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

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Keywords: Trademarks; Product lines; New products; Mergers and acquisitions; Product market overlap
JEL Classification: G34; O32; O34

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Abstract

This paper is one of the first to employ novel trademark data to shed light on whether and how M&As shape acquirers' new product development and affect acquirers' and target firms' product offerings. Using a large and unique trademark-merger dataset over the period 1983-2016, we first show that companies with larger trademark portfolios, newer trademarks, and faster growth in trademarks are more likely to be acquirers, whereas companies with smaller trademark portfolios, and newer and more focused trademarks are more likely to be target firms. Further, firms with overlapping product lines are more likely to merge. Post-merger, compared to their non-acquiring peers, acquirers register fewer new trademarks, especially in classes common to both acquirers and targets, and in classes unique to target firms. Moreover, acquirers discontinue more acquirers' and targets' trademarks in common classes and classes unique to themselves, whereas discontinue fewer trademarks in classes unique to target firms. Finally, acquirers with a greater overlap in product lines to their target firms register even fewer trademarks in common classes and discontinue even more targets' trademarks in common classes. We conclude that M&As provide an opportunity for acquirers to gain access to different products and to reduce overlapping product offerings.

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I. Introduction

One important question in Mergers & Acquisitions (M&As) literature is how acquisitions change the product market landscape of the combined firm? In a pioneer study, Hoberg and Phillips (2010) analyze product descriptions in 10-Ks and find that increased product differentiation versus rivals and new product development accompany increases in operating performance post-merger. Relatedly, using a sample of consumer goods sold by firms involved in M&As 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. While both Hoberg and Phillips (2010) and Sheen (2014) shed light on why and how profits increase post-merger, they are silent about what firm product market characteristics trigger a deal, and whether and how product offerings of acquirers and targets are affected by M&As. Using novel and comprehensive trademark data, this paper fills a void in the literature and helps address why mergers take place from a product market perspective.

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. 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 (Millot 2009).[1] For example, the word "iPad" is a trademark for the product line of tablet computer devices produced by Apple, and the word "Big Mac" is a trademark for a particular type of hamburgers sold by McDonald's. Different from patents that measure technological innovation, trademarks 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). In particular, trademarks can be used to capture new product development in industries where corporate innovation typically does not involve filing patents, such as service, banking, and retail industries (Mendonca, Pereira, and Godinho 2004; Millot 2009; Faurel, Li, Shanthikumar, and Teoh 2017).

[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).

There is very little empirical work on trademarks in finance and economics despite their prevalence and importance in the economic activities of firms, in large part because there were no comprehensive data on trademarks until very recently, see Graham, Hancock, Macro, and Myers (2013) and Graham, Macro, and Myers (2015) for an introduction to the United States Patent and Trademark Office (USPTO) Trademark Case Files Dataset and the USPTO Trademark Assignment Dataset, and recent studies by Faurel et al. (2017) and Heath and Mace (2017).

To shed light on product market dynamics in M&As, we compile an economy-wide trademark-merger dataset, and develop a set of trademark measures that capture firm product market characteristics and potential competition stemming from product market overlap between merger partners. We first show that companies with larger trademark portfolios, newer trademarks, and faster growth in trademarks are more likely to be acquirers, whereas companies with smaller trademark portfolios, newer and more focused 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 show that the greater overlap between any two firms' product lines, the more likely these two firms will end up doing a deal. The effect of product market overlap remains after controlling for similar technologies of Bena and Li (2014) and similar product descriptions of Hoberg and Phillips (2010).

Post-merger, compared to their non-acquiring peers, we show that acquirers experience a significant drop in both their trademark count and trademark growth. In addition, acquirers' trademark portfolios become more concentrated. Moreover, we find that acquirers register fewer new trademarks overall, and discontinue more their existing trademarks and trademarks of targets'. We then delve into the year-to-year change in trademark count and differentiate trademarks by classes common to acquirers and targets, classes unique to acquirers, classes unique to targets, and classes new to merging firms. Compared to their non-acquiring peers, we show that post-merger, acquirers register fewer new trademarks overall, especially in classes common to both acquirers and targets, and in classes unique to target firms, whereas register more new trademarks in new classes. This set of results does not support knowledge spillover between merging firms, but does support path-breaking innovation taking place post-merger.

Moreover, acquirers discontinue more acquirers' and targets' trademarks in common classes and classes unique to themselves, whereas discontinue fewer trademarks in classes unique to target firms, suggesting that M&As provide an opportunity for acquirers to reduce overlapping product offerings and to gain access to targets' unique products from their own. Finally, compared to other acquirers with a lower overlap in product lines to their target firms, acquirers with a greater overlap register even fewer trademarks in common classes, whereas discontinue even more targets' trademarks in common classes, and discontinue even fewer targets' trademarks in unique classes. The overall evidence seems to suggest that M&As provide an opportunity for acquirers to gain access to target trademarks in different classes from their own, instead of developing those products on their own, and in the meantime, to reduce overlapping product offerings, especially on the target side.

Post-merger, compared to their non-acquiring peers, we show that acquirers experience significant improvements in return on assets (ROA), return on sales (ROS), and market share. Compared to other acquirers with a lower overlap in product lines to their target firms, acquirers with a greater overlap experience a bigger improvement in ROS, whereas a significant drop in market share. These results are consistent with our earlier findings that M&As triggered by product market rivalry are not undertaken for market share but are used for acquirers to gain access to different products and to reduce overlapping product offerings.

Our paper is related to two strands of the M&A literature: complementarity-driven acquisitions and product market outcome of M&As. In the former, prior work shows that relatedness of merger participants is critical for post-merger outcomes. Ahuja and Katila (2001) show that technological relatedness is associated with improved innovation output of acquiring firms in the chemicals industry. Fan and Goyal (2006) find that vertical mergers are associated with positive wealth effects significantly larger than those for diversifying mergers. Hoberg and Phillips (2010) show that mergers between firms with product market similarities achieve bigger product range expansions, and higher operating profitability and sales growth. Maksimovic, Phillips, and Prabhala (2011) find that productivity of acquired assets increases in industries in which the acquirer operates. Bena and Li (2014) find that synergies obtained from combining innovation capabilities are important drivers of acquisitions. In the latter, Kim and Singal (1993) find that prices increase on routes served by merging airlines relative to a control group of routes unaffected by the merger. Karim and Mitchell (2000) study the relative extent of change by acquiring and non-acquiring businesses, focusing on product line addition, retention, and deletion as forms of changing resources, and conclude that acquisitions play a major role in business reconfiguration, offering opportunities for firms to both build on existing resources and obtain substantially different resources. Focarelli and Panetta (2003) investigate the long-run price effects of mergers and find that in the long run, efficiency gains dominate over the market power effect, leading to more favorable prices for consumers. Ashenfelter and Hosken (2010) employ retail scanner data and show that that four of the five mergers that they study result in some increases in consumer prices. Sheen (2014) shows that when two competitors in a product market merge, their products converge in quality, and prices fall relative to the competition.

Our paper also 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 USPTO that allows us to track acquirers' and targets' product lines post-merger, we can address the important questions of whether and how M&As shape acquirers' new product development and affect acquirers' and target firms' product offerings differentially; both questions have not been examined at an economy-wide level prior to our paper.

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. 2017). Faurel et al. (2017) argue that new product development as captured by trademarks can occur either separate from, or in conjunction with, patent-related innovation; in low-patent industries, it is more likely to occur as the primary form of innovative activity and hence a better measure of corporate innovation, whereas in high-patent industries it is more likely that technological, research, and innovation play a large role. We develop a novel measure of pairwise product market overlap, and show its importance in merger pair formation and post-merger product market and performance outcome. Notably, this measure is distinct from traditional industry affiliations as captured by the Standard Industry Classification (SIC) codes or the Fama-French industries.

Third and finally, our paper joins the management literature by highlighting the idea that rivals before an M&A are likely to benefit from important economies of scale, both through specialization and elimination of duplication (see, for example, Capron, Mitchell, and Swaminathan 2001; Cassiman, Colombo, Garrone, and Veugelers 2005).

The paper proceeds as follows. In the next section, we development our hypotheses. We describe the USPTO trademark datasets, our empirical methodology including the construction of key variables, and provide a sample overview in Section III. We examine the relation between firms' product market characteristics and transaction incidence in Section IV. In Section V, we explore post-merger product market dynamics of both acquirers and targets, and acquirer product market and operating performance. We conclude in Section VI.

II. Hypothesis Development

A. Product Market Overlap and Merger Pairing

We first ask how acquirers identify prospective target firms. Hart and Holmström (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 hypothesize that the overlap in firms' product lines may lead to merger-pairing decisions for the following reasons.

First, 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, Hoskisson, Johnson, and Moesel 1996; Kaplan 2000; Higgins and Rodriguez 2006).

Second, acquiring targets with overlapping product lines 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, resulting in operational efficiency, and hence can trigger mergers (Henderson and Cockburn 1996; Hart and Holmström 2010).

Third and finally, when the overlap in product lines between merging firms 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. Eckbo (1983, 1985) finds that firms acquire competitors to collude on Cournot competition.

We thus expect that acquirers will pursue target firms with which they have overlapping product lines. Empirically, we capture the extent of overlap in product lines using a cosine similarity measure of any two firms' trademark portfolios. The above discussions lead to our first hypothesis:

H1: M&As are more likely to occur between firm-pairs with a greater product market overlap.

B. Product Market Overlap and New Product Development

We next ask how the overlap in merging firms' product lines affects acquirers' post-merger new product development. On the one hand, the overlap in product lines promotes post-merger new product line development due to assets/skills complementarity and combination of related expertise leading to more innovation (Rhodes-Kropf and Robinson 2008; Hoberg and Phillips 2010; Bena and Li 2014). 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. Another possible channel for M&A success is that post-merger integration takes up managers' time and energy (Hitt, Hoskisson, and Ireland 1990), and hence new product development may be delayed and/or curtailed (Hitt et al. 1996). The overlap in product lines facilitates the integration and lowers related costs and stress associated with consolidation, thus allowing managers to devote more time to developing new product lines after the merger. Moreover, target firm inventors whose expertise is closely related to the acquirer will not encounter disruption and worry about job security, leading to more effort and higher innovation performance (Paruchuri, Nerkar, and Hambrick 2006).

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.[2] First,

[2] 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, Hoskisson, Ireland,

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 lines, suggesting them possessing similar technologies/know-how, there is not much new knowledge to be gained from an acquirer's point of view. Second, M&As create disruption and lead to job separation. When acquirers and targets have greater overlaps in product lines, employees are more worried about job security and under higher levels of stress from internal competition (Hitt and Hoskisson 1991; Paruchuri et al. 2006). Such disruption and stress could result in fewer new product launches. Our second hypothesis is thus two-sided:

H2a: Post-merger, acquirers will develop more product lines when the pre-merger product market overlap with targets is high.

H2b: Post-merger, acquirers will develop fewer product lines when the pre-merger product market overlap with targets is high.

In our empirical investigation, we use 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 insights 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 Datasets, Methodology, and Sample Overview

A. The USPTO Trademark Case Files Dataset and the USPTO Trademark Assignment 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

and Harrison (1991) provide empirical support for that argument showing lower R&D expenditures and patent output after mergers.

customer loyalty and maintain market power, and it can signal quality and uniqueness, helps consumers reduce search costs, and differentiates itself from competitors' products/services (e.g., Landes and Posner 1987; Besen and Raskind 1991; Graham et al. 2013).

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.[3] 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).[4] 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.[5] 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 this use-in-commerce requirement is not satisfied, the trademark cannot be registered and will not be protected by the federal trademark laws. The process of trademark registration can take from about one year to several years.

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[3] 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 that 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.

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

[5] 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. See Appendix IA2 in the Internet Appendix for the complete list of NICE classification.

After registration, trademarks can be renewed with the USPTO periodically as long as the use-in-commerce requirement is satisfied and the renewal fee is paid.[6] 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. In the 10th year after initial registration, the owner must show evidence of continued use and pay a renewal fee, or the registration will expire. 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 will expire.[7] 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 Our trademark dataset

The USPTO Trademark Case Files Dataset is our primary dataset, which contains detailed information on 7.9 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

[6] 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.

[7] 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. Although both registration and renewal fees are economically trivial, the vast amount of money spent in trademark-related litigation cases suggests both registration and renewal are economically significant corporate events.

cancellation), status (registered, abandoned, renewed, or cancelled),[8] trademark class, mark content, and owner information.

Trademark ownership is not static. According to Graham, Marco, and Myers (2015), about a third of trademarks registered between 1978 and 2013 have been involved in certain types of ownership transfer. Recording such transfer is not mandatory, although statutory and regulatory laws provide compelling incentives for parties involved to record it with the USPTO throughout the entire life of a registered mark.[9]

To capture ownership transfer, we make use of the USPTO Trademark Assignment Dataset, which contains information on 875,143 assignments between 1952 to 2015 involving around 1.5 million unique registered trademarks. For each assignment, it has the following information: assignor, assignee, assignment type (assignment, merger, security interests, release, name change, etc.),[10] date, and the list of trademarks involved.

We take the following steps to link these two trademark datasets to the Compustat/CRSP database. From the Trademark Case Files Dataset, we obtain a list of owner names, denoted as list A. From the Trademark Assignment Dataset, we obtain a list of assignor and assignee names, denoted as list B. Next, from the Compustat/CRSP database, we obtain a list of public company names and their permno numbers, denoted as list C1. It is worth noting that list C1 has taken into account name changes for public companies, such as “Minnesota Mining and Manufacturing Company” to “3M.” However, list C1 only identifies the public company itself, not its subsidiaries. To partially address this problem, we expand list C1 by a list of (current) subsidiaries’ names for public companies from Capital IQ; denoted as list C2. In this way,

[8] 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.

[9] According Graham, Marco, and Myers (2015), there are a number of reasons for registering assignments at the USPTO. First, the law presumes that any recorded assignment was actually executed, therefore placing the burden on any challenger to prove otherwise. Second, any unrecorded assignment is void against subsequent purchasers, i.e., if a trademark is assigned and there is no recording at the USPTO, and the same original owner assigns the mark again ex post and the new owner records, this second assignment takes priority. Third and finally, the USPTO regulations prohibit owners from taking administrative actions (such as paying periodic fees required to keep the mark active) unless a chain of title in the trademark has been established.

