Product Reallocation and Market Concentration

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Abstract

Market concentration is the result of the reallocation of market shares across firms. The reallocation of market shares occurs through products – product creation and destruction, product maturity, and product ownership exchange. This paper connects concentration to product reallocation by employing a matched product-firm dataset that links the universe of registered brands to their prices and sales. We find that i) consumer markets are dominated by large firms and mature products; ii) product creation, maturity and transactions shift firm-level sales shares and market power; iii) product sales increase and decline over long life-cycle horizons, while transactions increase monotonically with age. To interpret these patterns and study counterfactual policies, we build an endogenous growth model with product innovation and maturing, variable markups, and frictional trading in product ownership. This framework incorporates three key margins through which market share reallocation occurs: i) the entry margin through product innovation; ii) the product maturing margin; and iii) the acquisition margin through buying and selling of product ownership. We estimate the model and ask how these three margins interact and impact aggregate concentration and efficiency. In markets with fast-maturing products, concentration is less costly due to the entry and growth of new products. In markets where old products dominate, the costs of concentration are higher. Innovation policy must incorporate product dynamics to be effective. Antitrust policy has a non-monotonic effect on efficiency.

Key Words: Concentration, Product Innovation, Firm Dynamics, Reallocation

JEL Code: D22, D43, L11, L13, L22, O31, O34

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1 Introduction

Large firms are multi-product in nature. The product scope of firms explains a large share of the concentration of sales (Hottman et al., 2016). Further, the creation of new products is central to economic growth and welfare (Romer, 1990; Grossman and Helpman, 1991a). While there is a rising interest amongst economists in the product creation and destruction margin (e.g., Argente et al., 2020a) less is known regarding the reallocation of market share across products and product ownership across firms. With rising interest in product market concentration and its implications on welfare, a careful quantitative analysis of this reallocation process is needed.

This paper documents the empirical patterns of product (sometimes referred to as brands in this paper) reallocation in the US, and quantifies its welfare impacts through the lens of an endogenous growth model with product dynamics and firm dynamics. To do so, we make three distinct contributions. First, we integrate two datasets central to firm and product-level analysis: USPTO Trademark data, to study firm-level reallocation of product ownership and product age, and Nielsen retail scanner data, to study product-level reallocation. We use these datasets to document novel facts relating firm concentration to product reallocation and growth.

Second, we build an endogenous growth model with product innovation and maturity, variable markups, and frictional trading in product ownership. This framework incorporates three key margins through which market share reallocation occurs: i) the entry margin through product innovation; ii) the product maturing margin; iii) the acquisition margin through buying and selling product ownership. This process differentiates the role of individual products and the holding firms. Some strong firms hold weak products, and vice versa. The interaction of these margins changes the costs and benefits of concentration and thus its welfare implications.

Third, we quantify the model with the micro-data on products to understand the role of reallocation across firms and optimal antitrust and innovation policies. We explore a rich set of out-of-sample moments before turning to policy counterfactuals, comparing optimal policy to current anti-trust frameworks. As a result, this paper addresses a question central to a growing debate on concentration and reallocation: What is the impact of firm and product-level reallocation on concentration and efficiency, and what are the policy implications?

Our findings inform an important and growing debate in macroeconomics and industrial organization on the interconnection of concentration, markups, and innovation. We begin by building an empirical framework that links the life-cycle of products, and their distribution across firms, to aggregate concentration. We motivate our analysis with three facts about firms and products from USPTO Trademark data and Nielsen Scanner data. We merge these two datasets to explore the intersection of product dynamics and firm dynamics and find the following three key facts.

Fact 1 *Trademark and consumer product markets are dominated by large firms, who persistently lead their market group.*

Fact 2 *New product creation, existing product growth, and product ownership transfer play a significant role in reallocation and firm concentration.*

Fact 3 *Products are dynamic; few products survive, but those that mature are more likely to grow, become transacted, and make up a large share of sales in the market.*

Few firms dominate product markets consistently (see Fact 1). These firms build their portfolios through both product development and product acquisition (also see Fact 2). They tend to purchase products that are more mature and have bigger market share (see Fact 3). Product sales growth and product purchases contribute to the reallocation of products across firms and product dynamism (also see Fact 3). To study how these forces interact and policy counterfactuals, a quantitative model is needed.

We build an endogenous growth model with product creation, product life-cycle and variable markups to interpret these facts. In the model, *product innovation* happens through innovation of multi-product leaders or entry of single-product fringe firms. Products are imperfect substitutes to each other, and go through a life-cycle. All products enter the market as *young*, and can age into a *mature* product with some probability. Mature products have higher appeal than young ones. This simple overlapping generation structure of imperfectly substitutable products replicate the inverted-U pattern of product sales in data.

We allow firms to trade the ownership of products with each other. To gain tractability, we assume the trading of product ownership is organized according to *competitive search*. Specifically, sellers of products can post the terms of trade they require to exchange ownership. Buyers can create recruiting teams with a constant search cost, and these recruiting teams direct their search to sellers. In the equilibrium, young products and old products trade with different rates. Old products have a larger customer base, and thus have higher profit. However, older products are also less elastic in supply, because it takes time for entering products to mature.

In the model, market shares are constantly reallocated across firms, through three mechanisms that are salient in data. First, new products capture market shares from existing products, which we refer to as reallocation on the *entry* margin; Second, young products mature over time and build market share, which we refer to as reallocation on the *maturing* margin; Lastly, products change hands in firms with different market shares and different pricing strategies, which we refer to as reallocation on the *acquisition* margin. These reallocation mechanisms are closely linked to the gross and net reallocation measures from Davis et al. (1996).

With this model in hand, we return to our earlier question: *What is the impact of firm and product-level reallocation on concentration and efficiency, and what are the policy implications?* We answer this

question both analytically and quantitatively. Analytically, a faster reallocation from small to big firms leads to higher concentration. Second, the parameters that drive these reallocation flows also change the innovation and entry strategy of firms. In net, the welfare impact is ambiguous. The relevant parameters to answer these questions are the costs associated with entry, innovation, and acquisition.

We link our model to the empirical results to identify the parameters that underlie these three forces. Through the lens of the estimated model, we address the welfare incidence of product reallocation. Along the entry margin, a lower fixed cost leads to more entry, less concentration, and higher welfare in the steady state; Along the acquisition margin, a lower search cost can increase or decrease welfare; Along the maturing margin, a faster growth of entering products leads to higher entry yet higher concentration. The welfare cost of concentration interacts with the life-cycle of products. Concentration becomes less costly and can even lead to higher welfare when products mature fast. We find that encouraging acquisition of products can increase welfare, but too high a transaction subsidy eventually decreases efficiency.

The paper is structured as follows. The rest of this section reviews the literature. Section 2 introduces the USPTO Trademark Dataset and Nielsen Scanner Data. Section 3 documents the key empirical facts that frame our investigation. Section 4 introduces the model of product creation and acquisition with variable firm productivity and variable markups. Section 5 estimates the quantitative model and uses it to understand the contribution of specific margins and perform policy counterfactuals. Section 6 concludes.

Related Literature

This paper builds on and contributes to several literatures. With product life-cycles at the core of our analysis, we build on a recent body of work on product market dynamics and their life-cycles. We link this literature to work on firm dynamics and endogenous growth. The questions we attempt to answer are connected to significant work in industrial organization and macroeconomics on firm concentration, markups, and welfare.

There is a long literature on how brands play a significant role in economics (e.g., Brown, 1953; Nelson, 1970, 1974). Firms spend capital to invest in building their brands in order to connect with consumers (Sutton, 1991). Industrial organization economists have noted that brands are potentially the most powerful force in generating monopoly rents (Bain, 1956). While there are countervailing views of advertising and branding as good and bad (discussed in Becker and Murphy, 1993). Economists have shown brands are persistent across space and time (Bronnenberg et al., 2009, 2012), often due to persistent consumer loyalty (Dubé et al., 2010) rather than more short-run considerations such as search or limited options. Bronnenberg et al. (2019) reviews this literature, discussing the economics of brands and branding.

This relates to a discussion also of rising interest amongst economists in the life-cycle of products.

Argente et al. (2018, 2020a) explore how product creation and destruction are pervasive in product markets. Argente et al. (2021) and Einav et al. (2021) document that the expansion of product sales is largely due to expansion of the customer base. Foster et al. (2016) discuss how plants grow also through building a consumer base, as entrants start out well behind incumbents, and converge to them. We find this to be true in the product space as well.

Given that firms hold many products, the product life-cycle has important implications for firm concentration. Hottman et al. (2016) study multi-product firms and find the scope of products explains a large share of sales variations across firms. In this paper, the sources of market power come from oligopolistic competition across firms, which follows Atkeson and Burstein (2008). This captures how the nature of product substitution interacts with market power and productivity (as noted by Syverson, 2004a,b; Melitz and Ottaviano, 2008). These sources of monopoly power interact with the size of firms, thus connecting to concerns about dominant superstar firms that potentially hold significant market power both in product and labor markets (Autor et al., 2020; Berger et al., 2019).

The introduction of new products is a bedrock component of much of modern endogenous growth theory (Romer, 1990; Grossman and Helpman, 1991a), as well as consumer welfare (Jaravel, 2018). Product creation has also been noted as a key empirical component of both economic growth and gains from trade as in Bils and Klenow (2001) and Broda and Weinstein (2006). Further, the ability of individuals to exchange products allows for products to expand into new markets and may spur upstream innovation (Eaton and Kortum, 1996). We contribute to this literature by documenting how products continue to grow post-introduction and how their transaction shapes new product innovation.

The quantitative model in this paper is based on the endogenous product creation model developed by Grossman and Helpman (1991b) and oligopolistic competition model by Atkeson and Burstein (2010). Markups are a central incentive for innovation in most models of endogenous growth. Models that incorporate tend to assume limit pricing in order to gain tractability, for example Peters (2020). A recent paper by Liu et al. (2019) differs by considering a model with duopolistic competition. This current paper, like Liu et al. (2019), features endogenous markup dispersion, yet we feature alongside this endogenous acquisition and brand heterogeneity.

Intellectual property transfer plays an important role in the distribution of technologies and products across firms. Our paper is thus related to Akcigit et al. (2016), who study the effect of patent transfers on productivity growth, where the gains from trade in patent transfers come from matching firms to technologies. Shi and Hopenhayn (2017) study how the appropriability of innovation, e.g. the ability to license or sell intellectual property induces upstream incentives. This is related to Abrams et al. (2019), who illustrate how middlemen in intellectual property transfers can have competing negative and positive effects. We focus this paper on the demand side by documenting facts of trademark transfers.

Monopoly power is not an exogenous force. There are multiple layers at which market structure

interacts with monopoly power (Sutton, 1991 , Berry, 1992). The industrial organization literature has paid significant attention to this interaction (Bresnahan, 1989; Bresnahan and Reiss, 1991). Our goal is to speak to these papers through focusing on the sources of reallocation driving concentration. This relates to recent work on the core assumptions that can be taken for granted in measuring the current status of concentration and markups (Berry et al., 2019).

One source of monopoly power is the stickiness of consumer preferences. The stickiness of brand preferences (e.g., as noted by Bronnenberg et al., 2012 and reviewed by Bronnenberg et al., 2019) naturally lead to a product life-cycle. Products are born, build a consumer base, and then achieve profits off of consumer appeal. As a result, a firm must incorporate their set of products into how they optimize (Dhingra, 2013). Gourio and Rudanko (2014) note how as a result, consumer goodwill is a relevant state variable for firms and products. Our current paper points out that when brand ownership is transacted, this life-cycle element becomes essential for understanding concentration.

