Product Market Dynamics and Mergers and Acquisitions: Insights from the USPTO Trademark Data*

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This version: July 2017

Abstract

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Keywords: Trademarks; Product lines; Trademark similarity; Mergers and Acquisitions; Synergies; Product market competition
JEL Classification: G34; O32; O34

* We are grateful for helpful comments from Tania Babina, Benjamin Balsmeier, Shai Bernstein, Thomas Chemmanur, Michael Ewens, Lee Fleming, Will Gornall, Gustavo Manso, Roni Michaely, Christine Parlour, Liu Yang, Sandy Yu, and conference participants at the Berkeley Innovation and Finance Conference and the Financial Management Association Asia/Pacific Conference (Taipei) for their valuable comments. All errors are our own.

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Abstract

Using a large and unique trademark-merger dataset over the period 1983 to 2016, we show that companies with large trademark portfolios, newer trademarks, and fast growth in trademarks are more likely to be acquirers, while companies with newer and more focused trademarks, and slower growth in trademarks are more likely to be target firms. Further, firms with overlapping product lines as captured by trademark similarity are more likely to be merged and these deals are associated with high combined announcement period returns. Post-merger, merger partners with overlapping product lines cancel more trademarks as well as to register fewer new trademarks, and are associated with lower costs of goods sold, lower advertising expenses, higher return on sales, and larger market shares. We conclude that eliminating product market competitors is an important driver of acquisitions.

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I. Introduction

A trademark is a word, phrase, symbol, and/or design that identifies and distinguishes the source of the goods or services of one party from those of others. Examples of well-known trademarks include the word "McDonald's," Nike's "swoosh" symbol, and Coca Cola's unique design of its glass bottle. A trademark signifies the launch of a new product line, i.e., a group of related products under a single brand sold by the same company.[1] For example, the word "iPad" is a trademark for the product line of tablet computer devices produced by Apple. Despite the prevalence and importance of trademarks in the economic activities of firms, there is little direct evidence of whether and how a firm's product market dynamics as captured by its portfolio of trademarks drive its decisions to participate in mergers and acquisitions (M&As) and how M&As in turn affects its future product market development.[2]

One important question in the M&A literature is how do mergers create value? Prior research has suggested two sources of synergistic gains. First, mergers may generate productive efficiencies that result in higher operating profits and/or reduced capital spending. Second, potentially anticompetitive mergers among firms with similar products could enable the combined firm to exercise market power, with the merger gains arising at the expense of customers and suppliers. Eckbo (1983, 1985) refers to the first form as the operational efficiency hypothesis, and the second as the market power hypothesis. Prior studies based on single industry or small samples produce mixed evidence (see, for example, Kim and Singal, 1993; Houston, James, and Ryngaert, 2001; Maksimovic and Phillips, 2001; Sapienza, 2002; Devos, Kadapakkam, and Krishnamurthy, 2009).

The central idea guiding our empirical analysis is that eliminating product market competition to gain market power is one major impetus for M&As, which is supported by abundant anecdotal evidence. For example, Microsoft is famous for its strategy of "buying out competitors." Appendix 1 in the Internet Appendix illustrates how Microsoft executes this strategy. Panel A shows that a significant portion of Microsoft's target firms' trademarks (i.e., product lines) are cancelled after being acquired. In the acquisition case of Visio Corporation,

[1] There are two types of trademarks: product and marketing. For our purpose, we focus on product trademarks and have developed a classification scheme to identify product trademarks (more details later in the paper).

[2] Very little empirical work has shed light on such effects, in large part because there was no comprehensive data on trademarks until very recently (see Graham et al., 2013; Graham, Macro, and Myers, 2015) for an introduction to the USPTO database on trademarks and recent studies by Faurel et al., (2016) and Heath and Mace (2017).

Microsoft competed with this target firm in the area of diagramming application software. Visio Corporation had 24 trademarks before the acquisition and 10 of them were cancelled after the deal. The cancellation rate is 42%. In the case of Navision, Microsoft competed with this target firm in the area of enterprise resource planning (ERP) software. Navision had 8 trademarks before the deal and 6 of them were cancelled afterwards. Panel B provides a detailed list of target firms' trademarks from before to after deal completion.

We conjecture that firms active in product development like Microsoft may wish to acquire firms overlapping in product offerings to help reduce product market competition, to cut costs of operating duplicate product lines, or to develop new product lines that help differentiate them from rivals. As such, we expect that parties with inter-firm linkages in the product market space will be more likely to form merger pairs. We also expect that transactions involving merger partners with overlapping product lines will result in more concentrated product lines (of the combined firm) by reducing overlaps and launching fewer new and differential product lines post-merger.

To examine the role of product market dynamics in M&As, we compile an economy-wide trademark-merger dataset, and develop a set of trademark measures that capture firms' product market dynamics and potential synergistic gains stemming from product line overlap between merger partners. We first show that firms with large trademark portfolios, newer trademarks, and fast growth in trademarks are more likely to be acquirers, while firms with newer and more focused trademarks, and slower growth in trademarks are more likely to be target firms. These findings suggest that innovative firms in terms of actively developing new product lines are also more acquisitive.

We then find that the overlap between any two firms' product lines, as captured by trademark similarity, has a significant effect on the probability of a merger pair formation. The role of product line overlap remains after controlling for overlapping technologies of Bena and Li (2014) and overlapping product descriptions of Hoberg and Phillips (2010). Moreover, trademark similarity between acquirers and targets is positively associated with combined announcement period abnormal returns, suggesting positive synergies in deals involving firms with overlapping product lines.

Using a quasi-experiment involving bids withdrawn due to reasons exogenous to product market outcome of either the acquirer or the target firm, we estimate the treatment effect of a merger on post-merger trademark cancellations and registrations.[3] Following Seru (2014) and Bena and Li (2014), we argue that the assignment of deals into the treatment sample (i.e., completed deals) versus the control sample (i.e., withdrawn bids due to reasons exogenous to product market outcome) can be treated as random. As such, any selection concerns are differenced out by comparing firms' product lines in the treatment sample, pre- and post-merger, with that of the control sample. We show that the greater overlap in product lines of the acquirers and targets leads to more cancelled trademarks on the target side, fewer newly registered trademarks on the acquirer side, and no significant improvement in trademark growth on the acquirer side. Moreover, we show that post-merger, the greater overlap in product lines of merger partners does not lead to any improvement in operational efficiency, whereas it lowers costs of goods sold and advertising expenses, and leads to higher return on sales and larger market shares of the acquirers. Taken together, our results suggest that acquirers' overlap in product lines with targets prompts them to eliminate competition in order to gain market power; in the process, synergies are realized as acquirers trim overlapping products, cut costs of good sold, and gain stronger market positions.

Our paper differs from prior work and thus contributes to the M&A literature in the following dimensions. First, using recently available and comprehensive data on trademarks from the United States Patent and Trademark Office (USPTO) that allows us to track the evolution of acquirers' and targets' product lines post-merger, we can address the important questions of whether and how merger synergies are realized and whether acquirers and targets are affected differentially by the merger; both have not been examined at an economy-wide level prior to our paper. By focusing on post-merger product market dynamics, our paper provides direct evidence on the importance of eliminating product market competition to gain market power as a driver of M&As. Second, the trademark data allows us to capture corporate innovation that goes beyond R&D expenditures and patents (Lev, 1999; Koh and Reeb, 2015; Faurel et al., 2016). Different from patents that measure technological innovation, trademarks

[3] See Li and Prabhala (2007) for more detailed discussion on selection effects versus treatment effects in corporate finance.

capture the launch, continuation, and termination of product lines, and thus are another important marker of corporate innovation in the literature on intellectual property (Lev, 1999; Mendonca, Pereira, and Godinho, 2004; OECD, 2010a, 2010b; Sandner and Block, 2011). We develop a novel measure of pairwise product line overlap, and show its importance in merger pair formation. Notably, this measure is distinct from traditional industry affiliations as captured by the Standard Industry Classification (SIC) codes or the Fama-French industries.

Our paper is motivated by and closely related to Hoberg and Phillips (2010), Bena and Li (2014), and Sheen (2014). Using text-based analysis of 10-K product descriptions to examine whether firms exploit product market synergies through asset complementarities, Hoberg and Phillips (2010) find that transactions are more likely to occur between firms using similar product market language and that post-merger, stock returns, operating performance, and growth in product descriptions all increase for transactions with similar product market language. Using a large patent-merger data set over the period 1984-2006 and patent-based measures for technological overlap, Bena and Li (2014) find that synergies obtained from combining innovation capabilities are important drivers of acquisitions. Using a sample of over 9,000 brands in 20 consumer goods categories by 372 firms over the period 1980-2009, Sheen (2014) shows that the real changes in quality and price of products sold by merging firms are consistent with consolidation by related merging firms to achieve operational efficiencies and lower costs.

Our paper differs from these three papers in a number of ways. First, we are one of the first to use comprehensive trademark data to examine the role of overlapping product lines in M&As, while Hoberg and Phillips' (2010) measure is based on textual analysis of 10-K's and hence captures similarity in product descriptions. We view our measure of product line overlap and their measure of similar product descriptions as complementary. Second, the detailed data on trademark registrations and cancellations allows us to address the important question of real product market implications of M&As at an economy-wide level, while Sheen's (2014) pioneering work in the area is limited to fewer than 100 deals and their effect on products within the 20 consumer goods categories in his sample. Finally, our analysis highlights another important marker of corporate innovation—trademarks that are distinctly different from R&D expenditures and patents, extending the analysis of Bena and Li (2014) using patents as an innovation metric.

The paper proceeds as follows. In the next section, we develop our hypotheses. We describe the USPTO trademark data set, our empirical methodology including the construction of key variables, and provide a sample overview in Section III. We examine the ex-ante selection effects of product lines on transaction incidence and merger pairing in Section IV. In Section V, we explore the ex-post treatment effect of a merger on firms' product lines, operating efficiency, and product market performance. We conclude in Section VI.

II. Hypothesis Development

A. Product Market Characteristics and Transaction Incidence

Innovation as a key driver of firm value is a well-established fact (Bloom and Van Reenen, 2002; Pastor and Veronesi, 2009). Complementing prior literature on corporate innovation primarily based on R&D and patents, in this paper, we use a firm's portfolio of trademarks to capture its innovation activities with a focus on new product development. Our trademark-based innovation metric echoes Lev (1999) who says, "Research capability should be assessed primarily by output measures, such as the number of new products that have emerged from the development process, as well as the number of patents, patent citations, and trademarks registered… " (p. 32).

However, buying innovation is generally not feasible because establishing an innovation's value requires disclosure, and a potential buyer has no incentive to pay once such information has been revealed. Holmström and Roberts (1998) thus argue that many M&A transactions are made to source innovation. Cohen and Levinthal (1989) and Cassiman and Veugelers (2006) further point out that only firms with valuable experience from internal innovation activities are capable of assessing external acquisition opportunities and potential targets and implementing post-merger integration. The arguments above lead to our first hypothesis:

H1: The likelihood of a firm to participate in M&As increases in the size of its trademark portfolio.

B. Product Line Overlap and Merger Pairing

We next ask how acquirers identify prospective target firms. Hart and Holström (2010) note that when two firms' production functions exhibit externalities—for example, when they need to coordinate their technologies—a merger facilitates coordination that cannot otherwise be achieved. We conjecture that the overlap in firms' product lines may lead to merger-pairing decisions for the following reasons.

First, when the overlap in product lines between merger participants is high, the target firm and the acquirer are likely to be direct competitors before the merger, and hence the acquirer has strong incentives to eliminate (potential) competition through an acquisition. On a related note, Eckbo (1983, 1985) find that firms acquire competitors to collude on Cournot competition.

Second, buying target firms with overlapping product lines helps overcome information asymmetry in acquisitions. Intellectual property and technological knowhow, by nature, are more difficult to evaluate than tangible assets. One concern for an acquirer, and to a less extent for a target firm, is its ability to accurately value a target firm (an acquirer). If the acquirer and its target firm have similar product lines and hence are familiar with each other's innovation capabilities and operations, then information asymmetry between merger participants is largely mitigated (Hitt et al., 1996; Kaplan, 2000; Higgins and Rodriguez, 2006).

Third and finally, acquiring targets with overlapping product lines also generates synergies. The overlap in product lines suggests that the acquirer and its target firm may often pursue related activities. These related acquisitions are expected to perform better since the acquirer is likely to have skills in operating its target firm's assets, and has similar/complementary technologies to continue with its target firm's new product launches (Cassiman and Colombo, 2006; Cassiman and Veugelers, 2006). Moreover, the overlap in product lines can lead to economies of scale and scope in innovation and marketing, for example, through reducing duplicate R&D and marketing effort, and hence can trigger mergers (Henderson and Cockburn, 1996; Hart and Holström, 2010).

As such, we expect that acquirers will pursue target firms with which they have overlapping product lines, or similar innovation capabilities. Empirically, we capture the extent of overlap in product lines using trademark similarity—a cosine similarity measure of any two firms' trademark portfolios. The above discussions lead to our second hypothesis:

H2a: M&As are more likely to occur between firm-pairs with greater trademark similarity.

To the extent that firms pursue target firms with greater overlap in product lines to eliminate competition and/or generate operational efficiency, we conjecture that the market anticipates such gains when the deal is publicly announced, which leads to the following hypothesis:

H2b: The M&A synergies are larger for deals involving firm-pairs with greater trademark similarity.

Empirically, we capture merger synergies using the combined announcement period return following Bradley, Desai, and Kim (1988).

C. Product Line Overlap and Eliminating Competition

So far, we have developed hypotheses about the ex-ante selection effects of product market dynamics as captured by trademarks on transaction incidence and merger pairing, focusing on the role of overlap in product lines. To establish that merging firms with overlap in product lines can generate synergies, we must ascertain the ex-post treatment effect of a merger on post-merger product market development. As we have argued before, when the overlap in product lines (trademark similarity) between merger participants is high, the target and the acquirer are likely to be direct competitors before the merger, and hence acquirers have strong incentives to eliminate product market competition through consolidation. Kim and Singal (1993) show that airline mergers lead to airfare increases in routes served by merging airlines, suggesting that one incentive for airlines to merge is to gain market power.

We conjecture that when acquirers and targets share similar product lines, a merger transaction is less motivated by the need to create new products but more by consolidation and efficiency considerations. The overlap in product lines makes it easier for acquirers to understand target firms' operations and to replace inefficient management and/or production processes in order to achieve efficiency and higher profitability (Hitt et al., 1991). Karim and Mitchell (2000) further note that competitive advantages come from the combination of distinctive resources of merging firms, and thus acquirers are more likely to keep (drop) targets' assets and product lines that are different from (similar to) theirs, which offers a rationale for post-merger path-breaking changes. Based on the above discussion, we expect that acquirers are more likely to cancel target firms' trademarks after the merger, when the pre-merger trademark similarity is high. Our third hypothesis is thus as follows:

H3: Post-merger, acquirers are more likely to cancel target firms' trademarks when their trademark similarity is high.

Finally, how does the interaction between overlap in merging firms' product lines and M&As affect post-merger acquirers' product lines? On the one hand, some prior work has shown that the relatedness of merger participants is critical for post-merger success. Maksimovic, Phillips, and Prabhala (2011) find that the productivity of acquired assets increases in industries where the acquirer operates. Hoberg and Phillips (2010) show that mergers between firms with similar product descriptions achieve bigger product range expansions, and higher operating profitability and sales growth. Fan and Goyal (2006) find that vertical mergers are associated with positive wealth effects significantly larger than those for diversifying mergers. Ahuja and Katila (2001) show that technological relatedness is associated with improved innovation output of acquiring firms in the chemicals industry. Bena and Li (2014) find similar results based on economy-wide evidence. One possible channel for the success is that post-merger integration takes up managers' time and energy, and hence new product development may be delayed and/or curtailed. The overlap in product lines facilitates the integration and lowers related costs and stress associated with consolidation, thus giving managers more time to devoted to developing new product lines after the merger.

On the other hand, there are a number of counter arguments suggesting that M&As may lead to fewer new product launches when acquirers and targets share similar product lines.[5] First, one of the primary reasons to do a deal is to acquire new knowledge because only new knowledge may offer a new solution to an old problem and serve as a catalyst for absorbing additional stimuli and information from an absorptive capacity perspective (Cohen and Levinthal, 1990; Ahuja and Katila, 2001). When acquirers and targets share similar product

[5] Hitt, Hoskisson, and Ireland (1990) argue that acquisitions consume managers' energy and attention during negotiations and post-merger integration and thus lead to less subsequent innovation, and Hitt et al., (1991) provide empirical support for that argument showing lower R&D expenditures and patent output after mergers.

lines, suggesting them possessing similar technologies/knowhow, there is not much new knowledge to be gained from an acquirer point of view. Second, M&As create disruption and lead to job separation. When acquirers and targets overlap in product lines, employees are more worried about security and under greater pressure from internal competition (Hitt and Hoskisson, 1991; Paruchuri, Nerkar, and Hambrick, 2006). Such disruption and stress could result in fewer new product launches. Our fourth and final hypothesis is thus two-sided:

H4a: Post-merger, acquirers will develop more product lines when the pre-merger trademark similarity is high.

