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Consolidating Product Lines via Mergers and Acquisitions: Evidence From the USPTO Trademark Data

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Abstract

Using a new trademark-based product market competition measure and a novel trademark-merger data set over the period 1983–2016, we show that companies facing greater product market competition are more likely to be acquirers. We further show that postmerger, compared to their nonacquiring peers, acquirers consolidate their product offerings by discontinuing more existing product lines and developing fewer new product lines. Using a quasi-experiment based on bids withdrawn due to exogenous reasons helps us establish the causal effect of deal completion on product-market consolidation. We conclude that acquisitions create product market synergies by cutting overlapping product offerings to achieve cost efficiency.

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I. Introduction

An important question in the mergers and acquisitions (M&As) literature is how product market synergies are achieved. In a pioneering study, Hoberg and Phillips (2010) analyze product descriptions in annual reports and find that post-merger, increased product differentiation by acquirers vs. their rivals and new product development are accompanied by increases in operating performance. Relatedly, using a sample of consumer goods sold by firms involved in M&As, Sheen (2014) shows that 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 papers shed light on how profits increase postmerger, they are silent regarding how changes in the product landscape trigger a deal, and whether and how the product offerings of acquirers and target firms change postmerger. Using novel and comprehensive trademark data, this article fills a void in the literature by addressing why mergers take place and how they shape the product space of the combined firm to achieve synergies.

A trademark is any word, name, symbol, device, or any combination thereof that identifies and distinguishes the source of the goods or services of one party from those of others.[1] For example, the word “iPad” is a trademark for tablet computer devices produced by Apple, and the words “Big Mac” are a trademark for a particular type of hamburgers sold by McDonald’s. Despite their prevalence and importance in the economic activities of firms (see, e.g., Hall, Helmers, Rogers, and Sena (2014)), there is limited large-sample evidence on trademarks in economics and finance, in large part due to a lack of comprehensive data on trademarks before 2013 (Graham, Hancock, Marco, and Myers (2013)).[2] To investigate product market synergies in M&As, we compile an economy-wide trademark-merger data set, and develop a set of trademark-based measures that capture firm-level product market characteristics such as competition and new product development.

Our new firm-level measure for product market competition makes use of trademark class-level information on active trademarks within the economy, and of granular information on a firm’s own trademark portfolio.[3] Our measure is constructed as a weighted exposure of a firm’s product offerings to competition from providers of similar products in the same trademark class. As a result, our measure captures competition from all existing players offering similar products and is more comprehensive and timely than conventional measures based on industry affiliations or annual report disclosures.

Using a sample of close to 15,000 deals announced between the period 1983–2016, we first show that companies facing greater product market competition are more likely to make acquisitions. We further show that the explanatory power of our

[1]This definition is from the United States Patent and Trademark Office (USPTO) website at https://www.uspto.gov/trademarks-getting-started/trademark-basics.

[2]Two notable exceptions are Faurel, Li, Shanthikumar, and Teoh (2020) and Heath and Mace (2020). The former studies the value of trademarks and how firms motivate trademark innovation; the latter examines the effects of trademark protection on firms’ profits and strategies.

[3]Compared to other data sources (discussed in detail in Section III), our trademark data offer a far more granular depiction of firms’ products/services, including coverage of both small and major new product lines for almost all product/service categories.

trademark-based measure remains after we control for competition measures based on the Standard Industrial Classification (SIC) and Hoberg and Phillips' (2010), (2016) Text-based Network Industry Classification (TNIC).

Next, we show that postmerger, compared to their nonacquiring peers, acquirers experience a significant drop in their trademark stock. Moreover, we show that compared to their nonacquiring peers, acquirers achieve better operating and stock performance. Finally, we show that postmerger, acquirers experience higher sales growth and lower cost of goods sold than their nonacquiring peers. These results suggest product market consolidation can achieve both revenue expansion and cost efficiency.

To shed light on how product market synergies take place, we take advantage of the fact that the granular trademark class-level data allow us to track both acquirers' and target firms' trademark deployment after deal completion. We first show that postmerger, compared to their nonacquiring peers, acquirers discontinue more acquirers' and target firms' trademarks in common classes (i.e., classes in which both acquirers and their target firms have trademarks premerger, suggesting that M&As provide opportunities for acquirers to restructure their product offerings by reducing overlapping product lines). Acquirers also discontinue more trademarks in classes unique to themselves, but such cuts are smaller than those in classes common to acquirers and their target firms. Moreover, we show that postmerger, acquirers register fewer new trademarks in classes unique to target firms, whereas acquirers register more new trademarks in new classes (i.e., classes in which neither acquirers nor their target firms had any trademarks premerger). The latter finding suggests that synergies from combining merging firms' assets and resources result in new products, M&As' primary impact (consolidation of the combined firm's product offerings) notwithstanding.

To cleanly delineate the treatment effect of a merger on postmerger acquirer product market outcomes, we use a quasi-experiment, involving bids withdrawn due to reasons exogenous to product market outcomes of either the acquirer or the target firm. Following Bena and Li (2014) and Seru (2014), we argue that the assignment of deals into the treatment sample (i.e., completed deals) vs. 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, premerger and postmerger, with those in the control sample. We show that postmerger, compared to their peers with failed bids, acquirers discontinue more existing trademarks and register fewer new trademarks, consistent with our main findings using a matched control sample.

We conclude that firms facing greater product market competition are more likely to make acquisitions, and product market synergies are achieved via consolidating product offerings of the combined firms to achieve revenue expansion and cost efficiency.

Our paper is related to three strands of the M&A literature: determinants of deal incidence, postmerger product market outcomes, and sources of synergistic gains in acquisitions. In the first strand, prior studies focus on deal financing, agency, regulatory shocks, and technology/market opportunities (e.g., Jensen (1988), Andrade, Mitchell, and Stafford (2001)). In the second strand, prior work provides mixed evidence on mergers' effects on product offerings and business

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reconfiguration.[4] In the third strand, prior work identifies the following motives for acquisitions: to improve efficiency by achieving economies of scale, to eliminate excess capacity and potential competition, and/or to create new opportunities by combining technological know-how and production capabilities.[5]

Our paper differs from prior work and thus contributes to the M&A literature in the following dimensions. First, using a recently available and comprehensive data set on trademarks from the USPTO, we develop a new measure that captures competition from all market players offering similar products, rather than being limited to public firms only, and that is not subject to strategic considerations associated with financial disclosures. Second, by tracking acquirers' and target firms' product lines postmerger, we can address the important questions of whether and how M&As change the product offerings of the combined firm, which has significant implications for economic growth and consumer welfare. Third and finally, we provide new large-sample evidence on the sources of gains in acquisitions from the product market perspective. Our findings suggest that product market synergies come from eliminating duplicate product offerings and achieving revenue growth and cost efficiency.

The article proceeds as follows: In the next section, we develop our hypotheses. We describe the USPTO trademark data set, our empirical methodology, our new measure for product market competition, and our sample formation in Section III. We examine the relation between firms' product market competition and deal incidence in Section IV. In Section V, we explore acquirers' postmerger product market outcomes and operating and stock performance. In Section VI, we address the identification challenge using a quasi-experiment. We conclude in Section VII.

II. Hypothesis Development

A. Product Market Competition and Deal Incidence

Prior literature suggests a number of reasons why product market competition triggers M&As. First, firms acquire product market rivals to ease competitive

[4]Berry and Waldfogel (2001) find that consolidation of radio stations increases programming variety. Fan (2013) shows that ownership consolidation of newspapers leads to lower content quality and variety and higher subscription prices. Hoberg and Phillips (2010) show that mergers between firms with product market similarities achieve larger product range expansions, and higher operating profitability and sales growth. Sheen (2014) shows that when two competitors in a product market merge, their products converge in quality, and prices fall relative to the competition.

