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

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Abstract

Using a novel trademark-merger data set over the period 1983-2016, we shed light on the sources of synergies in mergers and acquisitions (M&As). We show that post-merger, compared to their non-acquiring peers, acquirers reduce new product offerings as measured by fewer new trademark registrations, especially in trademark classes common to both acquirers and targets. Moreover, acquirers discontinue more acquirers' and targets' trademarks in common classes and classes unique to themselves, but discontinue fewer trademarks in classes unique to target firms. We conclude that M&As provide opportunities for acquirers to gain access to different products and to reduce overlapping product offerings.

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

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Abstract

Using a novel trademark-merger data set over the period 1983-2016, we shed light on the sources of synergies in mergers and acquisitions (M&As). We show that post-merger, compared to their non-acquiring peers, acquirers reduce new product offerings as measured by fewer new trademark registrations, especially in trademark classes common to both acquirers and targets. Moreover, acquirers discontinue more acquirers' and targets' trademarks in common classes and classes unique to themselves, but discontinue fewer trademarks in classes unique to target firms. We conclude that M&As provide opportunities for acquirers to gain access to different products and to reduce overlapping product offerings.

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I. Introduction

An important question in mergers and acquisitions (M&As) literature is how acquisitions shape 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 by acquirers versus their 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, Sheen (2014) shows that the real changes in the 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 the 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 (from the United States Patent and Trademark Office (USPTO) website). 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 (Mendonca, Pereira, and Godinho 2004; Millot 2009). 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. As opposed to patents that measure technological innovation, trademarks capture the launch, continuation, and termination of product lines, and thus are an 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).

Limited empirical work is available on trademarks in finance and economics despite their prevalence and importance in the economic activities of firms, in large part because no comprehensive data on trademarks existed until 2013; see Graham, Hancock, Macro, and Myers (2013) and Graham, Macro, and Myers (2015) for an introduction to the USPTO Trademark Case Files Dataset and the USPTO Trademark Assignment Dataset, and recent studies by Faurel, Li, Shanthikumar, and Teoh (2017) and Heath and Mace (2017).

To shed light on product market dynamics in relation to M&As, we have compiled an economy-wide trademark-merger data set, and developed 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 and 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, complementing the findings in Bena and Li (2014), who use patents as a marker for corporate innovation.

We then show that the greater the overlap between any two firms' product lines, the more likely that these two firms will end up doing a deal. The effect of product market overlap remains after controlling for similar technologies (Bena and Li 2014) and similar product descriptions (Hoberg and Phillips 2010) of the firm-pair involved.

We show that post-merger, compared to their non-acquiring peers, acquirers experience a significant drop in both their trademark count and trademark growth, and that acquirers' trademark portfolios become more concentrated. Moreover, we find that acquirers register fewer new trademarks overall, and discontinue more of their own and their targets' trademarks. 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. We show that 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, whereas acquirers register more new trademarks in new classes. This set of results does not support knowledge spillover between merging firms, but does support the notion of path-breaking innovation taking place post-merger. Moreover, acquirers discontinue more acquirers' and targets' trademarks in common classes and classes unique to themselves, whereas they discontinue fewer trademarks in classes unique to target firms, suggesting that M&As provide opportunities for acquirers to reduce overlapping product offerings and to gain access to targets' unique products. Finally, compared to other acquirers with a lower overlap of product lines with their target firms, acquirers with a greater overlap register even fewer trademarks in common classes, whereas they 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 classes different from theirs, instead of developing those products on their own, and, in the meantime, to reduce overlapping product offerings, especially on the target's side.

We show that post-merger, compared to their non-acquiring peers, acquirers experience significant improvements in return on assets (ROA), return on sales (ROS), and market share. Compared to other acquirers with a lower overlap of product lines with their target firms, acquirers with a greater overlap experience a bigger improvement in ROS, whereas they experience 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 rather are used by acquirers to gain access to different products and to reduce overlapping product offerings.

Finally, we use a quasi-experiment, involving bids withdrawn due to reasons exogenous to the product market activities of either the acquirer or the target firm, to estimate the treatment effect of a merger on post-merger product market outcomes. Following Seru (2010) and Bena and Li (2014), we argue that the assignment of deals into the treatment sample (i.e., completed deals) versus the control sample (i.e., withdrawn bids due to exogenous reasons) can be treated as random. As such, any selection concerns are differenced out by comparing firms' product market outcomes in the treatment sample, pre- and post-merger, with those in the control sample. We show that the presence of a pre-merger product market overlap between merging firms leads to acquirers registering fewer new trademarks and discontinuing more target firms' trademarks in common classes.

Our paper is related to three strands of the M&A literature: complementarity-driven acquisitions, the product market outcomes of M&As, and sources of synergistic gains in horizontal acquisitions. In the first strand, prior work shows that the relatedness of merger participants is critical for post-merger outcomes.[1] In the second strand, prior work provides

[1] Healy, Palepu, and Ruback (1992) find significant improvements in asset productivity, leading to higher operating cash flow returns in the five years following mergers, and these improvements are particularly strong for firms in highly overlapping businesses. Ahuja and Katila (2001) show that technological relatedness is associated with an improved innovation output from 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

mixed findings of mergers' effects on consumer prices and business reconfiguration.[2] In the third strand, prior work identifies three motives for horizontal acquisitions: to improve efficiency by achieving economies of scale, to eliminate excess capacity, or to create new opportunities by combining technological know-how and production capabilities.[3]

Our paper differs from prior work and thus contributes to the M&A literature in the following dimensions. First, using recently available and comprehensive data on trademarks from the USPTO that allow us to track acquirers' and targets' product lines post-merger, we can address the important questions of whether and how M&As change acquirers' new product development and affect acquirers' and target firms' product offerings differentially; neither has been examined at an economy-wide level prior to our paper.

Second, we develop a novel measure of pairwise product market overlap based on trademarks, and show its importance in merger pair formation and post-merger product market and performance outcomes. 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, we provide new evidence on the sources of gains in horizontal acquisitions (i.e., acquiring targets with greater product market overlaps than acquiring those with less overlap) from the perspective of product market dynamics. Our results suggest that

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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 the 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.

[2] 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 lines' 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 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.

[3] While Barro and Cutler (2000) argue that the merger of hospitals does not lead to economies of scale, Banker, Chang, and Cunningham 2004 (2004) show that the merger of accounting firms can be attributed to greater economies of scale. Ravenscraft and Long (2000) find that pharmaceutical firms' mergers are mainly driven by the intention to eliminate excess capacity rather than to achieve greater economies of scale. Using a data set that identifies the corporate customers, suppliers, and rivals of the firms initiating horizontal mergers, Fee and Thomas (2004) provide evidence consistent with improved productive efficiency and buying power as sources of gains to horizontal mergers.

these acquisitions are driven by specialization and the elimination of duplication rather than economies of scale and scope.

The paper proceeds as follows. In the next section, we development our hypotheses. We describe the USPTO trademark data sets and 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 the post-merger product market dynamics of both acquirers and targets, and acquirer product market and operating performance. In Section VI, we address the identification challenge using a quasi-experiment. We conclude in Section VII.

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, acquirers buying target firms with overlapping product lines helps them overcome information asymmetry in acquisitions. Intellectual property and technological know-how are, by nature, more difficult to evaluate than tangible assets. One concern for an acquirer, and to a lesser extent for a target firm, is valuing a target firm (an acquirer). If an 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 partners will largely be 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 an acquirer and its target firm may often pursue related activities. These related acquisitions are expected to perform better than they would otherwise since the acquirer will likely have skills in operating its target firm's assets, and will have similar/complementary technologies applicable to its target firm's new product launches (Cohen and Levinthal 1990; 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, an acquirer and its target firm are likely to have been direct competitors before the merger, and hence the acquirer has strong incentives to eliminate (potential) competition through an acquisition. According to the collusion hypothesis of Eckbo (1983, 1985), the merging firms and their rivals benefit from a merger because it increases the probability of successful collusion among rivals. Bhattacharyya and Nain (2011) provide supporting evidence that horizontal mergers create buying power, thereby adversely affecting dependent suppliers' performance.