H4b: Post-merger, acquirers will develop fewer product lines when the pre-merger trademark similarity is high.

In our empirical investigation, we use the trademark data to examine whether and how product lines of acquirers and targets are combined post-merger and how the combined firm continues (or discontinues) its product lines to test those hypotheses. Our data, measures, and empirical investigation will offer new insight into the sources of synergistic gains in M&As. In the next section, we describe our new dataset on trademarks, empirical methodology, and present a sample overview.

III. The Trademark Dataset, Methodology, and Sample Overview

A. The USPTO Trademark Case Files Dataset

A.1 Trademark basics

A trademark is a word, phrase, symbol, and/or design that identifies and distinguishes the source of the goods or services of one party from those of others. Essentially, a trademark is anything that can serve the function of differentiation for consumers. It is a valuable asset to trademark owners as it offers them the exclusive right to use the mark and from which to build customer loyalty and maintain market power.

In the U.S., a trademark can be registered at either the state or federal level. A state-level registered trademark will be protected only within the jurisdiction of the state under the common law. In contrast, a federally registered trademark (through the USPTO) can enjoy nationwide protection under the federal trademark law and is also eligible to attach the symbol ® adjacent to the mark itself.

To apply for a trademark, the applicant must select the appropriate content of the mark and specify the trademark class.[6] A trademark must be registered within one or multiple classes of goods or services, and the scope of aforementioned exclusivity right is only effective within the registered class(es).[7] For example, if the word "Apple" is registered only in the class of "Electrical and scientific apparatus", it cannot prevent others from using "Apple" in classes such as "Pharmaceuticals." There are 45 different classes, including 34 goods classes and 11 services classes, for trademark registration purpose according to the international NICE Classification of Goods and Services.[8] The applicant must also provide evidence that the trademark is currently used or bona fide intended to be used in commerce within the specified class. If the use-in-commerce requirement is not satisfied, the trademark cannot be registered. The process of trademark registration can take from about one year to several years.

After registration, trademarks can be renewed with the USPTO every 10 years as long as the use-in-commerce requirement is satisfied and the renewal fee is paid.[9] To renew, in the 6th year after initial registration, the owner must show evidence of continued use and pay a maintenance fee, or face cancellation, and in the 10th year, pay a renewal fee. Afterwards, in every successive 10th year, the owner is again required to show evidence of continued use as well as file a renewal application and pay both the maintenance and renewal fees, or the registration

[6] The basic requirements for word marks are uniqueness and non-generic. Uniqueness means no prior registration with the same content in the same class. Non-generic means the mark itself should be more arbitrary and less descriptive. For example, the words "very good bicycle" cannot be registered as a trademark for bicycles because the mark is purely descriptive. Examples of arbitrary marks include "Colgate" for toothpaste and "MacBook" for laptop, as they are not related to the goods themselves but only associated with the providers of the goods.

[7] The current cost of registering for a trademark is $225 per class of goods/services.

[8] If a mark holder wants to expand protection of the mark for use on other products, she/he must apply for a new registration of the same mark identifying the additional goods and services. As such, there may be multiple registrations for the same mark within and across classes. Using "Ford" as an example, Graham et al., (2013) show that this mark has been issued as four active registrations in the vehicles goods class between 1909 and 1990, reflecting expanded use of the mark on related goods within the same class, such as chassis, gasoline tanks, and tire covers, thus reflecting the development of automobile products, and increasing vertical integration, over time. Moreover, in 1994 alone, the same mark was registered in nine different classes for use on such goods as pocket knives, watches, stationery, travel bags, novelty buttons, cloth flags, belt buckles, toy vehicles, and ashtrays, suggesting expanded use of the mark into complementary markets or on promotional or collateral products.

[9] The renewal frequency was 20 years prior to November 1989. After the enactment of Trademark Law Revision Act of 1988 [Title 1 of Pub. L. 100-667, 102 Stat. 3935 (15 U.S.C. 1051)], the renewal frequency was reduced to 10 years thereafter.

will expire.[12] For the 1990 cohort of new trademark registrations, 64% were renewed in 2000 and 54% of those were renewed a second time in 2010 (Graham et al., 2013).

Trademarks in general fall into two categories: product trademarks and marketing trademarks. A trademark can be either new product name, new product logo, company logo, or marketing slogan. In the next section, we will discuss the specific steps taken to differentiate these two types of trademarks.

A.2 Trademark dataset and sample construction

The USPTO Trademark Case Files Dataset is downloaded from the USPTO website.[13] It contains detailed information on 7.7 million trademark applications filed with or registrations issued by the USPTO between January 1870 and December 2015. It is derived from the USPTO main database for administering trademarks and includes data on trademark characteristics, prosecution events, ownership, classification, third-party oppositions, and renewal history. For each data record, it has the following information: key dates (filing, registration, renewal, or cancellation), status (registered, abandoned, renewed, or cancelled),[14] trademark class, mark content, and owner information. From the trademark dataset, we obtain a list of owner names, denoted as list A. About two thirds of the owners in the database are corporations.

Next, from the Compustat/CRSP database, we obtain a list of public company names and their permno numbers, denoted as list B1. It is worth noting that list B1 has taken into account name changes for public companies, such as “Minnesota Mining and Manufacturing Company” to “3M.” However, list B1 only identifies the public company itself, not its subsidiaries. To partially address this problem, we expand list B1 by a list of (current) subsidiaries’ names for public companies from Capital IQ; denoted as list B2. In this way, subsidiaries whose names are

[12] In brief, the maintenance threshold is in the 6th, 10th, 20th … year. At the 6th year after initial registration, a mark holder must submit the §8 form (declaration of use) together with a specimen to prove the actual usage of a trademark. The cost of filing the §8 form is $125 per class of goods/services. At the 10th year after initial registration, the same holder submits the §9 form (application for renewal) at a cost of $300 per class. Afterwards, a mark holder must submit both the §8 form and the §9 form at consecutive 10th year for renewal at a total cost of $425.
[13] See: https://www.uspto.gov/learning-and-resources/electronic-data-products/trademark-case-files-dataset-0.
[14] According to the USPTO, “abandoned” trademarks refer to cases where a trademark registration process is not completed and thus the trademark involved is not registered; “cancelled” trademarks refer to cases where a trademark is no longer renewed after registration. Later, we use “cancelled” trademarks for some of our analysis.

totally different from their parent companies' are captured, such as "Geoffrey" of "Toys "R" Us," or "LinkedIn" of "Microsoft."

We then conduct fuzzy matching between list A and list B2 using the Levenshtein distance to keep the closest ten possible matches. To ensure the matching is correct, we make use of the location information in the trademark dataset and compare it with the location of a public company from Compustat/CRSP and also manually verify each possible match to rule out incorrect cases. In the end, we are able to match 528,219 registered trademark records to 14,856 public companies over the period 1887 to 2015.

One thing worth noting is that Capital IQ only provides a snapshot of current subsidiaries, which means that the time at which a subsidiary became owned by the parent company is not known. This could be problematic for our empirical analysis. For example, if firm A acquired firm T in 2002, all the trademarks owned by firm T will be treated as owned by firm A starting 2002. However, since we only observe firm T being a subsidiary of firm A in 2015 based on Capital IQ while do not observe the time of transfer, we might end up erroneously assigning firm T's trademarks to firm A from the very beginning of our sample period. To partially rectify this problem, we use the Thomson One Banker SDC database on M&As to identify the year of deal completion. For example, if the M&A database indicates the year of deal completion (firm A takeovers firm T) is 2002, we only combine firm T's and firm A's trademarks starting 2002.[15]

In this paper, we use trademarks to capture product market dynamics, so we focus on product trademarks, instead of marketing trademarks, in our empirical analysis. To differentiate between the two, we employ the following procedures. We classify marks that have no text (i.e., pure logos), or have text comprising 4 or more words (i.e., advertising slogans) as marketing trademarks. We classify marks that have text of fewer than 4 words, and the text is the first time to appear in a trademark class as product trademarks (i.e., product names). Any subsequent marks with the same text in the same class are marketing trademarks (i.e., updating logos).

[15] It is worth noting that there is a dataset on trademark transfers—the USPTO Trademark Assignment Dataset covering over 785,000 transactions recorded during 1952-2013 affecting almost 4.2 million trademark registrations and applications. However, according to Graham et al., (2015), mergers recorded with the USPTO involving trademark properties represent only one fifth to one-quarter of all U.S. M&A activity over the period 1997-2003.

Appendix 2 in the Internet Appendix provides a detailed description of our classification scheme. According to our classification, slightly over 80% of the marks are related to product lines.

B. Methodology

B.1 Trademark similarity

Our measure of trademark similarity is computed as a cosine similarity measure:

$$Trademark\ Similarity_{\mathrm{acq,targ,t}} = \frac{\mathrm{T}_{\mathrm{acq,t}}\mathrm{T}'_{\mathrm{targ,t}}}{\sqrt{\mathrm{T}_{\mathrm{acq,t}}\mathrm{T}'_{\mathrm{acq,t}}}\sqrt{\mathrm{T}_{\mathrm{targ,t}}\mathrm{T}'_{\mathrm{targ,t}}}}, \tag{1}$$

where the vector $T_{acq,t} = (T_{acq,1}, ..., T_{acq,K})$ is the number of trademarks in each trademark class for the acquirer, the vector $T_{targ} = (T_{targ,1}, ..., T_{targ,K})$ is the number of trademarks in each trademark class for the target, and $k \in (1, K)$ is the NICE trademark class index (K = 45). Each scalar in the vector is set to zero if a firm does not have any trademarks in that class. The higher is the value of this cosine measure, the greater overlap in product lines between the acquirer and its target firm.

In a nutshell, our trademark similarity variable provides a continuous measure of the pairwise relatedness of any two firms in the product market space, both within and across conventional industry affiliations—a critical aspect of capturing product market synergies in an M&A setting.

B.2 Matched sample and model specification

We test our first hypothesis by estimating selection models of firms becoming acquirers and target firms. We run a conditional logit regression[16] using cross-sectional data as of the fiscal year end before the bid announcement:

$$Event\ Firm_{im,t} = \alpha + \beta_1 Trademark\ Characteristics_{im,t-1} + \beta_2 Firm\ Characteristics_{im,t-1} + Deal\ FE_m + e_{im,t}. \tag{2}$$

[16] See McFadden (1974) and Greene (2008, Chapter 23) for an introduction to the conditional logit regression, and Kuhnen (2009), Dyck, Morse, and Zingales (2010), and Bena and Li (2014) for recent applications in finance.

The dependent variable, *Event Firm*$_{im,t}$, is equal to one if firm *i* is the acquirer (target firm) in deal *m*, and zero otherwise. *Trademark Characteristics*$_{im,t-1}$ are four measures of a firm's trademark portfolio to capture its product market dynamics: trademark count, defined as the number of active trademarks; trademark age, defined as the average age of active trademarks; trademark growth, defined as the growth rate in trademarks; and trademark concentration, defined as the Herfindahl index of trademarks across classes. *Firm Characteristics*$_{im,t-1}$ include the size of the trademark portfolio, the age of trademarks, the growth rate of trademarks, trademark concentration, firm size, M/B, ROA, leverage, cash holdings, sales growth, and prior-year stock return. Detailed variable definitions are provided in the Appendix. For each deal, there is one observation for the acquirer (target firm), and multiple observations for the control acquirers (control target firms). *Deal FE*$_m$ is the fixed effect for each acquirer (target firm) and its control acquirers (control target firms).

We use three different control samples as pools of potential merger participants. First, to form the *Random Control Sample*, for each acquirer (target firm) of a deal announced in year *t*, we randomly draw five firms from Compustat/CRSP in year *t-1* that were neither an acquirer nor a target firm in the three-year period prior to the deal. Our pool of potential merger participants thus captures M&A clustering in time (Mitchell and Mulherin, 1996; Maksimovic, Phillips, and Yang, 2013).

Second, to form the *Industry- and Size-Matched Control Sample*, for each acquirer (target firm) of a deal announced in year *t*, we find up to five matching acquirers (matching target firms) by industry—the industry definitions are based on the narrowest SIC grouping that includes at least five firms[17]—and by size from Compustat/CRSP in year *t-1* that were neither an acquirer nor a target firm in the three-year period prior to the deal. Such matching creates a pool of potential merger participants that captures clustering not only in time, but also by industry (Andrade, Mitchell, and Stafford, 2001; Harford, 2005).

[17] Specifically, we start with 4-digit SIC industry groups to search for matching acquirers (target firms). If there are no more than five industry peers to the actual acquirer (target firm) within the 4-digit SIC industry group, we move up to the 3-digit SIC industry group. If there are no more than five industry peers to the actual acquirer (target firm) within the 3-digit SIC industry group, we move up to the 2-digit SIC industry group. 81% (9%) acquirers are matched at the 4-digit (3-digit) level, while 84% (9%) target firms are matched at the 4-digit (3-digit) level; the remaining matches are at the 2-digit level. We use historical SIC industry codes from Compustat.

Third and finally, to form the *Industry-, Size-, and M/B-Matched Control Sample*, for each acquirer (target firm) of a deal announced in year *t*, we find up to five matching acquirers (matching target firms)—first matched by industry, second matched by size (ten closest are selected), and last matched by M/B ratios (five closest are selected)—from Compustat/CRSP in year *t-1* that were neither an acquirer nor a target firm in the three-year period prior to the deal. We add the book-to-market ratio to our matching characteristics, because the literature has argued that it captures growth opportunities (Andrade et al., 2001), overvaluation (Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004), and asset complementarity (Rhodes-Kropf and Robinson, 2008)—all important drivers of M&As.

To test our second hypothesis for merger pair formation, we run a conditional logit regression using cross-sectional data as of the fiscal year end before the bid announcement, with one observation for each deal and multiple observations for the control deals:

$$
\begin{aligned}
&Acquirer\text{–}Target_{ijm,t} = \alpha + \beta_1 Trademark\ Similarity_{ijm,t-1} + \\
&\beta_2 Acquirer\ Trademark\ Characteristics_{im,t-1} + \beta_3 Target\ Trademark\ Characteristics_{jm,t-1} + \\
&\beta_4 Acquirer\ Characteristics_{im,t-1} + \beta_5 Target\ Characteristics_{jm,t-1} + \\
&\beta_6 Horizontal\ Deal_{ijm} + \beta_7 Patent\ Similarity_{ijm,t-1} + \beta_8 HP\ Similarity_{ijm,t-1} + \\
&Deal\ FE_m + e_{ijm,t}. \qquad (3)
\end{aligned}
$$

The dependent variable, *Acquirer-Target*$_{ijm,t}$, is equal to one if the firm pair *ij* is the acquirer-target firm pair, and zero otherwise. *Trademark Similarity*$_{ijm,t-1}$ is one of the four pairwise measures, capturing the overlap in product lines. The three other pairwise measures are whether a deal is horizontal or not, patent similarity (Bena and Li, 2014), and HP similarity (Hoberg and Phillips, 2010). Definitions of these variables are provided in the Appendix. Other firm-level controls include the size of the trademark portfolio, firm size, M/B, ROA, leverage, cash holdings, sales growth, and prior-year stock returns.

Since the overlap in product lines is only defined between firms with trademarks, to estimate Equation (3) we employ samples of actual and control deals involving acquirers and target firms that both have trademarks before the bid. We form the *Random Control Sample* by pairing the target firm with five randomly drawn control firms for the acquirer, and by pairing the acquirer with five randomly drawn control firms for the target firm. We form the *Industry-*

and Size-Matched Control Sample (*Industry-, Size-, and M/B-Matched Control Sample*) by pairing the target firm with up to five of the closest matches to the acquirer, and by pairing the acquirer with up to five of the closest matches to the target firm.

In summary, our conditional logit models, together with three different control samples, allow us to examine whether the overlap in product lines is an important driver of transaction incidence and merger pairing after accounting for M&A clustering (in time and by industry), and size and book-to-market effects.