[5]While Barro and Cutler (2000) argue that the merger of hospitals does not lead to economies of scale, Banker, Chang, and Cunningham (2003) show that the blending of professional skills and experience resulting from a merger of accounting firms creates new opportunities and generates additional revenues. Jeziorski (2014) shows that consolidation of radio stations leads to cost savings. 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. In a recent study, Cunningham, Ederer, and Ma (2021) show that pharmaceutical firms acquire innovative targets solely to discontinue the latter's innovation projects and preempt future competition. Using a data set that identifies the corporate customers, suppliers, and rivals of those firms initiating horizontal mergers, Fee and Thomas (2004) provide evidence consistent with the idea of improved productive efficiency and buying power serving as sources of gains in horizontal mergers.

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pressure and enhance monopolistic power (Kim and Singal (1993), Mitchell and Mulherin (1996), and Nevo (2000)). Kim and Singal (1993) find that prices increase on routes served by merged airlines relative to a control group of routes unaffected by such mergers. Ashenfelter and Hosken (2010) employ retail scanner data and show that four of the five mergers in their study result in some increases in consumer prices.[6]

Second, intense product market competition amplifies the resource advantage large established firms have via their ability to acquire other firms (Maksimovic and Phillips (2008)). Moreover, such product market competition leaves firms that produce at a loss vulnerable to takeover (Erel, Jang, and Weisbach (2015)).

Third, product market competition forces incumbent firms to seek new technologies and/or markets. Given that in-house innovation takes time and is highly uncertain, firms often choose to acquire other firms as a solution to such uncertainty (Phillips and Zhdanov (2013), Bena and Li (2014), and Chen, Hsu, Officer, and Wang (2020)).

Based on the discussions above, our first hypothesis relating product market competition to deal incidence is as follows:

Hypothesis 1. The likelihood of a firm doing deals increases in proportion to the degree of product market competition it faces.

B. Postmerger Product Market Outcome

Prior literature largely shows major downsizing in product offerings postmerger. Horizontal acquisitions, in particular, are driven by economies of scale and/or the elimination of overlapping facilities (Ravenscraft and Long (2000), Banker et al. (2003), and Fee and Thomas (2004)), resulting in some product pruning. Moreover, M&As give acquirer management the opportunity to reduce inefficient operations, eliminate redundant product lines, and consolidate overlapping product lines (with their target firms) to save on costs. Relatedly, given that M&As consume acquirer management's attention during the negotiation and postmerger integration, management teams may not be able to sustain the same number of product lines, resulting in the discontinuation of some lines. The discussion above leads to our second hypothesis, which connects deal completion to trimming the combined firm's product offerings:

Hypothesis 2. Postmerger, acquirers will discontinue more product lines than their nonacquiring peers.

Prior literature has mixed predictions on new product development postmerger. On the one hand, M&As may result in fewer new product launches for the following reasons. First, as managers focus on postmerger reorganization and asset reallocation, they do not have time and energy left for new product development.

[6]On the other hand, 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. This argument is supported by Sheen (2014), who finds that when two competitors in a product market merge, their products converge in quality, and prices fall.

Second, M&As create disruption and may lead to job separation for rank-and-file employees. Thus, employees may be worried about job security due to reorganization and are under high levels of stress from internal competition (Ravenscraft and Long (2000)). Such disruption and stress can result in fewer new product launches. Third, M&As offer acquirers access to target firms' product lines, which reduces the need for developing new product lines, especially if consolidating existing product lines of acquirers and their target firms is a top priority postmerger.

On the other hand, M&As may result in more new product launches because acquiring new knowledge and technology is among the primary reasons for doing a deal (Phillips and Zhdanov (2013), Bena and Li (2014), and Chen et al. (2020)). Moreover, the combination of complementary assets/skills/expertise may accelerate new inventions (Rhodes-Kropf and Robinson (2008), Hoberg and Phillips (2010), and Bena and Li (2014)). Berry and Waldfogel (2001) find that the ownership consolidation of radio stations increases programming variety, and Hoberg and Phillips (2010) show that mergers between firms with product market similarities achieve larger product range expansions. Our third hypothesis on product market outcomes is thus 2-sided:

Hypothesis 3a. Postmerger, acquirers will develop fewer new product lines.

Hypothesis 3b. Postmerger, acquirers will develop more new product lines.

III. Trademark Data, Methodology, and Sample Formation

A. Trademark Data

1. Trademark Basics

When a firm prepares to launch a new product line or service, it will first register a new trademark for marketing that line or service (Gao and Hitt (2012), Flikkema, Castaldi, de Man, and Seip (2019), and Hsu, Li, Li, Teoh, and Tseng (2022)). A trademark is valuable because it offers its owners the exclusive right to use the mark and to build customer loyalty and maintain market power based on the mark (Block, Fisch, Hahn, and Sandner (2015)). A trademark also helps consumers limit search costs and differentiates itself from competitors' products/services (e.g., Landes and Posner (1987), Besen and Raskind (1991)). The prevalence of trademark activities has led Hall et al. (2014) to conclude that trademarking is probably the most widely used form of intellectual property protection, as it is applicable to essentially *any* product or service. For example, Air New Zealand recently launched a new service that features a cabin containing six full-length lie-flat sleep pods for economy-class passengers and filed a trademark, *Economy Skynest*, for the service in Feb. 2020 (https://www.airnewzealand.co.nz/press-release-2020-airnz-to-put-economy-travellers-to-sleep).

To apply for a trademark, the applicant must select the appropriate content of the mark and provide proof of use-in-commerce, such as a specimen, to complete registration.[7] A trademark must be registered within one or multiple classes of goods or services, and the scope of the exclusivity right is only effective within the registered class(es). There are 45 different classes, including 34 goods classes and 11 services classes, for trademark registration purposes according to the International Classification of Goods and Services (and henceforth, the Nice Classification; see Appendix IA1 in the Supplementary Material for the complete list).

After registration, trademarks can periodically be renewed with the USPTO as long as the use-in-commerce requirement is satisfied and the renewal fee is paid. To renew, in the sixth year after initial registration the owner must show evidence of continued use and pay a maintenance fee, or face cancelation. In the tenth year after initial registration, the owner must again show evidence of continued use and pay a renewal fee, or the registration will expire. In every successive tenth year thereafter, the owner is again required to show evidence of continued use, as well as file a renewal application and pay both 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 again in 2010 (Graham et al. (2013)).

Our trademark data provide unique insight into product market dynamics compared to other product data sets used in prior studies, including product descriptions in 10-K's, product announcements from news outlets, retail sales data, and *Consumer Reports* magazine. Compared to product descriptions in 10-K's used in Hoberg and Phillips (2010), our trademark data offer coverage of products for both public and private firms, including both small and major product lines, and are not subject to firms' strategic choices/disclosures in financial reports. Moreover, our trademark data allow researchers to track all new product lines since the 1970s. Compared to retail sales data (such as Nielsen's Retail Scanner data used by Argente, Baslandze, Hanley, and Moreira (2020), and Aparicio, Metzman, and Rigobon (2021)) that often cover sales and prices of customer products, our trademark data cover *all* product/service categories (both industrial and consumer products as well as services). Compared to new product announcements used in Mukherjee, Singh, and Žaldokas (2017) based on media coverage of the launch of new products/services, our trademark data cover not only the creation but also the disappearance of any new product lines. In addition, our trademark data are not subject to biases related to firms' marketing strategies and media coverage preferences. Compared to consumer survey data, our trademark data offer more comprehensive coverage in terms of product/service categories, firms, and new product lines. On the other hand, we acknowledge that our trademark data lack information about the price and quality of a product/service as in Sheen (2014).

[7]The current cost of registering for a trademark is $225 per class of goods/services; the process of trademark registration can take from several months to several years.

[8]Despite total renewal fees of $425, 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)), in 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, median litigation costs are $325,000, $500,000, $720,000, and $1.6 million, respectively.