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 significant 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 combined 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 an improved innovation output from acquiring firms in the chemical industry. Bena and Li (2014) find similar results based on economy-wide evidence. Banker, Chang, and Cunningham (2004) show that the blending of professional skills and experience resulting from a merger of accounting firms creates new opportunities and generates additional revenues. In another possible channel for M&A success, the overlap in product lines facilitates 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. For example, Hitt, Hoskisson, and Ireland (1990) argue that acquisitions consume managers' energies and attention during negotiations and post-merger integration and thus lead to less subsequent innovation; Hitt, Hoskisson, Ireland, and Harrison (1991) and Hitt, Hoskisson, Johnson, and Moesel (1996) provide empirical support for that argument by showing lower R&D expenditures and patent output post-merger. All such post-merger disruption and required integration is reduced when acquirers and targets share similar product market activities. Moreover, target firm inventors whose expertise is closely related to the acquirer will not encounter disruption and worry about job security, leading to more productive efforts and higher innovation performance (Paruchuri, Nerkar, and Hambrick 2006).

On the other hand, a number of counter arguments suggest that M&As may lead to fewer new product launches when acquirers and targets share similar product lines. First, horizontal acquisitions are driven by economies of scale or the elimination of overlapping facilities (Ravenscraft and Long 2000; Banker, Chang, and Cunningham 2003; Fee and Thomas 2004). As managers focus on post-merger re-organization and asset re-allocation, they do not have time and energy left for new product development. Second, acquiring new knowledge is one of the primary reasons for doing a deal, because only such knowledge can potentially offer new solutions to existing problems, 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—indicating that they possess similar technological know-how—from an acquirers' point of view little new knowledge will be gained. Third, 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 due to re-organization and are under high levels of stress from internal competition (Ravenscraft and Long 2000; Hitt and Hoskisson 1991). 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, to test those hypotheses 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. In the next section, we describe our new data set on trademarks, explain our 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. It is a valuable asset to trademark owners, as it offers them the exclusive right to use the mark and from which to build customer loyalty and maintain market power, and it can signal quality and uniqueness. A trademark 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 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 have the symbol ® attached 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.[4] A trademark must be registered within one or multiple classes of goods or services, and the scope of the aforementioned exclusivity right is only effective within the registered class(es).[5] 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

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[4] The basic requirements for word marks are uniqueness and being non-generic. Uniqueness means that the mark has had no prior registration with the same content in the same class. Non-generic means that the mark itself should be arbitrary and not 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.

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

services classes, for trademark registration purposes according to the International Classification of Goods and Services (and henceforth, the Nice Classification).[6] 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 federal trademark laws. The process of trademark registration can take from about several months to several years.

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.[7] To renew, in the sixth year after initial registration, the owner must show evidence of continued use and pay a maintenance fee, or face cancellation. In the tenth 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 tenth 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.[8] For the 1990 cohort of newly registered trademarks, 64% were renewed in 2000, and 54% of those were renewed a second time in 2010 (Graham et al. 2013).

[6] If a mark holder wants to expand the 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 the 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. See Appendix IA1 in the Internet Appendix for the complete list of Nice classification.

[7] 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.

[8] In brief, the maintenance threshold is in the sixth, tenth, twentieth … year. At the sixth 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 tenth 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 tenth 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 that both registration and renewal are economically significant corporate events (Bone 2004; Hoti, McAleer, and Slottje 2006). According to a survey by the American Intellectual Property Law Association (AIPLA, 2015), for trademark infringement cases of less than $1 million, between $1 million and $10 million, between $10 million and $25 million, and above $25 million at risk, their median litigation costs are $325,000, $500,000, $720,000, and $1.6 million, respectively.

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

A.2 Our trademark data set

The USPTO Trademark Case Files Dataset is our primary data set, 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, classifications, third-party oppositions, and renewal history. For each data record, it has the following information: key dates (filing, registration, renewal, or cancellation), status (registered, abandoned, renewed, or cancelled),[9] trademark class, mark content, and owner information.

Trademark ownership is not static. According to Graham et al. (2015), about a third of trademarks registered between 1978 and 2013 have been involved in certain types of ownership transfers. Recording such transfers is not mandatory, although statutory and regulatory laws provide compelling incentives for the parties involved to record these transfers with the USPTO throughout the entire life of a registered mark.[10]

To capture ownership transfer, we use 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:

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[9] 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 in this paper, we use "cancelled" trademarks for our analysis of discontinued trademarks.

[10] According to Graham et al. (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.

assignor, assignee, assignment type (assignment, merger, security interests, release, name change, etc.),[11] date, and the list of trademarks involved.

We take the following steps to link these two trademark data sets 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 the "Minnesota Mining and Manufacturing Company" switching 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, subsidiaries whose names are totally different from their parent companies' names are captured, such as "Geoffrey" of "Toys "R" Us," or "LinkedIn" of "Microsoft."

We then conduct fuzzy matching between lists 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 use the location information in the trademark data set 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 the product market development of a public company in our sample, we start with registered trademarks and adjust them for assignment. Specifically, if a company has purchased trademarks from a third party, we add them to the company's existing trademark portfolio from the transaction date; if a company has sold its trademarks to a third party, we remove them from the company's trademark portfolio.

[11] After studying a large number of assignment cases closely, we focus on "assignment" and "merger" types of assignments.

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., 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 appearing for the first time 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., updated logos). Appendix IA2 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 compares industry distributions of product trademark-producing firms and patent-producing firms. 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.[12] 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, trademarks can be used to capture

[12] Our patent data ending in 2014 is compiled following Chen, Chen, Hsu, and Podolski (2016) and Bereskin, Hsu, and Rotenberg (2017). We first collect information on patents and citations granted to U.S. public firms by the USPTO in 1976-2010 from the NBER patent database and the patent data set of Kogan, Papanikolaou, Seru, and Stoffman (2017). We then extend firm-level patent and citation data to 2014 by using Google patent and citation data, following the matching method of Chen et al. (2016) and Gao, Hsu, and Li (2018).

new product development in industries where corporate innovation typically does not involve filing patents, such as the service, banking, and retail industries (Mendonca, Pereira, and Godinho 2004; Millot 2009; Faurel et al. 2017). In contrast, patents are concentrated among a small set of high-tech industries, such as electronic and electrical equipment, and various measuring instruments.

B. Methodology

B.1 Product market overlap

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

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

where the vector $T_{acq,t} = (T_{acq,1}, ..., T_{acq,K})$ is the number of active trademarks in each trademark class for the acquirer, the vector $T_{targ} = (T_{targ,1}, ..., T_{targ,K})$ is the number of active trademarks in each trademark class for the target, and $k \in (1, K)$ is the Nice trademark class index ($K = 45$).[13] Each scalar in the vector is set to zero if a firm does not have any trademarks in that class. The higher the value of this cosine measure, the greater the 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 The 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:[14]

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

[14] See McFadden (1974) and Greene (2008, Chapter 23) for an introduction to the conditional logit regression, and Bena and Li (2014) for a recent application in finance.

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

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 active trademarks; and trademark concentration, defined as the Herfindahl index of active 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 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[15]—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).

[15] 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.

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 (up to the ten closest matches are selected), and last matched by M/B ratios (up to the five closest matches 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 argues that doing so 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:

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

The dependent variable, *Acquirer-Target*$_{ijm,t}$, is equal to one if firm pair *ij* is the acquirer-target firm pair, and zero otherwise. 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.

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 those matches closest to the acquirer, and by pairing the acquirer with up to five of those matches closest to the target firm.

To examine the effect of M&As on post-merger acquirers' and targets' product market outcomes, we require that the control firms have levels of trademark growth rates similar to those of the event firms (i.e., parallel trend assumptions). We start with the matched acquirer (target) sample based on industry, size, and M/B (with up to five control firms to each event firm). We first require that control firms were neither an acquirer nor a target firm in the five-year period after their event firms' deal completion. We then pick up to three control firms having the closest trademark count (i.e., the natural logarithm of (1 + number of trademarks)) to the event firm. We further pick one control firm out of the three that has the closest trademark growth. Given our focus on new product development, we further require that within the five-year window prior to the bid announcement, each event (acquirer or target) and its control firm have at least one trademark registration.

