Don't Dress Like Me: The Value Implications of Trade Dress Protection*

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Abstract

This study examines an important yet underexplored form of intellectual property: trade dress and its valuation implications. We exploit the Supreme Court's ruling in *Two Pesos, Inc. v. Taco Cabana, Inc.* (1992), which strengthened the enforceability of unregistered trade dress that applies to all company and brand images. Using a difference-in-differences-in-differences design, we find that retail-reliant firms with relatively limited trademark portfolios experience an increase in market value following the ruling. This valuation effect is concentrated in industries for which imitation risk is most salient, suggesting an imitation mitigation mechanism underlying the regulatory change. Consistent with this mechanism, treated firms experience greater profit margins and higher profits after the ruling. Moreover, treated firms reoptimize their intellectual property strategies in response to the improved enforceability of trade dress protection.

***Keywords**:* trade dress, trademarks, intellectual property, intangible assets, brand name, market value

***JEL codes**:* G14, G32, K11, O34

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1. Introduction

Brand names constitute the most important intangible assets for firms, in as much as these brand names offer firms a durable competitive advantage. Firms must therefore protect their brand names legally by using trademarks (either registered or unregistered), which are governed by the 1946 Lanham Act. "Trade dress" is the ultimate form of trademark rights in the sense that it offers infinite-horizon protection for the overall "look and feel" that encompasses all customers' images of a product or service and identifies its source (i.e., a particular manufacturer and provider). Once a firm establishes its brand image in consumers' minds, it can then claim trade dress (with or without official registration) to initiate lawsuits against alleged infringers that use similar images. For instance, Coca-Cola's Contour Bottle was first registered as a design patent that expired 14 years after its grant in 1923, but was later covered by Coca-Cola's trade dress until today.[1] A more recent and prominent example is that of Apple Inc. v. Samsung Electronics Co., in which the jury awarded Apple $382 million in damages associated with trade dress in 2012, which is a substantial part of the total damage of $930 million in the district court's verdict (Ferenc, Mazur, and Wakolbinger 2015; Menell and Corren 2021).[2]

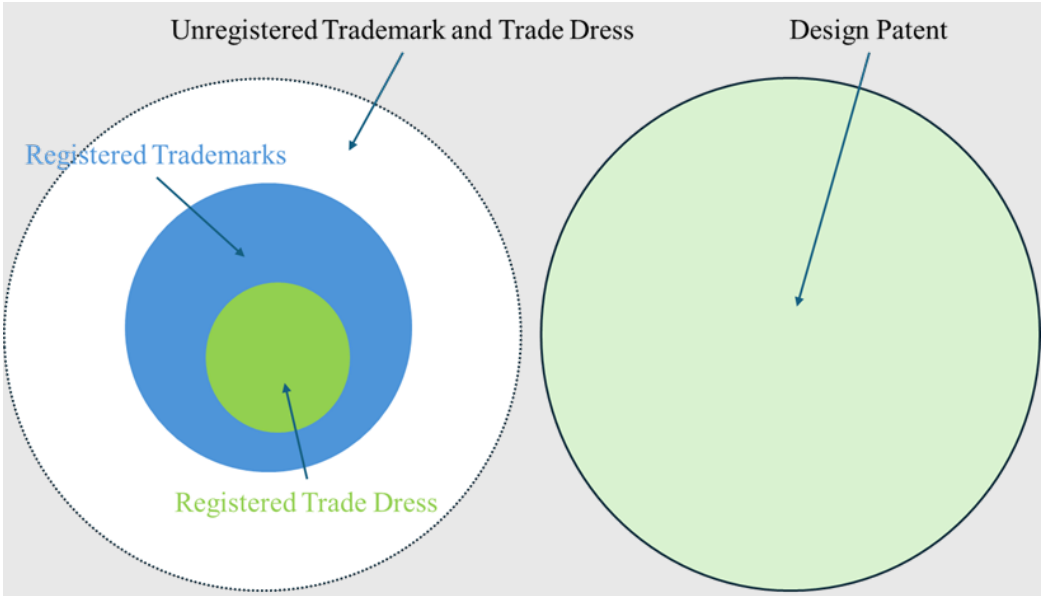
Despite the importance of trade dress with respect to intellectual property protection and its prevalence in retail markets, the extent to which trade dress is assessed by stock markets remains an unexplored research topic in the finance literature. This paper serves as the first attempt to address this topic; we do so by exploiting an important Supreme Court ruling on *Two Pesos, Inc. v. Taco Cabana, Inc.*, 505 U.S. 763 in 1992 ("the *Two Pesos* case" hereafter) that fundamentally altered the legal landscape for trade dress protection. The ruling itself has particularly direct implications for unregistered trade dress.

When a firm invests in a distinctive store layout, packaging aesthetic, or broader product presentation, it creates a source-identifying intangible asset whose value depends critically on its defensibility. If rivals can freely imitate the look and feel of a successful company and brand image, then the firm cannot fully appropriate returns on these investments (Teece 1986; Lemley and

[1] https://www.uspto.gov/sites/default/files/about/offices/ous/20130328.pdf and https://community.pdma.org/knowledgehub/bok/product-innovation-process/deliberate-differentiation

[2] Other parts of the total damage include utility patents and design patents. Source: https://www.theguardian.com/technology/2015/may/18/apple-samsung-trademark-lawsuit-reversal

McKenna 2023). Notably, such company and brand images cannot be covered by design patents, which are intended to incentivize novelty in ornamental design for a specific "functional" article of manufacture, rather than to protect "non-functional" features that serve to identify the source of a product or service to consumers[3] (as presented in the chart below for their conceptual separation). Such images are mainly protected by trademark laws that safeguard the overall image and appearance of a product insofar as they function as a source identifier. It is noteworthy that trademark laws protect company and brand images even without official registration (to be detailed in Section 2). Firms may also seek protection through official trademark registration of trade dress, as presented in the chart below. In practice, however, much trade dress is never formally registered (Bone 2004; Buccafusco et al. 2024), in part because the design space is vast and a largely text-based registration system cannot feasibly enumerate or formalize *all* potentially protectable visual and stylistic features (Tushnet 2011, 2017; Lemley and McKenna 2023). Changes in the enforceability of unregistered trade dress are therefore economically consequential for firms' brand value.



Relationship among Trademark, Trade Dress, and Design Patent

[3] "Functional" in this context means serving a utilitarian purpose. A "non-functional" feature is one that is not essential to the product's use or purpose. Company and brand images are "non-functional" features as they are not essential to the use of any product or service.

The protection scope of unregistered trade dress was, however, of high uncertainty prior to the *Two Pesos* case. Federal appellate courts were split on plaintiffs' evidentiary burden to prove infringement. In addition to requiring proof of inherent distinctiveness (i.e., customers' ability to recognize a design as unique), some federal appellate courts require "secondary meaning" (i.e., customers' ability to associate a design with a particular provider of a product or service) as a prerequisite, while others permit protection for inherently distinctive trade dress that does not show secondary meaning.[4] In other words, firms relying on unregistered trade dress face substantial litigation and evidentiary burdens to establish secondary meaning, limiting effective deterrence against copying.

The Supreme Court decided to step in and resolved this conflict by holding that proof of secondary meaning is *not* required to prevail on an unregistered trade dress claim, which greatly reduced the evidentiary burden for the plaintiffs. The Supreme Court only used 66 days to make its decision. By removing the secondary meaning requirement for inherently distinctive trade dress, the ruling substantially lowered the expected cost of obtaining and enforcing protection for unregistered trade dress (Johnson 1993). More importantly, the ruling extended the scope of unregistered trade dress to encompass a broad range of nontraditional, design-oriented source identifiers (Johnson 1993).

It is noteworthy that the impact of the *Two Pesos* case is not uniform across firms, which creates a compelling setting for us to evaluate the value implications of trade dress protection. We expect the ruling to matter more for firms whose business lines are consumer-facing and retail-oriented—those settings in which trade dress is economically salient and imitation risk is particularly acute (Landes and Posner 1987; Warlop and Alba 2004; Aribarg et al. 2014). The *Two Pesos* case also benefits firms with relatively limited protection through registered trademarks that may offset unregistered trade dress (Heath and Mace 2020; Lemley and Mckenna 2023). We thus design a difference-in-differences-in-differences (DDD) strategy that examines how firms' market values differ along the cross-sectional heterogeneity in firms' exposure to the ruling, as the *Two*

[4] The Supreme Court defines secondary meaning as the mental association whereby "in the minds of the public, the primary significance of a [mark] is to identify the source of the product rather than the product itself." For some federal appellate courts, *Vibrant Sales, Inc. v. New Body Boutique, Inc.*, 652 F.2d 299 (1981) is cited as an example that required secondary meaning, and *Chevron Chemical Co.* v. *Voluntary Purchasing Groups, Inc.,* 659 F.2d 695, 702 (5th Cir. 1981) is cited as an example that only required inherently distinctive trade dress without secondary meaning.

Pesos case strengthened firms' ability to protect valuable visual identity and presentation assets that can be translated into improved product-market outcomes and higher firm value.

To implement our DDD test, we first collected information about firms' reliance on retail markets. We utilized the National Establishment Time Series (NETS) data, which track approximately 87 million U.S. establishments annually from 1990 onward. After linking NETS establishments to Compustat/CRSP firms through a fuzzy name-matching procedure and manual verification, we identify 5.5 million retail establishments out of 15.6 million total matched establishments. The scale and granularity of the NETS data allow us to capture retail presence for a broad cross-section of public firms: for example, we identify 5,979 unique store locations for McDonald's, 2,830 gas station locations for ExxonMobil, and 11,426 Starbucks locations. Using these linked establishments, we aggregate establishment-level retail sales and scale by total firm sales to obtain a firm-level retail sales share, which serves as our measure of retail channel reliance.

We also collect public firms' trademark data from the United States Patent and Trademark Office's (USPTO) trademark records and construct firm-level trademark inventories. Tracking trademark ownership requires careful attention to ownership dynamics because trademark rights can be applied, assigned to another firms, transferred through mergers and acquisitions, and allowed to lapse through non-renewal. We therefore adopt a two-step procedure. First, we fuzzy-match trademark applicant and owner names to public firms and then manually verify high score matches. Second, we construct a time-varying trademark inventory by tracking ownership changes dynamically through USPTO assignment records, trademark renewal records, and merger and acquisition activities from Refinitiv SDC. Our resulting dataset contains 1,404,605 trademarks linked to public firms at the end of 2024. We define trademark inventory as the total number of alive trademarks owned by a firm in a given year.

With the NETS and USPTO trademark data, we capture firms' exposure to the ruling along two dimensions: (i) *RetailReliance*, an indicator variable capturing the extent to which a firm's business model relies more on retail markets relative to industry peers, and (ii) *LowTrademark*, an indicator variable capturing a smaller size of existing trademark portfolios relative to industry peers.[5] We interact these two variables with *Post*, an indicator variable for years after 1992, and

[5] Firms with relatively fewer trademarks, relative to industry peers, plausibly have thinner formal branding portfolios and weaker protection through registered marks, making their competitive position more sensitive to a doctrinal

the coefficient on this triple interaction term offers an estimate for the market-assessed value of the strengthened protection of unregistered trade dress.

In our baseline test based on firms' market-to-book ratio, we find that retail-reliant firms with relatively weaker trademark portfolios experience a significantly more favorable stock valuation response after the *Two Pesos* case. The economic magnitude of such a response is sizable. The treated firm's market-to-book ratio increases by 0.453 (or more), which corresponds to a 23.6% increase in the sample mean (1.907). Our regression model controls for firm size, leverage, asset tangibility, capital expenditures, R&D expenditures, sales growth, and advertising expenditures.

It is noteworthy that our DDD regression offers a strong identification interpretation for the following reasons: (i) we employ a short window (1990-1994) to avoid the influence of other confounding economic and regulatory factors; (ii) our regression model includes firm fixed effects and industry-year joint effects to absorb time-invariant firm factors (e.g., culture) and time-varying industry-specific factors (e.g., market opportunities, industry structure changes); and (iii) our regression model also includes the interaction of *RetailReliance* and *Post* that absorbs time-varying factors specific to retail market conditions (e.g., business cycles in retail industries, consumer sentiment), as well as the interaction of *LowTrademark* and *Post* that absorbs time-varying factors specific to trademark protection (e.g., policy changes, merger and acquisition waves).

Following Olden and Moen (2022), we verify the parallel trends assumption in our DDD by estimating dynamic treatment effects around the *Two Pesos* case, and show that treated and control firms exhibit statistically indistinguishable valuation trajectories prior to 1992, with divergence emerging only in the post-ruling period. To rule out the alternative explanation that our baseline result is driven by firms' financial constraints due to infringement litigation, we further control for an extensive list of variables that include profitability, cash flow, payout policy, and financial distress; when we do so, we find consistent results. In addition, we confirm our findings to be robust to alternative industry classifications and to our use of Tobin's Q in place of the market-to-book ratio.

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change that enhances the enforceability of unregistered trade dress. Consistent with the view that much trade dress remains unregistered (Buccafusco et al. 2024; Tushnet 2017) and is commonly enforced through Section 43(a) of the Act, firms that have not built extensive registered trademark portfolios may rely more heavily on unregistered brand presentation assets, which is the category most directly affected by the Supreme Court's decision in the *Two Pesos* case.

To complement the panel-based valuation test, we further implement an event test for stock price changes in a short window (two to five days) around the Supreme Court's ruling on the *Two Pesos* case. This is a sharp test to assess whether investors viewed the ruling as value-relevant, and whether the response was concentrated among firms most exposed to this regulatory change in trade dress. We find a significant increase in the stock prices of firms with high retail reliance and weak trademark inventory, thus confirming our baseline results.

Given that stock markets react to such rulings due to enhanced trade dress protection, we next investigate an imitation mitigation mechanism: that is, the ruling mitigates imitation risk and strengthens the appropriability of consumer-facing differentiation investment. We implement our mechanism tests along the following dimensions: consumer orientation, design orientation, and advertising intensity. Consistent with this mechanism, we find that the valuation effect is concentrated in consumer-facing industries, design-intensive industries, and advertising-intensive industries for which imitation risk is most salient.

As another mechanism test, we examine firms' profitability changes in response to the ruling because the enhanced protection of trade dress should safeguard affected firms' customers and profits against competitors' imitations. We replace firm value with forward-looking operating outcomes (gross margin and return on assets (ROA)) in our DDD setting, and show that the triple-interaction coefficient is positive and statistically significant, indicating that retail-reliant firms with relatively sparse trademark portfolios realize higher profit margins and stronger operating performance following the *Two Pesos* case. In terms of economic significance, a treated firm improves its gross profit margin approximately 14.3 percentage points and increases its ROA by 3.0 percentage points. These findings, together with earlier industry-specific subsample analyses, strongly support the imitation mitigation underlying our baseline results.

Finally, we examine whether firms adjust their intellectual property (IP) strategies in response to doctrinal changes in IP protection. As Johnson (1993) predicts, expanded trade dress protection may strengthen the substitution effect between patents and trademarks, thus incentivizing firms to reduce their patenting activity because trademarks (and trade dress rights) can be renewed indefinitely as long as the marks remain in use (Heath and Mace 2020). Consistent with this prediction, we find that treated firms reduce their utility patent filings but increase their trade dress filings related to store-design (in the form of trademarks) after the *Two Pesos* case.

More interestingly, we also find that treated firms reduce their advertising expenses, consistent with such firms' post-ruling reduced reliance on marketing costs needed to fulfill secondary meaning requirements.

Our paper makes several contributions to the finance and economics literature on intangible assets, laws, IP, and competition. First, to the best of our knowledge, our paper is the first to introduce trade dress — a fundamental yet largely overlooked form of IP — to the finance literature and reveal how intangible assets contribute to firm value from this new perspective.[6] The economic relevance of trade dress, considered to be the ultimate legal form of permanent protection to brand owners, is substantiated by our empirical evidence on stock pricing. Thus, our investigation not only fills a prominent gap in the finance literature but also promotes economists' exploration of the role that intangible assets play with respect to corporate value and economic growth.

Second, a large literature has established that appropriability is a key determinant of whether firms can capture profits from their innovations (Teece 1986; Lee et al. 2000; Ethiraj and Zhu 2008; Canayaz and Gurun 2023). Our evidence based on an important ruling on trade dress confirms that better-protected corporate visual identity enhances the appropriability of firms' differentiation strategies, as reflected in their higher profit margins and operating performance.

Third, we contribute to the literature that explores how IP policy and regulation shape competition dynamics and corporate strategies. Our finding that treated firms reduced filing utility patents but increased trade dress registrations after the *Two Pesos* case is consistent with a re-optimization of a firm's IP portfolio in response to improved relative attractiveness of trade dress. We thus add new insights to an ongoing discussion regarding the choice among (and the optimal combination of) various IP tools (e.g., Hall et al. 2014).

Finally, we contribute to the literature on the real effects of regulatory changes in IP domain. An extensive list of prior studies have examined how regulatory changes in utility patents influence

[6] A substantial body of research documents that intangible assets, including patents, registered trademarks, copyrights, and advertising capital, are important determinants of firm value and corporate policy (Hall, Jaffe, and Trajtenberg 2005; Kogan et al. 2017; Mortimer 2007; Galasso and Schankerman 2015; Fang, Lerner, and Wu 2017; Heath and Mace 2020; Hsu et al. 2022; Chan, Lakonishok, and Sougiannis 2001). Nonetheless, the related literature has largely ignored the issue of trade dress.

corporate operations and competition.[7] However, only a limited number of studies have examined the consequences of regime switches in laws and regulations of trademarks (e.g., Heath and Mace 2020; Hsu et al. 2022), design patents (e.g., Chan, Hsu, and Tseng 2025), copyrights (Khan 2004; Baker and Cunningham 2006; Luo and Mortimer 2017), and trade secrets (Glaeser 2018; Wang 2023). More broadly, we contribute to the literature that examines how legal institutions and judicial decisions shape firm value and corporate behavior.[8]

2. Institutional Background

In this section, we (i) define trade dress and describe its enforcement framework, (ii) summarize the Supreme Court's decision on *Two Pesos, Inc. v. Taco Cabana, Inc.* and its resultant implications, and (iii) explain why that decision generates heterogeneous exposure across firms that underpins our empirical design.

