Global giants and local stars: How changes in brand ownership affect competition*

Vanessa Alviarez† Keith Head‡ Thierry Mayer§

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Abstract

Multinational acquisitions, unlike greenfield investments, can subtract from the number of active competitors. The outcomes for consumers depends on the change in markups and whether new owners implement significant quality or productivity improvements. We assess consequences of multinational acquisitions in beer and spirits. By applying recent methods with minimal data requirements, we undertake a global evaluation, rather than one confined to an individual market. After correcting for severe limited mobility bias, owner fixed effects contribute very little to the performance of brands. On average, foreign ownership tends to raise costs and lower appeal. Using the estimated model, we simulate the consequences of counterfactual national merger regulation. The US beer price index would be 4–7% higher had competition authorities not forced divestitures. On the other hand, up to 30% savings could have been obtained in Latin America by emulating the pro-competition policies of the US and EU.

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†Sauder School of Business, University of British Columbia, vanessa.alviarez@sauder.ubc.ca

‡Sauder School of Business, University of British Columbia, CEPR, CEP, CEMFI (visiting 2019–2020) keith.head@sauder.ubc.ca

§Sciences Po, Banque de France, CEPII, and CEPR, thierry.mayer@sciencespo.fr

1 Introduction

Concern—and controversy—over the rise of market power has spread well beyond competition policy specialists and industrial organization economists. One reason is attention-grabbing findings of rising concentration and markups. Grullon et al. (2019) report that concentration indexes increased in three quarters of US industries from 1997 to 2014. De Loecker et al. (2020) and De Loecker and Eeckhout (2018) show rises in sales-weighted markups in the US (from 1.2 to 1.7) and globally (from 1.1 to 1.8) since 1980. Such observations have kindled debate over the mechanisms that might drive widespread increases in markups. Reviewing other major phenomena documented during the same period (1980–2016), it is natural to ask what role globalization might play. Intuitively, lower trade and investment frictions should increase competitive pressure and thereby *decrease* markups.[1] However, this reasoning ignores a number of mechanisms that could push markups in the opposite direction.

There are at least three channels through which globalization might increase markups. Recent research has investigated two of them. Autor et al. (2020) propose that "greater product market competition (e.g., through globalization)" has allowed the most productive firms—with the highest markups—to increase their market shares. Thus, *aggregate* (share-weighted) markups can rise even in an increasingly competitive world.[2] Arkolakis et al. (2018) formalize this argument as a "direct" markup effect that exceeds the more intuitive "indirect" effects coming from greater competition. A very different channel works through imported inputs: decreases in input tariffs tend to lower the overall costs of production. When firms fail to pass on completely those cost reductions, markups rise (De Loecker et al., 2016).[3] A third mechanism for globalization to raise markups is via growth in cross-border mergers and acquisitions (M&A). As large multinationals absorb previously competing entities, the acquiring firms have the ability and the incentive to increase markups.

This paper focuses on this third channel, estimating and quantifying the ways that ownership changes affect competition in two beverage industries, beer and spirits. A key to understanding the market power effect of international mergers is found in the market

[1] Brander and Krugman (1983) is a pioneering model of the "pro-competitive" effects of trade liberalization in which markups fall along with lower transport costs.

[2] Autor et al. (2020) marshal evidence supporting a rise in aggregate markups through what they call the "superstar firm framework." (Syverson, 2019a, p. 27) and (Berry et al., 2019, p. 58) develop variations on this composition argument.

[3] This paper finds that Indian tariff reductions led to rising markups through this channel. The World Bank (2020) reports that global value chain participation has increased markups of large corporations in developed countries.

interactions between brands referred to as "global giants" and "local stars." The former comprise the brands owned by MNCs and that sell across many markets, whereas the latter are brands that obtain high market shares exclusively in their country of origin. For example, Diageo's purchase of Yeni Raki, the most popular spirits brand in Turkey, would have had no direct impact on the optimal markup if Diageo had not already been selling the global giant Johnnie Walker there. The merger raised Diageo's share of the Turkish spirits market from 6% to 63%, motivating it to elevate and harmonize brand-level markups.

Not all governments were passive during the recent phase of multinational brand amalgamation. The US and EU authorities in particular intervened to force acquiring firms to divest brands in markets where they deemed the mergers to have anti-competitive effects. For example, AB InBev had to transfer the US market rights on Corona to Constellation Brands when it acquired the parent company, Grupo Modelo. Later, the EU compelled AB InBev to divest Peroni and several other European brands to Asahi after the acquisition of SABMiller in 2016. This form of "structural remedy" is attractive because it dis-incentivizes firms from raising markups. However, the potential downside to forcing divestitures is foregone efficiencies. For example, AB InBev claimed it had achieved savings of $2.3 billion per year after its purchase of 2008 Anheuser Busch and ownership of Grupo Modelo would lead to a further $600mn per year.[4] The need to quantify the consequences of divestitures motivates this paper's estimates of how new ownership affects the costs and appeal of the acquired brands. We conduct counterfactuals applying these estimates within a multi-product oligopoly model, considering the impact of more and less permissive mergers policies on the price index.

This paper centers around two distinct empirical exercises. In the first, we estimate changes in the cost-adjusted appeal of a brand following acquisition by a new owner, often headquartered in a different country. The second exercise plugs those estimates into a calibrated oligopoly model to solve for new equilibrium prices in each country impacted by mergers. In both exercises we assume that markup determination can be adequately approximated by a Nash equilibrium (with either prices or quantities as the strategic variables).[5]

The reasoning behind our approach of estimating cost/appeal changes, but simulating price changes comes from the relative strengths of our data set and our view of the

[4] *Financial Times*, "AB InBev/Modelo: no cheap round" June 29, 2012.

[5] Pinkse and Slade (2004) find that static Nash oligopoly in prices is not rejected in the British beer market. Miller et al. (2019) argue that conduct in the US beer industry is better characterized by price leadership. This conduct exacerbates the price-increasing effects of mergers as compared to Bertrand. Throughout this paper we consider both Bertrand and the "softer" competition implied by Cournot conduct.

most important knowledge gaps in the literature. A number of studies of mergers support the oligopoly prediction that merger-driven concentration increases lead to higher prices. Ashenfelter and Hosken (2010) find significant prices increases ("typically between 3 and 7 percent") in four of five mergers they study, including one very relevant for this paper, the merger which created Diageo. Dafny et al. (2012) established the methodology of regressing change in log price on the change in concentration predicted by a naive merger analysis. They report significant causal effects of merger-induced concentration on premiums in the insurance industry. Ashenfelter et al. (2015) and Miller and Weinberg (2017) estimate similar regressions exploiting geographic variation within the US to show that merger shocks to the Herfindahl concentration index increase the price of beer.

The mechanism linking mergers, rising concentration, and price increases thus receives firm empirical backing from high-quality studies of multiple sectors. However, this body of work tends to consider the US market in isolation.[6] Since many of the largest mergers involve cross-border acquisitions, there are two important knowledge gaps. First, how do the consequences of multinational mergers vary across affected countries depending on their initial market structures? Second, are consumers harmed when acquisitions alter the headquarter country for their favored brands? The data we employ are uniquely well qualified for these tasks as they track brand ownership and market shares for all major markets during a decade featuring widespread ownership changes. Some of those markets start out with much higher levels of concentration than the US and are therefore more adversely impacted by mergers.

The core quantitative analyses in this paper compute markups under the observed set of ownership relationships then compare those markups to those that would have arisen in alternative ownership scenarios. There are two prominent methods of revealing markups. The first method, pioneered by Berry (1994), relies on the first-order conditions linking marginal revenue to marginal cost under particular conduct assumptions. Once a demand curve has been estimated, the ratio of price to marginal cost can be inferred. A second markup method, developed by De Loecker and Warzynski (2012), eschews conduct assumptions and instead reveals markups from the firms' cost minimization problem. It relies on input use data and estimated production function parameters. We follow the first approach here for three reasons. First, we lack data on firm-level input use that is critical for the production function approach. Second, even if we could observe input use for all the firms in our data set, one cannot use the production function approach to determine markups in different countries without imposing additional struc-

[6] The most comprehensive collection of high quality retrospective merger studies, Kwoka (2014), restricts attention to 47 studies of mergers that affected the United States.

ture to allocate input use across markets.[7] Third, and most importantly for our purposes, the structure imposed in the demand-side method is well-suited to computing markup changes in response to counterfactual reallocations of brands to different owners. The precise model we use combines elements from Atkeson and Burstein (2008); Edmond et al. (2015); Hottman et al. (2016); Nocke and Schutz (2018b). The key features are multi-product oligopoly and nested constant elasticity of substitution (CES) demand.

Our paper contributes four key findings. First, we quantify across all major markets the potential savings to consumers from forcing divestitures of brands as a condition of merger approval. Relative to the counterfactual of a permissive merger policy, the actual remedies imposed on AB InBev lower the price index for US beer by four to six percent. Conversely, passive countries paid as much as 30% more for beer than they would have by emulating US and EU remedies. Our second contribution is to show that the owner of a brand contributes surprisingly little to its performance. Since firm effects explain less than 4% of variation in a brand cost-adjusted appeal, compelling a divestiture need not imply forgoing important synergies. However, a third important result is that the *geography* of ownership matters. Being owned by a firm with a faraway headquarter tends lower cost-adjusted appeal in a market by ten to twenty percent. We believe this is the first study to estimate this negative effect of overseas ownership on the cost-adjusted appeal of a product. Finally, we show that superstar effects played little role in either beer or spirits markets over the last 12 years: Aggregate markups of the largest firms grew by putting big brands under common ownership, rather than by expanding the market shares of the high-markup brands.

In addition to the substantive findings described above, our paper makes three methodological advances. Most importantly, we show how to adapt the exact hat algebra approach pioneered in Dekle et al. (2008) to run counterfactuals in settings where a few large multi-product firms interact as oligopolists, while a fringe of individually small firms price as in monopolistic competition. This generalization is valuable because it offers a framework for addressing oligopoly issues that is more economical in its data requirements than the standard industrial organization approach. The other method contribution is a simple way to estimate the upper level elasticity of the increasingly deployed Atkeson and Burstein (2008) model. That elasticity plays a vital role in constraining markups near monopoly. We show how to ensure that its magnitude is consistent with consolidated accounting data on markups. Third, we show how to apply recent techniques from labor economics to diagnose limited mobility bias and mitigate its im-

[7] De Loecker et al. (2016) devise an input allocation method for firms that sell multiple products.

pact on measuring the contribution of firms.[8] This application in the context of measuring owner value-added in product markets provides a template for research on related questions.

The remainder of the paper proceeds as follows. Section 2 describes the data we use, highlighting its advantages and limitations. Section 3 displays how oligopoly Lerner indexes vary with conduct under nested CES demand. There we also describe the method to back out cost-adjusted appeal for each brand in each market. Section 4 estimates the effects of firm ownership on this determinant of brand performance. Here we exploit the extra market-level variation contained in our data which permits estimation with brand-firm interactive effects. Using estimates of the systematic changes in cost-adjusted appeal associated with the identity and headquarters of the owner, we compute counterfactuals in section 5 for alternative patterns of ownership that might have prevailed in 2018 had different merger policies been adopted. This allows us to quantify the impact of multinational brand amalgamation on consumer welfare and aggregate markups.

2 Data: sources and patterns

Our data set combines four distinct components. The first data set provides sales at the brand-country-year level. Crucially, this data tracks the ultimate owner of each brand in a given period. The second set of data, created as part of this study, determines the origin of each brand. The third, also original to this study, identifies the headquarter country for the firm owning each brand. Finally, we use standard data (available from CEPII) on bilateral distances and common languages.

2.1 Market shares and ownership

The Global Market Information Dataset (GMID), from Euromonitor, reports sales information for individual brands and their corresponding owners for specific consumer products in 75 to 80 countries for the most recent 10 years. We have extended this by two years, yielding a sales panel running from 2007 to 2018. Within each combination of product category, market, and year GMID lists sales for all brands above a threshold market share, which the documentation lists as 0.1%. GMID sums the sales of smaller brands in a given market and lists their collective shares under the brand names "Private Label" and "Others." Private Label has less than 1% market share in the median country for both beer

[8] Jochmans and Weidner (2019) provide our connectivity measure and Andrews et al. (2008) and Bonhomme and Manresa (2015) provide the mitigation techniques.

and spirits. The market share of Others is generally small for beer (median of 11%) but accounts one third of the German market. In the US, Others have risen from 11% in 2007 to 20% in 2018. Liquor markets are more fragmented, with Others accounting for a median of 26% of sales. We calculate the shares of brands and firms in each national market using as a denominator the sales of all brands, including Others and Private Label.

GMID tracks all changes in majority ownership at the brand level occurring over the 2007–2018 period. This feature is distinctive in that most M&A datasets record changes in ownership at the firm level, without providing explicit information about which product lines or brands are involved in the transaction.

The GMID market share data addresses several concerns that have been raised concerning concentration measures derived from the economic census or firm-level databases such as Compustat and Orbis. First, markets are defined from the consumer point of view considering horizontal substitutes whereas other databases rely on standard industry classifications that were mainly designed to capture similarities between firms. Berry et al. (2019) point out that "industrial classifications in the Census often fail to reflect well-defined economic markets." They give the example of software, but an example given by Grullon et al. (2019) provides a more striking illustration. One of their 3-digit NAICS industries is leather products. Sub-industries include handbags and footwear, two products we might think of as complements. Another sub-industry, leather tanning, should be thought of as an input to the other two. It makes little sense to think of a firm with a high share of aggregate production in leather products as having market power in a particular consumer market. We focus on beverage categories, within which varieties relate to each other as substitutes.

A second big advantage of GMID for calculating market shares and concentration in a way that is relevant for markups is that we see brand-level sales in a given market including imported products. Other data sets such as the census or Compustat report the revenue of a set of firms, aggregating over all markets. Such revenue measures include exports to other markets but exclude imports. Thus, census data does not measure sales in the market in question.[9] Imports supplied by foreign firms should increase competition. On the other hand, imports carried out by large domestic firms, with little or no local production, can actually increase concentration relative to measures based on domestic shipments. Our data overcomes these issues since brand sales aggregate to total expenditures in a market.

Studies of concentration using Compustat omit private companies, which include a

[9]Compustat has the larger concern that it mainly reports consolidated data which includes sales from majority affiliates in other countries than the one where the firm is based.

few large firms (e.g. Bacardi) and the often large fringes of small firms. Both Compustat and census omit sales of multi-category companies outside their assigned SIC. This issue could be quantiatively important since Compustat classifies Pernod Ricard, the second largest spirits distiller in the world, as a winery.

Table 1: Firms and their brands in the GMID beverage data

Category	**Brands**			**Firms**	**Countries**		
	All	multi-n	multi-f		HQ	Origin	Market
Beer	2425	368	672	464	79	93	78
Spirits	2894	598	528	849	87	106	77
Wine	1540	235	221	699	54	54	53
Water	1210	212	220	735	81	97	88
Carbonates	938	238	164	401	79	86	92
Coffee	617	153	156	390	74	79	91
Juice	1193	305	236	758	85	93	90

Table 1 shows that each category comprises hundreds of firms and there are thousands of brands in most categories. The figure illustrates the diversity of headquarters and brand origins represented in the data. The regression method we use to estimate firm ownership effects on brand performance depends on observing the same brand sold by different firms and in different markets. Beer and spirits stand out in table 1 as having large numbers of brands that changed ownership. 28% of the beer brands in the data set had more than one owner. This includes some cases of brands, such as Corona and Fosters, that have different owners in different markets. Spirits also exhibits substantial mobility of brands across owners, with about 18% having more than one owner. Spirits has the highest count of multi-market brands, which is important for backing out both brand effects and brand-origin frictions. For all these reasons, the rest of the paper focuses on beer and spirits, though we report regression results for other beverages in the appendix.

2.2 Corporate headquarters and brand origins

GMID lists the global ultimate owner for each brand. This is based on majority ownership and omits the minority share positions that the multinationals sometimes take.[10] The headquarter country of each company in GMID dataset is obtained by combining Orbis from Bureau van Dijk, the historical Directory of Corporate Affiliations from Lexis-Nexis,

[10]For instance, the 49% of China Resources owned by SABMiller is insufficient to show SABMiller as the owner of the Snow brand in China (before it was forced to divest its share).

and Capital IQ. Matching the name of each brand's owners in the GMID dataset with the names of firms in the Orbis, Lexis Nexis, and Capital IQ datasets, we take the headquarter to be the location of the firm highest up the hierarchy of ownership. The exceptions are where this ultimate owner appears to be a holding company located in a tax haven. In those cases we do additional investigation to assign a HQ location that corresponds to the place where management decisions are taken.