C. Sample Overview

To form our M&A samples, we begin with all announced and completed U.S. M&A deals with announcement dates between January 1, 1983 and December 31, 2016 covered by the Thomson One Banker SDC Database. We impose the following filters to obtain our final sample: i) the deal is classified as "Acquisition of Assets (AA)", "Merger (M)," or "Acquisition of Majority Interest (AM)" by the data provider; ii) the acquirer is a U.S. public firm listed on the AMEX, NYSE, or NASDAQ; iii) the acquirer holds less than 50% of the shares of the target firm before deal announcement and ends up owning 100% of the shares of the target firm through the deal; iv) the deal value is at least $1 million (in 1982 dollar value); v) the relative size of the deal (i.e., the ratio of transaction value over acquirer book assets), is at least 1%; vi) the acquirer (target) owns at least one trademark prior to the deal; vii) the target firm is a public firm, a private firm, or a subsidiary; viii) multiple deals announced by the same acquirer on the same day are excluded; and ix) basic financial and stock return information is available for the acquirer, the target, or the acquirer-target pair. These filters yield 14,357 deals with available information on acquirers, 4,569 deals with available information on target firms, and 1,901 deals with available information on both acquirers and their target firms. It is worth noting that our samples are one of the largest to study synergies in M&As (see, for example, in comparison to Hoberg and Phillips, 2010; Bena and Li, 2014; Sheen, 2014) due to the prevalent usage of trademarks by U.S. companies.

Table 1 presents the temporal distribution of our three M&A samples. We show that our samples capture different merger waves during our sample period including the 2000 high-tech bubble and the period leading to the 2007 financial crisis.

Table 2 presents descriptive statistics for the acquirer sample and its industry- and size-matched control sample. In Panel A, we show that acquirers have more trademarks and newer trademarks than their matching peers, as measured by the number of trademarks and trademark age, respectively. Moreover, acquirers' portfolios of trademarks are growing faster than those of their matching peers, and acquirers' trademarks are less focused (i.e., across more different trademark classes) than those of their matching peers.

We further note that our sample acquirer firms are large (the mean of total assets is in the 9^{th} decile of the Compustat/CSRP universe over the same time period), and show that they are larger, and have higher M/B ratios, higher ROA, lower cash holdings, higher sales growth, and better stock market performance than their industry- and size-matched peer firms.

Panel B presents correlations between acquirer trademark and firm characteristics. Among trademark characteristics, the size of a firm's trademark portfolio is positively associated with the average age of its constituent trademarks, and is negatively associated with trademark concentration. The average age of a firm's trademark portfolio is negatively associated with its growth rate. These correlations are largely consistent with intuition. Moreover, we show that the size of a firm's trademark portfolio is positively associated with firm size and operating performance, whereas it is negatively associated with sales growth. The age of a firm's trademark portfolio is positively associated with firm size and operating performance, whereas it is negatively associated with cash holdings and sales growth. Trademark concentration is negatively associated with firm size and operating performance. Trademark growth is positively associated with sales growth. Overall, we conclude that most correlations (with the exception of the correlation between trademark count and trademark concentration at -0.468) are low and that multicollinearity is unlikely to be an issue.

Table 3 presents descriptive statistics for the target firm sample and its industry- and size-matched control sample. We show that target firms have a similar number of trademarks and a similar level of trademark concentration as their matching peers, whereas target firms have slightly younger trademarks (with the exception of the median), and their trademark portfolios are growing at a slightly lower rate than those of their matching peers. We further note that our sample target firms are large (the mean of total assets is in the 8^{th} decile of the Compustat/CRSP universe over the same time period). Finally, we show that most correlations among target firm trademark and firm characteristics are low and conclude that multicollinearity is unlikely to be an issue.

IV. Ex-ante Selection Effects

In this section, we implement various multivariate analyses to test our first two hypotheses regarding the role of product market dynamics in firms' decision to do a deal.

A. Who Will Become Acquirers/Target Firms?

Table 4 Panel A presents coefficient estimates from the conditional logit regression in Equation (2) to predict acquirers. Column (1) presents the median and standard deviation of the empirical distribution of coefficient estimates from conditional logit models bootstrapping 500 randomly drawn control groups of acquirers.

Using three different control samples and four measures to capture product market dynamics, we show that firms with a larger trademark portfolio, younger trademark portfolios, and faster growth in trademarks are more likely to become acquirers. In all cases, the coefficients on the three trademark characteristics are significant at the one percent level.

Based on the model in column (2) of Panel A, Panel B presents the predicted likelihood of a firm becoming an acquirer when one of the trademark variables changes while other variables are at their mean values. We show that when trademark count (trademark age/trademark growth rate) changes from its 25^{th} percentile to 75^{th} percentile, the likelihood of a firm becoming an acquirer changes by 6.72% (-2.85%/0.35%).

Other findings not directly related to product market characteristics are consistent with prior work in M&As (see, for example, Maksimovic and Phillips, 2001; Moeller, Schlingemann, and Stulz, 2004; Gaspar, Massa, and Matos, 2005). In particular, we show that larger firms, as well as firms with better operating performance, faster sales growth, and higher prior-year stock returns, are more likely to engage in M&As as acquirers. It is worth noting that our findings that firms with larger trademark portfolios, younger trademark age, and faster growth in trademarks are more likely to become acquirers remain after controlling for two measures of acquirer stock market performance—the M/B ratio and prior-year stock returns, or employing samples of control acquirers matched on industry, size, and M/B. We conclude that our findings are unlikely to be due to market overvaluation.

Table 5 Panel A presents coefficient estimates from the conditional logit regression in Equation (2) to predict target firms. Column (1) presents the median and standard deviation of the empirical distribution of coefficient estimates from conditional logit models bootstrapping 500 randomly drawn control groups of target firms.

Different from the results for acquirers, we show that there is no significant association between the size of a firm's trademark portfolio and the likelihood of it becoming a target firm. Further, we show that firms with younger trademarks, slow-growing trademark portfolios, and more focused trademark portfolios are more likely to become target firms. We further show that larger firms, as well as firms with poor prior-year stock returns, are more likely to become target firms.

Based on the model in column (2) of Panel A, Panel B presents the predicted likelihood of a firm becoming a target firm when one of the trademark variables changes while other variables are at their mean values. We show that when trademark age (trademark growth rate/trademark concentration) changes from its 25^{th} percentile to 75^{th} percentile, the likelihood of a firm becoming a target firm changes by -1.17% (-0.23%/1.90%).

Overall, our results provide strong support for our first hypothesis that firms actively engaged in product development as measured by trademarks are more likely to be involved in merger transactions as buyers, and those experiencing slowdown in product development are most likely to end up as sellers.

B. How Are Merger Pairs Formed?

Table 6 Panel A presents the summary statistics of acquirer-target pairs and their industry- and size-matched control pairs. Comparing acquirers and their target firms, we find that acquirers have far more trademarks, are much larger, have higher M/B ratios, higher ROA, higher leverage, lower cash holdings, and much better stock market performance than their target firms. Overall, our samples are similar to those used in other studies of mergers between public firms (see, for example, Gaspar et al., 2005; Harford, Jenter and Li, 2011).

At the bottom of Panel A, using four different pairwise measures, we show that actual acquirer-target pairs have similar frequencies of being in the same 2-digit SIC industry (*Horizontal*) as their matching pairs by construction, while actual pairs have significantly higher trademark similarity, patent similarity, and HP similarity than their matching pairs.

Panel B presents the correlations between different pairwise measures capturing overlap in activities. We show that trademark similarity is positively associated with all other measures of similarities. However, the correlations are modest, suggesting that all these measures contain distinct information.

Table 7 Panel A presents coefficient estimates from the conditional logit regression in Equation (3) to predict merger pairs. Columns (1) to (3) present the median and standard deviation of the empirical distribution of coefficient estimates from conditional logit models bootstrapping 500 randomly drawn control groups of deals. Columns (1), (4), and (7) only include one pairwise measure—trademark similarity. Columns (2), (5), and (8) further control for patent similarity of Bena and Li (2014) and the sample is materially reduced due to the requirement of non-zero patents to compute the measure. Columns (3), (6), and (9) further control for HP similarity of Hoberg and Phillips (2010) and the sample is moderately reduced due to the availability of 10-Ks on Edgar since 1997. We show a positive and significant association between any of the four measures of merger participants' overlap in activities including product lines, patenting, product descriptions, and industry affiliation, and the likelihood of a merger pair formation. It is worth noting that our new measure of overlap in product lines remains significant after controlling for three known determinants of merger pairing. This finding is both important and new in the literature, as prior work has not been able to capture product market interactions using trademark data.

Based on the model in column (4) – (6) of Panel A, Panel B presents the predicted likelihood of a merger pair formation when one of the similarity measure changes while other variables remain at their mean values. We show that when trademark similarity (patent similarity/HP similarity) changes from its 25th percentile to 75th percentile, the likelihood of merger pair formation increases by 18.03% (12.50%/10.25%).[18]

[18] The economic magnitude for trademark similarity, patent similarity, and HP similarity is based on the model of column (4), (5) and (6) in Panel A of Table 7, respectively.

Our evidence in Table 7 provides strong support for our second hypothesis, that mergers are more likely to take place between parties with similar product lines. Our findings provide direct evidence on how asset complementarity triggers merger pairing, as argued by Rhodes-Kropf and Robinson (2008). By focusing on a specific form of complementarity—synergies in product market—we complement the results on product market synergies based on 10-K descriptions in Hoberg and Phillips (2010) and technological synergies in Bena and Li (2014).

C. Trademark Similarity and Merger Synergies

So far we have shown that the incidence of a merger is positively associated with merging firms' trademark similarity. If trademark similarity leads to synergistic gains, we would expect the stock returns around the deal announcement—a measure of the value gains in mergers (Bradley et al., 1988)—to be positively associated trademark similarity.

Our measure of merger synergies is the combined announcement period abnormal returns of an acquirer and its target (using acquirer/target market capitalization as weights), over a three-day window centered at the announcement day (day 0, CAR(-1, 1)). The daily abnormal return is computed using the daily return on the CRSP value-weighted index as the benchmark.

Table 8 presents summary statistics of announcement period abnormal returns and deal characteristics. In Panel A, we show that consistent with conventional wisdom about M&As, acquirers on average do not make money from doing deals, the mean/median CAR(-1, 1) are -1.4%/-0.9%. In contrast, the mean/median CAR(-1, 1) for target firms are 19.3%/14.6%. the combined CAR(-1, 1), our measure of merger synergies, has a small mean/median given the relatively large size of the acquirer vis-à-vis the target firm. In Panel B, we further show that the correlation between the combined CAR(-1, 1) and the acquirer CAR(-1, 1) is 0.424, and the correlation between the target CAR(-1,1) and the acquirer CAR(-1,1) is 0.749, suggesting the possibility of merger partners sharing synergies.

Table 9 presents the regression results relating different measures of deal quality to trademark similarity controlling for deal and firm characteristics. In column (1) where the dependent variable is the combined CAR(-1,1), we find that the coefficient on *Trademark similarity* is positive and significant at the 5% level, suggesting that merger synergies are positively associated with merger participants' product line overlap. In column (2) where the dependent variable is acquirer announcement returns, we show that acquirer returns are not significantly associated with trademark similarity. In column (3) where the dependent variable is target announcement returns, we show that target announcement returns are positively associated with trademark similarity.[19] These results suggest that most of the synergies in product market are taken by the target firm. M&As may create significant value for target firms' stockholders because acquiring firms can replace inefficient managers (Hitt et al., 1991), which is more likely to occur when information asymmetry is low and common knowledge is high. It is worth noting that stock returns only provide a summary measure of the valuation impact, which does not lend itself to a natural decomposition into underlying components of the value gains. Using the USPTO trademark data, our paper tries to shed light on sources of merger gains.

V. Ex-post Treatment Effect

So far, we have examined and established the ex-ante selection effects of product market dynamics on merger participants, focusing on the role of overlap in product lines. We now investigate whether and how the pre-merger overlap in product lines affects the product lines of acquirers and targets following deal completion—the ex-post treatment effect.

A. The Quasi-Experiment

The identification challenge of our treatment effect analysis is that the association between the pre-merger overlap and post-merger product market activities could be due to the endogenous selection of firm pairs into a treatment group, rather than due to the impact of product market synergies on post-merger product market outcome. As we showed earlier, acquisitions are more likely to occur between firms with overlapping product lines. As a result, simply comparing the average product market outcome of merged firms with more overlap in product lines to that of merged firms with little overlap would lead to biased estimates.

To address such selection concerns, we exploit a quasi-experiment. Specifically, following Seru (2014) and Bena and Li (2014), we employ a control sample of withdrawn bids that failed for reasons exogenous to the product market activities of either merger partner. In this

[19] Roll (1986), Jensen (1988), and Hitt et al., (1991) have mentioned that the acquiring firm tend to bid the target's price to an amount equal to or beyond its value for various reasons.

case, the assignment of firm pairs to the treatment sample (completed deals) versus the control sample can be treated as random with respect to the product market outcome variables that we examine.[20]

To examine how the overlap in product lines affects post-merger trademark and performance outcomes, we employ samples of completed and withdrawn deals, where acquirers and targets both have trademarks before the takeover. To form the control sample, we begin with 877 withdrawn bids with necessary firm-level information in Compustat/CRSP announced over the period 1983 to 2010. We then read news articles for each withdrawn bid and only select those that fail due to reasons exogenous to the outcome variables that we examine, namely competing bids, regulatory objections, or adverse market conditions. In the end, we obtain 179 withdrawn bids as potential control firms to match with the completed bids.[21]

Panel A of Appendix 3 in the Internet Appendix summarizes the steps taken to arrive at our sample of 179 withdrawn bids. First, for each withdrawn bid, we require that there exists at least one completed deal with the same acquirer and target (2-digit SIC) industry. This results in a reduction of 93 bids. Next, we require both the acquirer and the target of a withdrawn bid have at least one trademark one year prior to the bid announcement year. This results in a reduction of 47 deals. Finally, we require that both the acquirer and the target of a matched completed deal (by acquirer size and ROA) and of a withdrawn bid have at least one valid observation of cancelled trademarks and newly registered trademarks within a ten-year window centered at the deal announcement year. This results in a reduction of 13 deals. We end up with 179 withdrawn bids as our control sample.

Next, we form a sample of completed deals over the same period that: (i) occur in the same acquirer-target industry pairs that match industry pairs of the bids in the control sample, and are announced within the three-year window centered at the announcement year of the bids in the control sample; (ii) involve acquirers and targets that have trademark one year prior to the

[20] Seru (2014) exploits a sample of withdrawn bids to examine whether and how conglomerate mergers stifle innovation, and Bena and Li (2014) examine whether and how technological overlap affects post-merger innovation output. Bernstein (2015) employs a sample of withdrawn IPOs to investigate whether and how going public affects innovation.

[21] According to the USPTO guideline on trademark renewal, it takes six years to know if a trademark will not be renewed (and thus cancelled), we thus only include bids in our control sample with an announcement date (and deals in our treatment sample with a transaction completion date) on or before December 31, 2010, which is six years before our trademark data ending in 2016.

deal. Using this approach, we ensure that the treatment and control samples are similar along key dimensions relevant for M&As—industry composition and time clustering (see Roberts and Whited (2013)). In the end, we arrive at a sample of 179 pairs of completed and withdrawn bids.

To examine the heterogeneity in the treatment effect of a merger on post-merger product market outcomes, we first estimate the following regression using a panel dataset that contains information on deals in the treatment and control samples from five years prior to bid announcement (*ayr-5*) to five years after deal completion/withdrawal (*cyr+5*). We estimate the treatment effect for both the subsample of high and low premerger trademark similarity.

$$Firm\ Outcome_{it} = \alpha + \beta_1\ After_{it} + \beta_2 After_{it}\ \times\ Complete_{ij}$$
$$+Deal\ FE_{ij} + Year\ FE_t + e_{ijt}. \quad (4)$$

The dependent variable, $Firm\ Outcome_{it}$, is firm *i*'s trademark outcome such as the ratio of cancelled trademarks, the ratio of newly registered trademarks, or product market performance measure such as cost of goods sold. $After_{it}$ is an indicator variable equal to one for the post-merger time period (from *cyr+1* to *cyr+5*), and zero otherwise. $Complete_{ij}$ is an indicator variable equal to one for treatment deals, and zero otherwise (i.e., for control bids). We include deal fixed effects to difference away any time-invariant differences among deals.[22] As a result, our approach estimates the differences over time in *Firm Outcome* for the same cross section units (Wooldridge, 2002, p. 284). We also include year fixed effects to difference away a common trend affecting deals in both the treatment and control samples.