2.1. Trade dress and its enforcement

Trade dress is a concept once used to describe product packaging (i.e., "dressing" of products) but that has now been extended to include the "total image" or overall "look-and-feel" of a product or service presentation that identifies source to ensure that customers know which company/organization is the producer or provider. The infringement claim of trade dress falls into the trademark doctrine as a subcategory based on the Lanham Act, which protects a producer from others using words or symbols that are likely to cause confusion about the origin of the product or service. This objective is different from the objective of the Patent Act, which is intended to incentivize innovation. Design patents, for instance, fall under the Patent Act and protect novelty in ornamental design, rather than protecting the company and brand images from imitation. Trade dress, by contrast, specifically protects such source-identifying features.

Trade dress does *not* need to be officially registered to be protected by the Act. Registered trade dress is protected similar to a traditional trademark under Section 2 of the Act, while

[7] See Sakakibara and Branstetter (2001), Lerner (2002, 2009), Branstetter, Fisman, and Foley (2006), Qian (2007), Arora, Branstetter, and Chatterjee (2008), Fang, Lerner, and Wu (2017), Mezzanotti and Simcoe (2019), Mezzanotti (2021), Suh (2023), and Bereskin, Hsu, and Wang (2025).

[8] A growing body of evidence shows that changes in the legal environment (e.g., securities regulation, labor law, contract enforcement, IP protection) generate significant and heterogeneous firm-level effects (Cheng, Nagar, and Rajan 2005; Greenstone, Oyer, and Vissing-Jorgensen 2006; Autor, Donohue, and Schwab 2006; Klasa et al. 2018; Mann 2018; Appel, Farre-Mensa, and Simintzi 2019).

unregistered trade dress is protected under Section 43(a) of the Act[9]. Section 43(a) provides protection to confusion-producing elements, and this protection is not limited solely to word and symbol marks, but also includes trade dress, which originally included only the packaging of a product. However, trade dress has never been clearly defined (Lemley and McKenna 2023), and the *Two Pesos* case has extended that definition even further.

A central practical feature of trade dress is that it is frequently not registered (Buccafusco et al. 2024; Tushnet 2017). The primary reason why trade dress is not registered lies in the structure of the registration framework itself. Because the current system is largely *text*-centric (Tushnet 2011, 2017), visually defined trade dress is difficult to categorize and enumerate within this current system (Lemley and McKenna 2023). A firm's visual presentation can be described in infinitely many ways, making it impossible to exhaust all potential trade dress claims through registration. Compounding this structural limitation, the substantial costs of establishing secondary meaning and the uncertainty surrounding the scope of trade dress protection make registration both burdensome and strategically unattractive (Buccafusco et al. 2024). As a result, trade dress claims are commonly litigated under Section 43(a) of the Lanham Act, the provision that extends federal protection to unregistered trade dress (Berzins 2003).

To establish trade dress infringement under Section 43(a), plaintiffs generally must show all of the following conditions: (i) that there is a likelihood of consumer confusion as to source, (ii) that the asserted features are nonfunctional, and (iii) that the trade dress is distinctive[10]. Of these three conditions, the last one regarding *distinctiveness* is an important (yet difficult-to-define) common law requirement "universally imposed" to prevent "confusion ... as to ... origin." (*Wal-Mart Stores, Inc. v. Samara Bros.,* 529 U.S. 205, 210 (2000)). Before the *Two Pesos* case, distinctiveness was established in one of two ways. First, the trade dress may have been inherently distinctive. Second, when the asserted trade dress was descriptive (or otherwise not inherently distinctive), it sought protection by acquiring "secondary meaning." The Supreme Court defines

[9] Much of our discussion in this paper refers to unregistered trade dress, which was the focus in *Two Pesos, Inc. v. Taco Cabana, Inc.,* 505 U.S. 763 (1992).

[10] See more details under Section II of Berzins (2003). *A likelihood of confusion* refers to "any word, term, name…. or any combination thereof … which is likely to cause confusion … as to the origin, sponsorship, or approval of his or her goods" (See 15 U.S.C. Section 1125(a)(1)(A)(2000) for the statutory language). *Nonfunctional* requires a symbol or "aesthetic" that distinguishes a firm's goods and identifies its source without serving any other significant function (*Qualitex Co. v. Jacobson Products Co.,* 514 U.S. 159 (1995)).

secondary meaning as a mental association whereby "in the minds of the public, the primary significance of a [mark] is to identify the source of the product rather than the product itself."[11] In other words, secondary meaning captures the extent to which consumers *associate* a design with a particular source, which is the provider of the product or service.

Firms that seek to establish secondary meaning, however, find that the process can be very costly. Firms must not only develop consumer association through sustained marketplace activity, which often involves heavy advertising and promotion expenses, but also bear litigation and evidentiary burdens to demonstrate that association. In many lawsuits, courts evaluate secondary meaning using factors such as advertising expenditures, sales success, length and manner of use, and direct evidence of consumer perception, which are all inputs that can be expensive and time-consuming (Buccafusco et al. 2024). Bone (2004) argues that proving secondary meaning is especially expensive and difficult for products or services in early stages of commercialization when consumer association is still forming. These costs can be substantial, potentially reaching hundreds of thousands or even millions of dollars (Buccafusco et al. 2024; Bone 2004). As a result, even when a firm's trade dress is distinctive in an economic sense, some firms may underinvest in building and documenting secondary meaning.

Prior to the *Two Pesos* case, federal appellate courts were split on whether a plaintiff asserting trade dress under Section 43(a) of the Lanham Act *must* prove secondary meaning even when the asserted dress was inherently distinctive. Some courts effectively required secondary meaning as a prerequisite to protection (e.g., *Vibrant Sales, Inc. v. New Body Boutique, Inc.*, 652 F.2d 299 (1981)), while others permitted protection for inherently distinctive trade dress without showing secondary meaning (e.g., *Chevron Chemical Co.* v. *Voluntary Purchasing Groups, Inc.,* 659 F.2d 695, 702 (5th Cir. 1981)). In other words, the protection of trade dress is fairly confusing and has generated mixed legal interpretations before the Supreme Court's *Two Pesos* ruling.

2.2. The 1992 Supreme Court ruling in *Two Pesos, Inc. v. Taco Cabana, Inc.*

The *Two Pesos, Inc. v. Taco Cabana, Inc.* case involves two Mexican-style restaurant chains operating in Texas. After Taco Cabana developed a distinctive dining and patio presentation, Two Pesos adopted a similar overall look and feel (see Figure 1). Taco Cabana sued Two Pesos

[11] *Inwood Labs., Inc. v. Ives Labs., Inc.,* 456 U.S. 844, 851 n.11 (1982).

under Section 43(a) of the Lanham Act, alleging unregistered trade dress infringement. The case reached the Supreme Court against a backdrop of disagreement among federal courts of appeals regarding whether inherently distinctive trade dress requires that proof of secondary meaning be protected under Section 43(a). The Supreme Court granted certiorari[12] to resolve that split among federal courts of appeals, and issued its decision on June 26, 1992.

The decision has two implications that are particularly relevant for firm behavior and valuation. First, it removed secondary meaning as a categorical prerequisite for inherently distinctive trade dress. This decision plausibly lowered the expected cost of obtaining protection for unregistered trade dress (Johnson 1993). Traditionally, to seek protection under the Lanham Act, plaintiffs often needed to demonstrate secondary meaning.[13] However, as we discussed earlier, secondary meaning is costly to build and prove. By removing secondary meaning requirements for distinctive unregistered trade dress, the *Two Pesos* case lowered the expected barrier to enforcement. This channel is especially relevant for firms whose differentiation relies on distinctive packaging, store format (as in the case), or other visual presentation, assets that are often difficult to protect through trade dress registration and that are easier for rivals to imitate.

Second, the ruling reinforced that trade dress can encompass a *broad* range of nontraditional, design-oriented source identifiers when they are inherently distinctive and nonfunctional. Although trade dress historically focused on product packaging, doctrine increasingly treated overall commercial presentation, including store format and decor, as potentially protectable. Johnson (1993) notes that the decision reinforced this broader understanding of trade dress by validating protection for the restaurant's overall look and feel, including features such as "some light fixtures and a few murals on the wall." As a result, the ruling reinforced trade dress as a viable tool for protecting commercial presentation.

[12] Certiorari is the procedure by which the Supreme Court exercises discretionary review over lower court decisions. A grant of certiorari reflects the Court's decision to hear a case due to an important legal question or a conflict among federal appellate courts, both of which warrant resolution at the national level (see Rules of the Supreme Court of the United States r. 10 (2019)).

[13] See, e.g., *First Brands Corp. v. Fred Meyer, Inc.*, 809 F.2d 1378, 1381 (9th Cir. 1987); *Stormy Clime Ltd. v. Progroup, Inc.*, 809 F.2d 971, 974 (2d Cir. 1987); *American Greetings Corp. v. Dan-Dee Imports, Inc.*, 807 F.2d 1136, 1141 (3d Cir. 1986); *Prufrock Ltd. v. Lasater*, 781 F.2d 129, 132 (8th Cir. 1986); *Kwik-Site Corp. v. Clear View Mfg.*, 758 F.2d 167, 178 (6th Cir. 1985); and *Keebler Co. v. Rovira Biscuit Corp.*, 624 F.2d 366, 378 (1st Cir. 1980).

2.3. The heterogenous effects of the *Two Pesos* case

The decision strengthened the protectability of inherently distinctive trade dress, shifting expected payoffs from investing in and defending consumers and markets to designs and brand presentation. We therefore expect the valuation impact of the ruling to be stronger for firms whose business models make trade dress economically salient, especially those firms with greater reliance on retail storefronts and retail market channels. For such firms, visual presentation, store format, and packaging are central to differentiation and are highly observable, making them relatively easy targets for competitors to imitate. Moreover, these presentation assets are often protected, if at all, through unregistered trade dress claims rather than through formal registration (Gaske 1989; Tushnet 2017; Buccafusco et al. 2024).

We further propose heterogeneity based on firms' pre-existing brand portfolios and deterrence through intellectual property (i.e., reduced requirement for secondary meaning and expanded coverage of inherently distinctive designs), which also affect the enforceability of unregistered trade dress. Since much trade dress remains unregistered, firms that have not built extensive registered trademark portfolios may rely more heavily on unregistered trade dress, which is the category most directly affected by the Supreme Court's decision in the *Two Pesos* case.

Accordingly, to design our identification strategy for our empirical analysis, we use the cross-sectional variation in retail reliance and trademark inventory to define the treatment. Our main hypothesis is that firms benefit more from the Supreme Court's decision if they (i) are more retail-oriented and (ii) hold weaker trademark portfolios to protect their trade dress.

2.4. The effect on the Second Circuit

Prior to the *Two Pesos* case, the Second Circuit took a relatively restrictive approach to unregistered trade dress claims under Section 43(a) of the Lanham Act by requiring plaintiffs to prove secondary meaning even when the trade dress was claimed to be inherently distinctive[14]. For example, the district court granted injunctive relief in *Vibrant Sales, Inc. v. New Body Boutique, Inc.*, yet the Second Circuit reversed that decision and emphasized that an unregistered trade dress

[14] Please refer to the following lawsuits: *Stormy Clime Ltd. v. ProGroup, Inc.,* 809 F. 2d, at 974; *Union Mfg. Co. v. Han Baek Trading Co.*, 763 F. 2d 42, 48 (1985); and *LeSportsac, Inc. v. K mart Corp.*, 754 F. 2d 71, 75 (1985).

plaintiff must establish secondary meaning to obtain protection under Section 43(a).[15] The Supreme Court later highlighted the *Vibrant Sales* case as reflecting the Second Circuit's view on this issue in describing the doctrinal landscape prior to the *Two Pesos* case.

This institutional feature implies that the *Two Pesos* case should have been particularly consequential for retail shops located in the jurisdiction of the Second Circuit, where the pre-ruling burden to prove secondary meaning was more stringent. In our empirical analysis, we exploit this specific circuit pre-*Two Pesos* legal environment as an additional robustness check. Specifically, we predict a stronger effect on treated firms (i.e., firms of high retail reliance and low trademark inventory) whose retail sales are disproportionately concentrated in Second Circuit states.[16]

3. Data and Sample Construction

To measure firms' reliance on retail channels, we use the National Establishment Time-Series (NETS) database (2020 vintage). NETS covers approximately 87 million U.S. establishments and reports establishment-level sales annually over the period 1990–2020, together with detailed eight-digit SIC codes that allow us to identify retail-oriented establishments.[17] To link NETS establishments to publicly traded firms, we begin with NETS' "HQ Company" field, which identifies the top domestic entity within a corporate family tree. We then perform a fuzzy match between the HQ Company name and Compustat/CRSP firm names using the Jaro–Winkler algorithm. We manually review all algorithmic matches to construct a verified mapping table. This procedure yields 37,424 establishment–firm pairs relative to 45,247 unique Compustat GVKEYs.

Our matched sample contains 15.6 million establishments, 5.5 million of which operate in the retail sector. Specifically, we observe 49,811 establishment-year records across 5,979 unique store locations for McDonald's, 19,872 records across 2,830 gas station locations for ExxonMobil, and 110,870 records across 11,426 unique locations for Starbucks.

Using these linked establishments, we construct a firm-level measure of retail reliance. We classify an establishment as retail-oriented if its two-digit SIC code falls between 52 and 59. We then aggregate sales across a firm's retail-oriented establishments to obtain annual firm-level retail

[15] Please refer to the Opinion of the Court: *Vibrant Sales, Inc.* v. *New Body Boutique, Inc.,* 652 F. 2d 299 (1981), cert. denied, 455 U. S. 909 (1982).
[16] For institutional context, the Second Circuit includes Connecticut, New York, and Vermont.
[17] For more details more about the NETS dataset, please refer to: https://nanda.isr.umich.edu/2024/07/26/netsupdate/

sales, which we scale by total firm sales reported in Compustat to derive a retail sales share. Our baseline indicator, *RetailReliance*, equals one if a firm's pre-decision average retail sales share (measured over 1990–1991) exceeds the within-industry median, defined at the two-digit SIC level, and zero otherwise.

To measure firms' formal trademark portfolios, we construct firm-level trademark inventories from USPTO trademark records.[18] We link trademarks to Compustat/CRSP firms using a three-step procedure. First, we fuzzy match trademark owner names in the USPTO case files to firm and subsidiary names appearing in Compustat/CRSP. Second, we manually verify each algorithmic match to ensure accurate assignment to the corresponding public firm. Third, we then construct a time-varying trademark inventory by tracking ownership dynamically through USPTO assignment records and incorporating merger and acquisition activity from Refinitiv SDC. The resulting dataset contains 1,404,605 trademarks linked to public firms.[19] Our indicator *LowTrademark* equals one if a firm's pre-decision average trademark inventory falls below the within-industry median (two-digit SIC) and zero otherwise.

We obtain firm fundamentals from Compustat. Our control variables, which follow standard practice in the empirical corporate finance literature, include *Firm size* (log of book assets, *Leverage* (debt to total assets), *Tangibility* (property, plant, and equipment scaled by total assets), *Investment intensity* (capital expenditures scaled by total assets), *Sales growth* (the growth rate of total sales), *R&D intensity* (research and development expenditure scaled by total assets), and *Advertising intensity* (advertising expense scaled by total assets). We also include indicator variables for missing R&D and advertising expenditures and set missing values to zero when we construct the corresponding intensity measures. All definitions of variables are provided in the Appendix.

Our final regression sample merges NETS-based retail reliance, USPTO-based trademark portfolios, and Compustat fundamentals. Since NETS coverage begins in 1990 and our empirical design exploits the *Two Pesos* case, the baseline sample spans 1990–1994, with 1992 excluded as

[18] The USPTO Trademark Case File Data set (updated in 2023) and the USPTO Trademark Assignment Dataset (updated in 2023) are downloaded from https://www.uspto.gov/ip-policy/economic-research/research-datasets/trademark-case-files-dataset and https://www.uspto.gov/ip-policy/economic-research/research-datasets/trademark-assignment-dataset (Graham et al. 2013; Graham, Marco, and Myers 2018).
[19] See more detailed information about our matching procedure in the Internet Appendix. The mapping table, which links trademarks to U.S. public firms, is available online at: https://github.com/Shiheli1992/Trademark_CRSP

a partial-treatment year in terms of annual data. We choose a short window to mitigate the concern that our estimation is subject to other macro or industry-specific confounding factors. This sample includes 15,165 firm-year observations of 4,178 unique firms.

Table 1 reports summary statistics for our regression sample. The mean market-to-book ratio is approximately 2, which is consistent with sample firms trading at a premium to book value. Approximately one quarter of firm-year observations are classified as both retail-reliant and as having thin trademark portfolios. The average firm holds approximately 24 trademarks, and retail sales constitute roughly 6% of total firm sales on average. The final sample comprises 15,165 firm-year observations.

4. Firm Value and Trade Dress Protection

4.1. Firm value

Our baseline test focuses on market value, which reflects stock market investors' assessment of the real value of a publicly listed firm under the rational expectation hypothesis. As the U.S. economy has shifted toward service- and technology-based industries, intangible assets related to customers and brands have become increasingly central to firm valuation (Heath and Mace, 2020; Hsu et al., 2022).

