Market Power through the Lens of Trademarks

Kyle Kost Jeremy Pearce Liangjie Wu*

March 31, 2020

Abstract

This paper explores the link between market power and brands using new comprehensive data on trademarks from the U.S. Patent and Trademark Office (USPTO). We construct a dataset that links the life-cycle of a trademark to its full set of owners and dates of registration, transfer, and cancellation. We combine this dataset with pricing data and an oligopolistic model of firm pricing to understand the implications of the microeconomics and macroeconomics of trademarks and brand loyalty. Empirically, we start with the macroeconomic trends in brand ownership and then turn to the microeconomic impact of brand transactions on markups at the firm and product level. Using reallocation measures from Davis et al. (1996), we find an increase in brand reallocation since 1960, indicating a rising dynamism in the brand market. We then build a bridge from the trademark firms to their balance sheet information. We find that after a trademark purchase event, the buying firm's profit margin increases. Lastly, we build a quantitative model to unite the microeconomics and macroeconomics of trademarks. We unite this model with data on trademark transactions across firms and product level information to connect firm concentration and market power. We find that the concentration of brands has important links to the aggregate markup but there is not a significant rising trend in brand concentration.

*We thank Simon Mongey, Steve Davis and Jean-Pierre Dube for helpful comments and Simon Mongey and the University of Chicago for data funding. Author affiliations and contact information. All: University of Chicago, Department of Economics (kkost@uchicago.edu, jgpearce@uchicago.edu, liangjie@uchicago.edu).

1 Introduction

Market power is of central interest to economists due to efficiency and distributional implications. One important source of market power is a firm's set of brands, where a firm can mark up the price of a good due to consumer goodwill. The number of brands and their distribution across firms has important implications for understanding the level and trend of the profit margin of firms. While there is an active literature on trends in firms' profit margins (De Loecker et al., 2016; De Loecker and Eeckhout, 2017, 2018), there is not a quantitative framework that links the evolution of brands to the evolution of market power.

In this paper, we introduce a new dataset and model to study the microeconomics and macroeconomics of brands and market power. We process the universe of trademarks registered with the U.S. Patent and Trademark Office (USPTO) and link each trademark to its firm to observe both trademark and firm life-cycles. We then link this dataset to firm-level outcomes (in CRSP/Compustat) and product-level outcomes (in Nielsen Scanner Data). Using this merged dataset, we document several macroeconomic and microeconomic facts regarding brands about (1) the aggregate trend in the ownership of brands, such as the entry rate, exit rate, and reallocation rate of brands across firms and (2) the impact of brand transactions on firm-level outcomes. We then build a quantitative model of competition among multi-product firms to evaluate how changing brand ownership affects aggregate product market power. This quantitative model informs us on counterfactuals regarding the distribution of brands across firms and allows us to speak to trends in market power.

Brands matter for economic activity. Marketing experts have long known that brand loyalty is a lynchpin of a firm's success (Brown, 1953). Economists and marketing experts alike have acknowledged that brand loyalty is an important barrier to entry (Bain, 1956; Bronnenberg et al., 2019), yet also upholds firm's incentives to maintain quality (Economides, 1988). Bronnenberg et al. (2012) have shown that individual preferences have inertia to brands even over long time horizons. Thus, brand building is a key component of the life-cycle and survival of a firm's products. Firms build large marketing departments to think about how to build, trade, and maintain brands. In addition, brands change hands across firms. When a firm buys brands from another firm, it inherits consumer goodwill and loyalty to the purchased brands. This enables the purchasing firm to price above marginal cost thanks to this brand appeal.

In this paper, we treat trademarks as the empirical analog of brands. When a trademark is granted to an assignee, this assignee gets the exclusive right of the product's public association and, thus, the corresponding loyalty. Existing trademarks can be exchanged, or canceled by competing firms if they are too broad in scope. The USPTO keeps records of all of the trademarks registered with the office, including information on owners and dates of registration/transaction/cancellation. Using the records provided by USPTO, we further link registration and transaction records across a firm's history through fuzzy matching. Thus, the dataset encompasses the life-cycle of brands and their movement across firms, delivering a novel opportunity to investigate the ownership of U.S. brands and their evolution over time.

We link the trademark dataset to CRSP/Compustat data in order to examine features of the firms involved in branding and address how sales and profit margins react to trademark transaction events. We link USPTO and Compustat data using a name matching algorithm. This dataset links firm balance sheet information, firm-level stock data, and flows of trademarks. With this merged dataset in hand, we further evaluate the role of trademarks from a macroeconomic and microeconomic perspective.

For the macroeconomic trend, we first address the trends of brand ownership in the U.S. We explore some general trends of trademarks, including their relationship to GDP, employment, and the number of firms. Directing our attention to a measure of dynamism, we apply reallocation measures that Davis et al. (1996) developed to measure reallocation in the labor market. This paper employs these measures to focus on the trademark market. Contrary to the diminishing dynamism found in other markets, trademarks exhibit increasing reallocation.

We then ask about the microeconomics of trademarks. We look into the connection between individual trademark transactions and firm outcomes on both the buying and selling sides. We find a markup effect for the buying firm; sales increase more than costs. We find small negative responses in markups from selling firms, who are losing brand power when they sell.

The main goal of this paper is to quantitatively unite the microeconomics and macroeconomics of trademarks. We do this by quantifying a model of competition between multi-brand firms. Merging the USPTO Trademark data with Nielsen scanner data enables the use of brand transactions as experiments to identify the substitution elasticity across brands and brand appeal. We then ask: What is the counterfactual evolution of aggregate markup if the brands are owned by the same firms as in 1980s and 1990s?

In our theoretical framework, both firms and brands matter for market power. Stronger consumer goodwill in the economy, or stronger brands, allows for larger markups. In addition, larger firms can leverage their size to allow for larger markups. Because brand *concentration* matters, studying brands in and of themselves will not lead to a better understanding of market power. Because brand *composition* matters, studying sales shares at the firm-level will not yield a full understanding of market power.

The paper is structured as follows. The rest of this section details the institutional background of trademarks and reviews the related literature. Section 2 introduces the USPTO Trademark Dataset in a more complete manner and describes some aggregate trends in trademarks. We then discuss the merge of trademarks to CRSP/Compustat in order to map out some of these trends and their relation to firms. Section 3 discusses empirical results through the lens of the macroeconomics and microeconomics of trademarks. Section 4 introduces a quantitative model. Section 5 connects the quantitative model to Nielsen scanner data and discusses the model estimation. Section 6 concludes.

Institutional Background

All firms build brands. The most straightforward way of demarcating an exclusive brand is through trademarks – either registering new trademarks or buying existing trademarks. Trademarks are often transacted, and many products are understood through their brand rather than through the underlying firm. For instance, Procter & Gamble (P&G) currently holds 1700 trademarks, which represent a host of well-known brands. Many consumers reliably purchase brands such as *Pantene*, without knowledge or concern that P&G is the underlying parent company. Nearly the entire universe of P&G brands has at least one trademark. Figure 1 shows some of the many brands associated with P&G.[1]

Figure 1: Firm as a collection of brands (P&G)

While P&G has built some brands from the ground up, it has purchased others. In the data, each purchase shows up as a trademark transaction. For instance, *Pantene* was introduced in 1945 by *Hoffman-La Roche*. In 1983, *Richardson-Vicks Inc* purchased the trademark. In 1985, *Richardson-Vicks Inc* was acquired by P&G, and in 1994 the trademark was consolidated to P&G as a firm. These transfers illustrate the dynamic nature of brands. With a host of transactions in the data, we can separate out the brand component from the firm component that will be a key feature of our

[1]Appendix Figure A.5 shows the stock of brands P&G holds, which saw a large expansion in the late 1990s through the 2000s

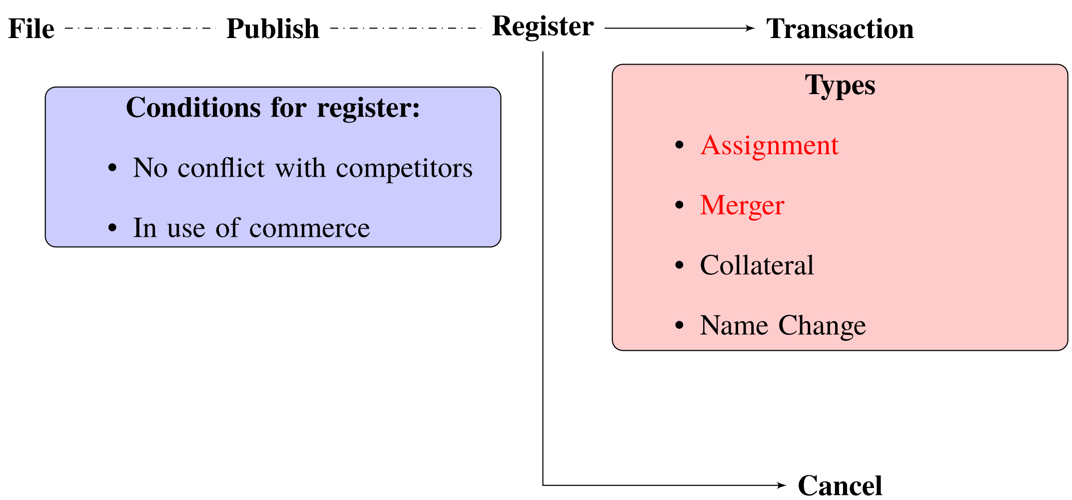


Figure 2: Steps to Trademark Registration through Exchange and Cancel

analysis.

The lifecycle of trademarks is another key component of our analysis. Figure 2 visualizes the process a trademark goes through from inception to end stage along with the hurdles it faces along the way.

Related Literature

Our project unites two literatures: microeconomic work on brands and marketing and macroeconomic work on market power.

A long literature on brands and advertising stretches back to the 19th century (Marshall, 1890; Fogg-Meade, 1901). Academics have noted that advertisement overcomes information frictions (Stigler, 1961), and provides incentives for firms to maintain or build their reputation (Nelson, 1970, 1974). Other papers have suggested that branding is socially wasteful because it inspires a zero-sum spirit and increases barriers to entry (Galbraith, 1958). Nonetheless, there is essentially unanimous agreement among economists and marketers alike that brands matter.

Recent studies use micro-data to show how brands affect consumer decisions. Bronnenberg et al. (2012) show that because of brand inertia, individuals may stay attached to brands over long periods of time, implying leverage for increasing prices on the basis of consumer goodwill. Bronnenberg et al. (2009) find an important path-dependent element of entry wherein a firm has more persistence in areas closer to its initial launching point. However, these papers do not leverage trademark data to understand brands. We link the datasets used in these studies (Nielsen scanner data) to the new trademark dataset.

We use the trademark dataset to address the trends in market power. Market power is of increasing interest to economists. Papers have explored trends in both markups (Furman and Giuliano, 2016; Autor et al., 2017a,b; Barkai, 2017; Grullon et al., 2017) and market concentration

(Nekarda and Ramey, 2013; De Loecker and Eeckhout, 2017; Gutiérrez and Philippon, 2017; Eggertsson et al., 2018; Hall, 2018). In our framework, the concentration of brands and markups will have an important connection. In the existing literature, there are papers evaluating the connections between aggregate trends and the role of brands. Some papers have focused on more general concerns, such as intellectual property as a source of monopoly power, but this is most often related to patents rather than trademarks (Boldrin and Levine, 2013; Farrell and Shapiro, 2008).

We introduce trademarks as another lens through which to view this burgeoning discussion. In building the bridge from brands to market power, we make use of empirical exercises related to market dynamism pioneered by Davis and Haltiwanger (1992); Davis et al. (1996). We link these results with a quantitative framework inspired by geographical variation in market power.

Our work builds on a paper studying multi-product firms (Hottman et al., 2016) and another studying labor market competition (Berger et al., 2019). In these papers, firms are modeled as oligopolies. They charge a size-based markup on prices or a size-based markdown on wages. Through the lens of the equilibrium model, one can recover the substitution elasticity and firm/product heterogeneities from observed data on market shares and prices/wages. This paper shares a similar interest in that we care about the welfare implications of markups and the contribution of concentration to the aggregate markup. Our paper contributes by providing a new dataset to the discussion in order to explore the role of brand concentration. Our identification strategy follows in a similar spirit to Berger et al. (2019) who deliver a parameter that helps characterize the labor market; our setting focuses on the product market.