In one important case, AB InBev, we consider the firm to have dual headquarters, the US and Belgium. While the official head office remains in Belgium, New York City is listed as a second "Global Headquarters" on the `www.ab-inbev.com` site. According to reporting in the St. Louis Post-Dispatch (15 July 2018)"many key corporate functions, including a bulk of sales and marketing positions, now operate out of New York City." We set the headquarters as varying by market depending on whether the US or Belgium is closer and treat the firm as having three official languages (English, French, and Dutch).

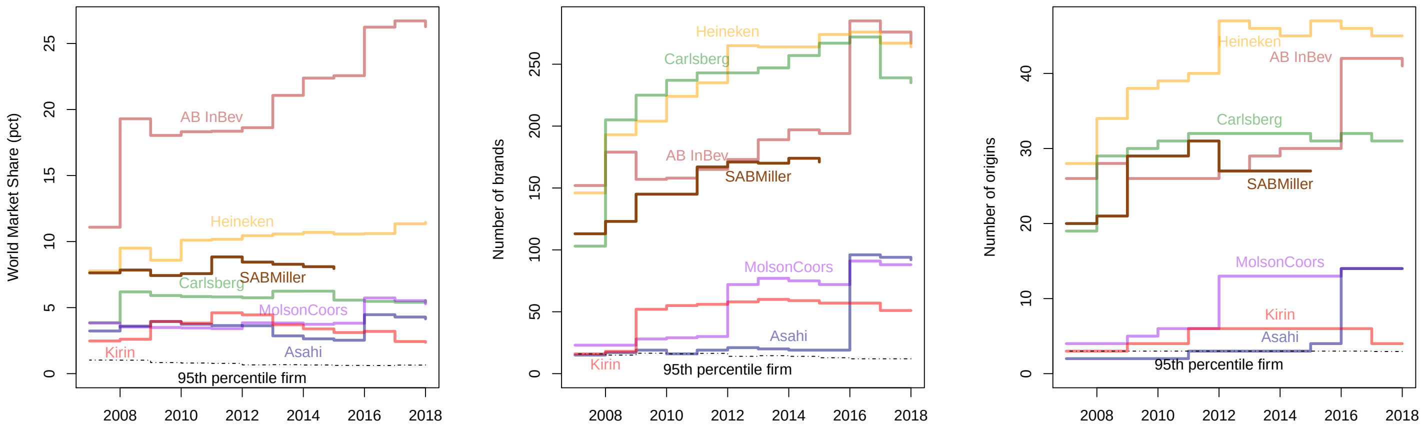
The origin of a brand is the country where it was developed and introduced. Thus Lagunitas is an American brand and Tecate is a Mexican brand even though both are currently owned by the Dutch firm Heineken NV. Generally speaking the origin coincides with the country where an independent firm founded the brand. We determined origins for brands by combining information from corporate websites, Google Images, news articles, Wikipedia, and trademark registries. For beer and spirits, the categories with the most brands, we often relied on crowd-sources websites that rate each product.

2.3 Visualizing multinational brand amalgamation

Figure 1 and 2 illustrate the rise in market shares, brand ownership, and diversity of brand origins for the seven largest companies in the beer and spirits industries. The first panel of each figure shows the growth of market share. AB InBev goes from just over 10% (when it was still just InBev) to about one quarter of the world beer market (with much higher market shares in specific countries). Heineken, Asahi, MolsonCoors, Diageo, and Suntory also register gains. The center plot shows that these firms have even more notable increases in the number of brands. By 2018, the top beer makers had brands from around 40 countries in their portfolios. The top spirits makers held brands from about 25 brand origins each (though Pernod Ricard appeared to be retreating from international diversification).

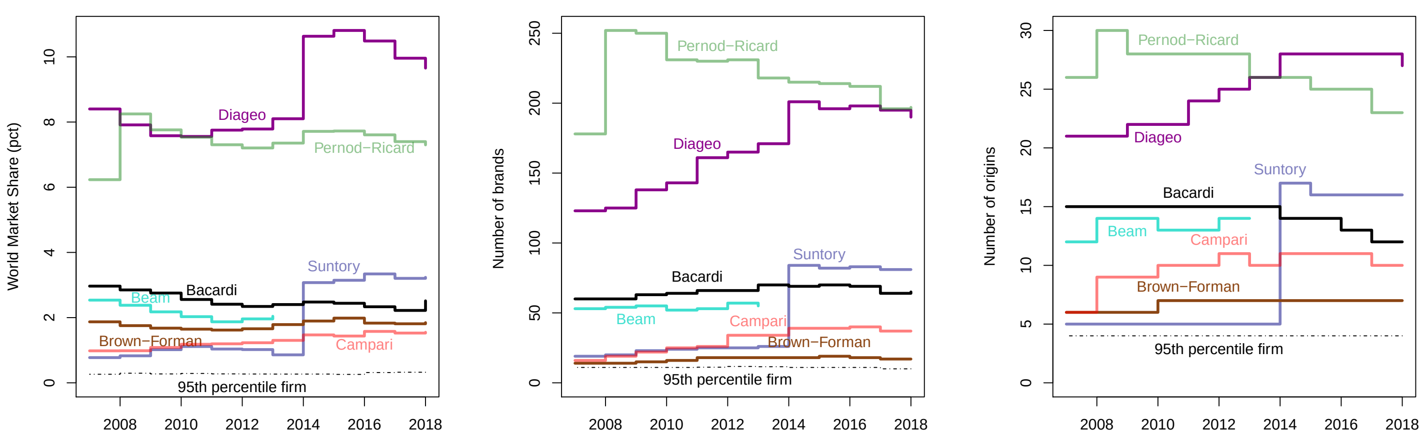
Diageo, the largest and most multinational of spirits makers, was formed in 1997 as a merger of Grand Metropolitan and Guinness. It dramatically expanded its portfolio of spirits brands when took over the brands of the failing Seagram company in 2001. On its

Figure 1: The growth of beer multinationals



Note: In 2008 InBev purchases Anheuser-Busch and Heineken and Carlsberg jointly purchase Scottish & Newcastle (along with BBH) and redistribute the acquired brands among themselves. In 2009 AB InBev sells off Korean and East European brands (forming Starbev) and Kirin acquires Lion (NZ). In 2012 MolsonCoors buys Starbev and Heineken buys Asia Pacific Breweries. In 2016, AB InBev buys SABMiller, while divesting some SABMiller brands to MolsonCoors and others to Asahi to comply with antitrust orders.

Figure 2: The growth of spirits multinationals



Note: In 2008 Pernod-Ricard buys Vin & Sprit (owner of Absolut and 74 other brands). In 2014 Suntory buys Beam (which had been spun off from Fortune Brands in 2011) and Diageo buys UB Group.

website Diageo distinguishes between its portfolios of "Global Giants" and "Local Stars." This categorization motivates the title of our paper. Global giants are brands that are sold in many countries. Local stars are brands sold in few markets, but which achieve very high market share in their country of origin. Table 2 Diageo's most prominent global giants and selects seven illustrative local stars.

Table 2: A selection of Diageo brands

Global Giants

	Johnnie Walker	Gordon's	Tanqueray	Smirnoff	Captain Morgan	Baileys	Guinness
Origin:	UK	UK	UK	Russia	Jamaica	Ireland	Ireland
# Markets:	68	21	28	64	43	57	30
rank (world):	2nd	30th	46th	1st	12th	24th	21st
born (bought):	1860 (1997)	1769 (1997)	1830 (1997)	1864 (1987)	1944 (2001)	1973 (n/a)	1759 (1997)

Local Stars

	Ypióca	McDowell's No1	Yeni Raki	Cacique 500	Bundaberg Rum	Crown Royal	Tusker Lager
Origin:	Brazil	India	Turkey	Venezuela	Australia	Canada	Kenya
# Markets:	2	2	2	4	1	3	1
rank (origin):	6/44	1/47	1/51	2/44	5/119	5/87	1/14
born (bought):	1846 (2012)	1963 (2012)	1944 (2011)	1961 (2001)	1888 (2000)	1939 (2001)	1923 (2000)

Note: Rank of Global Giants is out of 1681 spirits brands (first 6 columns) and 1567 beer brands (7th column). Rank of Local Stars shown relative to number of brands offered in the origin country. The year in () refers to acquisition by Diageo or its predecessor Grand Metropolitan.

A striking aspect of the brands shown in table 2 is they are mainly very old, originating from 47 to 260 years ago. None was invented by Diageo.[11] Diageo has mainly expanded its brand portfolio by acquiring brands invented by other firms. The same is true for the major beer brand owners.

Brands selling in more than 30 markets are rare in the data: just 0.4% of beer brands, 0.9% of spirits, 1.2% of carbonates. While rare, the global giants account for a disproportionate amount of sales. Carbonates brands sold in 30+ countries deliver 64% of all sales. In beer and spirits, the global giant share is under 10%. The flip side of this is that single-market brands, which constitute over 80% of brands for all three goods, are relatively unimportant in world sales of carbonates (16%) whereas they account for a substantial majority of beer and spirits sales. While most single-market brands have low market shares, a few—the local stars—are the leading brands in most markets. This dis-

[11] Bailey's Irish Cream was invented in 1973 within a division of Grand Metropolitan.

tributional pattern of sales means that the potential for increases in market power via multinationals buying local brands is much bigger in beer and spirits than in carbonates.

3 The nested CES multi-product oligopoly model

The model we use is guided by the data described above. A finite number of firms compete oligopolistically, selling one or more brands. We observe brand-level market shares in multiple markets. Each brand has a national origin and each firm a national headquarters. The next two subsections describe the assumptions we make about demand and market conduct.

3.1 Demand

Consumers have CES preferences over product categories with Constant Elasticity of Substitution (CES) η. Within product categories, there is a lower nest of substitution between brands with a CES of σ. This is the same preference structure as used by Atkeson and Burstein (2008), Gaubert and Itskhoki (2018), and Burstein et al. (2019), among others. Unlike those papers, we consider multiproduct firms. Adding a third nest of substitution between products made by the same firm would be possible and is the approach used by Hottman et al. (2016). However, in the absence of ownership changes, Nocke and Schutz (2018b) show that intra-firm CES nesting does not affect the oligopoly markups. Ownership changes are very important in our context and here the lower nest would create problems. Either one would have to assume that brands change their substitution elasticities following ownership changes, or the model must distinguish incumbent versus acquired brands with different elasticities. The latter assumption would make the model intractable and would not make much sense for companies like AB InBev and Diageo that are constituted almost entirely of brands purchased from other companies.[12]

While the IO literature mainly uses random coefficient logit demand, we will demonstrate that the nested CES has advantages of high tractability and low data requirements that are essential for the exercises conducted in this paper. These features permit us to replicate the analysis across 75 national markets. The CES model imposes stronger restrictions on substitution elasticities than the random coefficients methods preferred in a large part of the IO literature. However, Head and Mayer (2018) show that a CES model (calibrated to replicate the observed average elasticity of substitution between brands) does a

[12]Taking a concrete example, it is not consistent with what we know of the product market to assume that Smirnoff becomes a closer substitute for Tanqueray, simply by changing ownership from Seagram to Diageo (the owner of the latter brand).

good job of approximating aggregate outcomes of rich substitution models in counterfactual simulations.

The appeal of a brand, A_{bnt}, is market-time specific. Market-dependent brand appeal allows the model to capture the feature that a brand can be popular in one country (very often its origin), but be less attractive to consumers in other countries. In section 4.2 we estimate how much of the variation in brand's appeal across countries can be explained by a brand being particularly appealing to consumers in the same country as where the brand was originally designed, this is we estimate the importance of "home bias." Time-variant appeal allow us to capture changes in taste, if any, that consumers experience when a brand changes owners after an acquisition.[13] For simplicity, we suppress the time t subscripts for the rest of this section.

Formally, consumers allocate their income among a continuum of sectors, indexed $g \in [0, 1]$, with utility

$$U_n = \left[\int_0^1 Q_{gn}^{\frac{\eta-1}{\eta}} dg\right]^{\frac{\eta}{\eta-1}}, \tag{1}$$

which gives the equilibrium expenditure on sector g in n as

$$X_{gn} = (P_{gn}/P_n)^{1-\eta} X_n \quad \text{with} \quad P_n = \left[\int_0^1 P_{gn}^{1-\eta} dg\right]^{\frac{1}{1-\eta}}, \tag{2}$$

where P_{gn} is the price index of sector g in market n, P_n is the overall price index, and X_n is aggregate expenditure.

Inside g, the quantity index Q_{gn} is given by

$$Q_{gn} = \left[\sum_b (A_{bn} q_{bn})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{3}$$

where q_{bn} denotes the quantity consumed of each brand b in market n. Each brand is implicitly associated with a unique sector g, so we dispense with g subscripts on all variables that are indexed by b.

The market share conditional on brand b serving market n is:

$$s_{bn} = (p_{bn}/A_{bn})^{1-\sigma} P_{gn}^{\sigma-1}, \tag{4}$$

where p_{bn} is the price of brand b in market n, and P_n is the market price index which

[13]Consumers could change their valuations of the brand because they perceived an actual change in the quality of the product after the acquisition, or simply because their valuation of the brand also factors in their perception of its owner.

aggregates over all the brands offered in the market n, as indicated by $\mathbb{I}_{kn}$:

$$P_{gn} = \left[\sum_k \mathbb{I}_{kn} \left(\frac{p_{kn}}{A_{kn}} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \tag{5}$$

The total market share of firm f in market n, S_{fn}, is obtained by aggregating the market shares of all the brands the firm's portfolio ($\mathcal{F}_f$) and offers in market n ($\mathbb{I}_{bn} = 1$):

$$S_{fn} = \sum_{b \in \mathcal{F}_f} \mathbb{I}_{bn} s_{bn}. \tag{6}$$

As shown in table 1, in the cross section the extensive margin of where brands are offered is very important. However over the decade of data we have, there is not much action across time in $\mathbb{I}_{bnt}$. Appendix section A documents the very low rates of adding and dropping brands across markets. Since it does not appear to be an important aspect of the data and would prevent us from using exact hat algebra for the counterfactuals, we treat $\mathbb{I}_{bnt}$ as an exogenous characteristic of brands, like their appeal and production cost.

The brand-level profits earned by firm f in market n is:

$$\pi_{bn} = q_{bn}(p_{bn} - c_{bn}) = s_{bn} \frac{(p_{bn} - c_{bn})}{p_{bn}} X_{gn} = s_{bn} L_{bn} X_{gn}, \tag{7}$$

where c_{bn} is the marginal cost of delivering brands to market n, and $L_{bn} \equiv (p_{bn} - c_{bn})/p_{bn}$ is the Lerner index relevant in that brand-market combination. The firm maximizes the sum of π_{bn} over the set of brands it owns:

$$\Pi_{fn} = \sum_{b \in \mathcal{F}_f} \mathbb{I}_{bn} \pi_{bn}, \tag{8}$$

3.2 Markups for different conduct assumptions

The pricing strategy of firms conforms with the "small in the large but large in the small" assumption of Atkeson and Burstein (2008) and Neary (2016). Firms realize and account for their influence on the price index within a sector (large in the small), but treat the aggregate expenditure and price level (X_n and P_n) as given (small in the large).

We find it useful to express price-cost relationships in two different ways, both of which we refer to as "markups." To see how costs affect prices and how markups affect market shares it is useful to work with $\mu \equiv p/c$, the price/cost markup. When computing profits on the other hand, the Lerner index is more convenient as seen in equation (7). The first order conditions for maximization of equation (8) yield equations for the brand-level price/cost markup and the Lerner index expressed as functions of the *firm-level* perceived elasticity of demand, ϵ_{fn}:

$$\mu_{bn} = \mu_{fn} = \frac{\epsilon_{fn}}{\epsilon_{fn} - 1}, \quad \text{and} \quad L_{bn} = L_{fn} = \frac{1}{\epsilon_{fn}} \quad \forall b \in \mathcal{F}_f. \tag{9}$$

Prices can be expressed in terms of either markup:

$$p_{bn} = \mu_{fn} c_{bn} = c_{bn}/(1 - L_{fn}). \tag{10}$$

The property that, under CES demand, firms equate markups across all their products was derived by Feenstra (2003, p. 267) and features prominently in Hottman et al. (2016) and Nocke and Schutz (2018b).[14]

The functional form of markups depends on the assumed mode of oligopoly conduct. The Lerner indices implied by the two standard conduct assumptions are

$$\underbrace{L_{fn} = \frac{1}{\sigma - (\sigma - \eta) S_{fn}}}_{\text{Bertrand}} \quad \text{and} \quad \underbrace{L_{fn} = \frac{1}{\sigma} - \left(\frac{1}{\sigma} - \frac{1}{\eta} \right) S_{fn}}_{\text{Cournot}} \tag{11}$$

In addition to the firms selling listed brands, the GMID data record sales attributable to "other" and "private label" brands, whose owners are not reported individually. Since the threshold markets share a separately reported brand is just 0.1%, we treat other and private label brands as forming a monopolistically competitive fringe. We therefore assume $L_{0n} = 1/\sigma$ for those brands.