We thus propose a positive market response to the *Two Pesos* case, particularly among treated firms that (i) rely more on retail customers and (ii) hold weaker trademark portfolios, as we discussed in Section 2.3. We design a difference-in-differences-in-differences (DDD) framework to identify the incremental valuation response attributable to firms' heterogeneous exposures to the decision. Specifically, we estimate the following ordinary least squares regression:

$$\begin{aligned} Market\ to\ book_{i,t} = {} & \alpha_0 + \alpha_1 Post_t \times RetailReliance_i \times LowTrademark_i + \\ & \alpha_2 Post_t \times RetailReliance_i + \alpha_3 Post_t \times LowTrademark_i + \\ & \alpha_4 RetailReliance_i \times LowTrademark_i + \alpha_5 Post_t + \alpha_6 RetailReliance_i + \\ & \alpha_7 LowTrademark_i + \boldsymbol{\alpha} Firm\ characteristic_{i,t} + Firm\ FE_i + Industry \times \\ & Year\ FE_{i,t} (\text{or } Year\ FE_t) + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

in which *i* and *t* index firms and years, respectively. The dependent variable is firms' market-to-book ratio. The main explanatory variables include three indicators: $Post_t$, $RetailReliance_i$, and

$LowTrademark_i$. $RetailReliance_i$ is an indicator variable that captures firms' dependence on retail operations, and equals one if firm *i*'s average ratio of retail sales (from the NETS database) to total sales exceeds the median within its two-digit SIC industry in periods prior to the *Two Pesos* case (e.g., 1990 to 1991), and zero otherwise. $LowTrademark_i$ is an indicator variable that equals one if firm *i*'s average trademark inventory in the pre-ruling period is below the industry median, and zero otherwise. We use $LowTrademark_i$ to identify those firms that are relatively under-protected by trademark inventory, and for which the marginal benefit of improved unregistered trade dress enforceability should be larger. $Post_t$ is an indicator variable for the post-ruling period and equals one for 1993 and 1994, and zero for 1990 and 1991. We exclude 1992 because the Supreme Court decision occurred mid-year of 1992.

Our coefficient of interest is α_1 on the triple interaction $Post_t \times RetailReliance_i \times LowTrademark_i$. This coefficient captures the incremental change in market valuation for firms that are both retail-oriented and low in trademark inventory in the post-ruling period, relative to the corresponding change for other firms.[20] The triple difference structure differences out common time shocks around the decision and time-varying differences associated with retail orientation (e.g., retail-related business cycles, consumer sentiment) and trademark inventory (e.g., trademarks policy changes, merger and acquisition waves), so we may identify the valuation response that is specific and attributable to the legal shock that is the focus of our study. We expect α_1 to be positive, consistent with the *Two Pesos* case that reduced the expected costs of enforcing inherently distinctive unregistered trade dress and increased the expected payoff to the most exposed firms.

Furthermore, $Firm\ characteristic_{i,t}$ denotes a standard set of time-varying firm characteristics that may affect market valuation: the natural logarithm of total assets (size), book leverage, asset tangibility, capital expenditures scaled by total assets, R&D intensity, sales growth, advertising intensity, and indicator variables for missing R&D and advertising expenditures.

We estimate Equation (1) with firm fixed effects and either SIC two-digit or year fixed effects. We note that industry-year fixed effects absorb all industry-specific factors (even unobservable ones), such as business cycles, innovation opportunities, and customer sentiment.

[20] The comparison group includes (i) retail-oriented firms with higher trademark inventory, (ii) non-retail firms with low trademark inventory, and (iii) non-retail firms with higher trademark inventory.

For our robustness checks, we consider Fama-French 48 industry-year fixed effects. To accommodate autocorrelation and other estimation errors at the firm level, we cluster standard errors by firm.

We report our baseline estimates in Table 2. Column (1) presents specifications with firm fixed effects and industry-year fixed effects, while Column (2) replaces industry-year fixed effects with year fixed effects. Across these two specifications, the coefficient on the triple interaction term (i.e., our DDD estimate) is positive and statistically significant at the 1 percent level. This result is consistent with a positive valuation response among retail-oriented firms with relatively low trademark inventory following the *Two Pesos* case. The economic magnitude is sizable. In Column (1), the point estimate implies a 0.453 increase in the market-to-book ratio. This is a 23.6% increase in market-to-book ratio relative to the latter's sample mean (1.907).

We note that the coefficients on *Post* × *Retail Reliance* are insignificant, suggesting that firms' market value does not change with retail-orientation after the decision, which confirms that our DDD estimate is not driven by some events/factors specific to retail businesses after 1992. We find a negative and statistically significant coefficient on $Post_t \times LowTrademark_i$. This pattern suggests that absent strong retail exposure, firms with relatively low trademark inventories exhibit weaker valuation dynamics over time. This finding is intuitive because formal intellectual property protection becomes increasingly valuable as competition intensifies and because intangible assets account for a larger share of firm value. Since our identification strategy relies on the incremental post-decision change for firms that are jointly retail-oriented and low in trademarks, the negative coefficient on $Post_t \times LowTrademark_i$ contrasts with the positive coefficient on the triple interaction term, underscoring the rigor of our identification strategy.

As an additional check, we compare the magnitude of the triple interaction coefficient, $Post_t \times RetailReliance_i \times LowTrademark_i$, to the magnitude of the $Post_t \times LowTrademark_i$ coefficient. In both Columns (1) and (2), the triple interaction estimate is larger in absolute value, suggesting that the valuation response for the most exposed firms is not offset by the broader post-period dynamics among low trademark firms.[21]

[21] In fact, the sum of two coefficients is larger than zero with marginal significance in Column (1), as shown in the row t-test in the table.

4.2. Additional identification tests

We consider several additional checks to strengthen the causal interpretation of our baseline results. We first exploit cross-circuit variation in the legal standard governing secondary meaning for inherently distinctive unregistered trade dress under Section 43(a) prior to the Supreme Court decision. As we discussed earlier, the Second Circuit required proof of secondary meaning to protect unregistered trade dress under Section 43(a). This implies that, all else equal, the ruling should have been more consequential for firms whose retail exposure is concentrated in states within the Second Circuit, where the pre-decision legal environment was less favorable to unregistered trade dress claims.

To operationalize this idea, we redefine retail reliance by focusing on sales in states within the Second Circuit. Specifically, we construct the retail reliance indicator by using only a firm's total sales in Second Circuit states when we form the retail sales intensity measure. Columns (3) and (4) of Table 2 report our results when we use this circuit-focused measure of retail reliance. Consistent with Columns (1) and (2), the coefficient on the triple interaction term remains positive and statistically significant, which supports that the baseline effect reflects differential exposure to the legal change rather than broader concurrent valuation shifts.

We next assess whether our DDD design satisfies the parallel trends requirement by estimating the following event time specification (Olden and Moen 2022; Bereskin, Hsu, and Wang 2025):

$$Market\ to\ book_{i,t} = \alpha_0 + \alpha_1 \sum_{\tau=-2}^{2} Year_\tau \times RetailReliance_i \times LowTrademark_i + \alpha_2 \sum_{\tau=-2}^{2} Year_\tau \times RetailReliance_i + \alpha_3 \sum_{\tau=-2}^{2} Year_\tau \times LowTrademark_i + \alpha_4 RetailReliance_i \times LowTrademark_i + \alpha_5 \sum_{\tau=-2}^{2} Year_\tau + \alpha_6 RetailReliance_i + \alpha_7 LowTrademark_i + \boldsymbol{\alpha} Firm\ characteristic_{i,t} + Firm\ FE_i + Industry \times Year\ FE_{i,t} + \varepsilon_{i,t}, \quad (2)$$

in which we replace $Post_t$ in Equation (1) with event time indicators. Here, $Year_\tau$ corresponds to τ = –2, –1, 0, +1, and +2, which map to years 1990 through 1994, respectively. In Figure 2, we present the coefficient estimates and confidence intervals of $Year_\tau \times RetailReliance_i \times LowTrademark_i$ from Equation (2). The year 1992 is used as the base year, so its coefficient is omitted. Panels A and B of Figure 2 report estimates using firm fixed effects with industry by year

fixed effects, and firm fixed effects with year fixed effects, respectively. In both panels, the estimated triple interaction coefficients are statistically indistinguishable from zero prior to 1992 and then turn positive after the ruling. These patterns provide no evidence of differential pre-trends and are consistent with the identifying assumption underlying our DDD design.[22]

As an additional check, we implement the pre-trend test in the spirit of Moser and Voena (2012) and Bereskin, Hsu, and Wang (2025) by estimating Equation (2) using only pre-event observations (τ = –2, and –1), with 1992 as the omitted base year. Figure 3 reports the resulting DDD coefficients and 95% confidence intervals under both fixed-effect structures. The estimates are again statistically indistinguishable from zero, further corroborating the absence of differential pre-trends in the pre-decision period.

4.3. Robustness checks

We conduct several robustness analyses to assess whether our baseline DDD results are sensitive to alternative measurement choices and potential omitted-variable concerns. Table 3 present the results. First, we check whether our findings depend on a particular industry partition. We re-construct both $RetailReliance_i$ and $LowTrademark_i$ indicators using the Fama-French 48 industry classification. Specifically, we recompute each firm's pre-decision average retail sales intensity and trademark inventory, and then define $RetailReliance_i$ and $LowTrademark_i$ based on whether these pre-period averages are above or below the FF48-industry median, respectively. Our results in Columns (1) and (2), in which the coefficients on the triple interaction term remain positive and statistically significant, indicate that our baseline inference is not driven by the two-digit SIC classification.

Next, we replace our main dependent variable, market-to-book, with Tobin's Q. Doing so addresses concerns that market-to-book may partly reflect variation in book equity rather than valuation. Columns (3) and (4) report the corresponding estimates. The triple interaction coefficients remain positive and statistically significant, and are consistent with our baseline results, suggesting that the documented valuation effect is not an artifact of the particular valuation proxy.

Lastly, to mitigate concerns that our results are driven by financial constraints associated with infringement litigation, we augment Equation (1) with additional controls that capture

[22] See Olden and Moen (2022) for a discussion of a pre-trend test in a DDD framework.

operating performance, liquidity, payout policy, and financial distress.[23] Columns (5) and (6) report the estimates. The coefficients on the triple interaction term remain positive and statistically significant, indicating that our findings cannot be attributed to firms' financial constraints related to legal dispute.

Overall, these robustness checks support the interpretation of a positive post-decision valuation response for firms that are both retail-oriented and relatively low in trademark inventory. The magnitude of the triple interaction coefficient is stable across specifications and remains comparable to the baseline estimate. This stability strengthens the case that our results are driven neither by industry classification choices nor by a particular valuation proxy or financial constraints.

4.4. Stock market reactions

To complement our annual panel DDD evidence, we examine the stock market's short-run reaction to the Supreme Court's decision on *Two Pesos, Inc. v. Taco Cabana, Inc.* Under the efficient market hypothesis, new and value relevant information should be incorporated into prices in a short window around the decision on June 26, 1992. An event-study design therefore offers a sharp test of whether investors viewed the ruling as value-relevant, and whether the response was concentrated among firms most exposed to the strengthened protection for unregistered trade dress.

Following standard event-study methodology (Brown and Warner 1985), we compute daily abnormal returns as the difference between realized returns and expected returns from an estimation model fitted over a pre-event window (e.g., trading days [- 250, -30] relative to the decision date). We then cumulate abnormal returns over short windows around the decision date, including [-1, +1], [-2, +2], and [0, +1]. For firm *i*, the cumulative abnormal return over window [a, b] is:

$$CAR_i[a,b] = \sum_{\tau=a}^{b} \left(R_{i,\tau} - \left(\widehat{\alpha}_i + \widehat{\beta}_i R_{m,\tau} \right) \right), \quad (3)$$

[23] Specifically, profitability equals net income scaled by total assets, cash flow equals net cash flow scaled by total assets, payout policy equals dividends scaled by total assets, and financial distress equals the Altman Z-score (Altman 1968).

for which $R_{i,\tau}$ is the daily return of firm i on day τ, and $R_{m,\tau}$ is the market return. We implement a Fama and French (1993) three-factor model to calculate the expected stock return using daily data over the pre-event window with a minimum of 120 trading days of pricing data.

We then test whether the announcement-period valuation responses are stronger for firms with greater *ex-ante* exposure to the ruling. Because the decision occurs on a single date, identification comes from cross-sectional heterogeneity rather than time-series variation. Specifically, we estimate the following DiD regression for CARs:

$$CAR_i[a,b] = \alpha_0 + \alpha_1 RetailReliance_i \times LowTrademark_i + \alpha_2 RetailReliance_i + \alpha_3 LowTrademark_i + \boldsymbol{\alpha} Firm\ characteristic_i + Industry\ FE_j + Year\ FE_i + \varepsilon_i, \quad (4)$$

in which $RetailReliance_i$ and $LowTrademark_i$ are defined using pre-decision information (as in the panel analysis), $Firm\ characteristic_i$ controls for firm characteristics at the end of fiscal year 1991, and $Industry\ FE_j$ is based on two-digit SIC codes. Our coefficient of interest is α_1 on $RetailReliance_i \times LowTrademark_i$. A positive α_1 indicates that investors react more favorably to the ruling for firms that are both more reliant on retail channels and less protected by formal trademark portfolios, consistent with the marginal value of improved trade dress enforceability being greatest for these firms.

In Table 4, we present our results of estimates in Columns (1) and (3), and show results across different event windows. Across all event windows, the coefficient on $RetailReliance_i \times LowTrademark_i$ is positive and statistically significant. The point estimate is 1.7% for the [0, +1] window, 2.0% for the [-1, +1], and 3.0% for [-2, +2]. Overall, the CAR evidence complements our panel DDD results, suggesting that investors reacted more favorably to the *Two Pesos* case for firms whose business models make trade dress economically salient and whose formal trademark protection is relatively limited. These patterns are consistent with the ruling increasing expected enforceability and reducing the expected cost of protecting inherently distinctive but unregistered trade dress.

5. Mechanism: Imitation Mitigation

The underlying rationale of our hypothesis is that trade dress is subject to competitors' imitation and that such imitation is later mitigated by the *Two Pesos* case. Imitation refers to rivals

and market entrants copying a firm's distinctive product or retail storefront design and appearance to free-ride on consumer recognition and thus divert sales. If the imitation mitigation mechanism is operative, then the valuation response to the ruling should be concentrated in firms under the following scenarios: (i) consumer perception and visual identity are central to competition, (ii) design is a salient competitive instrument, and (iii) the investment of establishing consumer association through advertising is high. In this section, we attempt additional tests to examine this imitation mitigation mechanism.

5.1. Heterogeneous effect: B2B v. B2C industries

The economic salience of trade dress is inherently tied to consumer perception and consumer search. Accordingly, the valuation implications of the *Two Pesos* case should be strongest in business to consumer industries (i.e., B2C industries) in which firms compete on consumer-facing visible attributes such as packaging, store format, and product appearance. In contrast, purchasing decisions in predominantly business to business industries (i.e., B2B industries) are more likely driven by contracting, technical specifications, and procurement processes. This reduces the marginal role of consumer visible design cues and, in turn, the expected benefits from strengthened trade dress enforceability. We therefore expect any post-ruling valuation gains to be concentrated in B2C industries.

We perform a subsample analysis to validate our conjecture. First, we partition industries into B2C and B2B industries. Following Lev et al. (2010) and Emery (2025), we classify industries using SIC codes based on Sharpe (1982), which designates consumer goods and finance as B2C industries and all other industries as B2B industries. We assign a firm to the B2C (B2B) subsample if it is consistently classified as operating in B2C (B2B) industries prior to the *Two Pesos* case. Second, we re-estimate Equation (1) within each subsample using the same set of controls, fixed effects, and clustering approach as in the baseline specification.

We present our results in Table 5. Columns (1) and (2) present estimates for the B2C subsample, while Columns (3) and (4) present estimates for the B2B subsample. The triple interaction coefficient is positive and statistically significant in the B2C subsample, but statistically indistinguishable from zero in the B2B subsample. This pattern indicates that the valuation response is concentrated in consumer-facing industries, consistent with trade dress being most value relevant in industries where competition focuses on presentation assets. Taken together, these

subsample results are consistent with the proposed mechanism rather than a broad revaluation unrelated to consumer-oriented designs.

5.2. Heterogeneous effect: Industry design intensity

Next, we evaluate whether the *Two Pesos* effect is stronger in industries where visual design is a key source of competitive advantage. In such design-intensive industries, firms devote substantial resources to product appearance, packaging aesthetics, and other presentation attributes to differentiate themselves from rivals. Because these visual features are both valuable and comparatively easy to copy, imitation risk is particularly salient; as a result, legal protection that strengthens appropriability should be most consequential in these settings (Posen et al. 2023; Yilmaz et al. 2023). We therefore predict that enhanced trade dress protection following the *Two Pesos* case generates more pronounced valuation effects in design-intensive industries.

To test this conjecture, we split our sample by industry-level design intensity. We proxy design intensity using the intensity of design innovation scaled by industry sales. Following Chan, Hsu, and Tseng (2025), we use USPTO design patents granted to measure design innovation. Design patents provide a scalable measure of product-form innovation and stylistic differentiation, making them well suited to capture the salience of visual design in competition. We aggregate the number of design patents and scale this count by total industry sales within each two-digit SIC industry over the pre-ruling period (1990-1991). We then classify an industry as high design intensity if this ratio is above the cross-industry median (and as low design intensity otherwise). The classification is held fixed across all sample periods.

Table 6 reports our subsample estimates when we re-estimate Equation (1) separately for the high and low design-intensity groups. Columns (1) and (2) present results for the high design-intensity subsample. The coefficient on $Post \times RetailReliance \times FewerTrademark$ is positive and statistically significant, indicating a pronounced valuation response among firms most exposed to the ruling in design-salient industries. In contrast, Columns (3) and (4) show that the corresponding triple-interaction coefficient is statistically indistinguishable from zero in the low design-intensity subsample. Overall, these findings support our prediction that the valuation impact of the ruling is concentrated in industries where visual presentation is central to competition

and where imitation incentives are consequently stronger, supporting the proposed imitation mitigation mechanism.