[10] After studying a large number of assignment cases closely, we focus on “assignment” and “merger” types of assignment.

subsidiaries whose names are 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/B and list C2 using the Levenshtein distance to keep the closest ten possible matches and then manually verify each possible match to rule out incorrect cases. To ensure accuracy in matching, we also make use of the location information in the trademark dataset and compare it with the location of a public company from the Compustat/CRSP database. In the end, for the Trademark Case Files Dataset, we are able to match 528,219 registered trademark records to 14,856 public companies over the period 1887 to 2015. For the Trademark Assignment Dataset, we are able to match 81,514 transaction records involving 318,594 trademarks in which either the assignor or assignee is a public company in the Compustat/CRSP database.

To fully capture product market development of a public firm in our sample, we start with registered trademarks and adjust them for assignment. Specifically, if a company purchases trademarks from a third party, we add them to the company's existing trademark portfolio from the transaction date; if a company sells its trademarks to a third party, we remove them from the company's trademark portfolio.

Throughout our empirical analysis, we use product trademarks, instead of marketing trademarks due to our focus on product market dynamics. 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 four or more words (i.e., advertising slogans) as marketing trademarks. We classify marks that have text of fewer than four 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). Appendix IA1 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 and are thus classified as product trademarks.

A.3 Trademark overview

Figure 1 illustrates the difference in industry concentration between new product trademarks and new patents. Panel A presents the industry distribution of product trademark-producing firms. The sample consists of product trademark-producing public firms from 1983 to 2016. The top five product trademark-producing industries based on two-digit SIC codes are: Chemicals and Allied Products (14%, SIC 28), Industrial and Commercial Machinery and Computer Equipment (8%, SIC 35), Electronic and Other Electrical Equipment and Component (7%, SIC 36), Business Services (7%, SIC 73), and Measuring, Analyzing, and Controlling Instruments; Photographic, Medical and Optical Goods; Watches and Clocks (7% , SIC 38). The top five industries take up 43% of the total number of trademarks. Panel B presents the industry distribution of patent-producing firms. The sample consists of patent-producing public firms from 1983 to 2014.[11] The top five patent-producing industries are: Electronic and Other Electrical Equipment and Component (33%, SIC 36), Industrial and Commercial Machinery and Computer Equipment (21%, SIC 35), Measuring, Analyzing, and Controlling Instruments; Photographic, Medical and Optical Goods; Watches and Clocks (11%, SIC 38), Chemicals and Allied Products (10%, SIC 28), and Transportation Equipment (8%, SIC 37). The top five industries take up 83% of the total number of patents. Clearly, compared to trademarks, patents are concentrated among a small set of high-tech industries. Notably, among the top five industries, there is an overlap of four industries in terms of producing the most trademarks and patents – SIC 28, SIC 36, SIC 35, and SIC 38.

B. Methodology

B.1 Product market overlap

Our measure of product market overlap is computed as a cosine similarity measure:

$$Product\ Market\ Overlap_{\mathrm{acq,targ,t}} = \frac{\mathrm{T_{acq,t}T'_{targ,t}}}{\sqrt{\mathrm{T_{acq,t}T'_{acq,t}}}\sqrt{\mathrm{T_{targ,t}T'_{targ,t}}}}, \tag{1}$$

where the vector $T_{acq,t} = (T_{acq,1}, \ldots, T_{acq,K})$ is the number of active trademarks in each trademark class for the acquirer, the vector $T_{targ} = (T_{targ,1}, \ldots, T_{targ,K})$ is the number of active trademarks in each trademark class for the target, and $k \in (1, K)$ is the NICE trademark class index ($K = 45$).[12]

[11] The patent data we have end in 2014.

[12] Active trademarks refer to registered trademarks that have not expired, cancelled, or abandoned.

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 product market overlap 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 competition in an M&A setting.

B.2 Matched sample and model specification

To examine what trademark characteristics of a firm are associated with it becoming an acquirer (target firm), we run a conditional logit regression using cross-sectional data as of the fiscal year end before the bid announcement:[13]

$$Event\ Firm_{im,t} = \alpha + \beta_1 Trademark\ Characteristics_{im,t-1} + \beta_2 Firm\ Characteristics_{im,t-1} + Deal\ FE + e_{im,t}. \quad (2)$$

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 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 *actual* acquirer (target firm), and multiple observations for the *control* acquirers (*control* target firms). *Deal FE* is the fixed effect for each deal that includes an acquirer (target firm) and its control acquirers (control target firms).

We use two different control samples as pools of potential merger participants. To form the *Industry- and Size-Matched Control Sample*, for each acquirer (target firm) of a deal

[13] 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.

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[14]—and by size from the Compustat database in year *t-1* that were neither an acquirer nor a target firm in the five-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 (Mitchell and Mulherin 1996; Andrade, Mitchell, and Stafford 2001; Maksimovic, Phillips, and Yang 2013; Harford 2005).

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 the Compustat database in year *t-1* that were neither an acquirer nor a target firm in the five-year period prior to the deal. We add the market-to-book 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.

For generality, we also use the population of Compustat firms and estimate a logit model and a linear probability model (LPM), both including industry times year fixed effects.

To examine the role of product market overlap in 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:

$$\begin{aligned} &Acquirer\text{–}Target_{ijm,t} = \alpha + \beta_1 Product\ Market\ Overlap_{ijm,t-1} + \\ &\beta_2 Acquirer\ Trademark\ Characteristics_{im,t-1} + \beta_3 Target\ Trademark\ Characteristics_{jm,t-1} + \\ &\beta_4 Acquirer\ Characteristics_{im,t-1} + \beta_5 Target\ Characteristics_{jm,t-1} + Deal\ FE + e_{ijm,t}. \end{aligned} \tag{3}$$

[14] Specifically, we start with four-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 four-digit SIC industry group, we move up to the three-digit SIC industry group. If there are no more than five industry peers to the actual acquirer (target firm) within the three-digit SIC industry group, we move up to the two-digit SIC industry group. 78% (8%) acquirers are matched at the four-digit (three-digit) level, while 81% (9%) target firms are matched at the four-digit (three-digit) level; the remaining matches are at the two-digit level. We use historical SIC industry codes from the Compustat database.

The dependent variable, $Acquirer\text{-}Target_{ijm,t}$, is equal to one if the firm pair *ij* is the acquirer-target firm pair, and zero otherwise. Definitions of these variables are provided in the Appendix. Other firm-level controls include the size of the trademark portfolio, trademark age, trademark growth, trademark concentration, firm size, M/B, ROA, leverage, cash holdings, sales growth, and prior-year stock returns of acquirers and targets.

Since product market overlap 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 *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.

To examine the effect of M&As on post-merger acquirers' and targets' product market outcome, we need to make sure that the control firms have a similar level of and growth rate in trademarks (i.e., parallel trend assumption). To do so, we start with the matched acquirer (target) sample based on industry, size, and M/B (with five matching firms to each event firm). We then select three control firms out of the five based on trademark count (i.e., the natural logarithm of (1 + number of trademarks)). We further select one control firm out of the three based on having the closest trademark growth with the event firm. Given our focus on new product development, we further impose the requirement that within the five-year window prior to bid announcement, each event firm (acquirer or target) have at least one trademark registration.

Using this control sample and the event sample, we run the following regression using a panel dataset from five years prior to bid announcement (*ayr-5* to *ayr-1*) to five years after deal completion (*cyr+1* to *cyr+5*):

$$\begin{aligned}&Firm\ Outcome_{im,t} = \alpha + \beta_1\ After_{im,t} + \beta_2\ Deal_m + \beta_3 After_{im,t}\ \times\ Deal_m\\&\beta_4 Trademark\ Characteristics_{im,t-1} + \beta_5 Firm\ Characteristics_{im,t-1}\\&+Firm\ FE + Year\ FE + e_{im,t}.\end{aligned} \tag{4}$$

The dependent variable, $Firm\ Outcome_{im,t}$, is firm *i*'s trademark and performance outcome such as the number of newly registered trademarks, or product market performance measures such as ROA. $After_{im,t}$ is an indicator variable equal to one for the post-merger time period (from *cyr+1* to *cyr+5*), and zero otherwise. $Deal_m$ is an indicator variable equal to one for treatment deals, and zero otherwise (i.e., for control firms that have not done a deal in the ten-year period). We include trademark characteristics when the dependent variables are measures of product market dynamics like new trademark registration as Capron, Mitchell, and Swaminathan (2001) and Bahadir, Bharadwaj, and Srivastava (2008) show that acquirer trademark characteristic are directly associated with investment and divestiture decisions post-merger. We include firm fixed effects to difference away any time-invariant differences among firms. 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 any temporal differences in the outcome variable. There are 1,695 completed deals and 1,695 control firm-pairs for this analysis.

Next, we directly estimate the heterogeneity in the treatment effect through Equation (5), where the key variable of interest is the triple interaction term $After_{im,t} \times Deal_m \times Product\ Market\ Overlap_{ij}$. $Product\ Market\ Overlap_{ij}$ is time-invariant measured at the year prior to bid announcement (*ayr-1*):

$$\begin{aligned} Firm\ Outcome_{im,t} &= \alpha + \beta_1\ After_{im,t} + \beta_2 Deal_m + \beta_3 After_{im,t} \times Deal_m + \\ &\beta_4 Product\ Market\ Overlap_{ij} + \beta_5 After_{im,t} \times Product\ Market\ Overlap_{ij} \\ &+ \beta_6 Deal_m \times Product\ Market\ Overlap_{ij} + \beta_7 After_{im,t} \times Deal_m \times \\ &Product\ Market\ Overlap_{ij} + Firm\ FE + Year\ FE + e_{im,t}. \end{aligned} \tag{5}$$

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 14,558 deals with available information on public acquirers, 4,697 deals with available information on public target firms, and 1,886 deals with available information on acquirers and their target firms that both are public. It is worth noting that our samples are one of the largest to study product market outcome associated with M&As (see, for example, in comparison to Hoberg and Phillips 2010; Sheen 2014) due to the prevalent usage of trademarks by U.S. companies (Faurel et al., 2017 and our Figure 1).

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 the descriptive statistics for the acquirer sample and its *Industry- and Size-Matched Control Sample*. In Panel A, we present the number of active trademarks as *Number of trademarks*, the natural logarithm of (1 + *Number of trademarks*) as *Trademark count*, the age of active trademarks as *Trademark age*, simple growth rate of the number of active trademarks as *Trademark growth*, and the Herfindahl-Hirschman Index (HHI) of a firm's trademarks across its existing trademark classes as *Trademark concentration*. 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., covering more 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 9th decile of the Compustat/CSRP universe over the same time period), and they are larger, and have higher M/B ratios, higher ROA, lower leverage, 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, trademark count is positively associated with the average age of its constituent trademarks, and is negatively associated with trademark growth rate and trademark concentration. The average age of a firm's trademark portfolio is negatively associated with its growth rate and concentration. 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, M/B, operating performance (ROA), and leverage, whereas it is negatively associated with cash holdings and sales growth. The age of a firm's trademark portfolio is positively associated with firm size, operating performance, and leverage, whereas it is negatively associated with M/B, cash holdings, sales growth, and prior-year stock return. Trademark growth is positively associated with M/B, cash holdings, sales growth, and prior-year stock return, whereas it is negatively associated with firm size, operating performance, and leverage. Trademark concentration is positively associated with cash holdings, whereas it is negatively associated with firm size, operating performance, leverage, sales growth, and prior-year stock return. Overall, we conclude that most correlations are low and that multicollinearity is unlikely to be an issue.

Table 3 presents the descriptive statistics for the target firm sample and its *Industry- and Size-Matched Control Sample*. We show that target firms have fewer trademarks, younger trademarks, and slightly higher trademark concentration than their matching control firms. We further note that our sample target firms are large (the mean of total assets is in the 8^{th} decile of the Compustat 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. Product Market Characteristics and M&As

In this section, we implement various multivariate analyses to relate firm product market characteristics to them becoming acquirers (target firms) in M&As.

A. Who Will Become Acquirers/Target Firms?

Table 4 Panel A presents coefficient estimates from the conditional logit regression in Equation (2) using matched samples (columns (1) and (2)), as well as logit and LPM specifications using Compustat population to predict acquirers (columns (3) and (4)).

We show that firms with a larger trademark portfolio, newer trademarks, 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 25th percentile to 75th percentile, the likelihood of a firm becoming an acquirer changes by 6.47% (-2.78%/0.34%). For comparison, when acquirer ROA (prior-year stock return) changes from its 25th percentile to 75th percentile, the likelihood of a firm becoming an acquirer changes by 6.47% (4.02%). The unconditional likelihood of a Compustat firm becoming an acquirer is 13%.

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 higher M/B, better operating performance, faster sales growth, and higher prior-year stock returns, are more likely to engage in M&As as acquirers.

Table 5 Panel A presents coefficient estimates from the conditional logit regression in Equation (1) using matched samples (columns (1) and (2)), as well as logit and LPM specifications using Compustat population to predict target firms (columns (3) and (4)). In contrast to the results for acquirers, we show that there is a negative and significant association between the size of a firm's trademark portfolio and the likelihood of it becoming a target firm, and that there is a positive and significant association between the concentration level of a firm's trademark portfolio and the likelihood of it becoming a target firm. Further, we show that firms with newer trademarks are more likely to become target firms (columns (2) to (4)). We further show that larger firms, firms with lower M/B, higher ROA, slower sales growth, and 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 count (trademark age/ trademark concentration) changes from its 25th percentile to 75th percentile, the likelihood of a firm becoming a target firm changes by -2.94% (-0.39%/1.61%). For comparison, when target ROA (prior year stock return) changes from its 25th percentile to 75th percentile, the likelihood of a firm becoming a target changes by -0.23% (-1.72%). The unconditional likelihood of a Compustat firm becoming a target is 4.2%.

Overall, our results provide strong support for the notion 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 summary statistics of the acquirer-target pairs and their five industry- and size-matched control pairs. The control pairs are formed based on the acquirer industry- and size-matched control firms and the target industry- and size-matched control firms.

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 (using median), lower cash holdings, higher sales growth, 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 three different pairwise similarity measures (with the exception of same industry as we match on industry), we show that actual acquirer-target pairs have significantly greater product market overlap and higher patent similarity and HP similarity than their matching pairs.

Panel B presents the correlations between different pairwise measures capturing overlap in activities. Patent similarity is constructed as in Bena and Li (2014), and HP similarity follows Hoberg and Phillips (2010) and is obtained from Gerard Hoberg's website. We show that product market overlap is positively associated with all other measures of similarities. However, the correlations are modest in terms of economic magnitude, suggesting that all these measures contain distinct information.[15]

Table 7 Panel A presents coefficient estimates from the conditional logit regression in Equation (3) to predict merger pairs. Columns (1) to (4) employ the *Industry- and Size-Matched*

[15] Table IA1 in the Internet Appendix provides examples of merger pairs together with different pairwise similarity measures. It is clear that all these measures capture very distinct aspects of a merger pair and have different levels of data availability.