2. The USPTO Trademark Data

The USPTO Trademark Case Files Data Set is our primary data set; it contains detailed information on 7.9 million trademark registrations issued by the USPTO between Jan. 1870 and Dec. 2015. For each data record, the data set has the following information: key dates (filing, registration, renewal, or cancelation); status (registered, abandoned, renewed, or canceled); trademark class; mark content; and owner information. Appendix IA2 in the Supplementary Material describes our procedure for matching trademark assignees to public firms in the Compustat/CRSP database.

Trademarks fall into two categories: product trademarks and marketing trademarks (Faurel et al. (2020)). Because our study focuses on a company's product lines, we divide its trademarks into product and marketing categories and use only the former in our empirical analysis. Appendix IA3 in the Supplementary Material provides a detailed description of our classification scheme, which largely follows Faurel et al. (2020). According to our classification, slightly over 80% of the trademarks are related to products and are thus classified as product trademarks.

If a trademark is not renewed, our analysis considers it discontinued in the year in which it should have been renewed. Appendix IA4 in the Supplementary Material provides a case study of Microsoft's recent large acquisitions in which a significant fraction of target firms' trademarks were not renewed. This case study highlights the granularity of our data, which allows us to uncover whether and how acquirers' or target firms' premerger product offerings are affected by M&As.

Table 1 provides an overview of product market characteristics for the universe of Compustat/CRSP firms across 12 Fama–French industries over the period 1982–2015. We show that in terms of revenue (in millions) per active trademark, the top three industries are utilities; oil, gas, and coal extraction and products; and finance; the bottom three industries are healthcare, medical equipment, and drugs; business equipment; and consumer durables. We also show that chemicals and allied products are the most active industry in terms of the share of firms owning trademarks, the share of firms filing new trademarks, and the average number of newly registered trademarks, while finance is the least active industry in all the above dimensions. These statistics suggest large cross-industry differences in the importance of trademarks (or the product lines).

To establish the value-relevance of trademarks, we correlate a firm's trademark stock (in all classes or in the top two classes) in year t with its performance over year $t+1$ to $t+6$. Table IA1 in the Supplementary Material presents the results. We show that firms with more active trademarks are associated with significantly higher sales growth and profitability in the next 5 years. This finding confirms our use of trademarks as economically meaningful proxies for product lines.

3. Our Product Market Competition Measure Using Trademarks

The USPTO trademark data set provides trademark class-level information on active, newly registered, and discontinued trademarks within the economy, as well as data on firms' individual trademark portfolios; the combination of both allows us to capture economy-wide product market competition. We first calculate a class-level product market concentration measure as the Herfindahl index of the trademark age-adjusted number of active trademarks of all firms. A firm's

TABLE 1

Overview of Product Market Characteristics Among Public Firms Across 12 Fama–French Industries

Table 1 provides an overview of product market characteristics for the universe of Compustat/CRSP firms across 12 Fama–French industries over the period 1982–2015. The summary statistics of PRODUCT_MARKET_CONCENTRATION and REVENUE_PER_TRADEMARK are based on firms with active trademarks, and the summary statistics of other variables are based on all Compustat/CRSP firms. Definitions of the variables are provided in the Appendix.

	PRODUCT_MARKET_CONCENTRATION					REVENUE_PER_TRADEMARK				
	Mean	Std. Dev.	25th Percentile	Median	75th Percentile	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
Business equipment	0.013	0.015	0.006	0.009	0.015	31.965	87.690	3.844	10.156	26.643
Chemicals and allied products	0.049	0.034	0.024	0.038	0.066	58.270	154.255	3.689	12.472	33.845
Consumer durables	0.031	0.030	0.012	0.022	0.038	48.345	117.058	5.114	14.058	35.765
Consumer nondurables	0.054	0.043	0.026	0.044	0.064	55.763	169.956	4.963	13.676	34.629
Finance	0.022	0.016	0.014	0.020	0.026	139.247	217.695	22.123	64.157	155.815
Healthcare, medical equipment, and drugs	0.036	0.023	0.018	0.035	0.049	26.522	86.237	1.626	5.108	17.531
Manufacturing	0.027	0.025	0.012	0.019	0.032	54.249	129.684	6.528	17.039	46.053
Oil, gas, and coal extraction and products	0.038	0.045	0.009	0.017	0.051	291.382	391.748	24.335	108.257	389.569
Other	0.025	0.029	0.007	0.015	0.031	99.682	199.177	8.817	29.734	94.293
Telephone and television transmission	0.051	0.044	0.016	0.035	0.075	75.762	170.231	9.870	27.933	70.612
Utilities	0.022	0.023	0.008	0.014	0.025	342.931	357.591	96.793	206.411	422.563
Wholesale, retail, and some services	0.026	0.030	0.008	0.016	0.032	121.594	227.821	14.651	41.223	108.907
Total	0.028	0.029	0.009	0.018	0.035	81.940	187.561	5.790	19.355	66.557

	Ratio of Firms Owning Trademarks					Number of Newly Registered Trademarks				
	Mean	Std. Dev.	25th Percentile	Median	75th Percentile	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
Business equipment	0.736	0.441	0.000	1.000	1.000	1.715	5.276	0.000	0.000	1.000
Chemicals and allied products	0.787	0.410	1.000	1.000	1.000	4.999	13.011	0.000	1.000	4.000
Consumer durables	0.761	0.426	1.000	1.000	1.000	2.812	7.766	0.000	0.000	2.000
Consumer nondurables	0.756	0.429	1.000	1.000	1.000	4.200	18.994	0.000	0.000	3.000
Finance	0.230	0.421	0.000	0.000	0.000	0.375	2.225	0.000	0.000	0.000
Healthcare, medical equipment, and drugs	0.697	0.460	0.000	1.000	1.000	1.755	6.574	0.000	0.000	1.000
Manufacturing	0.754	0.430	1.000	1.000	1.000	1.990	5.789	0.000	0.000	2.000
Oil, gas, and coal extraction and products	0.289	0.453	0.000	0.000	1.000	0.546	3.053	0.000	0.000	0.000
Other	0.513	0.500	0.000	1.000	1.000	1.000	4.141	0.000	0.000	0.000
Telephone and television transmission	0.534	0.499	0.000	1.000	1.000	3.184	13.379	0.000	0.000	1.000
Utilities	0.485	0.500	0.000	0.000	1.000	0.659	2.366	0.000	0.000	0.000
Wholesale, retail, and some services	0.704	0.456	0.000	1.000	1.000	1.790	5.345	0.000	0.000	1.000
Total	0.529	0.499	0.000	1.000	1.000	1.433	6.634	0.000	0.000	1.000

	Ratio of Firms Filing a Trademark				
	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
Business equipment	0.376	0.484	0.000	0.000	1.000
Chemicals and allied products	0.515	0.500	0.000	1.000	1.000
Consumer durables	0.441	0.497	0.000	0.000	1.000
Consumer nondurables	0.454	0.498	0.000	0.000	1.000
Finance	0.094	0.292	0.000	0.000	0.000
Healthcare, medical equipment, and drugs	0.340	0.474	0.000	0.000	1.000
Manufacturing	0.369	0.483	0.000	0.000	1.000
Oil, gas, and coal extraction and products	0.099	0.299	0.000	0.000	0.000
Other	0.218	0.413	0.000	0.000	0.000
Telephone and television transmission	0.304	0.460	0.000	0.000	1.000
Utilities	0.180	0.384	0.000	0.000	0.000
Wholesale, retail, and some services	0.337	0.473	0.000	0.000	1.000
Total	0.257	0.437	0.000	0.000	1.000

PRODUCT_MARKET_CONCENTRATION measure is the age-weighted average of the class-level product market concentration measure across the top two classes in the firm's active trademark portfolio. The measure is multiplied by 100. A low value of this measure indicates the greater competitive pressure faced by a firm in its product space.