5.3. Heterogeneous effect: Industry advertising intensity

Industry advertising intensity captures the extent to which competition depends on building brand associations through marketing. Prior research shows that advertising is an important investment in brand-related intangible assets and is linked to firm value (Erickson and Jacobson 1992; Joshi and Hanssens 2010; Srinivasan and Hanssens 2009). In advertising-intensive industries, visual presentation is more likely to be economically important because firms use advertising to help consumers recognize and remember a given product or service provider. Firms in these industries may also face higher imitation risk, since the returns to appropriating heavily advertised brands and visual presentation are higher. If enhanced trade dress protection mitigates imitation, then the valuation effects of the ruling should be more pronounced in industries for which brand-related intangible assets are more valuable. Accordingly, trade dress should be more value-relevant in industries with high advertising intensity.

We test this prediction by performing a subsample analysis. First, we partition industries into high and low advertising intensity groups based on industry advertising intensity. Specifically, we measure industry advertising intensity as total advertising expenditures scaled by total sales within each two-digit SIC industry, aggregated over the pre-ruling period (1990–1991). An industry is placed in the high advertising intensity group if this ratio exceeds the cross-industry median (and as low advertising intensity otherwise). This industry-level classification is held fixed across all sample years. Second, we re-estimate Equation (1) within each subsample using the same set of controls, fixed effects, and clustering approach as in the baseline specification.

We present our results in Table 7. Columns (1) and (2) present the estimates for the high advertising intensity subsample, while Columns (3) and (4) present the estimates for the low advertising intensity subsample. The triple interaction coefficient is positive and statistically significant in the high advertising intensity subsample, but insignificant in the low advertising intensity subsample. These results suggest that the positive valuation response is concentrated in industries for which advertising plays a larger role in shaping consumer perceptions and building brand associations, consistent with the imitation mitigation mechanism.

Across our mechanism tests, the evidence consistently supports an imitation mitigation mechanism underlying the *Two Pesos* effect. The incremental post-decision valuation effect for retail-reliant, low-trademark firms is concentrated precisely in settings where trade dress is expected to be most economically salient and where imitation incentives are strongest: consumer-facing (B2C) industries, design-intensive industries, and advertising-intensive industries. Taken together, these results support a causal interpretation of our baseline results. For an omitted variable to explain our subsample results, it would need to covary with all variables used in our sample splitting in a consistent direction. As it is difficult for us to think of such an omitted variable, a more plausible interpretation for our results in this section is that the *Two Pesos* case indeed increases the market valuation of firms more exposed to unregistered trade dress protection.

6. Profitability

We next examine whether the *Two Pesos* effect translates into real operating outcomes. Stronger trade dress enforceability can generate product-market benefits by deterring imitation and strengthening the appropriability of consumer-oriented differentiation strategies. If the *Two Pesos* case mitigates imitation and thus reduces the erosion of distinctive designs that serve as source identifiers, then exposed firms should face weaker competitive pressure, enabling them to improve operating performance in subsequent years. We therefore expect retail-reliant firms with lower trademark inventory to exhibit stronger post-ruling profitability.

We test our proposition by estimating a DDD model similar to our baseline valuation regressions, except that we replace the outcome variable with forward-looking profitability measures. In particular, we estimate:

$$Profitability_{i,t+1} = \alpha_0 + \alpha_1 Post_t \times RetailReliance_i \times LowTrademark_i + \alpha_2 Post_t \times RetailReliance_i + \alpha_3 Post_t \times LowTrademark_i + \alpha_4 RetailReliance_i \times LowTrademark_i + \alpha_5 Post_t + \alpha_6 RetailReliance_i + \alpha_7 LowTrademark_i + \boldsymbol{\alpha} Firm\ characteristic_{i,t} + Firm\ FE_i + Industry \times Year\ FE_{i,t} + \varepsilon_{i,t}, \quad (5)$$

in which $Profitability_{i,t+1}$ denotes the profitability measures of firm *i* in year *t* +1. We measure profitability using gross profit margin and return on asset (ROA). Gross profit margin is defined as sales revenue minus the cost of goods sold and scaled by total sales revenue. ROA is defined as

operating income before depreciation scaled by total assets. As in the baseline model, we include the full set of firm controls as well as firm fixed effects and industry by year fixed effects.

Our coefficient of interest is α_1 on the triple interaction term. This DDD estimator captures the change in subsequent profitability for firms that are both retail-oriented and low in trademark inventory from the pre-ruling period to the post-ruling period, relative to the corresponding change for all other firms. We expect the coefficient estimate for α_1 to be significantly positive, consistent with exposed firms benefiting from stronger appropriability of consumer-oriented differentiation strategies.

We present our results in Table 8. Column (1) uses gross profit margin as the dependent variable to assess whether exposed firms improve their product-market power following the ruling. The coefficient on $Post \times RetailReliance \times FewerTrademark$ is positive and statistically significant, indicating an increase in gross margins for the most exposed firms after the ruling. Column (2) examines ROA and yields a positive and statistically significant estimate on the DDD term, consistent with higher operating profitability for retail-reliant firms with relatively fewer trademarks. Economically, the estimates imply an improvement in gross profit margin of approximately 14.3% as shown in Column (1), and an increase in ROA of 3.0% as shown in Column (2).

Overall, these results indicate that most exposed firms reveal stronger subsequent operating performance than other firms following the *Two Pesos* case. Taken together, the profitability evidence strengthens our interpretation that the ruling enhanced trade dress enforceability and mitigated imitation, which in turn improved exposed firms' product-market performance as reflected in higher margins and stronger operating performance.

7. IP strategies

Prior research has documented that changes in IP rights and regulation can trigger economically meaningful adjustments in firm behavior and innovation strategy (Lerner 2002, 2010; Fang, Lerner, and Wu 2017; Heath and Mace 2020). In this section, we examine whether firms adjust their IP strategies after the *Two Pesos* case.

The ruling clarified that inherently distinctive trade dress is protectable under the Lanham Act, even without secondary meaning. This not only protects unregistered trade dress, but also

increases firms' incentive to file trade dress for trademark-based protection as such protection may be more reliable. In particular, firms may respond by formalizing protection through the USPTO by filing for trade dress registration (i.e., trademark applications covering retail store design or other trade-dress elements). In addition, we note that registered trade dress captures only a subset of the trade dress that a firm actually holds, since registration cannot exhaustively formalize all protectable visual features as we discussed earlier (see Section 2.1). Nonetheless, registered trade dress filings provide a quantifiable and observable proxy for firms' strategic responses to improved trade dress enforceability following the *Two Pesos* ruling, and we use them for this purpose. We therefore predict an increase in filings related to retail store design trade dress after the ruling.

In addition, as suggested by Johnson (1993), expanded trade dress protection may partially substitute for patent-based protection and potentially reducing incentives to seek protection under patent law. This substitution logic predicts a decline in patent filings following the ruling, particularly among firms most exposed to the change in trade dress protectability.

To test these predictions, we model firms' IP filing activity using a Poisson regression. Because the dependent variable is a nonnegative filing count with many zeros, we estimate the model using Poisson pseudo–maximum likelihood (PPML) with high-dimensional fixed effects (absorbing firm and industry-by-year effects) and cluster standard errors at the firm level. Specifically, the Poisson regression takes the following form:

$$\begin{aligned} IP\ filing_{i,t} = \exp(&\alpha_0 + \alpha_1 Post_t \times RetailReliance_i \times LowTrademark_i + \\ &\alpha_2 Post_t \times RetailReliance_i + \alpha_3 Post_t \times LowTrademark_i + \\ &\alpha_4 RetailReliance_i \times LowTrademark_i + \alpha_5 Post_t + \alpha_6 RetailReliance_i + \\ &\alpha_7 LowTrademark_i + \boldsymbol{\alpha} Firm\ characteristic_{i,t} + Firm\ FE_i + Industry \times \\ &Year\ FE_{i,t} + \varepsilon_{i,t}) \end{aligned} \tag{6}$$

in which $IP\ filing_{i,t}$ denotes the number of IP filings by firm *i* in year *t*. We consider two filing outcomes: (i) registered trade dress filings related to store-design (in the form of trademarks) and (ii) utility patent applications. We identify store design trade dress using the USPTO's published design search codes. Specifically, we count trademarks assigned to Design Search Code category 7 (marks related to buildings and structures),[24] which captures filings most closely aligned with retail store design and related trade dress elements. We obtain patent data from the Kogan et al.

[24] See the USPTO Trademark Design Search Code Manual for more details: https://tmdesigncodes.uspto.gov/category/07

(2017) patent database and construct firm-year counts of utility patent applications by aggregating applications to the firm level by fiscal year.

Our coefficient of interest is α_1 on the triple interaction term. This DDD estimator captures the change in firms' IP strategies, especially for firms that are both retail-oriented and low in trademark inventory before the ruling, relative to the corresponding change for other firms. If the *Two Pesos* case increased the attractiveness of registered trade dress protection for consumer-facing design, then we expect α_1 to be positive when the dependent variable is the count of store design trade dress trademark filings. In contrast, if expanded trade dress protection partially substitutes for patent-based protection (Johnson 1993), then we expect α_1 to be negative when the dependent variable is the count of utility patent applications.

We also examine whether the ruling affected firms' reliance on advertising-based investments in consumer association. Prior to the *Two Pesos* case, firms seeking to protect distinctive trade dress often faced stronger incentives to invest in advertising to build and demonstrate secondary meaning, which is required as key evidence in infringement disputes. If the ruling reduced the need to prove secondary meaning for inherently distinctive trade dress, then the marginal benefit of advertising for establishing source association should decline. We therefore predict a decrease in advertising expenditures following the ruling, especially among retail-reliant firms with relatively thin trademark portfolios. We test this prediction by estimating Equation (1) while replacing the dependent variable with advertising intensity, measured as advertising expenditures scaled by total sales.

Table 9 presents our results. Columns (1) and (2) present PPML estimates when the dependent variable is the annual count of store-design trade dress filings and utility patent applications, respectively. In Column (1), the coefficient on $Post \times RetailReliance \times FewerTrademark$ is positive and significant, indicating an increase in building-design trademark applications following the *Two Pesos* case among retail-reliant firms with relatively few trademarks. In contrast, Column (2) shows a negative estimate on the triple-interaction term, consistent with reduced patenting activity for firms most exposed to the ruling. Column (3) presents results when we estimate Equation (1) in OLS with advertising intensity as the dependent variable. The coefficient on the DDD estimator is negative, suggesting that exposed firms reduce advertising intensity after the ruling. We note that the PPML estimations in Columns (1) and (2)

condition on strictly positive counts, excluding firm-year observations with zero filings or applications, which substantially reduces the number of observations relative to the OLS sample in Column (3).

Taken together, the results in Table 9 indicate that firms adjust their IP strategies in response to the doctrinal change. As the scope and expected enforceability of trade dress protection expanded, exposed firms appeared to shift protection toward trademark-based filings and away from patenting. This pattern is consistent with a substitution channel in which trademark/trade dress protection, which is potentially renewable and long-lived conditional on continued use, becomes relatively more attractive than patent protection, which expires after a finite term. The decline in advertising intensity further suggests that firms may rely less on advertising-based investments aimed at building and evidencing secondary meaning, consistent with the *Two Pesos* case reducing the expected need to prove acquired distinctiveness in disputes involving inherently distinctive trade dress.

8. Conclusion

We examine how an important yet underexplored form of intellectual property—trade dress—influences firm value. We exploit the U.S. Supreme Court's 1992 decision in *Two Pesos, Inc. v. Taco Cabana, Inc.*, which resolved the conflict among federal appellate courts and expanded protection for unregistered trade dress under the Lanham Act. Prior to the case, firms' unregistered trade dress faced substantial litigation and evidentiary burdens to establish secondary meaning, limiting effective deterrence against copying. By removing the secondary meaning requirement for inherently distinctive trade dress, the *Two Pesos* case plausibly strengthened firms' ability to protect valuable visual identity and presentation assets, translating into improved product-market outcomes and higher firm value. Because the ruling is expected to matter most for firms whose value depends on consumer-facing presentation and whose formal branding protection is relatively limited, we implement a triple-interaction design to identify the valuation effect of enhanced trade dress protection for the most exposed firms.

Our results show that retail-reliant firms with relatively thin trademark portfolios prior to the *Two Pesos* case experience a significant increase in valuation following the ruling. This pattern is consistent with an imitation mitigation mechanism, as the effect is stronger in settings where visual identity is central and imitation risk is high. Complementing our long-horizon valuation

evidence, we document more favorable short-window stock market reactions around the decision date for the most exposed firms. We further show that this valuation effect is accompanied by improved operating performance, consistent with enhanced appropriability of consumer-facing differentiation investment translating into real product-market benefits. Finally, we provide evidence that firms adjust their IP strategies after the doctrinal change by increasing registrations related to store-design trade dress trademarks, reducing utility patent registrations, and lowering advertising intensity, consistent with substitution toward trademark-based protection and reduced reliance on advertising-based investments aimed at establishing secondary meaning.

We use our collective findings to highlight trade dress as an economically meaningful yet often overlooked component of IP protection and demonstrate that doctrinal shifts in IP laws can generate material valuation effects, real operating changes, and strategic re-optimization of firms' IP and marketing activities.

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Appendix
Variable Definitions

This appendix provides definitions for all variables used in the empirical analysis.

Variable	Definition
Dependent Variable	
Market-to-Book	The sum of book value of total debt and market value of equity, scaled by book value of total assets. Book value of total debt is the sum of long-term debt (Compustat: dltt) and short-term debt (dlc). Market value of equity is shares outstanding (csho) multiplied by fiscal year-end closing price (prcc_f). Total assets is Compustat item at.
CAR[-1,+1]	Cumulative abnormal return over the three-day window centered on the Two Pesos decision date. Abnormal returns are computed as the difference between the firm's daily return and the expected return estimated from the Fama and French (1993) three-factor model, estimated over a pre-event window using a minimum of 120 trading days of daily pricing data.
CAR[-2,+2]	Cumulative abnormal return over the five-day window centered on the Two Pesos decision date. Expected returns are estimated as described for CAR[-1,+1].
CAR[0,+1]	Cumulative abnormal return over the two-day window beginning on the Two Pesos decision date. Expected returns are estimated as described for CAR[-1,+1].
Gross Profit Margin	Sales revenue minus cost of goods sold (Compustat: sale minus cogs), scaled by total sales revenue (sale), measured in fiscal year t+1 relative to the ruling year.
ROA	Operating income before depreciation (Compustat: oibdp), scaled by total assets (at), measured in fiscal year t+1 relative to the ruling year.
Trademark Filings	The number of retail store design trade dress trademark filings by a firm in a given fiscal year. Store design trade dress trademarks are identified using USPTO Design Search Code category 7, which covers marks related to buildings and structures and captures filings most closely aligned with retail store design and related trade dress elements.
Utility Patent Applications	The number of utility patent applications filed by a firm in a given fiscal year, aggregated to the firm level by fiscal year from the Kogan et al. (2017) patent database.
DDD indicators	
Post	An indicator variable equal to one for fiscal years 1993 and later, and zero otherwise. The year 1992 is excluded from the sample as a partial-treatment year.
RetailReliance	An indicator variable equal to one if a firm's average retail sales share over the pre-ruling period (1990-1991) exceeds the median retail sales share among firms in the same two-digit SIC industry, and zero otherwise. Retail sales are defined as the sum of establishment-level sales from NETS for establishments

Variable	Definition
	whose two-digit SIC code falls between 52 and 59. Retail sales share is retail sales scaled by total firm sales reported in Compustat.
LowTrademark	An indicator variable equal to one if a firm's average trademark inventory over the pre-ruling period (1990-1991) falls below the median trademark inventory among firms in the same two-digit SIC industry, and zero otherwise. Trademark inventories are constructed from USPTO trademark records, with ownership tracked dynamically using USPTO assignment records and merger and acquisition activity from Refinitiv SDC.
Post × RetailReliance × LowTrademark	The triple interaction term and the key variable of interest. It captures the incremental valuation effect of the Two Pesos case for firms that are simultaneously retail-reliant and have below-median trademark inventories relative to industry peers, i.e., the firms most plausibly exposed to the doctrinal shift.
Control Variables	
Firm Size	The natural logarithm of total assets (Compustat: at).
Leverage	The sum of long-term debt (dltt) and short-term debt (dlc), scaled by total assets (at).
Tangibility	Net property, plant, and equipment (ppent), scaled by total assets (at).
CAPX Intensity	Capital expenditures (capx), scaled by total assets (at).
R&D Intensity	Research and development expenditure (xrd), scaled by total assets (at). Set to zero when R&D expenditure is missing in Compustat.
Missing R&D	An indicator variable equal to one if a firm's R&D expenditure (xrd) is missing in Compustat for a given firm-year, and zero otherwise. Included to absorb any systematic valuation differences between firms that report and firms that do not report R&D expenditure.
Advertising Intensity	Advertising expenditure (xad), scaled by total sales (sale). Set to zero when advertising expenditure is missing in Compustat.
Missing Advertising Expense	An indicator variable equal to one if a firm's advertising expenditure (xad) is missing in Compustat for a given firm-year, and zero otherwise. Included to absorb any systematic valuation differences between firms that report and firms that do not report advertising expenditure.
Sales Growth	The log difference in total sales (sale) between fiscal year t and fiscal year t-1.
ROA	Net income (Compustat: ni), scaled by total assets (at). Included as an additional control in robustness tests to mitigate concerns that time-varying operating performance drives baseline results.
Cash Flow	Cash and short-term investments (Compustat: che), scaled by total assets (at). Included as an additional control in robustness tests to capture cross-sectional variation in firm liquidity.
Payout Policy	Total dividends paid (Compustat: dv), scaled by total assets (at). Included as an additional control in robustness tests to capture cross-sectional variation in payout behavior.