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

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

The dependent variable, $Firm\ Outcome_{im,t}$, is firm *i*'s trademark and performance outcome such as the number of newly registered trademarks or 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 the event firm, and zero otherwise (i.e., for its control firm that has not done a deal in the ten-year period). We include trademark characteristics when the dependent variables are product market measures like new trademark registrations, 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 the bid announcement (*ayr-1*):

$$Firm\ Outcome_{im,t} = \alpha + \beta_1\ After_{im,t} + \beta_2 Deal_m + \beta_3 After_{im,t} \times\ Deal_m + \beta_4 Product\ Market\ Overlap_{ij}\ + \beta_5 After_{im,t} \times\ Product\ Market\ Overlap_{ij} + \beta_6 Deal_m \times\ Product\ Market\ Overlap_{ij}\ + \beta_7 After_{im,t} \times\ Deal_m \times\ Product\ Market\ Overlap_{ij}\ + Firm\ FE + Year\ FE + e_{im,t}. \quad (5)$$

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 public acquirers and their public target firms. It is worth noting that our samples are among the largest employed to study product market outcomes 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*. 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., spanning 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, compared to their industry- and size-matched peer firms, they are larger and have higher M/B ratios, higher ROA, higher leverage, lower cash holdings, higher sales growth, and better stock market performance.

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 8th decile of the Compustat universe over the same time period).[16]

IV. Product Market Characteristics and M&As

In this section, we implement various multivariate analyses to relate firm product market characteristics to the likelihood of a firm becoming an acquirer (target firm or merger partner).

A. Who Will Become Acquirers/Target Firms?

[16] Table IA1 in the Internet Appendix presents the correlation matrix. In Panel A, we show that acquirer trademark count is positively associated with the average age of its constituent trademarks, and is negatively associated with the trademark growth rate and trademark concentration. The average age of an acquirer's trademark portfolio is negatively associated with its growth rate and concentration. Panel B exhibits similar pattern using the target sample. Overall, most correlations between trademark and firm characteristics are low and multicollinearity is unlikely to be an issue.

Table 4 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 the 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 1% level.

Based on the model in column (2), we compute the predicted likelihood of a firm becoming an acquirer when one of the trademark variables changes while other variables remain at their mean values. We find that when the trademark count (trademark age/trademark growth rate) changes from its 25th percentile to the 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 the 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, higher ROA, faster sales growth, and higher prior-year stock returns, are more likely to engage in M&As as acquirers.

Table 5 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 the Compustat population to predict a firms' likelihood of becoming a target (columns (3) and (4)). In contrast to the results for acquirers, we show a negative and significant association between the size of a firm's trademark portfolio and the likelihood of it becoming a target firm, and 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), we compute the predicted likelihood of a firm becoming a target firm when one of the trademark variables changes while other variables remain at their mean values. We find that when the trademark count (trademark age/ trademark concentration) changes from its 25th percentile to the 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 the 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 a 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 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 the median value), lower cash holdings, higher sales growth, and significantly 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, we present the summary statistics for four pairwise similarity measures capturing overlapping activities in different dimensions. 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 actual acquirer-target pairs have significantly greater product market overlap and higher patent similarity and HP similarity than their matching pairs (matched on industry affiliations).

Panel B presents the correlations between different pairwise measures. 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.[17]

Table 7 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 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 and the sample is materially reduced due to the requirement of non-zero patents for computing the measure. Columns (3) and (7) further control for HP similarity and the sample is moderately reduced due to the availability of 10-Ks on the SEC's EDGAR Online database since 1997. Columns (4) and (8) include all three pairwise measures. In all columns, we control for both acquirer trademark and firm characteristics as appeared in Table 4 and target trademark and firm characteristics as appeared in Table 5.

We show a positive and significant association between any of the three pairwise measures of overlapping activities and the likelihood of a merger pair formation. It is worth noting that our measure of product market overlap remains significant after controlling for two other determinants of merger pairing: patent similarity and HP similarity. This finding is both important and new in the literature, as prior work does not use trademark data to capture product market interactions.

Based on the model in column (8), we compute 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 the 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.

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[17] Table IA2 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.

V. Post-Merger Outcomes

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

A. Post-Merger Product Market Outcomes

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

To properly examine the effect of M&As on product market outcomes, we need to introduce a control sample that provides the benchmark of what would have happened had the event firm not been 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 data set on both acquirers and their matched controls by industry, size, M/B, trademark count, and trademark growth, as discussed in Section III B.2.

We show that the coefficient on *After* is positive and significant at the 1% level when the dependent variables are the trademark count and trademark growth, suggesting that over time, both acquirers and their control firms increase the size of their trademark portfolios and experience strong 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 the trademark count and trademark growth, suggesting that acquirers have larger trademark portfolios and are growing faster than their control firms, whereas this coefficient 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 the trademark count and trademark growth, suggesting that post-merger, acquirers experience a significant drop in both their trademark count and 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 acquirers' new trademark registration and the termination of acquirers' and targets' existing trademarks.

B. Acquirers' New Trademark Registrations

The richness of the trademark data allows us to examine how M&As change 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 with those of its acquirer.

Table 9 Panel A presents the summary statistics. We show that post-merger, 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.[18] 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 it 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 it is

[18] Throughout our analysis of newly registered trademarks, discontinued trademarks, and their respective components, we control for trademark and firm characteristics and *Same industry*, an indicator variable that takes the value of one if the acquirer and its target firm are in the same industry (based on two-digit SIC codes), and zero otherwise.

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 it is positive and significant at the 5% level when the dependent variable is trademarks in new classes. This finding suggests that post-merger, acquirers experience a significant drop in new trademark registrations compared to 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 (as otherwise we would see more new trademarks in common classes), but does support path-breaking innovation taking place post-merger.

Next, to differentiate between hypotheses H2a and H2b, we explore the role of product market overlap in the decision to develop new trademarks. 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 variable 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, they tend to develop significantly fewer trademarks post-merger, especially in common classes to acquirers and targets, which is inconsistent with H2a, while is consistent with H2b.[19]

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

[19] Parallel to the analysis in Table 7, Table IA3 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.

suggests that M&As are more driven by eliminating excess capacity than by achieving economies of scale.[20]

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 outcomes, we are able to clearly delineate the 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 and more by efficiency and consolidation considerations (Ravenscraft and Long 2000; Banker et al. 2003; Fee and Thomas 2004). The overlap in product lines helps acquirers understand target firms' operations and 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 shown in Table 9 Panel B). Based on the above discussion, we expect that when the pre-merger product market overlap is high, acquirers will be more likely to discontinue their own and target firms' trademarks after the merger.

Table 10 Panel A reports the summary statistics of our sample acquirers in terms of discontinued trademarks from before to after deal completion.[21] Discontinued trademarks refer to trademarks that are not renewed in the next renewal deadline (i.e., the sixth, tenth, twentieth, ..., from the registration year). We show that acquirers significantly increase their number of

[20] A number of prior studies also find little support for post-merger economies of scale. Barro and Cutler (2000) examine hospital mergers and show that larger hospitals in fact hire more employees per bed. Ravenscraft and Long (2000) examine mergers of pharmaceutical firms and find that their primary reason for doing a deal is to eliminate excess capacity and inefficiencies.

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

discontinued trademarks across all classes, including trademarks in common classes as well as trademarks in classes unique to acquirers.[22]

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 their targets' number of discontinued trademarks across all classes, including trademarks in common classes as well as trademarks in classes unique to the 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 it 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, and in particular trademarks in common classes, than their non-acquiring peers. Our results support the idea that M&As are used for business reconfiguration, and specifically for reducing 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 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 discontinue 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, suggesting that fewer target firms' trademarks in unique classes are discontinued than those of their control firms. Importantly, the coefficient on the two-way interaction term $After \times Deal$ is positive and significant at the 1% level when the

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

dependent variables are all trademarks and trademarks in common classes, suggesting that post-merger, acquirers discontinue significantly more target firms' trademarks in common classes than their peers. This finding reinforces our finding on the acquirers' side, supporting the idea that M&As are used for business reconfiguration, and in particular for reducing 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 peers. Combining this finding with the finding in Table 9 Panel B, which shows that post-merger acquirers tend to register fewer new trademarks in classes unique to targets, we conclude that M&As allow acquirers to gain access to targets' different products instead of developing on their own post-merger.

Next, we explore the role of product market overlap in firms' decisions 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 acquirers discontinue more targets' trademarks in their common classes post-merger when the merging firms' product offerings overlap significantly. The overlap in product offerings between merging firms will cause a cannibalization of cash flows. Consequently, to minimize such cannibalization, the acquirers' likelihood of retaining target products will be low (Bahadir at al. 2008). Our evidence thus far supports this argument.

Comparing 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 merging firms' product offerings have a greater overlap, acquirers discontinue significantly more target trademarks in common classes post-merger compared to target firms with a lower overlap of product lines with their acquirers; in contrast, acquirers with a greater overlap of product lines with their targets do not discontinue significantly more of their own trademarks in common classes compared to acquirers with a lower overlap of product lines with their targets. This finding suggests that acquirers seek to enhance their own product lines through M&As by not renewing 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 be more exploratory in their innovation effort.