Our new measure has a number of advantages over conventional measures of product market competition such as the sales-based Herfindahl index. First, our measure captures competition from all market participants offering similar products in the same trademark class, rather than being limited to competition arising only from public firms in the economy; most alternative measures require that market participants be public firms. Second, our measure accounts for the differing levels of importance of a trademark based on its longevity/age (Heath and Mace (2020)). Other alternative product market data do not have such granular information. Finally, our measure is timely and not subject to strategic choices in financial disclosures, because firms have to file trademarks as soon as possible in order to receive legal protection for their new product lines (Landes and Posner (1987), Besen and Raskind (1991)).

Table 1 presents the descriptive statistics for our PRODUCT_MARKET_CONCENTRATION measure across the 12 Fama–French industries. We show that our measure ranges from 0.013 in business equipment to 0.054 in consumer non-durables (with a standard deviation of 0.012 for industry averages). These statistics suggest that competition measured by trademark data indeed varies across industries in a meaningful way.

B. M&A Sample Formation

To form our M&A sample for deal incidence analysis, we begin with all announced and completed U.S. M&A deals with announcement dates between Jan. 1, 1983 and Dec. 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 the 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 constant 1982 dollars); 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 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. These filters yield 14,558 deals with available information on public acquirers.

C. Methodology: Product Market Competition and Deal Incidence

To examine whether the product market competition faced by a firm is associated with it becoming an acquirer, we employ the population of Compustat/CRSP firm-years and estimate the following regression using both the linear probability model (LPM) and logit model:

$$
\begin{aligned}
(1)\quad \mathrm{ACQUIRER}_{i,t} = {} & \alpha + \beta_1 \mathrm{PRODUCT\_MARKET\_CONCENTRATION}_{i,t-1} \\
& + \beta_2 \mathrm{OTHER\_CONCENTRATION\_MEASURES}_{i,t-1} \\
& + \beta_3 \mathrm{FIRM\_CHARACTERISTICS}_{i,t-1} + \mathrm{YEAR\_FE} + e_{i,t}.
\end{aligned}
$$

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The dependent variable, $\text{ACQUIRER}_{i,t}$, takes the value of 1 if firm i is an acquirer in year t, and 0 otherwise. All independent variables are measured as of the fiscal year end before bid announcement. $\text{PRODUCT\_MARKET\_CONCENTRATION}_{i,t\text{-}1}$, an inverse indicator for product market competition, is our new measure of product market concentration. $\text{OTHER\_CONCENTRATION\_MEASURES}_{i,t\text{-}1}$ are two alternative concentration measures: SIC_CONCENTRATION and HP_CONCENTRATION. SIC_CONCENTRATION is the Herfindahl index of sales of all firms in the same 2-digit SIC industry, and HP_CONCENTRATION is the Herfindahl index of sales based on the TNIC industry of Hoberg and Phillips (2016). We include these two common concentration measures to demonstrate that our measure contains information that is distinct and independent from other concentration measures. $\text{FIRM\_CHARACTERISTICS}_{i,t\text{-}1}$ include FIRM_SIZE, market-to-book ratio (M/B), return on assets (ROA), LEVERAGE, CASH, SALES_GROWTH, and PRIOR-YEAR_STOCK _RETURN. Detailed variable definitions are provided in the Appendix. We do not include industry-fixed effects in equation (1) in order to capture the explanatory power of different (industry-level) competition measures for deal incidence. In robustness checks, we also add industry-fixed effects.

D. Methodology: Postmerger Acquirers' and Target Firms' Outcomes

For postmerger analysis, we require that both the acquirer and its target firm be public firms so we can contrast their product offerings before vs. after deal completion. To examine the effect of M&As on postmerger acquirers' and target firms' product market and performance outcomes, we form a sample of Trademark class-, Size-, and M/B-matched control firms that are similar to those of the event firms but do not engage in M&As as follows:[9] For each event firm (i.e., acquirer or target) of a deal announced in year t, we find up to five matching firms, first matched by trademark classes (i.e., we require that control firms' top two trademark classes match those of the event firm), second matched by size, and last matched by M/B ratios, from the Compustat database in year $t-1$ that were neither an acquirer nor a target firm in the 5-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 product lines. We add the M/B ratio to our matching characteristics, because the literature argues that doing so captures growth opportunities (Andrade et al. (2001)), overvaluation (Shleifer and Vishny (2003)), and asset complementarity (Rhodes-Kropf and Robinson (2008)) – all important drivers of M&As.

We next require that control firms were neither an acquirer nor a target firm in the 5-year period after their event firms' deal completion. We pick up to three control firms possessing the TRADEMARK_STOCK (i.e., the natural logarithm of

[9]We thank an anonymous referee for suggesting that we match by primary trademark classes. We use the two classes with the greatest number of trademarks in an acquirer's/target firm's trademark portfolio for matching. For the universe of Compustat/CRSP firms with active trademarks, about 60% of an average firm's trademarks fall within its top class, and over three-quarters of its trademarks fall within its top two classes. The median/average number of unique classes of firm-year observations in our sample is 2/3.78. Using the top two classes of an event firm's trademark portfolio as a matching criterion helps capture the bulk of our sample firms' product lines.

(TRADEMARK_STOCK + 1)) closest to that of the event firm. We further pick the 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 5-year window prior to bid announcement, each event (acquirer or target) and its control firm have at least one trademark registration. In the end, we have 986 completed deals and the same number of control firm-pairs for this analysis.

We run the following difference-in-differences (DiD) regression using a panel data set of the event sample and its control sample from 5 years prior to bid announcement (*ayr-5* to *ayr-1*) to 5 years after deal completion (*cyr + 1* to *cyr* + 5):

$$\begin{aligned}(2)\quad \text{FIRM\_OUTCOME}_{i,t} = {} & \alpha + \beta_1 \text{AFTER}_{i,t} \times \text{TREAT}_i + \beta_2 \text{AFTER}_{i,t} \\ & + \beta_3 \text{PRODUCT\_MARKET\_CHARACTERISTICS}_{i,t-1} \\ & + \beta_4 \text{FIRM\_CHARACTERISTICS}_{i,t-1} \\ & + \text{FIRM\_FE} + \text{YEAR\_FE} + e_{i,t}.\end{aligned}$$

The dependent variable, $\text{FIRM\_OUTCOME}_{i,t}$, is firm *i*'s product market and performance outcomes, such as the number of newly registered trademarks or ROA. $\text{AFTER}_{i,t}$ is an indicator that takes the value of 1 for the postmerger period (*cyr* + 1 to *cyr* + 5), and 0 otherwise. TREAT_i is an indicator variable that takes the value of 1 for the event firm, and 0 otherwise. $\text{PRODUCT\_MARKET\_CHARACTERISTICS}_{i,t\text{-}1}$ are four measures of a firm's product portfolio: PRODUCT_ MARKET_CONCENTRATION, TRADEMARK_STOCK, TRADEMARK_HHI, and AVERAGE_TRADEMARK_AGE (with definitions provided in the Appendix). We include trademark characteristics when the dependent variables are product market outcomes such as new trademark registrations, as Capron, Mitchell, and Swaminathan (2001) and Bahadir, Bharadwaj, and Srivastava (2008) show that acquirer trademark characteristics are directly associated with investment and divestiture decisions postmerger. When we compute any postmerger trademark measures for a focal deal, we exclude trademarks of other target firms purchased by an acquirer *after* the focal deal.[10] We include firm-fixed effects to account for any time-invariant differences across 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 account for any temporal differences in the outcome variable.

IV. Product Market Competition and Deal Incidence

In this section, we implement various multivariate analyses to relate firm product market competition to the likelihood of a firm becoming an acquirer using a sample of Compustat/CRSP firm-years with active trademarks.