Control Sample, and columns (5) to (8) employ the *Industry-, Size-, and M/B-Matched Control Sample*. Columns (1) and (5) only include one pairwise measure—product market overlap. Columns (2) and (6) 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) and (7) 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. Columns (4) and (8) include all three pairwise measures.

We show a positive and significant association between any of the three measures of merger participants' overlap in activities including product lines, patenting, and product descriptions, 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 two other determinants of merger pairing. This finding is both important and new in the literature, as prior work has not yet using trademark data to capture product market interactions.

Based on the model in column (8) of Panel A, Panel B presents the predicted likelihood of a merger pair formation when trademark similarity (patent similarity/HP similarity) 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 29.57% (12.23%/7.38%).

Our evidence in Table 7 provides strong support for our first hypothesis H1 that mergers are more likely to take place between firm pairs with overlapping product lines.

V. Post-Merger Outcome

So far, we have established a significant association between product market characteristics and deal incidence, and we now investigate whether and how M&As shape acquirers' new product development and acquirers' and targets' product offerings following deal completion.

A. Post-Merger Product Market Outcome

Table 8 Panel A reports the summary statistics of our sample acquirers in terms of trademark characteristics from before bid announcement to after deal completion. We show that post-merger, acquirers' trademark count goes up, their trademarks are getting older, they experience faster trademark growth, and their trademark portfolios become less concentrated.

To properly examine the effect of M&As on product market outcome, we need to introduce a control sample that provides the benchmark of what could have happened if the event firm were not involved in an M&A. Panel B presents the difference-in-differences estimates of Equation (4) where the dependent variables are the four trademark characteristics and we employ a panel dataset on both acquirers and they matched controls by industry, size, M/B, trademark count, and trademark growth, as discussed in Section II B.2.

We show that the coefficient on *After* is positive and significant at the 1% level when the dependent variables are trademark count and trademark growth, suggesting that over time, both acquirers and their control firms increase the size of their trademark portfolios and experience fast growth in trademarks. The coefficient on *After* is negative and significant at the 1% level when the dependent variable is trademark concentration, suggesting that over time, both acquirers' and their control firms' trademark portfolios become less concentrated. The coefficient on *Deal* is positive and significant when the dependent variables are trademark count and trademark growth, suggesting that acquirers have larger trademark portfolios and are growing faster than their control firms, and the coefficient on *Deal* is negative and significant when the dependent variable is trademark concentration, suggesting that acquirers have more dispersed trademark portfolios than their control firms.

Importantly, the coefficient on the two-way interaction term $After \times Deal$ is negative and significant when the dependent variables are trademark count and trademark growth, suggesting that post-merger, acquirers experience a significant drop in both their trademark count and trademark growth compared to their non-acquiring peers. In contrast, the coefficient on the two-way interaction term $After \times Deal$ is positive and significant when the dependent variable is trademark concentration, suggesting that post-merger, acquirers tend to have more focused trademark portfolios compared to their non-acquiring peers. To shed light on how these significant changes take place, we delve into new trademark registration and termination of existing trademarks on both acquirers' and targets' sides.

B. Acquirers' New Trademark Registration

The richness of the trademark data allows us to examine how M&As shape acquirers' new product offerings. The variable of interest is the number of newly registered trademarks post-merger, as well as the decomposition of all newly registered trademarks into trademarks belonging to classes common to acquirers and targets (pre-merger), classes unique to acquirers, classes unique to targets, and classes new to both acquirers and targets. For this analysis, we combine a target's post-merger newly registered trademarks into its acquirer.

Table 9 Panel A presents the summary statistics. We show that acquirers significantly increase their new trademarks across most classes at the 1% level (with the exception of trademarks in classes unique to acquirers).

Panel B presents the difference-in-differences estimates of Equation (4) where the dependent variables are all newly registered trademarks and their components. We show that the coefficient on *After* is positive and significant when the dependent variables are all trademarks, trademarks in common classes, trademarks in classes unique to targets, and trademarks in new classes, whereas the coefficient on *After* is negative and significant when the dependent variable is trademarks in classes unique to acquirers. The coefficient on *Deal* is positive and significant when the dependent variables are all trademarks and trademarks in common classes, whereas the coefficient on *Deal* is negative and significant when the dependent variable is trademarks in classes unique to acquirers. Importantly, the coefficient on the two-way interaction term *After* × *Deal* is negative and significant at the 1% level when the dependent variables are all trademarks, trademarks in common classes, and trademarks in classes unique to targets, whereas the coefficient on *After* × *Deal* is positive and significant at the 5% level when the dependent variable is trademarks in new classes, suggesting that post-merger, acquirers experience a significant drop in new trademark registrations than their non-acquiring peers, with the exception of new trademarks in totally new classes. Overall, the evidence in Panel B does not support knowledge spillover between merging firms, but does support path-breaking innovation taking place post-merger.

Next, we explore the role of product market overlap in the decision to develop new trademarks to differentiate between hypotheses H2a and H2b. Panel C presents the triple differences estimates of Equation (5) where the dependent variables are all newly registered trademarks and their components. We show that post-merger, compared to non-acquiring peers, acquirers tend to develop fewer new trademarks: The coefficient on *After* × *Deal* is negative and significant at the 1% level when the dependent variables is trademarks in new classes. When the pre-merger product market overlap is high, there is a greater drop in new trademarks: The coefficient on *After* × *Deal* × *Product Market Overlap* is negative and significant at the 5% level when the dependent variable is all trademarks and at the 1% level when the dependent variable is trademarks in common classes. Overall, when acquirers and targets have a greater product market overlap, post-merger they tend to develop significantly fewer trademarks, especially in common classes to acquirers and targets, inconsistent with H2a.[16]

In summary, we find that post-merger, acquirers with a greater overlap in product lines to their target firms register fewer trademarks in general, and in common classes in particular, compared to their peers with a lower overlap in product lines to their target firms, suggesting limited economies of scale.

C. Post-Merger Discontinued Trademarks

In this subsection, we examine how acquirers' and targets' existing trademarks are affected after deal completion. 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 keep track of acquirers' and targets' trademarks.

We conjecture that when acquirers and targets share similar product lines, a merger transaction is less motivated by the need to create new products/markets but more by efficiency and consolidation 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 (as we have shown in Table 9 Panel B). Based on the above

[16] Parallel to the analysis in Table 7, Table IA2 in the Internet Appendix replicates the analysis in Table 9 Panel C by replacing product market overlap with either patent similarity or HP similarity. In either case, the coefficient on the three-way interaction term is not statistically significantly different from zero.

discussion, we expect that acquirers are more likely to discontinue their own and target firms' trademarks after the merger, when the pre-merger product market overlap is high.

Table 10 Panel A reports the summary statistics of our sample acquirers in terms of discontinued trademarks from before to after deal completion.[17] Discontinued trademarks refer to trademarks that are not renewed in the next renewal deadline (i.e., the 6th, 10th, 20th, ..., from the registration year) after mergers. We show that acquirers significantly increase their number of discontinued trademarks across all classes, including trademarks in common classes as well as trademarks in classes unique to acquirers.[18]

Panel B reports the summary statistics of our sample targets in terms of discontinued trademarks from before to after deal completion. We show that acquirers significantly increase targets' number of discontinued trademarks across all classes, including trademarks in common classes as well as trademarks in classes unique to targets.

Table 10 Panel C presents the difference-in-differences estimates of Equation (4) where the dependent variables are acquirers' discontinued trademarks and their components. We show that the coefficient on *After* is negative and significant at the 1% level when the dependent variables are all trademarks and trademarks in common classes, suggesting that over time, firms discontinue fewer trademarks. The coefficient on *Deal* is positive and significant when the dependent variable is trademarks in common classes, whereas the coefficient on *Deal* is negative and significant when the dependent variable is trademarks in classes unique to acquirers. Importantly, the coefficient on the two-way interaction term $After \times Deal$ is positive and significant at the 1 % level when the dependent variables are all trademarks and trademarks in common classes, suggesting that post-merger, acquirers discontinue significantly more trademarks, in particular, trademarks in common classes than their non-acquiring peers. Our results support the idea that M&As are used for business reconfiguration, specifically to reduce duplication.

Panel D presents the difference-in-differences estimates of Equation (4) where the dependent variables are targets' discontinued trademarks and their components. We show that

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

[18] On the acquirer (target) side, we do observe non-zero discontinued trademarks in classes unique to targets (acquirers) or in new classes, possibly due to trademark transfers or other M&As that are not part of the sample. It is worth noting that these numbers tend to be really small.

the coefficient on *After* is negative and significant at the 1% level when the dependent variable is trademarks in common classes, whereas it is positive and significant at the 1% level when the dependent variable is trademarks in classes unique to targets, suggesting that over time, firms discontinue fewer common trademarks and more trademarks unique to themselves. The coefficient on *Deal* is negative and significant at the 1% level when the dependent variable is trademarks in classes unique to target firms. Importantly, the coefficient on the two-way interaction term *After* × *Deal* is positive and significant at the 1% level when the dependent variables are all trademarks and trademarks in common classes, suggesting that post-merger, acquirers discontinue significantly more trademarks in common classes than their non-acquiring peers. This finding reinforce our finding on the acquirer side, support the idea that M&As are used for business reconfiguration, in particular to reduce duplication. In contrast, the coefficient on the two-way interaction term *After* × *Deal* is negative and significant at the 1% level when the dependent variable is trademarks in classes unique to targets, suggesting that post-merger, acquirers tend to preserve more of targets' unique trademarks than their non-acquiring peers. Combining this finding with the finding in Table 9 Panel B where we show that post-merger acquirers tend to register fewer new trademarks in classes unique to targets, we show that M&As allow acquirers to gain access to different products instead of developing on their own.

Next, we explore the role of product market overlap in firms' decision to discontinue trademarks. Panel E presents the triple differences estimates of Equation (5) where the dependent variables are acquirers' discontinued trademarks and their components. We show that the coefficient on the three-way interaction term *After* × *Deal* × *Product Market Overlap* is not significantly different from zero, suggesting that product market overlap has little role in acquirers' trademark renewal decision.

Panel F presents the triple differences estimates of Equation (5) where the dependent variables are targets' discontinued trademarks and their components. We show that the coefficient on *After* × *Deal* × *Product Market Overlap* is positive and significant when the dependent variable is targets' discontinued trademarks in common classes, suggesting that post-merger, acquirers discontinue more targets' trademarks in their common classes when there is a greater overlap in merging firms' product offerings. The overlap in product offerings between merging firms will cause a cannibalization of cash flows. Consequently, to minimize the cash flow cannibalization, the acquirers' likelihood of retaining target products will be low (Bahadir, Bharadwaj, and Srivastava 2008). Our evidence thus far supports this argument.

Comparing between Panels E and F, we find that M&As have a differential effect on acquirers' and their targets' products competing in the same markets. When there is a greater overlap in merging firms' product offerings, post-merger, acquirers discontinue significantly more target trademarks in common classes compared to target peers; in contrast, they do not discontinue significantly more acquirer trademarks in common classes compared to acquirer peers with a lower overlap in product lines with their targets. This suggests that through M&As, acquirers seek to enhance their own product lines by retiring their target's competing product lines.

Taken together, our results in Tables 9 and 10 support the idea that acquirers use M&As to gain access to product lines that are different from their own, and to trim their own product offerings. We do find some evidence of acquirers developing more path-breaking new products post-merger, suggesting that M&As allow acquirers to gain different resources.

D. Post-merger Performance

Next we examine post-merger operating performance including ΔROA, Δ ROS, sales growth, market share, and annual buy-and-hold return (BHR). Table 11 presents the results.

Panel A presents the summary statistics of acquirer performance from before to after deal completion. Panel B presents the difference-in-differences estimates of Equation (5) where the dependent variables are performance measures. We show that post-merger, compared to their non-acquiring peers, acquirers experience significant increases in ROA, ROS, and market share.

Panel C presents the triple differences estimates of Equation (5). We find that product market overlap plays an important role in post-merger performance. Compared to acquirers with a lower overlap in product lines to their targets, acquirers with a greater overlap experience a significantly bigger increase in ROS whereas a significantly bigger drop in market share. These results are consistent with our earlier findings that M&As triggered by product market rivalry are not undertaken for market share but are used for acquirers to gain access to different products and to reduce overlapping product offerings.

VI. Conclusions

This paper is one of the first to employ novel trademark data to shed light on whether and how M&As shape acquirers' new product development and affect acquirers' and target firms' product offerings. Using a large and unique trademark-merger dataset over the period 1983-2016, we first show that companies with larger trademark portfolios, newer trademarks, and faster growth in trademarks are more likely to be acquirers, whereas companies with smaller trademark portfolios, and newer and more focused trademarks are more likely to be target firms. Further, firms with overlapping product lines are more likely to merge. Post-merger, compared to their non-acquiring peers, acquirers register fewer new trademarks, especially in classes common to both acquirers and targets, and in classes unique to target firms. Moreover, acquirers discontinue more acquirers' and targets' trademarks in common classes and classes unique to themselves, whereas discontinue fewer trademarks in classes unique to target firms. Finally, acquirers with a greater overlap in product lines to their target firms register even fewer trademarks in common classes and discontinue even more targets' trademarks in common classes. We conclude that M&As provide an opportunity for acquirers to gain access to different products and to reduce overlapping product offerings.

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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.