Several papers have noted the high potential returns to integrating trademark data into the discussion of brands. Graham et al. (2013) provide a general overview of the dataset and provide insights about the uses of trademarks. Schautschick and Greenhalgh (2016), who document the importance of trademarks to firms, review other literature that confirms the growing recognition of the importance of trademarks. Dinlersoz et al. (2018) document the newly available USPTO bulk dataset on trademarks and document facts about trademarks over a firm's life cycle. Castaldi (2019) discusses the potential of this rich dataset in providing empirical analogs of a host of subjects in management research.

Our goal is to link the potential of this data and the microeconomic understanding to a macroeconomic discussion on brands and markups. Some papers have made these connections to address institutional environments across industries (Ferrucci et al., 2020) or the role of innovation and brand power in a firm's portfolio (Castaldi et al., 2020). In linking USPTO trademarks to Nielsen scanner data, we follow a similar procedure to Argente et al. (2018), who link the USPTO patent dataset to the Nielsen data.

2 Data

Our project makes use of a variety of datasets, the most central of which is the US Patent and Trademark Office (USPTO) Trademark data. We also employ two other datasets: CRSP Compustat data on firm sales, firm costs, and industry; and stock market data from CRSP, which allow us to look at how stocks move around trademarks registration and assignment dates. In uniting our quantitative model with the microdata, we merge the USPTO and Compustat CRSP data to Nielsen scanner data and focus on a subset of the firms in our dataset that are active in retail markets. Figure 3 shows the different data sources and some of their relevant features.

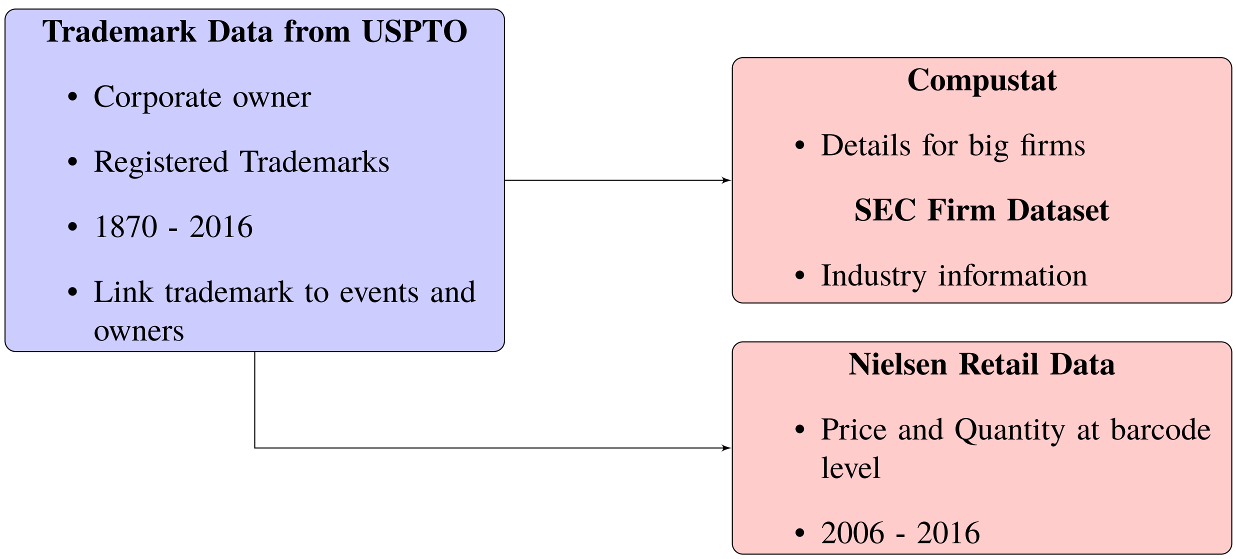


Figure 3: Data Layout

2.1 USPTO Trademark Data

USPTO Trademark data can potentially provide significant insights into brands and advertisements, but they have received little attention from economists. Trademarks are a central and dynamic arena of the economy: firms register for trademarks whenever they want their brand protected. In Figure 4, we see the "R" trademark, indicating that Coca-Cola has registered their trademark. Coca-Cola now holds the intellectual property on this insignia, and any entity that improperly represents itself as this brand can be held liable and taken to court.

To register for a trademark, a firm must undergo a process. First, an initial fee that ranges from \$225-\$400 is turned in with a trademark application. Within three months of filing, an examining attorney checks for compliance and if the application is approved, it "publishes for opposition." After this, there is a 30-day period during which third parties that may be affected by the trademark

Figure 4: Coca-Cola Registered Trademark

registration can step forward to file an "Opposition Proceeding" to stop the registration. This process is again evaluated by an examiner. If all passes, the trademark will get filed in "due course."

With a registered trademark in hand, the owner now has *exclusive* rights to use the mark within the sphere of activity designated in the process. For the most part, trademark law also allows the owner to prevent any unauthorized use even outside the domain of their products and services. Underlying this law is the principle that consumer confusion should be minimized. If consumer confusion is possible, the trademark owner has a case. However, one can still petition to cancel a trademark and end the exclusive rights of the owner. This often comes from competing firms that think the intellectual property is too broad. Cancellations are an important part of the data.

In addition to registration (new trademarks) and cancellations (ending trademarks), firms can exchange trademarks. For several reasons, the exchange of trademarks will be a key component of our analysis. First, it allows us to identify a component of branding rather than firm-specific activity. Second, trends in these exchanges can be very informative about the patterns in markups. Third, because the life-cycle of brands is a key component, studying mature (and tradable) trademarks will allow us to understand the evolution of brand behavior.

While some economists have used Nielsen scanner data to identify brands, it is impossible to build a history of brands across firms in this dataset. Even within firms, it is also difficult to link a component of the brand to its history through an evolving basket. Furthermore, because trademark data have a long history, we can examine long-run trends in branding – a possibility not available in other datasets.

Trademarks have a long history. The first legislative act concerning trademarks was passed in 1266 under Henry III. In France, the first comprehensive trademark system passed in 1857. In our US dataset, the first registered trademark was granted to Averill Chemical Paint Company in 1870. Since then, there has been massive growth in trademarks through the 20th and 21st century.

The USPTO Trademark data consists of more than 5.3 million unique trademark registrations since 1870. Using a fuzzy match, we identify over 1.3 million unique owners from 1870 to the present. Table 1 provides summary statistics for the dataset. Many trademarks have been registered and many firms trademark. Overall, there are over one million unique "firms" in our dataset that have produced at least one trademark in the past. Lots of firms are active, but the median firm has only two trademarks.

Table 1: Summary statistics on Trademarks from USPTO

	Overall
# unique "firms"	1.35M
# unique registrations	5.36M
# unique transactions by bundle	915076
# unique transactions by ID	4.46M
# unique cancels	2.12M
1st percentile firm size**	83
25th percentile firm size	5
Median firm size	2

Note: Firm size is defined as the number of trademarks within a firm

One striking feature of the data noted in Table 1 is the number of cancellations and transactions. This indicates that the market for trademarks is highly contested and dynamic. Cancels either require that other firms are concerned about the territory – many cancellations suggests a competitive market for accruing goodwill, or that a firm is not using its trademark. The contested aspect of the trademark market has been noted in prior literature as an important element of firm dynamics (Fosfuri and Giarratana, 2009).

Trademarks Over Time

Here, we document some long-run trends in trademarks. Figure 5 shows the trends in trademark registration. Since 1870, trademark registrations have averaged 3.8% growth per year. This trend is slightly larger than the growth rate of real GDP. However, trademarks exhibit even larger cycles than GDP.[2]

[2]Figure A.1 shows how trademarks move with employment/population and compares this to patents. Trademarks are highly cyclical relative to patents.

Figure 5b plots the ratio of trademark stock to GDP. By plotting this ratio we ask how much branding activity fluctuates relative to overall economic production (measured by real GDP). Trademarking seems to be procylical, but takes on long cycles. In particular, we note the early 1900s compared to the later 1990s. World War I and World War II saw low trademarking relative to GDP, while the 1920s boom saw high trademarking. Since the 1980s, trademark registrations have exploded relative to GDP.

Figure 6 illustrates over a time series the facts suggested in Table 1. Trademarks are often traded, renewed, and canceled. We note from this figure that overall registrations are a more important part of the economy than cancellations and exchanges, yet all three are very significant, with cancellations showing the largest increase since 1980. Overall, Figure 6 illustrates the dynamism of the trademark market.

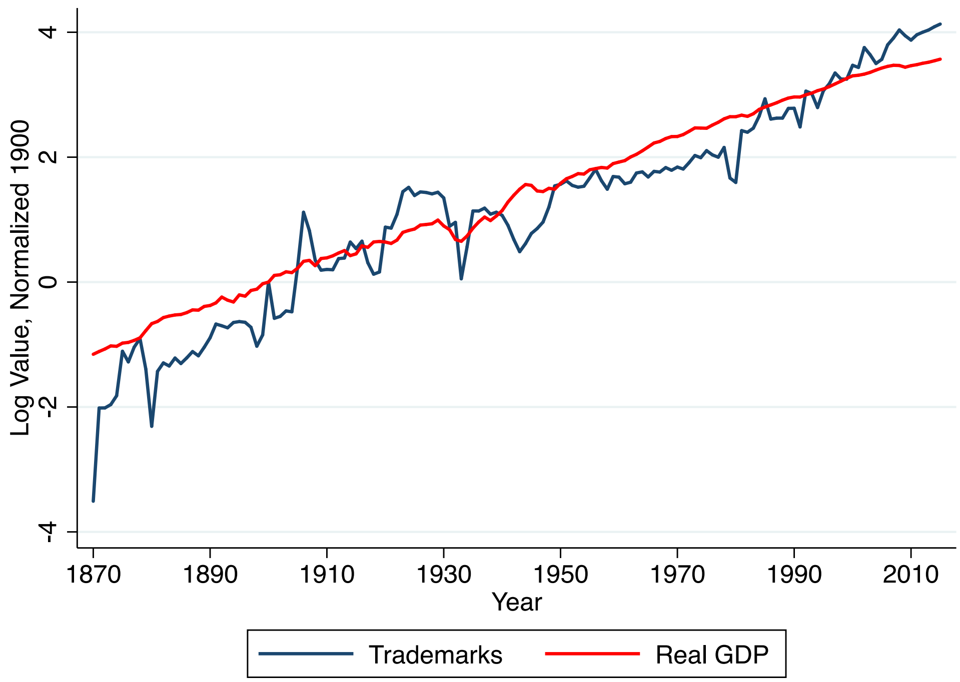
Trademarks by Industry

The USPTO trademark data is classified into categories according to 45 NICE codes.[3] While these are convenient for many analyses, our goal is to build a bridge from this dataset to a host of other datasets to better understand the relationship between brands and other economic data, such as markups. For this reason, we would prefer a more general industry classification. Zolas et al. (2017) use a probabilistic method to match in order to match NICE industries to 2007 NAICS industries at various granularities. Given that this is a probabilistic match, a single NICE code can be mapped to multiple two digit NAICS industries. Therefore, we assign a fraction of each trademark to industry codes on the basis of the given probability weights associated with the two-digit NAICS classification. An advantage of this concordance is that it does not require mapping trademarks to firms and then using the firm industry classifications. Instead, in our analysis we work directly at the trademark level.

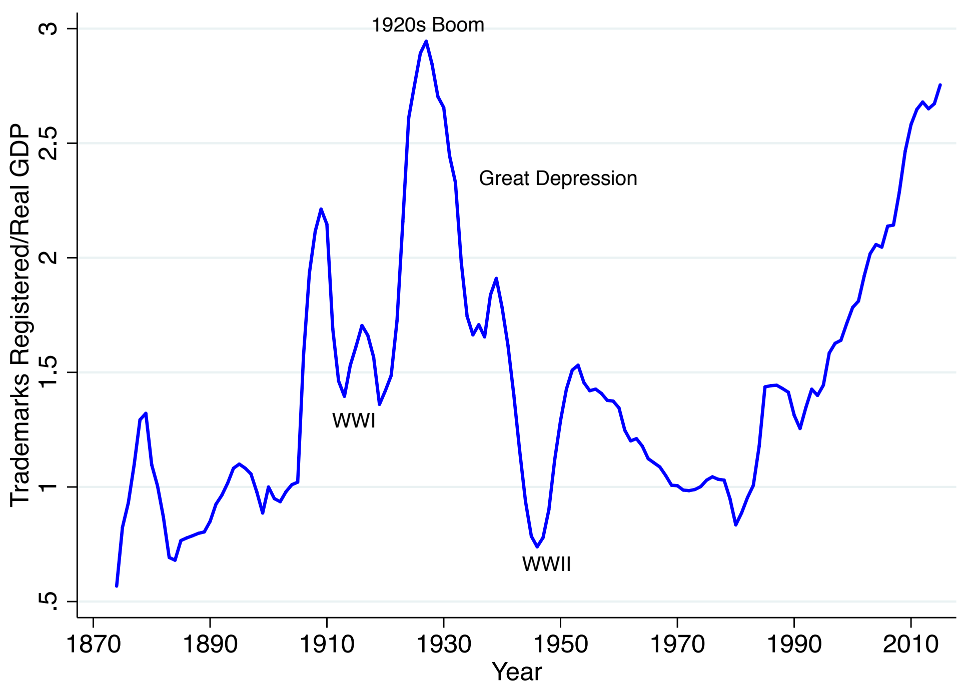
Figure 7 plots the percent of trademarks in each of the two-digit NAICS industries using the probabilistic weighting of the previously mentioned concordance. Most trademarks are in the manufacturing sectors of NAICS 31-33 with Agriculture, Forestry, Fishing, and Hunting (NAICS 11) and Professional, Scientific, and Technical Services (NAICS 54) following slightly behind. This aligns with our understanding as illustrated in Figure 7, wherein scientifically related industries are some of the predominant factors along with some manufacturing, such as clothing.