Variable	Definition
Altman Z-Score	A modified composite measure of financial distress following Altman (1968), constructed as: 1.2 x (working capital / total assets) + 3.3 x (operating income / total assets) + 0.6 x (market value of equity / total liabilities) + 1.0 x (sales / total assets), using Compustat items wcap, at, oiadp, sale, and csho x prcc_f for market value of equity. The retained earnings component of the original Altman (1968) specification is excluded due to data availability. Total liabilities is approximated as the sum of long-term debt (dltt), short-term debt (dlc), and non-debt current liabilities (lct minus dlc). A lower Z-score indicates greater financial distress. Included as an additional control in robustness tests to mitigate concerns that cross-sectional differences in distress risk drive baseline results.
Stock Return	The fiscal-year buy-and-hold return, computed as the compounded monthly return over the fiscal-year window defined by the month following the prior fiscal year-end through the current fiscal year-end month. Monthly returns are obtained from the CRSP monthly stock file (msf) and adjusted for delisting using CRSP delisting returns (msedelist). A minimum of six monthly return observations is required. Returns are linked to Compustat firm-years using the CRSP/Compustat Merged link table.
Stock Volatility	The annualized standard deviation of monthly returns over the fiscal-year window, computed as the standard deviation of monthly returns multiplied by the square root of 12. Monthly returns are defined as described for Stock Return. A minimum of six monthly return observations is required.
Sample Indicators	
B2C Industry	An indicator variable equal to one if a firm operates in a business-to-consumer (B2C) industry, and zero otherwise. Industries are classified as B2C if their two-digit SIC code corresponds to consumer goods or finance sectors following the classification in Sharpe (1982), as applied in Lev et al. (2010) and Emery (2025). All remaining industries are classified as business-to-business (B2B). We assign a firm to the B2C (B2B) subsample if it is consistently classified as operating in B2C (B2B) industries prior to the *Two Pesos* case.
High Design Intensity	An indicator variable equal to one if a firm operates in a high design-intensity industry, and zero otherwise. Design intensity is measured at the industry level as the number of USPTO design patents granted to firms within a two-digit SIC industry, scaled by total industry sales over the pre-ruling period (1990-1991). An industry is classified as high design intensity if this ratio exceeds the cross-industry median. This classification is held fixed across all sample periods.
High Advertising Intensity	An indicator variable equal to one if a firm operates in a high advertising intensity industry, and zero otherwise. Industry advertising intensity is measured as total advertising expenditures (Compustat: xad) scaled by total sales (Compustat: sale) within each two-digit SIC industry, aggregated over the pre-ruling period (1990–1991). An industry is classified as high advertising intensity if this ratio exceeds the cross-industry median, and as low advertising intensity otherwise. This classification is held fixed across all sample years.

Figure 1
Taco Cabana and Two Pesos Restaurant Designs

This figure displays courtroom exhibits from *Two Pesos, Inc. v. Taco Cabana, Inc.*, 505 U.S. 763 (1992), illustrating the visual similarity between the trade dress of the two restaurant chains that formed the basis of the infringement dispute. Panel A shows exterior photographs of a Taco Cabana location (top) and a Two Pesos location (bottom), depicting comparable building structures, signage placement, striped awnings, and overall architectural presentation. Panel B presents aerial floor plan models of the two restaurants (Taco Cabana (top) and Two Pesos (bottom)), revealing similar spatial layouts including the arrangement of kitchen, dining, and patio areas. Panel C shows panoramic interior photographs of Taco Cabana (top) and Two Pesos (bottom), illustrating the comparable decorative schemes, seating arrangements, and overall dining environment. All images are reproduced from plaintiff's trial exhibits submitted in the underlying district court proceedings. Source: https://courses2.cit.cornell.edu/sociallaw/student_projects/Tradedresspage2.html

Panel A: Exteriors



Panel B: Floor plans





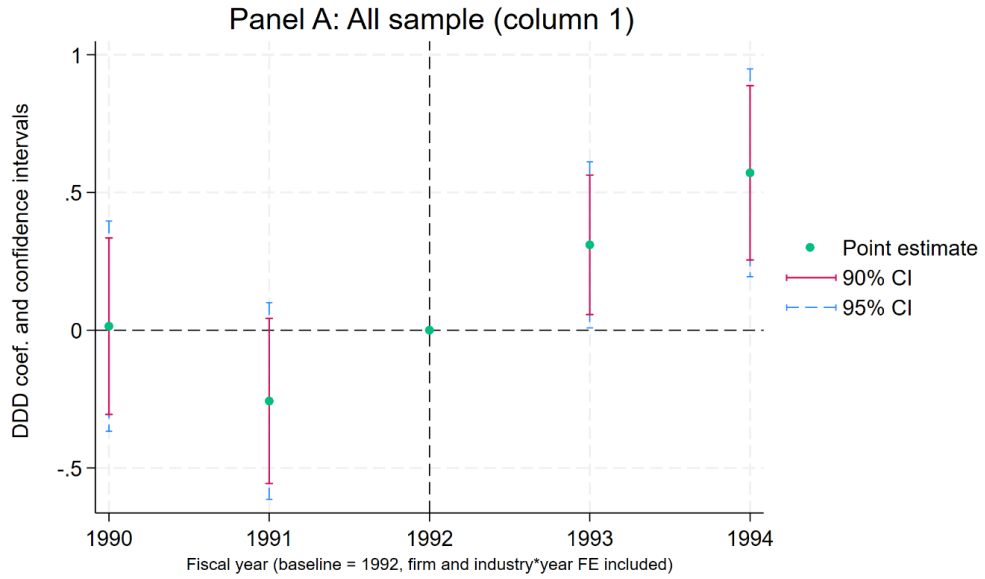
Panel C: Interiors

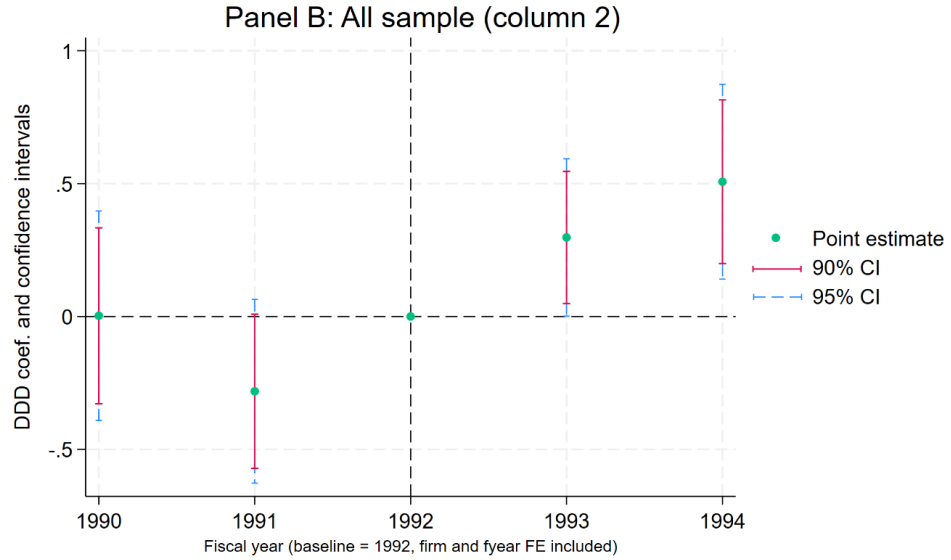


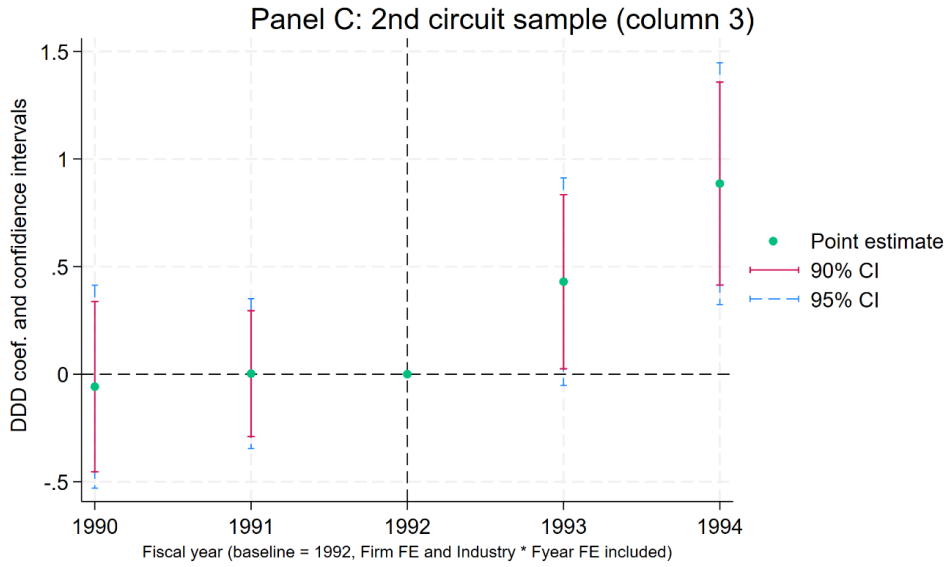


Figure 2
Dynamic DDD Estimates: Parallel Trends

This figure plots year-by-year DDD coefficient estimates and confidence intervals from Equation (2), in which the post-period indicator in the baseline specification is replaced with event-time indicators corresponding to fiscal years 1990 through 1994. Fiscal year 1992 is the omitted base year, so its coefficient is normalized to zero. The vertical dashed line marks the ruling date. The dependent variable is the *Market-to-Book*. Dots represent point estimates; red solid bars and blue dashed bars represent 90% and 95% confidence intervals, respectively. Panels A and B report estimates for the full sample using firm and industry-year fixed effects, and firm and year fixed effects, respectively, corresponding to Columns (1) and (2) of Table 2. Panels C and D report the corresponding estimates for the Second Circuit sample, in which retail reliance is measured using sales concentrated in Second Circuit states, corresponding to Columns (3) and (4) of Table 2. Pre-ruling coefficients that are statistically indistinguishable from zero and post-ruling coefficients that are positive and increasing are consistent with the parallel trends assumption underlying the DDD identification strategy.






Panel C: 2nd circuit sample (column 3)
DDD coef. and confidence intervals
1.5
1
.5
0
-.5
1990
1991
1992
1993
1994
Fiscal year (baseline = 1992, Firm FE and Industry * Fyear FE included)
Point estimate
90% CI
95% CI

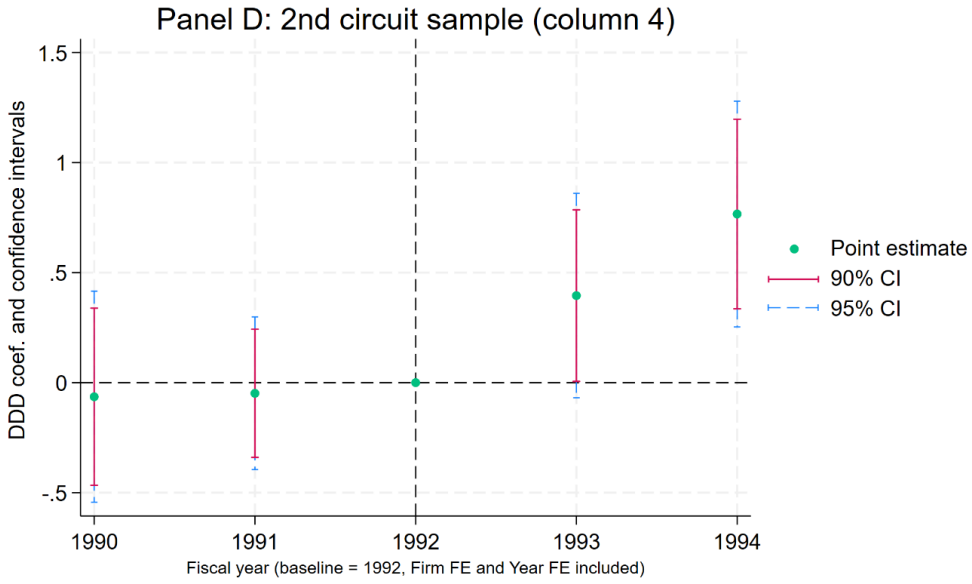
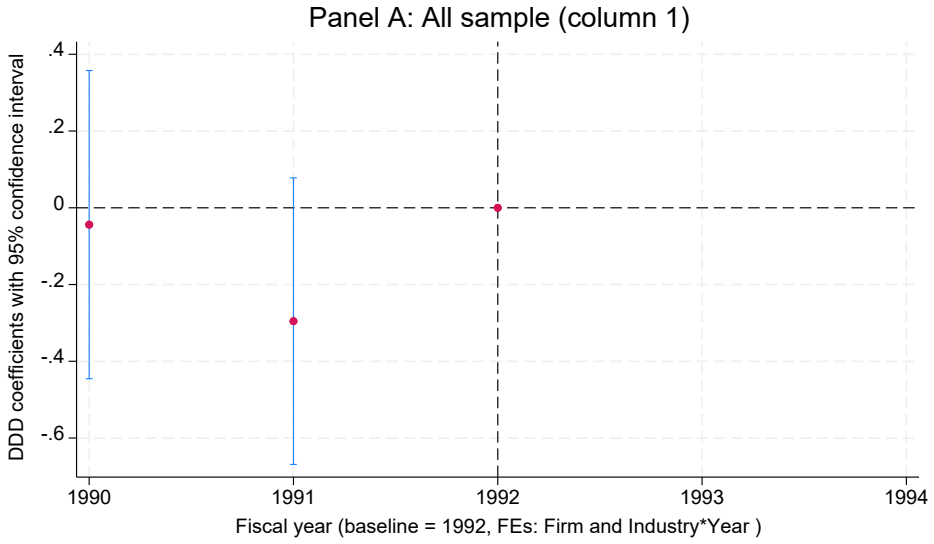
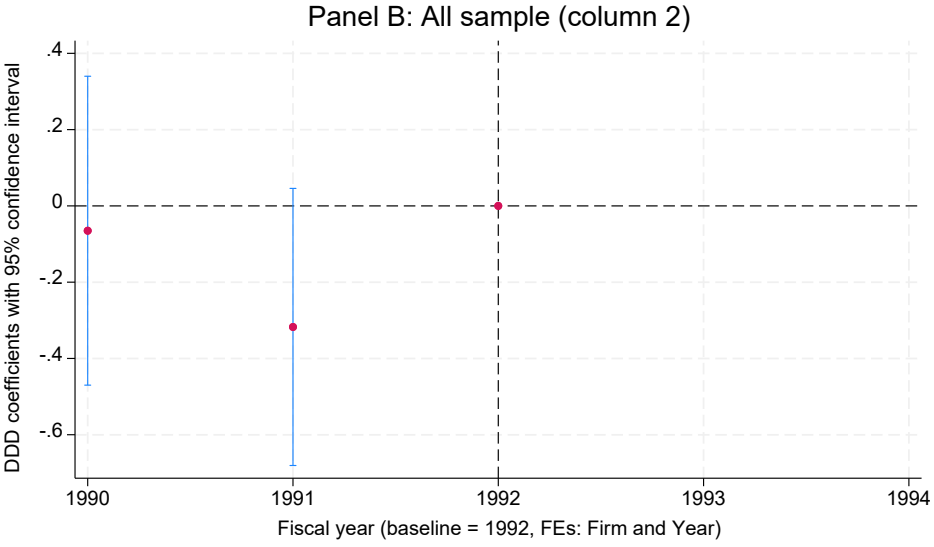
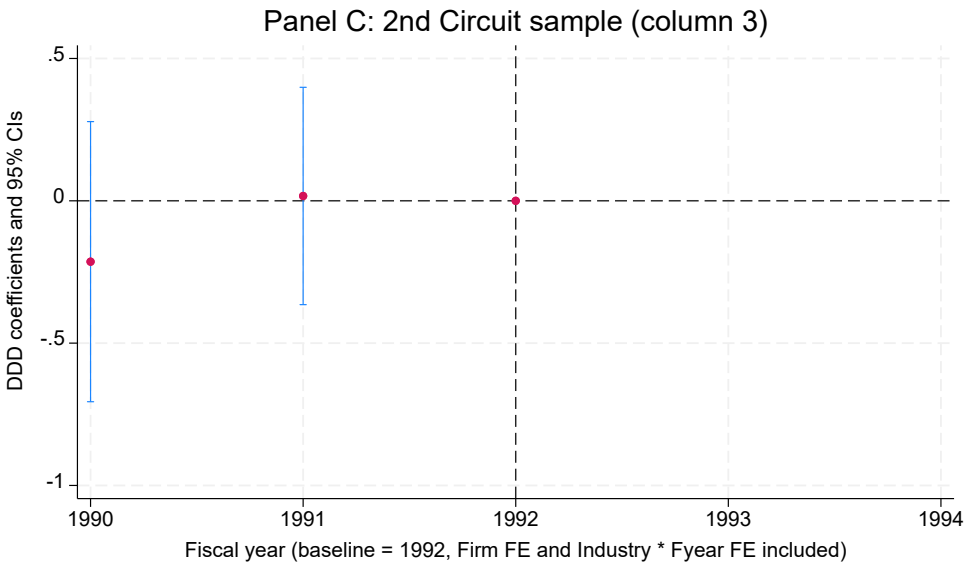

Panel D: 2nd circuit sample (column 4)
DDD coef. and confidence intervals
1.5
1
.5
0
-.5
1990
1991
1992
1993
1994
Fiscal year (baseline = 1992, Firm FE and Year FE included)
Point estimate
90% CI
95% CI

Figure 3
Dynamic DDD Estimates: Pre-Event Sample

This figure plots DDD coefficient estimates and 95% confidence intervals from Equation (2) estimated using only pre-ruling observations (fiscal years 1990 and 1991), with fiscal year 1992 as the omitted base year, following Moser and Voena (2012) and Bereskin, Hsu, and Wang (2025). The vertical dashed line marks the ruling date. The dependent variable is the *Market-to-Book*. Dots represent point estimates; blue bars represent 95% confidence intervals. Panels A and B report estimates for the full sample using firm and industry-year fixed effects, and firm and year fixed effects, respectively, corresponding to Columns (1) and (2) of Table 2. Panels C and D report the corresponding estimates for the Second Circuit subsample, corresponding to Columns (3) and (4) of Table 2. All pre-ruling coefficients are statistically indistinguishable from zero across all four specifications, providing no evidence of differential pre-trends prior to the ruling and further corroborating the parallel trends assumption underlying the DDD identification strategy.