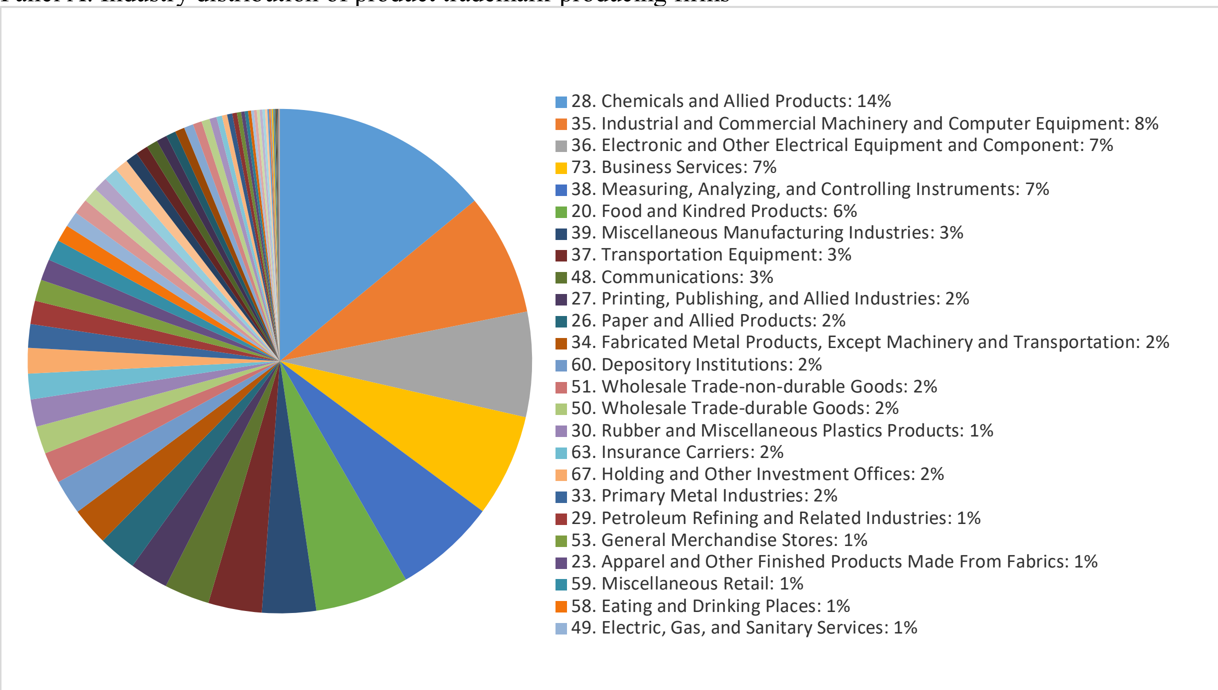
Trademark Measures	
Trademark count	Ln (1 + number of active trademarks).
Trademark age	The average age of all active trademarks in a firm's portfolio. Age for each trademark is calculated as the present year minus the year of its application.
Trademark growth	The growth rate of the number of active trademarks.
Trademark concentration	The Herfindahl-Hirschman Index (HHI) of a firm's active 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.
Product market overlap	The cosine correlation is computed as $\frac{\mathrm{T_{acq}T'_{targ}}}{\sqrt{\mathrm{T_{acq}T'_{acq}}}\sqrt{\mathrm{T_{targ}T'_{targ}}}}$, 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.
Registered trademarks	Ln (1 + number of newly registered trademarks) in a year.
Discontinued trademarks	Ln (1 + number of discontinued 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 bid announcement (month 0) and the analogously defined buy-and-hold stock return on the value-weighted CRSP index.
ΔROA	ROA minus lagged ROA
ROS	Operating income before depreciation scaled by sales.
ΔROS	ROS minus lagged ROS
Market share	The share in the sales of all public firms in the same two-digit SIC industry.
BHR	The buy-and-hold stock return (monthly compounded).
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 $P_{acq} = (P_{acq,1}, \ldots, P_{acq,J})$ is the number of granted patent in each technology class for the acquirer, the vector $\mathrm{P}_{targ} = (P_{targ,1}, \ldots, P_{targ,K})$ 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).
Same industry	An indicator variable that takes the value of one if an acquirer's and its target's two-digit SIC industries are the same, and zero otherwise.

Figure 1. Industry distribution of trademarks and patents

This figure provides an overview of product trademark- and patent-producing industries. Panel A presents the two-digit SIC industry distribution of product trademarks. The sample consists of product trademark-producing public firms over the period 1983-2016. Panel B presents the two-digit SIC industry distribution of patents. The sample consists of patent-producing public firms over the period 1983-2014.

Panel A: Industry distribution of product trademark-producing firms



Panel B: Industry distribution of patent-producing firms

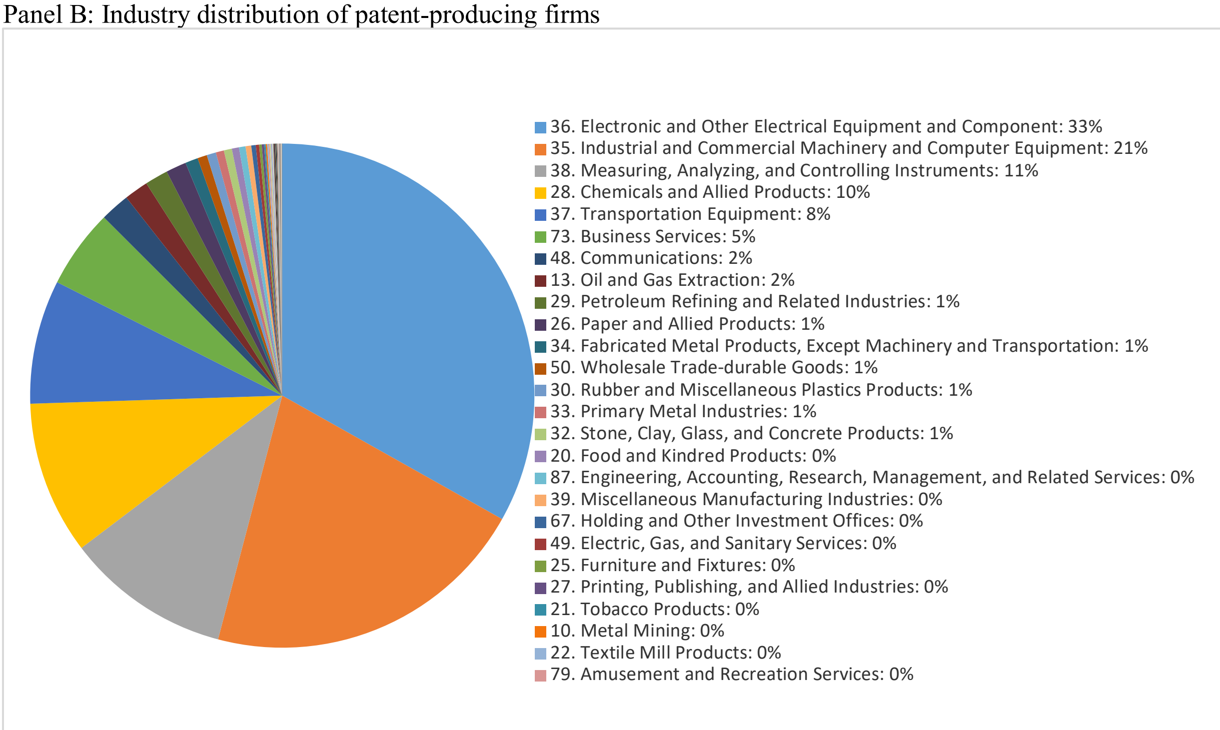


Table 1. Temporal distribution of M&A deals

The sample consists of completed M&A transactions over the period 1983-2016 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 transaction value to acquirer book assets), is at least 1%; vi) the acquirer owns at least one product trademark prior to the deal; vii) multiple deals announced by the same acquirer on the same day are excluded; and viii) basic financial and stock return information is available for the acquirer, the target, or the acquirer-target pair. In addition, for the acquirer sample, we require the target firms to be either public firms, private firms, or subsidiaries; for the target sample, we require the acquirer firms to be either public firms, private firms or subsidiaries; for the acquirer-target pair sample, we require both the acquirers and targets to be public firms.

	Acquirer sample		Target sample		Acquirer-target pair sample	
Year	# deals	Percentage	# deals	Percentage	# deals	Percentage
1983	193	1.33%	55	1.17%	14	0.74%
1984	206	1.41%	85	1.81%	20	1.06%
1985	164	1.13%	94	2.00%	39	2.07%
1986	205	1.41%	136	2.90%	43	2.28%
1987	153	1.05%	109	2.32%	31	1.64%
1988	191	1.31%	157	3.34%	33	1.75%
1989	202	1.39%	114	2.43%	35	1.86%
1990	170	1.17%	58	1.23%	21	1.11%
1991	183	1.26%	44	0.94%	25	1.33%
1992	291	2.00%	44	0.94%	24	1.27%
1993	381	2.62%	50	1.06%	30	1.59%
1994	465	3.19%	91	1.94%	46	2.44%
1995	573	3.94%	160	3.41%	79	4.19%
1996	651	4.47%	168	3.58%	75	3.98%
1997	847	5.82%	240	5.11%	116	6.15%
1998	897	6.16%	295	6.28%	144	7.64%
1999	771	5.30%	327	6.96%	126	6.68%
2000	666	4.57%	255	5.43%	102	5.41%
2001	491	3.37%	201	4.28%	80	4.24%
2002	536	3.68%	118	2.51%	53	2.81%
2003	529	3.63%	147	3.13%	65	3.45%
2004	598	4.11%	127	2.70%	64	3.39%
2005	596	4.09%	166	3.53%	71	3.76%
2006	580	3.98%	199	4.24%	72	3.82%
2007	600	4.12%	215	4.58%	79	4.19%
2008	400	2.75%	125	2.66%	44	2.33%
2009	290	1.99%	98	2.09%	54	2.86%
2010	386	2.66%	149	3.17%	50	2.65%
2011	374	2.57%	122	2.60%	25	1.33%
2012	423	2.91%	128	2.73%	43	2.28%
2013	383	2.63%	106	2.26%	38	2.01%
2014	458	3.15%	107	2.28%	49	2.60%
2015	416	2.86%	128	2.73%	58	3.08%
2016	289	1.99%	79	1.68%	38	2.01%
Total	14,558	100.00%	4,697	100.00%	1,886	100.00%

Table 2. Summary statistics for the acquirer sample

This table reports the summary statistics of the acquirers (in 14,558 deals) as well as their industry- and size-matched control firms (67,643 firms). Panel A presents the 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- and size-matched controls					Test of differences	
	Mean	SD	5th Percentile	Median	95th Percentile	Mean	SD	5th Percentile	Median	95th Percentile	T-test	Wilcoxon test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(1) - (6)	(4) - (9)
Number of trademarks	55.790	93.750	2	20	247	36.730	69.260	1	13	156	19.060***	7.000***
Trademark count	3.114	1.358	1.099	3.045	5.513	2.724	1.291	0.693	2.639	5.056	0.390***	0.406***
Trademark age	11.020	7.201	3	9	25.950	11.780	8.289	3	9.216	29.290	-0.760***	-0.216***
Trademark growth	0.144	0.341	-0.111	0.031	0.800	0.113	0.326	-0.133	0.000	0.667	0.031***	0.313***
Trademark concentration	0.477	0.276	0.155	0.389	0.010	0.529	0.291	0.154	0.476	1.000	-0.052***	-0.087***
Total assets	4959	29184	35	659	18684	3439	23223	28	437	12698	1520***	222***
Firm size	6.553	1.871	3.584	6.491	9.835	6.149	1.822	3.341	6.023	9.404	0.404***	0.468***
M/B	3.337	3.807	0.792	2.404	9.617	2.817	3.783	0.403	1.957	8.651	0.520***	0.447***
ROA	0.120	0.120	-0.050	0.130	0.280	0.090	0.140	-0.170	0.110	0.280	0.030***	0.002***
Leverage	0.200	0.190	0.000	0.170	0.580	0.220	0.210	0.000	0.170	0.630	-0.012***	-0.002**
Cash	0.180	0.200	0.010	0.100	0.610	0.190	0.210	0.000	0.100	0.660	-0.010***	-0.006***
Sales growth	0.279	0.585	-0.165	0.137	1.076	0.183	0.550	-0.257	0.081	0.821	0.096***	0.056***
Prior-year stock return	0.193	0.628	-0.498	0.061	1.393	0.043	0.590	-0.687	-0.045	1.089	0.150***	0.105***

Panel B: Correlation matrix

	Trademark count	Trademark age	Trademark growth	Trademark concentration	Firm size	M/B	ROA	Leverage	Cash	Sales growth
Trademark count	1									
Trademark age	0.306***	1								
Trademark growth	-0.056***	-0.276***	1							
Trademark concentration	-0.507***	-0.217***	-0.007	1						
Firm size	0.426***	0.148***	-0.042***	-0.222***	1					
M/B	0.058***	-0.089***	0.063***	0.003	-0.001	1				
ROA	0.219***	0.136***	-0.058***	-0.115***	0.150***	0.119***	1			
Leverage	0.024***	0.101***	-0.045***	-0.128***	0.171***	-0.085***	-0.022***	1		
Cash	-0.121***	-0.243***	0.099***	0.158***	-0.259***	0.200***	-0.235***	-0.389***	1	
Sales growth	-0.067***	-0.097***	0.075***	-0.041***	0.001	0.166***	-0.057***	0.087***	0.033***	1
Prior-year stock return	0.005	-0.054***	0.034***	-0.011**	-0.007*	0.245***	0.094***	-0.029***	0.084***	0.178***

Table 3. Summary statistics for the target sample

This table reports the summary statistics of the targets (in 4,697 deals) as well as their industry- and size-matched control firms (22,327 firms). Panel A presents the 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- and size-matched controls					Test of differences	
	Mean	SD	5th Percentile	Median	95th Percentile	Mean	SD	5th Percentile	Median	95th Percentile	T-test	Wilcoxon test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(1) - (6)	(4) - (9)
Number of trademarks	31.910	67.040	1	12	128	38.040	90.770	1	14	153	-6.130***	-2.000***
Trademark count	2.462	1.208	0.693	2.303	4.654	2.595	1.244	0.693	2.485	4.890	-0.133***	-0.182***
Trademark age	10.810	7.687	2.750	8.333	27	11.080	7.681	3	8.846	27.390	-0.270**	-0.513***
Trademark growth	0.111	0.335	-0.143	0.000	0.750	0.118	0.328	-0.125	0.000	0.750	-0.007	0.000***
Trademark concentration	0.580	0.304	0.168	0.506	1.000	0.554	0.296	0.162	0.500	1.000	0.026***	0.006***
Total assets	2828	22862	16	250	9190	3047	31096	17	264	9401	-219	-13.724
Firm size	5.689	1.877	2.850	5.525	0.126	5.697	1.880	2.878	5.529	9.113	-0.008	-0.004
M/B	2.489	3.343	0.430	1.731	7.405	2.762	3.704	0.449	1.858	8.676	-0.273***	-0.126***
ROA	0.069	0.173	-0.274	0.101	0.259	0.075	0.169	-0.247	0.101	0.276	-0.006**	0.000**
Leverage	0.214	0.208	0.000	0.170	0.619	0.208	0.207	0.000	0.160	0.616	0.006*	0.001**
Cash	0.181	0.207	0.004	0.098	0.649	0.188	0.211	0.005	0.099	0.660	-0.007*	-0.001**
Sales growth	0.167	0.465	-0.266	0.080	0.828	0.201	0.522	-0.259	0.097	0.915	-0.034***	-0.017***
Prior-year stock return	-0.051	0.529	-0.741	-0.122	0.872	0.005	0.565	-0.711	-0.075	1.035	-0.056***	-0.047***

Panel B: Correlation matrix

	Trademark count	Trademark age	Trademark growth	Trademark concentration	Firm size	M/B	ROA	Leverage	Cash	Sales growth
Trademark count	1									
Trademark age	0.161***	1								
Trademark growth	-0.066***	-0.296***	1							
Trademark concentration	-0.234***	-0.126***	0.001	1						
Firm size	0.155***	0.035***	-0.019***	-0.046***	1					
M/B	0.052***	-0.068***	0.049***	-0.016***	-0.011**	1				
ROA	0.130***	0.143***	-0.022***	-0.118***	-0.004	0.063***	1			
Leverage	0.039***	0.065***	-0.012**	-0.107***	0.029***	-0.080***	0.003	1		
Cash	-0.083***	-0.192***	0.043***	0.096***	-0.058***	0.203***	-0.272***	-0.372***	1	
Sales growth	-0.067***	-0.157***	0.116***	0.049***	-0.026***	0.167***	-0.084***	0.008*	0.139***	1
Prior-year stock return	0.006	-0.014***	0.006	-0.001	0.000	0.172***	0.121***	-0.047***	0.075***	0.046***

Table 4. Who will become acquirers?