Although the CES oligopoly model lacks closed-form solutions for prices, equilibrium can be obtained via fixed point iteration, starting with a guess of prices (such as the monopolistic competition price vector $p^0_{bn} = (\sigma/(\sigma - 1)) c_{bn}$). At each step, market shares are obtained for a given set of markups, which then imply a new set of optimal markups, new market shares, until convergence to unique price and market share vectors is reached.

A major attraction of the CES oligopoly model is that it provides simple expressions for the markups that rely on observable firm-level market shares, to be combined with two parameters, σ and η. We now describe how we obtain those two critical elasticities.

[14] It contrasts sharply with the case of linear demand analyzed by Mayer et al. (2014).

3.3 Matching elasticities to moments

Industrial organization economists have already devoted considerable efforts to the estimation of brand-level own-price elasticities for the very products we study. We will treat those estimated elasticities as moments used to pin down σ for each of the categories we consider.

Table 3: Estimates of own-price elasticities and implied elasticities of substitution

Product group	Mean σ	Mean ϵ_b	# Estimates	# Papers
Beer	4.49	4.48	9	5
Spirits	3.38	3.37	9	2

The IO literature summarized in Table 3 reports mean or median of brand-level own price elasticities, estimated from the demand side of their models before imposing a specific market structure. Those demand elasticities cannot be interpreted as direct estimates of the elasticity of substitution σ_g because of non-negligible market shares. We can, however, use the brand-level formula for CES own-price elasticity $\epsilon_b = \sigma_g - (\sigma_g - \eta)s_b$ and invert it to solve for σ_g as a function of either the mean or the median (denoted with function $m_g()$ of estimated demand elasticities in the category:

$$\sigma_g = \frac{m_g(\epsilon_b) - m_g(s_b)\eta}{1 - m_g(s_b)}.$$

We hold these σ_g constant over time and across markets.

In contrast to the abundance of high quality brand-level elasticity estimates, the literature does not provide obvious candidates for η, the CES between product categories. Atkeson and Burstein (2008), the pioneering work using nested CES oligopoly, impose $\eta = 1.01$ and consider $\eta = 1.5$ in a sensitivity analysis. Burstein et al. (2019) exploit a linear relationship between the inverse of the harmonic mean markup and the Herfindahl index to estimate a parameter corresponding to $\frac{1}{\sigma} - \frac{1}{\eta}$ using cross industry variation. They impose $\sigma = 7$ and this leads to an η estimate of 1.7. Using $\sigma = 4.5$ (the value for beer) would imply $\eta = 1.5$. Because η is so important in our quantification of markups, our η estimate should conform with markup data from the industries we focus on, beer and spirits.

We calibrate η to provide the best fit between theoretical and accounting markups. If there are constant returns to scale and no fixed costs, then the profit to sales ratio can be expressed as $(pq - cq)/pq = (p - c)/p = L$. Accounting data are generally unavailable at the market level because firms report their "consolidated" accounts, aggregating over all markets they serve. Therefore, our accounting measure of the firm-level Lerner index, denoted L_f^A, is the ratio of a firm's worldwide profits over worldwide sales. The theoretical counterpart to L_f^A, denoted L_f, must therefore also be constructed by aggregating profits implied by the model in each country. Since profit in a market is given by $L_{fn} S_{fn} X_{gn}$, the aggregate theoretical markup is just a sales-weighted average of the firm's theoretical Lerner indexes in each country:

$$L_f = \sum_n \omega_{fn} L_{fn}, \quad \text{where} \quad \omega_{fn} = \frac{S_{fn} X_{gn}}{\sum_n S_{fn} X_{gn}}. \tag{12}$$

To calculate the accounting markup, L_f^A, in a way that corresponds to the theoretical markup, we need to purge accounting measures of costs from their fixed cost components. However, as discussed in Syverson (2019b), accounting expense categories do not map cleanly to economic concepts of fixed and variable costs. Most firms report two major categories of operating expenses: "cost of goods sold" (COGS) and "selling, general, and administrative" (SGA) expenses.[15] The accounting markup expressed in terms of the underlying Compustat variables is

$$L_f^A = \frac{\text{sale}_f - \vartheta_1 \text{cogs}_f - \vartheta_2 \text{xsga}_f}{\text{sale}_f},$$

where ϑ_1 and ϑ_2 denote the fractions of each cost category assumed to be marginal costs. As in De Loecker et al. (2020), we take COGS to be entirely variable costs, implying $\vartheta_1 = 1$. For ϑ_2 we consider two bounding cases. Our conservative markup measure treats all of SGA as variable costs ($\vartheta_2 = 1$), leading to our lower bound on accounting markups. Since SGA includes cost categories such as administration and R&D that seem like classic examples of overhead costs, the conservative markups are likely too low.[16] On the other hand, SGA includes distribution costs, which almost certainly vary with the amount of beer being distributed. AB InBev's annual reports provide a distinct line for distribution costs. On average they comprise 32% of SGA from 2008 to 2018. Hence, we calculate a liberal markup deducting only $\vartheta_2 = 0.32$ of SGA.

The ω_{fn} in equation (12) are data. The L_{fn} markup formulae in equation (11) use the S_{fn} data, the calibrated σ_g (now taken as known), leaving a single unknown parameter, η. The loss function used to calibrate η is the squared deviations between theory and

[15] In the few instances in Compustat where xsga is incomplete, we replace it with operating expenses (xopr) minus cogs.

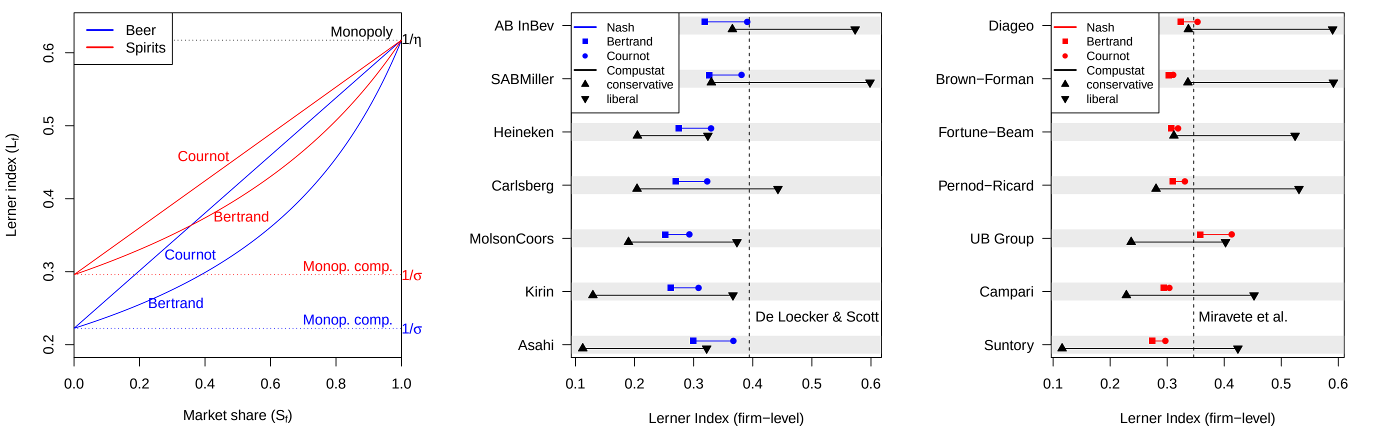
[16] Administrative expenses constitute a small share of SGA for the four companies that report them separately. Their share of SGA over 2008–2018 are 20% for Carlsberg and AB InBev, 14% for Royal Unibrew and 21% for Tsingtao.

accounting markups:

$$\ell(\eta) = \sum_f \sum_t \left(\left[\frac{L_{ft}^{\text{Bertrand}}(\eta) + L_{ft}^{\text{Cournot}}(\eta)}{2} \right] - L_{ft}^A \right)^2. \tag{13}$$

We compute L_{ft}^A and the conduct-specific L_{ft} for the 14 largest publicly traded multinationals in beer and spirits (shown in Figures 3) over the 2007–2018 period. There are 157 observations (some firms are absorbed via mergers, leading to an unbalanced panel). For the estimation of η we set $\vartheta_2 = 0.66$, the average of the conservative and liberal values. The η that minimizes equation (13) is 1.62, which corresponds to a monopoly Lerner index of 62%.

Figure 3: Oligopoly markups for Bertrand and Cournot, compared to accounting data



(a) Theory (b) Beer data (c) Spirits data

With σ_g and η in hand, we can graphically compare the theoretical markups to those obtained from accounting data. Figure 3(a) graphs the Lerner index functions under Bertrand and Cournot conduct assumptions. The blue lines use our σ estimate for beer (4.5) whereas the red line uses our spirits estimate ($\sigma = 3.4$). In both Cournot and Bertrand, L_f ranges from $1/\sigma$ for $S_f = 0$ (the monopolistic competition benchmark) to $1/\eta = 0.62$ for $S_f = 1$ (monopoly). For a given product, the Lerner index for Bertrand lies under the corresponding index for Cournot for $0 < S_f < 1$.

Figures 3(b) and 3(c) display for 2013 (before several large mergers) the Bertrand to Cournot range of Lerner indexes (in blue for beer and red for spirits). Below each theoretical interval, we show the range between our conservative and liberal bounds for accounting markups (L_f^A, in black). As a third type of comparison, vertical dashed lines display the average markups reported by De Loecker and Scott (2016) for beer and Miravete et al. (2018) for spirits. Both papers use random-coefficients logit demand models and De Loecker and Scott (2016) also provides estimates based on the De Loecker and Warzynski (2012) method.[17]

There are three salient points in the markup figures. The accounting and theory intervals overlap for every beer maker and for all but one (Brown-Forman) spirits maker. For beer, AB InBev and SABMiller have both the highest predicted markups (based on market shares) and the largest accounting markups. The fact that the theoretical markups (based on calibrated σ_g and η) are broadly consistent with the accounting data provides evidence that the CES oligopoly model passes a first stress test of its suitability for the two industries we consider. The second point is that markups in the nested CES model are reasonably close to those obtained using methods preferred in the IO literature. The beer estimates of De Loecker and Scott (2016) are on the high side but they are sales-weighted and apply to the highly concentrated US market. The third noteworthy aspect of the figure is that Bertrand and Cournot theoretical markups differ less from each other than the reasonable range for accounting markups. Neither conduct assumption can be ruled out, so we will consider results for both.

3.4 Backing out cost-adjusted appeal (brand type)

Borrowing from Nocke and Schutz (2018b), the term "brand type" refers to the attribute that determines a brand's market share. Denote it φ following Melitz (2003) footnote 7 pointing out that firm heterogeneity could be isomorphically represented as either a demand shifter or physical productivity.[18] In terms of determining equilibrium brand market shares, all that matters in the CES model is the ratio, $\varphi_{bn} \equiv A_{bn}/c_{bn}$, which we will also refer to as cost-adjusted appeal. With estimates of the demand elasticicities, data on brand sales shares in a market allow us to back out all the φ_{bn} up to a normalization. The n subscripts are important here because unlike the basic Melitz model, the data reveal large variation in φ_{bn} across markets.

Substituting for equilibrium price and then inverting equation (4) we obtain

$$\varphi_{bn} = s_{bn}^{1/(\sigma-1)} \mu_{f(b)n} P_{gn}. \tag{14}$$

[17] Miravete et al. (2018) report weighted average Lerner indexes obtained through the standard IO demand-side approach. De Loecker and Scott (2016) report sales-weighted price-cost markups (μ) ranging from 1.6 to 1.7 in different specifications of the demand-side method and 1.65 using the production function approach. We transform the average μ to Lerner equivalents by $L = 1 - 1/1.65 = 0.39$.

[18] Melitz (2003) made this point in a model of CES single-variety monopolistic competition. Nocke and Schutz (2018b) generalize it to multi-product oligopoly and also show that a similar isomorphism applies in the logit model with the φ expressed as a *difference* between appeal and cost.

In order to isolate brand type as a function of observables, we need to eliminate the price index, which can be accomplished by dividing by any other $\varphi_{b'n}$ (or index of brand types) since they all depend on the same price index.

Aggregating the brands in each $\mathcal{F}_f$ portfolio that firm f offers in market n,

$$S_{fn} = \sum_{b \in \mathcal{F}_f} \mathbb{I}_{bn} s_{bn} = \mu_{fn}^{1-\sigma} P_n^{\sigma-1} \sum_{b \in \mathcal{F}_f} \mathbb{I}_{bn} \varphi_{bn}^{\sigma-1} = (1 - L_{fn})^{\sigma-1} T_{fn} P_n^{\sigma-1}, \tag{15}$$

where T_{fn} is the firm-market level aggregator of brand characteristics, called firm type by Nocke and Schutz (2018b) since they only consider a single market, whereas here firm type varies by market.

$$T_{fn} = \sum_{\mathcal{F}(b,t)=f} \mathbb{I}_{bn} \varphi_{bn}^{\sigma-1} \tag{16}$$

The key point about T_{fn} is that it is a sufficient statistic for the performance (market share, profit) of the firm. Computationally, this means that equilibrium firm market shares can be calculated without considering individual brands if T_{fn} is known.

The market share of other brands, a monopolistically competitive fringe, is $S_{0n} = \mu_{0n}^{1-\sigma} T_{0n} P_n^{\sigma-1}$. Inverting, we have $T_{0n} = \mu_{0n}^{\sigma-1} S_{0n} P_n^{1-\sigma}$. Therefore, we can normalize the measure of cost-adjusted appeal φ_{bn} in equation (14) by $T_0^{1/(\sigma-1)}$ to obtain

$$\check{\varphi}_{bn} = \frac{\varphi_{bn}}{T_{0n}^{1/(\sigma-1)}} = \left(\frac{s_{bn}}{S_{0n}}\right)^{1/(\sigma-1)} \frac{\mu_{f(b)n}}{\mu_0}, \tag{17}$$

where $\mu_0 = \sigma/(\sigma-1)$ in all markets. Markups for all other brands are obtained by applying a conduct assumption inside equation (11, and using $\mu_{fn} = 1/(1 - L_{fn})$. $T_0^{1/(\sigma-1)}$ is a CES index of the φ of the unlisted brands. If there were a single other brand, indexed 0, it would have $T_0^{1/(\sigma-1)} = \varphi_0$.

With data on brand prices as well as market shares, one can further separate out brand appeal (A_{bn}). To see this, take logs of equation (4) yielding

$$\ln s_{bnt} = (\sigma-1)\ln A_{bnt} - (\sigma-1)\ln p_{bnt} + (\sigma-1)\ln P_{gnt}. \tag{18}$$

Since the price index is a gnt variable, it is common to all brands in a given product-market-year and can therefore removed through demeaning. As in Hottman et al. (2016), a tilde over a variable denotes its geometric mean over the relevant market-year (specified in its subscript).[19] So long as we have an estimate of σ we can express inferred appeal as

[19] When calculating the geometric means of market shares and prices, we include only the individually "listed" brands.

a function of observables:

$$\ln(A_{bnt}/\tilde{A}_{gnt}) = \frac{\ln(s_{bnt}/\tilde{s}_{gnt})}{\sigma - 1} + \ln(p_{bn}/\tilde{p}_{gnt}). \tag{19}$$

Only relative A_{bnt} within a product-market-year can be identified since multiplying all the A_{bnt} by a scalar would not change the equilibrium market shares conditional on prices.

Equation (19) is equivalent to the regression approach of Khandelwal et al. (2013) equation (7) except that they aggregate over multiple sectors (and therefore include sector fixed effects), whereas we calculate appeal within each category of goods. Equation (19) is also equivalent to a logged version of Redding and Weinstein (2018) equation (17).

4 Estimation of ownership effects on brand performance

The focus in this section is to estimate the impact of firm ownership on brand performance (market share, appeal, and cost-adjusted appeal). We consider both a pure ownership effect, i.e. the way an individual firm improves performance everywhere, and a localized effect that depends on the proximity of the firm's HQ to each market served by the brand. To isolate these two ways that the owner of a brand matters, we need to control for factors that operate at the brand level. Here again, there are two aspects: the global brand appeal and the differential appeal associated with proximity between the brand's origin and the market where it is being sold.