[3]Which came from the Nice agreement in Nice, France, in 1957. "The countries party to the Nice Agreement constitute a Special Union within the framework of the Paris Union for the Protection of Industrial Property. They have adopted and apply the Nice Classification for the purposes of the registration of marks. Each of the countries party to the Nice Agreement is obliged to apply the Nice Classification in connection with the registration of marks, either as the principal classification or as a subsidiary classification, and has to include in the official documents and publications relating to its registrations of marks the numbers of the classes of the Classification to which the goods or services for which the marks are registered belong."–https://www.wipo.int/classifications/nice/en/preface.html

Figure 5: Trademarks over Time

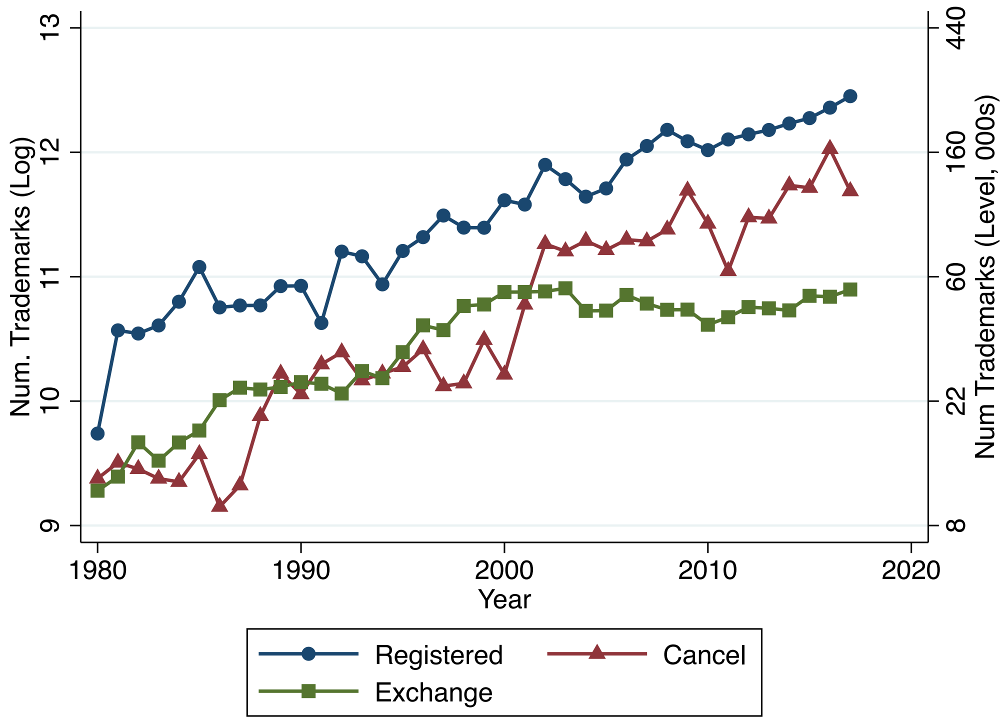


(a) Log Trademarks and Real GDP, Normalized to 0 in 1900



(b) The Ratio of Trademark Registrations to Real GDP, Normalized to 1 in 1900

Figure 6: Registered, Exchanged, Canceled since 1980



Understanding the distribution of trademarking firms across industries provides intuitive results on the role of trademarks in industry. Appendix A.2 provides more information on the underlying NICE classification, which finds many trademarking firms in computers and advertising.

2.2 Compustat/CRSP Data

We link trademarks to Compustat/CRSP data in order to evaluate how company balance sheet information changes with trademark transactions and registrations. There is no unique firm ID that bridges these two datasets, and, thus, we proceed by string-name matching.

After trimming the data for punctuation and spaces, we perform an exact match on company names. We then supplement this algorithm with a fuzzy match. Following Autor et al. (2016), we build in company location information with an exact match on year.

The merge links 40% of Compustat firms (70% weighted by observations) to firms with at least one trademark in the USPTO data. The incomplete merge could be due to limits in the algorithm. Table 2 provides summary statistics on the data and merge. The matched trademarking firms are larger on average than the average Compustat firm across many dimensions including total assets, capital, and sales. They also are over-represented in manufacturing and services. This is to be expected given the public nature of the firms in Compustat.

Figure 7: Share of Trademarks by NAICS Classifications

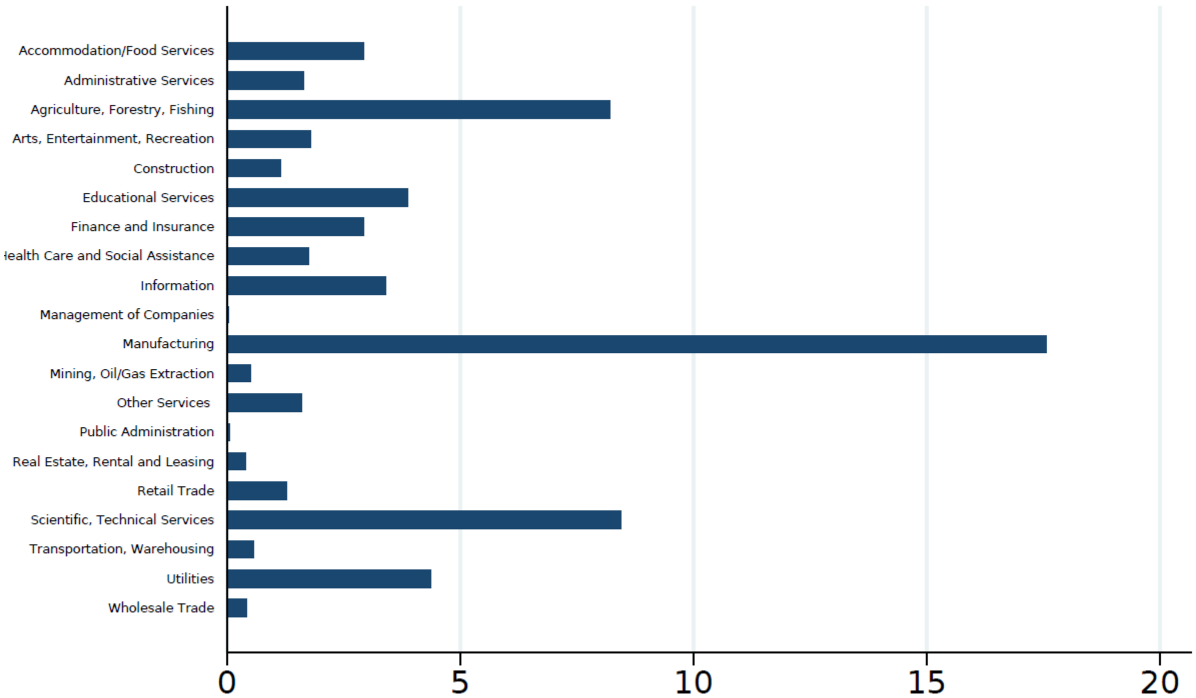


Table 2: Summary Statistics on Industries, Compustat-USPTO merge

	Unmatched mean	Matched mean	Difference
total assets	964.71	2865.96	1901.25
capital	458.25	1059.66	601.41
net invest	6.84	11.34	4.50
real sales	102.02	316.45	214.44
agriculture	0.02	0.00	-0.02
mining	0.15	0.03	-0.12
construction	0.02	0.01	-0.01
manufacturing	0.38	0.57	0.18
transportation	0.10	0.06	-0.04
wholesale	0.05	0.04	-0.01
retail	0.08	0.08	-0.00
services	0.19	0.22	0.02
N	99888	371979	471867

2.3 Nielsen Scanner Data

Uniting trademark data with Nielsen scanner data will enable an understanding of the impact of trademarks on prices and quantities. In particular, Nielsen scanner data has detailed information at store-region level on prices and quantities of consumer packaged goods. Many of the firms in this dataset have trademarks to protect their brands. We connect this to the trademark data with a similar exercise as in the previous section to unite the USPTO Trademark data with Nielsen scanner data.

The merge, which is achieved in multiple steps, uses GS1 barcode information as a bridge to link the separate pieces together. The GS1 Company Database includes information about each firm that has registered a barcode with GS1, such as company name, location information, and the company GS1 prefix information. A GS1 company prefix is a unique identifier assigned to the beginning of every barcode registered by that company. The prefix allows us to assign individual produce UPC codes to the owning company.

First, we link the Nielsen retail scanner data to the GS1 Company Database using the GS1 company prefix. Next, we separately use a fuzzy merge on company name and location information to merge our USPTO trademark dataset to the GS1 Company Database; the method resembles that used to match the USPTO trademark data with Compustat. Finally, we combine these two pieces to obtain a link between trademarking companies in the USPTO dataset and Nielsen retail scanner data.

In total, Nielsen scanner data has approximately 1.6 million unique products identified by a UPC code. There are different aggregations of these products. There are 1,070 product modules, 114 product groups, and 10 product departments.[4]. We do the analysis at the MSA level, where we have 371 regions. For our analysis of this data, discussed in Section 5, we evaluate outcomes at the group level as we want to leverage the specific product market wherein a brand transaction would affect the pricing of the brands in this market.

Among the total of $71,113$ unique firm prefixes that we find in both the GS1 and Nielsen data, $24,961$, or 35% of all prefixes can be linked to trademark data. These firms, which tend to be large firms, account for 55% of UPCs observed in the Nielsen Scanner data. We then link these firms to the transaction records of trademarks between 2006 and 2017. In $1,307$ of these transactions both the buyer and the seller of a particular transaction can be found in the Scanner data. $8,758$ transactions involve selling firms that are in the Scanner data, and $6,327$ transactions involve buying firms that are in the Scanner data.

[4]Ten major departments: i) Health and Beauty aids, ii) Dry Grocery, iii) Frozen Foods, iv) Dairy, v) Deli, vi) Packaged Meat, vii) Fresh Produce, viii) Non-Food Grocery, ix) Alcohol, and x) General Merchandise.

3 Empirical Results

To frame our discussion and quantitative model, we document some striking facts in the data that illustrate both trademark dynamism and evidence trademarks matter at the firm-level. Adopting a "macro-micro" approach, we start with an analysis of trademarks through a macro lens, then look into the response to trademarks at the firm, or micro, level. To evaluate the macroeconomics of trademarks, we follow the literature that documents labor market dynamism and apply this framework to trademarks. This provides preliminary evidence of the connection between firms and brands and how the connection changes over time.

3.1 The Macroeconomics of Trademarks

To understand the cross-sectional properties of trademarks over time, we apply the intuition of Davis et al. (1996) to collect measures of reallocation in the market for trademarks. While Davis et al. (1996) build a framework on labor markets, we think this reallocation measure in trademarks generates an understanding of churn in a similar spirit. Building on this, and to understand the composition of the market for trademark exchange, we examine the structure of firms engaged in the buying and selling of trademarks and, in particular, their size.

To motivate our question related to the macroeconomics of trademarks, we apply the sales-weighted aggregate markup from De Loecker and Eeckhout (2017):

$$\text{MARKUP}_t^{-1} = \sum_i \underbrace{\frac{\text{sales}_{it}}{\text{SALES}_t}}_{\text{firm sales share}} \times \underbrace{\text{markup}_{it}^{-1}}_{\text{markup at firm-level}} \tag{1}$$

Markups can change over time in two ways. First, the markup can increase even when the sales share is held constant. This occurs when the distribution of brands across firms is held equal, but individual firms accrue more brand loyalty and market power. Second, the sales share of high markup firms can increase. For instance, a firm that consolidates brands and holds high markups can increase its market share at the same time that the market share of small firms declines.