Panel A presents the regression results where the dependent variable is equal to one for the actual acquirer, and to zero for firms in the control group. Columns (1) and (2) use the conditional logit model with deal fixed effects. Robust standard errors, which cluster at the deal level, are reported in the parentheses. Control firms in column (1) are matched on industry and size dimensions, and in column (2) are matched on industry, size, and market-to-book dimensions. Column (3) uses the logit model, column (4) uses the linear probability model (LPM) specification, and both employ the population of Compustat firms. Robust standard errors, which cluster at the firm level, are reported in the parentheses. Panel B presents the economic significance of our trademark variables in predicting acquirers based on the model in column (2) of Panel A. The predicted transaction incidence is tabulated under different values of one trademark variable while holding other variables' values at their means. Definitions of the variables are provided in the Appendix. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Predicting acquirers

	Industry- and size-matched controls (clogit)	Industry-, size-, and M/B-matched controls (clogit)	Full sample (logit)	Full sample (LPM)
Variables	(1)	(2)	(3)	(4)
Trademark count	0.290***	0.205***	0.155***	0.020***
	(0.014)	(0.014)	(0.020)	(0.002)
Trademark age	-0.021***	-0.019***	-0.015***	-0.002***
	(0.002)	(0.002)	(0.003)	(0.000)
Trademark growth	0.143***	0.164***	0.134***	0.014***
	(0.035)	(0.035)	(0.036)	(0.004)
Trademark concentration	-0.064	-0.092*	-0.126*	0.001
	(0.054)	(0.054)	(0.075)	(0.007)
Firm size	0.514***	0.283***	0.188***	0.019***
	(0.016)	(0.009)	(0.012)	(0.001)
M/B	0.007**	0.217***	0.006*	0.002***
	(0.003)	(0.012)	(0.004)	(0.000)
ROA	1.656***	2.714***	2.013***	0.120***
	(0.113)	(0.115)	(0.126)	(0.008)
Leverage	-0.316***	0.459***	-0.380***	-0.034***
	(0.072)	(0.084)	(0.100)	(0.009)
Cash	-0.643***	-0.257***	0.571***	0.056***
	(0.080)	(0.080)	(0.100)	(0.010)
Sales growth	0.278***	0.289***	0.396***	0.042***
	(0.017)	(0.016)	(0.028)	(0.004)
Prior-year stock return	0.491***	0.440***	0.307***	0.037***
	(0.020)	(0.020)	(0.019)	(0.002)
Observations	81712	80944	106918	107119
Pseudo R^2/Adjusted R^2	0.123	0.179	0.105	0.076
Deal FE	Yes	Yes	No	No
Industry × Year FE	No	No	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	13.41%	16.67%	19.87%	6.47%
Trademark age	18.33%	16.67%	15.55%	-2.78%
Trademark growth	16.39%	16.67%	16.73%	0.34%
Trademark concentration	17.06%	16.67%	16.30%	-0.76%

Table 5. Who will become targets?

Panel A presents the regression results where the dependent variable is equal to one for the actual target, and to zero for firms in the control group. Columns (1) and (2) use the conditional logit model with deal fixed effects. Robust standard errors, which cluster at the deal level, are reported in the parentheses. Control firms in column (1) are matched on industry and size dimensions, and in column (2) are matched on industry, size, and market-to-book dimensions. Column (3) uses the logit model, column (4) uses the LPM specification, and both employ the population of Compustat firms. Robust standard errors, which cluster at the firm level, are reported in the parentheses. Panel B presents the economic significance of our trademark variables in predicting targets based on the model in column (2) of Panel A. The predicted transaction incidence is tabulated under different values of one trademark variable while holding other variables' values at their means. Definitions of the variables are provided in the Appendix. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Predicting targets

	Industry- and size-matched controls (clogit)	Industry-, size-, and M/B-matched controls (clogit)	Full sample (logit)	Full sample (LPM)
Variables	(1)	(2)	(3)	(4)
Trademark count	-0.098***	-0.042**	-0.123***	-0.005***
	(0.022)	(0.022)	(0.019)	(0.001)
Trademark age	-0.003	-0.008***	-0.008***	-0.0003***
	(0.003)	(0.003)	(0.002)	(0.000)
Trademark growth	-0.067	0.011	-0.045	-0.002
	(0.055)	(0.055)	(0.051)	(0.002)
Trademark concentration	0.181**	0.245***	0.183***	0.008***
	(0.077)	(0.077)	(0.069)	(0.003)
Firm size	0.039	0.115***	0.032***	0.001***
	(0.026)	(0.013)	(0.011)	(0.000)
M/B	-0.014**	0.146***	-0.017***	-0.001***
	(0.005)	(0.016)	(0.005)	(0.000)
ROA	-0.102	0.585***	0.480***	0.019***
	(0.135)	(0.133)	(0.105)	(0.004)
Leverage	0.118	0.627***	0.104	0.005
	(0.103)	(0.115)	(0.090)	(0.004)
Cash	-0.289**	-0.367***	0.371***	0.015***
	(0.119)	(0.112)	(0.096)	(0.004)
Sales growth	-0.205***	-0.061*	-0.090**	-0.003**
	(0.045)	(0.036)	(0.038)	(0.001)
Prior-year stock return	-0.198***	-0.100***	-0.195***	-0.007***
	(0.037)	(0.036)	(0.034)	(0.001)
Observations	24005	23350	104971	105150
Pseudo R^2/Adjusted R^2	0.010	0.023	0.033	0.010
Deal FE	Yes	Yes	No	No
Industry × Year FE	No	No	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	18.25%	16.67%	15.31%	-2.94%
Trademark age	16.90%	16.67%	16.51%	-0.39%
Trademark growth	16.78%	16.67%	16.64%	-0.14%
Trademark concentration	15.90%	16.67%	17.51%	1.61%

Table 6. Summary statistics for the acquirer-target sample

This table reports the summary statistics of the acquirer-target pairs (in 1,885 deals) as well as their industry- and size-matched control pairs (8,555 observations). Panel A presents the 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

	Sample firms					Industry- and size-matched controls					Test of differences	
	Mean	SD	5th Percentile	Median	95th Percentile	Mean	SD	5th Percentile	Median	95th Percentile	T-test	Wilcoxon test
	Acquirers					Acquirer controls					Test of differences	
Number of trademarks	125.600	168.30	4	51	564	56.770	101.20	2	19	248	68.830***	32***
Trademark count	3.943	1.451	1.609	3.951	6.337	3.083	1.388	1.099	2.996	5.517	0.860***	0.955***
Total assets	16148	65038	79	2581	64145	16903	67730	86	2772	70560	-755	-191***
Firm size	7.802	2.002	4.376	7.856	11.070	7.014	2.050	3.779	6.892	10.660	0.788***	0.964***
M/B	4.432	35.620	0.919	2.553	9.791	4.277	33.510	0.919	2.502	9.791	0.155*	0.051*
ROA	0.126	0.119	-0.007	0.133	0.281	0.125	0.119	0.001	0.132	0.282	0.001	0.001
Leverage	0.202	0.173	0.000	0.180	0.521	0.204	0.171	0.000	0.182	0.518	-0.002	-0.002
Cash	0.161	0.180	0.006	0.088	0.571	0.157	0.177	0.006	0.085	0.565	0.004*	0.003*
Sales growth	0.551	13.400	-0.165	0.114	0.905	0.426	10.890	-0.167	0.109	0.867	0.125*	0.005*
Prior-year stock return	0.137	0.610	-0.468	0.030	1.023	0.127	0.573	-0.462	0.030	0.982	0.010*	0.000
	Targets					Target controls					Test of differences	
Number of trademarks	28.160	50.530	1	11	120	34.460	61.320	1	12	152	-6.300**	-1.000**
Trademark count	2.554	1.226	0.693	2.485	4.796	2.700	1.266	0.693	2.565	5.030	-0.146***	-0.080***
Total assets	4415	33781	20.340	320.700	13064	4648	35115	21.440	347.700	13949	-233	-27*
Firm size	5.958	1.941	3.061	5.774	9.478	5.983	1.953	3.058	5.807	9.583	-0.025	-0.033
M/B	2.887	3.879	0.594	2.003	8.424	2.928	4.136	0.482	1.946	9.040	-0.041	0.057*
ROA	0.072	0.168	-0.286	0.103	0.270	0.075	0.164	-0.245	0.100	0.274	-0.003*	0.003
Leverage	0.198	0.198	0.000	0.151	0.589	0.202	0.204	0.000	0.152	0.611	-0.004*	-0.001
Cash	0.200	0.218	0.004	0.113	0.674	0.198	0.218	0.005	0.104	0.672	0.002	0.009
Sales growth	0.185	0.446	-0.221	0.093	0.854	0.207	0.517	-0.245	0.101	0.916	-0.022***	-0.008*
Prior-year stock return	-0.038	0.526	-0.715	-0.112	0.881	0.015	0.565	-0.695	-0.065	1.045	-0.053***	-0.047***
	Acquirer-target pairs					Pair controls					Test of differences	
Product market overlap	0.744	0.294	0.077	0.875	0.999	0.568	0.367	0.000	0.658	0.999	0.176***	0.217***
Patent similarity	0.058	0.094	0.000	0.030	0.188	0.019	0.044	0.000	0.000	0.117	0.039***	0.029***
HP similarity	0.360	0.330	0.000	0.277	0.939	0.181	0.282	0.000	0.029	0.898	0.179***	0.248***
Same industry	0.687	0.464	0.000	1.000	1.000	0.688	0.463	0.000	1.000	1.000	0.001	0.000

Panel B: Correlation matrix

	Product market overlap	Patent similarity	HP similarity	Same industry
Product market	1			
Patent similarity	0.322***	1		
HP similarity	0.187***	0.295***	1	
Same industry	0.378***	0.284***	0.179***	1

Table 7. Acquirer-target pairing

Panel A presents the results for conditional logit regression where the dependent variable is equal to one for the actual acquirer-target pair, and to zero for pairs in the control group. Control firms in columns (1) to (4) are matched on industry and size dimensions, and in columns (5) to (8) are matched on industry, size, and market-to-book dimensions. Columns (1) and (5) present results for the baseline models. The other columns further control for Patent similarity or HP similarity or both. Robust standard errors, which cluster at the deal level, are reported in the parentheses. 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, based on column (4). All specifications include deal fixed effects as well as acquirer and target trademark and firm characteristics. Definitions of the variables are provided in the Appendix. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Predicting acquirer-target pairs

	Industry- and size-matched controls				Industry-, size-, and M/B-matched controls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Product market overlap	2.735***	2.150***	2.692***	2.421***	2.484***	2.071***	2.379***	2.628***
	(0.163)	(0.306)	(0.215)	(0.428)	(0.183)	(0.366)	(0.235)	(0.519)
Patent similarity		2.285***		1.723***		1.853***		1.005**
		(0.248)		(0.328)		(0.289)		(0.422)
HP similarity			17.898***	35.143***			21.531***	38.944***
			(1.537)	(3.789)			(1.802)	(4.883)
Acquirer trademark count	0.495***	0.505***	0.515***	0.657***	0.446***	0.528***	0.494***	0.682***
	(0.044)	(0.083)	(0.057)	(0.117)	(0.045)	(0.093)	(0.063)	(0.140)
Acquirer trademark age	-0.003	-0.003	-0.003	-0.020	-0.002	0.009	-0.008	0.023
	(0.006)	(0.012)	(0.008)	(0.016)	(0.006)	(0.012)	(0.008)	(0.018)
Acquirer trademark growth	0.340***	0.746***	0.278*	0.608	0.133	0.495*	-0.105	-0.125
	(0.126)	(0.282)	(0.160)	(0.382)	(0.120)	(0.286)	(0.160)	(0.404)
Acquirer trademark concentration	-0.001	-0.067	-0.110	0.115	-0.177	-0.622*	-0.211	-0.632
	(0.183)	(0.346)	(0.241)	(0.468)	(0.186)	(0.352)	(0.247)	(0.516)
Target trademark count	-0.257***	-0.303***	-0.286***	-0.419***	-0.176***	-0.213**	-0.241***	-0.504***
	(0.045)	(0.082)	(0.057)	(0.131)	(0.046)	(0.094)	(0.057)	(0.148)
Target trademark age	-0.007	-0.000	-0.007	-0.003	-0.008	0.001	-0.009	-0.008
	(0.006)	(0.012)	(0.007)	(0.017)	(0.006)	(0.011)	(0.007)	(0.019)
Target trademark growth	0.045	0.095	0.037	0.041	0.189	0.088	0.140	-0.261
	(0.111)	(0.249)	(0.148)	(0.412)	(0.120)	(0.254)	(0.144)	(0.384)
Target trademark concentration	0.242	0.026	-0.055	-0.605	0.264	0.104	-0.064	-0.702
	(0.160)	(0.311)	(0.199)	(0.424)	(0.168)	(0.365)	(0.221)	(0.539)
Acquirer firm size	0.822***	0.996***	0.844***	1.103***	0.474***	0.574***	0.459***	0.579***
	(0.052)	(0.109)	(0.061)	(0.144)	(0.031)	(0.068)	(0.040)	(0.099)