Next, we directly estimate the heterogeneity in the treatment effect through Equation (5), where the key variable of interest is the triple interaction term $After_{ijt} \times Complete_{ij} \times High\ Trademark\ Similarity_{ij}$. $Trademark\ Similarity_{ij}$ are time-invariant and is measured at the year prior to the deal announcement:

$$Firm\ Outcome_{it} = \alpha + \beta_1\ After_{it} + \beta_2 After_{it}\ \times\ Complete_{ij}$$
$$+\ \beta_3 After_{it}\ \times\ High\ Trademark\ Similarity_{ij}$$
$$+\beta_4 After_{it} \times\ Complete_{ij}\ \times\ High\ Trademark\ Similarity_{ij}$$

[22] We cannot estimate the coefficients on $Treat_{ij}$, $Complete_{ij}$, or $Complete_{ij} \times High\ Trademark\ Similarity_{ij}$ as they are subsumed by deal fixed effects $Deal\ FE_{ij}$.

$$+Deal\ FE_{ij} + Year\ FE_t + e_{ijt}. \quad (5)$$

B. Post-Merger Trademark Cancellations

In this subsection, we first test our third hypothesis related to changes in trademark strategies from before to after the merger in terms of the ratio of cancelled trademarks—the number of cancelled trademarks scaled by the number of trademarks. Unlike prior studies of post-merger outcome, we are able to clearly delineate product market outcomes of acquirers and target firms even after deal completion as the USPTO trademark data allows us to keep track of acquirers' and targets' trademarks. Table 10 reports the summary statistics of our sample acquirers and targets in terms of trademark cancellations from before to after deal completion.[23]

In Panel A, we show that post-merger, acquirers experience a significant increase in the ratio of cancelled trademarks as compared to the same ratio pre-merger (3.04% vs. 4.56%). To understand how cancellation decisions are made, we further decompose cancelled trademarks by their age and class. One rationale for M&As is to reduce duplicate products in the market, and hence we would expect differential outcome on products that are offered by both acquirers and target versus those only offered by one of the merger participants.

When looking at the cancellation ratio sorted by trademarks of different ages, we find that newer trademarks (< 6 years old) are most likely to be cancelled; in contrast, there is little (economic) difference in acquirers' tendency to cancel proven trademarks (> 10 years old) post-merger vs. pre-merger. When looking at the cancellation ratio sorted by trademarks belonging to classes common to acquirers and targets or belonging to classes unique to acquirers, we find that acquirers' trademarks belonging to common classes are more likely to be cancelled after mergers (2.11% vs. 3.33%) as compared to acquirers' unique trademarks (0.93% vs. 1.23%), providing some support to our conjecture that M&As are used by acquirers to trim duplicate product lines on their side.

In Panel B, we show that post-merger, target firms experience an even bigger increase in the ratio of cancelled trademarks as compared to the same ratio pre-merger (2.60% vs. 7.78%). When looking at the ratio sorted by trademarks of different ages, we find that newer trademarks (< 6 years old) are most likely to be cancelled, and trademarks of between 6 to 10 years old also

[23] The median values are largely zero and hence are not reported.

experience a significantly greater drop post-merger vs. pre-merger. When looking at the ratio sorted by trademarks belonging to classes common to acquirers and targets or belonging to classes unique to target firms, we find that targets' trademarks belonging to common classes are more likely to be cancelled after mergers (2.29% vs. 7.00%) as compared to targets' unique trademarks (0.30% vs. 0.77%). Again, the evidence provides some support to our conjecture that M&As are used by acquirers to trim duplicate product lines on targets' side. Importantly, when comparing across acquirers and targets, we find that target trademarks belonging to common classes are far more likely to be cancelled post-merger as compared to those of acquirers (7.00% vs. 3.33%). Using the trademark data, our paper is one of the first in the M&A literature to provide large-sample evidence on the differential effect of M&As on acquirers and target firms, which helps to gain a better understanding whether and how merger synergies are realized.[24]

In summary, Table 10 show that post-merger, acquirers trim some overlapping product lines on both their and targets' sides. Importantly, targets' trademarks belonging to classes common to acquirers and targets take the brunt of the trimming, suggesting that one major incentive of M&As is for acquirers to eliminate product market competition.

Table 11 reports the difference-in-differences (DiD) estimations of post-merger trademark cancellations based on Equation (4) using a sample of completed deals and deals that are withdrawn due to exogenous reasons.[25] Panel A reports DiD results for acquirers' ratio of cancelled trademarks. We find that the coefficients on the interaction term $After_{ijt} \times Complete_{ij}$ are insignificant in all columns. Panel B reports DiD results for targets' ratio of cancelled trademarks. We find that the coefficient on the interaction term $After_{ijt} \times Complete_{ij}$ is positive and significant using all trademarks (column (1)), suggesting that there are a significant number of targets' trademark cancellations post-merger. Moreover, the coefficients on $After_{ijt} \times Complete_{ij}$ are positive and significant when the dependent variables are the ratio of cancelled trademarks limiting to targets' newer trademarks (< 6 years old) and the ratio of cancel trademarks limiting to targets' trademarks belonging to common classes. The findings suggest

[24] Our large-sample results are consistent with Karim and Mitchell's (2000) findings based on the medical industry that, while both acquirers' and targets' product lines are more likely to be deleted after M&As, targets' product lines are more likely to be dropped than acquirers'.
[25] Panels B and C of Appendix 3 in the Internet Appendix provide summary statistics for this estimation sample.

that targets' newer and overlapping product lines with acquirers are more likely to be cancelled post-merger.

Panel C reports triple differences results for acquirers' and targets' trademark cancellations separated by high versus low trademark similarity groups. Columns (1) and (2) employ the acquirer/target subsamples with high pre-merger trademark similarity and Equation (4). Columns (3) and (4) employ the acquirer/target subsamples with low pre-merger trademark similarity and Equation (4). Columns (5) and (6) employ the full samples of acquirers and targets and Equation (5).

For acquirer trademark cancelations, we find that there are not any significant number of cancellations post-merger in either the high or low trademark similarity groups (columns (1) and (3)). Moreover, there is no significant effect on high trademark similarity on acquirers' trademark cancellation decision (column (5)). In contrast, for target trademark cancelations, we find that such cancelations are significant for targets with higher pre-merger trademark similarity to their acquirers (columns (2), (4), and (6)).

Taken together, our results in Tables 10 and 11 support our third hypothesis that post-merger, acquirers are more likely to cancel target firms' trademarks when their trademark similarity is high, suggesting that one motive of M&As is for acquirers to eliminate their product market competitors by cancelling target firms' duplicate product lines.[26]

C. New Trademark Registrations

So far, we show that both acquirers and targets experience cancellations of trademarks belonging to classes common to them, and that targets suffer disproportionally more cancellations than acquirers. These findings are consistent with our conjecture that one important motive of M&As is for acquirers to eliminate product market competition. However, these findings could also be consistent with an alternative story whereby acquirers are buying production capacity or human capital associated with target firms' non-competing products. In this case, the expanded production facility and increased employee headcount allow acquirers to

[26] To check the internal validity of our DiD estimator, we conduct falsification tests. The results are reported in Appendix 3. There is no significant treatment effect when we falsely assume the deal takes place three years earlier than its true date. It is worth noting that our DiD results are qualitative similar when we limit the analysis to trademarks that are more than 6 years old (see Appendix 4).

develop more non-competing product lines (i.e., trademarks unique to acquirers) and/or totally new product lines (i.e., trademarks new). As such, eliminating competition is not the whole story, but rather, acquirers are shifting target resources to strengthening its market position and/or to develop totally new product lines. Next we test our fourth hypothesis to shed light on this possibility. The variable of interest, the ratio of newly registered trademarks, is defined as the number of newly registered trademarks scaled by the number of trademarks. Table 12 reports the results. Panel A reports the summary statistics, and Panel B reports the results from DiD analyses.

In Panel A, we show that post-merger, acquirers experience a significant decrease in the ratio of newly registered trademarks, as compared to the same ratio pre-merger (11.79% vs. 6.04%). When looking at the ratio sorted by trademarks belonging to classes common to acquirers and targets, classes unique to acquirers, classes unique to target firms, and new classes, we find that the share of newly registered trademarks belonging to common classes is greatly reduced post-merger (70.43% pre-merger vs. 61.84% post-merger), so as the share belonging to classes unique to acquirers (29.57% pre-merger vs. 22.27% post-merger). Instead, we see some newly registered trademarks belonging to classes unique to target firms (4.70%) and totally new classes (11.19%). These results show that both acquirers' competing (common class) and non-competing (i.e., unique class) product lines do not increase, and the increase in acquirers' unique product lines or totally new product lines is not large enough to offset the decrease in acquirers' existing lines, suggesting that acquirers are not primarily buying target firms' capacity/expanding their human capital out of M&As.

In Panel B, we estimate Equations (4) and (5) using a sample of completed deals and deals that are withdrawn due to exogenous reasons.[27] We find that the decrease in new trademark registrations is stronger for acquirers with higher pre-merger trademark similarity to their targets. These results provide support for our hypothesis H4b that post-merger, acquirers will develop fewer product lines when the pre-merger trademark similarity is high.

D. Post-merger Performance

[27] Panel D of Appendix 3 provides summary statistics for this estimation sample.

Merger gains typically come in two forms. First, mergers may generate productive efficiencies that result in higher operating profits and/or reduced capital spending. Second, potentially anticompetitive mergers among firms with similar products could enable the combined firm to exercise market power, with the merger gains arising at the expense of customers and suppliers. In this subsection, we examine whether and how trademark similarity affect post-merger operating efficiency and product market performance.

Panel A, Table 13 presents the results based on Equation (5) where the dependent variables are different measures of operating efficiency: R&D expenses, capital expenditures (CAPX), and changes in working capital (Devos et al., 2009). If the merger gains arise from scale or scope economies, they would lead to operating synergies due to cost savings or cutbacks in investments. We show that the coefficients on the interaction term $After_{ijt} \times Complete_{ij} \times High\ Trademark\ Similarity_{ij}$ are statistically insignificant, suggesting that when firms with similar product lines are combined, there is no obvious gain in operating efficiency.

Panel B presents the results based on Equation (5) where the dependent variables are different measures of product market performance: costs of goods sold, advertising expenses, return on sales, and market share. We find that the coefficients on the interaction term $After_{ijt} \times Complete_{ij} \times High\ Trademark\ Similarity_{ij}$ are significantly negative when the dependent variables are cost of goods sold and advertising expenses (column (1) and (2)). This result suggests that acquirers are able to cut more production and marketing costs when buying targets with overlapping product lines, possibly due to the elimination of competition and hence increased market power. Our findings are consistent with Sheen (2014) and Hoberg and Phillips (2016) that when competitors merge, their product market offerings tend to converge, which save R&D and advertising expenses. We also find that the coefficients on $After_{ijt} \times Complete_{ij} \times High\ Trademark\ Similarity_{ij}$ are significantly positive when the dependent variables are return on sales and market share (columns (3) and (4)). This result further suggests that acquirers buying targets with overlapping product lines are able to consolidate their market position with bigger market shares and stronger profitability.

In summary, we provide corroborative evidence in support of the market power hypothesis that one major source of merger synergies is to eliminate product market competitors by buying target firms with overlapping product lines. We show that after buying their product market competitors, acquirers drop competing products from their target firms, cut cost of goods sold and advertising expenses, resulting in greater profitability and stronger market positions.

VI. Conclusions

Using a large and unique trademark-merger dataset over the period 1983 to 2016, we show that companies with large trademark portfolios, newer trademarks, and fast growth in trademarks are more likely to be acquirers, while companies with newer and more focused trademarks, and slower growth in trademarks are more likely to be target firms. Further, firms with overlapping product lines as captured by trademark similarity are more likely to be merged and these deals are associated with high combined announcement period returns. Post-merger, merger partners with overlapping product lines cancel more trademarks as well as to register fewer new trademarks, and are associated with lower costs of goods sold, lower advertising expenses, higher return on sales, and larger market shares. We conclude that eliminating product market competitors is an important driver of acquisitions.

References:

Ahuja, Gautam, and Riitta Katila, 2001. Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study, *Strategic Management Journal* 22, 197-220.

Andrade, Gregor, Mark Mitchell, and Erik Stafford, 2001. New evidence and perspectives on mergers, *Journal of Economic Perspectives* 15, 103-120.

Bena, Jan, and Kai Li, 2014. Corporate innovations and mergers and acquisitions. *Journal of Finance* 69, 1923-1960.

Bernstein, Shai, 2015. Does going public affect innovation? *Journal of Finance* 70, 1365-1403.

Bloom, Nicholas, and John Van Reenen, 2002. Patents, real options and firm performance, *Economic Journal* 112, 97-116.

Bradley, Michael, Anand Desai, and E. Han Kim, 1988. Synergistic gains from corporate acquisitions and their division between the stockholders of target and acquiring firms, *Journal of Financial Economics* 21, 3-40.

Cassiman, Bruno, and Massimo G. Colombo (eds.), 2006, *Mergers and Acquisitions: The Innovation Impact*, Edward Elgar Publishing, Northampton MA.

Cassiman, Bruno, and Reinhilde Veugelers, 2006. In search of complementarity in innovation strategy: Internal R& D and external knowledge acquisition, *Management Science* 52, 68-82.

Cohen, Wesley M., and Daniel A. Levinthal, 1989. Innovation and learning: The two faces of R & D, *Economic Journal* 99, 569-596.

Cohen, Wesley M., and Daniel A. Levinthal, 1990. Absorptive capacity: A new perspective on learning and innovation, *Administrative Science Quarterly* 35, 128-152.

Devos, Erik, Palani-Rajan Kadapakkam, and Srinivasan Krishnamurthy, 2009. How do mergers create value? A comparison of taxes, market power, and efficiency improvements as explanations for synergies, *Review of Financial Studies* 22, 1179-1211.

Dyck, Alexander, Adair Morse, and Luigi Zingales, 2010. Who blows the whistle on corporate fraud? *Journal of Finance* 65, 2213-2253.

Eckbo, B. Espen, 1983. Horizontal mergers, collusion, and stockholder wealth, *Journal of Financial Economics* 11, 241-273.

Eckbo, B. Espen, 1985. Mergers and the market concentration doctrine: Evidence from the capital market, *Journal of Business* 58, 325-349.

Fan, Joseph P. H., and Vidhan K. Goyal, 2006. On the patterns and wealth effects of vertical mergers, *Journal of Business* 79, 877-902.

Faurel, Lucile, Qin Li, Devin M. Shanthikumar, and Siew Hong Teoh, 2016. CEO incentives and product development innovation: Insights from trademarks, Arizona State University working paper.

Gaspar, José-Miguel, Massimo Massa, and Pedro Matos, 2005. Shareholder investment horizons and the market for corporate control, *Journal of Financial Economics* 76, 135-165.

Graham, Stuart, Galen Hancock, Alan Macro, and Amanda Myers, 2013. The USPTO Trademark Case Files Dataset: Descriptions, lessons, and insights, *Journal of Economics and Management Strategy* 22, 669-705.

Graham, Stuart J. H., Alan C. Marco, and Amanda F. Myers, 2015. Monetizing marks: Insights from the USPTO Trademark Assignment Dataset, USPTO Economic Working Paper.

Greene, William H., 2008. *Econometric Analysis*. Pearson Education.

Harford, Jarrad, 2005. What drives merger waves? *Journal of Financial Economics* 77, 529-560.

Harford, Jarrad, Dirk Jenter, and Kai Li, 2011. Institutional cross-holdings and their effect on acquisition decisions, *Journal of Financial Economics* 99, 27-39.

Hart, Oliver, and Bengt Holmström, 2010. A theory of firm scope, *Quarterly Journal of Economics* 125, 483-513.

Heath, Davidson, and Christopher Mace, 2017. What's a brand worth? Trademark protection, profits and product quality, University of Utah working paper.

Henderson, Rebecca, and Iain Cockburn, 1996, Scale, scope, and spillovers: The determinants of research productivity in drug discovery, *Rand Journal of Economics* 27, 32-59.

Higgins, Matthew J., and Daniel Rodriguez, 2006. The outsourcing of R&D through acquisitions in the pharmaceutical industry, *Journal of Financial Economics* 80, 351-383.

Hitt, Michael A., and Robert E. Hoskisson,1991. Strategic competitiveness, in: L. Foster (ed.), *Advances in Applied Business Strategy*, 1-36, Greenwich, GT: JAI Press.

Hitt, Michael A., Robert E. Hoskisson, and R. Duane Ireland, R. D, 1990. Mergers and acquisitions and managerial commitment to innovation in M-form firms, *Strategic Management Journal* 11, 29-47.

Hitt, Michael A., Robert E. Hoskisson, and R. Duane Ireland, and J. S. Harrison, 1991. Effects of acquisitions on R&D inputs and outputs, *Academy of Management Journal* 34, 693-706.

Hitt, Michael A., Robert E. Hoskisson, and Richard A. Johnson, and Douglas D. Moesel, 1996. The market for corporate control and firm innovation, *Academy of Management Journal* 39, 1084-1119.

Hoberg, Gerard, and Gordon Phillips, 2010. Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Review of Financial Studies* 23, 3773-3811.