D. Post-merger Performance

Next we examine post-merger acquirer operating performance including ΔROA (change in ROA), ΔROS (change in 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 (4) where the dependent variables are performance measures. We show that acquirers experience significant increases in ROA, ROS, and market share post-merger compared with their non-acquiring peers.

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 of product lines with their target firms, acquirers with a greater overlap experience a significantly bigger increase in ROS but 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 gaining market share (in absolute terms) but rather are used by acquirers to gain access to targets' different products and to reduce overlapping product offerings.

VI. Post-Merger Outcomes: The Quasi-experiment

The identification challenge of our post-merger analysis is that the association between pre-merger product market overlap and post-merger outcome could be due to the endogenous selection of firm pairs into the completed deal group. As shown above, acquisitions are more likely to occur between firms with significant product market overlap. As a result, simply comparing the average product market outcomes of merged firms with significant product line overlap to those of merged firms with little overlap would lead to biased estimates.

To address such selection concerns, we exploit a quasi-experiment. Following Seru (2010) and Bena and Li (2014), we employ a control sample of withdrawn bids that failed for reasons exogenous to the product market outcome of either merger partner. In this case, the assignment of firm pairs to the treatment sample (completed deals) versus the control sample (withdrawn bids) can be treated as random with respect to the outcome variables, mainly related to new product development and renewal, that we examine.[23]

We begin with 850 withdrawn bids with the necessary firm-level information from Compustat and CRSP over the period 1983-2010. We then read news articles for each withdrawn bid and only keep those bids that failed due to reasons exogenous to the product market outcome: competing bids, regulatory objections, or adverse market conditions. In the end, we have 246 withdrawn bids as potential control firms to match with the completed deals.[24]

To form the treatment and control samples, we begin with 1,695 completed deals, described in Section III B.2, and 246 withdrawn bids. We first require that acquirers of withdrawn bids have at least one newly registered trademark before the deal announcement. This results in our dropping 18 withdrawn bids. Then we match each completed deal with a withdrawn bid with the same acquirer and target industry affiliations (at the two-digit SIC level) announced within a ten-year window centered around the deal announcement of the completed deal, and with the closest acquirer size. This matching results in our dropping 822 completed deals and 128 withdrawn bids. Finally, we require that for each matched complete

[23] Seru (2010) exploits a sample of withdrawn bids to examine whether and how conglomerate mergers stifle innovation, and Bena and Li (2014) examine whether and how technological overlap affects post-merger innovation output. Relatedly, Bernstein (2015) employs a sample of withdrawn IPOs to investigate whether and how going public affects innovation.

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

deal/withdrawn bid, the acquirer and target have at least two valid observations of the four measures of trademark characteristics, both in the five-year window before the bid announcement and in the five-year window after deal completion/withdrawal. This requirement results in our dropping 235 completed deals and 6 withdrawn bids. Table 12 Panel A summarizes our sample formation steps. In the end, we have 94 unique withdrawn bids and 638 completed deals, and a sample of 638 pairs of completed deals and withdrawn bids.

Table IA4 presents the results for testing the pre-trend assumption. Before$^{4|5}$ (Before$^{2|3}$) is an indicator variable that takes the value of one when the year is in the fourth or fifth (second or third) year prior to the bid announcement, and zero otherwise. The indicators After$^{4|5}$ and After$^{2|3}$ are defined analogously. We show that before the bid announcement, there is either a common trend or an absence of significant differences in the three post-merger product market outcome variables, and that after deal completion, there seem to be significant differences between the treatment and control groups.

Table 12 Panel B presents the difference-in-differences estimates of Equation (4) where the dependent variables are acquirer newly registered trademarks, acquirer discontinued trademarks in common classes, and target discontinued trademarks in common classes. We show that the coefficient on the interaction term *After* × *Complete* is negative and significant at the 1% level when the dependent variable is the acquirer's newly registered trademarks, whereas it is positive and significant at the 5% level when the dependent variable is the target's discontinued trademarks in common classes.

Panel C presents the triple differences estimates of Equation (5) with the same three dependent variables. We show that the coefficient on the interaction term *After* × *Complete* × *High product market overlap* is positive and significant at the 5% level when the dependent variable is the target's discontinued trademarks in common classes. This finding suggests that when merging firms' product offerings have significant overlap, acquirers post-merger will discontinue more target trademarks in common classes compared to target firms with less overlapping product lines with their acquirers. These results are consistent with our large sample evidence that (i) acquirers focus on re-organizing product lines rather than developing new products after M&As when acquirers and targets have greater product market overlap, and (ii)

M&As have differential effects on acquirers and targets: Trademarks in common classes are more likely to be discontinued on the targets' side (rather than on the acquirers' side).

In Panel D, we examine the effect of product market overlap on post-merger performance. We find that when acquirers and targets have greater product market overlap, post-merger acquirer ROA is significantly higher at the 5% level. Taken together, our results suggest that the large sample evidence in Tables 9-11 is robust to using withdrawn deals to alleviate endogeneity concerns.

VII. Conclusions

This paper is one of the first to employ novel trademark data to shed light on whether and how M&As change acquirers' new product development and affect acquirers' and target firms' product offerings. Using a large and unique trademark-merger data set 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, whereas acquirers register more new trademarks in new classes. Moreover, acquirers discontinue more acquirers' and targets' trademarks in common classes and classes unique to acquirers, but discontinue fewer trademarks in classes unique to target firms. Finally, acquirers having significant product overlap with their target firms register even fewer trademarks in common classes and discontinue even more of their 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.

References:

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

AIPLA, 2015. *Report of the Economic Survey* 2015.

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

Ashenfelter, Orley, and Daniel Hosken, 2010. The effect of mergers on consumer prices: Evidence from five mergers on the enforcement margin, *Journal of Law and Economics* 53, 417-466.

Bahadir, S. Cem, Sundar G. Bharadwaj, and Rajendra K. Srivastava, 2008. Financial value of brands in mergers and acquisitions: Is value in the eye of the beholder? *Journal of Marketing* 72, 49-64.

Banker, Rajiv D., Hsihui Chang, and Reba Cunningham 2003. The public accounting industry production function, *Journal of Accounting and Economics* 35, 255-281.

Barro, Jason, and David M. Cutler, 2000. Consolidation in the medical care marketplace, a case study from Massachusetts, in: S. N. Kaplan (ed.), *Mergers and Productivity*, Chicago: University of Chicago Press, 9-50.

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

Bereskin, Frederick, Po-Hsuan Hsu, and Wendy Rotenberg, 2017. The real effects of real earnings management: Evidence from innovation, *Contemporary Accounting Research* forthcoming.

Besen, Stanley M., and Leo J. Raskind, 1991. An introduction to the law and economics of intellectual property, *Journal of Economic Perspectives* 5, 3-27.

Bhattacharyya, Sugato, and Amrita Nain, 2011. Horizontal acquisitions and buying power: A product market analysis, *Journal of Financial Economics* 99, 97-115.

Bone, Robert G., 2004. Enforcement costs and trademark puzzles, *Virginia Law Review* 90, 2099-2185.

Capron, Laurence, Will Mitchell, and Anand Swaminathan, 2001. Asset divestiture following horizontal acquisitions: A dynamic view, *Strategic Management Journal* 22, 817-844.

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

Cassiman, Bruno, Massimo G. Colombo, Paola Garrone, and Reinhilde Veugelers, 2005. The impact of M&A on the R&D process: An empirical analysis of the role of technological- and market-relatedness, *Research Policy* 34, 195-220.

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

Chen, Chen, Yangyang Chen, Po-Hsuan Hsu, and Edward J. Podolski, 2016. Be nice to your innovators: Employee treatment and corporate innovation performance, *Journal of Corporate Finance* 39, 78-98.

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

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

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

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

Faurel, Lucile, Qin Li, Devin M. Shanthikumar, and Siew Hong Teoh, 2017. CEO incentives and product development innovation: Insights from trademarks, Arizona State University working paper.

Fee, C. Edward, and Shawn Thomas 2004. Sources of gains in horizontal mergers: Evidence from customer, supplier, and rival firms, *Journal of Financial Economics* 74, 423-460.

Focarelli, Dario, and Fabio Panetta, 2003. Are mergers beneficial to consumers? Evidence from the market for bank deposits, *American Economic Review* 93, 1152-1172.