Acquirer M/B	0.008	-0.008	0.013	-0.005	0.295***	0.302**	0.303***	0.336*
	(0.011)	(0.025)	(0.013)	(0.030)	(0.050)	(0.148)	(0.059)	(0.194)
Acquirer ROA	0.691*	0.236	0.791	0.845	1.180***	-0.488	1.654***	-0.271
	(0.379)	(0.718)	(0.498)	(1.089)	(0.376)	(0.534)	(0.525)	(0.871)
Acquirer leverage	-0.729***	-0.711	-0.928***	-0.697	-0.248	-0.803	-0.059	-0.610
	(0.246)	(0.541)	(0.311)	(0.735)	(0.303)	(0.597)	(0.431)	(0.902)
Acquirer cash	-0.611**	-0.430	-1.294***	-1.881***	-0.206	0.100	-0.656**	-1.007
	(0.253)	(0.465)	(0.306)	(0.609)	(0.273)	(0.560)	(0.327)	(0.712)
Acquirer sales growth	0.606***	0.524***	0.675***	0.691***	0.442***	0.390***	0.458***	0.444**
	(0.088)	(0.143)	(0.116)	(0.236)	(0.083)	(0.148)	(0.111)	(0.225)
Acquirer prior-year stock return	0.454***	0.277**	0.519***	0.273	0.363***	0.428***	0.434***	0.312
	(0.072)	(0.135)	(0.090)	(0.186)	(0.075)	(0.153)	(0.097)	(0.198)
Target firm size	-0.003	0.060	-0.134*	-0.121	0.048*	-0.030	-0.069*	-0.143
	(0.058)	(0.109)	(0.069)	(0.162)	(0.029)	(0.069)	(0.039)	(0.104)
Target M/B	-0.014	-0.028*	-0.024**	-0.056***	0.142***	0.200*	0.104**	0.207
	(0.009)	(0.017)	(0.010)	(0.021)	(0.048)	(0.119)	(0.050)	(0.140)
Target ROA	-0.123	0.080	0.572*	1.356**	0.374	0.812	0.788**	1.665**
	(0.288)	(0.529)	(0.327)	(0.626)	(0.270)	(0.499)	(0.369)	(0.694)
Target leverage	0.145	0.148	0.288	0.155	0.608**	0.682	0.739**	0.726
	(0.219)	(0.403)	(0.270)	(0.581)	(0.264)	(0.527)	(0.343)	(0.809)
Target cash	-0.300	-0.508	-0.089	-0.375	-0.664***	-0.714*	-0.915***	-1.314**
	(0.229)	(0.411)	(0.265)	(0.531)	(0.234)	(0.430)	(0.296)	(0.595)
Target sales growth	-0.129	0.053	-0.062	0.108	-0.025	0.301**	-0.052	0.500**
	(0.093)	(0.174)	(0.113)	(0.228)	(0.086)	(0.137)	(0.131)	(0.199)
Target prior-year stock return	-0.295***	-0.214*	-0.329***	-0.222	-0.186**	-0.069	-0.148	0.024
	(0.073)	(0.128)	(0.087)	(0.173)	(0.082)	(0.128)	(0.106)	(0.205)
Observations	8598	2679	6150	1946	8176	2233	5867	1672
Pseudo R^2	0.353	0.481	0.472	0.634	0.472	0.581	0.593	0.716
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

	(1)	(2)	(3)	(3) - (1)
	25th Percentile	Mean	75th Percentile	
Product market overlap	5.92%	16.67%	35.48%	29.57%
Patent similarity	10.57%	16.67%	22.80%	12.23%
HP similarity	10.59%	16.67%	17.97%	7.38%

Table 8. Post-merger product market outcome

This table compares product market outcome from before to after deal completion. For each deal, we track its acquirer's trademarks from five years before bid announcement to five years after deal completion. Panel A presents the summary statistics of acquirer trademark characteristics from before to after deal completion. Panel B presents the regression results for acquirer product market outcome using a sample of completed deals and a sample of control firms. Robust standard errors, which cluster at the deal level, are reported in the parentheses. 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

	Before			After			Test of difference	
	Mean	Median	SD	Mean	Median	SD	t-test	Wilcoxon test
	(1)	(2)	(3)	(4)	(5)	(6)	(4) – (1)	(5) – (2)
Number of trademarks	108.800	37	175.701	153.698	70	208.799	44.898***	33***
Trademark count	3.718	3.611	1.419	4.306	4.248	1.234	0.588***	0.638***
Trademark age	12.253	9.945	7.336	13.407	11.343	6.796	1.154***	1.398***
Trademark growth	0.121	0.042	0.283	0.177	0.039	0.453	0.056***	-0.003***
Trademark concentration	0.458	0.393	0.267	0.400	0.333	0.233	-0.058***	-0.060***

Panel B: Post-merger trademark portfolio

	Trademark count	Trademark age	Trademark growth	Trademark concentration
	(1)	(2)	(3)	(4)
After	0.243***	0.117*	0.379***	-0.039***
	(0.012)	(0.070)	(0.016)	(0.004)
Deal	0.051***	-0.080	0.086***	-0.011***
	(0.011)	(0.056)	(0.015)	(0.002)
After × Deal	-0.125***	0.026	-0.197***	0.031***
	(0.012)	(0.067)	(0.016)	(0.003)
Same industry	0.010	0.020	0.013	0.005***
	(0.008)	(0.037)	(0.009)	(0.001)
Trademark count	0.729***	0.341***	-0.385***	0.007***
	(0.008)	(0.037)	(0.011)	(0.002)
Trademark age	-0.011***	0.838***	-0.013***	0.000
	(0.001)	(0.007)	(0.001)	(0.000)
Trademark growth	0.001	-0.124***	-0.026***	0.004***
	(0.005)	(0.022)	(0.007)	(0.001)
Trademark concentration	-0.005	0.053	0.089**	0.729***
	(0.027)	(0.124)	(0.039)	(0.009)
Firm size	0.044***	-0.061**	0.062***	-0.006***
	(0.006)	(0.027)	(0.007)	(0.001)
M/B	0.001	0.009*	0.001	0.000
	(0.001)	(0.005)	(0.002)	(0.000)
ROA	-0.038	-0.032	-0.074**	0.012
	(0.023)	(0.129)	(0.035)	(0.008)
Leverage	-0.064***	0.254*	-0.096***	0.004

	(0.024)	(0.135)	(0.034)	(0.007)
Cash	-0.034	0.090	-0.037	-0.002
	(0.026)	(0.138)	(0.038)	(0.008)
Sales growth	0.025***	-0.076*	0.049***	0.000
	(0.007)	(0.042)	(0.011)	(0.002)
Prior-year stock return	-0.003	-0.006	-0.006	0.000
	(0.004)	(0.021)	(0.006)	(0.001)
Intercept	0.636***	1.037***	0.882***	0.142***
	(0.066)	(0.309)	(0.093)	(0.018)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	20467	20463	20464	20467
Adjusted R-squared	0.973	0.962	0.254	0.931

Table 9. Product market overlap and post-merger new trademark registration

This table compares acquirers' new trademark registration from before to after deal completion. For each deal, we track its acquirer's trademarks from five years before bid announcement to five years after deal completion. We separate trademarks by class. Common class refers to trademarks in a class that both the acquirer and its target have registered trademarks. Unique to acquirer (target) 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 A presents the summary statistics of acquirers' newly registered trademarks from before to after deal completion. Panel B presents the difference-in-differences (DD) regression results for acquirers' newly registered trademarks using a sample of completed deals and a sample of control firms. Panel C presents the triple differences (DDD) regression results for acquirers' newly registered trademarks using a sample of completed deals and a sample of control firms. Robust standard errors, which cluster at the deal level, are reported in the parentheses. 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 acquirer newly registered trademarks

	Before		After		Test of difference
	Mean	SD	Mean	SD	t-test
	(1)	(2)	(3)	(4)	(3) – (1)
Raw number					
All	7.546	13.670	9.502	17.362	1.956***
Common	3.559	10.348	4.884	13.663	1.325***
Unique to acquirer	3.987	8.295	4.067	9.005	0.080
Unique to target	0.000	0.000	0.168	0.861	0.168***
New	0.000	0.000	0.383	1.129	0.383***
Log number					
All	1.422	1.145	1.618	1.195	0.196*
Common class	0.714	1.035	0.925	1.091	0.211***
Unique to acquirer	0.922	1.033	0.902	1.052	-0.020
Unique to target	0.000	0.000	0.071	0.263	0.071***
New	0.000	0.000	0.189	0.189	0.189***

Panel B: Post-merger acquirer newly registered trademarks

	All	Common class	Unique to acquirer	Unique to target	New
	(1)	(2)	(3)	(4)	(5)
After	0.135***	0.137***	-0.071**	0.101***	0.170***
	(0.026)	(0.033)	(0.029)	(0.010)	(0.011)
Deal	0.090***	0.455***	-0.321***	-0.006	-0.011
	(0.033)	(0.079)	(0.066)	(0.010)	(0.012)
After × Deal	-0.164***	-0.138***	-0.001	-0.084***	0.031**
	(0.029)	(0.028)	(0.027)	(0.011)	(0.013)
Same industry	0.012	0.160**	-0.153***	-0.001	0.000
	(0.022)	(0.065)	(0.048)	(0.006)	(0.009)
Trademark count	0.251***	0.165***	0.068***	0.057***	0.012
	(0.022)	(0.028)	(0.024)	(0.009)	(0.008)

Trademark age	-0.025***	-0.006	-0.028***	0.003**	-0.006***
	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)
Trademark growth	0.119***	0.078***	0.065***	0.008	0.002
	(0.016)	(0.015)	(0.014)	(0.005)	(0.007)
Trademark concentration	0.075	0.159**	0.116	-0.128***	-0.063**
	(0.071)	(0.078)	(0.071)	(0.025)	(0.029)
Firm size	0.040**	0.034*	0.021	-0.008*	0.003
	(0.017)	(0.020)	(0.018)	(0.004)	(0.006)
M/B	0.003	0.004	0.002	-0.001	-0.000
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
ROA	-0.040	0.021	0.003	-0.027	-0.018
	(0.061)	(0.058)	(0.053)	(0.018)	(0.027)
Leverage	-0.146**	-0.049	-0.130*	0.012	0.009
	(0.068)	(0.078)	(0.071)	(0.020)	(0.028)
Cash	-0.091	-0.153*	0.064	0.021	-0.038
	(0.075)	(0.081)	(0.074)	(0.018)	(0.034)
Sales growth	0.048**	0.037**	0.012	0.006	-0.008
	(0.019)	(0.017)	(0.018)	(0.004)	(0.007)
Prior-year stock return	0.006	0.006	-0.002	0.003	0.002
	(0.011)	(0.010)	(0.010)	(0.003)	(0.004)
Intercept	0.054	-0.820***	0.869***	-0.159***	0.039
	(0.208)	(0.198)	(0.205)	(0.057)	(0.049)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	18002	18002	18002	18002	18002
Adjusted R-squared	0.692	0.537	0.576	0.232	0.175

Panel C: Product market overlap and post-merger acquirer newly registered trademarks: DDD

	All	Common	Unique to acquirer	Unique to target	New
	(1)	(2)	(3)	(4)	(5)
After	0.047	0.010	-0.128**	0.210***	0.171***
	(0.053)	(0.048)	(0.055)	(0.026)	(0.031)
Deal	-0.070	0.180	-0.182	0.004	0.001
	(0.064)	(0.150)	(0.123)	(0.026)	(0.022)
After × Deal	-0.010	0.078	0.051	-0.013	-0.095***
	(0.069)	(0.057)	(0.068)	(0.032)	(0.036)
Same industry	0.005	0.081	-0.074	-0.004	0.002
	(0.023)	(0.065)	(0.048)	(0.009)	(0.005)
Product market overlap	-0.099	0.214*	-0.342***	0.050**	0.035
	(0.062)	(0.118)	(0.101)	(0.023)	(0.022)
After × Product market overlap	0.107	0.197***	0.059	-0.054*	-0.097**
	(0.068)	(0.057)	(0.064)	(0.031)	(0.038)
Deal × Product market overlap	0.216***	0.374**	-0.186	-0.020	-0.010
	(0.075)	(0.178)	(0.151)	(0.029)	(0.026)

After × Deal × Product market overlap	-0.205**	-0.297***	-0.074	0.061	0.015
	(0.089)	(0.074)	(0.083)	(0.040)	(0.043)
Trademark count	0.274***	0.163***	0.071***	0.012	0.060***
	(0.022)	(0.028)	(0.024)	(0.008)	(0.009)
Trademark age	-0.024***	-0.006	-0.029***	-0.006***	0.003**
	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)
Trademark growth	0.292***	0.073***	0.068***	0.002	0.008
	(0.029)	(0.015)	(0.014)	(0.007)	(0.005)
Trademark concentration	0.064	0.126	0.143**	-0.062**	-0.112***
	(0.068)	(0.078)	(0.071)	(0.029)	(0.026)
Firm size	0.042**	0.036*	0.019	0.003	-0.007
	(0.017)	(0.020)	(0.018)	(0.006)	(0.004)
M/B	0.003	0.003	0.002	-0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
ROA	-0.046	0.015	0.000	-0.016	-0.029
	(0.060)	(0.058)	(0.053)	(0.027)	(0.018)
Leverage	-0.152**	-0.061	-0.120*	0.008	0.011
	(0.067)	(0.077)	(0.070)	(0.029)	(0.020)
Cash	-0.087	-0.155*	0.065	-0.039	0.017
	(0.073)	(0.080)	(0.074)	(0.034)	(0.018)
Sales growth	0.044**	0.034**	0.015	-0.008	0.006
	(0.019)	(0.017)	(0.018)	(0.007)	(0.004)
Prior-year stock return	0.006	0.007	-0.003	0.002	0.003
	(0.011)	(0.010)	(0.010)	(0.004)	(0.003)
Intercept	0.015	-0.833***	0.972***	0.013	-0.193***
	(0.213)	(0.216)	(0.216)	(0.052)	(0.059)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	18002	18002	18002	18002	18002
Adjusted R-squared	0.694	0.542	0.581	0.176	0.237

Table 10. Product market overlap and post-merger discontinued trademarks

This table compares acquirers' (targets') discontinued trademarks from before to after deal completion. For each deal, we track its acquirer's trademarks from five years before bid announcement to five years after deal completion. We separate trademarks by class. Common class refers to trademarks in a class that both the acquirer and its target have registered trademarks. Unique to acquirer (target) 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 A presents the summary statistics of acquirers' discontinued trademarks from before to after deal completion. Panel B presents the summary statistics of targets' discontinued trademarks from before to after deal completion. Panel C presents the difference-in-differences (DD) regression results for acquirers' discontinued trademarks using a sample of completed deals and a sample of control firms. Panel D presents the difference-in-differences (DD) regression results for targets' discontinued trademarks using a sample of completed deals and a sample of control firms. Panel E presents the triple differences (DDD) regression results for acquirers' discontinued trademarks using a sample of completed deals and a sample of control firms. Panel F presents the triple differences (DDD) regression results for targets' discontinued trademarks using a sample of completed deals and a sample of control firms. Robust standard errors, which cluster at the deal level, are reported in the parentheses. 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 acquirer discontinued trademarks