Hoberg, Gerard, and Gordon Phillips, 2016. Text-based network industries and endogenous product differentiation, *Journal of Political Economy* 124, 1423-1465.

Holmström, Bengt, and John Roberts, 1998. The boundaries of the firm revisited, *Journal of Economic Perspectives* 12, 73-94.

Houston, Joel F., Christopher M. James, and Michael D. Ryngaert. 2001. Where do merger gains come from? Bank mergers from the perspective of insiders and outsiders, *Journal of Financial Economics* 60, 285-331.

Jaffe, Adam B., 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value, *American Economic Review* 76, 984-1001.

Jaffe, Adam B., 1989. Characterizing the "technological position" of firms, with application to quantifying technological opportunity and research spillovers, *Research Policy* 18, 87-97.

Jensen, Michael C. 1988. Takeovers: Their causes and consequences, *Journal of Economic Perspectives* 2, 21-48.

Kaplan, Steven N. (ed.), 2000. *Mergers and Productivity*, University of Chicago Press.

Karim, Samina, and Will Mitchell, 2000. Path-dependent and path-breaking change: Reconfiguring business resources following acquisitions in the US medical sector, 1978-1995, *Strategic Management Journal* 21, 1061-1081.

Kim, E. Han, and Vijay Singal, 1993. Mergers and market power: Evidence from the U.S. airline industry, *American Economic Review* 83, 549-569.

Koh, Ping-Sheng, and David M. Reeb, 2015. Missing R&D, *Journal of Accounting and Economics* 60, 73-94.

Kuhnen, Camelia. M., 2009. Business networks, corporate governance, and contracting in the mutual fund industry, *Journal of Finance* 64, 2185-2220.

Lev, Baruch, 1999. R&D and capital markets, *Journal of Applied Corporate Finance* 11, 21-35.

Li, Kai, and Nagpurnanand R. Prabhala, 2007. Self-selection models in corporate finance, in: Espen Eckbo (ed.), The Handbook of Corporate Finance: *Empirical Corporate Finance*, 37-86, Elsevier/North-Holland, Amsterdam.

McFadden, Daniel, 1974. Conditional logit analysis of qualitative choice behavior, in: P. Zarembka (ed.), *Frontiers of Econometrics*, 105-142, Academic Press, New York, NY.

Maksimovic, Vojislav, and Gordon Phillips, 2001. The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains? *Journal of Finance* 56, 2019-2065.

Maksimovic, Vojislav, Gordon Phillips, and N.R. Prabhala, 2011. Post-merger restructuring and the boundaries of the firm, *Journal of Financial Economics* 102, 317-343.

Maksimovic, Vojislav, Gordon Phillips, and Liu Yang, 2013. Private and public merger waves, *Journal of Finance* 68, 2177-2217.

Mendonca, Sandro, Tiago Santos Pereira, and Manuel Mira Godinho, 2004. Trademarks as an indicator of innovation and industrial change, *Research Policy* 33, 1385-1404.

Mitchell, Mark L., and J. Harold Mulherin, 1996. The impact of industry shocks on takeover and restructuring activity, *Journal of Financial Economics* 41, 193-229.

Moeller, Sara B., Frederik P. Schlingemann, and René M. Stulz, 2004. Firm size and the gains from acquisitions, *Journal of Financial Economics* 73, 201-228.

OECD, 2010a. Measuring innovation: A new perspective. OECD Publishing, Paris.

OECD, 2010b. The OECD innovation strategy: Getting a head start on tomorrow. OECD Publishing, Paris.

Pastor, Lubos, and Pietro Veronesi, 2009. Technological revolutions and stock prices, *American Economic Review* 99, 1451-1483.

Paruchuri, Srikanth, Atul Nerkar, and Donald C. Hambrick, 2006. Acquisition integration and productivity losses in the technical core: Disruption of inventors in acquired companies, *Organization Science* 17, 545-562.

Rhodes-Kropf, Matthew, and David T. Robinson, 2008. The market for mergers and the boundaries of the firm, *Journal of Finance* 63, 1170-1211.

Rhodes-Kropf, Matthew, and S. Viswanathan, 2004. Market valuation and merger waves, *Journal of Finance* 59, 2685-2718.

Roberts, Michael R., and Toni M. Whited, 2013. Endogeneity in empirical corporate finance, in: Constantinides, G., R. Stulz, and M. Harris (eds.), *Handbook of the Economics of Finance*, Vol. 2, Part A, 493-572, Elsevier/North-Holland, Amsterdam.

Roll, R., 1986. The hubris hypothesis of corporate takeovers, *Journal of Business* 59, 197-216.

Sandner, Philipp G., and Joern Block, 2011. The market value of R&D, patents, and trademarks, *Research Policy* 40, 969-985.

Sapienza, Paola, 2002. The effects of banking mergers on loan contracts, *Journal of Finance* 57, 329-367.

Seru, Amit, 2014. Firm boundaries matter: Evidence from conglomerates and R&D activity. *Journal of Financial Economics* 111, 381-405.

Sheen, Albert, 2014. The real product market impact of mergers, *Journal of Finance* 69, 2561-2688.

Shleifer, Andrei, and Robert W. Vishny, 2003. Stock market driven acquisitions, *Journal of Financial Economics* 70, 295-311.

Wooldridge, Jeffrey M., 2002. *Econometric Analysis of Cross Section and Panel Data*, MIT Press, Cambridge, MA.

Appendix. Definition of variables

All firm characteristics are measured as of the fiscal year end before the bid announcement and all dollar values are in 1982 constant dollars.

Trademark Measures	
Trademark count	Ln(1 + the number of trademarks).
Trademark age	The average age of all trademarks in a firm's portfolio. Age for each trademark is calculated as the present year minus the year of its application.
Trademark growth	The growth rate of the number of trademarks.
Trademark concentration	The Herfindahl-Hirschman Index (HHI) of a firm's trademarks across its existing trademark classes, computed as $$\sum_{j=1}^{n}\left(\frac{s_{ij}}{S_i}\right)^2$$ where s_{ij} is the number of trademarks firm i owns in class j, S_i is the number of trademarks firm i owns across all classes, and n is the number of classes where firm i owns trademarks.
Trademark similarity	Following Jaffe (1986), trademark similarity is the cosine correlation computed as $$\frac{\mathrm{T_{acq}}\mathrm{T'_{tar}}}{\sqrt{\mathrm{T_{acq}}\mathrm{T'_{acq}}}\sqrt{\mathrm{T_{tar}}\mathrm{T'_{tar}}}},$$ where the vector $T_{acq} = (T_{acq,1}, \ldots, T_{acq,K})$ is the number of trademarks in each trademark class for the acquirer, the vector $T_{targ} = (T_{targ,1}, \ldots, T_{targ,K})$ is the number of trademarks in each trademark class for the target, and $k \in (1,K)$ is the NICE trademark class index with $K = 45$.
High trademark similarity	An indicator variable that takes the value of one if *Trademark similarity* is above the median value of the sample consisting of both completed and withdrawn bids, and zero otherwise.
Ratio of cancelled trademarks	The number of trademarks cancelled in a year scaled by the number of existing trademarks in a year.
Ratio of newly registered trademarks	The number of newly registered trademark filed in a year scaled by the number of trademarks in a year.
Firm Characteristics	
Firm size	Ln(1 + total assets).
Sales growth	The growth rate of sales.
ROA	Operating income before depreciation scaled by total assets.
Leverage	Total debt scaled by total assets.
Cash	Cash and short-term investment scaled by total assets.

M/B	The market value of common equity scaled by the book value of common equity.
Prior-year stock return	The difference between the buy-and-hold stock return from month −14 to month −3 relative to the month of the bid announcement (month 0) and the analogously defined buy-and-hold stock return on the value-weighted CRSP index.
COGS	Cost of goods sold (COGS) scaled by sales.
Return on sales	Operating income before depreciation scaled by sales.
Advertising expenses	Advertising expense scaled by total assets.
Market share	The share in the sales of all public firms in the same 2-digit SIC industry.
Patent similarity	Following Jaffe (1989) and Bena and Li (2014), patent similarity is computed as $$\frac{\mathrm{P_{acq}P'_{tar}}}{\sqrt{\mathrm{P_{acq}P'_{acq}}}\sqrt{\mathrm{P_{tar}P'_{tar}}}},$$ where the vector $P_{acq} = (P_{acq,1}, ..., P_{acq,J})$ is the number of granted patent in each technology class for the acquirer, the vector $\mathrm{P}_{targ} = (P_{targ,1}, ..., P_{targ,K})$ is the number of granted patents in each technology class for the target, and $j \in (1,J)$ is the technology class index with J = 440.
HP similarity	The firm-level pairwise product market similarity score defined in Hoberg and Phillips (2010).

Deal Characteristics

Acquirer CAR (-1,1)	The cumulative abnormal announcement return from day -1 to day +1 surrounding the deal announcement date (day 0) for an acquirer. The abnormal return is computed using the market model with the CRSP value-weighted index as benchmark.
Target CAR (-1,1)	The cumulative abnormal announcement return from day -1 to day +1 surrounding the deal announcement date (day 0) for a target. The abnormal return is computed using the market model with the CRSP value-weighted index as benchmark.
Combined CAR (-1,1)	The sum of *Acquirer CAR (-1,1)* and *Target CAR (-1,1)* weighted by their respective market capitalization.
Horizontal	An indicator variable that takes the value of one if an acquirer's and its target's 2-digit SIC industries are the same, and zero otherwise.
All-cash	An indicator variable that takes the value of one if a deal is 100% financed by cash, and zero otherwise.
All-stock	An indicator variable that takes the value of one if a deal is 100% financed by stock, and zero otherwise.
Tender offer	An indicator variable that takes the value of one if a deal is a tender offer, and zero otherwise.
Toehold	An indicator variable that takes the value of one if an acquirer already has a stake in its target before the bid announcement, and zero otherwise.
Transaction value	In millions of 1982 constant dollars.

Deal size	Ln(1 + transaction value).
Complete	An indicator variable that takes the value of one if an announced bid is completed, and zero otherwise.
Relative size	Transaction value scaled by acquirer book assets.

Table 1. Temporal distribution of M&A deals

The sample consists of completed M&A transactions between 1983 and 2016 from the Thomson One Banker SDC database. We impose the following filters to obtain our final sample: i) the deal is classified as "Acquisition of Assets (AA)", "Merger (M)," or "Acquisition of Majority Interest (AM)" by the data provider; ii) the acquirer is a U.S. public firm listed on the AMEX, NYSE, or NASDAQ; iii) the acquirer holds less than 50% of the shares of the target firm before deal announcement and ends up owning 100% of the shares of the target firm through the deal; iv) the deal value is at least $1 million (in 1982 dollar value); v) the relative size of the deal (i.e., the ratio of transaction value to acquirer book assets), is at least 1%; vi) the acquirer owns at least one trademark prior to the deal; vii) the target firm is a public firm, a private firm, or a subsidiary; viii) multiple deals announced by the same acquirer on the same day are excluded; and ix) basic financial and stock return information is available for the acquirer, the target, or the acquirer-target pair.

	The Acquirer Sample		The Target Sample		The Acquirer-Target Pair Sample	
Year	No. of deals	Percentage	No. of deals	Percentage	No. of deals	Percentage
1983	191	1.33%	53	1.16%	14	0.74%
1984	199	1.39%	81	1.77%	25	1.32%
1985	160	1.11%	93	2.04%	38	2.00%
1986	205	1.43%	134	2.93%	43	2.26%
1987	151	1.05%	106	2.32%	30	1.58%
1988	188	1.31%	152	3.33%	34	1.79%
1989	201	1.40%	110	2.41%	36	1.89%
1990	167	1.16%	57	1.25%	21	1.10%
1991	181	1.26%	44	0.96%	24	1.26%
1992	279	1.94%	46	1.01%	27	1.42%
1993	372	2.59%	51	1.12%	30	1.58%
1994	453	3.16%	86	1.88%	48	2.52%
1995	562	3.91%	152	3.33%	80	4.21%
1996	637	4.44%	158	3.46%	76	4.00%
1997	835	5.82%	229	5.01%	125	6.58%
1998	880	6.13%	291	6.37%	145	7.63%
1999	756	5.27%	317	6.94%	133	7.00%
2000	656	4.57%	248	5.43%	102	5.37%
2001	482	3.36%	193	4.22%	82	4.31%
2002	533	3.71%	117	2.56%	56	2.95%
2003	527	3.67%	142	3.11%	67	3.52%
2004	594	4.14%	125	2.74%	64	3.37%
2005	591	4.12%	159	3.48%	67	3.52%
2006	569	3.96%	193	4.22%	74	3.89%
2007	594	4.14%	208	4.55%	75	3.95%
2008	395	2.75%	125	2.74%	43	2.26%
2009	287	2.00%	96	2.10%	56	2.95%
2010	385	2.68%	147	3.22%	50	2.63%
2011	373	2.60%	118	2.58%	23	1.21%
2012	421	2.93%	127	2.78%	44	2.31%
2013	380	2.65%	104	2.28%	40	2.10%
2014	455	3.17%	105	2.30%	49	2.58%
2015	413	2.88%	125	2.74%	57	3.00%
2016	285	1.99%	77	1.69%	23	1.21%
Total	14,357	100.00%	4,569	100.00%	1,901	100.00%

Table 2. Summary statistics for the acquirer sample

This table reports summary statistics of the acquirers as well as their industry- and size-matched control firms. Panel A presents basic summary statistics. Panel B presents the correlation matrix of acquirer characteristics. Definitions of the variables are provided in the Appendix. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Summary statistics

	Acquirers						Industry-size matched control firms						Test of differences	
	Mean	SD	5th Percentile	Median	95th Percentile	N	Mean	SD	5th Percentile	Median	95th Percentile	N	T-test	Wilcoxon test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(1) - (7)	(4) - (10)
Number of trademarks	46.313	80.595	1	15	224	14357	28.255	56.438	1	10	121	64182	18.058***	5.000***
Trademark age	7.729	5.605	1.391	6.294	18.836	14357	8.403	6.457	1.250	6.714	21.82243	64182	-0.674***	-0.420***
Trademark growth rate	14.56%	35.71%	-10.00%	0.00%	92.86%	14357	10.29%	32.15%	-12.50%	0.00%	0.6666667	64182	4.26%***	0.00%***
Trademark concentration	50.60%	29.02%	14.79%	43.35%	100.00%	14357	55.38%	29.79%	15.98%	50.00%	100.00%	64182	-4.78%***	-6.65%***
Total assets	1.954	4.713	0.021	0.344	10.223	14357	1.441	4.111	0.016	0.214	6.783	64182	0.513***	0.130***
M/B	3.337	3.755	0.790	2.413	9.633	14357	2.815	3.717	0.406	1.978	8.642	64182	0.522***	0.436***
ROA	12.20%	11.47%	-4.61%	12.90%	28.22%	14357	9.31%	13.82%	-16.21%	10.91%	27.99%	64182	2.89%***	1.99%***
Leverage	20.36%	19.18%	0.00%	16.84%	57.54%	14357	21.30%	21.08%	0.00%	16.62%	62.68%	64182	-0.94%***	0.22%
Cash	17.67%	19.49%	0.52%	9.67%	61.03%	14357	18.94%	20.85%	0.49%	10.35%	65.56%	64182	-1.27%***	-0.68%***
Sales growth	26.64%	51.03%	-16.55%	13.66%	107.23%	14357	16.61%	45.68%	-25.86%	8.03%	79.61%	64182	10.03%***	5.63%***
Prior-year stock return	19.29%	62.78%	-49.93%	6.10%	139.77%	14357	4.56%	58.55%	-68.30%	-4.11%	108.84%	64182	14.73%***	10.21%***

Panel B: Correlation matrix

	Trademark count	Trademark age	Trademark growth rate	Trademark concentration	Firm size	M/B	ROA	Leverage	Cash	Sales growth
Trademark count	1.000									
Trademark age	0.165***	1.000								
Trademark growth rate	-0.049***	-0.296***	1.000							
Trademark concentration	-0.468***	-0.111***	0.007*	1.000						
Firm size	0.391***	0.125***	-0.031***	-0.186***	1.000					
M/B	0.075***	-0.079***	0.049***	-0.020***	-0.019***	1.000				
ROA	0.201***	0.133***	-0.025***	-0.127***	0.174***	0.088***	1.000			
Leverage	0.001	0.062***	-0.003	-0.105***	0.175***	-0.079***	-0.002	1.000		
Cash	-0.074***	-0.195***	0.048***	0.111***	-0.270***	0.196***	-0.255***	-0.385***	1.000	
Sales growth	-0.116***	-0.174***	0.143***	0.050***	-0.086***	0.186***	-0.050***	-0.002	0.130***	1.000
Prior-year stock return	0.014***	-0.031***	0.023***	-0.003	0.001	0.190***	0.114***	-0.040***	0.076***	0.096***