This paper applies insights from search theory to study the market for trademark exchange. Some previous work has stressed the importance of reallocation and labor market frictions in driving economic growth. For instance, Lentz and Mortensen (2008) apply a random search framework to uncover the importance of entry, exit, and reallocation in how labor markets interact with firm dynamics. This current paper considers the frictions in the market for intellectual property, applying competitive search theory as developed in Menzio and Shi (2011).

A discussion of the reallocation of products naturally connects to a rich empirical literature on firm dynamics. Further, many researchers have noted a declining reallocation in the economy. For example, the reallocation rate of jobs has been decreasing, and the entry and exit rate of firms has been decreasing (Decker et al., 2014, Davis and Haltiwanger, 2014, and Decker et al., 2020). Our reallocation measure follows the work of Davis and Haltiwanger (1992) and Davis et al. (1996). Acemoglu et al. (2018) study reallocation and aggregate innovation focusing on selection as a key force in reallocation, whereas here we note the added ingredient of product dynamics.

A lot of product reallocation is due to exchanges from small firms to large firms. This connects to work on rising concentration and markups which has been studied extensively, both empirically (Barkai, 2020; De Loecker et al., 2020; Traina, 2018) and theoretically (Edmond et al., 2018; Peters, 2020; Akcigit and Ates, 2019, 2021). Some papers have deployed detailed methods to focus on the transfer of products and firms. Cunningham et al. (2021) focus on killer acquisitions, where incumbents purchase small firms in order to keep concentration high. However, this does not match the observation that large firms pay high premiums and often deploy the products from the firms they buy David (2020). This current paper integrates these two viewpoints by informing new empirical facts and a theoretical perspective that links these facts to current hypotheses on product market concentration. Further, we connect this framework to time trends on brand evolution in the data and apply it to antitrust policies. There are two recent

papers discussing the role of antitrust policies on growth, from the perspective of technology innovation (Cavenaile et al., 2021, Fons-Rosen et al., 2021). Our theoretical framework relates to these in integrating the dynamic effects of transactions, but differs in the focus on the life-cycle of products and the reallocation mechanism.

Lastly, we extend a new literature on the role of trademarks in marketing and strategy to a macroeconomic context. Graham et al. (2013) provide a general overview of the dataset and insights on 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. Heath and Mace (2019) focus the role of trademarks in the strategic interaction of firms. Castaldi (2019) discusses the potential of this rich dataset in providing empirical analogs of a host of subjects in management research. Kost et al. (2019) introduce trademarks in the context of macroeconomics, focusing on markups through the lens of trademarks. In this current paper, we integrate trademarks to more common datasets in order to understand in more granular detail the distribution of products across firms.

2 Data

This paper applies two datasets in order to track the creation, distribution, and prices and quantities of products. This section discusses the datasets and their unique contributions to our analysis. We start by discussing US Patent and Trademark Office (USPTO) Trademark Data. This carries with it details on brand creation, brand transfer, and cancellation.

To focus on the response of prices and quantities, we connect this firm-product level data to specific information on product prices and quantities sold by store in RMS Nielsen Scanner Data. The following two sections discuss the datasets in turn.

2.1 USPTO Trademark Data

USPTO Trademark data provides a unique and comprehensive insight into brand-building. Trademarks are a central and dynamic arena of the economy: firms register for trademarks whenever they want their brand protected.

In this paper, we direct attention to how trademark creation and exchange contribute to the growth of firms. When firms create new products, this is highly correlated with applications to protect the brand related to the product. Firms want to ensure that their consumer goodwill cannot be infringed by other firms. Further, when firms buy the rights to sell products from other firms, the trademark is reassigned

across firms.

To register for a trademark, a firm must undergo the following process. First, an individual who applies must pay a fee that ranges from $225-$400. 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 affected by the trademark registration can step forward to file an "Opposition Proceeding" to stop the registration. This process is again evaluated by an examiner. If it clears this process, the trademark is registered.

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. The main principle underlying trademark law is to minimize consumer confusion. If consumer confusion is possible, the trademark owner has a case against infringers. However, one can still petition to cancel a trademark and end the exclusive rights of the owner. The petition to cancel often comes from competing firms that think the intellectual property is too broad. Trademarks are also canceled if firms are not actively using them. Cancellations are a significant share of overall trademark activity. In addition to registration and cancellation, firms exchange a large share of trademarks, which delivers the rights to brand and sell the product.

One striking feature of the data is the number of cancellations and transactions (noted in Table 1). This activity indicates that the market for trademarks is highly contested and dynamic. Cancels either require that other firms are concerned about the territory – many cancellations suggest 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 component of firm dynamics (Fosfuri and Giarratana, 2009). Kost et al. (2019) discuss the institutional aspects of trademarks in greater detail. Further, Appendix A presents some examples of firms with multiple brands and Figure A3 shows an example from Procter & Gamble of firm brand growth.

2.2 Nielsen Scanner Data

The most comprehensive store-product level data comes from Kilts-Nielsen Retail Measurement Services Data from the University of Chicago Booth School of Business. The data is large and comprehensive in the consumer product space from years 2006-2018. We observe more than 100 billion observations at the product $\times$ store $\times$ time level. Product is defined by a UPC identifier, 12 digits that are uniquely assigned to each specific good. The store is defined at the local level with over 40,000 total; time is defined weekly. Total sales are approximately $300 billion per year, covering around half of consumption in the consumer goods industry, which itself covers approximately 8% of total consumption in GDP.

The barcodes from UPC provide a unique identifier for each product. Changes in any attribute of a good corresponds to a new barcode. Barcodes are widespread and thus cover a large amount of the

Consumer Packaged Goods Industry. However, the unique identifying feature of the barcodes may not be as relevant for our analysis. For instance,

A key departure from the literature in our case is identifying *brands* rather than *products*. There are three reasons for this. First, consumer goodwill tends to be brand rather than product-specific. Coke 12oz relies on the same core-branding that Coke 20oz relies on. Thus, when it comes to how the consumer interacts with the product, we think brand is a more core indicator. Second, when firms transact products, e.g. the right to sell a specific brand, they systematically transfer the full rights on the consumer goodwill, making the specific product differentiation within the brand less relevant. Third, our data enables identification at the brand-level in both Nielsen data and USPTO trademark data. Nielsen provides brand identifiers in addition to product identifiers. We collapse this information into brand sales by product group by year, with less geographical focus.

The volume represents over half of all transactions in grocery stores and drug stores, and slightly less than half in convenience and mass merchandise stores (Argente et al., 2020a). We apply a dataset from GS1 US to link parent firms to products through UPCs. While this links to most parent companies, the trademark dataset helps complement this to ensure the correct company is allocated to the correct brand.

2.3 Data Merge

To build a bridge between brand age and brand transaction and product evolution we employ a fuzzy merge to connect product names in RMS Nielsen Scanner data to USPTO Trademark data. While this is the first merge we know of that links USPTO Trademark data to Nielsen Scanner data, Argente et al. (2020b) link USPTO Patent data to RMS Nielsen product-level data. We follow generally a similar method to theirs, but get greater coverage in our merge, mostly we expect due to the different nature of patents and trademarks.

We start by normalizing names in each dataset both the firm and product-level. For example, we want to capture heterogeneous naming at the firm (e.g., General Mill Holdings (TM) + General Mills Minn. Operation (Nielsen)) and connect it to the parent company.

A core aspect of our exercise is that we attempt to identify activity at the point where consumer capital is built. This is important for two reasons: First, there are a lot of product offshoots (e.g., "Coke Christmas Edition") that add variance but not much clarity to product-level dynamics. Second, and more essentially, we want to capture the core economic component of this dynamic. The value of a product that firms attempt to maintain (e.g., see advertising expenditure) is at the brand-level, which is where we direct our attention.

In both USPTO and Nielsen Scanner Data, there is a firm $\times$ brand of observation of interest. Once firms and brands are identified, this creates what is ideally a many-to-1 matching between products (which

rely on the same goodwill) and brands. Once this match is complete, we treat brands as the relevant margin for the concepts in this paper.

We next turn to the quality of the match between brands and products. We focus in the USPTO case on brands, and note the products they connect to in Nielsen. Table 1 provides some information on the match between products and trademarks.

Table 1: Summary Statistics on Trademark Nielsen Merge

	Unique Count	Years Active	Share Match (%)
USPTO Trademark Data			
Brands	5.36M	1870-2020	
Firms	371021	1870-2020	
Canceled Brands	2.12M	1970-2020	
Transactions	915076	1970-2020	
RMS Nielsen Scanner Data			
Brands	1.64M	2006-2018	57%
Firms	23232	2006-2018	54%
Brand $\times$ sales		2006-2018	70%

We stress a couple points from the table. First, we note that multiple products are connected to a single brand (on average around 13 products per brand). Second, we note the overall matching is above 50% in terms of unique products, sales-weighted products, and the number of firms when we compare against the base of RMS Nielsen Scanner Data.

3 Empirics of Concentration and Reallocation

This section links the level and persistence of concentration to product dynamics. While single firms control significant market shares in consumer product markets, many products exhibit significant dynamics. This section splits the analysis into firm-level and product-level in order to demonstrate striking empirical patterns that link the product life-cycle to firm concentration.

Section 3.1 starts by focusing on firms. First, we document the degree of dominance of firms in product markets, illustrating the role of market leaders and their persistence. Second, we decompose the forces that contribute to firm-level market share. We focus on three core drivers of concentration: i) product creation and destruction, ii) existing product sales growth, and iii) product transactions across firms.

Section 3.2 unpacks products more directly, directing attention to the three core forces contributing to concentration – product creation, growth, and transactions of ownership across firms. The product

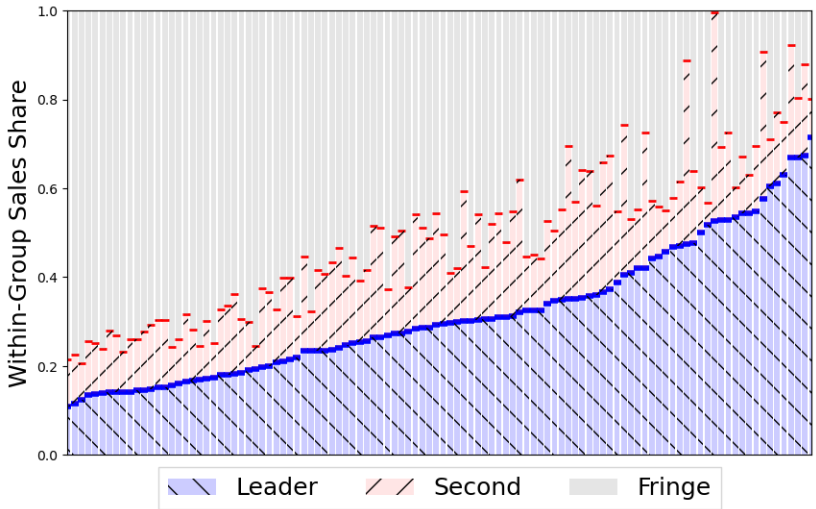
life-cycle exhibits striking patterns in the data. Older products tend to take up the largest share of sales. Yet, at the product-level, products exhibit an inverted-U relationship with respect to sales by age. Products exhibit a similar pattern with transactions, as products are more likely to be sold as the grow until the probability of sale declines. Section 5 develops further some of these insights and changes in these patterns over time.

3.1 Firm-Level Analysis

Market concentration is not a purely static force. Companies like Coca-Cola, Procter & Gamble, and General Mills at one time did not have large and persistent market shares. While concentration can be dynamic, concentration is also persistent. Coca-Cola was a market leader ten years ago, and still is today. We focus in this section on the level, persistence, and sources of market shares. We first focus on overall concentration and then turn to the persistence of market leadership.