Panel C: 2nd Circuit sample (column 3)
DDD coefficients and 95% CIs
.5
0
-.5
-1
1990
1991
1992
1993
1994
Fiscal year (baseline = 1992, Firm FE and Industry * Fyear FE included)

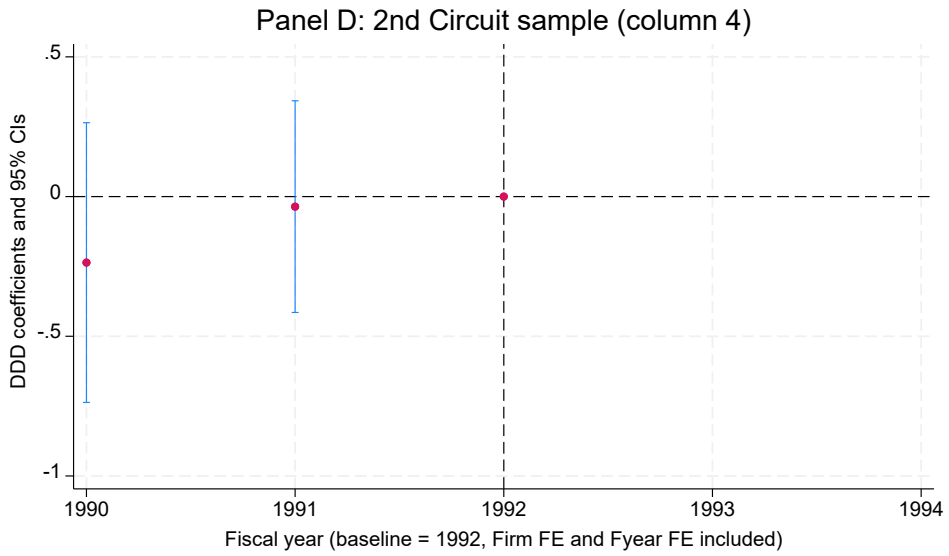

Panel D: 2nd Circuit sample (column 4)
DDD coefficients and 95% CIs
.5
0
-.5
-1
1990
1991
1992
1993
1994
Fiscal year (baseline = 1992, Firm FE and Fyear FE included)

Table 1
Summary Statistics

This table reports summary statistics for the full sample of 15,165 firm-year observations over the period 1990–1994, excluding fiscal year 1992. The sample consists of Compustat firms matched to the NETS database. *Market-to-Book* is defined as the sum of book debt and market equity divided by book assets. *RetailReliance* is an indicator equal to one if a firm's average retail sales share over 1990–1991 exceeds the within-industry median at the two-digit SIC level. *LowTrademark* is an indicator equal to one if a firm's average trademark inventory over 1990–1991 falls below the within-industry median at the two-digit SIC level. *# of Trademarks* is the count of active trademarks held by the firm in a given year, constructed from USPTO records. *Retail Sales Pct* is the share of firm-level sales attributable to retail-oriented establishments, defined as those with two-digit SIC codes between 52 and 59, based on NETS data. *Firm Size* is the natural logarithm of total assets. *Leverage* is total debt scaled by total assets. *Tangibility* is net property, plant, and equipment scaled by total assets. *CAPX Intensity* is capital expenditures scaled by total assets. *R&D Intensity* is research and development expenditure scaled by total assets, set to zero when missing. *Missing R&D* is an indicator equal to one if R&D expenditure is missing in Compustat. *Advertising Intensity* is advertising expenditure scaled by sales, set to zero when missing. *Missing Advertising* is an indicator equal to one if advertising expenditure is missing in Compustat.

	N	Mean	SD	P25	Median	P75
Market-to-Book	15165	1.906	3.537	1.026	1.294	1.923
RetailReliance	15165	0.265	0.441	0.000	0.000	1.000
LowTrademark	15165	0.222	0.416	0.000	0.000	0.000
# of trademarks	15165	23.381	85.205	0.000	1.000	10.000
Retail Sales pct	15165	0.059	0.197	0.000	0.000	0.002
Firm Size	15165	4.742	2.219	3.188	4.594	6.154
Leverage	15165	0.260	0.246	0.068	0.228	0.384
Tangibility	15165	0.318	0.244	0.121	0.257	0.475
CAPX intensity	15165	0.064	0.095	0.021	0.045	0.080
R&D intensity	15165	0.037	0.103	0.000	0.000	0.031
Missing R&D	15165	0.499	0.500	0.000	0.000	1.000
Sale growth	15165	0.080	0.436	-0.033	0.067	0.189
Advertising intensity	15165	0.016	0.358	0.000	0.000	0.011
Missing Advertising	15165	0.676	0.468	0.000	1.000	1.000

Table 2
Baseline regression

This table reports baseline difference-in-differences-in-differences (DDD) estimates of the valuation effect of the Two Pesos case. The dependent variable is the *Market-to-Book*, defined as the sum of book debt and market equity divided by book assets. The sample covers 15,165 firm-year observations over 1990–1994, excluding fiscal year 1992. *Post* is an indicator equal to one for fiscal years 1993 and later. *RetailReliance* is an indicator equal to one if a firm's average retail sales share over 1990–1991 exceeds the within-industry median at the two-digit SIC level. *LowTrademark* is an indicator equal to one if a firm's average trademark inventory over 1990–1991 falls below the within-industry median at the two-digit SIC level. Columns (1) and (3) include industry-year fixed effects; Columns (2) and (4) replace industry-year fixed effects with year fixed effects. Columns (3) and (4) restrict the retail reliance measure to sales generated within Second Circuit states. The row labeled t-test reports the one-side t-tests that the sum of the coefficients on Post × RetailReliance × LowTrademark and Post × LowTrademark is significantly greater than zero. All specifications include firm fixed effects and firm-level controls. All variables are defined in the Appendix. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Market-to-Book			
VARIABLES	(1)	(2)	(3)	(4)
Post × RetailReliance × LowTrademark	0.453***	0.456***	0.696***	0.667***
	(0.175)	(0.169)	(0.261)	(0.238)
Post × RetailReliance	-0.035	-0.068	-0.051	-0.087
	(0.077)	(0.077)	(0.099)	(0.075)
Post × LowTrademark	-0.284**	-0.354***	-0.236**	-0.302***
	(0.126)	(0.114)	(0.113)	(0.097)
Firm Size	-0.735***	-0.750***	-0.738***	-0.751***
	(0.200)	(0.204)	(0.199)	(0.203)
Leverage	0.648	0.594	0.641	0.589
	(0.404)	(0.408)	(0.404)	(0.408)
Tangibility (ppent/at)	0.814	0.748	0.813	0.750
	(1.389)	(1.416)	(1.388)	(1.416)
CAPX intensity	-14.185**	-14.049**	-14.184**	-14.048**
	(7.112)	(7.154)	(7.113)	(7.155)
R&D intensity(xrd/at)	2.142*	1.838	2.143*	1.841
	(1.148)	(1.164)	(1.148)	(1.165)
Sale growth	0.035	0.030	0.047	0.040
	(0.139)	(0.137)	(0.139)	(0.137)
Missing R&D	0.383***	0.403***	0.385***	0.404***
	(0.101)	(0.103)	(0.101)	(0.104)
Advertising intensity	0.195***	0.199***	0.195***	0.199***
	(0.011)	(0.010)	(0.012)	(0.010)
Missing Advertising expense	-0.118	-0.108	-0.119	-0.110
	(0.086)	(0.081)	(0.086)	(0.081)
Constant	5.845***	5.958***	5.851***	5.954***
	(1.004)	(1.033)	(0.996)	(1.023)
t-test:	0.169*	0.102	0.460**	0.365**
	(0.131)	(0.115)	(0.237)	(0.209)
Retail reliance	all	all	2nd Circuits	2nd Circuits
Firm FE	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	No	Yes	No
Year FE	No	Yes	No	Yes
Observations	15,157	15,165	15,157	15,165
R-squared	0.776	0.770	0.776	0.770

Table 3
Robustness tests

This table reports robustness checks on the baseline DDD estimates. The sample covers firm-year observations over 1990–1994, excluding fiscal year 1992. *Post* is an indicator equal to one for fiscal years 1993 and later. *RetailReliance* is an indicator equal to one if a firm's average retail sales share over 1990–1991 exceeds the within-industry median. *LowTrademark* is an indicator equal to one if a firm's average trademark inventory over 1990–1991 falls below the within-industry median. In Columns (1) and (2), both *RetailReliance* and *LowTrademark* are constructed using the Fama-French 48 industry classification. In Columns (3) and (4), the dependent variable is Tobin's Q. In Columns (5) and (6), the baseline specification is augmented with additional controls to mitigate concerns related to financial constraints. Odd-numbered columns include industry-year fixed effects; even-numbered columns replace industry-year fixed effects with year fixed effects. All specifications include firm fixed effects and firm-level controls. All variables are defined in the Appendix. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Market-to-Book	(2) Market-to-Book	(3) Tobin's Q	(4) Tobin's Q	(5) Market-to-Book	(6) Market-to-Book
Post × RetailReliance × LowTrademark	0.372**	0.350**	0.375**	0.356**	0.361**	0.354**
	(0.183)	(0.172)	(0.170)	(0.166)	(0.172)	(0.168)
Post × RetailReliance	-0.078	-0.067	-0.040	-0.064	0.010	-0.011
	(0.075)	(0.076)	(0.075)	(0.075)	(0.068)	(0.069)
Post × LowTrademark	-0.290**	-0.288**	-0.290**	-0.321***	-0.244**	-0.266**
	(0.136)	(0.126)	(0.121)	(0.111)	(0.122)	(0.109)
Firm Size	-0.719***	-0.755***	-0.690***	-0.698***	-0.442***	-0.445***
	(0.212)	(0.204)	(0.200)	(0.204)	(0.106)	(0.106)
Leverage	0.664	0.591	0.258	0.225	0.121	0.080
	(0.405)	(0.408)	(0.478)	(0.473)	(0.436)	(0.438)
Tangibility (ppent/at)	0.938	0.720	1.237	1.171	2.520*	2.563*
	(1.425)	(1.414)	(1.473)	(1.503)	(1.340)	(1.372)
CAPX intensity	-14.174**	-14.044**	-13.825*	-13.710*	-14.967**	-14.827**
	(7.157)	(7.157)	(7.274)	(7.321)	(6.840)	(6.897)
R&D intensity(xrd/at)	2.307**	1.829	2.211**	1.961*	0.756	0.633
	(1.139)	(1.169)	(1.101)	(1.124)	(1.298)	(1.298)
Sale growth	0.003	0.032	-0.004	-0.015	0.080	0.081
	(0.138)	(0.136)	(0.135)	(0.134)	(0.149)	(0.145)
Missing R&D	0.376***	0.407***	0.331***	0.348***	0.643***	0.664***
	(0.100)	(0.104)	(0.091)	(0.094)	(0.122)	(0.123)
Advertising intensity	0.195***	0.199***	0.194***	0.197***	0.067**	0.069**
	(0.011)	(0.010)	(0.011)	(0.010)	(0.032)	(0.032)
Missing Advertising expense	-0.106	-0.108	-0.087	-0.081	-0.088	-0.071
	(0.085)	(0.081)	(0.078)	(0.073)	(0.083)	(0.078)
ROA					-2.227***	-2.244***
					(0.648)	(0.660)
Cash					0.986**	1.008**
					(0.448)	(0.443)
Dividend					2.568**	2.590**
					(1.269)	(1.292)
Financial Distress					0.066***	0.068***
					(0.010)	(0.009)
Constant	5.731***	5.982***	5.516***	5.593***	3.467***	3.444***
	(1.075)	(1.032)	(1.002)	(1.029)	(0.490)	(0.495)

	0.372**	0.350**	0.375**	0.356**	0.361**	0.354**
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	No	Yes	No	Yes	No
Year FE	No	Yes	No	Yes	No	Yes
Industry classification	FF48	FF48	SIC2	SIC2	SIC2	SIC2
Observations	15,165	15,165	15,192	15,200	13,806	13,814
R-squared	0.777	0.770	0.803	0.797	0.817	0.813

Table 4
CARs around the Supreme Court decision

This table reports cross-sectional regression estimates of cumulative abnormal returns (CARs) around the Supreme Court's decision in *Two Pesos, Inc. v. Taco Cabana, Inc.*, issued on June 26, 1992. The dependent variable is the CARs computed over the [0, +1], [−1, +1], and [−2, +2] windows relative to the decision date, as indicated in the column headers. Abnormal returns are estimated using the Fama and French (1993) three-factor model fitted over the pre-event window [−250, −30] relative to the decision date, requiring a minimum of 120 trading days of pricing data. *RetailReliance* is an indicator equal to one if a firm's average retail sales share over 1990–1991 exceeds the within-industry median at the two-digit SIC level. *LowTrademark* is an indicator equal to one if a firm's average trademark inventory over 1990–1991 falls below the within-industry median at the two-digit SIC level. All specifications include industry and year fixed effects and firm-level controls measured at the end of fiscal year 1991. All variables are defined in the Appendix. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	CAR (-0, +1) (1)	CAR (-1, +1) (2)	CAR (-2, +2) (3)
RetailReliance × LowTrademark	0.017**	0.020**	0.030***
	(0.008)	(0.008)	(0.010)
RetailReliance	-0.004	-0.003	-0.004
	(0.004)	(0.004)	(0.005)
LowTrademark	-0.001	0.001	0.001
	(0.004)	(0.004)	(0.006)
Firm Size	-0.001*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Leverage	-0.010*	-0.018***	-0.008
	(0.006)	(0.006)	(0.008)
Tangibility (ppent/at)	0.014*	0.013	0.010
	(0.008)	(0.008)	(0.011)
CAPX intensity	-0.005	-0.018	-0.001
	(0.021)	(0.021)	(0.028)
R&D intensity(xrd/at)	0.021	0.011	-0.018
	(0.018)	(0.018)	(0.024)
Sale growth	0.001	0.002	0.003
	(0.003)	(0.004)	(0.005)
Missing R&D	-0.009***	-0.008***	-0.007*
	(0.003)	(0.003)	(0.004)
Advertising intensity	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.003)
Missing Advertising expense	-0.004	-0.003	0.002
	(0.003)	(0.003)	(0.004)
Constant	0.007	0.006	-0.003
	(0.005)	(0.005)	(0.007)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,966	3,966	3,966
R-squared	0.024	0.025	0.029

Table 5
Mechanism test: B2C v. B2B industries

This table reports DDD estimates of the valuation effect of the *Two Pesos* case separately for B2C-oriented and B2B-oriented industry subsamples. The dependent variable is the *Market-to-Book*. The sample covers firm-year observations over 1990–1994, excluding fiscal year 1992. *Post* is an indicator equal to one for fiscal years 1993 and later. *RetailReliance* is an indicator equal to one if a firm's average retail sales share over 1990–1991 exceeds the within-industry median at the two-digit SIC level. *LowTrademark* is an indicator equal to one if a firm's average trademark inventory over 1990–1991 falls below the within-industry median at the two-digit SIC level. Industries are classified as B2C or B2B following Sharpe (1982), as implemented in Lev et al. (2010) and Emery (2025), with consumer goods and finance designated as B2C-oriented and all remaining industries designated as B2B-oriented. We assign a firm to the B2C (B2B) subsample if it is consistently classified as operating in B2C (B2B) industries prior to the *Two Pesos* case. Columns (1) and (2) report estimates for the B2C subsample; Columns (3) and (4) report estimates for the B2B subsample. Odd-numbered columns include industry-year fixed effects; even-numbered columns replace industry-year fixed effects with year fixed effects. All specifications include firm fixed effects and firm-level controls. All variables are defined in the Appendix. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	B2C v. B2B industries			
	B2C		B2B	
VARIABLES	(1)	(2)	(3)	(4)
Post × RetailReliance × LowTrademark	0.694***	0.724***	0.132	0.136
	(0.260)	(0.255)	(0.195)	(0.187)
Post × RetailReliance	-0.095	-0.122	0.102	0.073
	(0.131)	(0.134)	(0.072)	(0.065)
Post × LowTrademark	-0.491**	-0.588***	0.010	-0.016
	(0.203)	(0.189)	(0.116)	(0.111)
Firm Size	-0.896**	-0.917**	-0.613***	-0.621***
	(0.355)	(0.359)	(0.092)	(0.092)
Leverage	0.699	0.627	0.616**	0.584**
	(0.804)	(0.807)	(0.261)	(0.265)
Tangibility (ppent/at)	0.786	0.783	-1.157***	-1.266***
	(1.440)	(1.457)	(0.359)	(0.345)
CAPX intensity	-19.007***	-18.816***	2.264***	2.364***
	(5.729)	(5.788)	(0.494)	(0.504)
R&D intensity(xrd/at)	2.858	2.269	0.691	0.705
	(1.921)	(1.945)	(1.069)	(1.047)
Missing R&D	-0.071	-0.104	0.076	0.101
	(0.164)	(0.163)	(0.203)	(0.196)
Sale growth	0.475***	0.499***	0.189	0.202*
	(0.136)	(0.139)	(0.117)	(0.114)
Advertising intensity	0.202	0.248	0.204***	0.206***
	(0.362)	(0.334)	(0.005)	(0.004)
Missing Advertising expense	-0.215*	-0.195	-0.019	-0.027
	(0.124)	(0.120)	(0.119)	(0.115)
Constant	6.996***	7.135***	4.745***	4.827***
	(1.732)	(1.768)	(0.469)	(0.456)
Observations	7,689	7,689	7,446	7,454
Firm FE	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	No	Yes	No
Year FE	No	Yes	No	Yes
R-squared	0.815	0.809	0.677	0.669