Trademark transactions can affect both of these channels. In addition, by tracking the dynamics of trademarks we can speak to the distribution of brands across firms and better understand a brand's lifecycle. We begin this discussion by evaluating trademark dynamism.

Trademark Dynamism

Equation (1) provides the framework of our analysis of trademark dynamism. In order to link components of trademarks to an understanding of market dynamism, we apply the Davis et al. (1996) framework to trademarks. After this, we look into what is driving the reallocation of trademarks across firms by focusing on trademark exchange. We start by defining i) x_{ft}, the average stock of trademarks for firm f at t; ii) X_t, the average stock of all firm trademarks at time t; and iii) g_{ft}, $\frac{\Delta stock}{x_{ft}}$

Thus, we define the reallocation rate first as positive and negative as in Davis and Haltiwanger (1992) where:

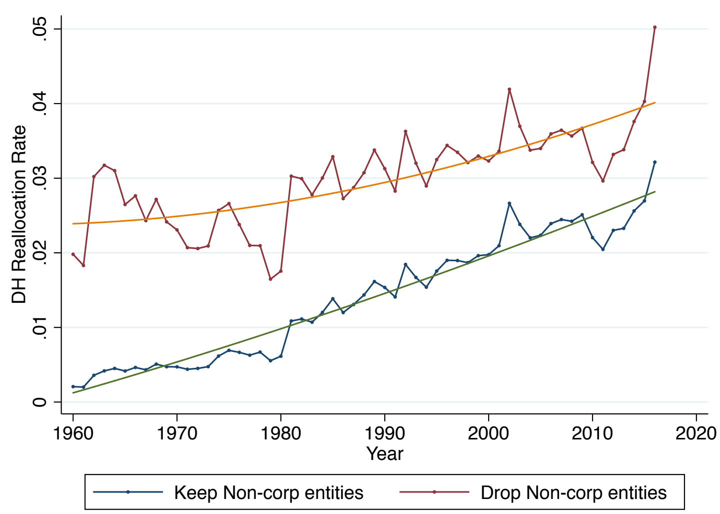
$$POS_t = \sum_{g_{ft}>0} \left(\frac{x_{ft}}{X_t}\right) g_{ft}$$

$$NEG_t = \sum_{g_{ft}<0} \left(\frac{x_{ft}}{X_t}\right) |g_{ft}|$$

Then, following Davis and Haltiwanger (1992), we define the total reallocation rate $RE_t = POS_t + NEG_t$. The reallocation measure gets at the degree of churn in the economy. The process is normalized by the general growth of the stock, which is increasing. When trademarks are more frequently registered to growing firms or canceled or exchanged, the aggregate dynamics exhibit a higher reallocation.

Figure 8 illustrates the trend since the 1960s in reallocation among trademarks. We note that the overall reallocation in trademarks has risen over time. This is of interest for two reasons. First, the rising reallocation confirms that dynamism in the trademark market remains high even though previous work has documented falling reallocation in other areas of the economy (Decker et al., 2018; Gourio et al., 2014). Second, the overall reallocation rate of trademarks is consistent with what we have previously noted: as discussion of markups heats up, so does the trademark market.

Figure 8: Davis and Haltiwanger (1992) Reallocation Rate by Year



There are two main results in this section. First, the movement of trademarks in aggregate indicate that unlike other markets (i.e., firm, labor), trademark dynamism is on the rise. Given that economists have noted the declining dynamism in other markets, this should be of interest to those thinking about the sources and consequences of falling dynamism on these other margins. Second, even controlling for the increase in activity in the trademark market, the churn of the economy is also rising in trademarks. This speaks to the fact that trademarks provide information about aggregate trends in brand dynamism. Next, we evaluate what occurs at the firm level in a brand transaction.

3.2 The Microeconomics of Trademarks

In the previous section, we illustrated trends in the distribution and dynamism of trademarks. Trademarks make up an important and growing component of the US economy. Now we turn our attention to the role of trademarks at the firm-level. This section uses an event study framework to understand how sales and costs respond to trademark events. A firm could take two sides in an event, as a buyer or a seller. We evaluate both sides for firms in the USPTO and Compustat data.

Our y-variable will be a measure of markups. The markup is measured as the gross profit margin on variable cost in an accounting sense. It is as follows:

$$\text{markup}_{it} = \Xi_i \times \frac{\text{sales}_{it}}{\text{variable cost}_{it}}$$

The economic interpretation of the above equation is a measure of the marginal markup, with Ξ_i as the elasticity of output elasticity with respect to variable cost. In our event studies, we condition on a firm fixed effect to deliver as follows:

$$\log \text{markup}_{it} = \xi_i + \log \frac{\text{sales}_{it}}{\text{variable cost}_{it}}$$

Thus, the relevant markup of interest is the log-difference between sales and variable cost. We plug this in as our relevant y-variable but we also test measures of sales and two measures of marginal cost in the following equation:

$$\log Y_{i,t} = \beta_0 + \beta_1 \text{Transaction}_{i,t} + \Gamma' \mathbf{X}_{i,t} + \xi_i + \phi_t + \epsilon_{i,t} \tag{2}$$

As we noted, we will plug in *Sales*, *COGS*, *OPEX*, or *markup* as $Y_{i,t}$. $\text{Transaction}_{i,t}$ measures the count of Transactions per quarter. We also include a host of controls in $\mathbf{X}_{i,t}$: *capital stock*; *assets*; *current ratio*; *long-term debt ratio*; and *lagged* Y.

We cluster at the firm-level. Table 3 shows the responsiveness of a buying firm to a trademark event both on the intensive and extensive margin. We find that the markup indeed increases for firms that experience a trademark buying event, and this effect remains when the full set of controls is used (Column (6)). Table 4 shows the responsiveness of a selling firm to a trademark event both on the intensive and extensive margin. Here, we also find a responsiveness of sales and costs, but we note that the markup does not increase or decrease. This matches expectations: firms purchasing brands see a response in markup, while firms selling brands do not see an increase in their markup.

Table 3: Buying Firm and Buying Event

Dependent: $\log(Sales)$						
N_{ee}	0.15***	0.49***	0.38***			
	(0.000)	(0.000)	(0.000)			
$\mathbb{I}\{N_{ee} > 0\}$				14.0***	2.09***	1.71***
				(0.000)	(0.000)	(0.000)
Dependent: $\log(OPEX)$						
N_{ee}	0.14***	0.31***	0.23***			
	(0.000)	(0.000)	(0.000)			
$\mathbb{I}\{N_{ee} > 0\}$				12.5***	1.11***	0.81***
				(0.000)	(0.000)	(0.000)
Dependent: $\log(MarkUp)$						
N_{ee}	0.0042	0.061	0.041			
	(0.536)	(0.138)	(0.280)			
$\mathbb{I}\{N_{ee} > 0\}$				1.42***	0.39**	0.29*
				(0.000)	(0.010)	(0.043)
N	219214	206240	188434	219214	208362	190423
Trim(1%)	No	Yes	Yes	No	Yes	Yes
Lag.LHS	No	Yes	Yes	No	Yes	Yes
Firm Control	No	No	Yes	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Transactions from 1980-2016; p-values in parentheses.

The regressions suggest a heterogeneous responsiveness of buying and selling firms. Given the richness of the data, we can apply a more comprehensive event study framework to understand the path that firm outcomes take in response to an event. Equation (3) illustrates this framework, which follows standard techniques in the event study literature. In particular, we want to track firms that exist through the sample but purchase a trademark at a given event date.

$$\log Y_{i,t} = \alpha + \sum_{\tau=-5}^{\tau=5} \beta_\tau \text{Transaction}_{i,t+\tau} + \xi_i + \phi_t + \epsilon_{i,t} \tag{3}$$

In Equation (3), we consider the same firm-level left-hand side variables as before: $Y_{i,t}$ = Sales, OPEX/COGS, Markup. The $\text{Transaction}_{i,t+\tau}$ dummy is the lead/lag/active quarter under which a

Table 4: Selling Firm and Selling Event

Dependent: $\log(Sales)$						
N_{or}	0.069**	0.58***	0.45***			
	(0.009)	(0.000)	(0.000)			
$\mathbb{I}\{N_{or} > 0\}$				12.0***	1.97***	1.61***
				(0.000)	(0.000)	(0.000)
Dependent: $\log(OPEX)$						
N_{or}	0.075**	0.44***	0.30***			
	(0.004)	(0.000)	(0.000)			
$\mathbb{I}\{N_{or} > 0\}$				11.9***	1.31***	0.98***
				(0.000)	(0.000)	(0.000)
Dependent: $\log(MarkUp)$						
N_{or}	-0.0063	-0.043	-0.036			
	(0.225)	(0.557)	(0.602)			
$\mathbb{I}\{N_{or} > 0\}$				0.054	-0.048	-0.064
				(0.880)	(0.781)	(0.707)
N	219214	206240	188434	219214	208362	190423
Trim(1%)	No	Yes	Yes	No	Yes	Yes
Lag.LHS	No	Yes	Yes	No	Yes	Yes
Firm Control	No	No	Yes	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Transactions from 1980-2016; p-values in parentheses.

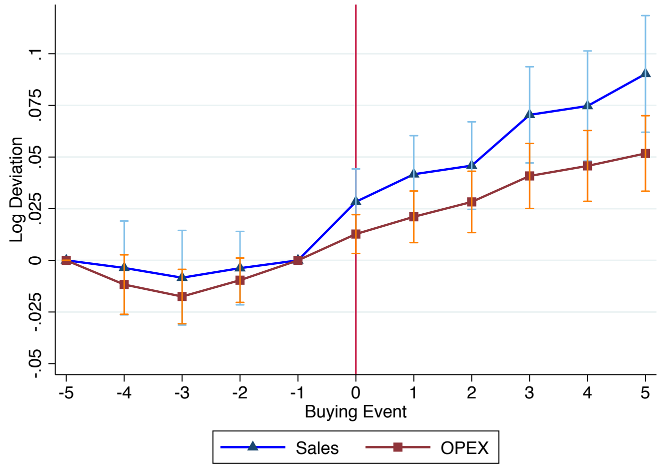
trademark event (buying or selling) occurs at the firm-level. We cluster our standard errors at the firm-level. ξ_i, ϕ_t are firm and time fixed effects, respectively. Due to the time and firm level fixed effects, the event-study regression has to omit two points in order to have identification. We omit the time -4 and -1 in the following results.

We use log sales and look at the first event of trademarking. Here, we plot two separate regressions on one graph with different outcome variables of interest: cost, sales, and markups. We plot each coefficient with the clustered standard error.

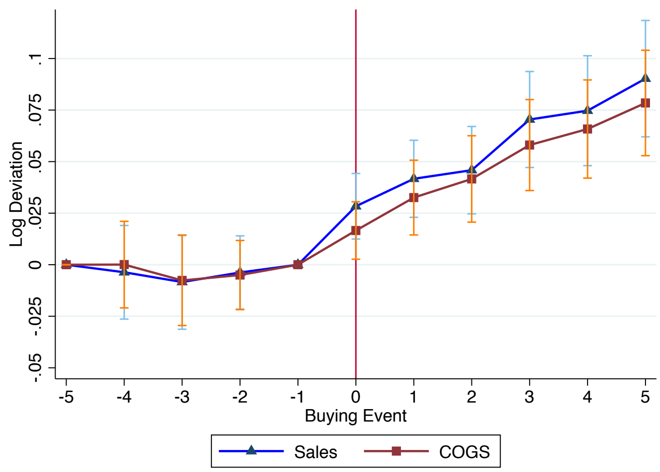
The results are consistent with the hypothesis that brands matter. For firms buying a trademark, there is a striking trend-break of sales and costs to the event. Both are fairly flat prior to the event. Once a trademark transaction happens, sales and costs increase significantly – by almost 10% after 5 years. Further, sales increase more than costs. This provides evidence that after adding additional brands, firms may increase their market power over time.

Although compelling, this evidence is only suggestive. Firms that buy trademarks are simultaneously likely to expand their market presence. Due to these endogeneity concerns, and to better understand the transfer of brands, we build a quantitative model that leverages spatial variation. This topic is discussed next.