Table 3. Summary statistics for the target sample

This table reports summary statistics of the targets as well as their industry- and size-matched control firms. Panel A presents basic summary statistics. Panel B presents the correlation matrix of target characteristics. Definitions of the variables are provided in the Appendix. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Summary statistics

	Targets						Industry-size matched control firms						Test of differences	
	Mean	SD	5th Percentile	Median	95th Percentile	N	Mean	SD	5th Percentile	Median	95th Percentile	N	T-test	Wilcoxon test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(1) - (7)	(4) - (10)
Number of trademarks	20.306	36.394	1	8	84	4569	20.416	37.609	1	8	84	20610	-0.110	0.000
Trademark age	7.779	5.775	1.222	6.333	19.667	4569	8.008	6.164	1.000	6.427	20.77	20610	-0.229**	-0.094
Trademark growth rate	9.48%	31.48%	-13.33%	0.00%	66.67%	4569	10.62%	32.70%	-12.50%	0.00%	66.67%	20610	-1.14%**	0.00%***
Trademark concentration	59.51%	30.53%	17.33%	52.00%	100.00%	4569	58.71%	30.19%	16.67%	51.99%	100.00%	20610	0.79%	0.01%
Total assets	1.038	3.130	0.009	0.135	4.881	4569	1.022	3.188	0.009	0.121	4.664	20610	0.016	0.014***
M/B	2.479	3.308	0.426	1.745	7.461	4569	2.670	3.629	0.381	1.806	8.602	20610	-0.191***	-0.061***
ROA	6.91%	17.40%	-27.73%	10.24%	25.91%	4569	7.02%	17.51%	-27.41%	9.72%	28.10%	20610	-0.11%	0.52%
Leverage	21.44%	20.86%	0.00%	17.08%	61.74%	4569	20.54%	21.07%	0.00%	15.24%	62.39%	20610	0.89%	1.84%***
Cash	18.35%	20.76%	0.41%	10.15%	65.09%	4569	19.65%	21.81%	0.48%	10.43%	68.02%	20610	-1.30%***	-0.28%
Sales growth	16.63%	46.59%	-26.83%	8.01%	82.83%	4569	18.27%	53.24%	-27.94%	8.14%	90.02%	20610	-1.65%**	-0.13%***
Prior-year stock return	-5.11%	53.08%	-73.78%	-12.34%	89.38%	4569	-1.20%	55.95%	-72.82%	-8.95%	99.59%	20610	-3.91%***	-3.39%***

Panel B: Correlation matrix

	Trademark count	Trademark age	Trademark growth rate	Trademark concentration	Firm size	M/B	ROA	Leverage	Cash	Sales growth
Trademark count	1.000									
Trademark age	0.158***	1.000								
Trademark growth rate	-0.482***	-0.109***	1.000							
Trademark concentration	-0.028***	-0.291***	-0.011	1.000						
Firm size	0.330***	0.123***	-0.172***	-0.031***	1.000					
M/B	0.042***	-0.084***	-0.031***	0.039***	-0.062***	1.000				
ROA	0.175***	0.161***	-0.133***	-0.032***	0.245***	-0.004	1.000			
Leverage	0.008	0.043***	-0.088***	-0.001	0.197***	-0.085***	0.035***	1.000		
Cash	-0.072***	-0.177***	0.079***	0.030***	-0.287***	0.211***	-0.339***	-0.389***	1.000	
Sales growth	-0.112***	-0.149***	0.049***	0.101***	-0.076***	0.175***	-0.072***	0.008	0.129***	1.000
Prior-year stock return	0.039***	0.017**	-0.030***	-0.002	0.050***	0.152***	0.152***	-0.053***	0.036***	0.036***

Table 4. Who will become acquirers?

Panel A of this table presents the results for conditional logit regression with the dependent variable equal to one for the actual acquirer and to zero for firms in the control group. Control firms in column (1) are randomly drawn from the Compustat universe, in column (2) are matched on industry and size dimensions, and in column (3) are matched on industry, size, and book-to-market dimensions. Columns (1) presents the median and standard deviation of the empirical distribution of coefficient estimates from conditional logit models using 500 randomly drawn control groups of acquirers. Definitions of the variables are provided in the Appendix. All specifications include deal fixed effects. Robust standard errors, which cluster at the deal level, are reported in the parentheses; superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Panel B presents the economic significance of our trademark variables in predicting acquirers. The predicted transaction incidence is tabulated under different values of one trademark variable while holding other variables' values at their means.

Panel A: The conditional logit regression predicting acquirers

	Random	Industry & Size	Industry, Size, & M/B
Variables	(1)	(2)	(3)
Trademark count	0.193***	0.227***	0.213***
	(0.010)	(0.011)	(0.012)
Trademark age	-0.035***	-0.025***	-0.024***
	(0.002)	(0.002)	(0.002)
Trademark growth rate	0.240***	0.211***	0.203***
	(0.030)	(0.030)	(0.030)
Trademark concentration	-0.132***	-0.058	-0.013
	(0.039)	(0.046)	(0.047)
Firm size	0.196***	0.467***	0.290***
	(0.006)	(0.012)	(0.009)
M/B	0.007**	0.003	0.266***
	(0.003)	(0.003)	(0.010)
ROA	2.095***	1.576***	2.187***
	(0.077)	(0.093)	(0.105)
Leverage	-0.427***	-0.384***	0.417***
	(0.055)	(0.062)	(0.074)
Cash	0.491***	-0.546***	-0.348***
	(0.060)	(0.070)	(0.071)
Sales growth	0.359***	0.454***	0.480***
	(0.018)	(0.022)	(0.023)
Prior-year stock return	0.374***	0.389***	0.390***
	(0.016)	(0.017)	(0.018)
Observations	75,082	76,303	75,870
Deal FE	YES	YES	YES

Panel B: The economic magnitude of different trademark variables predicting acquirers

	(1)	(2)	(3)	(3) - (1)
	25th Percentile	Mean	75th Percentile	
Trademark count	13.39%	16.67%	20.11%	6.72%
Trademark age	18.38%	16.67%	15.52%	-2.85%
Trademark growth rate	16.35%	16.67%	16.70%	0.35%
Trademark concentration	16.92%	16.67%	16.41%	-0.50%

Table 5. Who will become targets?

Panel A of this table presents the results for conditional logit regression with the dependent variable equal to one for the actual target and to zero for firms in the control group. Control firms in column (1) are randomly drawn from the Compustat universe, in column (2) are matched on industry and size dimensions, and in column (3) are matched on industry, size, and book-to-market dimensions. Columns (1) presents the median and standard deviation of the empirical distribution of coefficient estimates from conditional logit models using 500 randomly drawn control groups of acquirers. Definitions of the variables are provided in the Appendix. All specifications include deal fixed effects. Robust standard errors, which cluster at the deal level, are reported in the parentheses; superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Panel B presents the economic significance of our trademark variables in predicting target firms. The predicted transaction incidence is tabulated under different values of one trademark variable while holding other variables' values at their means.

Panel A: The conditional logit regression predicting targets

	Random	Industry & Size	Industry, Size, & M/B
Variables	(1)	(2)	(3)
Trademark count	-0.007	-0.009	-0.014
	(0.017)	(0.020)	(0.020)
Trademark age	-0.023***	-0.011***	-0.009***
	(0.003)	(0.003)	(0.003)
Trademark growth rate	-0.138**	-0.151**	-0.135**
	(0.057)	(0.059)	(0.059)
Trademark concentration	0.153**	0.169**	0.185**
	(0.063)	(0.073)	(0.074)
Firm size	0.062***	0.198***	0.108***
	-0.009	(0.021)	(0.015)
M/B	-0.015***	-0.014***	0.183***
	(0.005)	(0.005)	(0.016)
ROA	0.615***	-0.027	0.233*
	(0.096)	(0.123)	(0.132)
Leverage	-0.007	0.099	0.875***
	(0.087)	(0.097)	(0.114)
Cash	0.338***	-0.494***	-0.397***
	(0.095)	(0.111)	(0.110)
Sales growth	-0.030	-0.070**	-0.072**
	(0.033)	(0.034)	(0.036)
Prior-year stock return	-0.141***	-0.130***	-0.129***
	(0.032)	(0.035)	(0.038)
Observations	23,837	24,159	24,364
Deal FE	YES	YES	YES

Panel B: The economic magnitude of different trademark variables predicting targets

	(1)	(2)	(3)	(3) - (1)
	25th Percentile	Mean	75th Percentile	
Trademark count	16.80%	16.67%	16.56%	-0.24%
Trademark age	17.37%	16.67%	16.20%	-1.17%
Trademark growth rate	16.88%	16.67%	16.65%	-0.23%
Trademark concentration	15.88%	16.67%	17.78%	1.90%

Table 6. Summary statistics for the acquirer-target sample

This table reports summary statistics of the acquirer-target pairs as well as their industry- and size-matched control pairs. Panel A presents basic summary statistics. Panel B presents the correlation matrix. Definitions of the variables are provided in the Appendix. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Summary statistics of acquirers/targets and their industry-size matched control firms

	Mean	SD	5th Percentile	Median	95th Percentile	N	Mean	SD	5th Percentile	Median	95th Percentile	N	T-test	Wilcoxon test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(1) - (7)	(4) - (10)
	Acquirers						Industry-Size Matched Acquirers						Test of differences	
Number of trademarks	101.563	157.492	2	32	521	1901	48.781	92.354	1	16	203	7363	52.782***	16***
Total assets (1982 USD billion)	6.283	12.357	0.045	1.395	32.536	1901	4.081	9.819	0.030	0.628	22.521	7363	2.202***	0.767***
M/B	3.530	3.499	0.919	2.542	9.924	1901	3.010	3.491	0.594	2.113	9.040	7363	0.520***	0.429***
ROA	12.89%	10.61%	-0.92%	13.42%	28.31%	1901	11.17%	10.87%	-4.92%	11.60%	27.20%	7363	1.72%***	1.82%***
Leverage	20.12%	16.57%	0.00%	17.80%	51.88%	1901	21.63%	18.74%	0.00%	18.69%	58.06%	7363	-1.51%***	-0.89%*
Cash	16.16%	17.93%	0.62%	8.85%	57.16%	1901	17.08%	18.67%	0.52%	9.31%	58.66%	7363	-0.92%**	-0.46%
Sales growth	22.36%	40.50%	-16.23%	11.60%	96.07%	1901	17.48%	36.16%	-16.87%	9.27%	76.50%	7363	4.88%***	2.33%***
Prior-year stock return	12.02%	48.46%	-47.32%	3.25%	102.33%	1901	4.60%	50.73%	-59.84%	-2.32%	92.71%	7363	7.42%***	5.57%***
	Targets						Industry-Size Matched Targets						Test of differences	
Number of trademarks	22.804	43.016	1	9	93	1901	23.338	41.807	1	9	100	7363	-0.534	0
Total assets (1982 USD billion)	1.505	4.500	0.011	0.173	6.898	1901	1.534	4.651	0.012	0.162	7.501	7363	-0.029	0.010
M/B	2.871	3.493	0.594	2.000	8.541	1901	2.838	3.474	0.518	1.896	8.561	7363	0.033	0.104**
ROA	7.19%	16.90%	-29.47%	10.37%	26.44%	1901	7.72%	15.93%	-23.46%	10.01%	27.15%	7363	-0.53%	0.36%
Leverage	19.76%	19.72%	0.00%	14.73%	57.40%	1901	19.98%	19.94%	0.00%	15.20%	60.08%	7363	-0.22%	-0.47%
Cash	20.12%	21.88%	0.41%	11.31%	67.55%	1901	19.91%	21.77%	0.48%	10.49%	68.11%	7363	0.21%	0.82%
Sales growth	19.63%	45.48%	-23.31%	9.43%	92.13%	1901	19.50%	47.49%	-24.71%	9.69%	86.77%	7363	0.13%	-0.26%
Prior-year stock return	-3.63%	53.24%	-70.98%	-11.25%	90.34%	1901	2.34%	55.15%	-68.03%	-5.98%	102.67%	7363	-5.97%***	-5.27%***
	Acquirer-Target Pairs						Industry-Size Matched Pairs						Test of differences	
Trademark similarity	70.03%	31.68%	1.74%	82.62%	100.00%	1901	60.09%	37.35%	0.00%	70.71%	100.00%	7363	9.94%***	11.91%***
Patent similarity	36.00%	32.98%	0.00%	26.90%	93.93%	823	24.03%	34.36%	0.00%	5.15%	100.00%	2975	11.97%***	21.75%***
HP similarity	5.97%	9.37%	0.00%	3.38%	18.77%	1324	1.88%	4.29%	0.00%	0.00%	10.97%	5076	4.09%***	3.38%***
Horizontal	68.07%	46.63%	0.00%	100.00%	100.00%	1901	68.78%	46.34%	0.00%	100.00%	100.00%	7363	-0.71%	0.00%

Panel B: Correlation matrix

	Trademark similarity	Patent similarity	HP similarity	Horizontal
Trademark similarity	1.000			
Patent similarity	0.350***	1.000		
HP similarity	0.131***	0.208***	1.000	
Horizontal	0.295***	0.299***	0.150***	1.000

Table 7. Acquirer-target pairing

Panel A of this table presents the results for conditional logit regression with the dependent variable equal to one for the actual acquirer-target pair and to zero for pairs in the control group. Control firms in columns (1) to (3) are randomly drawn from the Compustat universe, in columns (4) to (6) are matched on industry and size dimensions, and in columns (7) to (9) are matched on industry, size, and book-to-market dimensions. Columns (1), (4), and (7) are results for the baseline models. The other columns further control for Patent similarity or HP similarity. Columns (1) to (3) present the median and standard deviation of the empirical distribution of coefficient estimates from conditional logit models using 500 randomly drawn control groups of acquirer-target firm pairs. All specifications include deal fixed effects as well as acquirer and target control variables including firm size, market-to-book ratio, ROA, sales growth, leverage and trademark counts. Definitions of the variables are provided in the Appendix. Robust standard errors, which cluster at the deal level, are reported in the parentheses; superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Panel B presents the economic significance of our trademark variables in predicting merger pairing. The predicted transaction incidence is tabulated under different values of one trademark variable while holding other variables' values at their means.