[10]When choosing control firms, we require that they not have made any acquisitions in the next 5 years but do not impose the same requirement on event firms (if we were to do so, our sample size would be reduced by 75%). As a result, we may overestimate an acquirer's number of new trademarks postmerger because the acquirer might have purchased other firms in the interim and thus acquired new trademarks. The adjustment above helps address this concern, which we thank an anonymous referee for raising.

Panel A of Table 2 presents the summary statistics for our regression sample. We show that the unconditional likelihood of a Compustat/CRSP firm becoming an acquirer is 15%. Table IA2 in the Supplementary Material presents the correlation matrix of all explanatory variables. We show that the correlation between our trademark-based PRODUCT_MARKET_CONCENTRATION and industry-level SIC_CONCENTRATION is 0.03; between PRODUCT_MARKET_CONCENTRATION and firm-level HP_CONCENTRATION it is 0.08; and between industry-level SIC_CONCENTRATION and firm-level HP_CONCENTRATION it is 0.11, suggesting that all these competition measures contain distinct and independent information.

Panel B of Table 2 presents the coefficient estimates from the LPM in equation (1). We show that across all specifications, the coefficients on PRODUCT_MARKET _CONCENTRATION are negative and significant at the 1% level, suggesting that firms in a more competitive product market space are more likely to become acquirers. In terms of economic significance, based on the specification in column 4, we find that when PRODUCT_MARKET _CONCENTRATION changes from its 25th percentile to its 75th percentile, the likelihood of a firm becoming an acquirer decreases by 1.38%. For comparison, when SIC_CONCENTRATION changes from its 25th percentile to its 75th percentile, the likelihood of a firm becoming an acquirer decreases by 0.60%; when acquirer M/B (ROA) changes from its 25th percentile to its 75th percentile, the likelihood of a firm becoming an acquirer increases by 0.67% (0.31%).

Other findings not directly related to product market characteristics are consistent with prior work in M&As (see, e.g., Maksimovic and Phillips (2001), Bena and Li (2014)). In particular, we show that larger firms and firms with higher M/B, higher ROA, lower leverage, higher cash holdings, faster sales growth, and higher prior-year stock returns are more likely to become acquirers.

Panel C of Table 2 presents the coefficient estimates using the logit model. We find similar results across all specifications. In Table IA3 in the Supplementary Material, we include industry-fixed effects in equation (1) and find that PRODUCT_MARKET_CONCENTRATION remains statistically significant in explaining deal incidence. In addition, HP_CONCENTRATION becomes statistically significant across all specifications.

With our trademark class-level data, we also examine whether firms facing product market competition buy other players in the same core product space or simply leave the space. Table IA4 in the Supplementary Material presents the results. We find that the degree of product market concentration is negatively associated with the level of trademark similarity between an acquirer and its target firm, suggesting that with increasing product market competition, acquirers tend to buy target firms with similar product offerings. This finding is consistent with the main finding of our paper: M&As are triggered by acquirers' intentions to consolidate their own and target firms' product lines to reduce competition.

Overall, we conclude that firms facing greater product market competition are more likely to be involved in merger transactions as acquirers, supporting our Hypothesis 1. We next investigate whether and how M&As change acquirers' product offerings and performance following deal completion.

TABLE 2

Product Market Concentration and Becoming Acquirers

Table 2 examines the relation between product market concentration and the likelihood of a firm becoming an acquirer. The sample consists of M&A deals made by public firms over the period 1983–2016 (corresponding to trademark data and firm characteristics over the period 1982–2015). The dependent variable, ACQUIRER, takes the value of 1 for an acquirer in a given year, and 0 otherwise. Panel A reports the summary statistics for the sample in Panels B and C column 4. Panel B presents the regression results using the linear probability model (LPM). Panel C presents the regression results using the logit model. Definitions of the variables are provided in the Appendix. Robust standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary Statistics

	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
	1	2	3	4	5
ACQUIRER	0.151	0.358	0.000	0.000	0.000
PRODUCT_MARKET_CONCENTRATION	0.020	0.023	0.007	0.013	0.025
SIC_CONCENTRATION	0.060	0.061	0.030	0.040	0.068
HP_CONCENTRATION	0.284	0.275	0.086	0.169	0.386
TOTAL ASSETS	4,104.8	11,547.0	96.0	451.5	2,155.7
FIRM_SIZE	6.184	2.160	4.575	6.115	7.676
M/B	2.900	4.021	1.183	1.970	3.430
ROA	−0.042	0.362	−0.023	0.026	0.069
LEVERAGE	0.209	0.207	0.021	0.163	0.329
CASH	0.189	0.214	0.030	0.100	0.278
SALES_GROWTH	0.163	0.497	−0.026	0.075	0.215
PRIOR_YEAR_STOCK_RETURN	0.046	0.598	−0.304	−0.046	0.239

Panel B. Product Market Concentration and Becoming Acquirers (LPM)

	1	2	3	4
PRODUCT_MARKET_CONCENTRATION	−0.421***	−0.425***	−0.831***	−0.765***
	(0.066)	(0.066)	(0.110)	(0.103)
SIC_CONCENTRATION		−0.123***	−0.159***	−0.157***
		(0.022)	(0.038)	(0.040)
HP_CONCENTRATION			−0.044***	0.001
			(0.008)	(0.008)
FIRM_SIZE				0.022***
				(0.001)
M/B				0.003***
				(0.001)
ROA				0.034***
				(0.006)
LEVERAGE				−0.044***
				(0.012)
CASH				0.044***
				(0.012)
SALES_GROWTH				0.048***
				(0.005)
PRIOR_YEAR_STOCK_RETURN				0.046***
				(0.003)
YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	112,375	112,375	68,868	66,519
Adj. R^2	0.015	0.016	0.010	0.044

Panel C. Product Market Concentration and Becoming Acquirers (Logit)

	1	2	3	4
PRODUCT_MARKET_CONCENTRATION	−4.921***	−5.020***	−8.454***	−7.353***
	(0.878)	(0.887)	(1.326)	(1.233)
SIC_CONCENTRATION		−1.495***	−1.643***	−1.696***
		(0.313)	(0.422)	(0.434)
HP_CONCENTRATION			−0.380***	−0.063
			(0.069)	(0.069)
FIRM_SIZE				0.166***
				(0.010)
M/B				0.024***
				(0.004)
ROA				1.269***
				(0.134)
LEVERAGE				−0.284**
				(0.112)
CASH				0.424***
				(0.102)
SALES_GROWTH				0.369***
				(0.029)
PRIOR_YEAR_STOCK_RETURN				0.299***
				(0.022)
YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	112,375	112,375	68,868	66,519
Pseudo-R^2	0.022	0.023	0.013	0.057

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V. Postmerger Outcomes

To properly examine the effect of M&As on postmerger outcomes, we employ the DiD specification in equation (2) and a control sample (as described in Section III.D) that provides the benchmark of what would have happened had the event firm not been involved in a deal. The panel data set comprises acquirers/target firms and their controls spanning 5 years before bid announcement to 5 years after deal completion.

A. Postmerger Product Market and Performance Outcomes

Panel A of Table 3 reports the summary statistics of product market and performance outcomes. Panel B of Table 3 presents the DiD estimates of equation (2) where the dependent variable is TRADEMARK_STOCK (in natural logarithms). We show that the coefficient on the 2-way interaction term AFTER × TREAT is negative and significant, suggesting that postmerger, acquirers experience a significant drop in their trademark stock compared to their nonacquiring peers. Our finding that acquisitions are associated with a smaller trademark portfolio for acquirers postmerger is consistent with our product market consolidation Hypothesis 2.