Figure 9: IRF to Buying Events



(a) Sales and OPEX, Buying Event

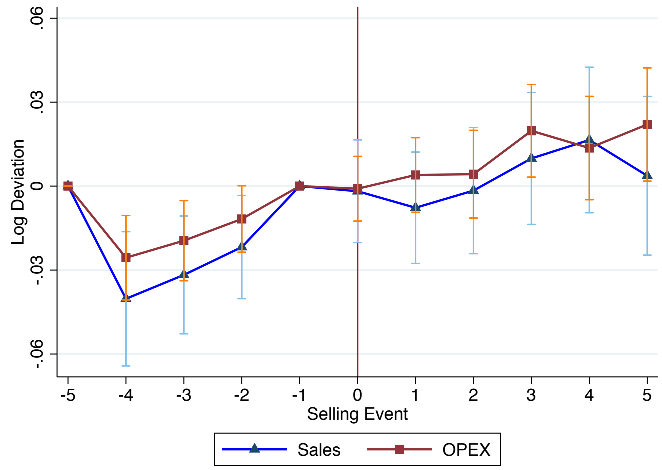


(b) Sales and COGS, Buying Event

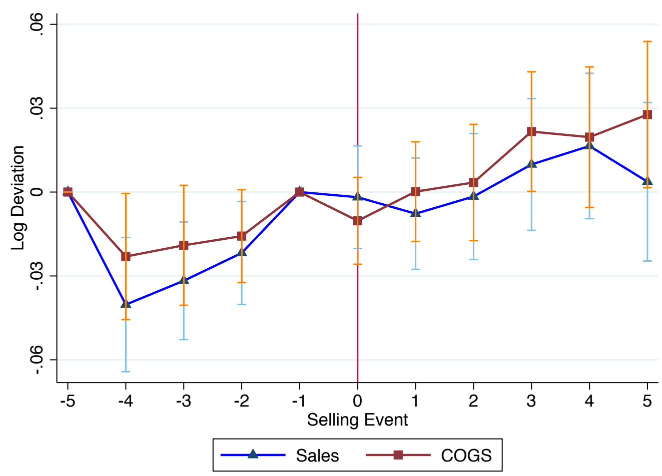
4 Quantitative Model

How is trademark ownership and the distribution of brands linked to overall market power? The reduced form results provide evidence on the importance of brands for both the level and trend of markups. In order to understand the welfare implications of the previous results, we build a theoretical framework to link the microeconomics and macroeconomics of trademarks. With this framework, we produce an identification strategy for extracting parameters that connects the

Figure 10: IRF to Selling Events



(a) Sales and OPEX, Selling Event



(b) Sales and COGS, Selling Even

evolution of brands to the evolution of market power. We connect this to the dataset on consumer product goods (CPG) in Nielsen Scanner data which provides significant detail on prices and quantities at the brand and product level.

The quantitative model features product differentiation and multi-product firms with brands. We rely on a large literature that indicates heterogeneous brand appeal across products that is sticky for consumers. We will rely on this for our identification strategy in Section 5.

4.1 Environment

Agents – The economy has K counties, each with a representative household. The representative household consumes from a set of I products and has a brand preference for product i given by ϕ_{ik}. There are a total of J firms that can hold any number of product lines. Firm j holds a set of product lines $\mathbb{I}_j$.

We assume the production process is national in the sense that firms operate in every county, can buy brands from any other firm, and the marginal cost is national. However, product market sales are regional in that each county has a separate product market. Thus, the preferences of each county will shape the production and pricing decisions of firms. As the competition is within the county, we investigate the product market in each county k individually.

Production and Preferences – The representative household in county k values consumption using a CES aggregator, as in Equation (4).

$$\left(\sum_{i=1}^{I}(\phi_{ik}C_{ik})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{4}$$

C_{ik} is the county k household's consumption from product i. ϕ_{ik} is the preference shifter for product i in county k, or the brand appeal. The substitutability across brands is measured by $\sigma > 1$. We note two points about the importance of trademarks in this setting. First, brands will be connected to the specific product preference that different regions have, ϕ_{ik}. Second, we will use brand transactions to identify the substitution elasticity across brands σ, discussed in Section 5.

Firms operate a product-specific constant returns to the scale production function. To produce one unit of output for product i, they incur a cost γ_i. We assume that this cost is uniform across all counties, but consumers in different counties might differ in their preference for brands. Because most of the goods we study in the scanner data are tradable, the uniform cost across counties is a reasonable assumption. We leverage the fact that the cost is common within time periods. Further, evidence from the brand inertia literature shows that product preferences tend to be localized. The preferences for brands exhibit significant dispersion across counties. Thus, we consider our preference and cost assumptions to be well-motivated.

4.2 Oligopoly Equilibrium

Household's Problem – First consider the household's problem in county k, given the prices of different brands within the county. The representative household chooses the consumption bundle to maximize the CES aggregator, subject to its budget constraint. We focus on the goods market equilibrium and take the income of household k, m_k, as given.

$$\mathbb{W} = \max_{C_{ik}} \left(\sum_{i=1}^{I} (\phi_{ik} C_{ik})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

s.t.

$$\sum_{i=1}^{I} C_{ik} P_{ik} = m_k$$

The household's problem yields a downward-sloping demand curve for brand i. The consumption for brand i is a decreasing function of the ratio of brand price P_{ik} and the price index in county k. The slope of this demand function is governed by elasticity of substitution.

$$C_{ik} = P_{ik}^{-\sigma} \phi_{ik}^{\sigma-1} P_k^{\sigma-1} m_k$$

where we define the aggregate price index in county k as:

$$P_k^{1-\sigma} = \sum_{i=1}^{I} (P_{ik}/\phi_{ik})^{1-\sigma}$$

Firm's Problem – Firm j has a collection of products, $\mathbb{I}_j$, which each maintain brand power across the K counties. It decides on the price to charge in every county. We assume the firms are large in the sense that they internalize their impact on the market price index. This assumption is motivated by the observation that many product markets are dominated by a few big players.[5] We are looking for an oligopoly equilibrium where firms engage in Bertrand competition.

Firm j chooses a price level P_{ik} at county k for product i, delivering consumption C_{ik}. The relationship between C_{ik} and P_{ik} comes from the household's optimization problem. The firm internalizes its impact on C_{ik} through two channels. First, through the demand curve for product i, a higher price leads to lower consumption of a particular product. Second, through the impact on the aggregate price index, a higher price from brand i induces households to substitute to product i', which may be held by the same firm.

The firm's problem takes the household demand as given and chooses a price P_{ik} for each good i held by the firm in country k:

$$\max_{P_{ik}} \sum_{i \in \mathbb{I}_j} [P_{ik} - \gamma_i] C_{ik},$$

s.t.

$$C_{ik} = P_{ik}^{-\sigma} \phi_{ik}^{\sigma-1} P_k^{\sigma-1} m_k,$$

[5]The top four firms in each department have a sales share ranging from 40%-80% of the market

With the firm's problem well-defined, we now turn to the oligopolistic equilibrium that emerges in each country k.

Equilibrium – We are looking for P_{ik} such that all firms maximize their profit given other firms' actions. We obtain a standard result, implying that in the equilibrium the oligopolistic firms charge a price above their marginal cost of production as follows:

$$P_{ik} = \left(1 + \frac{1}{(\sigma - 1)(1 - \bar{s}_{jk})}\right)\gamma_i,$$

where

$$\bar{s}_{jk} = \sum_{i \in \mathbb{I}_j} s_{ik},$$

and

$$s_{ik} = \frac{\left(\frac{P_{ik}}{\phi_{ik}}\right)^{1-\sigma}}{\sum_{i'=1}^{I}\left(\frac{P_{i'k}}{\phi_{i'k}}\right)^{1-\sigma}}.$$

We denote the markup as $\mu_{j(i),k} = \left(1 + \frac{1}{(\sigma-1)(1-\bar{s}_{jk})}\right)$. The markup is an increasing function of the market share of firm j in county k: $\bar{s}_{jk}$. Firms with a larger market share internalize their impact on the consumption of households more so through their impact on the price index P_k. On the contrary, a firm with a smaller market share will primarily ignore their impact on the general price level P_k and only consider the substitution of their product with competitors' products.

The market share of a firm in county k, $\bar{s}_{jk}$, is simply an aggregate of the market shares of all the firm's products, s_{ik}. This market share is governed ultimately by the brand appeal $\{\phi_{ik}\}_{ik}$, the cost γ_i, and the substitution elasticity σ. These three sets of parameters will be the key inputs for our quantitative analysis. We now turn to the markup, which is the key outcome of interest, and its connection to the distribution of brands.

4.3 Markup from the Model

From the oligopoly model, the aggregate markup can be written as the sales-weighted average of the firm-level markups. All products within the same firm in region k have the same markup. The brand preference parameter will determine the sales share of each product. The following equation links the model parameters to the aggregate markup of the economy in county k:

$$\text{Markup}_{k,t} = \frac{m_k}{\sum_i \gamma_i C_{i,k}}.$$

Utilizing the optimal pricing decisions and the market clearing conditions, the following equation links the markup in county k during period t to the costs of production, the demand shifters, and the market shares of multi-brand firms:

$$\text{Markup}_{k,t} = \frac{\sum_i \phi_{ik}^{1-\sigma} \gamma_i^{\sigma-1} \mu_{j(i),k}^{\sigma}}{\sum_i \phi_{ik}^{1-\sigma} \gamma_i^{\sigma-1} \mu_{j(i),k}^{\sigma-1}}$$

Whether the transactions of brands increase or decrease markup overall depends on the covariance between the brand appeals and market shares of buying and selling firms. We will turn to the estimation in order to answer questions on the trends in brands, the trends in markups, and identify the underlying parameters. We will then discuss the welfare implications of the distribution of brands.

5 Quantification

(Preliminary)

We now turn to the merged dataset between USPTO Trademark data and Nielsen Scanner data in order to evaluate the change in the prices of brands when they are exchanged across firms. Because the model predicts the relationship between prices and sales shares, we can use the model to understand the connection between brand concentration and markups. In this section, we discuss the identification of parameters, then turn to the trends in Nielsen scanner data, and our understanding of these trends through the given parameters. Lastly, we do a welfare analysis based on the parameters.

5.1 Parameter Identification

The model is parametrized by the substitution elasticity across products, σ, in addition to three sets of parameters. The sets of parameters are as follows: (1) the ownership structure of brands across firms $\{\mathbb{I}_j\}_j$, (2) the demand shifters $\{\phi_{i,k}\}_{i,k}$, and (3) the cost of production $\{\gamma_i\}$. This section proposes a method for uncovering these parameters utilizing brand transactions across firms and discusses the results within each product grouping.

We start by identifying the substitution elasticity σ, which delivers a parameter that enables a product-by-product analysis. With σ and the distribution of brands across firms $\mathbb{I}_j$, prices P_{ik} and sales shares s_{ik}, ϕ_{ik} and γ_i can be identified.

Estimation of Substitution Elasticity, σ – The transaction information on trademarks gives us a unique experiment with which to estimate the substitution elasticity and compare it to structural methods that rely on second moment variations of prices (Hottman et al., 2016). Our key identification assumption, made to recover the substitution elasticity, is that brand transactions happen on a national level and are orthogonal to the local sales shares of the particular brand. We think this is a reasonable assumption given the wide degree of national demand for products and large spatial heterogeneity.

We leverage spatial variation in brand sales shares across firms to identify the substitution elasticity. In the model, the price ratio across counties is linked to sales variation by Equation (5).

$$P_{itk} = \mu_{j(i),t,k}\gamma_{it}. \tag{5}$$

Taking an approximation of this equation, we reach an equation that links the log price ratio to the log competitor market shares, as in Equation (7):

$$\log P_{itk} = \log \mu_{j(i),t,k} + \log \gamma_{it}. \tag{6}$$

Recall $\mu_{j(i),t,k} = \left(1 + \frac{1}{(\sigma-1)(1-\bar{s}_{jk})}\right)$. The log approximation for this markup is then

$$\log \mu_{j(i),t,k} = \frac{1}{(\sigma-1)(1-\bar{s}_{jk})}.$$

If the sales distribution across local markets is exogenously given, then OLS produces an unbiased estimator for $\frac{1}{\sigma-1}$ from Equation (6). However, sales shares are endogenous both in this model and in reality. To estimate the substitution elasticity, we instead use the transaction of brands as an experiment. Here, we get an exogenous change to the local market structure through the brand transactions, and observe how the prices of brands change in response to changes in the brand shares of the holding firm. This can be seen in the following equation:

$$\log P_{i,t,k} - \log P_{i,t-1,k} = \log \mu_{j(i),t,k} - \log \mu_{j(i),t-1,k} + \log \gamma_{it} - \log \gamma_{i,t-1}. \tag{7}$$

In the estimation, the analysis at brand $\times$ location $\times$ time level. We use brand $\times$ time and location $\times$ time fixed effects, which controls for the firm's cost at time t. Then we direct our attention to the firm-level markup in location k. We compare the incremental change in firm sales through the transaction at the local level, as brands flow from firm j' to j in county k. This delivers a change in $\mu_{j(i),t,k}$ for brands transacted from firm j' to j at time t:

$$\log \mu_{j(i),t,k} - \log \mu_{j'(i),t-1,k} = \frac{1}{\sigma - 1}\left(\frac{1}{1-\bar{s}_{j,t,k}} - \frac{1}{1-\bar{s}_{j',t-1,k}}\right). \tag{8}$$

Our dataset consists of price changes when brand i is sold from firm j to firm j'. We regress the ratio of competitor market share $\frac{1-s_{j'}}{1-s_j}$ on the log-difference of prices. The identification assumption is that the transaction of brands is orthogonal to the specific market share of county k. We thus use the following equation in Nielsen Scanner data:

$$\log P_{i,t,k} - \log P_{i,t-1,k} = \beta\left(\frac{1}{1-\bar{s}_{j,t,k}} - \frac{1}{1-\bar{s}_{j',t-1,k}}\right) + \gamma_{it} + \omega_{kt} + \epsilon_{i,t,k}. \tag{9}$$

With Equation (9), we retrieve $\hat{\sigma} = \hat{\beta}^{-1} + 1$. With the estimated σ for each group, we can turn to the estimated demand shifter.