Panel A: The conditional logit regression predicting acquirer-target pairs

	Random			Industry & Size			Industry, Size, & M/B		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Trademark similarity	3.408***	3.083***	3.349***	1.579***	1.124***	1.583***	1.223***	0.537**	1.168***
	(0.171)	(0.547)	(0.274)	(0.134)	(0.246)	(0.169)	(0.137)	(0.260)	(0.175)
Patent similarity		5.341***			1.708***			1.525***	
		(0.988)			(0.205)			(0.236)	
HP similarity			42.273***			20.131***			23.043***
			(4.194)			(1.875)			(1.915)
Horizontal	3.001***	2.496***	2.417***						
	(0.144)	(0.446)	(0.213)						
Acquirer trademark count	0.405***	0.333	0.513***	0.240***	0.306***	0.307***	0.288***	0.407***	0.322***
	(0.045)	(0.151)	(0.070)	(0.034)	(0.061)	(0.046)	(0.035)	(0.060)	(0.047)
Target trademark count	-0.080	-0.173	-0.018	-0.158***	-0.205***	-0.159***	-0.144***	-0.219***	-0.142***
	(0.052)	(0.169)	(0.079)	(0.036)	(0.066)	(0.048)	(0.036)	(0.067)	(0.048)
Acquirer firm size	0.457***	0.603***	0.438***	0.966***	1.162***	0.951***	0.647***	0.709***	0.684***
	(0.035)	(0.125)	(0.055)	(0.048)	(0.095)	(0.059)	(0.033)	(0.062)	(0.046)
Target firm size	-0.113***	-0.264	-0.232***	0.127**	0.334***	0.032	-0.040	-0.126*	-0.103**
	(0.035)	(0.124)	(0.056)	(0.053)	(0.113)	(0.063)	(0.030)	(0.067)	(0.041)
Acquirer M/B	0.025	0.004	0.017	-0.000	-0.012	0.003	0.091***	0.088***	0.081***
	(0.015)	(0.051)	(0.021)	(0.011)	(0.023)	(0.014)	(0.016)	(0.029)	(0.019)
Target M/B	-0.008	-0.009	-0.003	-0.002	-0.032*	-0.001	0.044***	0.027	0.056***
	(0.015)	(0.047)	(0.022)	(0.010)	(0.017)	(0.012)	(0.015)	(0.030)	(0.018)
Acquirer ROA	1.060*	0.407	1.927**	1.082***	0.274	0.904*	1.070**	0.785	1.317**

	(0.438)	(1.317)	(0.680)	(0.394)	(0.725)	(0.483)	(0.435)	(0.746)	(0.528)
Target ROA	0.717*	1.520	1.309**	-0.312	-0.043	0.012	-0.561**	-0.064	-0.050
	(0.313)	(1.021)	(0.475)	(0.243)	(0.451)	(0.299)	(0.264)	(0.464)	(0.327)
Acquirer leverage	-0.459	-1.870	-0.468	-0.532**	-0.805*	-0.580*	-0.326	-0.417	-0.380
	(0.322)	(1.111)	(0.481)	(0.226)	(0.467)	(0.297)	(0.249)	(0.468)	(0.328)
Target leverage	0.572	1.077	0.910	0.042	0.446	0.052	0.619***	0.985**	0.785***
	(0.300)	(1.020)	(0.448)	(0.198)	(0.357)	(0.261)	(0.225)	(0.420)	(0.292)
Acquirer cash	0.208	-0.484	-0.594	-0.125	-0.289	-0.668**	-0.043	0.079	-0.434
	(0.355)	(1.053)	(0.555)	(0.232)	(0.412)	(0.291)	(0.243)	(0.419)	(0.305)
Target cash	0.141	-0.646	0.312	-0.384*	-0.603	-0.302	-0.416*	-0.752**	-0.428
	(0.314)	(0.976)	(0.449)	(0.206)	(0.369)	(0.261)	(0.212)	(0.371)	(0.274)
Acquirer sales growth	0.472***	0.384	0.398**	0.512***	0.265	0.357***	0.543***	0.327*	0.430***
	(0.112)	(0.434)	(0.184)	(0.091)	(0.179)	(0.124)	(0.094)	(0.184)	(0.121)
Target sales growth	-0.057	-0.073	0.000	-0.070	0.030	-0.158*	-0.204***	-0.146	-0.243***
	(0.110)	(0.361)	(0.168)	(0.068)	(0.120)	(0.087)	(0.072)	(0.142)	(0.091)
Acquirer prior-year stock return	0.403***	0.399	0.380**	0.377***	0.371***	0.400***	0.400***	0.425***	0.374***
	(0.104)	(0.334)	(0.155)	(0.065)	(0.124)	(0.083)	(0.072)	(0.139)	(0.090)
Target prior-year stock return	-0.333**	-0.243	-0.277	-0.225***	-0.104	-0.179**	-0.173**	-0.007	-0.221**
	(0.104)	(0.319)	(0.154)	(0.066)	(0.112)	(0.082)	(0.068)	(0.122)	(0.087)
Observations	9,643	1,382	6,501	9,034	2,816	6,193	8,788	2,630	6,028
Deal FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: The economic magnitude of different trademark variables predicting acquirer-target pairs

	(1)	(2)	(3)	(3) - (1)
	25th Percentile	Mean	75th Percentile	
Trademark similarity	9.32%	16.67%	27.35%	18.03%
Patent similarity	10.54%	16.67%	23.04%	12.50%
HP similarity	10.06%	16.67%	20.31%	10.25%

Table 8. Summary statistics of announcement period abnormal returns and deal characteristics

This table provides summary statistics for the cumulative abnormal announcement return (CAR) and deal characteristics. Panel A presents basic summary statistics. Panel B presents the correlation matrix. Definitions of the variables are provided in the Appendix. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Summary statistics

	Mean	SD	5th Percentile	Median	95th Percentile	N
Combined CAR (-1,1)	1.6%	7.7%	-8.8%	1.0%	13.8%	1926
Acquirer CAR (-1,1)	-1.4%	7.5%	-13.5%	-0.9%	9.9%	1926
Target CAR (-1,1)	19.3%	24.4%	-5.4%	14.6%	60.5%	1926
Horizontal	68.1%	46.6%	0	1	1	1926
All-cash	32.3%	46.8%	0	0	1	1926
All-stock	32.9%	47.0%	0	0	1	1926
Tender	24.4%	43.0%	0	0	1	1926
Toehold	4.4%	20.5%	0	0	0	1926
Transaction value	651.45	1495.53	8.81	152.48	3213.04	1926
Relative size	32.8%	57.3%	1.0%	12.3%	137.2%	1926

Panel B: Correlation matrix

	Combined CAR (-1,1)	Acquirer CAR (-1,1)	Target CAR (-1,1)	Horizontal	All-cash	All-stock	Tender	Toehold
Combined CAR (-1,1)	1.000							
Acquirer CAR (-1,1)	0.424***	1.000						
Target CAR (-1,1)	0.106***	0.749***	1.000					
Horizontal	-0.060**	0.017	-0.004	1.000				
All-cash	0.128***	0.117***	0.189***	-0.108***	1.000			
All-stock	-0.104***	-0.160***	-0.175***	0.079***	-0.484***	1.000		
Tender	0.141***	0.115***	0.122***	-0.101***	0.430***	-0.367***	1.000	
Toehold	0.052*	0.071**	0.049*	-0.043	0.062**	-0.075***	0.155***	1.000
Relative size	-0.112***	-0.036	-0.233***	0.058*	-0.223***	0.173***	-0.098***	-0.0212

Table 9. Trademark similarity and announcement period abnormal returns

This table examines the relation between trademark similarity and announcement period abnormal returns. Acquirer (2-digic SIC) industry, target industry, and year fixed effects are included in all models. Definitions of the variables are provided in Appendix. Robust standard errors, which cluster at the acquirer industry level, are reported in the parentheses; superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
	Combined CAR (-1,1)	Acquirer CAR (-1,1)	Target CAR (-1,1)
Trademark similarity	0.012**	-0.007	0.060***
	(0.006)	(0.006)	(0.022)
Horizontal	0.002	0.008**	-0.037***
	(0.004)	(0.003)	(0.011)
All-cash	0.008	0.013**	0.031*
	(0.005)	(0.005)	(0.016)
All-stock	0.008*	0.007*	0.024
	(0.004)	(0.004)	(0.016)
Tender	-0.017**	-0.009*	-0.037***
	(0.007)	(0.005)	(0.008)
Toehold	0.016**	0.003	0.042
	(0.008)	(0.005)	(0.031)
Relative size	-0.004	-0.031***	-0.039***
	(0.006)	(0.004)	(0.010)
Acquirer firm size	-0.006***	-0.004***	0.002
	(0.002)	(0.001)	(0.003)
Acquirer M/B	-0.001*	-0.000	
	(0.001)	(0.001)	
Acquirer ROA	-0.030*	-0.009	
	(0.016)	(0.013)	
Acquirer Leverage	0.016*	-0.011	
	(0.010)	(0.010)	
Target M/B	-0.001***		-0.006***
	(0.000)		(0.001)
Target ROA	0.039***		0.086***
	(0.009)		(0.031)
Target Leverage	0.003		0.033
	(0.013)		(0.042)
Observations	1,926	1,926	1,926
R-squared	0.176	0.188	0.168
Year FE	YES	YES	YES
Acquirer Industry FE	YES	YES	YES
Target Industry FE	YES	YES	YES

Table 10. Summary statistics of post-merger trademark cancellations

This table presents the ratio of cancelled trademarks from before to after deal completion. For each deal, we track its acquirer's and target's trademarks from five years before to five years after deal completion. We also separate trademarks by age or class. Common class refers to trademarks in a class that both the acquirer and its target have registered trademarks. Acquirer (Target) unique class refers to trademarks in a class that only the acquirer (target) has registered trademarks. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, for the two-sample t-test of mean.

Panel A: Acquirer ratio of cancelled trademarks

	Before			After			Test of difference
	Mean	SD	% of Total	Mean	SD	% of Total	t-test
	(1)	(2)	(3)	(4)	(5)	(6)	(4) – (1)
Total	3.04%	6.16%	100.00%	4.56%	7.59%	100.00%	1.52%***
By trademark age							
< 6 years	2.15%	5.41%	70.73%	3.15%	6.20%	69.06%	1.00%***
6-10 years	0.74%	2.55%	24.15%	1.21%	4.11%	26.58%	0.48%***
≥ 10 years	0.16%	0.88%	5.12%	0.20%	1.17%	4.36%	0.04%***
By trademark class							
Common class	2.11%	5.03%	69.41%	3.33%	6.68%	72.96%	1.21%***
Acquirer unique class	0.93%	3.30%	30.59%	1.23%	3.45%	27.04%	0.30%***

Panel B: Target ratio of cancelled trademarks

	Before			After			Test of difference
	Mean	SD	% of total	Mean	SD	% of total	t-test
	(1)	(2)	(3)	(4)	(5)	(6)	(4) – (1)
Total	2.60%	8.07%	100.00%	7.78%	16.40%	100.00%	5.19%***
By trademark age							
< 6 years	1.91%	6.92%	73.38%	5.84%	14.69%	75.04%	3.94%***
6-10 years	0.59%	3.78%	22.81%	1.77%	7.57%	22.69%	1.17%***
≥ 10 years	0.10%	1.40%	3.80%	0.18%	1.61%	2.27%	0.08%***
By trademark class							
Common class	2.29%	7.39%	88.34%	7.00%	15.42%	90.10%	4.70%***
Target unique class	0.30%	2.88%	11.66%	0.77%	4.92%	9.90%	0.47%***

Table 11. Trademark similarity and post-merger trademark cancellations: Difference-in-differences tests

This table reports the difference-in-differences (DiD) estimations of acquirer/target trademark cancelations from before to after deal completion using a sample of completed deals and deals that are withdrawn due to exogenous reasons. Each withdrawn deal is matched with one completed deal by acquirer industry, target industry, and acquirer size and ROA. Each deal is tracked from five years before to five years after deal completion. Only those deals with at least one observation before and one observation after deal completion are included. We also separate trademarks by age or class. Common class refers to trademarks in a class that both the acquirer and its target have registered trademarks. Acquirer (Target) unique class refers to trademarks in a class that only the acquirer (target) has registered trademarks. Panel A reports the post-merger trademark cancelations for the acquirer. Panel B reports the post-merger trademark cancelations for the target. Panel C reports the triple differences estimations of acquirer and target trademark cancelations and the DiD estimations for the subsamples of HIGH and LOW trademark similarity firms. Definitions of the variables are provided in the Appendix. All specifications include deal and year fixed effects. Robust standard errors, which cluster at the acquirer industry and year level, are reported in the parentheses; superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Acquirer ratio of cancelled trademarks: DiD

	Full	< 6 years	6-10 years	≥ 10 years	Common class	Acquirer unique class
Variables	(1)	(2)	(3)	(4)	(5)	(6)
After	0.006	0.007	-0.001	-0.000	0.006	-0.001
	(0.007)	(0.006)	(0.002)	(0.001)	(0.006)	(0.003)
After * Complete	-0.002	-0.003	0.001	-0.000	-0.000	-0.001
	(0.006)	(0.006)	(0.002)	(0.001)	(0.006)	(0.002)
Deal FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	3,244	3,244	3,244	3,244	3,244	3,244
R-squared	0.214	0.189	0.246	0.277	0.220	0.221

Panel B: Target ratio of cancelled trademarks: DiD

	Full	< 6 years	6-10 years	≥ 10 years	Common class	Target unique class
Variables	(1)	(2)	(3)	(4)	(5)	(6)
After	-0.006	-0.007	0.002	-0.001	-0.005	-0.001
	(0.009)	(0.009)	(0.003)	(0.001)	(0.009)	(0.003)
After * Complete	0.019**	0.018**	0.000	0.001	0.019**	0.000
	(0.009)	(0.008)	(0.004)	(0.001)	(0.008)	(0.003)
Deal FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	3,244	3,244	3,244	3,244	3,244	3,244
R-squared	0.202	0.172	0.166	0.202	0.209	0.161

Panel C: Acquirer and target ratio of cancelled trademarks: Triple differences tests

	HIGH trademark similarity		LOW trademark similarity		Full sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Acquirer ratio of cancelled trademarks	Target ratio of cancelled trademarks	Acquirer ratio of cancelled trademarks	Target ratio of cancelled trademarks	Acquirer ratio of cancelled trademarks	Target ratio of cancelled trademarks
After	-0.007	-0.021*	0.018	0.007	0.011	-0.007
	(0.008)	(0.013)	(0.011)	(0.012)	(0.008)	(0.011)
After * Complete	0.002	0.032***	-0.007	0.007	-0.006	0.006
	(0.007)	(0.012)	(0.009)	(0.012)	(0.009)	(0.012)
After * High trademark similarity					-0.011	0.001
					(0.007)	(0.010)
After * Complete * High trademark similarity					0.009	0.026*
					(0.011)	(0.015)
Observations	1,637	1,637	1,607	1,607	3,244	3,244
R-squared	0.248	0.231	0.220	0.195	0.215	0.204
Deal FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 12. Trademark similarity, post-merger new trademark registrations, and trademark growth

This table examines the relation between acquirer ratio of newly registered trademarks and trademark growth rate and trademark similarity between an acquirer and its target. Panel A presents the summary statistics for the ratio of newly registered trademarks. Common class refers to trademarks in a class that both the acquirer and its target have registered trademarks. Acquirer (Target) unique class refers to trademarks in a class that only the acquirer (target) has registered trademarks. New class refers to trademarks in a class that neither the acquirer nor its target has registered any trademarks. Panel B reports the difference-in-differences (DiD) estimations of acquirer trademark registration from before to after deal completion using a sample of completed deals and deals that are withdrawn due to exogenous reasons. Each withdrawn deal is matched with one completed deal by acquirer industry, target industry, and acquirer size and ROA. Each deal is tracked from five years before to five years after deal completion. Only those deals with at least one observation before and one observation after deal completion are included. Column (1) presents the DiD estimation for the subsample of HIGH trademark similarity firms, column (2) for the subsample of LOW trademark similarity firms, and column (3) presents the triple differences estimation for the full sample. Panel C repeats the analysis where the dependent variable is acquirer trademark growth rate. Definitions of the variables are provided in the Appendix. All specifications include deal and year fixed effects. Robust standard errors, which cluster at the acquirer industry and year level, are reported in the parentheses; superscripts *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Panel A: Summary statistics

	Before			After			Test of difference
	Mean	SD	% of Total	Mean	SD	% of Total	t-test
	(1)	(2)	(3)	(4)	(5)	(6)	(4) – (1)
Total	11.79%	17.54%	100.00%	6.04%	8.05%	100.00%	-5.75%***
By trademark class							
Common class	8.30%	14.53%	70.43%	3.73%	5.59%	61.84%	-4.57%***
Acquirer unique class	3.49%	9.02%	29.57%	1.34%	3.29%	22.27%	-2.14%***
Target unique class	/	/	/	0.28%	1.77%	4.70%	0.28%***
New class	/	/	/	0.68%	2.91%	11.19%	0.68%***

Panel B: Acquirer ratio of newly registered trademarks: Difference-in-differences tests

	(1)	(2)	(3)
Variables	HIGH trademark similarity	LOW trademark similarity	Full sample
After	-0.014	-0.065***	-0.041**
	(0.024)	(0.023)	(0.019)
After * Complete	-0.066***	-0.001	-0.003
	(0.021)	(0.018)	(0.018)
After * High trademark similarity			0.008
			(0.016)
After * Complete * High trademark similarity			-0.064**
			(0.027)
Observations	1,637	1,607	3,244
R-squared	0.238	0.246	0.233
Deal FE	YES	YES	YES
Year FE	YES	YES	YES

Panel C: Acquirer trademark growth rate: Difference-in-differences tests

	(1)	(2)	(3)
Variables	HIGH trademark similarity	LOW trademark similarity	Full sample
After	0.006	-0.131	-0.029
	(0.113)	(0.150)	(0.107)
After * Complete	-0.066	-0.059	-0.066
	(0.073)	(0.106)	(0.099)
After * High trademark similarity			-0.059
			(0.103)
After * Complete * High trademark similarity			0.012
			(0.123)
Observations	1,267	1,241	2,508
R-squared	0.236	0.218	0.210
Deal FE	YES	YES	YES
Year FE	YES	YES	YES

Table 13. Trademark similarity and post-merger operating efficiency and product market performance

This table presents the regression results for operating efficiency and product market performance from before to after deal completion using a sample of completed deals and deals that are withdrawn due to exogenous reasons. Each withdrawn deal is matched with one completed deal by acquirer industry, target industry, and acquirer size and ROA. Each deal is tracked from five years before to five years after deal completion. Only those deals with at least one observation before and one observation after deal completion are included. Panel A presents triple differences estimation results when different measures of operating efficiency are the dependent variables. Panel B presents triple differences estimation results when different measures of product market performance are the dependent variables. Definitions of the variables are provided in the Appendix. All specifications include deal and year fixed effects. Robust standard errors, which cluster at the acquirer industry and year level, are reported in the parentheses; superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Operating efficiency

	(1)	(2)	(3)
	R&D	CAPEX	ΔWorking capital
After	-0.000	0.002	-0.002
	(0.005)	(0.004)	(0.026)
After * Complete	-0.007	-0.008**	0.007
	(0.004)	(0.004)	(0.022)
After * High trademark similarity	0.005	-0.008***	-0.017
	(0.003)	(0.003)	(0.020)
After * Complete * High trademark similarity	-0.012	0.006	-0.003
	(0.008)	(0.005)	(0.037)
Observations	3,244	2,901	2,480
R-squared	0.791	0.652	0.150
Deal FE	YES	YES	YES
Year FE	YES	YES	YES

Panel B: Product market performance

	(1)	(2)	(3)	(4)
Variables	COGS	Advertising expenses	Return on sales	Market share
After	-0.013	-0.004**	0.062	0.003***
	(0.014)	(0.002)	(0.077)	(0.001)
After * Complete	0.071***	0.002	-0.119	-0.001
	(0.017)	(0.002)	(0.086)	(0.001)
After * High trademark similarity	0.019*	0.003**	-0.092*	-0.005***
	(0.011)	(0.002)	(0.050)	(0.001)
After * Complete * High trademark similarity	-0.076***	-0.006***	0.235**	0.006***
	(0.023)	(0.002)	(0.103)	(0.001)
Observations	3,242	3,242	3,242	3,242
R-squared	0.750	0.808	0.564	0.953
Deal FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Internet Appendix

Appendix 1. A case study on Microsoft

This appendix illustrates how Microsoft handles its target firms' trademarks after deal completion. By 2016, Microsoft has made nine acquisitions each worth over one billion dollars: Visio Corporation (2000), Navision (2002), aQuantive (2007), Fast Search & Transfer (2008), Skype (2011), Yammer (2012), Nokia (2013), Mojang (2014) and LinkedIn (2016). We will focus on the first five deals as the later ones are too recent to observe the full impact of takeovers on the trademarks of target firms after deal completion (i.e., the earliest maintenance threshold for a trademark is at the 6th anniversary since registration). The table below summarizes the number of product trademarks for each target and how many of them are cancelled afterwards.