4.1 Estimating equations

We now derive from the model the equations we estimate. There are three mappings that we use repeatedly in the specifications:

- $o(b,t)$ maps a brands to its *owner* in year t.
- $h(f)$ maps a firm to location of its *headquarters*.
- $i(b)$ maps a brand to its *origin*, the country where the brand was introduced.

Substituting for price in equation (18) and applying the definition of brand type, we have

$$\ln s_{bnt} = (\sigma - 1)\left[\ln \varphi_{bnt} - \ln \mu_{o(b,t)nt}\right] + (\sigma - 1)\ln P_{gnt}. \tag{20}$$

The last term in this equation can be eliminated with fixed effects defined at the product-market-year level. The delivered cost-adjusted appeal, φ_{bnt} can be further decomposed into a brand-specific term, φ_b^B, an owner-specific term, $\varphi_{o(b,t)}^F$, a friction between brand origin and market denoted $\delta_{i(b)nt}^B$, a friction between the current brand owner's headquarters and market denoted $\delta_{h(f,t)nt}^F$ and a residual.

$$\ln \varphi_{bnt} = \ln \varphi_b^B + \ln \varphi_{o(b,t)}^F + \ln \delta_{i(b)n}^B + \ln \delta_{h(o(b,t))n}^F + \varepsilon_{bnt}. \tag{21}$$

The function $i(b)$ maps brand b to its origin i, which is time invariant. On the other hand, ownership changes over time, implying that the mapping of a brand to the headquarter country of its owner, $h(o(b,t))$ depends on time.[20]

The δ^B and δ^F capture the impact of observable frictions on φ_{bnt}. We have in mind effects such as home bias in preferences, which enters via A_{bnt}, as well as costs of distributing remotely, which would enter via c_{bnt}. We estimate the magnitudes of such effects using two "home" variables. The first home$_{in}$ takes a value of 1 when brands sold in their country of origin ($i = n$). The second home variable is defined at the headquarter level and equals one when the owner of the brand has its HQ in the market ($h = n$). We also include common language and the log of distance, with both defined in terms of in and hn.

We can now be more concrete about the contents of the residual ε_{bnt}. All shocks to appeal or costs that are specific to the brand-market dyad enter there. In addition, it includes all the *unobserved* determinants of the δ frictions. Moreover, ε_{bnt} captures cost determinants related to the location of production—which our data does not report. The simplest case to consider are brands of Scotch Whisky or Champagne that by law must be produced in origin country i. In such cases the coefficient on log distance captures not only the elasticity of appeal with respect to distance, but also the elasticity of iceberg transport costs (from Scotland or France to market n). More generally, the estimates on each friction determinant will be increasing in multinational production costs associated with serving remote markets (either by horizontal investment or export platforms). Such effects would be most likely to show up in the hn dimension if management of overseas production is based the brand owner's headquarters.

The final estimating equation for cost-adjusted appeal uses our inferred values, $\check{\varphi}_{bnt}$ from (17) in place of the unobservable φ_{bnt}.

$$\ln \check{\varphi}_{bnt} = \mathrm{VFE}_b^B + \mathrm{VFE}_{o(b,t)}^F + \mathrm{VFE}_{gnt} + \mathbf{X}'_{i(b)n}\mathbf{d}^B + \mathbf{X}'_{h(o(b,t))n}\mathbf{d}^F + \varepsilon_{bnt}, \tag{22}$$

[20] Ownership of a brand sometimes differs across markets, for example when competition authorities force divestitures. We omit this infrequent case in the notation but take it into account in the estimation and counterfactuals.

where $\mathbf{X}$ comprises home, distance, and common language, measured with respect to the brand origin when subscripted with i and with respect to HQ when subscripted with h. The VFE (varphi fixed effect) have structural interpretations as $\ln \varphi_b^B$, $\ln \varphi_{o(b,t)}^F$, and $-\ln T_{0gnt}/(\sigma-1)$. To determine the effect of each friction variable working through the demand side alone, we also estimate a version of equation 22 where $\ln A_{bnt}$ replaces $\ln \check{\varphi}_{bnt}$ as the dependent variable. The differences between the coefficients in those two regressions corresponds to the cost effect.

The key identifying assumption for the estimating equation (22) is that the expectation of ε_{bnt} is zero, *conditional* on the firm and brand fixed effects and the frictions. One threat to this assumption would be interactions between unobserved brand and firm characteristics. While our baseline specification assumes that any such interactions are orthogonal to the friction determinants, we also consider a specification that allows for a general pattern of firm-brand interactions.

The primitive determinant of brand market shares in equation (20) is the brand's cost-adjusted appeal within the market, φ_{bnt}. It is also interesting to estimate the impact of frictions on the other variable featured in the same equation, the markup. We therefore regress log markups on the same set of fixed effects and frictions, yielding

$$\ln \mu_{bnt} = \mathrm{MFE}_b^B + \mathrm{MFE}_{o(b,t)}^F + \mathrm{MFE}_{gnt} + \mathbf{X}'_{i(b)n}\mathbf{g}^B + \mathbf{X}'_{h(o(b,t))n}\mathbf{g}^F + \upsilon_{bnt}. \tag{23}$$

In this regression, the coefficients do not reveal structural parameters because of the non-linear mapping from frictions to market shares to markups. The markup fixed effects (MFE) also do not map in any simple way to structural parameters.

Substituting the cost-adjusted appeal and markup equations into 20, we have the estimable log market share equation:

$$\ln s_{bnt} = \mathrm{SFE}_b^B + \mathrm{SFE}_{o(b,t)}^F + \mathrm{SFE}_{gnt} + \mathbf{X}'_{i(b)n}\mathbf{r}^B + \mathbf{X}'_{h(o(b,t))n}\mathbf{r}^F + \xi_{bnt}. \tag{24}$$

The additive-in-logs structure implies that market share friction coefficients are algebraically tied to the $\ln \check{\varphi}_{bnt}$ and $\ln \mu_{bnt}$ coefficients via $\mathbf{r} = (\sigma-1)(\mathbf{d}-\mathbf{g})$. Similarly, the coefficients on $\ln \check{\varphi}_{bnt}$ and $\ln \mu_{bnt}$ for different conduct assumptions are linked through equation (17): the difference between friction coefficients on the Cournot and Bertrand versions of φ is constrained to equal the corresponding difference in μ coefficients. The error term for market shares relates back to the two previous error terms via $\xi_{bnt} = (\sigma-1)(\varepsilon_{bnt}-\upsilon_{bnt})$. Thus this error captures brand-market idiosyncratic shocks (to appeal and cost), unobserved friction determinants, and specification error in the markup equation. The R^2 of the market share equation is 0.66, indicating that idiosyncratic shocks explain about one third of the variation in market shares. This is not surprising for any traveller who has noticed certain brands are inexplicably popular in certain countries. The fact motivates the usefulness of exact hat algebra for counterfactuals since this method implicitly takes into account the unobserved determinants of market share that are invariant to the counterfactual.

4.2 Baseline estimation results

Table 4 reports results for regressions that pool beer and spirits brands. The most striking result is that, on average, home-origin brands have huge advantages. Since $\exp(1.039) \approx 2.83$, home increases market share by 183%. The largest impact comes on the taste side (home bias). In particular being a home brand raises demand by an amount equivalent to a 25% price reduction. Brands from faraway countries also lower cost-adjusted appeal, with a distance elasticity of -0.045. The only comparable elasticity for distance to brand origin we know of is the Head and Mayer (2019) estimate of -0.088 for cars.

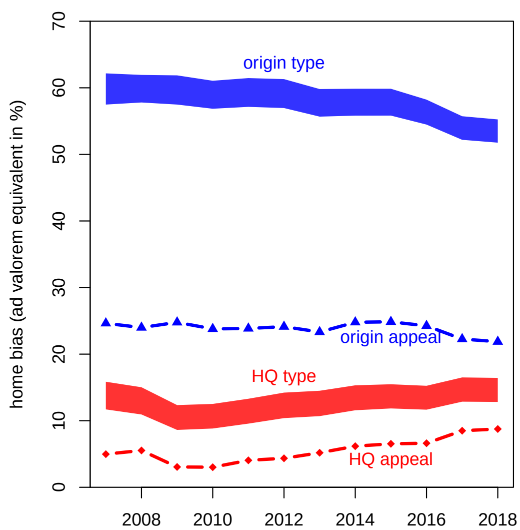
Table 4: Brand performance regressions: Beer and Spirits

			Bertrand		Cournot	
	$\ln s_{bn}$	$\ln A_{bn}$	$\ln \varphi_{bn}$	$\ln \mu_{bn}$	$\ln \varphi_{bn}$	$\ln \mu_{bn}$
home	1.029^a	0.223^a	0.353^a	0.016^a	0.367^a	0.030^a
	(0.135)	(0.072)	(0.051)	(0.004)	(0.053)	(0.006)
distance	−0.121^a	0.036	−0.044^a	−0.002^c	−0.046^a	−0.004^b
	(0.037)	(0.022)	(0.015)	(0.001)	(0.015)	(0.002)
common language	0.047	−0.054	0.008	0.0001	0.008	0.0003
	(0.078)	(0.050)	(0.031)	(0.002)	(0.032)	(0.003)
home (HQ)	0.354^a	0.104^c	0.179^a	0.031^a	0.204^a	0.056^a
	(0.106)	(0.061)	(0.042)	(0.003)	(0.043)	(0.006)
distance (HQ)	0.019	0.009	0.013	0.001	0.012	−0.001
	(0.033)	(0.020)	(0.013)	(0.001)	(0.014)	(0.001)
com. lang. (HQ)	0.114^c	0.048	0.052^b	0.003	0.056^b	0.006
	(0.062)	(0.038)	(0.025)	(0.003)	(0.026)	(0.004)
Observations	95,299	95,299	95,299	95,299	95,299	95,299
R^2	0.657	0.653	0.596	0.900	0.603	0.859

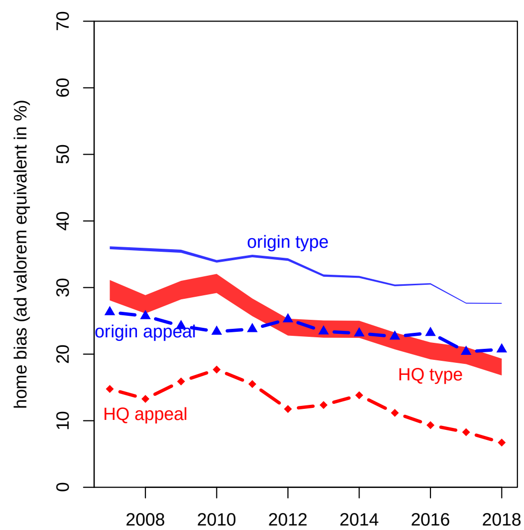
Standard errors in (), clustered by origin-market dyads. Fixed effects at the firm, brand-product and market-year-product dimensions included in each specification. HQ variables defined with respect to brand owner's headquarter country. Significance levels: 1% (a), 5% (b), and 10% (c).

The pooled regressions in Table 4 estimate the effect of frictions averaging over 12 years and two products. To assess how Beer and Spirits home bias compare to each other, and how they evolve over time, we estimate a model for each product separately, interacting the home origin and HQ dummies with year dummies. Figure 4 graphs the results, expressed as *ad-valorem* equivalents (AVE) of the home advantage for cost-adjusted appeal (φ).[21] The home bias estimated under the Cournot conduct assumption is systematically larger than under Bertrand. The graph displays the range between the two estimates using blue (origin) and red (HQ) ribbons. We use the same coloring schemes (with symbol-separated lines) to display the AVEs of the part of home bias that comes from the demand side. These appeal effects do not depend on conduct, since they are extracted directly as demand shifters.

Figure 4: Home bias by type and category over time



(a) Beer



(b) Spirits

Upper and lower bounds of each "ribbon" use Cournot and Bertrand markup assumptions, respectively.

As seen in panel (a) of Figure 4, the total effect of being a home origin beer brand is equivalent to a 55–60% tax imposed on foreign-origin competitors. This large home bias helps us understand the existence of the local stars phenomenon. Even if they lack universal appeal (which explains why they rarely sell in other markets), domestic brands can achieve very large home market shares under this estimated level of protection from foreign competition. As a consequence, foreign firms find it difficult to achieve high market shares without purchasing those local stars.

For beer brewers, the consumer preference for domestic brands (a 25% AVE) accounts for about one third of the home origin type advantage. The AVE if the consumer bias is almost the same in spirits (panel b). For that product, it represents a much larger share

[21] The formula is $100 \times [\exp(\mathbf{d}) - 1]$, where $\mathbf{d}$ is the home coefficient in the brand type (φ) regression.

of overall home advantage in cost-adjusted appeal. A natural explanation is that spirits have a much larger value-to-weight ratio. To the extent that domestic-origin brands are also produced locally, transport costs incurred by foreign brands should matter more for beer.[22] While other papers have estimated home bias, notably for the auto industry (Coşar et al. (2018), Head and Mayer (2019)), we believe this is the first paper to quantify what fraction of the home bias is accounted for by tastes.

The other novelty is that we can estimate the home bias related to the HQ country of the brand's owner. This is important in the context of industries with large waves of brand amalgamation by foreign firms. This HQ-related home bias is estimated as equivalent to around 10–15% home advantage for beer, and 20%–30% in spirits. This is the immediate cost imposed on a brand when bought by a foreign company. To rationalize acquisitions that transfer headquarters abroad, there would need to be some offsetting gain. The two candidates we consider are firm value-added and increased market power.

To estimate the value-added of firms we consider the firm-level fixed effects that form part of our regression specification. The difference between the seller and buyer firm fixed effects measures the change in cost-adjusted appeal of the brand (in all destinations) when changing owner. The structural interpretation of VFE_f in equation (22) is $\ln \varphi^F_{o(b,t)}$. A transfer of b to a new owner in period $t+1$, raises cost-adjusted appeal by $\ln \varphi^F_{o(b,t+1)} - \ln \varphi^F_{o(b,t)}$ The value-added of firms therefore depends on variance in the estimated firm-level fixed effects. Variance is not a sufficient condition since, in addition, brands should flow from the weak to the stronger firms. Because brand and firm effects enter multiplicatively in the sales and profits equations (before taking logs), there is some reason to expect that good brands will on average be matched with good firms. In the next subsection, we measure both the variance of firm fixed effects and their association with brand effects.

4.3 Estimating the contribution of firm effects

Before relating brand and firm fixed effects, we need to establish how these parameters can be separately identified. As is the case with firm and worker effects on wages, identification requires "mobility." In our context, movements are changes in the ownership of brands which connect different firms. This is analogous to how workers changing jobs connect establishments in the seminal paper by Abowd et al. (1999), now known by the initials AKM. Another helpful analogy is the literature on the value-added of teachers.

[22] This explanation is further supported by Tables 6 and C.8, where the distance coefficients for beer are more than twice as large as those for spirits.

As with brand owners, that literature can estimate fixed effects only for sets of teachers who are connected by in-common students.

The employer-employee and teacher-student literatures have highlighted several important lessons that are applicable to our estimation of brand and owner effects. First, the presence of firm fixed effects should not bias the estimation of the friction coefficients (home, distance, language) in Table 4.[23] Second, firm fixed effects are estimated relative to a reference firm, with *a different reference firm for each connected set*. It is therefore meaningless to compare firm fixed effects across sets or to estimate the overall variance of fixed effects. The third point coming from the AKM literature is that even within the connected set, the fixed effects are often noisily measured. The reason for this has come to be termed "limited mobility bias." When few workers connect firms, Andrews et al. (2008) find that the variance of the fixed effects will be over-estimated and spurious negative correlations can appear between worker and employer fixed effects.

Jochmans and Weidner (2019) recast the concern over limited mobility as a network problem. Starting from a bipartite network—teachers and students in their example—one constructs the induced teacher-to-teacher network weighting the edges by the number of student-course combinations shared by each teacher pair (the edges in the induced graph). They show that the amount of excess variance in the teacher fixed effect estimates will be bounded from above by a function of a particular measure of the global connectivity of the induced network. This measure, denoted λ_2, is calculated as the smallest non-zero eigenvalue of the normalized weighted Laplacian of the induced network.[24] In our context, a firm whose brands have never been owned by any other firm is disconnected from other firms. Brands with multiple owners, in time or space, connect firms. But it may be that the network is only barely connected, i.e. loss of a few brands would break it into disjoint components. Figure B.1 (a) and (b) in the appendix illustrate this possibility using a graph featuring 12 firms and 12 brands. The loss of just one brand is sufficient to break the firm-to-firm network into two unconnected graphs.

