Sales change, Leverage, Cash, ROA, B/M, R&D intensity, Citation-weighted patents,* and *Tech specialization* of both acquirers and targets at the fiscal year end before deal announcement as well as a dummy variable which indicates whether the acquirer and target are from the same state. Variables *Total assets* and *Citation-weighted patents* are in natural logarithms. *ROA*, *Sales change*, *R&D intensity*, *Total assets*, *Leverage*, *Cash*, *B/M*, and *Stock return* are winsorized at levels of 1% and 99%. Definitions of variables are provided in the Appendix. Robust standard errors (clustered at the deal level) are reported in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively. The marginal effect equals the odds ratio change caused by one standard deviation increase of the corresponding variable. If the focal variable is included in the interaction term, we calculate marginal effect as the change in odds ratio caused by one-standard-deviation increase of the focal variable while holding the other variable at its median.

## Table 4: Acquisition price

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Target characteristics* | | | | |
| Target tech differentiation | 2.140* | 4.645* | 5.364** | 5.716** |
| | (1.155) | (2.364) | (2.468) | (2.473) |
| Target R&D intensity | 1.003*** | 2.013*** | 2.097*** | 2.158*** |
| | (0.375) | (0.594) | (0.607) | (0.612) |
| Target citation-weighted patents | 0.095*** | 0.068* | 0.061 | 0.062 |
| | (0.022) | (0.038) | (0.040) | (0.040) |
| Target tech specialization | 0.230** | 0.179 | 0.202 | 0.213 |
| | (0.090) | (0.164) | (0.163) | (0.163) |
| *Acquirer-target pair characteristics* | | | | |
| Tech similarity | | | 0.240 | 0.309 |
| | | | (0.264) | (0.264) |
| Prod similarity | | | -0.613 | -0.873** |
| | | | (0.373) | (0.375) |
| Target tech differentiation * Prod similarity | | | | 21.661* |
| | | | | (12.572) |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Number of observations | 902 | 311 | 311 | 311 |
| r2 | 0.897 | 0.903 | 0.904 | 0.905 |
| | *Marginal effects (%)* | | | |
| *Target characteristics* | | | | |
| Target tech differentiation | 6.583 | 13.991 | 16.325 | 16.635 |
| Target R&D intensity | 13.574 | 31.593 | 33.110 | 34.227 |
| Target citation-weighted patents | 16.931 | 11.738 | 10.409 | 10.673 |
| Target tech specialization | 7.655 | 5.605 | 6.379 | 6.722 |
| *Acquirer-target pair characteristics* | | | | |
| Tech similarity | | | 4.241 | 5.486 |
| Prod similarity | | | -5.440 | -6.780 |

*Notes*: The upper panel of the table reports coefficient estimates from OLS. Column (1) is based on 902 actual targets whose *transaction value* is available. Column (2) to Column (4) are restricted to 311 actual targets whose *prod similarity* with acquirer is available. We take the natural logarithm of the dependent variable *Transaction value* in millions of 2006 constant dollars. In case of collinearity, independent variables are centered before constructing the interaction term. Control variables include *Total assets, Stock return, Sales change, Leverage, Cash, ROA, B/M, R&D intensity, Citation weighted patents*, and *Tech specialization* of targets. Variables *Total assets* and *Citation weighted patents* are in natural logarithms. *ROA, Sales change, R&D intensity, Total assets, Leverage, Cash, B/M*, and *Stock return* are winsorized at levels of 1% and 99%. Industry dummies are generated based on the first digit of SIC code. Definitions of variables are provided in the Appendix. Robust standard errors are reported in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively. The bottom panel of the table reports the marginal effects which equal the standard deviation of the given variable times its coefficient estimated by OLS. If the focal variable is included in the interaction term, we calculate marginal effect as the response in *Transaction value* caused by one-standard-deviation increase of the focal variable while holding the other variable at its median.

# Online Appendix

## Table A.1: Corporate Acquisitions over Time, 1984-2006 (industry, size, and B/M-matched sample)

| | Acquirer Sample | | Target Sample | | Deal (Acquirer-Target) Sample | |
|---|---|---|---|---|---|---|
| Year | Acquirers | Acquirers with Patents | Targets | Targets with Patents | Deals | Acquirers and Targets with Patents |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 1984 | 23 | 8 | 34 | 6 | 13 | 0 |
| 1985 | 124 | 42 | 102 | 20 | 43 | 6 |
| 1986 | 211 | 82 | 137 | 19 | 49 | 8 |
| 1987 | 179 | 64 | 117 | 12 | 44 | 3 |
| 1988 | 215 | 75 | 152 | 37 | 51 | 9 |
| 1989 | 255 | 81 | 120 | 32 | 34 | 11 |
| 1990 | 242 | 78 | 79 | 18 | 33 | 5 |
| 1991 | 258 | 79 | 59 | 12 | 23 | 5 |
| 1992 | 362 | 100 | 58 | 11 | 24 | 7 |
| 1993 | 487 | 127 | 74 | 9 | 33 | 3 |
| 1994 | 593 | 164 | 143 | 28 | 54 | 12 |
| 1995 | 694 | 191 | 195 | 43 | 92 | 17 |
| 1996 | 860 | 247 | 199 | 35 | 108 | 13 |
| 1997 | 1,079 | 289 | 271 | 42 | 130 | 15 |
| 1998 | 1,137 | 334 | 337 | 87 | 159 | 36 |
| 1999 | 970 | 365 | 364 | 103 | 163 | 45 |
| 2000 | 934 | 431 | 283 | 84 | 138 | 37 |
| 2001 | 649 | 275 | 225 | 61 | 102 | 30 |
| 2002 | 615 | 281 | 130 | 36 | 75 | 20 |
| 2003 | 595 | 269 | 125 | 43 | 71 | 24 |
| 2004 | 640 | 291 | 113 | 41 | 65 | 19 |
| 2005 | 683 | 266 | 145 | 66 | 78 | 30 |
| 2006 | 701 | 276 | 147 | 58 | 83 | 24 |
| Total | 12,506 | 4,415 | 3,609 | 903 | 1,665 | 379 |