Panel A: The number of target trademarks before vs. after deal completion

Target	Date of deal completion	# of target trademarks before the deal	# of target trademarks cancelled after the deal	Ratio of cancelled trademarks
Visio Corporation	07 Jan 2000	24	10	42%
Navision	12 Jul 2002	8	6	75%
aQuantive	13 Aug 2007	11	9	82%
Fast Search & Transfer	25 Apr 2008	17	17	100%
Skype	10 May 2011	20	10	50%

On average, about 70% of target trademarks are cancelled after the takeover, suggesting a significant shrinking of the target's product lines. The table below provides a detailed list of involved trademarks. Bold number inside the parentheses indicates the number of trademarks under the same name.

Panel B: The list of target trademarks before vs. after deal completion

Target	Target trademarks before the deal	Target trademarks cancelled after the deal
Visio Corporation	VISIORX; VISIO FINANCIAL SERVICES; SWISS VISIO; AFORNISTA; FLUXLD; XIRM; VISIERO; SATAGO; CRISTILINE; NISI; R E O R; EXESTO; ADNUO; ARCHT; VISIO **(3)**; SHAPESHEET; AUTODISCOVERY; VISUALIZE YOUR BUSINESS; VISIO SOLUTIONS LIBRARY; DESIGNED FOR VISIO; DRAG, DROP, DONE; POLJOT;	VISIO (**3**); AUTODISCOVERY; VISUALIZE YOUR BUSINESS; VISIO SOLUTIONS LIBRARY; DESIGNED FOR VISIO; DRAG, DROP, DONE; POLJOT
Navision	FLOWFILTER; FLOWFIELD; THE WAY TO GROW; NAVISION; NAVISION ATTAIN; NAVISION AXAPTA; ASSISTBUTTON; SUMINDEXFIELD	THE WAY TO GROW; NAVISION; NAVISION ATTAIN; NAVISION AXAPTA; ASSISTBUTTON; SUMINDEXFIELD
aQuantive	FRANCHISE GATOR; RAZORFISH; PARTNER FOR RESULTS **(2)**; BIDMANAGER **(2)**; SELECTOR; CHANNELSCOPE; ATLAS ON DEMAND; AQUANTIVE **(2)**	PARTNER FOR RESULTS **(2)**; BIDMANAGER **(2)**; SELECTOR; CHANNELSCOPE; ATLAS ON DEMAND; AQUANTIVE **(2)**

Fast Search & Transfer	FAST IMPULSE; FAST ESP; FAST METAWEB; FAST CONTEXTUAL INSIGHT; FAST MSEARCH; CORPORATE RADAR; FAST SCOPE SEARCH; FAST PROPUBLISH; FAST INSTREAM; FAST INPERSPECTIVE; FAST SENTIMETER; FAST MARKETRAC; NXT; LIVEPUBLISH; FAST; UNDERHEAD TECHNOLOGY; FOLIO	FAST IMPULSE; FAST ESP; FAST METAWEB; FAST CONTEXTUAL INSIGHT; FAST MSEARCH; CORPORATE RADAR; FAST SCOPE SEARCH; FAST PROPUBLISH; FAST INSTREAM; FAST INPERSPECTIVE; FAST SENTIMETER; FAST MARKETRAC; NXT; LIVEPUBLISH; FAST; UNDERHEAD TECHNOLOGY; FOLIO
Skype	SKYPE MANAGER; SKYPE TO GO; S (2); SKYPE **(2)**; QIK; SKYPE ACADEMY; SKYPE ACCESS; SILK; SKYPE PRIME; SKYPE CERTIFIED; SKYPE OUT **(2)**; SKYPE ME; SKYPE IN **(2)**; SKYPECASTS; SKYPEFIND; SKYPE ZONES	SKYPE CERTIFIED; SKYPE OUT **(2)**; SKYPE ME; SKYPE IN **(2);** SKYPE IN; SKYPECASTS; SKYPEFIND; SKYPE ZONES

Appendix 2. Classifying product and marketing trademarks

Most trademarks are registered when new products are launched. However, there are trademarks that are not related to specific products (such as a company logo), or are registered for marketing purposes (such as an advertising slogan or a redesign of a product logo). Given that our study focuses on a company's product lines, we will separate its trademark portfolio into product and marketing trademarks and only use the former in our empirical analysis. Here are some examples of well-known product and marketing trademarks.

Panel A: Examples of product and marketing trademarks

Product trademarks	Marketing trademarks
Big Mac®	i'm lovin' it®
Coca-Cola zero™	the Coke side of life
MacBook Air	

Our classification scheme relies on two key variables in the trademark dataset.

1) **mark drawing code**: A four-digit code which indicates whether the registration or application is for a standard character mark, a mark with stylized text, a design with or without text (such as sound, smell, etc.), or a mark for which no drawing is possible. The large majority of annual registrations are consistently issued for standard character marks. According to Graham et al., (2013), registrations of standard character marks and design marks with characters make up over 90% of registrations issued during the last decade.
2) **mark identification character**: If the mark includes any words, letters, or numbers, this variable will contain that text. If the mark is a design without text, this variable is missing.

First, we classify a mark whose 'mark drawing code' is design without text (such as pure logo, sound, smell, etc.) to be a marketing trademark. This is because these marks are usually not associated with any specific new products. If they do, it is merely for registering a product logo rather than a product name. Examples include Nike's swoosh logo, Starbuck's mermaid logo, and MGM's sound of a roaring lion.

Second, for a mark (1) whose 'mark drawing code' is stylized text or design with text and (2) whose number of words within the mark is equal to or more than 4, we classify it to be a marketing trademark. This is because these marks are very likely to be an advertising slogan. Note that our classification is not perfect. Product names such as 'Mac OS X Server Essentials' are classified as a marketing trademark because it has a long product name of 5 words. Advertising slogans such as Nike's 'Just Do It' may not be captured because it has only 3 words. Nonetheless, the threshold '4' is believed to be optimally balancing the type I and type II errors.

Third, for a mark (1) whose 'mark drawing code' is standard character mark and (2) whose number of words within the mark is fewer than 4, we classify it as a product trademark.

Fourth, and finally, for a mark (1) whose 'mark drawing code' is design with text and (2) whose number of words within the mark is fewer than 4, this becomes somewhat complicated. It can be a product trademark when a company registers a new product name using a trademark with some designs and/or artistic drawings. It can also be a marketing trademark if a company has already registered the product name and the current registration is for protecting or updating the product logo. For instance, the text 'Coca Cola' has been registered 48 times, most of which are for redesigning the logo. To differentiate these two cases, if the text of a mark is the first to appear in its class, the mark is classified as a product trademark. All subsequent marks with the same text and registered in the same class are classified as marketing trademarks. The example below helps illustrate our classification scheme.

Panel B: A snapshot of 'Coca Cola' trademark history

	Mark content	Classification
In 1892, Coca cola registered its very first coca cola trademark (design with text) in the class 'light beverage' – indicating new product line.		Product
In 1927, it redesigned its trademark, thus registering a new trademark in the class 'light beverage' – no new product line, just updating logo.		Marketing
In 1982, it registered the coca cola trademark in a new class 'fabrics' – indicating that it has a new product line and sell under the name of coca cola.		Product
In 1982, it registered the coca cola trademark in a new class 'metal goods' – indicating that it has a new product line and sell under the name of coca cola.		Product
In 1986, it again redesigned its trademark, thus registering a new trademark in the class 'light beverage' – no new product line.		Marketing

Panel C: A summary of our classification scheme

		Mark drawing code		
		Plain text	Design with text	Design without text (such as sound, smell, etc.)
Mark identification character	≥ 4 words	**Marketing -** KFC slogan: 'It's finger lickin good' McDonald slogan: 'What we're made of'	**Marketing -**	**Marketing -**
	< 4 words	**Product -** MacBook Pro; IPAD PRO; XBOX 360	**Product -** If 'mark identification character' is the first in its class for the firm (The first 'coca cola' mark registered in the class 'light beverage') **Marketing** - Subsequent marks with the same 'mark identification character' and in the same class (The redesigned 'coca cola' mark in the class 'light beverage')	

Appendix 3. Trademark similarity and post-merger outcome: Additional tests

This appendix includes additional tables for Section 4. Panel A outlines the steps taken to form the sample of control deals, i.e. withdrawn bids due to reasons exogenous to product line (N = 179). Panel B presents the ratio of cancelled and newly registered trademarks before and after the deal completion for the sample of completed deals paired with withdrawn deal.

To check the internal validity of our difference-in-differences estimator, we conduct falsification tests following the suggestion in Roberts and Whited (2013). Specifically, we falsely assume that the onset of treatment (i.e., bid announcement) occurs three years before it actually does. In each case, we re-estimate Equation (4) and (5) using a five-year panel dataset that centers around the "pseudo" year of bid announcement. Panel C presents the results.

We show that the coefficient on the interaction term $After_{ijt} \times Complete_{ij} \times High\ Trademark\ Similarity_{ij}$ is statistically indistinguishable from zero, suggesting that the observed changes in trademark cancellation and registration (shown in Table 11 Panel B) are more likely due to the treatment, as opposed to some alternative force.

Panel A: Sample formation

Withdrawn deals due to competing bids, regulatory objections, or adverse market conditions.	332
For each withdrawn deal, there exists at least one completed deal that has the same acquirer and target industry (two-digit SIC level).	-93
Both the acquirer and target of a withdrawn deal have trademarks one year prior to the deal announcement year.	-47
Both the acquirer and the target of a matched completed deal (by acquirer size and ROA) and of a withdrawn deal have at least one valid observation of cancelled trademarks and newly registered trademarks within a five-year window both before and after the deal announcement year.	-13
Final control sample of withdrawn bids	179

Panel B: Acquirer ratio of cancelled trademarks

	Before			After			Test of difference
	Mean	SD	% of Total	Mean	SD	% of Total	t-test
	(1)	(2)	(3)	(4)	(5)	(6)	(4) – (1)
Total	2.40%	6.06%	100.00%	4.32%	8.00%	100.00%	1.92%***
By trademark age							
< 6 years	1.76%	5.49%	73.23%	3.25%	7.28%	75.18%	1.49%***
6-10 years	0.54%	2.34%	22.33%	0.92%	2.86%	21.23%	0.38%***
≥ 10 years	0.11%	0.88%	4.44%	0.16%	0.79%	3.60%	0.05%*
By trademark class							
Common class	1.80%	5.50%	75.12%	3.31%	7.10%	76.56%	1.51%***
Acquirer unique class	0.60%	2.36%	24.88%	1.01%	3.12%	23.44%	0.42%***

Panel C: Target ratio of cancelled trademarks

	Before			After			Test of difference
	Mean	SD	% of total	Mean	SD	% of total	t-test
	(1)	(2)	(3)	(4)	(5)	(6)	(4) – (1)

Total	2.42%	6.67%	100.00%	6.08%	13.11%	100.00%	3.66%***
By trademark age							
< 6 years	1.83%	6.02%	75.52%	4.52%	11.64%	74.34%	2.70%***
6-10 years	0.55%	2.77%	22.56%	1.35%	6.06%	22.16%	0.80%***
≥ 10 years	0.05%	0.41%	1.91%	0.21%	1.72%	3.50%	0.17%***
By trademark class							
Common class	2.02%	5.65%	83.69%	5.28%	12.12%	86.85%	3.26%***
Target unique class	0.39%	3.19%	16.31%	0.80%	3.76%	13.15%	0.41%***

Panel D: Acquirer ratio of newly registered trademarks

	Before			After			Test of difference
	Mean	SD	% of Total	Mean	SD	% of Total	t-test
	(1)	(2)	(3)	(4)	(5)	(6)	(4) – (1)
Total	12.33%	20.48%	100.00%	6.82%	10.48%	100.00%	-5.50%***
By trademark class							
Common class	9.21%	17.88%	74.72%	4.35%	7.33%	63.73%	-4.86%***
Acquirer unique class	3.12%	9.08%	25.28%	1.11%	3.23%	16.21%	-2.01%***
Target unique class	/	/	/	0.48%	3.39%	7.11%	0.48%***
New class	/	/	/	0.88%	3.90%	12.95%	0.88%***

Panel E: Falsification tests

This table presents the results from falsification tests where we falsely assume that the onset of treatment (i.e., bid announcement) occurs three years before the actual announcement year. Definitions of the variables are provided in the Appendix. All specifications include deal and year fixed effects. Robust standard errors, which cluster at the acquirer and year level, are reported in the parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Subsample of HIGH trademark similarity			Subsample of LOW trademark similarity			Full sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Acquirer ratio of cancelled trademarks	Target ratio of cancelled trademarks	Acquirer ratio of newly registered trademarks	Acquirer ratio of cancelled trademarks	Target ratio of cancelled trademarks	Acquirer ratio of newly registered trademarks	Acquirer ratio of cancelled trademarks	Target ratio of cancelled trademarks	Acquirer ratio of newly registered trademarks
After	0.004	-0.005	-0.019	0.007	-0.037**	-0.020	0.008	-0.022*	-0.011
	(0.011)	(0.008)	(0.026)	(0.007)	(0.016)	(0.025)	(0.008)	(0.012)	(0.021)
After * Complete	0.013	0.012	-0.003	-0.005	0.001	-0.002	-0.002	-0.001	0.000
	(0.015)	(0.009)	(0.024)	(0.008)	(0.013)	(0.022)	(0.008)	(0.013)	(0.021)
After * High trademark similarity							-0.009	0.010	-0.002
							(0.007)	(0.010)	(0.022)
After * Complete * High trademark similarity							0.017	0.011	-0.002
							(0.018)	(0.016)	(0.032)
Observations	718	718	718	700	700	700	1,422	1,422	1,422
R-squared	0.343	0.465	0.398	0.418	0.288	0.485	0.331	0.343	0.419
Deal FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Appendix 4. Robustness checks

This table show the estimation results of Equation (4) where the dependent variables is the ratio of number of cancelled trademarks (≥ 6 years old) to total number of trademarks (≥ 6 years old). Definitions of the variables are provided in the Appendix. All specifications include deal and year fixed effects. Robust standard errors, which cluster at the acquirer and year level, are reported in the parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	HIGH trademark similarity	LOW trademark similarity	Full sample
	(1)	(2)	(2)
After	-0.013	0.003	-0.001
	(0.010)	(0.012)	(0.011)
After * Complete	0.032**	-0.012	-0.014
	(0.014)	(0.013)	(0.012)
After * High trademark similarity			-0.008
			(0.012)
After * Complete * High trademark similarity			0.044**
			(0.018)
Observations	1,192	1,168	2,360
R-squared	0.253	0.212	0.212
Deal FE	YES	YES	YES
Year FE	YES	YES	YES