When graphs are poorly connected, AKM estimates of fixed effects exhibit excess variance. This is important for us because it means that we would be overstating the value added firms bring to brands. We therefore borrow two methods to mitigate this problem from the follow-up literature to AKM. In both cases the basic idea is to estimate fewer fixed effects to make those be fixed effects for well-connected firms. The first method comes from Andrews et al. (2008). They show that in labor data one can eliminate excess

[23] The coefficients are similar (differing mainly in the second decimal, and by less than a standard error) to those reported in Table C.1, which is estimated without firm fixed effects.

[24] Appendix section B provides greater detail on this procedure.

variance and spurious negative correlations between worker and plant fixed effects by restricting the set to movers (workers who change plants) and "high mobility" plants. In their context, "high mobility" is achieved by plants with 30 or more moving workers. Andrews et al. (2008) assign all the workers at low-mobility plants to a single "superplant." In our case, movers are brands who change ownership and high mobility refers to firms with *ten* or more brands that change ownership. We assign all brands at low-mobility firms to a "superfirm."

The second method for mitigating limited mobility bias comes from Bonhomme et al. (2019). While the focus of their paper is a random effects specification, the authors report that a *group fixed effects* specification achieves similar reductions in the bias in the variance of fixed effects. The first step of this method is to group firms using k-means clustering, based on the distribution of market shares achieved by the brands the firm owns in the first period (2007 for most firms).[25]

Table 5: The explanatory power of owner fixed effects

Type of FE	# of FE	λ_2	R^2 FE	ΔR^2 FE	Varshr	FE Corr
			Beer			
Firms	464	0.000	0.153	0.007	NA	NA
Firms	90	0.013	0.039	0.008	0.525	-0.529
Firms	22	0.171	0.032	0.004	0.039	-0.031
Clusters	15	0.461	0.096	0.001	0.032	0.060
Clusters	10	0.548	0.091	0.001	0.037	0.101
Clusters	5	0.618	0.089	0.001	0.033	0.106
			Spirits			
Firms	849	0.000	0.165	0.007	NA	NA
Firms	93	0.013	0.053	0.007	0.412	-0.454
Firms	18	0.071	0.057	0.006	0.066	-0.060
Clusters	15	0.426	0.094	0.002	0.079	0.118
Clusters	10	0.436	0.093	0.002	0.084	0.122
Clusters	5	0.904	0.082	0.001	0.039	0.259

Notes: # of FE is either number of firms or clusters. λ_2 measures network connectivity. R^2 FE is the share of variance explained by the firm/cluster FEs only. ΔR^2 FE is the difference in R^2 between the full specification and one excluding firm/cluster fixed effects. Varshr is the ratio of the variance of firm/cluster FEs to the total variance of brand type ($\ln \varphi_{bn}$, conduct =Bertrand). FE corr is the correlation between brand and firm/cluster FEs.

[25] As in Bonhomme et al. (2019), the features used in the clustering of firms are binned percentiles. Whereas they used 20 bins of the log wage distribution, we use five bins of $\ln s_{bn}$. Our use of fewer bins reflects the smaller number of brand-market observations per firm (about 6) than worker observations per establishment (about 37).

Table 5 summarizes our results on the firm effects for beer and spirits. The first row shows that firm effects *alone* can explain just over 15% of the variance in $\ln \varphi_{bnt}$ (derived using the Bertrand assumption[26]). However, firms add very little explanatory power to specification that already includes brand effects and the six friction variables—just 0.007 for both beverages.

The largest connected set includes 20% of the beer makers and 11% of the spirits makers. However, these firms accounts for the majority of world sales.[27] The second row for each beverage gives a startling—but misleading—impression of the importance of firms and it suggests strongly negative assortative matching between owners and brands. The λ_2 connectivity of both sets is just 0.01, compared to fully connected network of 1.00.[28]

The subsequent rows of Table 5 establish that when we succeed in increasing connectivity , the variance share of firm fixed effects—our metric for the value added of brand owners—shrinks to the 0.03–0.09 range. Moreover, the strong negative assortative matching is revealed to be an artifact of low connectivity. Restricting to the set of high mobility firms raises λ_2 up to 0.17, which is sufficient to put the variance share below 4% and leads to negligible correlation between brand and firm effects. The 21 individual firms remaining still account for a respectable 71% of total beer sales. This approach also raises connectivity substantially for spirits, lowering the variance share below 7% and mostly eliminating correlation between brand and firm fixed effects.[29]

Group fixed effects works very well for both beverages in the sense that it eliminates the suspicious negative assortative matching, and also that it generates results that tell approximately the same story whether we use $K = 10$ as in Bonhomme et al. (2019), or 50% more or fewer groups. We will focus on $K = 10$ since it seems a good balance between fit (measured by the R^2 of the fixed effects) and connectivity (λ_2). With $K = 10$, connectivity is over 0.44 and the value added of owners is 3.4% or 8.4% of the variance in brand type (φ_{bn}).

Table 6 shows how estimates of the frictions change as we deviate from the baseline specification of additively separable brand and firm effects (a la AKM). Columns (1) and (4) show, separately for beer and spirits brands, the baseline specification. Columns (2) and (5) show the clustered (or group) fixed effects. This is the same regression as the one reported for 10 Clusters in Table 5. Furthermore, this specification provides the friction

[26] As the results for Cournot conduct very similar, they are relegated to Appendix Table C.7.

[27] As can be seen in our appendix Table B.1, the largest component accounts for 80% of beer sales and 58% of spirits sales.

[28] Interestingly, the firm-to-firm network here is slightly more connected than $\lambda_2 = 0.004$ in the teacher-to-teacher network examined by Jochmans and Weidner (2019).

[29] The device of the superfirm plays an quantitatively important role, especially for spirits, in raising connectivity and lowering variance shares and negative assortative matching.

Table 6: Brand type regressions with alternative heterogeneity assumptions

	Beer			Spirits		
Fixed effects:	$b+f$	$b+k$	bf	$b+f$	$b+k$	bf
home	0.444^a	0.465^a	0.451^a	0.279^a	0.270^a	0.277^a
	(0.054)	(0.053)	(0.055)	(0.067)	(0.065)	(0.068)
distance	-0.073^a	-0.063^a	-0.081^a	-0.032^c	-0.031^c	-0.032^c
	(0.018)	(0.017)	(0.019)	(0.019)	(0.018)	(0.019)
common language	0.091^b	0.104^a	0.086^b	-0.019	-0.017	-0.020
	(0.041)	(0.039)	(0.041)	(0.039)	(0.038)	(0.040)
home (HQ)	0.103^c	0.060	0.096^c	0.210^a	0.201^a	0.226^a
	(0.053)	(0.044)	(0.056)	(0.056)	(0.052)	(0.059)
distance (HQ)	-0.032^c	-0.033^a	-0.030	0.029^c	0.028^c	0.030^c
	(0.016)	(0.012)	(0.020)	(0.017)	(0.015)	(0.017)
com. lang. (HQ)	-0.026	-0.035	-0.014	0.075^b	0.067^b	0.075^b
	(0.036)	(0.032)	(0.039)	(0.030)	(0.029)	(0.031)
Observations	34,675	34,675	34,675	60,624	60,624	60,624
R^2	0.736	0.730	0.748	0.549	0.544	0.553
RMSE	0.236	0.237	0.232	0.385	0.384	0.382

Standard errors in (), clustered by origin-market dyads. Dependent variable: $\ln \varphi_{bn}$. Market-year-product fixed effects in each regression. HQ variables determined by brand owner's headquarter country. Significance levels: 1% (a), 5% (b), and 10% (c).

and group fixed effect estimates underlying Figure 5 and the counterfactual exercises. Finally, columns (3) and (6) show a new specification that replaces add the additive b and f fixed effects with bf fixed effects. If interactions, or "match effects" in the worker-firm context, are important in determining which firms own which brands, there is the potential for bias because the error term in the additive specification could be correlated with the friction determinant or firm fixed effects. Analogously to the approach taken by Card et al. (2013), we respond to this concern by estimating a specification with a full set of brand-firm fixed effects. Since this specification nests the $b + f$ specification, the R^2 necessarily rises. However the change is very small (0.012 for beer, 0.004 for spirits) and the root mean squared error (RMSE) hardly declines. The implied standard deviation of the match effect is just 0.043 for beer and 0.047 for spirits.[30] The friction estimates themselves change very little across the three specifications, suggesting that the orthogonality assumption for the match effects is not strongly violated. We reproduce this set of regressions as Table C.8 in the Appendix, with Cournot $\breve{\varphi}_{bn}$ as the dependent variable. The friction coefficients are slightly larger and more statistically significant under Cournot, but the pattern of changes in R^2 and RMSE are essentially the same.

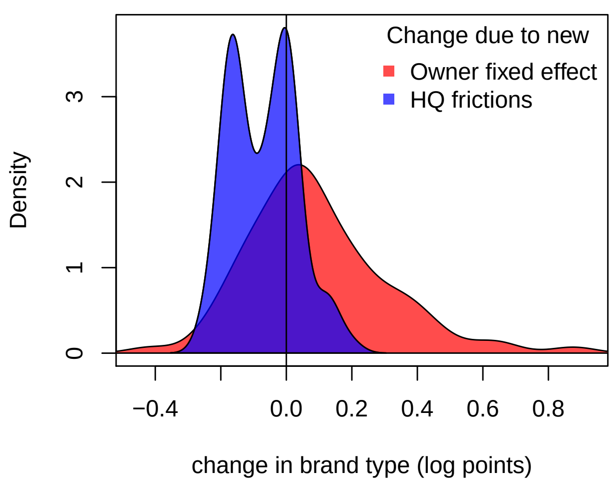
Figure 5 visualizes the distributions of changes in $\breve{\varphi}_{bn}$ that our estimates imply to have occurred as a consequence of the observed set of brand ownership changes. The blue densities shows changes in $\breve{\varphi}_{bn}$ attributable to headquarters moving countries. Since there are many same-country mergers, there is an important mode at zero. The second mode (at around -0.15) corresponds to domestic brands being acquired by foreign firms. The reverse phenomena—an increase in cost-adjusted appeal from domestic takeovers from foreign firms—is rare.

The red densities in Figure 5 show the effect of exchanging one firm (or firm-cluster in the lower row of graphs) for another. This has a strong peak near zero in every case, but it is especially high density for the firm-cluster fixed effects. This is because under group effects it is common that the new owner comes from the same group as the original one. For example, in beer, AB InBev was in the same group (5th as ordered by the median of the median market shares) as SAB Miller and Grupo Modelo (Corona). The difference in $\ln \breve{\varphi}_{bn}$ between the groups to which AB InBev and Anheuser Busch corresponds to a 0.02 reduction of Budweiser's brand type. On the other hand, when Heineken bought Lagunitas, the latter moved from group 10 to 5, a 0.28 improvement in $\ln \breve{\varphi}_{bn}$. The Belgian craft brewery Bosteels made the same large move when AB InBev acquired it in 2016.[31]

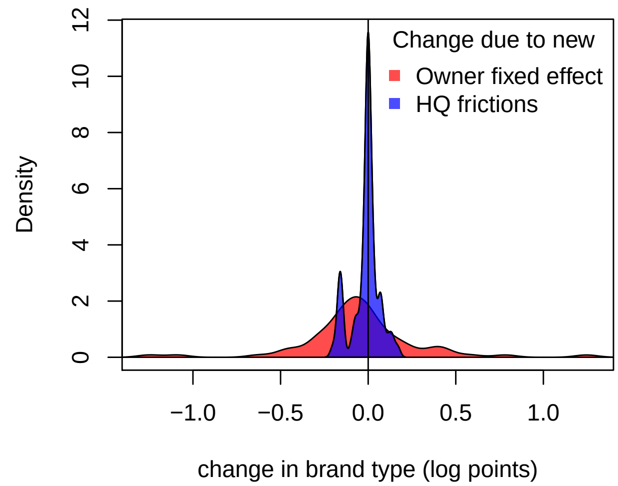
[30] As in Card et al. (2013), we calculate this as the square root of the difference between the squared RMSEs of the bf and $b + f$ columns.

[31] The Bosteels-owned brand in GMID, Triple Karmeliet, won the World Beer Awards in 2008 so it seems likely the rise in φ came from more efficient production processes or more intensive advertising as opposed

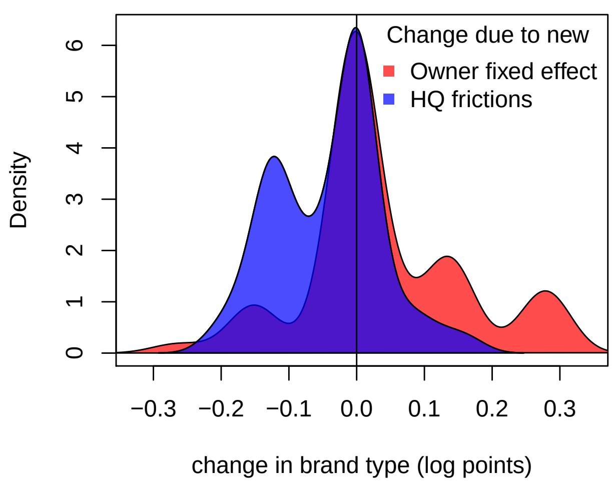
Figure 5: How ownership changes affect brand type (φ_{bn})



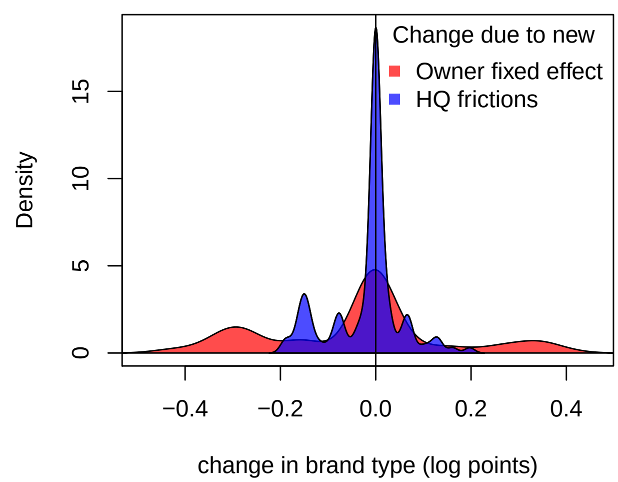
(a) Beer firms



(b) Spirits firms



(c) Beer firm clusters



(d) Spirits firm clusters

Another important finding displayed in figure 5 is that the range of group effects is about 0.7 for firm-clusters in beer which is much smaller than the 1.3 range for firm effects, just as predicted by low mobility bias. A similar range shrinkage occurs for spirits.

Our results echo the findings of Blonigen and Pierce (2016) although the methodologies are entirely different. They study productivity and markups before and after acquisitions, whereas we scrutinize the firm fixed effects in regressions explaining brand performance. Our results are also in line with the Kwoka (2014) survey of 41 different mergers where only one in four cases exhibited clear performance improvements following a merger.

There is an important consequence of our regressions in interpreting the role of firms in the beer and spirits industries. Since firm effects contribute so little to brand performance, we see little evidence of significant marginal cost or appeal synergies in the brand amalgamation process. This raises the question of why firms find it profitable to collect brands. The obvious explanation coming from recent critiques emphasizing rising market power, and formalized within our model, is that mergers suppress competition between brands. An additional explanation would be synergies that take the form of fixed costs reductions. Since synergies of this form would not influence brand market shares, they will not influence the price outcomes of ownership changes. Hence we do not need to take a stance on them in the counterfactuals when considering the consequences of mergers on the consumer surplus, an exercise to which we now turn.

5 Counterfactual merger policies and consumer welfare

Mergers and acquisitions of beer and spirits makers have been bring larger and larger sets of brands under the ownership of the largest multinationals (as seen in figure 1 and 2). To quantify the consequences for consumer welfare of this process of multinational brand amalgamation we consider counterfactual ownership configurations. Our first set of counterfactuals investigates the consumer surplus saved by antitrust remedies and foregone in less interventionist countries. We then measure the cumulative impact on concentration and consumer surplus from the recent wave of brand acquisitions by MNCs. We implement this by restoring the 2007 owners to each brand in 2018.

In addition to taking into account how alternative ownership patterns affect firm level market shares and hence their optimal markups, we also account for the changes in brand type (φ_{bn}) implied by the counterfactual ownership, using estimates from columns 2 and 5 (beer and spirits, respectively) of Tables 6 (Bertrand) or C.8 (Cournot), as illustrated in

to a pure change in quality.

Figure 5(c) and (d). Thus, we include the difference in the estimated group fixed effect corresponding to the actual and counterfactual owners. The simulations also include the changes in frictions that are estimated to result from any ownership change that moves headquarters out of the country in question, further away, or to a country with a different language. The next subsection describes the method used for all the counterfactual computations.