Figure 1 maps out sales share of the product leader, the second firm, and the rest of firms in the market. This split by product group contains 116 unique product group categories (such as e.g. "ICE CREAM" or "BEER"). The average top firm share is 34% of the total market, though in many markets the top firm holds a significantly larger share. Thus, understanding how large and fringe firms interact is essential to understanding concentration.

Figure 1: Sales Share of Leader, by Product Group



Note: This figure shows the sales share by product group (ordered by % share of leader) in 2010. *Source:* RMS Kilts-Nielsen Data Center & GS1 firm-product merge

Table 2 shows the average leader (and 2nd firm) share as well as the share from the median firm. The top 2 firms control on average more than half the sales in a given market. We note also that there are a host of small firms (median share as 0.04%), and in our framework we think of these firms as "fringe" in

Table 2: Firm Market Shares

Top firm share by group	Top 2 firm share	median share
33.6%	50.3%	0.04%

the sense they hold few products and small market share.

We also note that these leading firms are quite persistent. Across all categories, the leading firm in one period has a 97% chance of being amongst the top two firms in the product group in the next period. With products as the core unit of our analysis, we evaluate the level and persistence through evaluating the underlying basket of a firm's products.

Concentration in product markets is real and persistent, yet it is not made up of single products. On average, market leaders hold 27 unique brands within the product group they lead. Thus, it is essential to understand these brand or product dynamics in order to discover the sources of concentration.

Product market dominance does not happen in a day. Concentration is the result of the progressive reallocation of market shares of products across firms. The product life-cycle is intertwined with firm growth and decline through three core channels. First, and most noted within innovation literature, there is product creation and destruction. Second, once products are born, they grow and decay over time. Third, product ownership is transacted across firms.

The format of our data allows us to characterize these three forces. We set up three regressions where the sum of the coefficients add to one, and each coefficient is linked to the amount of variation of firm growth and decline the margin explains. We run the following regression of three distinct margins of change, y_{it}, on the change of sales in each period $\Delta sales_{it}$.

$$y_{it} = \alpha + \beta \Delta sales_{it} + \epsilon_{it} \tag{1}$$

Equation (1) focuses on three different margins for y_{it}. We substitue each of the three margins discussed above as y_{it} ($_{it}$=creation, growth, transction). We present the results of the three separate regressions in Table 3.

We note that each force has a non-negligible contribution to the distribution of market shares. This suggests two key points relevant to this paper. First, the classical channel contribution to growth, product creation, is only a small share of the driver of overall market concentration. The other two forces are essential to incorporate. Second, due to the necessity of incorporating growth and transaction, we need to provide data and framework in order to incorporate them into the firm-level growth. This requires us to employ the merge between scanner data and US Trademarks. We turn to this next, in particular focusing on growth, transactions, and product age.

Table 3: Sources of Reallocation

	(1) Entry	(2) Fitted Incumbents	(3) Transfer
Top 1%	0.041*	0.063*	0.12*
Average	0.0013	-0.013	-0.001
Top 1-25 %	0.065*	0.14*	0.10*
Average	0.0002	-0.018	-0.004
The Rest	0.14*	0.077*	0.19*
Average	-0.012	0.078	-0.029
Overall	0.13*	0.084*	0.18*
Average	-0.009	0.053	-0.022

p-values in parentheses
* $p < 0.001$

3.2 Product-Level Analysis

Products are at the core of concentration, but products are highly dynamic. Some products charge to dominance quickly (e.g. Chobani), others rise gradually but maintain leadership (e.g. Marlboro), whereas others survive but remain in obscurity. Yet all brands must build consumer capital in order to build market share. We direct our attention to brand *age* is as an ingredient to product market shares. We first focus on a snapshot of the distribution of sales by age, and then turn to an analysis of the life-cycle in order to understand the more granular dynamics.

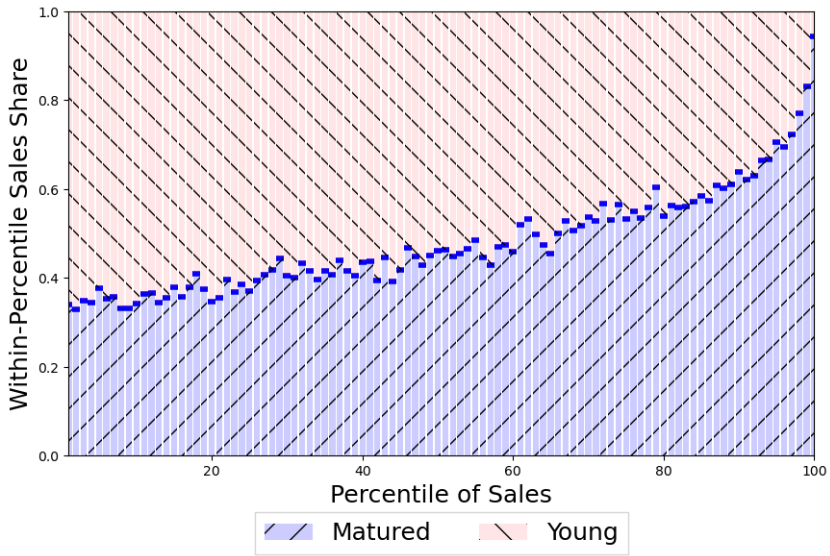
Products evolve over their life-cycle. Gourio and Rudanko (2014) and Foster et al. (2016), among many others, have noted that customer capital is not built in a day. By looking at trademark data and Nielsen data, one can observe the importance of senior brands. Figure 2 takes data from 2016. We plot the brand percentile in terms of overall sales on the x-axis. On the y-axis, we plot the share of sales in this group that belongs to brands older than 10 years and brands younger than 10 years.[1]

For brands created in 2006 and earlier, they maintain large sales share into the future. By 2016, those brands are still dominant in the top 1% of brands. Within the top 1% of brands, brands created before 2006 make up 92% of sales. Overall, old brands make up over 70% of sales, but only about 1/3rd of products. For the median brand in terms of sales, older brands make up less than half (38%) of total sales.

The dominance of mature brands could come from two forces. First, if few brands achieve such large

[1]We omit brands with less than $1000 in sales over an entire year, to have only brands that at least have a product line.

Figure 2: The Power of Mature Products



Note: This figure shows the log sales on average of products born before 2006 and after 2006 over time.

Source: RMS Nielsen Scanner Data.

sales, there may be a selection process. Young brands have less of a chance than old brands to have high consumer capital, as the brands that survive to maturity must have a high quality draw. The composition only selects for the best. Second, brands could increase their sales over the life-cycle such that only mature brands have significant sales share. We aim to understand this by linking a brand to its specific age.

We now turn to study the product life-cycle, where we leverage age data from trademarks registrations from the USPTO and sales data from RMS Nielsen. We use a method to study the life-cycle of brands, following similar work from Altonji and Shakotko (1987), Fitzgerald et al. (2016), and Argente et al. (2018). Figure **??** plots two regressions that illustrate the nature of the product life-cycle. This graph plots the coefficients to the following regressions:

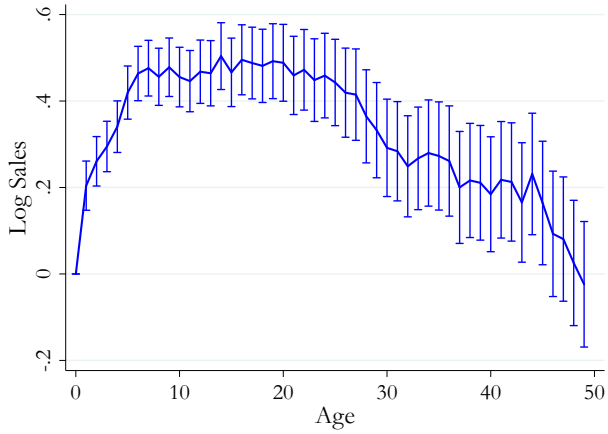
$$\log y_{it} = \alpha + \sum_{a=1}^{50} \beta_a D_a + \gamma_b + \lambda_t + \theta_i + \epsilon_{it} \tag{2}$$

The regression in Equation (2) considers the sales of brand i at time t, $\log y_{it}$ as a function of a constant (α), brand age indicators from 1 to 50, D_a, and fixed effects for cohort (γ_b) and time (λ_t).[2] The θ_i indicates either a brand or firm fixed-effect. The graph in Figure **??** has both regressions by age coefficient β_a. The blue line focuses just on a firm fixed effect, while the red line includes a brand fixed effect to control for the brand's level itself.

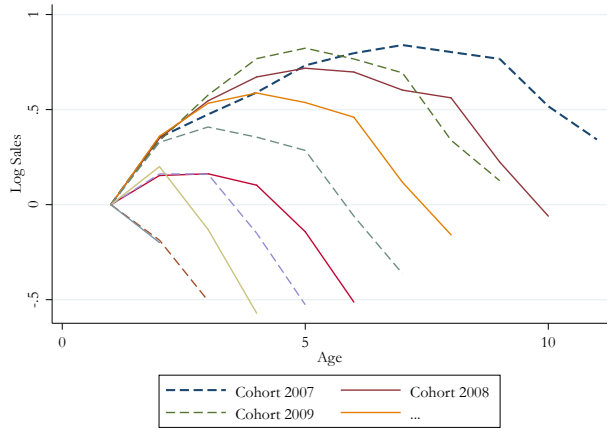
There are two main takeaways from Figure **??**. First, when looking at the cross-section of firms, we

[2]Given the linear relationship between age, time, and cohort, we follow a method developed by Deaton (1997) to correct for this issue. The normalization orthogonalizes the cohort trends such that growth components move with age and time effects.

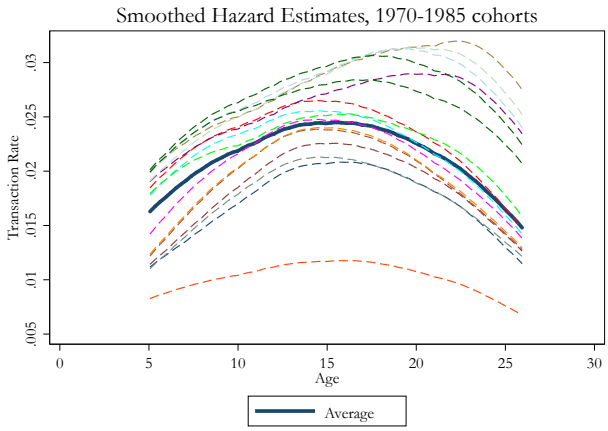
Figure 3: Product-Level Dynamics



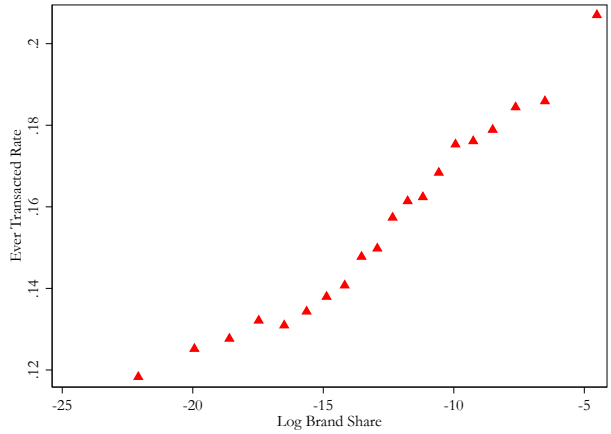
(a) Log Sales × Age, USPTO



(b) Log Sales × Age UPC



(c) Transaction Rate × Age



(d) Transaction Rate × Market Share

Notes:

find that older brands have a significantly larger sales share than younger brands. Once we control for a brand-level fixed effect, however, we see brands themselves exhibit an inverted-U pattern in sales over their life-cycle. This is consistent with Argente et al. (2018, 2021), yet in brands the product life-cycle is much longer and peaks far later.