Table 6
Mechanism test: Design intensity

This table reports DDD estimates of the valuation effect of the *Two Pesos* case separately for high and low design-intensity industry subsamples. The dependent variable is the *Market-to-Book*. The sample covers firm-year observations over 1990–1994, excluding fiscal year 1992. *Post* is an indicator equal to one for fiscal years 1993 and later. *RetailReliance* is an indicator equal to one if a firm's average retail sales share over 1990–1991 exceeds the within-industry median at the two-digit SIC level. *LowTrademark* is an indicator equal to one if a firm's average trademark inventory over 1990–1991 falls below the within-industry median at the two-digit SIC level. Design intensity is measured at the industry level as the number of USPTO design patents granted to firms within a two-digit SIC industry, scaled by total industry sales over the pre-ruling period (1990-1991). An industry is classified as high design intensity if this ratio exceeds the cross-industry median, and low design intensity otherwise. The classification is held fixed across all sample periods. Columns (1) and (2) report estimates for the high design-intensity subsample; Columns (3) and (4) report estimates for the low design-intensity subsample. Odd-numbered columns include industry-year fixed effects; even-numbered columns replace industry-year fixed effects with year fixed effects. All specifications include firm fixed effects and firm-level controls. All variables are defined in the Appendix. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Design intensity			
	High		Low	
VARIABLES	(1)	(2)	(3)	(4)
Post × RetailReliance × LowTrademark	0.541**	0.517**	0.081	0.034
	(0.218)	(0.210)	(0.199)	(0.185)
Post × RetailReliance	-0.092	-0.081	-0.048	-0.100
	(0.129)	(0.122)	(0.068)	(0.085)
Post × LowTrademark	-0.309**	-0.372**	0.019	-0.098
	(0.152)	(0.147)	(0.135)	(0.121)
Firm Size	-0.941***	-0.966***	-0.521***	-0.538***
	(0.334)	(0.344)	(0.079)	(0.082)
Leverage	0.693	0.621	0.490*	0.417
	(0.617)	(0.634)	(0.284)	(0.274)
Tangibility (ppent/at)	1.673	1.416	-1.394***	-1.350***
	(1.420)	(1.433)	(0.406)	(0.388)
CAPX intensity	-19.935***	-19.795***	0.970**	0.898*
	(5.309)	(5.386)	(0.479)	(0.471)
R&D intensity(xrd/at)	1.683	1.355	1.302	1.403
	(1.377)	(1.416)	(2.395)	(2.411)
Sale growth	-0.068	-0.105	0.008	0.073
	(0.214)	(0.212)	(0.164)	(0.162)
Missing R&D	0.360**	0.393***	0.306***	0.318***
	(0.146)	(0.151)	(0.073)	(0.072)
Advertising intensity	0.183***	0.187***	4.183	4.119
	(0.014)	(0.013)	(2.666)	(2.971)
Missing Advertising expense	-0.106	-0.116	-0.030	-0.009
	(0.104)	(0.103)	(0.133)	(0.121)
Constant	6.868***	7.099***	4.568***	4.621***
	(1.610)	(1.668)	(0.480)	(0.483)
Observations	8,432	8,432	6,725	6,733
Firm FE	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	No	Yes	No
Year FE	No	Yes	No	Yes
R-squared	0.825	0.819	0.703	0.695

Table 7
Mechanism test: Advertising intensity

This table reports DDD estimates of the valuation effect of the *Two Pesos* case separately for high and low advertising-intensity industry subsamples. The dependent variable is the *Market-to-Book*. The sample covers firm-year observations over 1990–1994, excluding fiscal year 1992. *Post* is an indicator equal to one for fiscal years 1993 and later. *RetailReliance* is an indicator equal to one if a firm's average retail sales share over 1990–1991 exceeds the within-industry median at the two-digit SIC level. *LowTrademark* is an indicator equal to one if a firm's average trademark inventory over 1990–1991 falls below the within-industry median at the two-digit SIC level. Industry advertising intensity is measured as total advertising expenditures scaled by total sales within each two-digit SIC industry, aggregated over the pre-ruling period (1990–1991). An industry is classified as high advertising intensity if this ratio exceeds the cross-industry median, and as low advertising intensity otherwise. This classification is held fixed across all sample years. Columns (1) and (2) report estimates for the high advertising-intensity subsample; Columns (3) and (4) report estimates for the low advertising-intensity subsample. Odd-numbered columns include industry-year fixed effects; even-numbered columns replace industry-year fixed effects with year fixed effects. All specifications include firm fixed effects and firm-level controls. All variables are defined in the Appendix. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Advertising intensity			
	High		Low	
VARIABLES	(1)	(2)	(3)	(4)
Post × RetailReliance × LowTrademark	0.304*	0.360**	0.099	-0.035
	(0.174)	(0.167)	(0.250)	(0.247)
Post × RetailReliance	-0.007	-0.066	-0.073	-0.073
	(0.093)	(0.102)	(0.122)	(0.110)
Post × LowTrademark	-0.180	-0.254**	-0.269	-0.195
	(0.131)	(0.127)	(0.183)	(0.178)
Firm Size	-0.704***	-0.739***	-0.837**	-0.841**
	(0.111)	(0.113)	(0.371)	(0.381)
Leverage	0.434	0.403	1.112*	1.019
	(0.282)	(0.288)	(0.668)	(0.667)
Tangibility (ppent/at)	-2.454***	-2.529***	1.660	1.554
	(0.546)	(0.533)	(1.307)	(1.327)
CAPX intensity	2.199***	2.245***	-18.138***	-18.024***
	(0.837)	(0.835)	(6.047)	(6.101)
R&D intensity(xrd/at)	3.393**	2.950**	-0.356	-0.366
	(1.395)	(1.434)	(1.346)	(1.346)
Sale growth	-0.146	-0.176	0.148	0.197
	(0.194)	(0.187)	(0.201)	(0.200)
Missing R&D	0.409***	0.443***	0.290**	0.300**
	(0.121)	(0.124)	(0.141)	(0.144)
Advertising intensity	0.239	0.353	0.184***	0.190***
	(0.298)	(0.260)	(0.012)	(0.011)
Missing Advertising expense	-0.066	-0.041	-0.173	-0.153
	(0.104)	(0.098)	(0.133)	(0.122)
Constant	5.525***	5.740***	6.400***	6.420***
	(0.547)	(0.551)	(2.023)	(2.084)
Observations	8,013	8,013	7,144	7,152
Firm FE	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	No	Yes	No
Year FE	No	Yes	No	Yes
R-squared	0.687	0.678	0.857	0.853

Table 8
Profitability

This table reports DDD estimates of the effect of the *Two Pesos* case on subsequent operating performance. The dependent variables are *Gross Profit Margin* in Column (1) and *Return on Assets* (ROA) in Column (2), both measured in year t+1. *Gross Profit Margin* is defined as sales revenue minus cost of goods sold, scaled by total sales revenue. *ROA* is defined as operating income before depreciation scaled by total assets. The sample covers firm-year observations over 1990–1994, excluding fiscal year 1992. *Post* is an indicator equal to one for fiscal years 1993 and later. *RetailReliance* is an indicator equal to one if a firm's average retail sales share over 1990–1991 exceeds the within-industry median at the two-digit SIC level. *LowTrademark* is an indicator equal to one if a firm's average trademark inventory over 1990–1991 falls below the within-industry median at the two-digit SIC level. All specifications include firm fixed effects, industry-year fixed effects, and firm-level controls, with the addition of stock return and stock volatility as controls. All variables are defined in the Appendix. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	Gross Profit Margin (1)	Return on Asset (2)
Post × RetailReliance × LowTrademark	0.143**	0.030**
	(0.065)	(0.014)
Post × RetailReliance	0.007	0.002
	(0.017)	(0.005)
Post × LowTrademark	-0.095**	-0.026***
	(0.042)	(0.010)
Firm Size	-0.015	-0.018**
	(0.030)	(0.007)
Leverage	0.048	-0.017
	(0.075)	(0.019)
Tangibility (ppent/at)	0.253	0.080*
	(0.173)	(0.047)
CAPX intensity	-0.070	-0.123***
	(0.156)	(0.037)
R&D intensity(xrd/at)	-0.727	-0.186**
	(0.567)	(0.092)
Sale growth	-0.064	-0.027*
	(0.042)	(0.015)
Missing R&D	0.061	0.012
	(0.062)	(0.007)
Advertising intensity	0.131***	0.008***
	(0.003)	(0.001)
Missing Advertising expense	-0.036*	0.006
	(0.019)	(0.006)
Stock return	0.028***	0.013***
	(0.010)	(0.004)
Stock volatility	-0.036*	-0.041**
	(0.021)	(0.019)
Constant	0.327**	0.190***
	(0.147)	(0.044)
Observations	13,965	13,826
Firm FE	Yes	Yes
Industry × Year FE	Yes	Yes
R-squared	0.741	0.750

Table 9
Changes in IP strategies

This table reports DDD estimates of the effect of the *Two Pesos* case on firms' IP strategies. Columns (1) and (2) report Poisson pseudo-maximum likelihood (PPML) estimates where the dependent variables are the annual count of store-design trade dress trademark filings and utility patent applications, respectively. Column (3) reports OLS estimates where the dependent variable is advertising intensity, measured as advertising expenditures scaled by total sales. Store-design trade dress filings are identified using USPTO Design Search Code category 7, which covers marks related to buildings and structures. Utility patent application counts are constructed from Kogan et al. (2017). The sample covers firm-year observations over 1990–1994, excluding fiscal year 1992. *Post* is an indicator equal to one for fiscal years 1993 and later. *RetailReliance* is an indicator equal to one if a firm's average retail sales share over 1990–1991 exceeds the within-industry median at the two-digit SIC level. *LowTrademark* is an indicator equal to one if a firm's average trademark inventory over 1990–1991 falls below the within-industry median at the two-digit SIC level. The PPML estimations in Columns (1) and (2) condition on strictly positive counts, excluding firm-year observations with zero filings or applications, which substantially reduces the number of observations relative to the OLS sample in Column (3). All specifications include firm fixed effects, industry-year fixed effects, and firm-level controls. All variables are defined in the Appendix. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	# Registered Trade dress (1)	# Patent (2)	Ad Expense (3)
Post × RetailReliance × LowTrademark	1.483*	-0.329*	-0.003*
	(0.847)	(0.198)	(0.002)
Post × RetailReliance	-0.149	0.004	0.001*
	(0.091)	(0.075)	(0.001)
Post × LowTrademark	-0.225	0.029	0.001
	(0.281)	(0.103)	(0.001)
Firm Size	-0.028	0.760***	0.000
	(0.105)	(0.095)	(0.000)
Leverage	-0.231	-0.531***	-0.000
	(0.229)	(0.201)	(0.000)
Tangibility (ppent/at)	1.113**	0.706	0.001
	(0.505)	(0.532)	(0.003)
CAPX intensity	-1.047*	0.210	0.002*
	(0.635)	(0.755)	(0.001)
R&D intensity(xrd/at)	-1.785	1.331***	0.005
	(1.388)	(0.396)	(0.004)
Sale growth	0.316*	0.009	-0.000
	(0.180)	(0.223)	(0.001)
Missing R&D	0.141	-0.117	-0.002***
	(0.149)	(0.089)	(0.001)
Advertising intensity	-0.061	0.201	0.004
	(1.819)	(0.855)	(0.003)
Missing Advertising expense	-0.069	-0.038	-0.025***
	(0.105)	(0.040)	(0.001)
Constant	1.076	-2.071**	0.026***
	(0.854)	(0.880)	(0.002)
Observations	1,245	3,295	15,668
Firm FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
R-square	0.4970	0.9383	0.8050

Online Appendix
Constructing the Trademark–CRSP Link Table

This appendix describes the procedure we used to construct the trademark–CRSP link table. The construction proceeds in six stages: (1) compiling the public-firm name universe; (2) preparing the trademark owner name file; (3) fuzzy name matching; (4) building the trademark lifecycle panel; (5) linking trademarks to public firms over time; and (6) adjusting ownership for Mergers and Acquisitions (M&A). The resulting table maps over 1.1 million USPTO trademark serial numbers to the permanent number (PERMNO) of the corresponding Compustat/CRSP public firm. The link table is publicly available on GitHub[1].

I. Compiling the Public-Firm Name Universe

A central challenge in linking trademark records to public firms is that the USPTO does not maintain a unique firm identifier that can identify the ultimate domestic parent in a corporate "family tree". At the trademark application stage, the USPTO requires only that applicants provide the owner's name as a free-text string. A public firm may therefore appear under dozens of variants—including the names of its subsidiaries, abbreviated forms, and historical names. We address this challenge by compiling a comprehensive name universe covering all Compustat/CRSP public firms and their subsidiaries. We then use this name universe to search USPTO records and link trademarks to public firms.

A. Source Datasets

We draw on five name fields from the Wharton Research Data Service (WRDS) suite. For each PERMNO, we extract: (i) *HCONM* (historical company name, available from 2007 onward), (ii) *COMNAM* (current company name), and (iii) *ISSUERNM* (issuer name) from CRSP; (iv) *CONM* (current company name) and (v) *CONML* (company legal name) from Compustat. CRSP name fields are downloaded at monthly frequency; Compustat name fields are downloaded at quarterly frequency. We supplement these with subsidiary names from the Subsidiary Data by WRDS dataset, which is constructed from 10-K and 10-Q filings submitted to the SEC between

[1] https://github.com/Shiheli1992/Trademark_CRSP

1995 and 2019 and records the names of all entities listed as subsidiaries in annual and quarterly reports.

B. GVKEY–PERMNO Panel

We construct a monthly GVKEY–PERMNO panel using the CRSP–Compustat Matching (CCM) table. Using the *LINKDT* and *LINKENDDT* fields, we generate a monthly date sequence covering the full valid-link window, expressed as end-of-month dates. Missing *LINKENDDT* values are set to the current date when the table was generated. We then merge all name fields downloaded in Section I.A onto this time-varying GVKEY–PERMNO panel. Table OA1 shows the structure of the panel for McDonald's Corp in January 2007. The name fields *CONM*, *CONML*, and *ISSUERNM* take distinct values across sources, and the last three columns contain duplicated entries across rows. The name stacking and deduplication step described in Section I.C below resolves these redundancies.

Table OA1: GVKEY-PERMNO Panel (McDonald's Corp in January 2007)

GVKEY	LPERMNO	Date	CONM	CONML	ISSUERNM	COMNAM	HCONM
7154	43449	31/01/2007	MCDONALD'S CORP	McDonald's Corp	MCDONALDS CORP	MCDONALDS CORP	MCDONALD'S CORP

We supplement the name universe with subsidiary names by merging them into the GVKEY–PERMNO panel constructed above, matching each subsidiary's report date to the panel date within a ±10-day window. We retain only subsidiaries reported in 10-K and 10-Q filings, and drop records with missing or empty name fields or a GVKEY equal to zero. Where a subsidiary name is associated with more than one GVKEY in the same reporting period, we exclude the observation to avoid ambiguous matches.

C. Name Stacking and Standardization

We apply a uniform cleaning pipeline to all names in the GVKEY–PERMNO panel (Bessen, 2009; Autor et al., 2020). The pipeline proceeds in the following steps:

- Convert all characters to upper case.
- Remove periods, commas, and other non-alphanumeric characters.

- Apply a standardization dictionary of approximately 60 common legal-form suffixes and industry terms, replacing each with a canonical abbreviated form using word-boundary matching (e.g., *CORPORATION* → *CORP.*; *HOLDINGS* → *HLDG.*; *INTERNATIONAL* → *INTL.*; *TECHNOLOGIES* → *TECH.*). The full replacement table covers entity types (Corp., Inc., Ltd., LLC, PLC, NV, SA, AG, AB), descriptive terms (Holdings, Group, Services, Products, Industries, Management, Communications, Manufacturing), and common abbreviations in multiple forms. This standardization approach follows the practice established in the patent-to-firm matching literature.
- Remove any remaining special characters introduced or retained after dictionary substitution, including apostrophes, percent signs, dollar signs, hash marks, parentheses, brackets, slashes, question marks, exclamation marks, plus signs, colons, and semicolons.
- Collapse consecutive single capital letters separated by spaces (e.g., *A A R* → *AAR*).
- Trim leading and trailing whitespace and collapse internal multi-spaces to single spaces.
- Convert all characters back to lower case.

After deduplication, the cleaned name universe contains approximately 795,000 unique name strings, each associated with at least one PERMNO. Each cleaned name is then assigned a unique numeric key that serves as the identifier in the subsequent matching stage. Table OA2 illustrates the name universe for McDonald's Corp after these steps. We identify 173 unique names associated with McDonald's Corp, the majority of which are subsidiary names.