5.1 Exact Hat Algebra (EHA) for M&A

The counterfactual stipulates a set of brand portfolios for each firm which we denote as $\mathcal{F}'_f$. Firm market shares adjust to new ownership sets and the changes in brand market shares entailed by rearranging ownership and therefore altering first-order conditions for pricing. So far as we know, this is the first application of EHA to merger analysis. Given the very low information requirements (just market shares of total value sold in each market, η and σ must be known) this approach seems attractive as compared to methods that involve solving the full model and thus require data on the levels of φ_{bn} which are generally unknown. With EHA, only changes in φ_{bn} need to be specified and they can be obtained from the regressions of the previous section.

The first (and last) step in the ownership change counterfactual is to aggregate up the new brand market shares predicted by EHA to the level of firms. Initially we set $s'_{bn} = s_{bn}$, implying $\hat{s}_{bn} = 1$ and sum up the shares of the brands in the new ownership sets, $\mathcal{F}'_f$, to yield

$$\hat{S}_{fn} = \frac{\sum_{b \in \mathcal{F}'_f} \mathbb{I}_{bn} \hat{s}_{bn} s_{bn}}{S_{fn}} \tag{25}$$

The second step uses data on initial firm market shares S_{fn} and estimates of η and σ to calculate the change in markups, applying a conduct assumption from equation (11). The proportional change in the Lerner index under the two alternative conduct assumptions are

$$\underbrace{\hat{L}_{fn} = \frac{\sigma - (\sigma - \eta) S_{fn}}{\sigma - (\sigma - \eta)\hat{S}_{fn} S_{fn}}}_{\text{Bertrand}}, \quad \text{and} \quad \underbrace{\hat{L}_{fn} = \frac{1 + (\sigma/\eta - 1)\hat{S}_{fn} S_{fn}}{1 + (\sigma/\eta - 1) S_{fn}}}_{\text{Cournot}}. \tag{26}$$

The adjustment of the firm-level price-cost markups is

$$\hat{\mu}_{fn} = \frac{1 - L_{fn}}{1 - \hat{L}_{fn} L_{fn}}. \tag{27}$$

With these markup adjustments calculated, the final step is to determine the brand-level market share changes. The main cause of brand-level market share changes is the adjustment of markups resulting from the change in ownership. However, the method allows for changes in the cost-adjusted appeal of brand b to market n, denoted $\hat{\varphi}_{bn}$. These could enter through two channels. First, a brand with a new owner f' inherits the potentially different $\varphi^F_{f'}$. Second, if $h(f') \neq h(f)$ then headquarter frictions, δ^F, change.

The proportional change in brand-level market share is given by

$$\hat{s}_{bn} = \left(\frac{\hat{\mu}_{fn}}{\hat{\varphi}_{bn} \hat{P}_{gn}} \right)^{1-\sigma} \tag{28}$$

with the change in country's price index given by:

$$\hat{P}_{gn} = \left(\sum_k \mathbb{I}_{kn} s_{kn} (\hat{\mu}_{kn} / \hat{\varphi}_{kn})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \tag{29}$$

The market share adjustments $\hat{s}_{bn}$ are re-aggregated to yield changes in firm-level market shares in equation (25). The algorithm then iterates until the vector of brand-level market share changes stabilize. The resulting $\hat{s}_{bn}$ is the same as the one obtained by solving for the equilibrium, s_{bn}, before and after the friction change and taking the ratio. The advantage is that it can be calculated without knowing the *levels* of all the model's parameters.

The presence of a set of "other" brands poses a challenge for determining counterfactual price indexes.[32] Since all the brands GMID places in the "other" category should have individual markets shares less than 0.1%, we model them as monopolistically competitive. Their markups are therefore fixed under CES demand, implying $\hat{\mu}_{bn} = 1$. A convenient feature of EHA counterfactual is that the aggregate market share of those brands—which we do observe and denote as s_{on}—is all we need to compute the counterfactual price index:

$$\hat{P}_{gn} = \left(s_{on} + \sum_{k \in \text{listed}_n} \mathbb{I}_{kn} s_{kn} (\hat{\mu}_{kn} / \hat{\varphi}_{kn})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \tag{30}$$

For the listed brands, markups (and type φ) adjust as ownership changes. The listed brand market shares adjust according to equation (28) with the price index change given by (30). For the other brands, we assume there are no cost and appeal changes ($\hat{\varphi}_{on} = 1$). Since markups are fixed as well, other brand market share evolves according to $\hat{s}_{on} =$

[32] Redding and Weinstein (2018) address an analogous problem, showing how to construct a CES price index with only aggregate information on the share of expenditure on non-traded varieties.

$\hat{P}_{gn}^{\sigma-1}$.

Finally, we need to account for the consequences of the counterfactual shock at the upper level. Since we assume that each sector is too small to affect the aggregate price index, it implies that $\hat{P}_n = 1$ and $\hat{X}_n = 1$. Hence, expenditures in category g adjust to price changes according to $\hat{X}_{gn} = \hat{P}_{gn}^{1-\eta}$.

The outcomes of the counterfactual we examine are the changes in price indexes and in market concentration. The percentage change in the price index for each product category-market $\hat{P}_{gn} - 1$, described in equation (30). The counterfactual level of concentration is $H'_{gn} = \sum_f (S'_{fn})^2$. A complete welfare calculation lies beyond the scope of this paper. This is because we do not know changes in fixed costs and we cannot map changes in profits to the nations of the ultimate claimants.[33]

5.2 Undoing forced divestitures: counterfactual results

Non-academic narratives frequently portray competition authorities as passively permitting monopolization. On the other hand, Gutierrez and Philippon (2018) distinguish the EU case as being strongly affected by regulation unlike the more lax US policy environment. We observe that in the beer industry competition authorities on both sides of the Atlantic have forced divestitures to avoid concentration and even multi-market coordination effects.[34]

Table 7: What if antitrust authorities had been more permissive?

Country	%Chg. P_{gnt} ($\hat{\varphi}_{bn} = 1$)		%Chg. P_{gnt} ($\hat{\varphi}_{bn} \neq 1$)	
	Bertrand	Cournot	Bertrand	Cournot
United States	4.23	5.88	4.37	5.90
United Arab Emirates	1.13	1.91	1.12	1.87
Netherlands	1.04	2.04	0.08	0.99
Hungary	1.03	1.83	-0.37	0.11
Italy	0.79	1.58	0.05	0.74
Czechia	0.54	0.78	-1.76	-1.91
Slovakia	0.20	0.34	-1.58	-1.81
Poland	0.00	0.00	-1.72	-2.07

Note: The table reports the effect of undoing divestitures imposed by the US and the EU since 2007 on the percent change in the price index for beer in each country in 2018. Countries included in table if at least one absolute price change exceeds 1%.

[33] Multinational firms have complex capital structures and the rules of corporate taxation are equally difficult to apply on a global scale.

[34] The ABI/Modelo decision by US DOJ and European Commission decision (Case M.7881: AB INBEV/SABMILLER) on the SABMiller acquisition point to both effects to justify divestitures.

AB InBev was compelled to divest large sets of brands in five separate cases. First, when InBev bought Anheuser Busch in 2008, it had to divest the US-market rights of Labatt brands (acquired in 1995) to a new company called North American Breweries (who later sold it to the Costa Rican firm FIFCO). Second, when it bought the Modelo Group, it had to divest the US-market rights of Corona several other brands to Constellation Brands (a company mainly active in wine). The acquisition of SAB Miller in 2016 triggered forced divestitures in the US, EU, and China. Specifically, a package of popular EU brands was sold to Asahi, all the Miller brands were sold to MolsonCoors, and AB InBev's minority share of China Resources was sold to its Chinese partner.

Our model and data are well-suited to evaluating the efficacy of these divestiture by simulating a counterfactual in which the competition authorities permit AB InBev to retain all the brands it in fact had to divest. Specifically, we undo the divestitures described above and recompute the equilibrium in all markets. The results for the countries where the elimination of the divestiture is predicted to change the price index by more than a percent are displayed in Table 7. Sorted in descending order by the price change for Bertrand without cost adjustments, the table also includes prices changes for Cournot, and both Bertrand and Cournot imposing the adjustment to φ_{bn} predicted in our regression analysis for beer.

The US consumer is by far the most important beneficiary of the forced divestitures. Had AB InBev been able to keep all the brands owned by the companies it acquired, the beer price index in the US would be four to six percent higher. The highest price increase occurs under Cournot competition. The third and fourth columns show that taking into changes in φ_{bn} leads to a small exacerbation of the market power effects. The main reason for this is that AB InBev is considered to have dual headquarters in Belgium and New York. Hence, the non-divestiture to MolsonCoors (Miller) and Constellation Brands (Corona) does not change HQ frictions. Moreover, all the firms involved in the divestitures have very similar group fixed effects, except for FIFCO who obtained the relatively small Labatt.[35]

The case of United Arab Emirates provides a clear example of the potential for positive spillovers in competition policy. The UAE did not force divestitures but it benefited from the US and EU preventing AB InBev from keeping Miller and Peroni worldwide. The UAE is a rare market where local stars are irrelevant; divestiture lowers the price index about a percent by promoting competition between global giants. The leading brands are Heineken followed by four of AB InBev's global giants.

[35] Non-divestiture to FIFCO helps (by very small amounts) in two ways: keeping Labatt with a better firm and keeping the headquarters in the US—rather than Costa Rica.

The EU commission's intervention protected consumers from increases in market power in Hungary, Netherlands, and Italy that would have lead to 0.5–2.0% increases in the price index. In the first case, AB InBev keeps the Dreher Brewery local stars (accounting for 31% of the market) it had to divest to Asahi. This allows AB InBev to avoid competition for its global giants Stella Artois (38 markets), Leffe (10 markets) and Becks (34 markets), which collectively held 7% of the market. In Italy AB InBev brands (led by Becks at 6%) accounted for 13% of market in 2016, similar to Asahi's 14% (8% of which was Peroni). Cost increases due to moving HQ from Belgium to Japan partially or fully offset the market power effects.

The market situations in Slovakia and Poland exemplify the unintended consequences of divestiture to a remote owner. In these countries, the simulation predicts minimal (or zero in the case of Poland) prices rises due to market power.[36] However, the move of HQ from Belgium to Japan increases frictions by enough to raise the price index of beer by 2.2 to 2.3%. The potential costs of distance between market and headquarters is an issue that can only be quantified by combining data from multiple markets as we do in this paper.

5.3 Forcing counterfactual divestitures

The US and EU competition authorities' policy of forced divestitures as pre-conditions for approving InBev and its successor's acquisitions appears to have resulted in sizeable savings in the US and modest savings in several other countries as well. This raises the question of whether competition agencies in other countries could have achieved similar consumer savings by emulating the US/EU approach.

The counterfactual reported in Table 8 reassigns the global rights to Labatt brands to FIFCO, the Modelo brands (including Corona) to Constellation, and all the local SAB-Miller brands to Asahi. Since FIFCO, Constellation, and Asahi had low or zero market presence in the markets where these brands had high market shares, this is tantamount to placing the pricing decisions for these brands under independent control.

The largest gains would accrue to consumers in three Andean countries where SAB-Miller had acquired the main local star brands. Forcing divestiture would have reduced the beer price index by 14–30% depending on the country and assumptions. The Dominican Republic and Uruguay would also experience gains as large or larger than those generated by divestiture for the US. For all countries except the first three listed in table 8, forcing divestitures yields larger price reductions under Cournot conduct than Bertrand.

[36] In Poland, AB InBev retained no other brands (above the GMID 0.1% threshold) after the divestiture. This implies no change in markups due to ownership changes considered in isolation. The EU Commission justified the divestiture of the Polish brands based on concerns based on multi-market contacts.

Table 8: What if antitrust authorities had followed EU/US lead?

Country	%Chg. P_{gnt} ($\hat{\varphi}_{bn} = 1$) Bertrand	%Chg. P_{gnt} ($\hat{\varphi}_{bn} = 1$) Cournot	%Chg. P_{gnt} ($\hat{\varphi}_{bn} \neq 1$) Bertrand	%Chg. P_{gnt} ($\hat{\varphi}_{bn} \neq 1$) Cournot
Colombia	-30.21	-25.87	-29.59	-24.62
Ecuador	-25.26	-22.69	-24.68	-21.49
Peru	-19.59	-14.05	-19.14	-12.62
Uruguay	-10.12	-11.54	-10.51	-11.73
Dominican Republic	-7.05	-4.18	-7.34	-4.27
Canada	-2.65	-5.50	-2.09	-4.58
Argentina	-2.24	-4.22	-2.25	-4.11
Australia	-1.97	-4.32	-3.92	-5.94
United Arab Emirates	-1.72	-3.77	-1.65	-3.47
Bolivia	-1.63	-2.12	-1.72	-2.17
Mexico	-1.35	-2.94	-2.06	-3.27
Chile	-1.16	-2.71	-1.33	-2.76
South Africa	-1.11	-2.05	-2.86	-3.48
Guatemala	-0.66	-1.50	-0.79	-1.58
India	-0.37	-0.95	-1.56	-2.01

Note: The table reports the effect of forcing divestitures on the percent change in the price index for beer in each country in 2018. Countries included in table if at least one absolute price change exceeds 1%.

The intuition for why the Bertrand effects are stronger for Colombia, Ecuador, Peru, can be found in the convexity of the Lerner index as a function of market share under Bertrand conduct illustrated in Figure 3(a). Those three countries started out in the region of market shares where further consolidation boosts markups more under Bertrand.

Australia and Canada both issued no-action letters in 2016, commenting that they did not foresee adverse effects of the SABMiller acquisition on competition in their respective beer markets. Table 8 suggests that implementing the three divestitures (Labatt, Modelo, and SABMiller EU brands) would have saved Canadian consumers between 2.7% and 6.4%. Australian beer drinkers would gain 1.9% to 4.3%. Mexico could also have generated substantial gains through compelling divestiture of the Modelo brands in the Mexican market.

The price reductions reported in Table 8 should be thought of as the cost-saving for individual countries to deviate from their historical permissive behavior. Had every country insisted on divestiture, the acquisition itself would not make sense. To obtain consent for its purchase of SABMiller, AB InBev had to divest more than half of the 155 brands SABMiller offered in 2015. In 2019 they sold their Australian brand portfolio to Asahi. Taking into account all the subsequent brand divestitures, AB InBev paid a net price of

\$83.4bn for the SAB Miller brands it retained.[37] Our counterfactuals suggest the main benefits were near monopolization of several Latin American beer markets.

5.4 Restoring 2007 owners: counterfactual results

The final counterfactual can be framed as implementing a ban on all changes in brand ownership. The simulation calculates a new equilibrium using 2018 brand market shares as an input but applying the 2007 mapping of brands to firms, that is $o(b, 2007)$. The EHA procedure then calculates the counterfactual 2018 brand market shares. We think of this counterfactual as a way of summarizing all the effects of the operation of the market for brands over the last 12 years rather than as an actual government policy.

Table 9: Summary of outcomes of the counterfactual restoring 2007 brand owners

Category	# of	Conduct	Chg. HHI		%Chg. P_{gnt}	
	Countries	assumed	Mean	Median	Mean	Median
				with $\hat{\varphi}_{bn} = 1$		
Beer	76	Bertrand	424	212	2.41	0.68
Beer	76	Cournot	481	251	3.10	1.56
Spirits	75	Bertrand	67	20	0.22	0.05
Spirits	75	Cournot	67	21	0.38	0.10
				with $\hat{\varphi}_{bn} \neq 1$		
Beer	76	Bertrand	376	172	3.30	1.16
Beer	76	Cournot	428	215	4.09	1.86
Spirits	75	Bertrand	48	18	0.87	0.41
Spirits	75	Cournot	47	20	1.02	0.51

Table 9 summarizes counterfactuals run on 76 (beer) or 75 (spirits) markets. Compared to a counterfactual of no changes in ownership, the simulation points to price indexes that are 0.2–4.1% higher for the average country.[38] The biggest increase is for beer with Cournot conduct including changes in brand type associated with ownership changes. The smallest changes are the pure market power effects of mergers in the spirits category.

The counterfactual points to larger price increases in two spirits markets: Turkey and Tunisia. In the former, Diageo's acquisition of the owner of Yeni Raki, the most popular spirit in the country, leads to a price rise between 3% (Bertrand, $\hat{\varphi}_{bn} = 1$) and 10% (Cournot, incorporating the higher costs from moving HQ to London). The Tunisia case

[37] The gross price paid in 2016 before any divestitures was \$122 billion. All values taken from *Financial Times*, "How deal for SABMiller left AB InBev with lasting hangover" (July 24, 2019).