In Appendix B, we explore these differences in greater detail. The main point we make here is that when the unit of analysis is the consumer brand goodwill (e.g. the level of a trademark), and we extend the panel beyond the limited Nielsen age distribution the goodwill peaks later in the life-cycle. Both of these ingredients lead to a later life-cycle peak in our case. Now we turn to the three main facts revealed in this section.

Fact 1 *Trademark and consumer product markets are dominated by large firms, who persistently lead their market group.*

Fact 2 *New product creation, existing product growth, and product ownership transfer all play a significant role in reallocation and firm concentration.*

Fact 3 *Products are dynamic; products that survive are more likely to grow over time, become transacted, and make up a large share of sales in the market.*

This section showed first that markets are concentrated, and this concentration is persistent over time (Fact 1). We decompose the forces driving market concentration from product reallocation, finding that creation, growth, and exchange all contribute to market shares (Fact 2). Directing more specific attention to products, we find interesting product-level dynamics in both sales and transactions (Fact 3). These results motivate a model that can incorporate these forces and develop counterfactuals. We turn to the model next.

4 Model

We introduce an equilibrium model of multi-product firms with (1) product creation, (2) variable markups, and (3) transfer of brand ownership. We use this model to study the role of different margins of reallocation on concentration and welfare. In the model, there is a representative household that consume imperfectly substitutable varieties from different product groups, and supply labor to firms. The consumption from different product groups is aggregated through a Cobb-Douglas utility function, and the consumption from varieties within each product group is aggregated through a constant elasticity of substitution (CES) aggregator. This formulation enables us to characterize the equilibrium within each product group separately. For expositional purpose, we first focus on the equilibrium within a product group.

4.1 Environment

Representative Household

Time is continuous. There is a representative household that endogenously supply labor $\mathbf{L}_t$ and spend in order to maximize its discounted utility. At instant t, the real consumption of the household $\mathbf{C}_t$ is given by a Cobb-Douglas aggregator across a unit measure of product groups, indexed by $k \in [0, 1]$. Within each product group, at time t, there are n_{kt} measure of imperfectly differentiable products. The real consumption from product group k, C_{kt}, is a CES aggregator across these varieties. Specifically, the real consumption is given by:

$$\mathbf{C}_t = \exp\left\{ \int_0^1 \alpha_k \ln\left(\int_0^{n_{kt}} \beta_{it}^{\frac{1}{\sigma}} c_{it}^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}} dk \right\}. \tag{3}$$

In equation (3), we allow product groups to differ in their importance to the representative household, represented by the shifter α_k. Within each product group, we allow the varieties to differ in their time-varying appeal to the representative household, captured by the shifter β_{it}. We assume the representative household has quasi-linear utility in labor, and can freely save or borrow. Through out the paper, we normalize the aggregate price index to be 1: $\mathbf{P}_t = \exp\left\{\int_0^1 \alpha_k \ln\left(\int_0^{n_{kt}} \beta_{it}^{\frac{1}{\sigma}} p_{it}^{1-\sigma} di\right)^{\frac{1}{1-\sigma}} dk\right\} = 1$. Denote $\mathbf{r}_t$ the real interest rate and $\mathbf{w}_t$ the real wage. The household's optimality requires:

$$\max_{c_{it},\mathbf{L}_t} \int_0^\infty e^{-\rho t}\left[\ln \mathbf{C}_t - \varphi_0 \mathbf{L}_t\right] dt,$$

s.t.

$$\dot{a} = \mathbf{r}_t a_t - \mathbf{C}_t + \mathbf{w}_t \mathbf{L}_t,$$

$$\mathbf{C}_t \text{ given by (3).}$$

The saving and labor supply decision of the household is standard. The optimal saving decision implies the Euler equation must hold:

$$\frac{\dot{\mathbf{C}}}{\mathbf{C}} = \mathbf{r}_t - \rho,$$

and the optimal labor supply decision requires the marginal rate of substitution between leisure and consumption must equals the real wage:

$$\varphi_0 = \frac{\mathbf{w}_t}{\mathbf{C}_t}.$$

The Cobb-Douglas aggregator across product groups implies that the household always allocate fixed share of its total expenditure to product group k. As a result, the total market sales of product group k at time t is $\alpha_k \mathbf{C}_t$. The optimal consumption decision within group k gives the demand curve for variety i:

$$c_{kt}(p,\beta) = \beta \times \left(\frac{p}{P_{kt}}\right)^{-\sigma} \times \frac{\alpha_k \mathbf{C}_t}{P_{kt}} \tag{4}$$

In equation (4), β is the appeal of variety and p is the price charged. The group level price index is given by $P_{kt} = \left(\int_0^{n_{kt}} \beta_{it}^{\frac{1}{\sigma}} p_{it}^{1-\sigma} di\right)^{\frac{1}{1-\sigma}}$.

Firms

In each product group, there is one multi-product firm and endogenous measure of fringe firms. We refer to the multi-product firm as the group leader. The leader and fringe firms are different in the following aspects: (1) *Capacity in operating varieties*. The leaders are able to own and operate positive measure of products, while the fringe firms are only able to operate a infinitesimal product. Among the N_{kt} varieties

that are available in group k at time t, we denote the set of varieties that belong to the leader as $\mathcal{I}_{kt}^L$ and the set of varieties that belong to the fringe firms as $\mathcal{I}_t^F$. (2) *Entry*. The leaders are not subject to entry and exit, while there is free entry of fringe firms. (3) *Productivity*. All varieties are produced using a linear technology in labor. The leader has productivity $e^{x/(\sigma-1)}$; All fringes have the same productivity 1. (4) *Pricing*. The leaders are big relative to their product groups, and they internalize their impact on the group-level price index. The fringe firms are small relative to the market, and they behave as monopolistic competitive firms.

As the fringe firms are infinitesimal relative to the market, they do not internalize their own impacts on the price indices. In the equilibrium, they charge a constant markup $\frac{\sigma}{\sigma-1}$. Given the demand curve for each variety in equation (4), the product group leader's pricing decision is:

$$\max_{p_i} \int_{i\in\mathcal{I}_{kt}^L} (p_i - \mathbf{w}_t) c_{kt}(p_i, \beta_i) di$$

s.t.

$$c_{kt}(p, \beta) \text{ given by equation (4)}$$

As in Liu et al., 2019, the competition of a group can be summarized by the gap between leaders' quality and fringe firms' quality. In our context, the relevant measure is the quality gap between the leader's basket of products and fringe firms' basket products, adjusted by the relative productivity x:

$$\phi = \frac{x \int_{i\in\mathcal{I}_{kt}^L} \beta_{it} di}{\int_{i\in\mathcal{I}_{kt}^F} \beta_{it} di}. \tag{5}$$

The pricing equilibrium within product group is summarized by the following lemma:

Lemma 1 *Given ϕ, the within-group market share of leader and markup (s, μ) jointly solve:*

$$s = \frac{\mu^{1-\sigma}}{\mu^{1-\sigma} + \phi^{-1}[\frac{\sigma}{\sigma-1}]^{1-\sigma}},$$

$$\mu = \frac{\epsilon(s)}{\epsilon(s) - 1}.$$

Denote the solution as $s(\phi)$ and $\mu(\phi)$.

It would be useful to derive the marginal profit from increasing ϕ for the product group leader. To do so, we totally differentiate the pricing equilibrium system in Lemma (1). To a first order, the marginal change in ϕ results in a change in Π as:

Lemma 2 *Given ϕ, the elasticity of profit $\Pi(\phi)$ from increasing ϕ under pricing competition is:*

$$\frac{\Pi'(\phi)\phi}{\Pi(\phi)} = 1 - s(\phi).$$

Innovation.- New products are created through product innovation. The leader can choose the measure of new products η_t by paying labor cost $D(\eta)$. $D(\eta)$ is increasing and convex in η, and $D(0) = 0$. The fringe firms have endogenous entry with entry cost κ_e. Once entering, the fringe creates a new product. All new products start with a customer base of n_0, and draw a quality z from a fixed distribution $G_0(z)$, with density $g_0(z)$. Over time, the customer base of a product grows by a per instant. The total appeal of a product i is thus given by $\beta_{it} = z_i \left[n_0 + a(t - \tau_i)\right]$. [3]

Acquisition.- The group leader and fringes can engage in frictional trading of the ownership of products. We assume search is directed. At each instant, the product group leader can choose to set up recruiting teams $\nu_{kt}(z, n)$ for products with state (z, n). Each of these teams cost a fixed cost κ_s. The fringe firms post the terms of trade they require in exchange for their products, τ. Recruiting teams then direct search to different fringe firms. The rate of contact between two sides of the market depends on the ratio of recruiting team and the measure of fringe firms, which we define as θ and refer to as tightness following the search and matching literature. The contact rate for fringe firms is $\lambda(\theta)$, which is assumed to be increasing and concave; the contact rate for recruiting teams is $\frac{\lambda(\theta)}{\theta}$, which is assumed to be decreasing and convex.

Leader's Innovation and Acquisition Decision

We set up the leader's dynamics decision in its sequential form. The leader in product group k aims to maximize its discounted profit, subject to the law of motion of the density of product appeal within its own basket and in its competitors' basket, given $\theta_t(z, n)$ and ϵ_t.

$$\max_{\eta_t, \nu_t(z,n)} \int_0^\infty e^{-\rho t} \left(\Pi(\phi_t) - D(\eta_t) - \int_{z,n} \nu_t(z, n) \left[\kappa_s + \tau_t(z, n)\right] dz dn \right) dt \tag{6}$$

s.t.

$$\dot{a}_t(z, n) = -\left[i a_t(z, n)\right]' + \frac{\lambda(\theta_t(z, n))}{\theta_t(z, n)} \nu_t(z, n) - \delta a_t(z, n) + \eta_t \mathcal{D}_{n=n_0} \tag{7}$$

$$\dot{b}_t(z, n) = -\left[i b_t(z, n)\right]' - \frac{\lambda(\theta_t(z, n))}{\theta_t(z, n)} \nu_t(z, n) - \delta b_t(z, n) + \epsilon_t \mathcal{D}_{n=n_0} \tag{8}$$

[3] We effectively assume that the product innovation cost scales down with the measure of matured products. This assumption is within the line of Grossman and Helpman (1991b). It captures the reality that mimicking is easier when there are more products, and also guarantees the existence of balanced growth path in our environment.

$$\phi_t = x\frac{\int zna_t(z,n)dndz}{\int znb_t(z,n)dndz} \tag{9}$$

Equation (6) summarizes the discounted net profit of the leader. For each instant t, the leader gets a flow profit from selling its products to the representative household $\Pi(\phi_t)$ given the competition ϕ_t. While choosing an innovation intensity η_t, the leader also pays a flow cost of $D(\eta_t)$. The last part of the flow profit is the cost of acquisition. Specifically, each recruiting team incurs both the fixed cost κ_s and the transfer to sellers $\tau_t(z,n)$. Equation (7) and equation (8) summarize the law of motion of the density of products of different quality and customer base, for the leadera $(a_t(z,n))$ and for the fringe firms $(b_t(z,n))$. Other than the exogenous growth and product retirement, there are two endogenous forces that are driving the changes of the two densities. First is an competition force due to leader's innovation (η_t) and fringes' innovation (ϵ_t). Second is an cooperative force due to the occasional transfers of product ownership. Note that in net, the transfers of product ownership does not directly creates more products, but instead is a pure reallocation from fringe firms to leaders.