Gao, Huasheng, Po-Hsuan Hsu, and Kai Li, 2018. Innovation strategy of private firms, *Journal of Financial and Quantitative Analysis* 53, 1-32.

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

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

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

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

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

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

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

Healy, Paul, Krishna Palepu, and Richard Ruback, 1992. Does corporate performance improve after mergers? *Journal of Financial Economics* 31, 135-175.

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

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

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

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

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

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

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

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

Hoti, Suhejla, Michael McAleer, and Daniel Slottje, 2006. Intellectual property litigation activity in the USA, *Journal of Economic Surveys* 20, 715-729.

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

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

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

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

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

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

Landes, William M., and Richard A. Posner, 1987. Trademark law: An economic perspective, *Journal of Law and Economics* 30, 265-309.

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

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

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

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

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

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

Millot, Valentine, 2009. Trademarks as an indicator of product and marketing innovations, OECD Science, Technology and Industry Working Papers, 2009/06, OECD Publishing, Paris.

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

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

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

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

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

Ravenscraft, David J., and William F. Long, 2000. Paths to creating value in pharmaceutical mergers, in: S. N. Kaplan (ed.), *Mergers and Productivity*, Chicago: University of Chicago Press, 287-326.

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

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

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

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

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

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

Appendix. Definition of variables

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

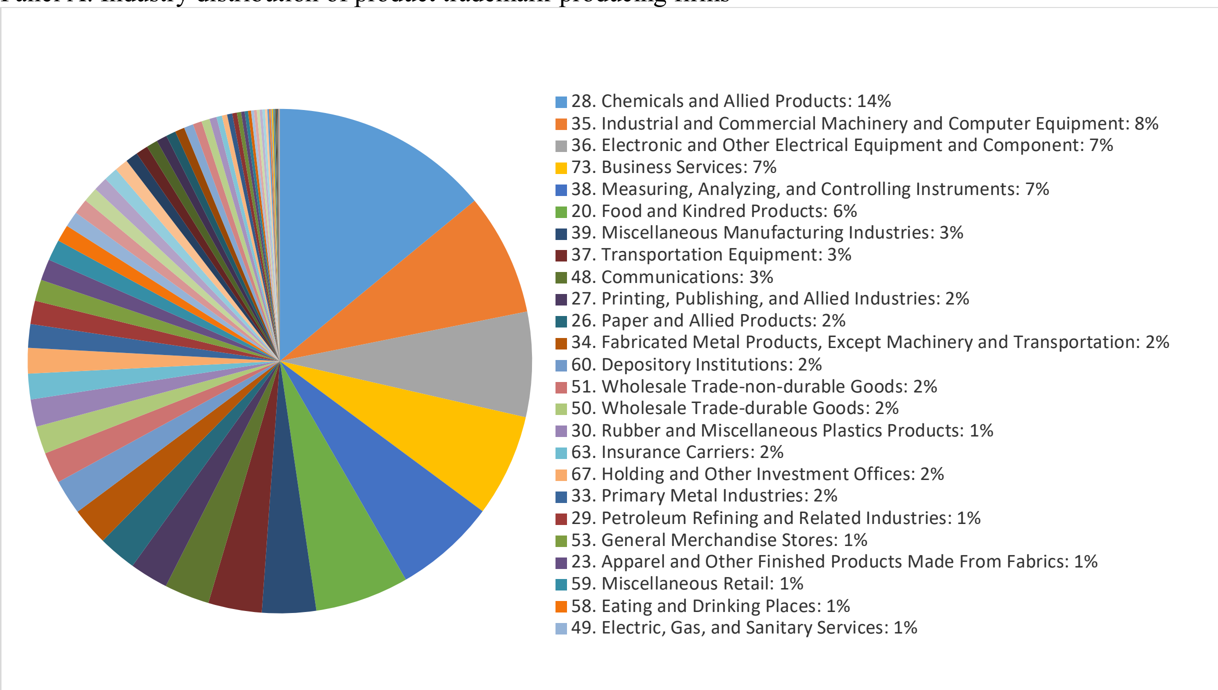
Trademark Measures	
Trademark count	Ln (1 + number of active trademarks).
Trademark age	The average age of all active trademarks in a firm's portfolio. Age for each trademark is calculated as the present year minus the year of its application.
Trademark growth	The growth rate of the number of active 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 $K = 45$.
High product market overlap	An indicator variable that takes the value of one when the product market overlap of a completed deal is above the sample median, and zero otherwise.
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 the bid announcement (month 0) and the analogously defined buy-and-hold stock return on the value-weighted CRSP index.
∆ROA	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 distributions 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 trademark-producing firms. The sample consists of product trademark-producing public firms over the period 1983-2016. Panel B presents the two-digit SIC industry distribution of patent-producing firms. 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

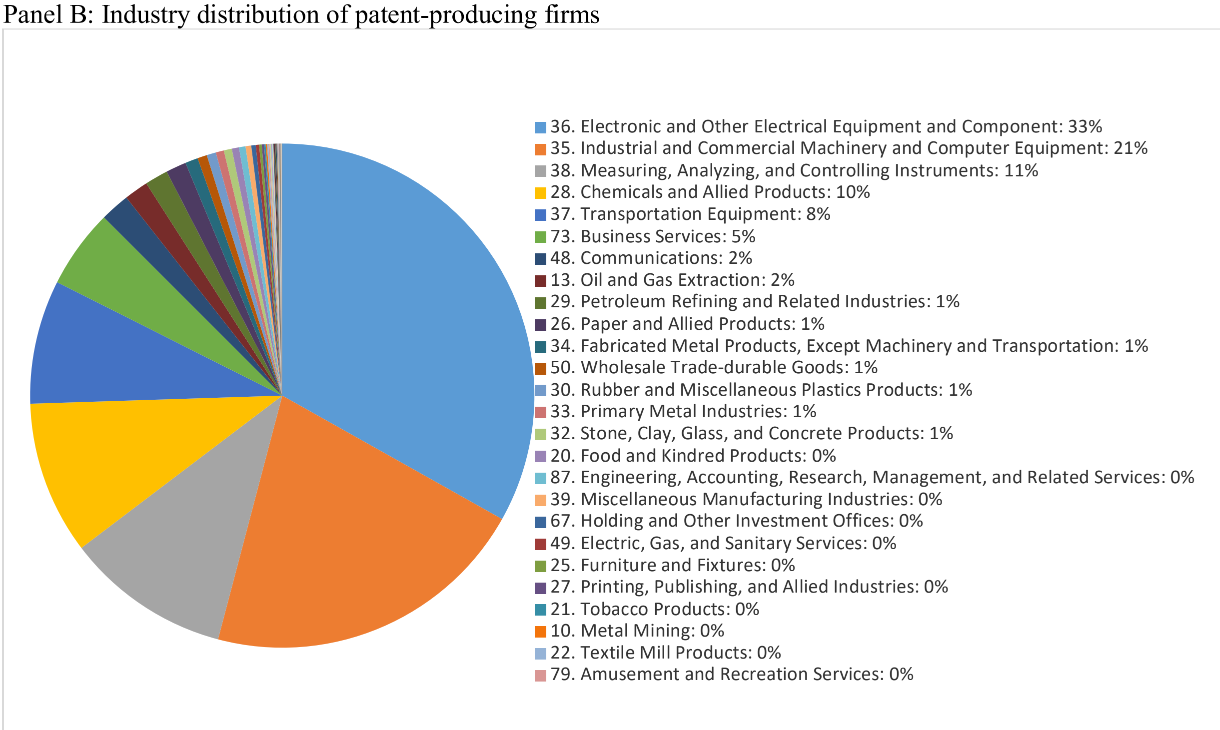


Table 1. Temporal distribution of M&A deals

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). Definitions of the variables are provided in the Appendix. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	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	56.004	93.379	3	21	244	36.179	67.699	2	13	151	19.824 ***	8.000***
Trademark count	3.085	1.369	1.099	3.045	5.497	2.665	1.297	0.693	2.565	5.017	0.421 ***	0.480***
Trademark age	10.891	7.221	3	8.839	25.787	11.501	8.314	2.545	9.000	29.052	-0.610 ***	-0.161***
Trademark growth	0.144	0.341	-0.111	0.031	0.800	0.113	0.327	-0.133	0.000	0.688	0.031 ***	0.031***
Trademark concentration	0.482	0.278	0.156	0.395	1	0.538	0.294	0.156	0.496	1.000	-0.057***	-0.100***
Total assets	3440	7943	42	691	17043	2525	6856	29	425	11867	914***	267***
Firm size	6.606	1.808	3.746	6.538	9.743	6.164	1.808	3.355	6.051	9.382	0.442 ***	0.487***
M/B	3.689	4.289	0.797	2.621	11.212	2.842	3.801	0.414	1.957	8.614	0.848***	0.664***
ROA	0.122	0.113	-0.027	0.125	0.285	0.091	0.139	-0.162	0.107	0.280	0.031***	0.018***
Leverage	0.220	0.203	0	0.186	0.605	0.214	0.211	0.000	0.168	0.627	0.007***	0.019 ***
Cash	0.168	0.190	0.005	0.086	0.594	0.189	0.209	0.005	0.101	0.657	-0.021***	-0.015***
Sales growth	0.555	1.443	-0.140	0.174	2.308	0.198	0.719	-0.252	0.080	0.793	0.357***	0.094***
Prior-year stock return	0.305	0.738	-0.457	0.121	1.701	0.047	0.604	-0.684	-0.044	1.086	0.259***	0.166***