Panel C of Table 3 presents the DiD estimates where the dependent variables are different performance measures: ROA, SALES_GROWTH, cost of goods sold (COGS), and annual buy-and-hold return (BHR). We show that acquirers experience significant increases in ROA and BHR (columns 1 and 4) postmerger compared with their nonacquiring peers. More importantly, we find that such performance improvement and value creation are driven by both an increase in SALES_GROWTH (column 2) and a significant drop in COGS (column 3). The reduction in COGS sheds light on an important yet previously underexplored channel in the M&A literature: the importance of cost savings. Together with our finding of a significant drop in the number of active trademarks in Panel B, we show that M&As are primarily used by acquirers to reduce overall product offerings of the combined firms, thereby achieving significant cost savings. Moreover, M&As may also lead to greater market power and economies of scale, resulting in sales growth and profitability, as supported by our results.

Next, we examine how product market consolidation takes place.

B. Postmerger Discontinued Trademarks

In this section, we examine how acquirers' and target firms' existing trademarks are affected after deal completion. Unlike prior studies of postmerger outcomes, this study is able to clearly delineate the product market outcomes of acquirers and target firms even after deal completion, as the USPTO trademark data mostly keep acquirers' and target firms' trademarks separate both before and after the deal incidence.[11] Moreover, the granular trademark-class level data allow us to classify

[11]We thank an anonymous referee for suggesting that we highlight this advantage of the USPTO trademark data. Given that registering transfer of ownership to the USPTO is voluntary, we keep track of any ownership transfer due to completed M&As (the focus of this article) following the patent literature

TABLE 3

Postmerger Product Market Outcome and Performance

Table 3 examines postmerger product market and performance outcomes using a sample of completed deals and a sample of control firms. For each deal, we track its acquirer's trademarks and performance from 5 years before bid announcement (*ayr*-5) to 5 years after deal completion (*cyr* + 5). Panel A presents the summary statistics. Panel B presents the DiD regression results where the dependent variable is product market outcome. AFTER is an indicator variable that takes the value of 1 for the 5-year period after year *cyr*, and 0 otherwise. TREAT is an indicator variable that takes the value of 1 for completed deals, and 0 otherwise. Panel C presents the DiD regression results where the dependent variables are different measures of performance. Other controls include acquirer product market and firm characteristics. Definitions of the variables are provided in the Appendix. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary Statistics

	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
	1	2	3	4	5
TRADEMARK_STOCK	126.215	209.796	20.000	47.000	133.000
ln(TRADEMARK_STOCK + 1)	3.971	1.326	3.045	3.871	4.898
ROA	0.035	0.098	0.012	0.045	0.084
SALES_GROWTH	0.114	0.250	−0.003	0.079	0.175
COGS	0.672	0.606	0.232	0.525	0.912
BHR	0.047	0.427	−0.210	−0.006	0.213

Panel B. Product Market Outcome DiD Regression

	ln(TRADEMARK_STOCK + 1)
	1
AFTER × TREAT	−0.261***
	(0.043)
AFTER	0.556***
	(0.040)
Other controls	Yes
FIRM_FE	Yes
YEAR_FE	Yes
No. of obs.	12,595
Adj. R^2	0.923

Panel C. Performance DiD Regression

	ROA	SALES_GROWTH	COGS	BHR
	1	2	3	4
AFTER × TREAT	0.011**	0.051***	−0.050***	0.035*
	(0.004)	(0.012)	(0.016)	(0.020)
AFTER	−0.012***	−0.031***	0.033**	−0.061***
	(0.004)	(0.010)	(0.014)	(0.017)
Other controls	Yes	Yes	Yes	Yes
FIRM_FE	Yes	Yes	Yes	Yes
YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	12,595	12,595	12,595	12,595
Adj. R^2	0.546	0.224	0.920	0.160

a firm's existing trademarks as common to acquirers and target firms (premerger); unique to acquirers; or unique to target firms.

Panel A of Table 4 reports the summary statistics of the number of acquirers' and of target firms' trademarks that are discontinued (in raw numbers) by groups: all acquirers' trademarks, acquirers' trademarks in common classes, acquirers' trademarks in their unique classes, and all target firms' trademarks.[12] We define

(e.g., Bernstein (2015)). Thus, when firm A purchases firm B, we assume that the former also acquires all trademarks of the latter that were originally assigned to the latter by the USPTO.

[12]In our sample, only 102 target firm-year observations have nonzero discontinued trademarks in classes unique to target firms (representing less than 1% of the target firm sample), which is too small for us to implement regression analysis. We thus exclude those trademarks from our sample, resulting in the

TABLE 4

Postmerger Discontinued Trademarks

Table 4 examines discontinued trademarks using a sample of completed deals and a sample of control firms. For each deal, we track its acquirer's and target's trademarks from 5 years before year *ayr* to 5 years after year *cyr*. We group trademarks by class as of year *ayr*-1. Common class refers to trademarks in a class that both the acquirer and its target firm have registered trademarks. Unique to acquirer (target firm) class refers to trademarks in a class that only the acquirer (target firm) has registered trademarks. Panel A presents the summary statistics of discontinued trademarks (in raw numbers) in different groups. AFTER is an indicator variable that takes the value of 1 for the 5-year period after year *cyr*, and 0 otherwise. TREAT is an indicator variable that takes the value of 1 for completed deals, and 0 otherwise. Panel B presents the DiD regression results where the dependent variables are the number of discontinued trademarks (in natural logarithms) in different groups. Other controls include acquirer/target product market and firm characteristics. Definitions of the variables are provided in the Appendix. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary Statistics of Discontinued Trademarks

		Mean	Std. Dev.	25th Percentile	Median	75th Percentile
		1	2	3	4	5
Acquirers	All	5.123	10.321	0.000	1.000	5.000
	Common	3.372	7.914	0.000	0.000	3.000
	Unique to acquirer	1.752	4.300	0.000	0.000	1.000
Target firms	All/Common	1.021	2.619	0.000	0.000	1.000

Panel B. Discontinued Trademark DiD Regression

	Acquirers			Target Firms
	All	Common	Unique to Acquirer	All/Common
	1	2	3	4
AFTER × TREAT	0.137***	0.152***	0.061**	0.163***
	(0.036)	(0.031)	(0.027)	(0.020)
AFTER	−0.196***	−0.244***	−0.090***	−0.002
	(0.035)	(0.033)	(0.033)	(0.020)
Other controls	Yes	Yes	Yes	Yes
FIRM_FE	Yes	Yes	Yes	Yes
YEAR_FE	Yes	Yes	Yes	Yes
No. of obs.	12,595	12,595	12,595	12,595
Adj. R^2	0.775	0.727	0.611	0.578

a control acquirer's (target firm's) trademarks as being unique or in common classes based on the trademark portfolio of the control acquirer (target firm), rather than that of the actual acquirer (target firm). Discontinued trademarks refer to trademarks that were not renewed in renewal deadline years (i.e., the sixth, tenth, and twentieth year from the registration year).

Columns 1–3 in Panel B of Table 4 present the DiD estimates of equation (2) where the dependent variables are the number of acquirers' discontinued trademarks and their components (in natural logarithms).[13] We show that the coefficient on AFTER is negative and significant in all columns, suggesting that over time, firms discontinue fewer trademarks. Importantly, the coefficient on the 2-way interaction term AFTER × TREAT is positive and significant at the 5% level or lower, suggesting that postmerger, acquirers discontinue significantly more trademarks, and in particular more trademarks in common classes, than their nonacquiring peers. Our results support Hypothesis 2 and its implication that M&As are used

number of target firms' discontinued trademarks across all classes being the same as the number of target firms' discontinued trademarks in common classes.

[13]Throughout our analysis of discontinued trademarks, newly registered trademarks, and their respective components, we control for product market and firm characteristics and *Same industry*, an indicator variable that takes the value of 1 if the acquirer and its target firm are in the same industry (based on 2-digit SIC codes), and 0 otherwise.

for business reconfiguration, and specifically for reducing overlapping product offerings.