We omit the details of derivation to the Appendix, and directly walk through the results in the main text. Denote $v_t(n,z)$ as the shadow value of additional product with quality (z,n) and $\tilde{u}_t(z,n)$ as the shadow value of additional product in fringe firms's basket. These two value functions must be solutions to the following Bellman equations:

(Own product value)

$$(\rho+\delta)v_t(z,n) = zn\frac{x\Pi'(\phi_t)}{B_t} + i\frac{\partial}{\partial n}v_t(z,n) + \dot{v}_t(z,n) \tag{10}$$

(Competitor product value)

$$(\rho+\delta)\tilde{u}_t(z,n) = -zn\frac{x\Pi'(\phi_t)\phi_t}{B_t} + i\frac{\partial}{\partial n}\tilde{u}_t(z,n) + \tilde{u}_t(z,n) \tag{11}$$

The optimality of innovation requires that the marginal cost of innovation equals the marginal benefit of having an additional new product:

$$D'(\eta_t) = \int_z v_t(z,n_0)g_0(z)dz \tag{12}$$

The optimal acquisition decision requires that the leader is indifferent between whether to create an additional recruiting team:

$$\kappa_s = \frac{\lambda(\theta_t(z,n))}{\theta_t(z,n)}\left[v_t(z,n) + \tilde{u}_t(z,n) - \tau_t(z,n)\right]. \tag{13}$$

Fringes' Innovation and Acquisition Decision

The fringe firms only make innovation decision when it enters the market, and it chooses the optimal price to request from its buyers. We focus on an equilibrium with positive entry and positive acquisition, which is the empirically relevant case. Under these conditions, the value of a fringe firm with quality (z, n) is:

$$(\rho+\delta)u_t(z,n) = \max_{\tau,\theta} \frac{zn}{B_t}\left[1-s(\phi)\right] + iu_n(z,n) + \lambda(\theta)\left[\tau - u_t(z,n)\right] + \dot{u}_t(z,n), \tag{14}$$

s.t.

$$\frac{\lambda(\theta)}{\theta}\left[v_t(z,n) - \tilde{u}_t(z,n) - \tau\right] = \kappa_s.$$

Under positive entry, the new fringe firm must be indifferent between whether to enter the market:

$$\kappa_e = \int_0^\infty e^{-(\rho+\delta)t}\left[\underbrace{(n_0+it)\frac{1-s(\phi)}{B_t}\bar{z}}_{Profit} + \underbrace{\frac{\gamma}{1-\gamma}\mathbb{E}_z\theta_t(z,n_0+it)\kappa_s}_{Selling}\right]dt$$

To understand the acquisition decision, it is helpful to define a new variable $\Omega_t(z,n) = v_t(z,n) - \tilde{u}_t(z,n) - u_t(z,n)$. $\Omega_t(z,n)$ measures the gains from trade when a product is transferred from a fringe firm to a leader. Using the results so far, this gains from trade must solve the following Bellman equation:

$$(\rho+\delta)\Omega(z,n) = \Delta_t\frac{1-s(\phi_t)}{B_t}zn + i\Omega_n(z,n) - \left[\max_\theta \lambda(\theta)\Omega_t(z,n) - \theta\kappa_s\right] + \dot{\Omega}_t(z,n) \tag{15}$$

where

$$\Delta_t = x\frac{1+\phi}{\phi}s(\phi)\left[1-\frac{1}{\mu(\phi)}\right] - \frac{1}{\sigma} \tag{16}$$

Lemma 3 (Gains from Trade) *If $x \geq 1$, $\Delta_t > 0$.*

Characterization of Within-Group Equilibrium

With the discussion so far, we are ready to write out the characterization of an equilibrium within each product group.

Definition 4 *(Within Group Equilibrium) A within-group equilibrium is characterized by $\{B_t, \phi_t\}$ and $\{v_t(z,n),\ \tilde{\Omega}_t(z,n),\ u_t(z,n)\}$ such that:*

1. *Given the path of $\{B_t, \phi_t\}$, $\{v_t(z,n),\ \tilde{u}_t(z,n)\}$ is consistent with leader's optimality (10) and (11);*
2. *Given the path of $\{B_t, \phi_t\}$ $\{v_t(z,n),\ \tilde{u}_t(z,n)\}$, $u_t(z,n)$ is consistent with fringe's optimality (14);*
3. *ϕ_t and B_t are consistent with their definitions.*

4.2 Steady States

For most of the quantitative analysis, we focus on the steady state of the economy, where the distribution of products in different states (z, n) no longer varies.

Analytical Result: Reallocation and Concentration without Product Heterogeneity

With the assumption that products have a constant appeal $\beta_{it} = 1$, the steady state equilibrium can be summarized by two equations in terms of quality gap ϕ and tightness θ: by two equations in (ϕ, π):

$$\phi = \frac{1}{\delta}\left[\frac{\bar{\eta}\left[\kappa_e - \frac{\gamma}{1-\gamma}\theta\kappa_s\right]}{1 - s(\phi)} + \lambda(\theta)\right]$$

$$\kappa_s = \lambda'(\theta)\left[\frac{(1+\phi)\Pi'(\phi)}{(\rho+\delta)}\frac{\left[\kappa_e - \frac{\gamma}{1-\gamma}\theta\kappa_s\right]}{1 - s(\phi)} - \kappa_e\right]$$

Consider a change to the search cost $\Delta\kappa_s$. The following lemma summarizes the first-order impacts of such a change in search cost on the steady state concentration and steady state buyer-seller ratio.

Lemma 5 *(Acquisition and Concentration) If* $\frac{a}{1-a} > \frac{1-\gamma}{b}$, *then* $\frac{d\log\phi}{d\log\kappa_s} > 0$.

Lemma (6) is one of core theoretical takeaway from our model: An increase in the cost of acquisition can lead to an increase in market concentration. Even more so, we derive an sufficient condition for when this will happen. This happens in a product group where the concentration is mainly due to difference in innovation activity (a is large), fringe firms derive large share of their value from the option value of selling (b is large) and the reallocation rate does not response too much to tightness.

Lemma 6 *(Entry and Concentration)* $\frac{d\log\phi}{d\log\kappa_e} > 0$.

4.3 General Equilibrium

There is a representative household that endogenously supplies labor to the economy at each instant t, denoted as $\mathbf{L}_t$. The household receives income from their labor and dividends from the corporate sector, according to a representative portfolio of firms. The income of the household is spent on differentiated varieties from measure 1 of product groups, indexed by $k \in [0, 1]$. At each instant of time t, there are measure n_{kt} varieties available for consumption. Each variety is indexed by (i, k) with $i \in [0, n_{kt}]$. Given the consumption choice c_{ikt}, the household's real consumption is given by the following nested CES function:

$$\mathbf{C}_t = \exp\left(\sum_k \alpha_k \log C_{kt}\right), \tag{17}$$

In equation (17), the real consumption from different product groups are aggregated according to a CES function, with θ being the substitution elasticity. In equation (**??**), the real consumption is aggregated across varieties with substitution elasticity σ. Products are different in their appeals ζ_{ikt}, which we use to capture the time-varying customer goodwills of products. We will discuss the evolution of the appeals in later sections on brand life-cycle.

The household can freely choose to save or borrow, in order to maximize its discounted lifetime utility. The household has separable period utility in its real consumption $\mathbf{C}_t$ and labor $\mathbf{L}_t$ per instant, with discount rate ρ. Throughout the paper, we normalize the price index for aggregate real consumption to be 1. The household has log utility in its real consumption $\mathbf{C}_t$ and perfectly elastic labor supply $\mathbf{L}_t$.[4]Thus the utility maximization problem of the representative household can be summarized as following

$$\max_{c_t(i,k),\dot{a}_t} \int_0^\infty e^{-\rho t}\Big(\log \mathbf{C}_t - \varphi_0 \mathbf{L}_t\Big)dt, \tag{18}$$

s.t.

$$\int_0^1 \int_0^{n_t(k)} p_{ikt}c_{ikt}didk + \dot{a}_t \leq r_t a_t + \mathbf{w}_t \mathbf{L}_t + \Pi_t, \tag{19}$$

$$\mathbf{C}_t \text{ is given by equation (17) and (??).}$$

Aggregate Balanced Growth Path.-

Labor demand by a firm with markup μ and price index P is

$$L(\phi) = \frac{\phi\mu^{-\sigma} + \bar{\mu}^{-\sigma}}{\phi\mu^{1-\sigma} + \bar{\mu}^{1-\sigma}}\frac{\mathbf{C}}{\mathbf{w}}$$

Thus the total labor demand for productive labor is:

$$\mathbf{L}^P = \frac{\mathbf{C}}{\mathbf{w}}\int\left[\frac{\phi\mu^{-\sigma} + \bar{\mu}^{-\sigma}}{\phi\mu^{1-\sigma} + \bar{\mu}^{1-\sigma}}\right]dk$$

The total labor demand for innovation is:

$$\mathbf{L}^I = [\kappa_e \nu g_k + D(\eta_k) + \kappa_s((1-m)\theta_M + \theta_N \nu)]$$

On the balanced-growth path, it must be

$$\varphi_0 = \frac{\mathbf{w}}{\mathbf{C}}$$

Under the assumption of Cobb-Douglas aggregation across product groups, the discounted utility of

[4]This assumption allows us to abstract away from the general equilibrium effect through innovation inputs. It does not change the qualitative characteristics of our model, but complicates the exposition. We show the model without this general equilibrium effect in main text, but show robustness checks with other utility functions.

the representative household can be written as the average utility $W(g_k, \phi_k)$,weighted by the expenditure share of group k:

$$\mathbf{W}^* = \sum_k \alpha_k W(g_k, \phi_k)$$

There exists an aggregate balanced growth path where real consumption and real wage grows with the same rate. On this balanced growth path, the aggregate labor input stays constant.

5 Quantitative Results

In this section, we describe the quantitative exercise to uncover the core parameters driving the observed shares and prices in the data. The advantage of the resulting simplicity of the model allows us to link each fundamental parameter to a specific object in the data. We discuss this process here.

5.1 Estimation

We start by presenting the externally calibrated parameters, and then turn to our estimation. For innovation production, we assume both the innovation cost function and the matching function have constant elasticity, $D(\eta) = \chi_0 \frac{\eta^{1+1/\chi}}{1+1/\chi}$ and $\lambda(\theta) = \theta^{1-\gamma}$. There are four sets of parameters we need to estimate. (1) the preference parameters $(\rho, \{\sigma\}_k, \varphi_0)$; (2) the innovation elasticity χ and the matching elasticity γ; (3) the aging process (β, q); (4) the three cost shifter $(d_k, \kappa_k^s, \kappa_k^e)$. We set the first two sets of variables to the values in the literature, and estimate the last two sets of parameters to match the empirical regularities documented in the empirical section.

Externally Calibrated Parameters

We set the discount rate to be the annual risk-free rate: $\rho = 0.03$. We calibrate φ_0 to match the aggregate labor income as a share of aggregate consumption. Following the literature, we set the innovation elasticity to be 1. By doing this, we set the innovation cost function to be quadratic. We also present results using different values of χ. Hottman et al. (2016) estimate the substitution elasticities in a demand system that is very similar to our setting. We thus directly take the estimates of UPC-level substitution elasticities from theirs.