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). Definitions of the variables are provided in the Appendix. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Acquirers					Industry- and size-matched controls					Test of differences	
	Mean	SD	5^{th} Percentile	Median	95^{th} Percentile	Mean	SD	5^{th} Percentile	Median	95^{th} Percentile	T-test	Wilcoxon test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(1) - (6)	(4) - (9)
Number of trademarks	26.245	53.938	1	10	104	31.360	72.376	1	11	124	-5.115***	-1.000***
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	10.814	7.687	2.750	8.333	27.000	11.079	7.681	3.000	8.846	27.389	-0.265**	-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	2942	23656	17	258	9275	3169	28566	18	276	9817	-226.819	-18.150
Firm size	5.717	1.876	2.870	5.555	9.135	5.773	1.886	2.925	5.623	9.192	-0.057	-0.068
M/B	2.495	3.341	0.435	1.737	7.405	2.753	3.624	0.460	1.865	8.500	-0.258***	-0.128***
ROA	0.074	0.166	-0.239	0.103	0.260	0.081	0.162	-0.221	0.104	0.278	-0.007**	-0.001**
Leverage	0.214	0.207	0.000	0.171	0.616	0.206	0.205	0.000	0.159	0.604	0.007*	0.012**
Cash	0.179	0.203	0.004	0.098	0.638	0.186	0.207	0.005	0.099	0.646	-0.007*	-0.001**
Sales growth	0.146	0.409	-0.262	0.077	0.728	0.179	0.451	-0.254	0.093	0.822	-0.032***	-0.016***
Prior-year stock return	-0.046	0.521	-0.723	-0.116	0.847	0.012	0.556	-0.691	-0.069	1.024	-0.057***	-0.047***

Table 4. Who will become acquirers?

This table 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. Definitions of the variables are provided in the Appendix. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	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	81,712	80,944	106,918	107,119
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

Table 5. Who will become targets?

This table 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. Definitions of the variables are provided in the Appendix. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	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	24,005	23,350	104,971	105,150
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

Table 6. Summary statistics for the acquirer-target pair 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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(1) - (6)	(4) - (9)
	Acquirers					Acquirer controls					Test of differences	
Number of trademarks	124.834	168.268	4	50	565	54.878	99.024	2	18	235	69.956***	32***
Trademark count	3.907	1.469	1.386	3.912	6.337	3.003	1.400	0.693	2.890	5.460	0.904***	1.022
Trademark age	12.291	7.528	4.000	9.927	27.333	11.980	8.094	3.000	9.500	28.662	0.311	0.427*
Trademark growth	0.122	0.271	-0.093	0.040	0.600	0.107	0.295	-0.111	0.000	0.667	0.015**	0.040***
Trademark concentration	0.443	0.260	0.133	0.370	1.000	0.517	0.286	0.143	0.456	1.000	-0.074***	-0.086***
Total assets	12260	24050	80	2637	70561	6820	17082	43	885	39189	5441***	1752***
Firm size	7.818	2.001	4.379	7.877	11.164	6.933	2.023	3.764	6.786	10.576	0.885***	1.091***
M/B	3.472	3.493	0.919	2.510	9.645	2.830	3.440	0.444	2.032	8.363	0.643*	0.479***
ROA	0.128	0.106	0.001	0.133	0.282	0.099	0.123	-0.114	0.109	0.272	0.030***	0.024***
Leverage	0.201	0.167	0.000	0.178	0.518	0.219	0.199	0.000	0.185	0.609	-0.018***	-0.008***
Cash	0.160	0.178	0.006	0.088	0.565	0.182	0.200	0.006	0.100	0.637	-0.022***	-0.012***
Sales growth	0.218	0.421	-0.162	0.113	0.901	0.163	0.438	-0.220	0.079	0.749	0.055***	0.034***
Prior-year stock return	0.120	0.482	-0.458	0.030	1.023	0.012	0.508	-0.652	-0.048	0.914	0.108***	0.078***
	Targets					Target controls					Test of differences	
Number of trademarks	29.157	50.530	2.000	12.000	121.000	35.457	61.320	2.000	13.000	153.000	-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***
Trademark age	10.456	7.527	2.500	8.196	26.698	11.066	7.609	3.000	8.800	27.358	-0.610***	-0.604***
Trademark growth	0.129	0.360	-0.133	0.000	1.000	0.121	0.320	-0.116	0.000	0.714	0.008	0.000**
Trademark concentration	0.586	0.300	0.175	0.531	1.000	0.552	0.292	0.160	0.500	1.000	0.034***	0.031***
Total assets	2928	8759	21	336	13950	3106	9090	22	348	16262	-178	-12

Firm size	5.997	1.942	3.067	5.818	9.543	6.033	1.963	3.096	5.851	9.697	-0.036	-0.034
M/B	2.840	3.633	0.599	1.997	8.398	2.854	3.838	0.503	1.936	8.448	-0.015	0.061
ROA	0.078	0.158	-0.246	0.105	0.272	0.083	0.155	-0.204	0.104	0.275	-0.004	0.001
Leverage	0.197	0.196	0.000	0.151	0.574	0.200	0.199	0.000	0.152	0.586	-0.003	0.000
Cash	0.196	0.213	0.004	0.112	0.668	0.192	0.211	0.005	0.102	0.654	0.004	0.011
Sales growth	0.169	0.401	-0.216	0.090	0.810	0.182	0.445	-0.235	0.096	0.804	-0.012	-0.006
Prior-year stock return	-0.036	0.509	-0.703	-0.105	0.851	0.021	0.552	-0.674	-0.059	1.016	-0.057***	-0.046***
	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	0.658	0.999	0.176***	0.217***
Patent similarity	0.366	0.330	0	0.285	0.942	0.176	0.278	0	0.028	0.894	0.190***	0.257***
HP similarity	0.058	0.096	0	0.030	0.188	0.019	0.042	0	0	0.116	0.040***	0.030***
Same industry	0.683	0.465	0	1	1	0.688	0.463	0	1	1	-0.004	0.000

Panel B: Correlation matrix

	Product market overlap	Patent similarity	HP similarity	Same industry
Product market overlap	1			
Patent similarity	0.340***	1		
HP similarity	0.246***	0.316***	1	
Same industry	0.364***	0.259***	0.199***	1

Table 7. Acquirer-target pairing

This table 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. 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.