	Before		After		Test of difference
	Mean	SD	Mean	SD	t-test
	(1)	(2)	(3)	(4)	(3) – (1)
Raw number					
All	4.718	11.299	6.675	12.887	1.957***
Common class	2.301	8.582	3.242	9.803	0.941***
Unique to acquirer	2.416	6.365	3.404	7.732	0.988***
Unique to target	0.294	1.468	0.445	2.151	0.151***
New	0.053	0.545	0.082	0.583	0.029***
Log number					
All	0.946	1.091	1.282	1.139	0.336***
Common class	0.469	0.872	0.660	0.987	0.191***
Unique to acquirer	0.610	0.902	0.812	0.986	0.202***
Unique to target	0.108	0.368	0.155	0.430	0.047***
New	0.020	0.135	0.033	0.171	0.013***

Panel B: Summary statistics of target discontinued trademarks

	Before		After		Test of difference
	Mean	SD	Mean	SD	t-test
	(1)	(2)	(3)	(4)	(3) – (1)
Raw number					
All	1.146	3.761	1.638	4.173	0.492***
Common class	0.992	3.531	1.383	3.821	0.391***
Unique to acquirer	0.000	0.000	0.007	0.142	0.007***
Unique to target	0.154	0.973	0.242	1.164	0.088***
New	0.000	0.000	0.006	0.097	0.006***
Log number					

All	0.378	0.668	0.547	0.741	0.169***
Common class	0.332	0.627	0.474	0.696	0.142***
Unique to acquirer	0.000	0.000	0.004	0.062	0.004***
Unique to target	0.045	0.170	0.071	0.211	0.026***
New	0.000	0.000	0.000	0.000	0.000

Panel C: Post-merger acquirer discontinued trademarks

	All	Common	Unique to acquirer
	(1)	(2)	(3)
After	-0.141***	-0.161***	-0.046*
	(0.025)	(0.026)	(0.026)
Deal	0.008	0.306***	-0.250***
	(0.031)	(0.065)	(0.055)
After × Deal	0.129***	0.140***	0.047*
	(0.027)	(0.021)	(0.025)
Same industry	0.005	0.153**	-0.145***
	(0.021)	(0.060)	(0.045)
Trademark count	0.370***	0.203***	0.178***
	(0.023)	(0.026)	(0.023)
Trademark age	-0.004	0.008**	-0.015***
	(0.003)	(0.003)	(0.003)
Trademark growth	-0.126***	-0.066***	-0.073***
	(0.012)	(0.010)	(0.011)
Trademark concentration	0.465***	0.302***	0.190***
	(0.067)	(0.066)	(0.065)
Firm size	0.080***	0.064***	0.019
	(0.016)	(0.020)	(0.018)
M/B	-0.001	0.000	-0.002
	(0.003)	(0.003)	(0.003)
ROA	-0.039	-0.113**	0.088*
	(0.058)	(0.054)	(0.051)
Leverage	-0.082	0.074	-0.090
	(0.067)	(0.073)	(0.066)
Cash	-0.090	-0.042	-0.053
	(0.069)	(0.067)	(0.071)
Sales growth	-0.043**	-0.031*	-0.020
	(0.017)	(0.016)	(0.016)
Prior-year stock return	-0.016	-0.009	-0.014
	(0.010)	(0.009)	(0.009)
Intercept	-2.098***	-1.615***	-0.671***
	(0.207)	(0.177)	(0.198)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	16284	16284	16284

Adjusted R-squared	0.755	0.558	0.589

Panel D: Post-merger target discontinued trademarks

	All	Common	Unique to target
	(1)	(2)	(3)
After	-0.011	-0.048***	0.036***
	(0.017)	(0.017)	(0.012)
Deal	-0.028	0.007	-0.064***
	(0.022)	(0.027)	(0.021)
After × Deal	0.089***	0.114***	-0.026***
	(0.018)	(0.017)	(0.008)
Same industry	0.003	0.072**	-0.081***
	(0.023)	(0.033)	(0.025)
Trademark count	0.390***	0.358***	0.049***
	(0.016)	(0.015)	(0.007)
Trademark age	0.009***	0.007***	0.001**
	(0.002)	(0.002)	(0.001)
Trademark growth	-0.075***	-0.071***	-0.008***
	(0.008)	(0.008)	(0.002)
Trademark concentration	0.224***	0.250***	-0.019
	(0.037)	(0.035)	(0.015)
Intercept	-1.024***	-0.993***	-0.053
	(0.084)	(0.076)	(0.061)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	21524	21524	21524
Adjusted R-squared	0.538	0.534	0.382

Panel E: Product market overlap and acquirer discontinued trademarks: DDD

	All	Common	Unique to acquirer
	(1)	(2)	(3)
After	-0.080	-0.175***	0.007
	(0.053)	(0.033)	(0.052)
Deal	0.054	0.195	-0.028
	(0.061)	(0.141)	(0.107)
After × Deal	0.063	0.124***	0.070
	(0.067)	(0.040)	(0.064)
Same industry	0.013	0.095	-0.075*
	(0.021)	(0.061)	(0.044)
Product market overlap	0.012	0.215**	-0.145*
	(0.059)	(0.106)	(0.085)
After × Product market overlap	-0.087	0.034	-0.091
	(0.066)	(0.034)	(0.061)
Deal × Product market overlap	-0.063	0.148	-0.302**

	(0.076)	(0.161)	(0.134)
After × Deal × Product market overlap	0.090	0.025	-0.034
	(0.083)	(0.052)	(0.077)
Trademark count	0.372***	0.199***	0.185***
	(0.023)	(0.026)	(0.023)
Trademark age	-0.004	0.007**	-0.015***
	(0.003)	(0.003)	(0.003)
Trademark growth	-0.126***	-0.068***	-0.070***
	(0.012)	(0.010)	(0.011)
Trademark concentration	0.474***	0.268***	0.242***
	(0.068)	(0.066)	(0.065)
Firm size	0.080***	0.066***	0.018
	(0.016)	(0.020)	(0.018)
M/B	-0.001	0.000	-0.003
	(0.003)	(0.003)	(0.003)
ROA	-0.038	-0.110**	0.084
	(0.058)	(0.054)	(0.052)
Leverage	-0.081	0.066	-0.081
	(0.067)	(0.073)	(0.066)
Cash	-0.091	-0.040	-0.056
	(0.069)	(0.067)	(0.070)
Sales growth	-0.042**	-0.034**	-0.016
	(0.017)	(0.016)	(0.016)
Prior-year stock return	-0.016	-0.009	-0.014
	(0.010)	(0.009)	(0.009)
Intercept	-2.121***	-1.659***	-0.705***
	(0.211)	(0.192)	(0.207)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	16284	16284	16284
Adjusted R-squared	0.755	0.561	0.594

Panel F: Product market overlap and target discontinued trademarks: DDD

	All	Common	Unique to target
	(1)	(2)	(3)
After	-0.047	-0.080***	0.011
	(0.035)	(0.030)	(0.015)
Deal	0.080	0.145*	-0.035
	(0.064)	(0.085)	(0.036)
After × Deal	0.043	0.033	0.013
	(0.047)	(0.039)	(0.018)
Same industry	-0.002	0.054*	-0.042***
	(0.022)	(0.029)	(0.015)
Product market overlap	0.027	0.099	-0.051*

	(0.052)	(0.067)	(0.031)
After × Product market overlap	0.050	0.047	0.014
	(0.043)	(0.034)	(0.017)
Deal × Product market overlap	-0.138*	-0.173*	-0.011
	(0.076)	(0.102)	(0.043)
After × Deal × Product market overlap	0.062	0.110**	-0.041*
	(0.060)	(0.050)	(0.021)
Trademark count	0.390***	0.357***	0.033***
	(0.016)	(0.015)	(0.005)
Trademark age	0.008***	0.007***	0.001**
	(0.002)	(0.002)	(0.001)
Trademark growth	-0.075***	-0.070***	-0.006***
	(0.008)	(0.008)	(0.002)
Trademark concentration	0.219***	0.244***	-0.021*
	(0.037)	(0.035)	(0.011)
Intercept	-1.059***	-1.077***	-0.007
	(0.095)	(0.097)	(0.043)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	21524	21524	21524
Adjusted R-squared	0.539	0.535	0.293

Table 11. Product market overlap and post-merger performance

This table compares firm performance from before to after deal completion. For each deal, we track acquirer performance from five years before bid announcement to five years after deal completion. Panel A presents the summary statistics of acquirer performance from before to after deal completion. Panel B presents the difference-in-differences (DD) regression results for acquirer performance using a sample of completed deals and a sample of control firms. Panel C presents the triple differences (DDD) regression results. Robust standard errors, which cluster at the deal level, are reported in the parentheses. 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

	Before			After			Test of difference	
	Mean	Median	SD	Mean	Median	SD	t-test	Wilcoxon test
	(1)	(2)	(3)	(4)	(5)	(6)	(4) – (1)	(5) – (2)
ΔROA	-0.002	0.001	0.065	-0.004	0.000	0.060	-0.002	-0.001***
ΔROS	0.006	0.003	0.097	0.001	0.001	0.092	-0.005	-0.002***
Sales growth	0.166	0.099	0.313	0.097	0.063	0.256	-0.069	-0.036***
Market share	0.020	0.004	0.046	0.024	0.005	0.054	0.004***	0.001***
BHR	0.085	0.015	0.478	0.031	-0.018	0.430	-0.054	-0.033***

Panel B: Post-merger performance

	ΔROA	ΔROS	Sales growth	Market share	BHR
	(1)	(2)	(3)	(4)	(5)
After	-0.004**	-0.005**	-0.013	-0.001	-0.046***
	(0.002)	(0.003)	(0.008)	(0.001)	(0.013)
Deal	-0.003**	-0.002	-0.002	-0.000	0.003
	(0.001)	(0.002)	(0.008)	(0.001)	(0.013)
After * Deal	0.004**	0.007**	0.019*	0.003***	0.027*
	(0.002)	(0.003)	(0.010)	(0.001)	(0.015)
Same industry	-0.000	-0.000	-0.008*	-0.001	-0.008
	(0.001)	(0.001)	(0.005)	(0.002)	(0.008)
Firm size	-0.006***	-0.020***	-0.088***	0.011***	-0.219***
	(0.001)	(0.002)	(0.007)	(0.001)	(0.010)
M/B	0.003***	0.000	0.017***	-0.000	-0.029***
	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
Cash	-0.011	-0.002	0.203***	-0.001	-0.215***
	(0.008)	(0.016)	(0.040)	(0.002)	(0.051)
Leverage	-0.034***	0.032***	0.058**	-0.005	0.298***
	(0.007)	(0.013)	(0.029)	(0.004)	(0.046)
Intercept	0.025**	0.099***	0.672***	-0.037***	1.401***
	(0.011)	(0.013)	(0.054)	(0.006)	(0.134)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	17439	17545	17603	17611	17550
Adjusted R-squared	0.015	0.036	0.241	0.863	0.126

Panel C: Product market overlap and post-merger performance: DDD

	ΔROA	ΔROS	Sales growth	Market share	BHR
	(1)	(2)	(3)	(4)	(5)
After	-0.004	0.002	-0.020	-0.003	-0.096***
	(0.004)	(0.007)	(0.019)	(0.003)	(0.028)
Deal	0.001	0.009*	-0.005	-0.007**	-0.013
	(0.003)	(0.005)	(0.018)	(0.003)	(0.028)
After × Deal	-0.001	-0.011	0.028	0.011***	0.069**
	(0.004)	(0.008)	(0.024)	(0.004)	(0.034)
Same industry	0.000	0.000	-0.011**	-0.002	-0.009
	(0.001)	(0.001)	(0.005)	(0.002)	(0.008)
Product market overlap	-0.002	0.006	0.014	-0.001	-0.027
	(0.004)	(0.006)	(0.019)	(0.003)	(0.032)
After × Product market overlap	0.000	-0.010	0.011	0.002	0.068*
	(0.005)	(0.009)	(0.024)	(0.004)	(0.037)
Deal × Product market overlap	-0.005	-0.016**	0.004	0.009***	0.023
	(0.004)	(0.007)	(0.024)	(0.003)	(0.037)
After × Deal × Product market overlap	0.007	0.024**	-0.013	-0.011**	-0.058
	(0.006)	(0.010)	(0.031)	(0.005)	(0.045)
Firm size	-0.006***	-0.020***	-0.087***	0.011***	-0.219***
	(0.001)	(0.002)	(0.007)	(0.001)	(0.010)
M/B	0.003***	0.000	0.017***	-0.000	-0.029***
	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
Cash	-0.010	-0.001	0.203***	-0.001	-0.213***
	(0.008)	(0.016)	(0.040)	(0.002)	(0.051)
Leverage	-0.034***	0.033***	0.058**	-0.005	0.299***
	(0.007)	(0.013)	(0.029)	(0.004)	(0.046)
Intercept	0.025**	0.093***	0.666***	-0.035***	1.415***
	(0.012)	(0.014)	(0.056)	(0.006)	(0.136)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	17439	17545	17603	17611	17550
Adjusted R-squared	0.015	0.037	0.240	0.864	0.126

Internet Appendix

Appendix IA1. 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 IA2: NICE classification[19]

GOODS

Class 1 Chemicals used in industry, science and photography, as well as in agriculture, horticulture and forestry; unprocessed artificial resins, unprocessed plastics; manures; fire extinguishing compositions; tempering and soldering preparations; chemical substances for preserving foodstuffs; tanning substances; adhesives used in industry

Class 2 Paints, varnishes, lacquers; preservatives against rust and against deterioration of wood; colorants; mordants; raw natural resins; metals in foil and powder form for painters, decorators, printers and artists

Class 3 Bleaching preparations and other substances for laundry use; cleaning, polishing, scouring and abrasive preparations; soaps; perfumery, essential oils, cosmetics, hair lotions; dentifrices

Class 4 Industrial oils and greases; lubricants; dust absorbing, wetting and binding compositions; fuels (including motor spirit) and illuminants; candles and wicks for lighting

Class 5 Pharmaceutical and veterinary preparations; sanitary preparations for medical purposes; dietetic substances adapted for medical use, food for babies; plasters, materials for dressings; material for stopping teeth, dental wax; disinfectants; preparations for destroying vermin; fungicides, herbicides