Estimation of Maturity Process

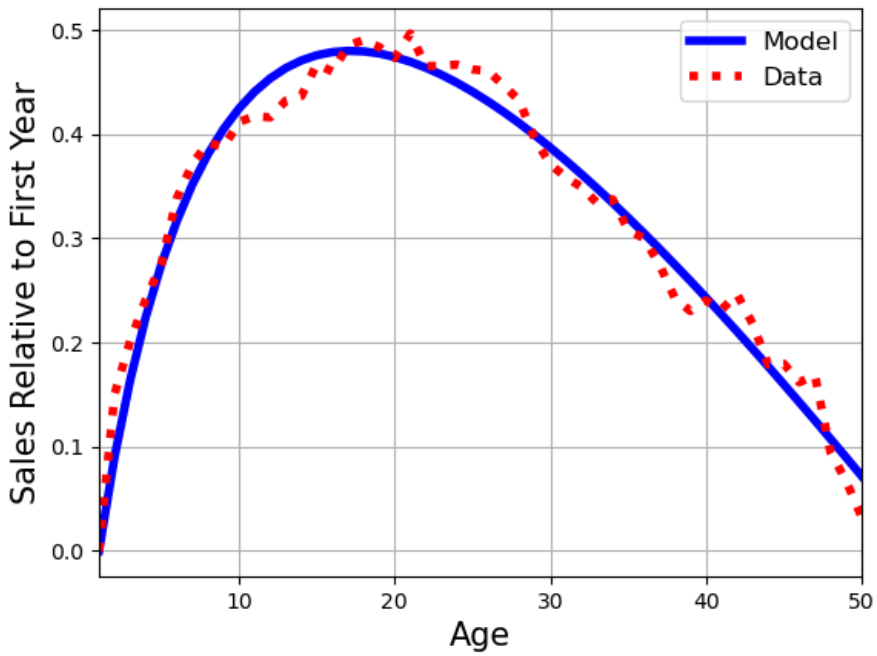
We estimate the maturity process to match the observed life-cycle pattern in product sales as in Figure 4. Specifically, we find the combination of (β, q) such that the simulated life-cycle of product sales is closest

Table 4: Externally Calibrated Parameters

Name	Symbol	Value	Target
Discount Rate	ρ	0.03	Annual Risk-free Rate
Substitution Elasticity	$\{\sigma_k\}$	-	Hottman et al. (2016)
Innovation Elasticity	χ	1.0	Hottman et al. (2016)
Disutility of Work	φ_0	5.46×10^{-9}	Wage - PCE Ratio

to data in the mean-square sense. As a result, we estimate $\beta = 0.061$ and $q = 3.4$. These estimates means that it takes on approximately 17 years in expectation to reach its maturity, and a matured product is 3.4 times higher in sales compared to a young product that is sold within the same firm.

Figure 4: The Product-Firm Life-cycle



Estimation of Leader Productivity

From our model, the relative price of products operated by the group leader and the fringe firms follows:

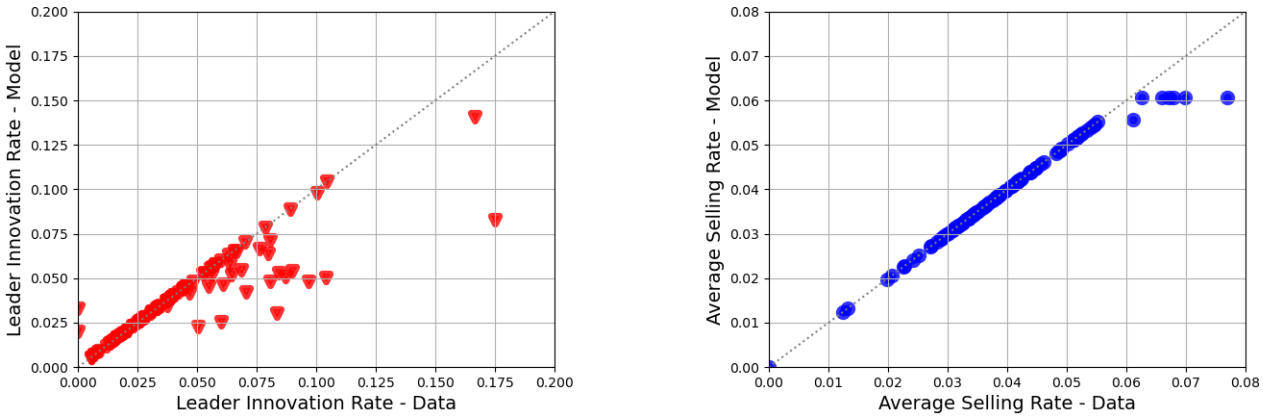
$$\frac{P_{leader}}{P_{fringe}} = \frac{\mu_k}{\bar{\mu}_k} \frac{1}{x_k} \tag{20}$$

With the estimated substitution elasticity from the literature and the observed market share of product group leader, we recover the leader's relative productivity x_k as a residual.

Estimation of Cost Shifters

There are three cost shifters we allow to vary by product groups: the innovation cost shifter d_k, the entry cost κ_k^e, and the search cost κ_k^s. Our model provides a direct link from observed market share and new product creation rate at the group level to these costs.

Figure 5: Innovation and Selling Rate: Model v. Data



(a) Innovation Rate (b) Selling Rate

Notes: The left panel plots the group-level leader innovation rate (red triangle points) from model (y-axis) and from data (x-axis). The right panel plots the group-level average selling (red triangle points) from model (y-axis) and from data (x-axis). In both panel, the grey dotted line is the 45-degree line.

We rely on the optimality conditions for innovation, entry, and acquisition to recover these parameters. First, we note that the marginal value of the state variables are can be written as functions of quality gap ϕ and growth rate g. Both variables have data counterparts. Specifically, the quality gap ϕ has one-to-one mapping to the observed market share given σ_k; the growth rate g is linked to new product introduction rate by the fringe firms. With these two variables in hand, we can directly calculate the marginal value of products to the group leader. For each product group, we find the set of parameters (κ_k^e, κ_k^s) that minimize the distance between data prediction of leader's innovation rate, average selling rate of fringe firms, and fringes' innovation rate.

Estimation of Matching Elasticity

We estimate the innovation and matching elasticity using indirect inference. The targeted moment for this elasticity is the age profile of a product getting transacted. In our model, the difference between transaction rate for a new product and for a matured product is governed by the difference in marginal benefits as well as the matching elasticity. The difference is in the matching elasticity. In the extreme, if the matching function is inelastic with respect to tightness, there is no differential in the young-old transaction rates. Our estimation yields a matching elasticity of 0.292.

5.2 Comparison of Untargeted Moments

We now compare the predictions of the model regarding the data moments that are not targeted in the estimation procedure.

M&A Premium

The way gains from trade are split between buyers and sellers of product ownership is important for the counterfactual analysis. We thus compare our model's prediction regarding the rent splitting to the ones observed in data. Specifically, we use the premium in Merger and Acquisition as our variable of interest.

In the data, the premium is calculated as the transfer paid to merger target as a ratio of accounting book value. The accounting book value from our model is defined as the flow profits adjusted by the real interest rate:

$$U^{book}(\phi, g) = \frac{(1+\beta q)\pi(\phi, g)}{\rho + g} \tag{21}$$

The transfer from buyer to seller on the balanced growth path is

$$\text{Premium}_{New} = \frac{\gamma \frac{\kappa_s}{\lambda'(\theta_N)} + \kappa_e}{\pi(\phi, g)/(\rho + g)} \tag{22}$$

$$\text{Premium}_{Mature} = \frac{\left(\frac{\gamma}{\lambda'(\theta_M)} + \frac{\gamma}{1-\gamma}\frac{\theta_M}{\rho+g}\right)\kappa_s + q\frac{\pi(\phi,g)}{\rho+g}}{q\pi(\phi, g)/(\rho + g)} \tag{23}$$

Price and Quantity Impact of Transaction

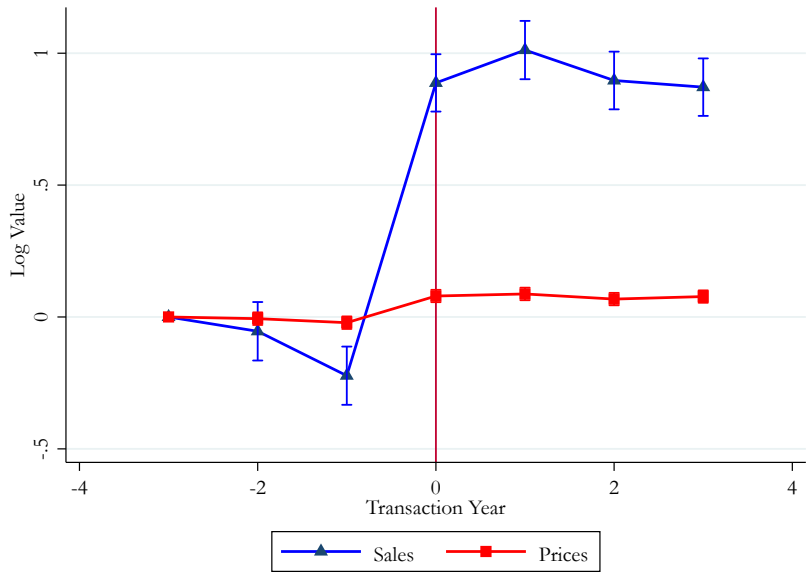
We use log sales and look at the first event of trademarking. Figure 6 plots two separate regressions on one graph with different outcome variables of interest: prices and sales. We plot each coefficient with the clustered standard error.

After the event, both prices and sales move strongly, with sales moving significantly more so. With the increase in prices, the results in Figure 6 provide evidence that after adding additional brands, firms may increase their market power over time. Combining this with the rising rate of transfer from small to large firms can help connect the importance of brand dynamism with the aggregate distribution of markups across firms. Further, the change in markups will be a key outcome of our model.

5.3 Reallocation and Concentration

With the estimated model, we ask how different reallocation margins affect concentration in the consumer product market. We first compare the average leaders' market shares in these years.

Figure 6: Event in Nielsen



Note: This figure shows the regression coefficients on a brand transaction across firms in RMS Nielsen.

Table 5: Role of Three Reallocation Margins

	(1)		(2)		(3)	
	$\beta = 0.33$		$\beta = 0.00$		$\beta = 10.00$	
a. varying fixed cost holding search cost constant						
	Leader Share	Welfare	Leader Share	Welfare	Leader Share	Welfare
Baseline	0.35	1.00	0.12	0.93	0.43	1.01
$0.1 \times \kappa_f$	0.14	1.05	0.12	0.95	0.51	1.08
$10 \times \kappa_f$	0.37	0.92	0.13	0.91	0.62	1.02
b. varying search cost holding fixed cost constant						
Baseline	0.35	1.00	0.12	0.93	0.43	1.01
$0.1 \times \kappa_s$	0.42	0.91	0.23	0.95	0.53	1.07
$10 \times \kappa_s$	0.32	0.94	0.12	0.92	0.39	1.04

Role of Entry.- In panel (a) of Table 5, we conduct counterfactuals regarding the role of fixed cost. In the first set of comparisons, we fix both the search cost κ_s and aging rate β, and vary the fixed cost κ_f. In the baseline case, the fixed cost is the estimated value $\kappa_f = 132$. We consider a case where the fixed cost is lowered to one-tenth of the benchmark level, and another where the fixed cost is increased by 10-times the benchmark level. Compared to the benchmark, a lowered fixed cost leads to lower concentration and higher welfare in the steady state. Mirroring the comparative statics in the steady state, as the fixed cost falls. Both leader innovation and fringe firm entry increase. In this specific numerical case, the effect from entry dominates the effect from innovation on concentration. Thus the average concentration of the economy falls. The welfare of the representative household at the steady state increases by 5%. On the contrary, an increase in the fixed cost increases concentration and decreases welfare.