[38] Most of the average price increases are smaller than 4% mean that Kwoka (2014) obtained in a meta-analysis of 47 merger retrospectives covering a variety of different products.

provides a rare example of market power rising through entirely through the combination of global giant brands. Pernod-Ricard, whose Chivas and Ballantines brands had significant market shares (17% in 2018), bought the most popular spirit in Tunisia, Absolut (32% market share in 2018). Since Absolut's prior owner was also foreign and had a similar group fixed effect, the ownership change did not change $\hat{\varphi}_{bn}$ by much.The market power effect raises the Tunisian spirit price index by 3–4%.

Appendix D graphs the counterfactual concentration and price index changes for all countries in our data set. Figures D.1(a) and D.1(c) illustrate the pure market power effects vary with concentration. The underlying simulation holds brand type constant ($\hat{\varphi}_{bn} = 1$). The results corroborate the approximation result in Proposition 5 of Nocke and Schutz (2018a). Namely, for all countries where the rise in concentration in less than 1000, the rise in the price index is roughly linear in the change in concentration (ΔH_n). This covers all spirits markets. For beer we see some non-linearity for $\Delta H_n > 1000$ under Bertrand, but linearity works quite well for Cournot for all changes. Figures D.1(b) and D.1(d) build in changes in φ_{bn} (resulting from owner and HQ changes). The positive relationship between counterfactual changes in price index and concentration persists but departs considerably from the tight line for spirits.

The model can be used to calculate changes in markups over markets to construct the counterfactual change in each firm's global Lerner index: ΔL_f. This provides a perspective on how mergers have transformed firms' market power which is complementary to the market-level perspective captured by changes in concentration and price indexes. The consolidated markup L_f, depends on brand-level market shares and the way they map to owners. As can be seen from inspecting equation (12), L_f is high when the firm has high market share in the markets that contribute importantly to its global revenues.

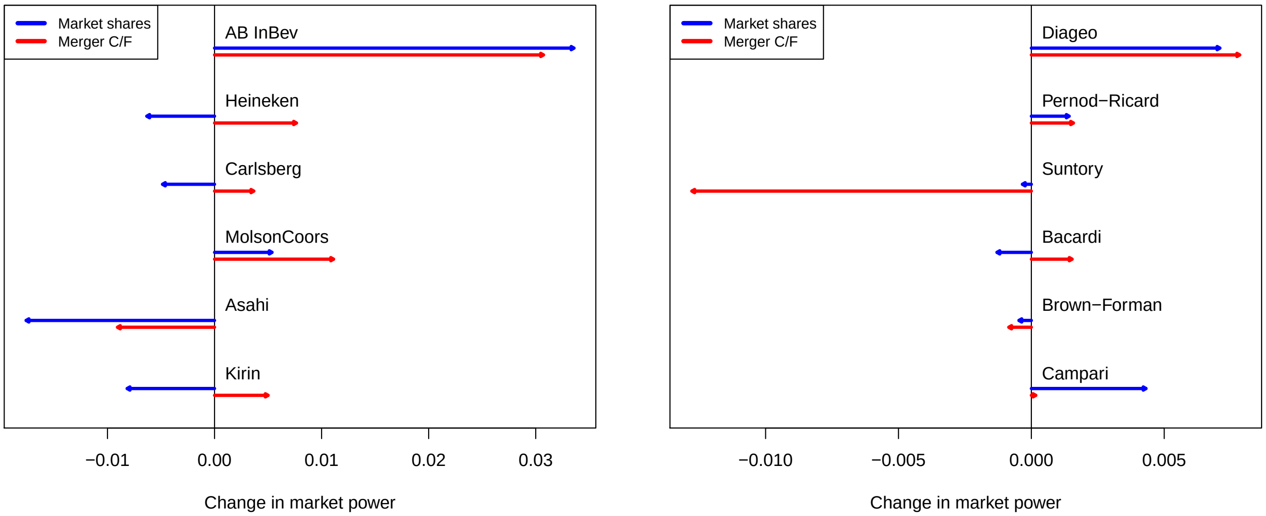
The first way we calculate ΔL_f is to plug the factual market shares and ownership patterns into equation (12) using 2007 and 2018 data. Let $\mathbf{S}_{ft}$ denote the vector of all firm-level market shares in each country n in year t. Recalling that $o(b, t)$ gives the mapping of brands to owners in any year t, the change in markups implied by the historical evolution of market shares is given by

$$\Delta L_f^{\text{blue}} = L_f(\mathbf{S}_{f18}, o(b, 18)) - L_f(\mathbf{S}_{f07}, o(b, 07)).$$

It is shown in blue in Figure 6. The second way to calculate ΔL_f isolates those changes that come purely from ownership changes entailed in switching from $o(b, 07)$ to $o(b, 18)$:

$$\Delta L_f^{\text{red}} = L_f(\mathbf{S}_{f18}, o(b, 18)) - L_f(\mathbf{S}'_{f18}, o(b, 07)),$$

Figure 6: Effects of ownership changes 2007–18 on firm-level markups



(a) Beer (b) Spirits

where $\mathbf{S}'_{f18}$ is the counterfactual vector of market shares if the brand owners of 2007 re-possessed their holdings in that year. Figure 6 shows this with red arrows.

The first term in both the blue and red versions is the same whereas the subtracted term differs in terms of whether it uses historical (blue) or counterfactual (red) market shares. The ΔL_f^{blue} arrows in Figure 6 combine changes in firm type coming from expansion of the brand portfolios with changes in the brand type (φ_{bn}) of the *incumbent* brands in each market where the brands are sold. The ΔL_f^{red} arrows exclude the changes in incumbent brands.

The most important takeaway from Figure 6 is the very close match between ΔL_f^{blue} and ΔL_f^{red} for the largest firms in each each category, AB InBev and Diageo. This tells us that M&A essentially tells the whole story for the growth in markups for these multinationals. Brand performance was static but by combining brands to increase firm-level market share these two firms increased their aggregate worldwide market power. Changes in market share by incumbent brands—a kind of superstar effect at the brand level—plays a small positive role for AB InBev and actually slightly holds Diageo back.

The second and third largest beers makers, Heineken and Carlsberg, present a puzzle in that their M&A activities should have been *increasing* market power, but the actual evolution of historical market shares points to falling market power. The explanation is that, despite numerous acquisitions in multiple markets (as shown in Figure 1), the losses of market share for flagship brands in the strongholds of those two firms (notably Spain, Poland and Greece for Heineken, and all Nordic countries for Carlsberg) dominated the gains in markets entered via acquisitions. This resulted in $\Delta L_f^{\text{blue}} < 0$ and $\Delta L_f^{\text{red}} > 0$ for both firms.

Asahi and Kirin represent paradoxical cases of firms whose expansion abroad led to *lower* indexes of market power. This happens because their portfolios transformed from a complete Japan focus, where their market shares were dominant (40% and 31% market shares, respectively), to diversified positions where lower market share brands contribute substantially to total sales.[39] In the case of Asahi this is the primary reason for its decline in L_f over the decade. Kirin, however, suffered from the same incumbent brand decline experienced by Heineken and Carlsberg.

In the case of spirits we see one case, Suntory, where M&A dragged down the firm-level measure of market power. This was not because Suntory was selling off brands, but rather because the brands it gained gave it higher sales shares in markets where it had low L_{fn}. Before purchasing Beam, Suntory had high market share (16%) in Japan and negligible sales elsewhere. With Beam's brands, Suntory's sales in the US vaulted over their sales at home. However, the Beam brands captured only an 8% share of the US market, implying relatively low markups. This depressed Suntory's worldwide L_f by over a percentage point.

The one firm in Figure 12 that displays superstar effects is Campari. This is in large part attributable to the outstanding growth of one of its incumbent brands, Aperol. The φ_{bn} of this brand rises in several major markets. The parent company also started to offer the brand in 21 new markets.

6 Conclusion

In the beer and spirits industries, a small group of large firms, headquartered in a handful of countries, have expanded primarily via cross-border acquisitions. This process of multinational brand amalgamation has the potential to impact competition in a number of different ways. On the efficiency side, merging firms have long justified horizontal combinations on the basis of synergies. Competition authorities, on the other hand, have at times rejected mergers that were predicted to harm consumers. This paper obtains several new findings related to this debate. First, we find that brand type—extracted from data on market shares—is, for the most part, invariant to the identity of the owner. That is, firm fixed effects explain no more than 5% of cost-adjusted appeal in the beer industry

[39] Both firms obtain 98% of sales from Japan at the start of our sample but by 2018, Japan's weight falls to 54% and 62%. In the new markets, the firms acquired strong brands but they only rarely matched their Japan market shares.

and 9% in spirits. The reduction in R^2 from excluding firm fixed effects is close to zero. There is one way that ownership *does* affect cost-adjusted appeal, however. In the spirits industry, and to a lesser extent, the beer industry, we estimate that brand type is higher in the countries where their owners are headquartered. These results suggest there is 10–20% penalty on cost-adjusted appeal from foreign acquisitions with little in the way of predictable synergies. From the firm's point of view, there may be compensating reductions in fixed costs, but the methods we use here cannot recover such effects. The other potential benefit to firms is increased market power, a concern our counterfactuals show to be important—but highly heterogeneous across markets.

Rises in concentration at the world level can substantially overstate the changes in concentration in specific countries. To see this, consider a firm that acquires local monopolists in two countries. The MNCs world market share rises but the market structure within those markets is unchanged. The crucial condition that makes acquisitions profitable for the MNC—and harmful for the local consumers—is whether mergers combine global giants and local stars in the same market.

Cross-country comparisons in our counterfactuals quantify the beneficial role of competition policy towards mergers. Divestitures forced by the US and EU led to significant consumer savings, especially in the US. Canada and Australia could have achieved similar savings by imposing divestitures along the same lines. The greatest potential for the use of these structural remedies would be in Latin America, where counterfactuals reveal that consumer prices increases of over 20% could have been avoided in some countries.

It would be imprudent to conclude without a caution on the ability to apply lessons from the beer and spirits experience to other sectors. Obviously, research and development is much more important in electronics, software, and pharma industries. Nothing in this paper can indicate how cross-border acquisitions would affect innovation. Nevertheless, in sectors as diverse as dog food, eyeglasses, and chocolate bars, the GMID data exhibit similar patterns of firm growth via brand amalgamation. Hence, we believe the issues we raise here—and the methods we have employed—have potentially broad applications.

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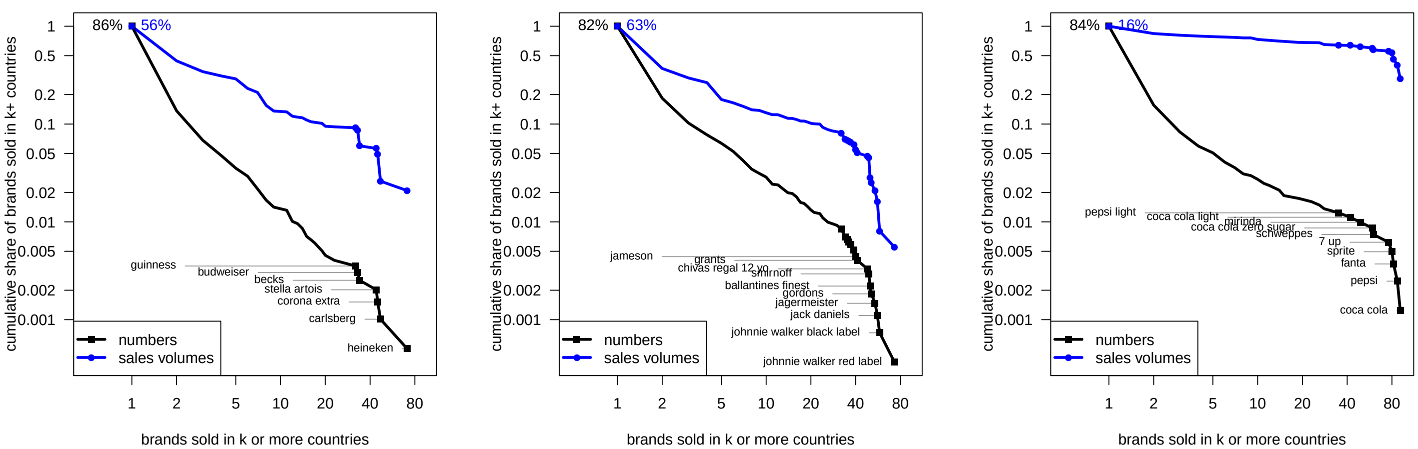
Appendix

A Extensive margins for brands and markets

In this section, we document the very important cross-sectional extensive margin of market entry as well as the relatively small entry rates over time for beer and spirits.

Figure A.1: Global giants are rare



(a) Beer (b) Spirits (c) Carbonates

Note: Symbols mark brands sold in >30 countries. They account for 9%, 8%, and 64% of volume in Beer, Spirits, and Carbonates. Log scales on both axes. Calculations exclude Others (counts, destinations not known).

Figure A.1 illustrates a few features of the distribution of brands across markets that play important roles in determining the outcomes of brand ownership changes in the beer and spirits industries. First, echoing a result shown repeatedly for exporters, a "happy few" brands are offered in many destinations and account for a disproportionate share of sales.[40]

Table A.1 investigates the entry margin, through which firms add or drop brands in selected markets or altogether. The main finding is one of fairly high stability over time in which brands are offered and where they exceed the 0.1% market share threshold. Furthermore, changes in ownership do not seem to spur elimination of brands. Nor do they spur increased distribution across markets.

[40]Bernard et al. (2007) show these patterns in US data, Mayer and Ottaviano (2007) coin the term and show that the pattern holds for many countries.

Table A.1: Adding and dropping brands in markets and overall: Beer and Spirits

Sample frame	Add rate (in percent)	Drop rate (in percent)
Beer		
Brand-level births and deaths:		
All brand/years (18,063 obs.)	3.07	2.34
Brands changing owners: before	NA	2.21
Brands changing owners: after	NA	2.49
Brands added/dropped in a market:		
All brand/market/years (1,498,802 obs.)	0.06	2.63
Continuing brands	0.02	0.85
Brands changing owners: before	0.02	0.32
Brands changing owners: after	0.03	1.90
Spirits		
(a) Brand-level births and deaths:		
All brand/years (25,601 obs.)	1.62	1.69
Brands changing owners: before	NA	1.69
Brands changing owners: after	NA	1.50
(b) Brands added/dropped in a market:		
All brand/market/years (1,919,019 obs.)	0.04	1.56
Continuing brands	0.02	0.61
Brands changing owners: before	0.01	0.51
Brands changing owners: after	0.04	1.93

B Connectivity of the brand-firm network

Table B.1: Brand mobility in the connected set

Product group	# Firms		Mobility		Sales share	
Beer	90	21	13.4	50.1	80.0	70.8
Spirits	93	17	8.0	32.5	57.5	41.9
Wine	12	2	6.4	27.5	6.3	2.9
Water	68	3	2.3	11.3	58.9	43.4
Carbonates	44	4	3.3	11.5	91.2	65.7
Juice	60	2	2.7	13.0	44.5	2.8
Coffee	3	NA	2.7	NA	33.1	NA
$\geq$ 10 movers		✓		✓		✓

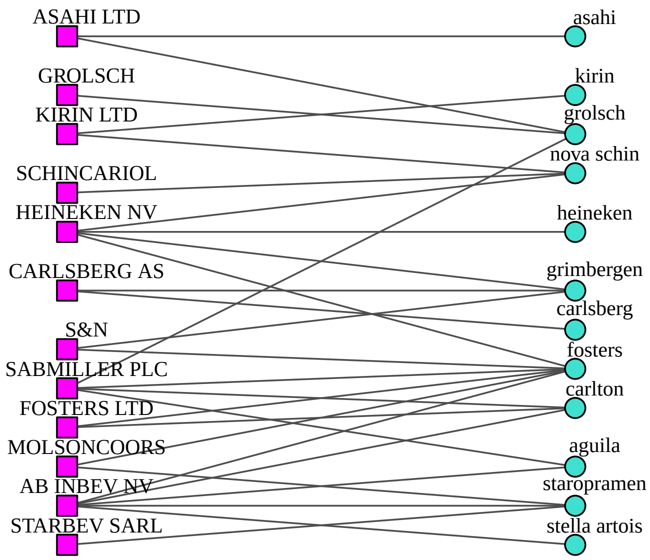
Notes: # Firms is the count of firms in the largest connected set with and without the restriction of 10 or more moving brands per firm. Mobility is the average number of ownership changes per firm in the specified set. Sales share is the set's percentage of world sales.