Table OA2: Name Universe -- McDonald's Corp (randomly selected 10 rows)

LPERMNO	Clean_Name	CCM_Name_Key
43449	mcd luxembourg hldg sa rl	236829
43449	mcdi hldg	236830
43449	mcdonalds amea llc	236831
43449	mcdonalds apmea llc	236832
43449	mcdonalds australia	236833
43449	mcdonalds australia hldg	236834
43449	mcdonalds australia ltd	236835
43449	mcdonalds australian property corp	236836
43449	mcdonalds australian property funding llc	236837
43449	mcdonalds beteiligungs gmbh	236838

II. Preparing the Trademark Owner Name File

To construct the trademark owner name universe for the fuzzy matching procedure, we download the *owner.csv* file directly from the USPTO Trademark Case Files Dataset (Graham et al. 2013). The file records the name and type of each trademark owner at each stage of the trademark's lifecycle. We first deduplicate owner names within each serial number, and then apply the same name-cleaning pipeline described in Section I.C to the *own_name* field of each trademark owner record. Each distinct cleaned owner name is assigned a unique numeric identifier used in the subsequent matching stage.

III. Fuzzy Name Matching

We match trademark owner names to public-firm names using a two-stage procedure. We first use TF-IDF vectorization to generate candidate matches and then apply Jaro–Winkler similarity to rank and filter those candidates. Cohen, Ravikumar, and Fienberg (2003) show that this combination outperforms either method alone on name-matching tasks, and our procedure closely follows the trademark-to-public-firm matching approach of Heath and Mace (2020).

A. Stage 1: TF-IDF Candidate Generation

We use the PolyFuzz library in Python, which implements TF-IDF vectorization over character-level tokens[2]. For each trademark owner name, the algorithm returns the top 50 candidate public-firm names ranked by cosine similarity of their TF-IDF vectors. The output is a candidate table of (trademark owner name, public-firm name, TF-IDF score) triples, yielding up to 50 candidates per trademark owner name.

B. Stage 2: Jaro-Winkler Scoring and Threshold Selection

For each candidate pair in the TF-IDF output, we compute a Jaro–Winkler similarity score using the *textdistance* Python library[3]. We retain all candidate pairs with a score above 0.97 for

[2] The TF-IDF approach has a well-established advantage over pure edit-distance methods in firm-name matching. It down-weights tokens that appear frequently across the entire corpus (such as common legal suffixes) and up-weights tokens that are distinctive. As a result, two strings that share a rare token (e.g., a specific brand term) receive a higher similarity score than two strings that share only a common suffix (e.g., CORP.). This property is particularly important in the trademark setting, where most names in both datasets contain the same small set of legal-form abbreviations after standardization. Cohen, Ravikumar, and Fienberg (2003) demonstrate empirically that a hybrid TF-IDF/Jaro–Winkler scheme outperforms either method alone across a range of name-matching benchmarks.

[3] We use Jaro–Winkler similarity because it is specifically designed for short name strings and accommodates the transpositions and prefix variations that are common in our setting. The metric was originally developed by Jaro (1989) and extended by Winkler (1990) to give additional weight to strings sharing a common prefix, which is particularly apt for company-name variants.

manual inspection. We select this threshold based on preliminary validation, which shows that credible matches rarely fall below this value, as reported in Table OA3. We additionally exclude pairs whose names are shorter than six characters and whose similarity score equals 1.00, as very short strings that match exactly are often common words or abbreviations shared by unrelated entities and cannot be reliably verified as true matches.

Table OA3: Manual inspection for setting the threshold

Row Number	# of Row checked	Matched	Similarity Score	Matching Rate
1-101	100	99	0.995238	99.00%
3000-3103	104	104	0.990000	100.00%
9998-10101	103	11	0.983333	10.68%
16272-16375	104	41	0.979487	39.42%
20000-20100	101	4	0.977778	3.96%
40000-40100	101	0	0.970833	0.00%
40101-40200	100	4	0.970833	4.00%
40201-40300	99	0	0.970833	0.00%
40301-40500	200	2	0.970833	1.00%

C. Manual Verification

Each candidate pair above the 0.97 threshold is manually reviewed. We retain only pairs for which we are confident that the trademark owner name and the public-firm name refer to the same underlying legal entity. Uncertain, ambiguous, and clearly incorrect matches are discarded. The resulting verified mapping table records, for each trademark owner name, the associated PERMNO and the matched public-firm name. Table OA4 presents an example. This mapping table is used in Section V to link trademark records to public firms.

Table OA4: Verified Mapping Table – McDonald's Corp

Trademark Owner Name	Public Firm Name	LPERMNO	Similarity Score
boston market corp	boston market corp	43449	1.0000
chipotle mexican grill inc	chipotle mexican grill inc	43449	1.0000
chipotle mexican grill inc	chipotle mexican grill inc	43449	1.0000
mcdoanlds corp	mcdonalds corp	43449	0.9857
mcdonald corp	mcdonalds corp	43449	0.9857
mcdonald s corp	mcdonalds corp	43449	0.9724
mcdonalds corp	mcdonalds corp	43449	1.0000
mcdonalds intl property com ltd	mcdonalds intl property com ltd	43449	1.0000
mcdonaldss corp	mcdonalds corp	43449	0.9867

IV. Building the Trademark Ownership Table

A second challenge is that the USPTO Trademark Case File does not record ownership structure over time. Each trademark is associated with an owner, but no timestamps indicate when that ownership began or ended. To identify the alive trademarks held by a public firm at any given point in time, we construct a trademark ownership table with dated ownership periods in two steps. First, we complete the trademark date fields using the *event.csv* file from the USPTO Trademark Case Files Dataset, establishing the lifespan of each trademark from application to expiration. We then reconstruct ownership histories over time using the USPTO Trademark Assignment Dataset.

A1. Completing Trademark Case File Dates

The *case_file.csv* file under USPTO Trademark Case File contains key lifecycle dates — filing, publication, and registration — but these fields contain missing values. We supplement missing dates using the *event.csv* file from the USPTO Trademark Case Files Dataset, which records a timestamped event for each status change in a trademark's prosecution history[4]. This step yields the starting date for each trademark.

A2. Determining Trademark Expiration Dates

We next identify the ending date for each trademark. A trademark's validity period ends upon cancellation, abandonment, or expiration of its registration term. We construct an expiration date for each trademark following a priority hierarchy:

1. If a cancellation date (*reg_cancel_dt*) is present in *case_file.csv*, we use it as the end date.
2. If no cancellation date is present but an abandonment date (*abandon_dt*) is available in *case_file.csv*, we use the abandonment date.
3. If neither cancellation nor abandonment is recorded but renewal activity is present, we determine the end date from the most recent renewal event. Where a renewal date (*renewal_dt*) is recorded directly in *case_file.csv*, we use it as the primary source; we further complete renewal histories using the *event.csv* file. The USPTO's renewal system has two regimes: renewals recorded before November 16, 1989 carry a 20-year term;

[4] For each event type, we extract the earliest event date per serial number and use it to populate the corresponding date field in the Case File. The relevant event codes are: *NWAP* and *NWOS* for new applications; *NPUB* for publication; and *NRCC* and *NRCS* for registration.

renewals recorded on or after that date carry a 10-year term. Accordingly, for each trademark, we identify the latest renewal date across all renewal event codes (*REN1–REN5* for 20-year renewals; *RNL1–RNL9*, *8.OK*, *8.PR*, *C15A*, and *C15P* for 10-year renewals) and set the end date to the renewal date plus the applicable term.

4. If no renewal activity is present but a registration date is available, we assign expiration as the registration date plus 20 years (if registered before November 16, 1989) or 10 years (if registered on or after that date), following the change in statutory term length.
5. For trademarks that were never registered, we use the publication date as the end date if available, or the filing date otherwise.

Trademarks with a computed end date beyond December 31, 2024 are assigned a placeholder end date of December 31, 2999 to indicate that the mark remains alive at the close of the sample period.

Table OA5 illustrates how we determine the ending date for a trademark under different conditions. In the first row, the trademark was renewed under the code *RNL2* (from the *event.csv* file), and it remains an alive trademark, as it is still within the 10-year validity period following the latest renewal date. Accordingly, the ending date is assigned December 31, 2999, to indicate that the mark remains alive at the time we generate the dataset. The second trademark expired on February 25, 2006: renewal activity is present, and the latest renewal predates November 16, 1989, so the trademark had a 20-year validity period from that renewal date. The third trademark would nominally expire on January 17, 2019 — ten years after the 2009 renewal — because no subsequent renewal is recorded. However, the *case_file.csv* records a cancellation on October 15, 2021; since *case_file.csv* cancellation takes priority under our hierarchy, we set the end date as recorded in the *case_file.csv* file.

As shown in the first three rows of Table OA5, each contains a renewal code, indicating that the renewal dates were populated by tracing prosecution history and documents in the *event.csv* file. In contrast, the last row records a renewal date directly in the original *case_file.csv* file under the *renewal_dt* column. This trademark expired 10 years after that renewal because no subsequent renewal is recorded.

Table OA5: Trademark End Date Determined under Different Conditions

Serial No	Filing Date	Reg Cancel Date	Renewal Date	Renewal Code	Renew Date	Registration Date	Expired Date
70013064	08/02/1886			RNL2	2/03/2016	02/03/1886	31/12/2999
70027864	24/01/1896			REN4	25/02/1986	25/02/1896	25/02/2006
70032301	18/11/1898	15/10/2021		RNL1	17/01/2009	27/12/1898	15/10/2021
71120899	24/07/1919		18/05/2000		18/05/2000	18/05/1920	18/05/2010

B. Reconstructing Ownership Periods from Assignment Records

The USPTO Trademark Assignment Dataset records each transfer of trademark ownership (Graham, Marco, and Myers 2018). We use it to construct a complete sequence of ownership periods for each trademark. The assignment file is assembled from five component tables: *tm_assignment* (transaction metadata including record date and conveyance text), *tm_docid* (mapping assignment transactions to serial numbers), *tm_assignee* (names of receiving parties), *tm_assignor* (names of transferring parties), and *tm_convey* (conveyance type classification). We exclude transactions classified as "security interest" or "release", as these represent collateral arrangements rather than changes in beneficial ownership.

Assignee names in Trademark Assignment Dataset could differ from the corresponding owner names in the *owner.csv* file from Trademark Case Dataset. We therefore apply the Jaro–Winkler algorithm to fuzzy-match owner names across the two sources. For each (serial number, owner name) pair in the *owner.csv* file, we compute the Jaro–Winkler distance to all assignee names associated with the same serial number in the *tm_assignee.csv* file, and retain the best match per owner name with a similarity score above 0.95. We then manually verify these pairs and construct a final matching table linking owner names in the USPTO Trademark Case File Dataset to assignee names in the USPTO Trademark Assignment Dataset.

Owner type codes in the *owner.csv* file in the USPTO Trademark Case File Dataset indicate the stage at which an owner was recorded: codes beginning with 1 correspond to filing-stage owners, codes beginning with 2 to publication-stage owners, codes beginning with 3 to registrant-stage owners, and codes beginning with 4 to renewal-stage owners. For owners at the filing, publication, and registration stages, we assign the corresponding lifecycle date (*filing_dt*, *publication_dt*, or *registration_dt*) as the ownership start date when no assignment record date is available.

Renewal-stage owners require additional steps. For each trademark, we collect all available renewal dates from the renewal date columns (*REN1–REN5*, *RNL1–RNL9*, *renewal_dt*, *8.OK*, *8.PR*, *C15A*, *C15P*) and rank them chronologically. We then rank renewal-stage owners by their owner type code — where 41 identifies the first renewal owner, 42 the second, and so on — and assign each the renewal date of the corresponding rank. We apply this rank-matching procedure only when the number of renewal-stage owners does not exceed the number of available renewal dates; observations that do not satisfy this condition are dropped, as they imply more owners identified in the USPTO Trademark Assignment Dataset than recorded owners in the *owner.csv* file, making the assignment ambiguous and prone to false positive matches.

Ownership periods are then sorted by serial number and start date. The end date of each ownership period is set to one day before the next owner's start date within the same serial number. The final ownership period for each trademark is terminated at the trademark's computed expiration date. Trademarks with no valid start date are dropped. Table OA6 shows the final data structure of the trademark ownership table. The first three rows show the ownership history for an active trademark with serial no. *70011210*. The last three rows show a trademark with three ownership spells that expired on October 15, 2021, as no renewal is recorded.

Table OA6: Trademark Ownership Table — Illustrative Example

Serial No.	Owner Name	Ownership Start Date	Ownership End Date	Trademark Expired Date
70011210	tolman jampes p	27/05/1884	23/05/1976	
70011210	samson ocean systems inc	24/05/1976	4/03/2003	
70011210	samson rope tech inc	5/03/2003	31/12/2999	
70017953	worcester royal porcelain com ltd	27/05/1890	15/02/1984	15/10/2021
70017953	royal worcester spode ltd	16/02/1984	29/10/2000	15/10/2021
70017953	porcelain and fine china companies ltd	30/10/2000	15/10/2021	15/10/2021

V. Linking Trademarks to Public Firms

Using the mapping table from Section III, we assign each dated trademark–owner pair to a PERMNO. Specifically, we merge the dated ownership panel with the mapping table on the cleaned owner name. We then match each trademark–PERMNO pair to the GVKEY–PERMNO link from the CCM linking table and enforce temporal validity. We assign a trademark to a GVKEY only when the ownership start date (Ownership Start Date in Table OA6) falls strictly within the CRSP–Compustat link window, i.e., *LINKDT* < Ownership Start Date < *LINKENDDT*.

VI. Adjusting for Mergers and Acquisitions

Trademark ownership does not always transfer in USPTO records at the time of a corporate acquisition, and assignment filings may be delayed or omitted. To ensure that trademark portfolios are attributed to the correct owner following a change of control, we refine ownership records using deal-level M&A data from SDC Platinum, following the dynamic reassignment approach of Arora, Belenzon, and Sheer (2021). We restrict to completed deals in which the acquirer obtains more than 50% voting control (*pctown* > 50), and identify the effective date (*dateeff*) as the date of ownership transfer.

A. Public Target Acquired by a Public Firm

For trademarks held by a public target at the time of acquisition, we reassign ownership to the acquirer's PERMNO as of the deal effective date. For each target–acquirer pair, we retain only the first deal that conveys controlling rights. We exclude buyback transactions (cases where the acquirer PERMNO equals the target PERMNO). The acquirer's ownership period begins on the deal effective date and extends through the trademark's expiration date. The original owner's ownership period is truncated to end on the day before the effective date of the deal.

B. Public Target Acquired by a Private Firm

When the acquirer is a private entity (no acquirer PERMNO), we cannot reassign ownership to a public firm. Instead, we truncate the target's ownership period at the deal effective date, removing the trademark from the target's portfolio as of that date.

Table OA7 illustrates the dynamic ownership adjustment using the acquisition of 21st Century Fox by Walt Disney Co, which became effective on March 20, 2019. The first three rows show a trademark with two prior owners, the second of which is 21st Century Fox. The Fox ownership period ends on the day before the deal effective date, and Walt Disney Co's ownership period begins the following day. Since no renewal activity is recorded for this trademark, it expired on March 20, 2020, at which point the Walt Disney Co ownership period also ends. The next three rows show an otherwise identical ownership transition, except that the trademark has been renewed and therefore remains alive under Walt Disney Co. The last row illustrates the special case where Fox became the recorded owner of a trademark after the deal effective date. Since beneficial ownership had already transferred to Walt Disney Co, we attribute this trademark directly to Walt Disney Co from the original filing date.

Table OA7: Dynamic Trademark Ownership Adjustment — Walt Disney Co Acquisition of 21st Century Fox

Serial No.	Target Company	Acquirer Company	Date effective	LPERMNO	Ownership Start Date	Ownership End Date	Trademark Expiration Date
73510999				10720	29/11/1984	4/05/2005	20/03/2020
73510999				90441	5/05/2005	20/03/2019	20/03/2020
73510999	21st Century Fox Inc	Walt Disney Co	20/03/2019	26403	21/03/2019	20/03/2020	20/03/2020
73531782				84145	12/04/1985	6/04/2005	31/12/2999
73531782				90441	7/04/2005	20/03/2019	31/12/2999
73531782	21st Century Fox Inc	Walt Disney Co	20/03/2019	26403	21/03/2019	31/12/2999	31/12/2999
73781174	21st Century Fox Inc	Walt Disney Co	20/03/2019	26403	30/07/2019	31/12/2999	31/12/2999

VII. Final Dataset

The final link table contains the following variables for each trademark–owner observation: USPTO serial number, CRSP PERMNO, filing date, registration date, ownership start date, ownership end date, trademark expiration date, and a flag indicating whether the trademark was reassigned to a new PERMNO as a result of the M&A adjustment. Table OA8 illustrates the data structure.

Table OA.8 Final Link Table — Data Structure

LPERMNO	Serial No.	Filing Date	Registration Date	Ownership Start Date	Ownership End Date	Trademark Expiration Date	M&A Buying
13598	71000233	3/04/1905	4/07/1905	10/10/2012	3/07/2015	31/12/2999	FALSE
13901	71000233	3/04/1905	4/07/1905	17/01/1995	9/10/2012	31/12/2999	FALSE
89006	71000233	3/04/1905	4/07/1905	4/07/2015	31/12/2999	31/12/2999	FALSE
26403	73781174	17/02/1989	17/10/1989	30/07/2019	31/12/2999	31/12/2999	TRUE

Table OA9 summarises the final Trademark–CRSP link table. The table contains approximately 1.4 million observations identifying ownership for 1.11 million unique trademarks held by 14,786 public firms, covering the period from October 1870 to March 2024.

Table OA.9 Summary of the Trademark–CRSP Link Table

Data	N
Trademark–owner–year	1,404,605
Unique trademark serial numbers	1,112,213
Distinct public firms (PERMNO)	14,786
Sample period	Oct. 1870 – Mar. 2024

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