Column 4 in Panel B of Table 4 presents the DiD estimates where the dependent variables are the number of target firms' discontinued trademarks (in natural logarithms). We show that the coefficient on the 2-way interaction term AFTER × TREAT is positive and significant at the 1% level, suggesting that postmerger, acquirers discontinue significantly more target firms' trademarks than their control firms. Product offerings in common trademark classes by merging firms may cause cannibalization of revenue. To minimize such cannibalization, acquirers are less likely to retain target firms' products that compete with their own (Bahadir et al. (2008), Cunningham et al. (2021)). Our evidence above supports this argument and Hypothesis 2.[14]

We also examine whether there is any differential trimming effect on trademarks of different vintages.[15] Table IA5 in the Supplementary Material presents the results. We find that newer trademarks are more likely to be discontinued than established ones. This finding is consistent with the idea that more vintage brands have broader customer bases and stronger market images than younger brands (Heath and Mace (2020)). Thus, upon deal completion, newer product lines are more likely to be discontinued.

C. Postmerger Newly Registered Trademarks

The trademark data also allow us to examine how M&As affect acquirers' launchings of new product lines. The variable of interest is the number of newly registered trademarks postmerger, as well as its components: trademarks belonging to classes common to acquirers and target firms (premerger), unique to both acquirers and target firms, and new to both acquirers and target firms. For this analysis, we combine a target's postmerger newly registered trademarks with those of its acquirer.[16]

Panel A of Table 5 presents the summary statistics of new trademarks (in raw numbers) in different groups. Panel B of Table 5 presents the DiD estimates of equation (2) where the dependent variables are the number of all new trademarks and their components (in natural logarithms). We find that the coefficient on the 2-way interaction term AFTER × TREAT is negative and significant at the 1% level when the dependent variables are the number of all new trademarks (column 1) and the number of new trademarks in classes unique to target firms (column 4), whereas this coefficient is insignificant when the dependent variable is the number of new trademarks in common classes (column 2) and in classes unique to acquirers (column 3). Moreover, we show that the coefficient on the 2-way interaction term AFTER × TREAT is positive and significant at the 5% level when the dependent

[14]In untabulated descriptive statistics, we find that acquirers discontinue a very small number of trademarks in classes unique to target firms (relative to target firms' trademarks in common classes), suggesting that postmerger, acquirers tend to preserve target firms' unique product lines.

[15]We thank an anonymous referee for suggesting this analysis.

[16]Postmerger, some target firms continue to register new trademarks under their old firm names, whereas others tend to register new trademarks under their acquirers' names. To capture all new trademarks postmerger, we combine new registrations from both firms whenever applicable.

TABLE 5

Postmerger Newly Registered Trademarks

Table 5 examines newly registered trademarks using a sample of completed deals and a sample of control firms. For each deal, we track its acquirer's trademarks from 5 years before year *ayr* to 5 years after year *cyr*. We group trademarks by class as of year *ayr*-1. Common class refers to trademarks in a class that both the acquirer and its target firm have registered trademarks. Unique to acquirer (target firm) class refers to trademarks in a class that only the acquirer (target firm) has registered trademarks. New class refers to trademarks in a class that neither the acquirer nor its target firm has registered any trademarks. Panel A presents the summary statistics of newly registered trademarks (in raw numbers) in different groups. Panel B presents the DiD regression results where the dependent variables are the number of newly registered trademarks (in natural logarithms) in different groups. AFTER is an indicator variable that takes the value of 1 for the 5-year period after year *cyr*, and 0 otherwise. TREAT is an indicator variable that takes the value of 1 for completed deals, and 0 otherwise. Other controls include acquirer product market and firm characteristics. Definitions of the variables are provided in the Appendix. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Summary Statistics of Newly Registered Trademarks

	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
	1	2	3	4	5
All	8.684	13.778	1.000	3.000	10.000
Common	5.297	9.922	0.000	2.000	6.000
Unique to acquirer	2.875	6.101	0.000	0.000	3.000
Unique to target	0.175	0.648	0.000	0.000	0.000
New	0.337	0.991	0.000	0.000	0.000

Panel B. Newly Registered Trademark DiD Regression

	All	Common	Unique to Acquirer	Unique to Target	New
	1	2	3	4	5
AFTER × TREAT	−0.110***	0.053	0.006	−0.146***	0.059**
	(0.042)	(0.034)	(0.035)	(0.019)	(0.023)
AFTER	0.193***	−0.032	−0.157***	0.276***	0.266***
	(0.038)	(0.032)	(0.039)	(0.017)	(0.020)
Other controls	Yes	Yes	Yes	Yes	Yes
FIRM_FE	Yes	Yes	Yes	Yes	Yes
YEAR_FE	Yes	Yes	Yes	Yes	Yes
No of obs.	12,595	12,595	12,595	12,595	12,595
Adj. R^2	0.688	0.686	0.600	0.239	0.264

variable is the number of new trademarks in new classes (column 5). These findings suggest that postmerger, acquirers register significantly fewer new trademarks (mainly in classes unique to target firms) compared to their nonacquiring peers. On the other hand, the significantly positive coefficient on the 2-way interaction term AFTER × TREAT for new trademarks in new classes suggests that combining two firms' innovative capabilities results in new product development synergies.

We conclude that postmerger, acquirers consolidate product lines by reducing new product offerings, supporting Hypothesis 3a. This finding suggests that M&As are likely driven by the need to eliminate unfocused product lines to achieve cost efficiency. In the meantime, acquirers retain product lines in classes unique to themselves and develop more new products in totally new classes compared to their nonacquiring peers.

Taken together, our results in Tables 4 and 5 support the thesis that acquirers use M&As to consolidate product offerings by cutting existing product lines that overlap with their target firms and by reducing new product launches in their target firms' unique product space. Moreover, we also find some evidence of acquirers developing more new products postmerger, suggesting that potential innovation synergies resulting from M&As allow acquirers to become more exploratory in the product space. Finally, our analysis using the economy-wide data set on trademarks shows that acquirers actively consolidate both the existing and new product lines of their target firms. Thus, our findings complement those of Cunningham et al. (2021), who show that acquired drug projects are less likely to be developed when they overlap with the acquirer's existing product portfolio.

VI. Postmerger Product Market Outcome: The Quasi-Experiment

We acknowledge that our postmerger analysis of product market outcome could be subject to the endogenous selection of firm pairs into the completed deal group, which would lead to biased estimates. To address this concern, we exploit a quasi-experiment. Following Bena and Li (2014) and Seru (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) vs. the control sample (withdrawn bids) can be treated as random with respect to the outcome variables we examine.

We begin with 825 withdrawn bids announced over the period 1983–2010.[17] We read news articles for each withdrawn bid and are able to identify reasons for those withdrawals for 461 bids. Appendix IA5 in the Supplementary Material provides the statistics for the different reasons for withdrawals, with two examples of each reason. We only keep those bids that failed due to reasons exogenous to the product market outcome: competing bids, regulatory objections, or adverse microeconomic/market conditions. We end up with 249 withdrawn bids as potential control firms to match with the completed deals. Panel A of Table 6 lists our sample formation steps. Ultimately, we have 104 unique withdrawn bids and 653 completed deals, and a sample of 653 pairs of completed deals and withdrawn bids. To examine our main hypothesis on product market consolidation, we focus on the discontinuation and new registration of trademarks. Panel B of Table 6 presents the summary statistics of acquirers' and target firms' discontinued and newly registered trademarks (in raw numbers).

Panel C of Table 6 presents the DiD estimates of equation (2) where the dependent variables are the number of acquirers discontinued trademarks grouped in different classes, the number of targets discontinued trademarks, and the number of acquirer newly registered trademarks grouped in different classes (in natural logarithms).[18] We show that the coefficient on the interaction term AFTER × COMPLETE is positive and significant when the dependent variables are the

[17]According to the USPTO guidelines on trademark renewal, it takes 6 years before the agency knows if a trademark will be renewed or not; 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 Dec. 31, 2010, when the last premerger year (*ayr-1*) is 2009, 6 years before our trademark data ends in 2015.