Role of Acquisition.- In panel (b) of Table 5, we conduct counterfactuals regarding the role of search cost. We consider a case where the search cost is lowered to one-tenth of the benchmark level, and another where the search cost is increased by 10-times the benchmark level. Compared to the benchmark, a lowered search cost enables product group leaders to increase their acquisitions. As a result, more products are reallocated toward group leaders, and the concentration of a representative product group increases. This leads to a lower welfare at the steady state for the representative household. On the contrary, a higher search cost decreases concentration. One striking difference between the comparison of varying search cost and varying fixed cost is that the counterfactual on search cost shows non-monotonicity. Both a higher and lower search cost results in lower welfare compared to the baseline case. This monotonicity comes from the entry effect of acquisitions. As the group leaders acquires more often, it becomes more profitable for fringe firms to enter the market, which increases welfare.

Role of Aging.- From column (1) to column (3), we consider how a different aging rate of products leads to different market concentration and welfare incidence. We consider two extreme cases, one where a product always stays young ($\beta = 0$) and another where a product becomes mature almost upon entry ($\beta = 10$). We note that a lower maturity rate of products leads to lower concentration of markets but also leads to lower welfare. A lower aging rate means on average products are of lower quality. Although concentration falls, the representative household is consuming on average lower quality products. Not only does aging itself have implications on welfare, it also interacts with entry cost and search cost. For instance, under the case of immediate maturity, a lower search cost leads to very high concentration, but higher welfare for the representative household. This result highlights that ignoring the life-cycle of products can lead to miscalculation of the welfare incidence of different mechanisms that lead to concentration. A higher concentration can be welfare-enhancing or welfare-reducing, depending on how fast new products can catch up to existing ones.

5.4 Policy Analysis: Transaction Tax and Entry Subsidy

Table 6: Counterfactual Analysis $\kappa_s(1+\tau)$

	Baseline	No Trade	50% Tax	10% Subsidy	50% Subsidy
Welfare					
Discounted	1.00	0.95	0.96	1.01	0.98
Steady State	1.00	0.94	0.94	1.03	1.01
Decomposition					
Consumption	1.00	0.89	0.89	1.08	1.08
Markup	1.00	0.90	0.91	1.07	1.15
Research Inputs	1.00	0.85	0.85	1.10	1.12

In Table 6, we consider a proportional taxation on the search cost. This can be interpreted as tighter antitrust law enforcement, that makes it more costly for the group leaders to set up recruitment teams. We consider a case where the trade of product ownership is completely shut down, and different levels of tax rate and subsidies. We again notice a non-monotonicity of the effect of transaction on welfare. A taxation on transactions decreases welfare, and a mild subsidy increases welfare. However, a big transaction subsidy eventually decreases welfare. These forces can change over time, and we turn to an analysis of the overall trends next.

5.5 Trends

In this section, we consider another application of our quantitative model. In Figure 7, we plot the average age of trademarks in the market (solid blue line) over time and the average age of transacted trademarks over time (dotted red line). Comparing to the 1980s, brands are younger at the year when they are transacted across firms, while the average age of brand is weakly increasing in the similar period. This indicates that, relative to an average brand in the economy, the transacted brands are getting younger.

Many factors could lead to this trend. Through the lens of our model, this trend could be driven by a time-varying cost of acquisition (κ_s), or an changing nature of product lifecycle (β). As the age-profile estimation is restricted by Nielsen data to be after 2006, we rely on indirect inference to recover these parameters. In the following table, we summarize the estimated results:

From Table 7, we observe the search cost along does not explain much of the decline age of transacted brands. In stead, the faster maturity of products explain much of the trend. Next we argue this trend has implications on the incidence of concentration. In Table, we summarize the conunterfactual welfare when beta is set to its 1980s level and post-2000 level. Relative to 1980s, concentration in current periods is less harmful to welfare.

Figure 7: Age of Transaction/Overall Over Time

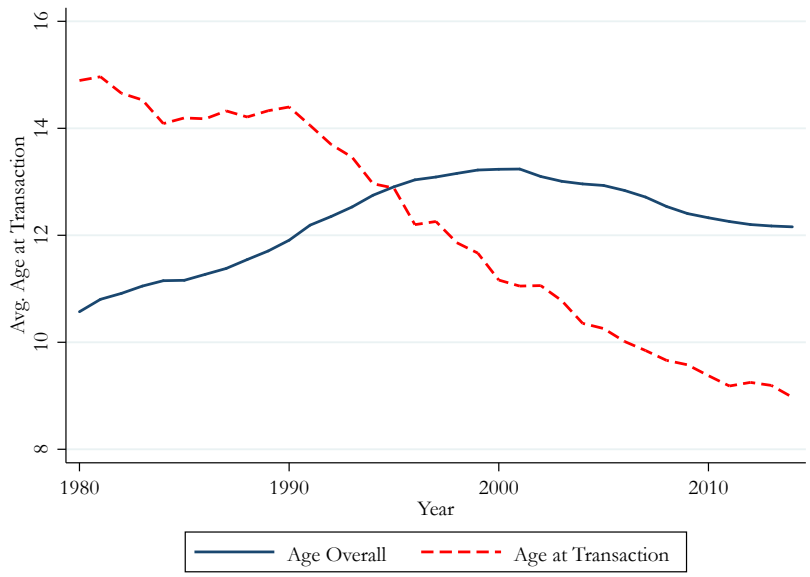


Table 7: Interpreting Trend in Transaction Age

	(1) $\beta = 0.33$		(2) $\beta = 0.21$ (1980)	
	Leader Share	Welfare	Leader Share	Welfare
κ_s baseline	0.35	1.00	0.27	0.95
κ_s counterfactual (1980)	0.34	0.99	0.21	0.94

6 Conclusion

The innovation and evolution of products plays a key role in sales concentration, firm dynamics and efficiency. We employ a novel dataset on the universe of brands in order to unpack this interaction. After illustrating key facts related to the dynamism of firms and products, we develop a model of multi-product firms with pricing power, product innovation and evolution, and product transaction.

We use the estimated model to study a relevant policy counterfactual: how does restricting brand exchange impact consumer welfare? We find three key parameters that interact with this policy counterfactual: i) the speed at which young products "catch up" to mature products ii) the cost of transaction, iii) the cost of entry. Overall, the efficiency gains from transactions outweigh the potential losses from pricing power in our calibration.

We plan to advance on two fronts: documenting heterogeneity across product groups and across time. First, we plan to document the heterogeneous patterns of reallocation and concentration in different product groups. Our quantitative model is parsimonious enough for us to handle this heterogeneity. By incorporating this heterogeneity we can better understand the different forces behind concentration in

different types of product markets. Second, we are interested in characterizing the different nature of concentration today compared to concentration in history.

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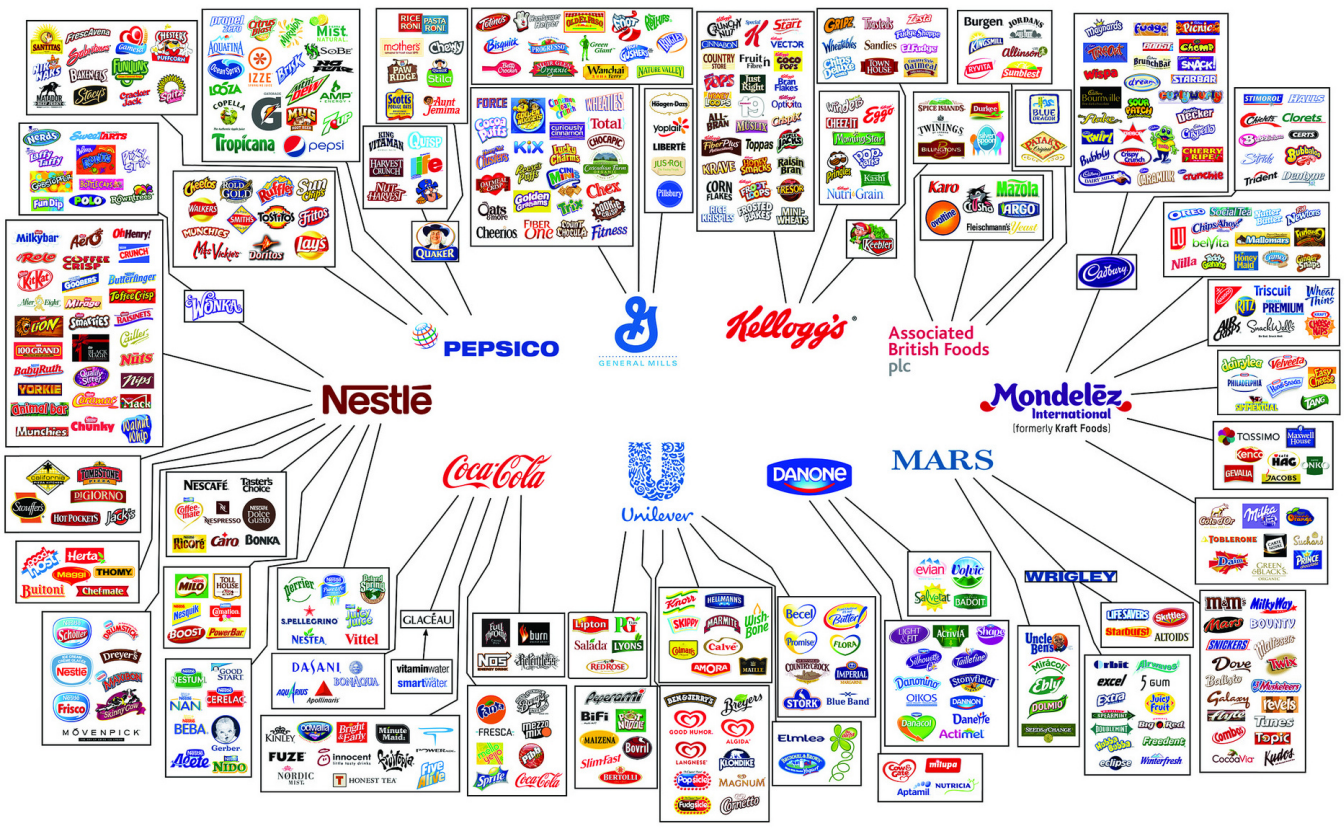
Appendix

A Data Appendix

A.1 Example of Product Market Concentration

As we discuss in the main text, product markets are dominated by large firms. We see this clearly in the following illustration, where many brands that individuals associate with only the brand are held by larger parent firms that aggregate brands.

Figure A1: Brands at Major Firms



This general pattern is true across an array of industries, but the empirical section of this paper directs our attention to the Consumer Packaged Goods (CPG) industry. As such, we turn to a specific example of a large firm in the CPG space.

A.2 Example of Brand-Building: Procter & Gamble

Figure A2 illustrates how many firms that rely specifically on their brand relationships are held by P&G.

Figure A3 shows how P&G's trademark holdings have grown over time. Much of this trademark increase has come through poaching trademarks from other firms or purchasing other firms.