Estimation of Demand Shifter – To recover the demand shifter, we rely on Equation (10), which links sales share of a brand to its price. Intuitively, when two brands have the same price, the more appealing brand will have larger sales share. With the constant elasticity of substitution, and with knowledge of the substitution elasticity σ, we can recover the demand shifter from the observation of sales share of brand i in county k and the price of brand i in county k. In Equation (10), both the sales share of brands and the price of brands are observed from Nielsen Scanner data. We cannot pin down the demand shifter to its level without a normalization because any multiplication of $\phi_{i,k}$ will result in the same relationship between prices and market shares. Following the literature, we normalize ϕ_{ik} according to Equation (11). With Equations (10) and (11), we can pin down the $\{\phi_{ik}\}_{i,k}$,

$$s_{i,k} = \frac{(P_{i,k}/\phi_{i,k})^{1-\sigma}}{\sum_{i'}(P_{i',k}/\phi_{i',k})^{1-\sigma}}, \tag{10}$$

$$1 = \sum_{i'} \phi_{i',k}^{1-\sigma}. \tag{11}$$

Estimation of Cost of Production – The price charged for brand i in county k is the marginal cost multiplied to a markup. This markup depends on the substitution elasticity and the market share of firm j in county k. Using the transaction events as an experiment, we obtain an estimate for σ. We directly observe the market shares from data. Given the estimator for substitution elasticity σ,

γ_i can be recovered by inverting Equation (12).

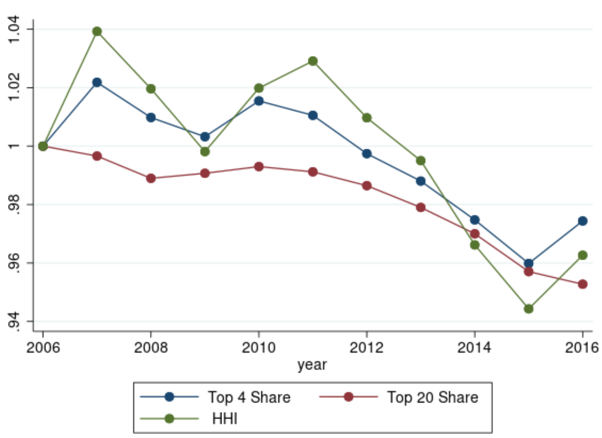
$$P_{itk} = \left(1 + \frac{1}{(\sigma - 1)(1 - \bar{s}_{jk})}\right)\gamma_{it}. \tag{12}$$

5.2 Concentration in Nielsen Data

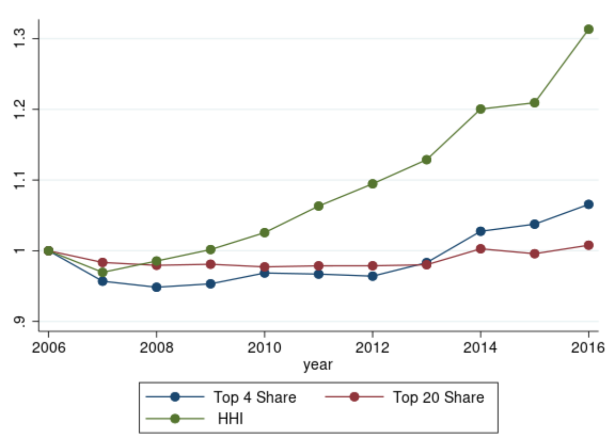
Before discussing consumer welfare and its dependence on the estimated parameters, we discuss the trends in Nielsen scanner data that reflect how changing market concentration is linked to changes in markups. The heterogeneity across product markets in changing concentration suggests the importance of identifying the relevant parameters in order to do welfare calculations.

Figure 11 shows the trends from 2006-2016 in terms of firm concentration within two distinct departments that make up a large share of overall sales (Health and Beauty; General Merchandise). We plot the concentration in Top 4 Share, Top 20 Share, and Herfindahl-Hirschman Index (HHI) normalized to 1 in 2006 in order to evaluate trends over time. Figure 12 illustrates for the other eight departments. These markets show different trends in brand concentration over time. The different sales shares within each department will influence the aggregate markup, but it will depend on the estimated substitution elasticity σ and brand preference parameters.

Figure 11: Two Major Nielsen Departments



(a) Health and Beauty



(b) General Merchandise

Note: All statistics normalized to their 2006 level.

5.3 Welfare Analysis and Counterfactuals

The estimated model is amenable to a host of counterfactuals and the corresponding welfare impact on the distribution of brands. We are interested in two counterfactuals that highlight the interaction between the evolution of brands and evolution of markups. First, what would happen if each firm in the market had the same sales share and brand share compared to the existing environment? Second, what if the distribution of brand ownership remained at its 1980s level instead of the observed distribution today?

The first counterfactual is the core question in Hottman et al. (2016)'s study of multi-product firms. In our study of the trademark dataset, the second counterfactual is novel, and we argue that it is of policy interest. The second counterfactual is linked to our previous discussion on how the transactions of brands across firms are linked to the aggregate markup. Recall the markup is connected to the sales share distribution across firms with the following:

$$\text{Markup}_{k,t} = \frac{\sum_i \phi_{ik}^{1-\sigma}\gamma_i^{\sigma-1}\mu_{j(i),k}^{\sigma}}{\sum_i \phi_{ik}^{1-\sigma}\gamma_i^{\sigma-1}\mu_{j(i),k}^{\sigma-1}} = \frac{\sum_i \phi_{ik}^{1-\sigma}\gamma_i^{\sigma-1}\left(1+\frac{1}{(\sigma-1)(1-\bar{s}_{j(i),k})}\right)^{\sigma}}{\sum_i \phi_{ik}^{1-\sigma}\gamma_i^{\sigma-1}\left(1+\frac{1}{(\sigma-1)(1-\bar{s}_{j(i),k})}\right)^{\sigma-1}} \tag{13}$$

The smaller the elasticity of substitution across brands (σ) and the more concentrated the sales share, the larger the aggregate markup for any given set of ϕ_{ik} and γ_{ik}.

The trademark dataset allows us to both extract σ and trace the ownership of brands observed in Nielsen data back to the 1980s. To our knowledge, no other comprehensive dataset allows for this type of study. Merger and acquisition can impact the market in many different ways. To provide a systematic answer to the question about aggregate markup, our paper employs a simple framework of oligopoly competition. We also draw attention to the transaction of brands, which includes mergers and acquisitions as well as other transactions. Our study contributes to the literature by studying the aggregate implications and exploring a realistic counterfactual. We do not compare a multi-brand firm equilibrium to a single-brand equilibrium. Instead, we examine an equilibrium in which brand ownership does not change.

Although the estimation and analysis using the trademark dataset is still in progress, we illustrate the practice using several simple counterfactuals with four largest product groups in the Nielsen scanner data. For the group Baked Goods, Electronics, Household Supplies, and Cosmetics, we calculate the model-predicted sales-to-cost ratio as in equation (13) using the observed firm-level sales share data. We observe heterogeneity in the trend of sales-to-cost ratio. Cosmetics sees a rise in the profit margin, while the other three groups experience declines. We then computes two counterfactual sales-to-cost ratios, by reassigning the sales shares of firms. The firm counterfactual assumes all firms have the same market share. The brand counterfactual assumes all brands have

Table 5: Profit Ratio From Selected Groups ($\sigma = 2$)

	Baked Goods			Electronics		
	M_{06}	M_{16}	ΔM(pp)	M_{06}	M_{16}	ΔM(pp)
Data	2.12	2.10	-2.00	2.06	2.06	-1.06
Firm	2.00	2.00	0.00	2.00	2.00	-0.04
Brand	2.01	2.01	-0.25	2.01	2.01	-0.06
	Household Supplies			Cosmetics		
	M_{06}	M_{16}	ΔM(pp)	M_{06}	M_{16}	ΔM(pp)
Data	2.10	2.09	-1.50	2.11	2.13	2.21
Firm	2.00	2.00	-0.03	2.00	2.00	0.00
Brand	2.01	2.00	-0.22	2.03	2.03	0.31

the same market share and keep the number of grands as in the data. We observe that moving from a multi-brand world with heterogeneity brands to an economy with either identical firms or identical brands reduces the profit margin in aggregate, and the heterogeneity in brands absorbs most of the reduction. Moreover, brand heterogeneity is important in explaining the decline from 2006 to 2016. While more work needs to be done to reach a conclusion, this preliminary result indicates the importance of studying brands and their ownerships in the macroeconomic study of product market power.

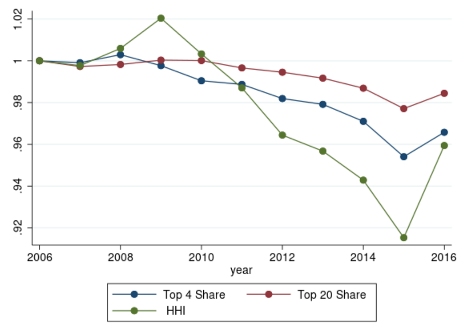
6 Conclusion

The evolution of market power has important connections to brands and their distribution across firms. This paper argues that trademarks are the best empirical analog for brands. We demonstrate the importance of brands at three levels: the aggregate level, the transaction level, and quantitatively. Understanding the patterns of trademarks elucidates the creation, transfer, and cancellation of brands.

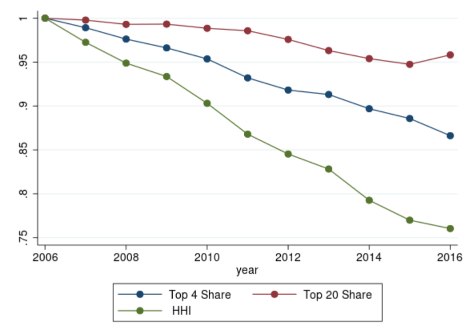
This paper proceeded in four steps, each of which provides a framework for further analysis. First, we introduce the trademark dataset and a host of new facts about branding over time. Second, we empirically document the interaction of trademarks and firms at the macro and micro levels. Third, to pose more penetrating structural questions about brand transactions and perform a tighter analysis, we build a quantitative model of oligopolistic competition with brands. This model delivers a novel result that links the distribution of brands across firms to aggregate markups through their sales shares. This provides a new framework for structurally analyzing markups. Fourth, we apply this framework to the study of brand transactions and discuss the key identifying assumptions of the process.

The evolution of market power and brands are closely linked. Trademarks are the most prominent empirical analog to brands and provide a rich source of data that can improve our understanding of innovation, market power, and institutional property arrangements. Standard quantitative frameworks applied to trademark data can open a broad examination of questions that are relevant for economists. We hope this paper is just the beginning of a fruitful investigation into these forces.