*Notes*: This table reports the number of completed acquisitions announced between January 1, 1984 and December 31, 2006. A deal enters acquirer sample (target sample) if the acquirer (target firm) is covered by Compustat/CRSP and has at least one pseudo acquirers (target firms) as the fiscal year end before the bid announcement. A deal enters acquirer-target sample if both acquirer and target are covered by Compustat/CRSP and have their respective pseudo firms. For the subsample acquirers with patents (targets with patents), we require that the acquirer and the pseudo acquirer (the target and the pseudo target) filed at least one patent from year *t-5* to year *t-1*, where *t* is the deal announcement year. Patent data are collected from DISCERN patent database.

## Table A.2: Definitions variables

| | |
|---|---|
| Innovation Measures | |
| Tech Similarity | Patent portfolio of firm *i* is represented by a vector $S_i = (S_{i1}, S_{i2}, \ldots, S_{iK})$, where $k \in (1,K)$ indicates a keyword identified from the entire patent vocabulary and $S_{ik}$ denotes the ratio of patents filed by firm *i* using word *k* between year *t-5* and *t-1* , where *t* is the deal announcement year, to the total number of patents filed by firm *i* over the same five-year period. Text vectors are adjusted by TFIDF. Text Similarity between firm *i* and *j* is calculated as $cos(S_i, S_j)$. |
| Tech differentiation | First, we construct the patent portfolio for firm *i* in year *t* by collecting all patents filed by it between year *t-5* and *t-1*. Second, we calculate the average text similarity between firm *i* and all other firms which filed at least one patent between year *t-5* and *t-1* as the average similarity. Finally, we deduct average similarity from 1 to obtain the Tech differentiation. |
| Tech differentiation (class) | First, we construct the patent portfolio for firm *i* in year *t* by collecting all patents filed by it between year *t-5* and *t-1*. Second, we calculate the average class similarity between firm *i* and all other firms which filed at least one patent between year *t-5* and *t-1* as the average similarity. Finally, we deduct average similarity from 1 to obtain the Tech differentiation (class). |
| Tech differentiation (subclass) | First, we construct the patent portfolio for firm *i* in year *t* by collecting all patents filed by it between year *t-5* and *t-1*. Second, we calculate the average subclass similarity between firm *i* and all other firms which filed at least one patent between year *t-5* and *t-1* as the average similarity. Finally, we deduct average similarity from 1 to obtain the Tech differentiation (subclass). |
| Tech differentiation (citation) | First, we construct the patent portfolio for firm *i* in year *t* by collecting all patents filed by it between year *t-5* and *t-1*. Second, we calculate the average citation similarity between firm *i* and all other firms which filed at least one patent between year *t-5* and *t-1* as the average similarity. Finally, we deduct average similarity from 1 to obtain the Tech differentiation (citation). |
| R&D intensity | Research and development expenses scaled by total assets. |
| Citation-Weighted Patents | Citation-weighted patent count with application years from *t-5* to *t-1*. Citation is counted within a five-year period starting from the patent grant year. |
| Tech specialization | First, we construct the patent portfolio for firm *i* in year t by collecting all patents filed by it between year *t-5* and *t-1*. Second, the patent portfolio of firm *i* is represented by a vector $S_i = (S_{i1}, S_{i2}, \ldots, S_{iK})$, where $k \in (1,K)$ indicates patent main class and $S_{ik}$ denotes the share of patents assigned to class *k*. Finally, firm *i*'s tech specialization is calculated as a Herfindahl index based on patent classification, namely $\sum_{k=1}^{K} s_k^{\,2}$. |
| Firm Characteristics | |
| Total Assets | The total assets in millions. |
| Δ Sales | Yearly sales growth rate. |
| ROA | Earnings before interest, taxes, depreciation, and amortization (EBITDA) scaled by total assets. |
| Leverage | Total debt (long-term debt and debt in current liabilities) scaled by total assets. |
| Cash | Cash and short-term investment scaled by total assets. |
| B/M | The book value of common equity scaled by the market value of common equity. Market value is common shares outstanding multiplied by the month-end price that corresponds to the period end date. |
| Stock Return | The difference between the buy-and-hold stock return from month -14 to month -3 relative to the deal announcement month and the analogously defined buy-and-hold stock return on the value-weighted CRSP index. |
| Asset Tangibility | Property plant and equipment divided by total assets |
| Firm Age | The number of years since the first entered Compustat (earliest date 1975) |
| Prod market competition | The sum of pairwise product similarity scores (based on the business descriptions from annual 10-K reports) between the focal firm *i* in year *t* and all other firms in year *t* (Hoberg and Philips 2016). |
| Tobin's Q | The ratio of the market value of a firm and the replacement (book) value of the firm's assets. A firm's market value is defined as the sum of market capitalization (share price multiplied by the number of common shares outstanding at the end of the year), preferred stock, minority interests, and total debt minus cash. |
| Sales | Yearly net sales. |
| Deal Characteristics | |
| Same State | Equal to one if the acquirer and the target firm are located in the same state, and zero otherwise. |
| Prod Similarity | Product similarity based on product descriptions in 10-K reports by Hoherg and Philips (2010,2016, 2021). |