Class 6 Common metals and their alloys; metal building materials; transportable buildings of metal; materials of metal for railway tracks; non-electric cables and wires of common metal; ironmongery, small items of metal hardware; pipes and tubes of metal; safes; goods of common metal not included in other classes; ores

Class 7 Machines and machine tools; motors and engines (except for land vehicles); machine coupling and transmission components (except for land vehicles); agricultural implements other than hand-operated; incubators for eggs

Class 8 Hand tools and implements (hand-operated); cutlery; side arms; razors

Class 9 Scientific, nautical, surveying, photographic, cinematographic, optical, weighing, measuring, signalling, checking (supervision), life-saving and teaching apparatus and instruments; apparatus and instruments for conducting, switching, transforming, accumulating, regulating or controlling electricity; apparatus for recording, transmission or reproduction of sound or images; magnetic data carriers, recording discs; automatic vending machines and mechanisms for coin-operated apparatus; cash registers, calculating machines, data processing equipment and computers; fire-extinguishing apparatus

Class 10 Surgical, medical, dental and veterinary apparatus and instruments, artificial limbs, eyes and teeth; orthopedic articles; suture materials

Class 11 Apparatus for lighting, heating, steam generating, cooking, refrigerating, drying, ventilating, water supply and sanitary purposes

Class 12 Vehicles; apparatus for locomotion by land, air or water

Class 13 Firearms; ammunition and projectiles; explosives; fireworks

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[19] "International Classification of Goods and Services for the Purposes of the Registration of Marks (Nice Classification)" (8th Edition, 2001), by World Intellectual Property Organization, Geneva.
A

Class 14 Precious metals and their alloys and goods in precious metals or coated therewith, not included in other classes; jewellery, precious stones; horological and chronometric instruments

Class 15 Musical instruments

Class 16 Paper, cardboard and goods made from these materials, not included in other classes; printed matter; bookbinding material; photographs; stationery; adhesives for stationery or household purposes; artists' materials; paint brushes; typewriters and office requisites (except furniture); instructional and teaching material (except apparatus); plastic materials for packaging (not included in other classes); printers' type; printing blocks

Class 17 Rubber, gutta-percha, gum, asbestos, mica and goods made from these materials and not included in other classes; plastics in extruded form for use in manufacture; packing, stopping and insulating materials; flexible pipes, not of metal

Class 18 Leather and imitations of leather, and goods made of these materials and not included in other classes; animal skins, hides; trunks and travelling bags; umbrellas, parasols and walking sticks; whips, harness and saddlery

Class 19 Building materials (non-metallic); non-metallic rigid pipes for building; asphalt, pitch and bitumen; non-metallic transportable buildings; monuments, not of metal

Class 20 Furniture, mirrors, picture frames; goods (not included in other classes) of wood, cork, reed, cane, wicker, horn, bone, ivory, whalebone, shell, amber, mother-of-pearl, meerschaum and substitutes for all these materials, or of plastics

Class 21 Household or kitchen utensils and containers (not of precious metal or coated therewith); combs and sponges; brushes (except paint brushes); brush-making materials; articles for cleaning purposes; steelwool; unworked or semi-worked glass (except glass used in building); glassware, porcelain and earthenware not included in other classes

Class 22 Ropes, string, nets, tents, awnings, tarpaulins, sails, sacks and bags (not included in other classes); padding and stuffing materials (except of rubber or plastics); raw fibrous textile materials

Class 23 Yarns and threads, for textile use

Class 24 Textiles and textile goods, not included in other classes; bed and table covers

Class 25 Clothing, footwear, headgear

Class 26 Lace and embroidery, ribbons and braid; buttons, hooks and eyes, pins and needles; artificial flowers

Class 27 Carpets, rugs, mats and matting, linoleum and other materials for covering existing floors; wall hangings (non-textile)

Class 28 Games and playthings; gymnastic and sporting articles not included in other classes; decorations for Christmas trees

Class 29 Meat, fish, poultry and game; meat extracts; preserved, dried and cooked fruits and vegetables; jellies, jams, compotes; eggs, milk and milk products; edible oils and fats

Class 30 Coffee, tea, cocoa, sugar, rice, tapioca, sago, artificial coffee; flour and preparations made from cereals, bread, pastry and confectionery, ices; honey, treacle; yeast, baking powder; salt, mustard; vinegar, sauces (condiments); spices; ice

Class 31 Agricultural, horticultural and forestry products and grains not included in other classes; live animals; fresh fruits and vegetables; seeds, natural plants and flowers; foodstuffs for animals; malt

Class 32 Beers; mineral and aerated waters and other non-alcoholic drinks; fruit drinks and fruit juices; syrups and other preparations for making beverages

Class 33 Alcoholic beverages (except beers)

Class 34 Tobacco; smokers' articles; matches

SERVICES

Class 35 Advertising; business management; business administration; office functions

Class 36 Insurance; financial affairs; monetary affairs; real estate affairs

Class 37 Building construction; repair; installation services

Class 38 Telecommunications

Class 39 Transport; packaging and storage of goods; travel arrangement

Class 40 Treatment of materials

Class 41 Education; providing of training; entertainment; sporting and cultural activities

Class 42 Scientific and technological services and research and design relating thereto; industrial analysis and research services; design and development of computer hardware and software; legal services

Class 43 Services for providing food and drink; temporary accommodation

Class 44 Medical services; veterinary services; hygienic and beauty care for human beings or animals; agriculture, horticulture and forestry services

Class 45 Personal and social services rendered by others to meet the needs of individuals; security services for the protection of property and individuals

Table IA1. Sample deals and their different measures of similarity

This tables provides a list of merger pairs with a wide variation in our key variable of interest – product market overlap. It also shows that these merger pairs differ in other measures of similarity.

Acquirer name	Target name	Product market overlap	Patent similarity	HP similarity	Same industry
AGILENT TECHNOLOGIES INC	STRATAGENE CORP	0.052	0.265	0.000	0
CISCO SYSTEMS INC	WEBEX COMMUNICATIONS INC	0.053	0.479	0.000	0
MERCK & CO	MEDCO HEALTH SOLUTIONS INC	0.069			0
SYSCO CORP	GUEST SUPPLY INC	0.297		0.000	0
TIME WARNER INC	MOVIEFONE INC -CL A	0.361		0.046	0
CORNING INC	NICHOLS INSTITUTE	0.416			0
TYSON FOODS INC -CL A	HILLSHIRE BRANDS CO	0.416	0.119	0.042	1
ABBOTT LABORATORIES	THERASENSE INC	0.440	0.252	0.000	0
K2 INC	FOTOBALL USA INC	0.740		0.000	1
PETCO ANIMAL SUPPLIES INC	PET FOOD WAREHOUSE INC	0.741			0
BANK ONE CORP	FIRST COMMERCE CORP	0.808		0.171	1
ALCOA INC	ALUMAX INC	0.808	0.137	0.067	0
PEPSICO INC	QUAKER OATS CO	0.834	0.873	0.055	0
GENZYME CORP	ILEX ONCOLOGY INC	0.835	0.538	0.073	1
JOHNSON & JOHNSON	ALZA CORP	0.837	0.477	0.027	1
PFIZER INC	ANACOR PHARMACEUTICALS INC	0.950		0.000	1
CISCO SYSTEMS INC	SOURCEFIRE INC	0.966	0.612	0.034	0
FEDEX CORP	TIGER INTERNATIONAL	0.967			1
INTEL CORP	DIALOGIC CORP-OLD	0.968	0.091	0.012	0
CHRYSLER CORP	GULFSTREAM AEROSPACE CORP	0.969			1

Table IA2. Other similarity measures and post-merger new trademark registration

This table compares acquirers' new trademark registration from before to after deal completion. For each deal, we track its acquirer's trademarks from five years before bid announcement to five years after deal completion. We separate trademarks by class. Common class refers to trademarks in a class that both the acquirer and its target have registered trademarks. Unique to acquirer (target) 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 A presents the triple differences (DDD) regression results focusing on patent similarity. Panel B presents the triple differences (DDD) regression results focusing on HP similarity. Robust standard errors, which cluster at the deal level, are reported in the parentheses. Definitions of the variables are provided in the Appendix. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Patent similarity and post-merger acquirer newly registered trademarks: DDD

	All	Common	Unique to acquirer	Unique to target	New
	(1)	(2)	(3)	(4)	(5)
After	0.173***	0.148***	-0.076	0.106***	0.151***
	(0.051)	(0.051)	(0.053)	(0.020)	(0.020)
Deal	0.193***	0.712***	-0.353***	-0.004	-0.014
	(0.060)	(0.130)	(0.123)	(0.017)	(0.019)
After × Deal	-0.209***	-0.160***	-0.021	-0.082***	0.036
	(0.060)	(0.053)	(0.055)	(0.021)	(0.024)
Patent similarity	0.074	0.110	-0.085	0.027	0.062**
	(0.077)	(0.133)	(0.139)	(0.030)	(0.027)
After × Patent similarity	-0.041	0.041	-0.065	-0.019	-0.001
	(0.097)	(0.083)	(0.081)	(0.046)	(0.040)
Deal × Patent similarity	-0.074	-0.180	-0.127	-0.013	-0.078**
	(0.101)	(0.231)	(0.216)	(0.035)	(0.037)
After × Deal × Patent similarity	0.033	0.003	0.077	0.001	0.030
	(0.124)	(0.112)	(0.101)	(0.049)	(0.053)
Same industry	0.056**	0.234***	-0.087	0.011*	0.001
	(0.027)	(0.089)	(0.069)	(0.006)	(0.012)
Trademark count	0.275***	0.184***	0.072*	0.069***	0.024*
	(0.034)	(0.043)	(0.038)	(0.013)	(0.012)
Trademark age	-0.027***	-0.005	-0.031***	0.002	-0.008***
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)
Trademark growth	0.102***	0.098***	0.049**	-0.005	-0.005
	(0.025)	(0.024)	(0.021)	(0.008)	(0.010)
Trademark concentration	0.015	0.197	-0.022	-0.138***	-0.045
	(0.115)	(0.128)	(0.117)	(0.039)	(0.051)
Firm size	0.066***	0.067**	0.015	-0.011*	-0.003
	(0.023)	(0.030)	(0.027)	(0.006)	(0.008)
M/B	0.000	-0.002	0.001	-0.001	-0.002
	(0.004)	(0.005)	(0.005)	(0.001)	(0.002)
ROA	-0.089	-0.034	-0.020	-0.024	0.021
	(0.079)	(0.080)	(0.070)	(0.022)	(0.034)

Leverage	-0.148	0.056	-0.159*	-0.003	0.048
	(0.092)	(0.112)	(0.094)	(0.028)	(0.038)
Cash	-0.129	0.032	-0.030	0.015	-0.083*
	(0.093)	(0.104)	(0.096)	(0.023)	(0.044)
Sales growth	0.035	0.022	0.010	0.005	-0.000
	(0.028)	(0.025)	(0.025)	(0.006)	(0.011)
Prior-year stock return	0.013	0.010	0.006	0.004	-0.002
	(0.016)	(0.015)	(0.015)	(0.004)	(0.006)
Intercept	0.231	-1.105***	1.362***	-0.184**	-0.034
	(0.234)	(0.309)	(0.258)	(0.084)	(0.083)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	8839	8839	8839	8839	8839
Adjusted R-squared	0.730	0.595	0.615	0.255	0.179

Panel B: HP similarity and post-merger acquirer newly registered trademarks: DDD

	All	Common	Unique to acquirer	Unique to target	New
	(1)	(2)	(3)	(4)	(5)
After	0.176***	0.260***	-0.096**	0.101***	0.185***
	(0.036)	(0.049)	(0.042)	(0.015)	(0.014)
Deal	0.051	0.468***	-0.308***	-0.010	-0.020
	(0.041)	(0.117)	(0.097)	(0.015)	(0.017)
After × Deal	-0.184***	-0.178***	0.003	-0.078***	0.036**
	(0.040)	(0.038)	(0.036)	(0.016)	(0.017)
HP similarity	-0.854**	-0.028	-0.811*	0.044	0.016
	(0.340)	(0.602)	(0.415)	(0.114)	(0.102)
After × HP similarity	0.168	-0.108	0.068	-0.038	-0.021
	(0.299)	(0.280)	(0.182)	(0.149)	(0.119)
Deal × HP similarity	0.526	-0.111	-0.220	-0.062	-0.207
	(0.393)	(0.791)	(0.702)	(0.125)	(0.139)
After × Deal × HP similarity	-0.004	-0.091	-0.031	0.023	-0.064
	(0.373)	(0.355)	(0.227)	(0.160)	(0.155)
Same industry	0.017	0.046	-0.021	-0.005	0.003
	(0.025)	(0.076)	(0.062)	(0.007)	(0.010)
Trademark count	0.194***	0.181***	0.018	0.062***	0.017
	(0.028)	(0.031)	(0.026)	(0.011)	(0.010)
Trademark age	-0.017***	-0.004	-0.020***	0.004***	-0.006***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Trademark growth	0.132***	0.070***	0.083***	0.011*	0.002
	(0.019)	(0.017)	(0.016)	(0.006)	(0.008)
Trademark concentration	0.046	0.147*	0.166**	-0.116***	-0.072**
	(0.083)	(0.086)	(0.074)	(0.031)	(0.034)
Firm size	0.086***	0.059***	0.057***	-0.002	0.010

	(0.019)	(0.022)	(0.020)	(0.005)	(0.008)
M/B	0.004	0.002	0.004	-0.001	-0.001
	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)
ROA	-0.094	-0.011	-0.031	-0.022	-0.030
	(0.065)	(0.063)	(0.056)	(0.018)	(0.029)
Leverage	-0.244***	-0.135	-0.169**	0.021	-0.026
	(0.082)	(0.086)	(0.084)	(0.023)	(0.035)
Cash	-0.083	-0.143	0.096	0.023	-0.081**
	(0.086)	(0.089)	(0.080)	(0.022)	(0.036)
Sales growth	0.022	-0.003	0.014	0.007	-0.007
	(0.023)	(0.020)	(0.020)	(0.005)	(0.008)
Prior-year stock return	-0.001	0.002	-0.005	0.004	0.005
	(0.013)	(0.012)	(0.012)	(0.003)	(0.005)
Intercept	0.278	-0.679***	0.817***	-0.181***	0.041
	(0.171)	(0.221)	(0.184)	(0.047)	(0.067)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	12762	12762	12762	12762	12762
Adjusted R-squared	0.703	0.559	0.608	0.216	0.191