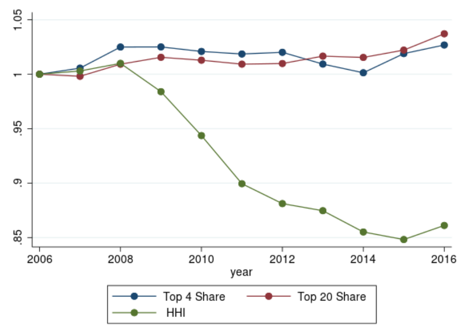
Figure 12: Concentration Across Nielsen Departments



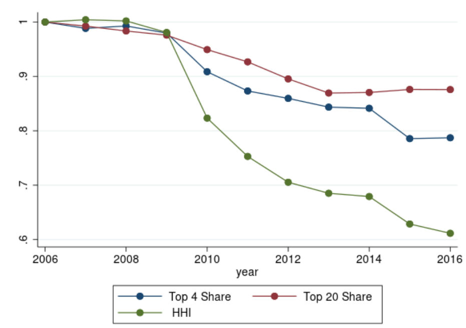
(a) Dry Grocery



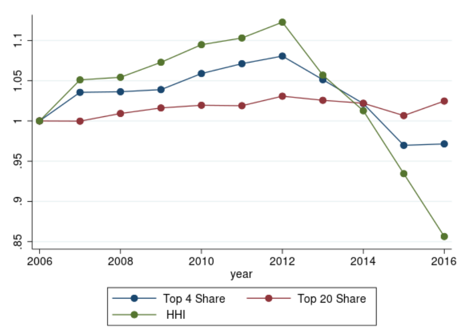
(b) Frozen Foods



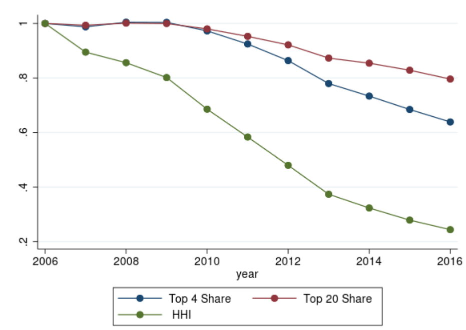
(c) Dairy



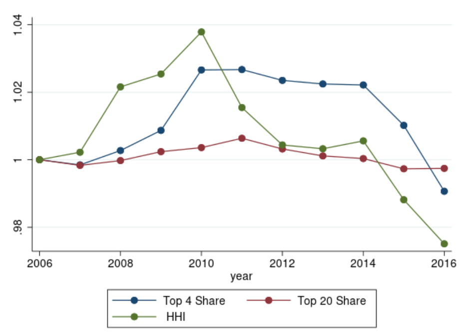
(d) Packaged Meat



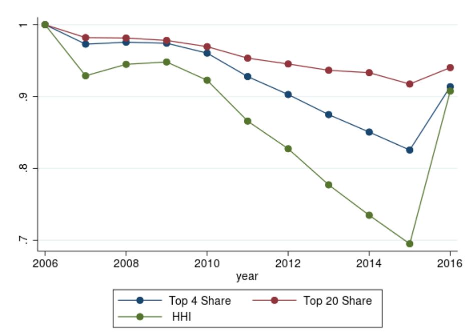
(e) Deli



(f) Fresh Produce



(g) Non-Food Grocery



(h) Alcohol

Note: All statistics normalized to their 2006 level.

References

Argente, David, Douglas Hanley, Salome Baslandze, and Sara Moreira, “Patents to Products: Innovation and Firm Performance,” Technical Report 2018.

Autor, David, David Dorn, Gordon H. Hanson, Gary Pisano, and Pian Shu, “Foreign Competition and Domestic Innovation: Evidence from U.S. Patents,” NBER Working Papers 22879, National Bureau of Economic Research, Inc December 2016.

_ , _ , Lawrence F. Katz, Christina Patterson, and John Van Reenen, “Concentrating on the Fall of the Labor Share,” *American Economic Review*, 2017, *107* (5), 180–85.

_ , _ , _ , _ , and _ , “The Fall of the Labor Share and the Rise of Superstar Firms,” 2017. National Bureau of Economic Research Working Paper 23396.

Bain, JS, *Barriers to New Competition*, Harvard University Press, 1956.

Barkai, Simcha, “Declining Labor and Capital Shares,” 2017. mimeo.

Berger, David W, Kyle F Herkenhoff, and Simon Mongey, “Labor Market Power,” Working Paper 25719, National Bureau of Economic Research March 2019.

Boldrin, Michele and David Levine, “The Case Against Patents,” *Journal of Economic Perspectives*, 2013, *27* (1), 3–22.

Bronnenberg, Bart J., Jean-Pierre Dubé, and Matthew Gentzkow, “The Evolution of Brand Preferences: Evidence from Consumer Migration,” *American Economic Review*, May 2012, *102* (6), 2472–2508.

_ , Jean-Pierre Dube, and Sridhar Moorthy, “Chapter 6 - The economics of brands and branding,” in Jean-Pierre Dube and Peter E. Rossi, eds., *Handbook of the Economics of Marketing, Volume 1*, Vol. 1 of *Handbook of the Economics of Marketing*, North-Holland, 2019, pp. 291 – 358.

_ , Sanjay K. Dhar, and Jean-Pierre Dubé, “Brand History, Geography, and the Persistence of Brand Shares,” *Journal of Political Economy*, 2009, *117* (1), 87–115.

Brown, GH, “Brand Loyalty: Fact or Fiction,” *The Trademark Reporter*, 1953, *43* (1), 251–258.

Castaldi, Carolina, “All the great things you can do with trademark data: Taking stock and looking ahead,” *Strategic Organization*, 2019, p. 1476127019847835.

_ , Joern Block, and Meindert J. Flikkema, “Editorial: why and when do firms trademark? Bridging perspectives from industrial organisation, innovation and entrepreneurship,” *Industry and Innovation*, 2020, *27* (1-2), 1–10.

Davis, Steven J. and John Haltiwanger, “Gross Job Creation, Gross Job Destruction, and Employment Reallocation*,” *The Quarterly Journal of Economics*, 08 1992, *107* (3), 819–863.

Davis, Steven, John Haltiwanger, and Scott Schuh, *Job Creation and Destruction*, Cambridge, MA: MIT Press, 1996.

De Loecker, Jan and Jan Eeckhout, "The Rise of Market Power and The Macroeconomic Implications," 2017. National Bureau of Economic Research Working Paper 23687.

_ and _ , "Global Market Power," 2018. National Bureau of Economic Research Working Paper 24768.

Decker, Ryan A., John C. Haltiwanger, Ron S. Jarmin, and Javier Miranda, "Changing Business Dynamism and Productivity: Shocks vs. Responsiveness," 2018. National Bureau Economic Research Working Paper 24236.

Dinlersoz, Emin M, Nathan Goldschlag, Amanda Myers, and Nikolas Zolas, "An Anatomy of U.S. Firms Seeking Trademark Registration," Working Paper 25038, National Bureau of Economic Research September 2018.

Economides, Nicholas, "The Economics of Trademarks," *Trademark Reporter*, 07 1988, *78*, 523–539.

Eggertsson, Gauti B., Jacob A. Robbins, and Ella Getz Wold, "Kaldor and Piketty's Facts: The Rise of Monopoly Power in the United States," 2018. National Bureau of Economic Research Working Paper 24287.

Farrell, Joseph and Carl Shapiro, "How Strong Are Weak Patents?," *American Economic Review*, 2008, *98* (4), 1347–1369.

Ferrucci, Edoardo, Maria Isabella Leone, Manuel Romagnoli, and Andrea Toros, "From a distinctive sign to an exchangeable asset: exploring the U.S. market for trademark licensing," *Industry and Innovation*, 2020, *27* (1-2), 25–51.

Fogg-Meade, Emily, "The Place of Advertising in Modern Business," *Journal of Political Economy*, 1901, *9*, 218–218.

Fosfuri, Andrea and Marco S. Giarratana, "Masters of War: Rivals' Product Innovation and New Advertising in Mature Product Markets," *Management Science*, 2009, *55* (2), 181–191.

Furman, Jason and Laura Giuliano, "New Data Show That Roughly One-Quarter of U.S. Workers Hold an Occupational License," 2016. https://obamawhitehouse.archives.gov/blog/2016/06/17/new-data-show-roughly-one-quarter-us-workers-hold-occupational-license.

Galbraith, John Kenneth, *The Affluent Society*, Houghton Mifflin, 1958.

Gourio, François, Todd Messer, and Michael Siemer, "What Is the Economic Impact of the Slowdown in New Business Formation?," *Chicago Fed Letter*, 2014, (Sep).

Graham, Stuart J.H., Galen Hancock, Alan C. Marco, and Amanda Fila Myers, "The USPTO Trademark Case Files Dataset: Descriptions, Lessons, and Insights," *Journal of Economics & Management Strategy*, 2013, *22* (4), 669–705.

Grullon, Gustavo, Yelena Larkin, and Roni Michaely, "Are U.S. Industries Becoming More Concentrated?," 2017. mimeo.

Gutiérrez, Germán and Thomas Philippon, "Declining Competition and Investment in the U.S.," 2017. National Bureau of Economic Research Working Paper 23583.

Hall, Robert E., "New Evidence on Market Power, Profit, Concentration, and the Role of Mega-Firms in the U.S. Economy," 2018. Standofrd University, mimeo.

Hottman, Colin J., Stephen J. Redding, and David E. Weinstein, " Quantifying the Sources of Firm Heterogeneity *," *The Quarterly Journal of Economics*, 03 2016, *131* (3), 1291–1364.

Loecker, Jan De, Pinelopi K. Goldberg, Amit K. Khandelwal, and Nina Pavcnik, "Prices, Markups, and Trade Reform," *Econometrica*, 2016, *84* (2), 445–510.

Marshall, Alfred, *The Principles of Economics*, McMaster University Archive for the History of Economic Thought, 1890.

Nekarda, Christopher J. and Valerie A. Ramey, "The Cyclical Behavior of the Price-Cost Markup," 2013. National Bureau of Economic Research Working Paper 19099.

Nelson, Phillip, "Information and Consumer Behavior," *Journal of Political Economy*, 1970, *78* (2), 311–329.

_ , "Advertising as Information," *Journal of Political Economy*, 1974, *82* (4), 729–754.

Schautschick, Philipp and Christine Greenhalgh, "Empirical studies of trade marks–The existing economic literature," *Economics of Innovation and New Technology*, 2016, *25* (4), 358–390.

Stigler, George J., "The Economics of Information," *Journal of Political Economy*, 1961, *69* (3), 213–225.

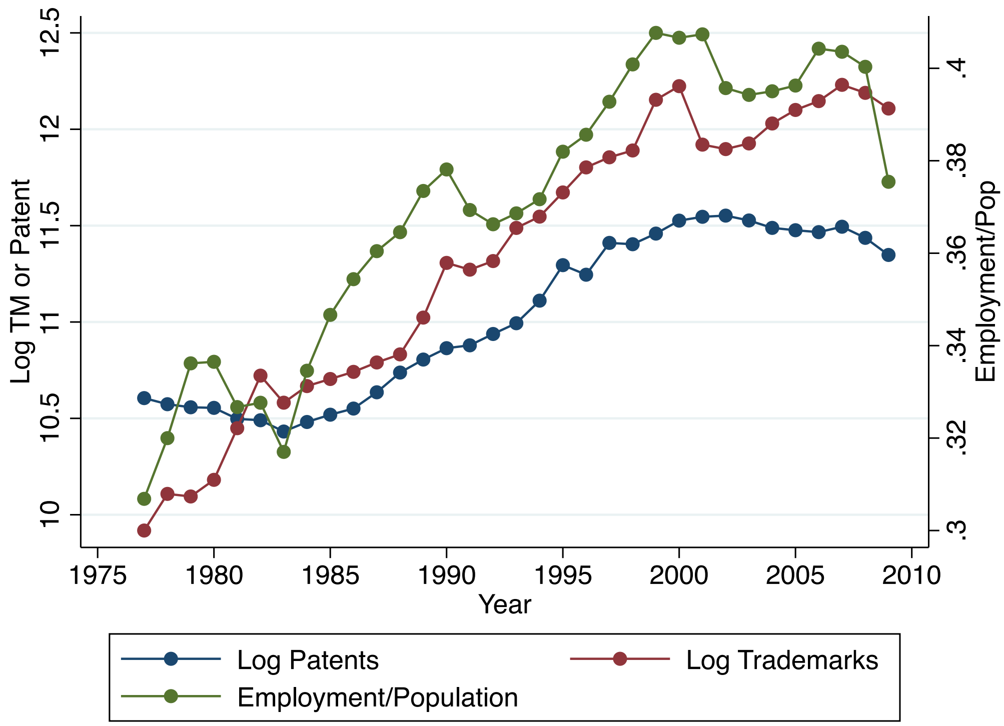
Zolas, Nikolas, Travis J. Lybbert, and Prantik Bhattacharyya, "An ÔAlgorithmic Links with ProbabilitiesÕ Concordance for Trademarks with an Application Towards Bilateral IP Flows," *The World Economy*, 2017, *40* (6), 1184–1213.