	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 controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Target controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,598	2,679	6,150	1,946	8,176	2,233	5,867	1,672
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

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 the 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 difference-in-differences (DD) 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 of acquirer product market outcome

	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 acquirer product market outcome: DD

	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)
Intercept	0.636***	1.037***	0.882***	0.142***
	(0.066)	(0.309)	(0.093)	(0.018)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	20,467	20,463	20,464	20,467
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 the 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: DD

	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)
Other controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	18,002	18,002	18,002	18,002	18,002

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)
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)
Other controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	18,002	18,002	18,002	18,002	18,002
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 the 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: DD

	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)
Other controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	16,284	16,284	16,284
Adjusted R-squared	0.755	0.558	0.589

Panel D: Post-merger target discontinued trademarks: DD

	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)
Other controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	21,524	21,524	21,524
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)
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)
Other controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	16,284	16,284	16,284
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)
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)
Other controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	21,524	21,524	21,524
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 the 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 of acquirer performance

	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 acquirer performance: DD

	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	17,439	17,545	17,603	17,611	17,550
Adjusted R-squared	0.015	0.036	0.241	0.863	0.126

Panel C: Product market overlap and post-merger acquirer 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	17,439	17,545	17,603	17,611	17,550
Adjusted R-squared	0.015	0.037	0.240	0.864	0.126

Table 12. Product market overlap and post-merger outcomes: identification test

This table compares product market outcome and firm performance from before to after deal completion using a sample of withdrawn bids as control firms. For each deal, we track acquirers and their control firms from five years before the bid announcement to five years after deal completion/withdrawal. Panel A lists steps taken to form the treatment and control samples. Panel B presents the difference-in-differences (DD) regression results for acquirer newly registered trademarks, and acquirer and target discontinued trademarks in common classes using a sample of completed deals and a sample of withdrawn bids as the control. Panel C presents the triple differences (DDD) regression results for the same dependent variables as in Panel B. Panel D presents the triple differences (DDD) regression results for measures of acquirer performance. 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: Sample formation

Steps	# Completed deals	# Withdrawn bids
Completed deals per Section III B.2; withdrawn bids announced between 1983 and 2010	1,695	850
Withdrawn bids due to competing bids, regulatory objections, or adverse market conditions.	1,695	246
For each completed deal, there exists at least one withdrawn bids with the same acquirer and target industry affiliations (at the two-digit SIC level).	-822	-128
Acquirers of withdrawn bids have at least one newly registered trademark before deal announcement.	0	-18
Acquirer of a matched completed deal (by acquirer size) and acquirer of a withdrawn bid both have at least two valid observations before the deal announcement and after the deal completion (withdrawal).	-235	-6
Final matched sample	638	94

Panel B: Newly registered trademarks and discontinued trademarks: DD

Variables	Acquirer newly registered trademarks	Acquirer discontinued trademarks in common classes	Target discontinued trademarks in common classes
After	0.210***	-0.157***	-0.087**
	(0.033)	(0.028)	(0.035)
Complete	0.085*	-0.042	-0.048
	(0.046)	(0.039)	(0.033)
After × Complete	-0.118***	0.042	0.066**
	(0.040)	(0.031)	(0.030)
Other controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	9,381	9,381	9,185
Adjusted R-squared	0.745	0.770	0.607

Panel C: Product market overlap and newly registered trademarks and discontinued trademarks: DDD

Variables	Acquirer newly registered trademarks	Acquirer discontinued trademarks in common classes	Target discontinued trademarks in common classes

After	0.202***	-0.175***	-0.060
	(0.042)	(0.033)	(0.042)
Complete	0.023	-0.079	0.017
	(0.051)	(0.049)	(0.031)
After × Complete	-0.049	-0.005	-0.002
	(0.053)	(0.043)	(0.040)
High product market overlap	-0.021	-0.006	0.025
	(0.026)	(0.015)	(0.019)
After × High product market overlap	0.006	0.034	-0.042
	(0.051)	(0.035)	(0.042)
Complete × High product market overlap	0.114**	0.102*	-0.194**
	(0.054)	(0.056)	(0.092)
After × Complete × High product market overlap	-0.122*	0.096*	0.125**
	(0.072)	(0.058)	(0.059)
Other controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	9,381	9,381	9,185
Adjusted R-squared	0.745	0.771	0.602

Panel D: Product market overlap and post-merger acquirer performance: DDD

Variables	ΔROA	ΔROS	Sales growth	Market share	BHR
After	-0.002	-0.004	0.007	-0.001	-0.129***
	(0.004)	(0.004)	(0.011)	(0.001)	(0.020)
Complete	0.010**	0.008**	-0.011	0.000	-0.035*
	(0.004)	(0.004)	(0.026)	(0.001)	(0.019)
After × Complete	-0.004	-0.008**	0.007	0.002**	0.064**
	(0.004)	(0.004)	(0.017)	(0.001)	(0.027)
High product market overlap	0.003	0.002	-0.003	-0.000	0.016
	(0.002)	(0.002)	(0.007)	(0.000)	(0.012)
After × High product market overlap	-0.005	-0.004	-0.010	-0.000	-0.026
	(0.005)	(0.005)	(0.014)	(0.001)	(0.024)
Complete × High product market overlap	-0.006*	-0.004	0.008	-0.002*	0.022
	(0.003)	(0.003)	(0.020)	(0.001)	(0.025)
After × Complete × High product market overlap	0.010**	0.009*	-0.004	0.001	-0.024
	(0.005)	(0.005)	(0.023)	(0.001)	(0.039)
Other controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	9,222	9,219	9,317	9,382	8,912
Adjusted R-squared	0.052	0.068	0.307	0.933	0.146

Internet Appendix for

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

Appendix IA1: Nice classification[25]

GOODS

Class 1 (Chemicals) Chemicals for use in industry, science and photography, as well as in agriculture, horticulture and forestry; unprocessed artificial resins, unprocessed plastics; fire extinguishing and fire prevention compositions; tempering and soldering preparations; substances for tanning animal skins and hides; adhesives for use in industry; putties and other paste fillers; compost, manures, fertilizers; biological preparations for use in industry and science.

Class 2 (Paints) Paints, varnishes, lacquers; preservatives against rust and against deterioration of wood; colorants, dyes; inks for printing, marking and engraving; raw natural resins; metals in foil and powder form for use in painting, decorating, printing and art.

Class 3 (Cosmetics and cleaning preparations) Non-medicated cosmetics and toiletry preparations; non-medicated dentifrices; perfumery, essential oils; bleaching preparations and other substances for laundry use; cleaning, polishing, scouring and abrasive preparations.

Class 4 (Lubricants and fuels) Industrial oils and greases, wax; lubricants; dust absorbing, wetting and binding compositions; fuels and illuminants; candles and wicks for lighting.

Class 5 (Pharmaceuticals) Pharmaceuticals, medical and veterinary preparations; sanitary preparations for medical purposes; dietetic food and substances adapted for medical or veterinary use, food for babies; dietary supplements for humans and animals; plasters, materials for dressings; material for stopping teeth, dental wax; disinfectants; preparations for destroying vermin; fungicides, herbicides.

Class 6 (Metal goods) Common metals and their alloys, ores; metal materials for building and construction; transportable buildings of metal; non-electric cables and wires of common metal; small items of metal hardware; metal containers for storage or transport; safes.

Class 7 (Machinery) Machines, machine tools, power-operated tools; motors and engines, except for land vehicles; machine coupling and transmission components, except for land vehicles; agricultural implements, other than hand-operated hand tools; incubators for eggs; automatic vending machines.

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

Class 9 (Electrical and scientific apparatus) 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; compact discs, DVDs and other digital recording media;

[25] Our description of the Nice Classifications is from two sources. The detailed class information is obtained from "International Classification of Goods and Services for the Purposes of the Registration of Marks (Nice Classification)" (11th Edition, 2018), by World Intellectual Property Organization, Geneva. (http://www.wipo.int/classifications/nice/nclpub/en/fr/). The class headings are obtained from https://www.oppedahl.com/trademarks/tmclasses.htm.

mechanisms for coin-operated apparatus; cash registers, calculating machines, data processing equipment, computers; computer software; fire-extinguishing apparatus.

Class 10 (Medical Apparatus) Surgical, medical, dental and veterinary apparatus and instruments; artificial limbs, eyes and teeth; orthopaedic articles; suture materials; therapeutic and assistive devices adapted for the disabled; massage apparatus; apparatus, devices and articles for nursing infants; sexual activity apparatus, devices and articles.

Class 11 (Environmental control apparatus) Apparatus for lighting, heating, steam generating, cooking, refrigerating, drying, ventilating, water supply and sanitary purposes.

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

Class 13 (Firearms) Firearms; ammunition and projectiles; explosives; fireworks.

Class 14 (Jewelry) Precious metals and their alloys; jewellery, precious and semi-precious stones; horological and chronometric instruments.

Class 15 (Musical instruments) Musical instruments

Class 16 (Paper goods and printed matter) Paper and cardboard; printed matter; bookbinding material; photographs; stationery and office requisites, except furniture; adhesives for stationery or household purposes; drawing materials and materials for artists; paintbrushes; instructional and teaching materials; plastic sheets, films and bags for wrapping and packaging; printers' type, printing blocks.