Figure A2: Example of P&G Brands

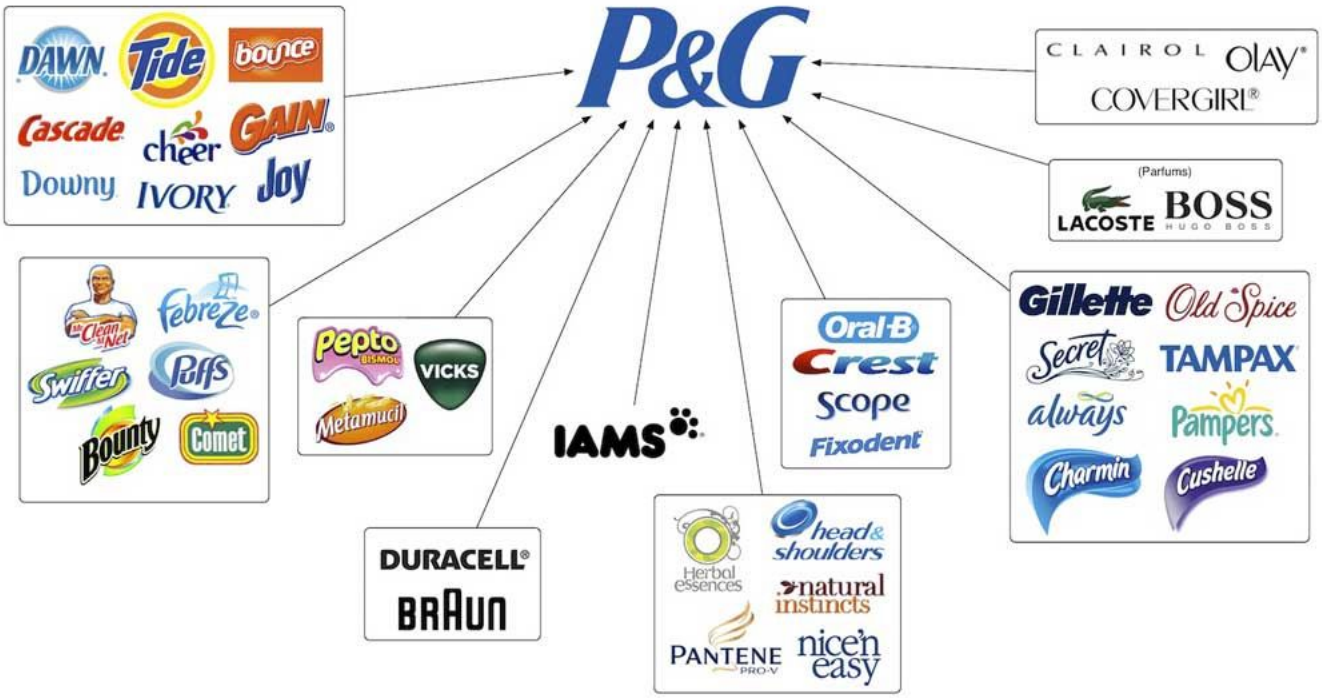


Figure A3: Tracing the brands of P&G over time

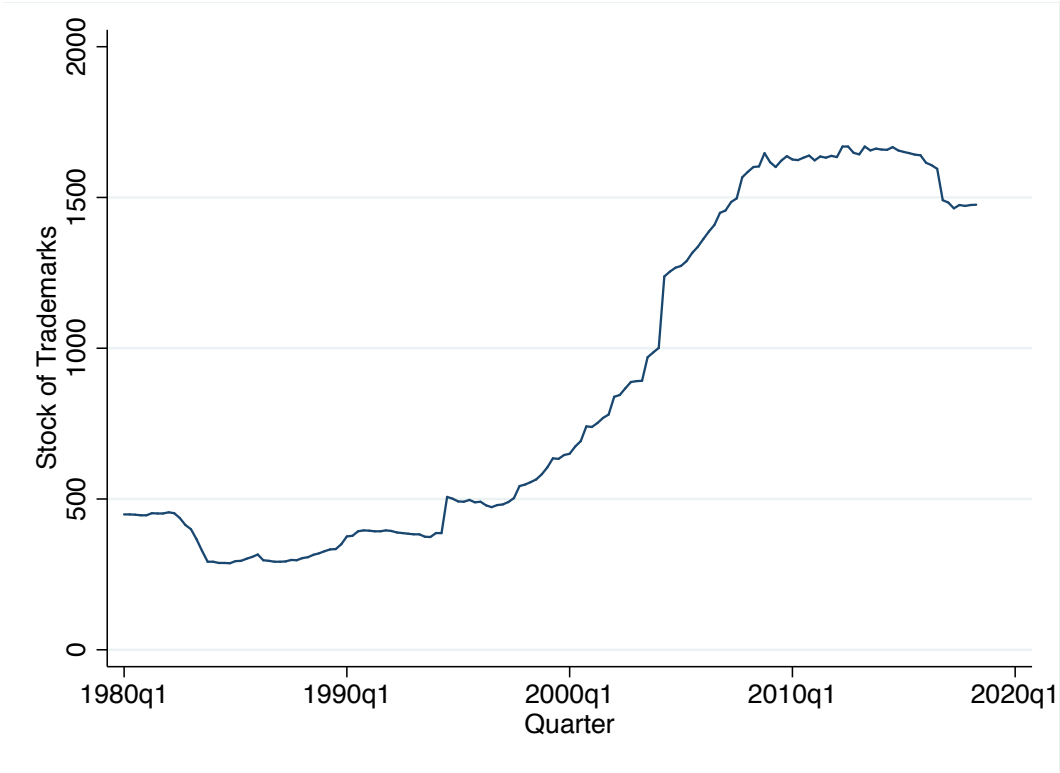
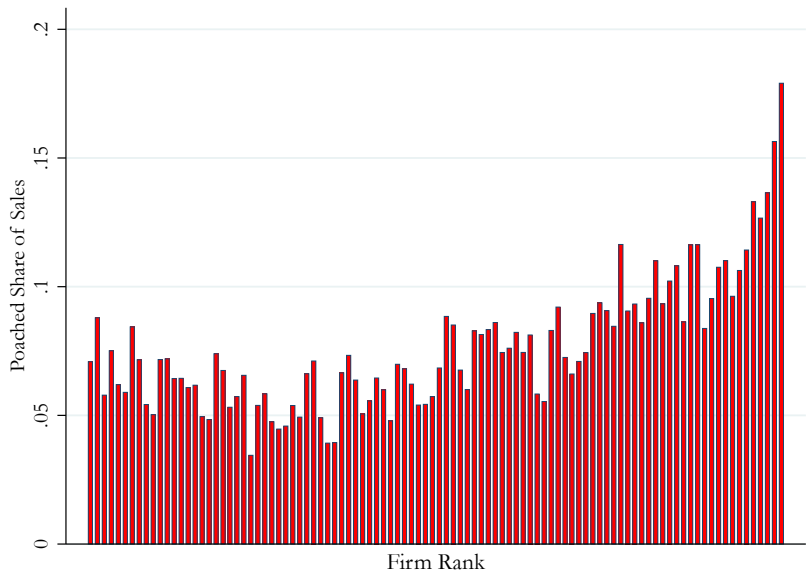


Figure B4: Contribution of Buying to Sales Share



B Empirical Appendix

B.1 Firm Concentration and Brand Buying

In Figure **??**, we showed how buying of brands contributes significantly to large firms market share. Figure B4 shows this pattern with respect to sales in Nielsen Scanner Data. We plot the share of sales from bought brands against the percentile (running from 1-100) of the firm size in sales.

We find that the highest-selling firms have almost 4-times as much poached share of sales that a median firm, indicating that the pattern we find in the Trademark data on its own is consistent in the sales-share data.

B.2 Literature Benchmark: Product Life-Cycle

Here we compare our benchmark against current product life-cycle benchmarks in the literature. Recent work has focused on the life-cycle of products applying Nielsen Scanner Data. This work is able to identify new products and brands and document their life-cycle patterns. However, it is not able to link brands and products to their history, and is thus unable to speak to the longer time horizon of persistent brands. We perform similar life-cycle regressions to the main text and compare them to a relevant current paper in the literature:

$$\log y_{it} = \alpha + \sum_{a=0}^{4} \beta_a D_a + \gamma_b + \lambda_t + \epsilon_{it} \tag{24}$$

Where the coefficients of interest are the coefficients on age (β_a) with controls for cohort and time

effects (and an adjustment on cohort from Deaton, 1997). Table B1 engages in the same specification as Argente et al. (2018) in the UPC data (panels 1 and 2) and Trademark merged data (panels 3 and 4) respectively.

Table B1: Log Sales, by Nielsen and Trademark Age

	(1) Log Sales	(2) Log Sales	(3) Log Sales	(4) Log Sales
Age 1	0.939***	1.095***	0.917***	0.953***
	(0.00841)	(0.0237)	(0.132)	(0.113)
Age 2	0.857***	1.159***	1.019***	1.060***
	(0.00876)	(0.0246)	(0.140)	(0.118)
Age 3	0.632***	1.016***	0.834***	0.832***
	(0.00914)	(0.0259)	(0.145)	(0.123)
Age 4	0.169***	0.644***	0.412*	0.488***
	(0.00995)	(0.0284)	(0.160)	(0.135)
N	668993	89203	3402	4136
R^2	0.138	0.179	0.256	0.050
Variation	UPC	Brand-Group	TM Brand	TM Brand-Group

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note that while at the level of brands and trademarks there are significantly fewer observations, the same general pattern holds. This indicates how age is picking up something similar in our context, yet due to the broader horizon of historical data we are able to connect brands to their histories, indicating a significantly longer brand life-cycle than found in Argente et al. (2018).

We also show here similar general trends as in the main text when we evaluate the life-cycle of products, controlling for brand-firm-group level, with robust standard errors.

When we go in the other direction and only control for brand, we find similar effects as in Figure B6.

Figure B5: Life-Cycle Regressions

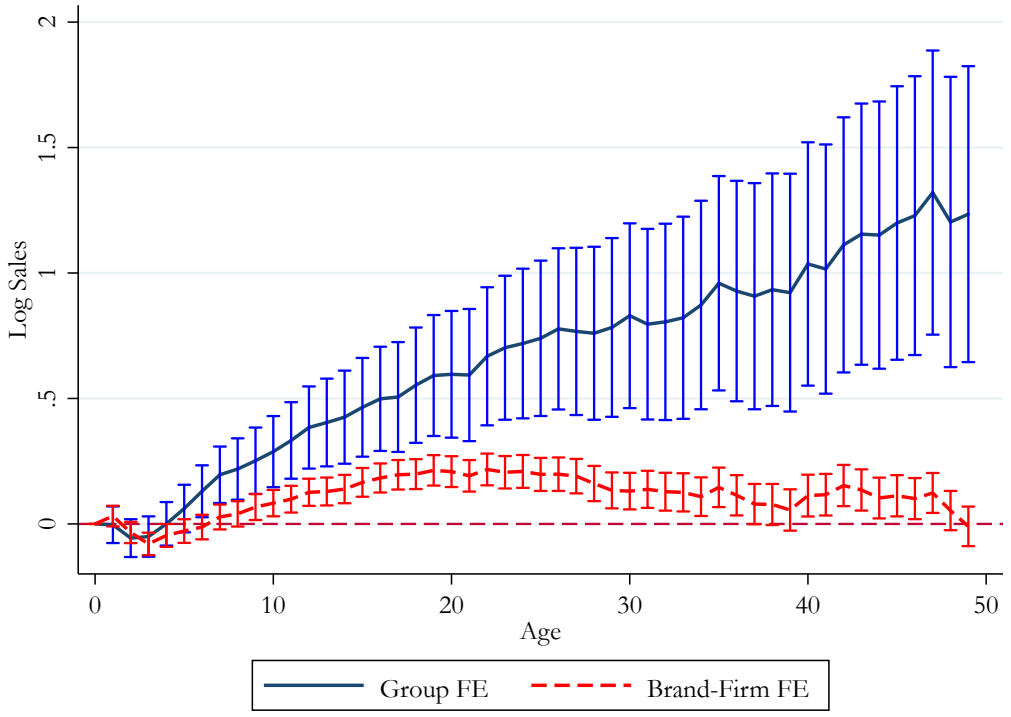


Figure B6: Life-Cycle Regressions