[18]Table IA6 in the Supplementary Material presents the results from testing the pre-trend assumption necessary for the DiD specification. $\text{BEFORE}^{4|5}$ ($\text{BEFORE}^{2|3}$) is an indicator variable that takes the value of 1 when the year is in the fourth or fifth (second or third) year prior to bid announcement, and 0 otherwise. The indicators $\text{AFTER}^{4|5}$ and $\text{AFTER}^{2|3}$ are defined similarly. We show that before bid announcement, there are no significant differences in the six postmerger product market outcome variables, and that after deal completion, there are significant differences between the treatment and control groups.

TABLE 6

Postmerger Product Market Outcome: Identification

Table 6 examines product market outcome using a sample of withdrawn bids as control firms. For each deal, we track acquirers and their control firms from 5 years before year *ayr* to 5 years after deal completion/withdrawal (year *cyr*). Panel A lists steps taken to form the treatment and control samples. Panel B presents the summary statistics (in raw numbers). Panel C presents the DiD regression results for discontinued trademarks and newly registered trademarks (in natural logarithms) using a sample of completed deals and a sample of withdrawn bids as the control. AFTER is an indicator variable that takes the value of 1 for the 5-year period after year *cyr*, and 0 otherwise. COMPLETE is an indicator variable that takes the value of 1 for completed deals, and 0 otherwise. Definitions of the variables are provided in the Appendix. Robust standard errors clustered at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Sample Formation

Steps	# Completed Deals	# Withdrawn Bids
Completed deals per Section IIID and withdrawn bids announced between 1983 and 2010	1,622	825
Withdrawn bids that we could identify and categorize reasons (see Appendix IA5 in the Supplementary Material for details and examples)	1,622	461
Withdrawn bids due to competing bids, regulatory objections, or adverse macroeconomic/market conditions	1,622	249
For each completed deal, there exists at least one withdrawn bid with the same acquirer and target firm core class (the top two classes) announced within a 10-year window centered around bid announcement of the completed deal	−676	−23
Acquirers of completed deals and withdrawn bids have at least one newly registered trademark before bid announcement	−51	−68
Acquirer of a matched completed deal (by acquirer size) and acquirer of a withdrawn bid both have at least two valid observations before bid announcement and after deal completion (withdrawal)	−242	−54
Final matched sample	653	104

Panel B. Summary Statistics

			Mean	Std. Dev.	25th Percentile	Median	75th Percentile
			1	2	3	4	5
Discontinued	Acquirers	All	5.690	13.311	0.000	1.000	5.000
		Common	3.983	9.505	0.000	1.000	4.000
		Unique to acquirer	1.707	6.162	0.000	0.000	1.000
	Target firms	All/Common	1.881	6.003	0.000	0.000	2.000
Newly registered	Acquirers	All	8.252	15.677	1.000	3.000	8.000
		Unique to target	0.192	1.138	0.000	0.000	0.000

Panel C. Discontinued and Newly Registered Trademark DiD Regression

	Discontinued				Newly Registered	
	Acquirers			Target Firms	Acquirers	
	All	Common	Unique to Acquirer	All/Common	All	Unique to Target
	1	2	3	4	5	6
AFTER × COMPLETE	0.065**	0.051*	0.083***	0.055**	−0.067*	−0.104***
	(0.031)	(0.030)	(0.023)	(0.026)	(0.039)	(0.019)
AFTER	−0.204***	−0.201***	−0.212***	0.131***	0.232***	0.200***
	(0.033)	(0.034)	(0.036)	(0.036)	(0.035)	(0.017)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
FIRM_FE	Yes	Yes	Yes	Yes	Yes	Yes
YEAR_FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	12,161	12,161	12,161	12,161	12,161	12,161
Adj. R^2	0.762	0.724	0.675	0.437	0.668	0.351

number of acquirers' trademarks (across different groups, columns 1–3), and the number of target firms' discontinued trademarks (column 4). This coefficient is negative and significant, however, when the dependent variables are the number of acquirers' newly registered trademarks across all classes and in classes unique to target firms (columns 5 and 6). These results further confirm our earlier findings in

Tables 4 and 5, and help establish the causal effect of M&As on postmerger product market consolidation.

VII. Conclusions

This article is one of the first in the M&A literature to employ novel trademark data to examine the important interaction between product market competition and product line consolidation.

Using a large and unique trademark-merger data set over the period 1983–2016, we first show that companies facing greater product market competition are more likely to initiate acquisitions. Because our trademark-based measure for product market competition captures competition from all market participants offering similar products, our measure is more comprehensive and timely than conventional measures based on industry affiliations or annual report disclosures.

We further show that postmerger, compared to their nonacquiring peers, acquirers experience higher ROA and buy-and-hold stock returns as well as higher sales growth and lower cost of goods sold. Moreover, compared to their nonacquiring peers, acquirers discontinue more acquirers' and target firms' trademarks in classes common to both merger partners and register fewer new trademarks in classes unique to target firms. On the other hand, acquirers register more new trademarks in classes new to both merger partners. These findings highlight the unique advantage of trademark data in capturing the creation and elimination of individual product lines.

Finally, our use of a quasi-experiment based on bids withdrawn due to reasons exogenous to acquirers' and target firms' product market outcomes helps establish the causal effect of deal completion on product market consolidation.

We conclude that M&As create product market synergies as combined companies cut overlapping product offerings, leading to revenue expansion and cost efficiency.

Appendix. Variable Definitions

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

Product Market Measures

PRODUCT_MARKET_CONCENTRATION: We first calculate a class-level product market concentration measure as the Herfindahl index of the trademark age-adjusted number of active trademarks of all firms. A firm's product market concentration measure is the age-weighted average of the class-level product market concentration measure across the top two classes in the firm's active trademark portfolio (i.e., the two classes with the most number of active trademarks across all its active trademarks). The measure is multiplied by 100.

TRADEMARK_STOCK: The number of a firm's active trademarks.

TRADEMARK_STOCK_TOP2: The number of active trademarks in the top two classes of a firm (i.e., the two classes with the most number of active trademarks across all its active trademarks).

REVENUE_PER_TRADEMARK: Sales divided by the number of active trademarks.

ACQUIRER-TARGET_TRADEMARK_SIMILARITY: The cosine similarity between an acquirer's and its target firm's trademark distributions across different classes.

SIC_CONCENTRATION: The Herfindahl index of sales of all firms in the same 2-digit SIC industry.

HP_CONCENTRATION: The Herfindahl index of sales based on the TNIC industry of Hoberg and Phillips (2016).

TRADEMARK_HHI: The Herfindahl–Hirschman Index (HHI) of a firm's active trademarks across classes.

TRADEMARK_AGE: For each trademark, its age is the present year minus its application year.

AVERAGE_TRADEMARK_AGE: The average age of a firm's active trademarks. Age for a trademark is calculated as the present year minus the year of its application.

Firm Characteristics

ROA: Operating income before depreciation divided by total assets.

ROE: Operating income before depreciation divided by book value of equity.

SALES_GROWTH: The growth rate of sales.

COGS: Cost of goods sold divided by sales.

BHR: The buy-and-hold stock return (monthly compounded) in a year.

FIRM_SIZE: ln(total assets).

M/B: Market value of equity divided by book value of equity.

LEVERAGE: Total liabilities divided by total assets.

CASH: Cash and short-term investment divided by total assets.

PRIOR_YEAR_STOCK_RETURN: The difference between the buy-and-hold stock return from month -14 to month -3 relative to the month of bid announcement (month 0) and the analogously defined buy-and-hold stock return on the value-weighted CRSP index.

SAME_INDUSTRY: An indicator variable that takes the value of 1 if an acquirer's and its target's 2-digit SIC industries are the same, and 0 otherwise.

Supplementary Material

To view supplementary material for this article, please visit https://doi.org/10.1017/S0022109022000230.

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