Class 17 (Rubber goods) Unprocessed and semi-processed rubber, gutta-percha, gum, asbestos, mica and substitutes for all these materials; plastics and resins in extruded form for use in manufacture; packing, stopping and insulating materials; flexible pipes, tubes and hoses, not of metal.

Class 18 (Leather goods) Leather and imitations of leather; animal skins and hides; luggage and carrying bags; umbrellas and parasols; walking sticks; whips, harness and saddlery; collars, leashes and clothing for animals.

Class 19 (Nonmetallic building materials) 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 and articles not otherwise classified) Furniture, mirrors, picture frames; containers, not of metal, for storage or transport; unworked or semi-worked bone, horn, whalebone or mother-of-pearl; shells; meerschaum; yellow amber.

Class 21 (Housewares and glass) Household or kitchen utensils and containers; cookware and tableware, except forks, knives and spoons; combs and sponges; brushes, except paintbrushes; brush-making materials; articles for cleaning purposes; unworked or semi-worked glass, except building glass; glassware, porcelain and earthenware.

Class 22 (Cordage and fibers) Ropes and string; nets; tents and tarpaulins; awnings of textile or synthetic materials; sails; sacks for the transport and storage of materials in bulk; padding, cushioning and stuffing materials, except of paper, cardboard, rubber or plastics; raw fibrous textile materials and substitutes therefor.

Class 23 (Yarns and threads) Yarns and threads, for textile use.

Class 24 (Fabrics) Textiles and substitutes for textiles; household linen; curtains of textile or plastic.

Class 25 (Clothing) Clothing, footwear, headgear

Class 26 (Fancy goods) Lace and embroidery, ribbons and braid; buttons, hooks and eyes, pins and needles; artificial flowers; hair decorations; false hair.

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

Class 28 (Toys and sporting goods) Games, toys and playthings; video game apparatus; gymnastic and sporting articles; decorations for Christmas trees.

Class 29 (Meats and processed foods) Meat, fish, poultry and game; meat extracts; preserved, frozen, dried and cooked fruits and vegetables; jellies, jams, compotes; eggs; milk and milk products; oils and fats for food.

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

Class 31 (Natural agricultural products) Raw and unprocessed agricultural, aquacultural, horticultural and forestry products; raw and unprocessed grains and seeds; fresh fruits and vegetables, fresh herbs; natural plants and flowers; bulbs, seedlings and seeds for planting; live animals; foodstuffs and beverages for animals; malt.

Class 32 (Light beverages) Beers; mineral and aerated waters and other non-alcoholic beverages; fruit beverages and fruit juices; syrups and other preparations for making beverages.

Class 33 (Wine and spirits) Alcoholic beverages (except beers).

Class 34 (Smokers' articles) Tobacco; smokers' articles; matches

SERVICES

Class 35 (Advertising and business) Advertising; business management; business administration; office functions.

Class 36 (Insurance and financial) Insurance; financial affairs; monetary affairs; real estate affairs.

Class 37 (Building construction and repair) Building construction; repair; installation services.

Class 38 (Telecommunications) Telecommunications

Class 39 (Transportation and storage) Transport; packaging and storage of goods; travel arrangement.

Class 40 (Treatment of materials) Treatment of materials

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

Class 42 (Computer, scientific & legal) Scientific and technological services and research and design relating thereto; industrial analysis and research services; design and development of computer hardware and software.

Class 43 (Hotels and Restaurants) Services for providing food and drink; temporary accommodation.

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

Class 45 (Personal) Legal services; security services for the physical protection of tangible property and individuals; personal and social services rendered by others to meet the needs of individuals.

Appendix IA2. 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 data set.

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’)	

Table IA1. Correlation matrix

This table presents the correlation matrix. Panel A presents the correlation matrix of acquirer characteristics using the sample in Table 2. Panel B presents the correlation matrix of target characteristics using the sample in Table 3.

Panel A: Correlation matrix of acquirer characteristics

	Trademark count	Trademark age	Trademark growth	Trademark concentration	Firm size	M/B	ROA	Leverage	Cash	Sales growth	Prior-year stock return
Trademark count	1										
Trademark age	0.334***	1									
Trademark growth	-0.060***	-0.278***	1								
Trademark concentration	-0.525***	-0.239***	-0.005	1							
Firm size	0.427***	0.164***	-0.047***	-0.229***	1						
M/B	0.032***	-0.102***	0.073***	0.021***	-0.026***	1					
ROA	0.226***	0.152***	-0.064***	-0.127***	0.161***	0.079***	1				
Leverage	0.031***	0.109***	-0.054***	-0.131***	0.176***	-0.094***	-0.005	1			
Cash	-0.140***	-0.257***	0.111***	0.170***	-0.276***	0.226***	-0.256***	-0.399***	1		
Sales growth	-0.099***	-0.125***	0.090***	0.004	-0.036***	0.207***	-0.110***	0.050***	0.102***	1	
Prior-year stock return	0.009***	-0.050***	0.034***	-0.013***	-0.007**	0.245***	0.093***	-0.032***	0.086***	0.180***	1

Panel B: Correlation matrix of target characteristics

	Trademark count	Trademark age	Trademark growth	Trademark concentration	Firm size	M/B	ROA	Leverage	Cash	Sales growth	Prior-year stock return
Trademark count	1										
Trademark age	0.320***	1									
Trademark growth	-0.036***	-0.269***	1								
Trademark concentration	-0.547***	-0.213***	-0.007	1							
Firm size	0.376***	0.135***	-0.039***	-0.204***	1						
M/B	0.046***	-0.082***	0.046***	-0.029***	-0.030***	1					
ROA	0.203***	0.175***	-0.048***	-0.155***	0.219***	0.022***	1				
Leverage	0.052***	0.101***	-0.025***	-0.109***	0.184***	-0.046***	0.033***	1			
Cash	-0.102***	-0.217***	0.065***	0.119***	-0.269***	0.204***	-0.321***	-0.390***	1		
Sales growth	-0.099***	-0.126***	0.09***	0.045***	-0.050***	0.197***	-0.005	0.010	0.109***	1	
Prior-year stock return	0.032***	-0.006	-0.008	-0.023***	0.040***	0.170***	0.146***	-0.050***	0.043***	0.081***	1

Table IA2. 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 IA3. 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 the 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	8,839	8,839	8,839	8,839	8,839
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	12,762	12,762	12,762	12,762	12,762
Adjusted R-squared	0.703	0.559	0.608	0.216	0.191

Table IA4. Product market overlap and post-merger outcomes: test of pre-trend assumption

This table reports the results that test the pre-trend assumption for the analysis of newly registered trademarks and discontinued trademarks in common classes from before to after deal completion, using withdrawn deals as the control sample in Table 12. For each deal, we track acquirer performance from five years before the bid announcement to five years after deal completion/withdrawal. 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.

Variables	Acquirer newly registered trademarks	Acquirer discontinued trademarks in common classes	Target discontinued trademarks in common classes
$Before^{4\|5}$	-0.134***	-0.004	-0.084*
	(0.037)	(0.033)	(0.047)
Complete × $Before^{4\|5}$	-0.026	0.060	0.037
	(0.045)	(0.040)	(0.041)
$Before^{2\|3}$	-0.149***	-0.036	-0.024
	(0.031)	(0.025)	(0.027)
Complete × $Before^{2\|3}$	0.017	0.064*	0.022
	(0.040)	(0.033)	(0.029)
$Post^{2\|3}$	0.162***	-0.190***	-0.028
	(0.037)	(0.026)	(0.037)
Complete × $Post^{2\|3}$	-0.241***	0.090***	0.118***
	(0.049)	(0.034)	(0.039)
$Post^{4\|5}$	0.083	-0.134***	0.073
	(0.051)	(0.037)	(0.058)
Complete × $Post^{4\|5}$	-0.130**	-0.005	0.077*
	(0.058)	(0.044)	(0.040)
Complete	0.099*	-0.068	-0.049
	(0.053)	(0.043)	(0.038)
Trademark count	0.194***	0.512***	0.418***
	(0.030)	(0.028)	(0.027)
Trademark age	-0.036***	0.046***	0.008**
	(0.006)	(0.005)	(0.004)
Trademark growth	0.174***	-0.173***	-0.140***
	(0.033)	(0.023)	(0.020)
Trademark concentration	0.020	0.550***	0.243***
	(0.111)	(0.090)	(0.063)
Intercept	0.896***	-2.856***	-0.809***
	(0.269)	(0.370)	(0.209)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	9,381	9,381	9,185
Adjusted R-squared	0.746	0.772	0.608