A Data Appendix

A.1 Trademarks in the Aggregate

In the main text, we argue that trademarks provide a great insight into certain components of market dynamism. Figure A.1 illustrates that trademarks move fairly closely with the aggregate employment/population dynamics. One more note from this figure is that trademarks are rising at an even more rapid rate than patents, which experienced a boom in the 1990s. Trademarks both move more closely with the business cycle than patents and are rising at a more rapid rate.

Figure A.1: Yearly Counts of Trademark/Patent Records



A.2 Trademarks by Industry

In this section, we illustrate more detail about trademarks at the NICE (Trademark classificaiton) and NAICS (industry classification) level. Figure A.2 plots the percent of trademarks in each of the 45 NICE categories. We see that a majority of trademarks fall into the following categories: Computers and software (NICE 9), Advertising (NICE 35), Education (NICE 41), Clothing (NICE 25), and Scientific and technological services (NICE 42). This is using data that is post-1973, so will pick up the rise of the computing sector over this time period.

Figure A.3 plots the percent of firms that on average trademark in a given year in each of the 2-digit NAICS industries. As expected, this pattern closely follows the pattern observed in Figure 7 in the text. The industries with the most trademarks also see the firms that trademark most. For instance, we again see that the most trademark-registration-intensive industries are Manufacturing (NAICS 31-33), Agriculture (NAICS 11), and Professional, Scientific, and Technical Services (NAICS 54). Thus, it appears that many industries, and many firms within those industries, trademark.

To further understand how trademark activities are linked to production activity, we examine two sectors, the manufacturing sector and the service sector, that underwent changes during the past decades. As has been documented elsewhere, the number of manufacturing firms is declining and the number of service firms is growing. Figure A.4 plots the number of newly registered trademarks within these two sectors against the number of firms. Panel (a) plots the number of firms from Business Dynamics Statistics and the number of registered trademarks, both of which are normalized as ratio to the 1980 level. We find that although the number of firms in manufacturing

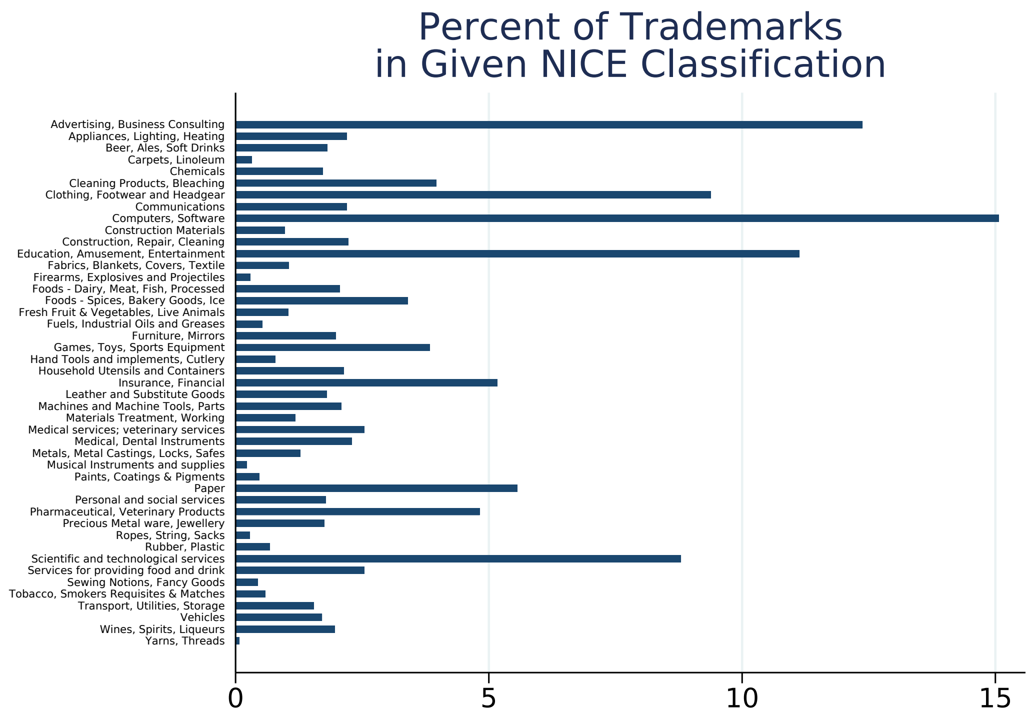
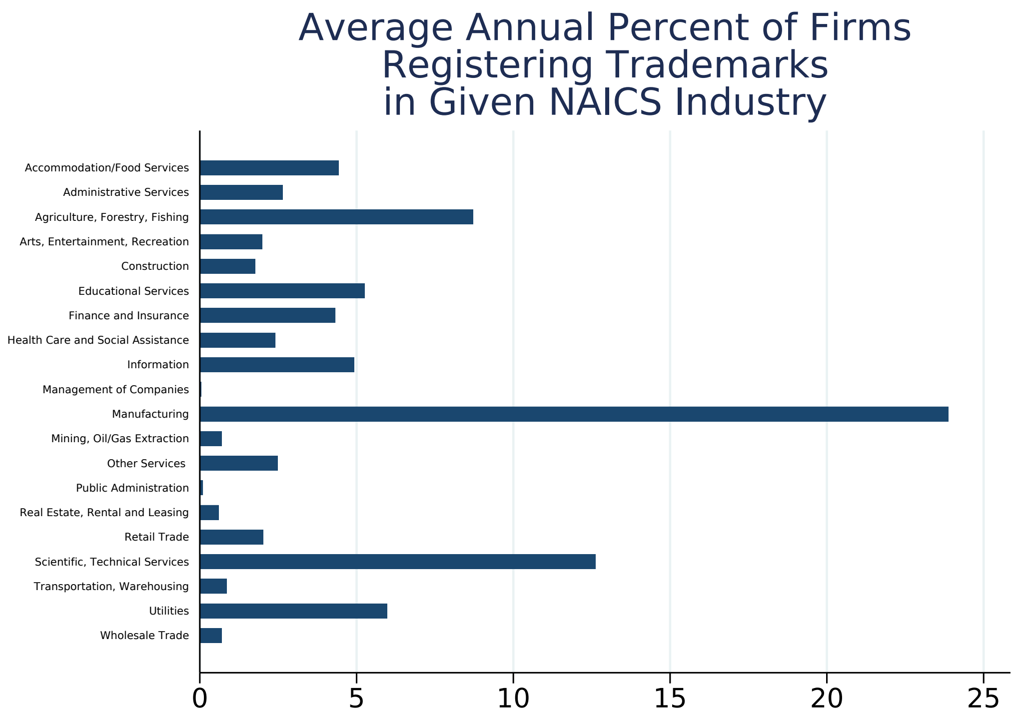


Figure A.2: Trademarks by NICE Classifications

Figure A.3: Firms by NAICS Classifications

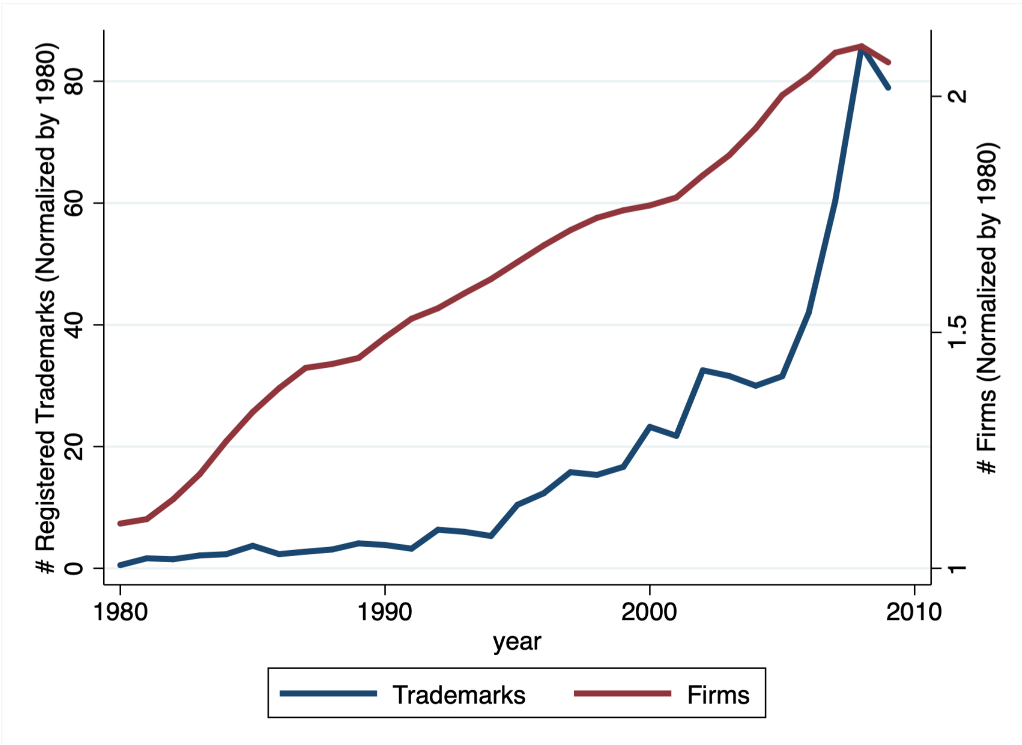


has declined since mid-1990, the number of registered trademarks has been rising since 1980. One potential interpretation is that while production activities are decreasing within manufacturing firms, branding activities are increasing. Panel (b) plots the same data series for service firms. As the number of firms doubled from 1980 to 2010, the number of trademarks grew 80 times. Comparing these two sectors, we observe that the fast-growing sector (service) experienced more growth in branding than the declining sector (manufacturing).

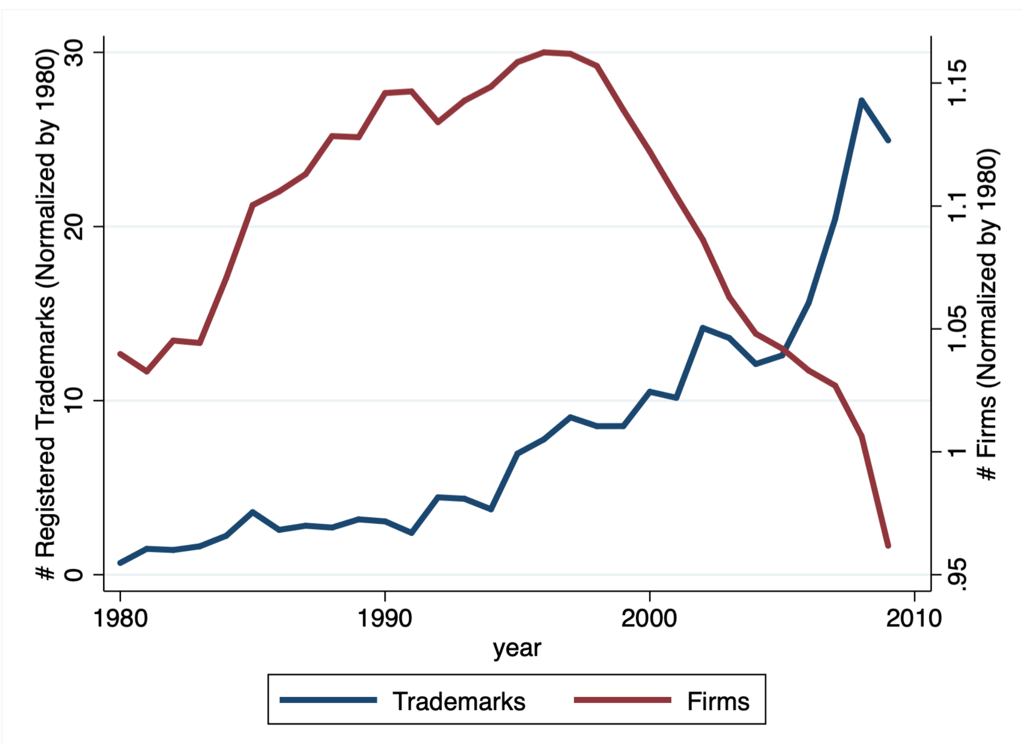
A.3 Specific Company: Procter and Gamble

Figure A.5 shows the evolution of the number of brands Procter and Gamble held in the trademark dataset. We see a large expansion in the early 2000s in their stock and then a leveling off.

Figure A.4: Trademarks over Time



(a) Registered Trademarks and Number of Firms



(b) Registered Trademarks and Number of Firms

Figure A.5: Tracing the brands of P&G over time