In the third and fourth columns of Table B.1, we report the mobility ratios for all beverages, showing it for the largest connected set, and within that group, for the firms that experience more than ten movements (the large mobility group). Beer, and to a slightly lesser extent spirits, are characterized by two desirable features in this type of regressions: a high number of ownership changes, combined with a large share of world sales accounted for by firms in the connected set (shown in columns 5 and 6).

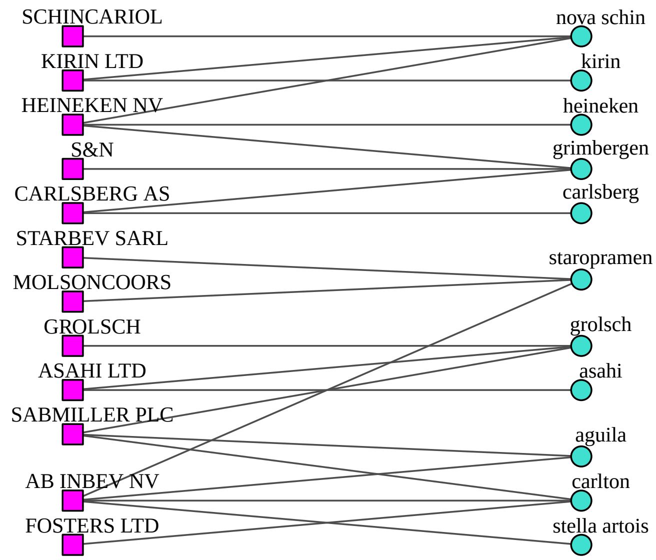
Figure B.1 illustrates the near-disconnectedness problem with an illustrative subset of firms and brands. Without the Fosters brand, the upper section of this graph (Schincariol, Kirin, Scottish & Newcastle, Carlsberg, and Heineken) would detach itself from the rest.

Chung (1997) showed how the eigenvectors of the graph capture whether network is just connected or thickly connected. Jochmans and Weidner (2019) Theorem 2 shows that higher λ_2 connectivity of the network shrinks the upper bound for the variance of the estimates of the fixed effects (of firms). In a bipartite network, edges connect two sets of nodesThere is an *induced firm-to-firm network* with weighted edges between firms The edge weight $w(u, v)$ is an increasing function of in-common brand-mkt-years (n.b. $w(u, u) = 0$) *Laplacian* of the weighted firm-to-firm network is a matrix with $L(u, v) = -w(u, v)$ and $L(u, u) = d_u$, where $d_v = \sum_u w(u, v)$. In the case where $w = 1$, d_v is the degree, that is the number of edges connecting to vertex v. *Normalized* Laplacian: $\mathcal{L}(u, v) = -w(u, v)/\sqrt{d_u d_v}$, $\mathcal{L}(u, u) = 1$ λ_2 is the smallest positive eigenvalue ($\lambda_1 = 0$) of $\mathcal{L}$ Max λ_2 is $n/(n-1)$. As $n \to \infty$, the max $\lambda_2 \to 1$.

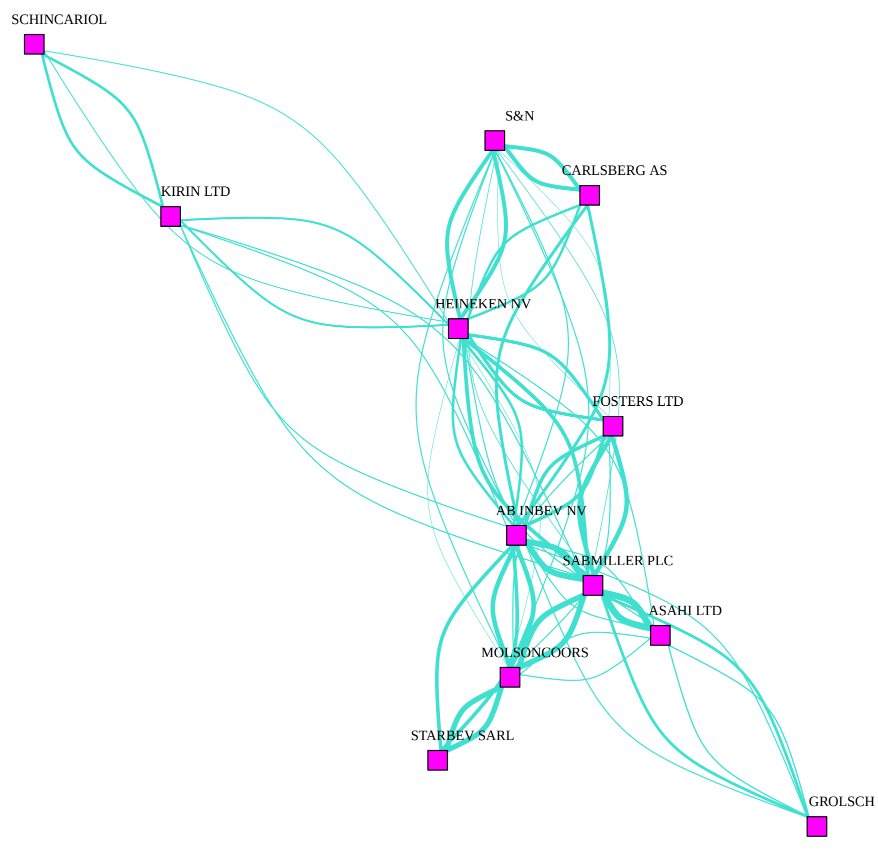
Figure B.1: Visualising connectivity via an illustrative subset of brands and firms



(a) A connected set of firms and brands



(b) Without the Fosters brand, the sets disconnect



(c) The *induced* firm-to-firm network from panel (a)

The Jochmans and Weidner (2019) weight calculation: For $u \neq v$ weights are given by:

$$w(u,v) = \sum_b \frac{n_{ub} n_{vb}}{N_b}$$

where n_{ub} is the count of market-years where brand b belongs to firm u.

$$n_{ub} = \sum_{nt} 1_{b \in \mathcal{F}_u} \times 1_{s_{bnt} > 0}$$

and N_b is the brand's total market-years under *all owners*:

$$N_b = \sum_f n_{fb}$$

Figure B.1(c) shows the induced network of firm-to-firm links where the turquoise edges are based on brand-market-years. The thickness of these lines is proportional to the log of the Jochmans and Weidner (2019) weights described above. In this panel, *all* the brands are used in the weight calculation, not just the 12 illustrative brands in panel (a).

C Additional regression results

Table C.1: Pooled beer + spirits regressions, without firm fixed effects

			Bertrand		Cournot	
	$\ln s_{bn}$	$\ln A_{bn}$	$\ln \varphi_{bn}$	$\ln \mu_{bn}$	$\ln \varphi_{bn}$	$\ln \mu_{bn}$
home	1.020^a	0.211^a	0.355^a	0.022^a	0.375^a	0.041^a
	(0.127)	(0.068)	(0.048)	(0.004)	(0.050)	(0.007)
distance	-0.110^a	0.030	-0.040^a	-0.001	-0.041^a	-0.003^c
	(0.035)	(0.020)	(0.014)	(0.001)	(0.014)	(0.002)
common language	0.053	-0.053	0.011	0.0004	0.012	0.001
	(0.076)	(0.049)	(0.030)	(0.002)	(0.031)	(0.003)
home (HQ)	0.285^a	0.082	0.140^a	0.018^a	0.154^a	0.032^a
	(0.090)	(0.051)	(0.036)	(0.003)	(0.037)	(0.006)
distance (HQ)	0.006	0.009	0.007	-0.0005	0.006	-0.002
	(0.026)	(0.016)	(0.011)	(0.001)	(0.011)	(0.001)
com. lang. (HQ)	0.096^c	0.046	0.042^c	0.001	0.044^c	0.003
	(0.058)	(0.035)	(0.023)	(0.003)	(0.024)	(0.004)
Observations	95,299	95,299	95,299	95,299	95,299	95,299
R^2	0.651	0.649	0.589	0.891	0.596	0.846

Standard errors in (), clustered by origin-market dyads. Fixed effects at the brand-product and market-year-product dimensions included in each specification. HQ variables defined with respect to brand owner's headquarter country. Significance levels: 1% (a), 5% (b), and 10% (c).

Table C.2: Pooled beer + spirits regressions within the largest connected set

			Bertrand		Cournot	
	$\ln s_{bn}$	$\ln A_{bn}$	$\ln \varphi_{bn}$	$\ln \mu_{bn}$	$\ln \varphi_{bn}$	$\ln \mu_{bn}$
home	1.056^{a}	0.238^{a}	0.363^{a}	0.019^{a}	0.379^{a}	0.035^{a}
	(0.151)	(0.079)	(0.056)	(0.004)	(0.057)	(0.007)
distance	-0.083^{b}	0.049^{b}	-0.026^{c}	-0.001	-0.027^{c}	-0.002
	(0.038)	(0.023)	(0.015)	(0.001)	(0.015)	(0.002)
common language	0.051	-0.051	0.012	0.001	0.012	0.001
	(0.079)	(0.052)	(0.032)	(0.002)	(0.032)	(0.003)
home (HQ)	0.263^{b}	0.084	0.154^{a}	0.041^{a}	0.186^{a}	0.073^{a}
	(0.117)	(0.065)	(0.046)	(0.005)	(0.048)	(0.008)
distance (HQ)	0.033	0.010	0.017	0.001	0.016	0.0001
	(0.035)	(0.021)	(0.014)	(0.001)	(0.014)	(0.002)
com. lang. (HQ)	0.117^{c}	0.054	0.054^{b}	0.004	0.058^{b}	0.008
	(0.066)	(0.041)	(0.027)	(0.003)	(0.028)	(0.005)
Observations	64,968	64,968	64,968	64,968	64,968	64,968
R^2	0.598	0.568	0.519	0.876	0.527	0.827

The sample is restricted to the largest connected set, within a product category. Standard errors in (), clustered by origin-market dyads. Fixed effects at the brand-product, firm, and market-year-product dimensions included in each specification. HQ variables defined with respect to brand owner's headquarter country. Significance levels: 1% (a), 5% (b), and 10% (c).

C.1 Results pooling 7 Beverages

Table C.3: Pooled regressions, 7 beverages, with firm fixed effects

			Bertrand		Cournot	
	$\ln s_{bn}$	$\ln A_{bn}$	$\ln \varphi_{bn}$	$\ln \mu_{bn}$	$\ln \varphi_{bn}$	$\ln \mu_{bn}$
home	1.004^a	0.269^a	0.395^a	0.018^a	0.409^a	0.032^a
	(0.099)	(0.055)	(0.040)	(0.003)	(0.041)	(0.005)
distance	-0.155^a	0.002	-0.052^a	-0.0003	-0.053^a	-0.001
	(0.029)	(0.017)	(0.012)	(0.001)	(0.012)	(0.001)
common language	0.117^c	-0.022	0.038	0.001	0.039	0.003
	(0.063)	(0.038)	(0.026)	(0.002)	(0.026)	(0.003)
home (HQ)	0.381^a	0.147^a	0.177^a	0.020^a	0.194^a	0.037^a
	(0.080)	(0.044)	(0.033)	(0.003)	(0.034)	(0.005)
distance (HQ)	0.026	0.017	0.013	-0.001	0.011	-0.002^c
	(0.026)	(0.015)	(0.011)	(0.001)	(0.011)	(0.001)
com. lang. (HQ)	0.152^a	0.062^b	0.068^a	0.003	0.070^a	0.006
	(0.053)	(0.032)	(0.022)	(0.002)	(0.023)	(0.004)
Observations	170,578	170,578	170,578	170,578	170,578	170,578
R^2	0.735	0.699	0.667	0.941	0.672	0.912

Standard errors in (), clustered by origin-market dyads. Fixed effects at the brand-product and market-year-product dimensions included in each specification. HQ variables defined with respect to brand owner's headquarter country. Significance levels: 1% (a), 5% (b), and 10% (c).

Table C.4: Pooled regressions, 7 beverages, without firm fixed effects

			Bertrand		Cournot	
	$\ln s_{bn}$	$\ln A_{bn}$	$\ln \varphi_{bn}$	$\ln \mu_{bn}$	$\ln \varphi_{bn}$	$\ln \mu_{bn}$
home	1.023^a	0.282^a	0.409^a	0.023^a	0.426^a	0.040^a
	(0.093)	(0.052)	(0.038)	(0.003)	(0.039)	(0.005)
distance	-0.148^a	-0.005	-0.052^a	0.00004	-0.053^a	-0.001
	(0.027)	(0.015)	(0.011)	(0.001)	(0.011)	(0.001)
common language	0.125^b	-0.019	0.041^c	0.0002	0.042^c	0.001
	(0.061)	(0.036)	(0.025)	(0.002)	(0.025)	(0.003)
home (HQ)	0.286^a	0.093^b	0.125^a	0.010^a	0.134^a	0.020^a
	(0.069)	(0.037)	(0.029)	(0.002)	(0.030)	(0.004)
distance (HQ)	0.011	0.016	0.008	-0.001	0.007	-0.002
	(0.021)	(0.012)	(0.009)	(0.001)	(0.009)	(0.001)
com. lang. (HQ)	0.109^b	0.043	0.048^b	0.003	0.050^b	0.005
	(0.050)	(0.029)	(0.021)	(0.002)	(0.021)	(0.003)
Observations	170,578	170,578	170,578	170,578	170,578	170,578
R^2	0.726	0.689	0.653	0.935	0.658	0.901

Standard errors in (), clustered by origin-market dyads. Fixed effects at the brand-product and market-year-product dimensions included in each specification. HQ variables defined with respect to brand owner's headquarter country. Significance levels: 1% (a), 5% (b), and 10% (c).

C.2 Correlations of brand and firm fixed effects, with low mobility bias

Table C.5 shows fixed effect correlations for regressions on the largest connected set. The underlying regressions do not apply the Andrews et al. (2008) restrictions to the estimating sample. As found in that paper, the patterns of correlations seem to exhibit *negative* assortative matching: all correlations between brands and firm fixed effects are negative and large in absolute value, for both beer and spirits.

Table C.5: Correlations between fixed effects

	Brand				Firm			
Dep. var.:	share (s_{bn})	appeal (A_{bn})	type B (φ_{bn})	type C (φ_{bn})	share (s_{bn})	appeal (A_{bn})	type B (φ_{bn})	type C (φ_{bn})
Beer								
brand market share	1.583							
brand appeal	0.700	1.408						
brand type B	0.989	0.688	1.664					
brand type C	0.983	0.688	0.998	1.591				
firm market share	-0.577	-0.258	-0.541	-0.536	0.560			
firm appeal	-0.384	-0.408	-0.329	-0.325	0.688	0.307		
firm type B	-0.561	-0.239	-0.529	-0.525	0.992	0.664	0.525	
firm type C	-0.544	-0.229	-0.511	-0.507	0.982	0.665	0.996	0.499
Spirits								
brand market share	0.940							
brand appeal	0.716	0.802						
brand type B	0.999	0.715	0.983					
brand type C	0.996	0.713	0.999	0.976				
firm market share	-0.463	-0.228	-0.465	-0.463	0.378			
firm appeal	-0.367	-0.315	-0.376	-0.380	0.738	0.158		
firm type B	-0.450	-0.221	-0.454	-0.453	0.996	0.746	0.412	
firm type C	-0.440	-0.215	-0.444	-0.444	0.990	0.748	0.998	0.421

Diagonal: ratio of FE variances to variance of the dependent variable. **Off-diagonal:** correlation. Underlying regressions keep the largest connected set.

We conduct the variance and covariance analysis of fixed effects for the two products with high brand mobility, beer and spirits. Table C.6 displays correlation between the fixed effects estimated for each brand and each firm in three different regressions using market shares, appeal and cost-adjusted appeal (assuming Bertrand) as dependent variables. Following the approach advocated by Andrews et al. (2008) to mitigate limited-mobility bias, these regressions restrict the sample to moving brands and high mobility firms. In each table, the diagonal shows the ratio of the variance of the relevant fixed effect to the variance of the dependent variable.

Firm effects explain a small part of the variance of performance measures for both beer and spirits. Therefore, the identity of the firm owning a brand explains relatively little of the variance in its market share, appeal and cost-adjusted appeal. Brand effects explain a much larger share of the overall variance. It is possible, in the presence of negative covariance between firm and brand fixed effects, for brand effects to explain more than 100% of the overall performance. We see this for beer in Table C.6.

The off-diagonal elements of Table C.6 show the sign and magnitude of assortative matching. For beer, firm and brand fixed effects are all negatively correlated, despite adopting the recommended approach to mitigate limited mobility bias. For spirits, the correlations have mixed signs, but all have small magnitudes (under 10%).

Table C.6: Correlations between fixed effects and their explanatory strength

	Brand				Firm			
Dep. var.:	share (s_{bn})	appeal (A_{bn})	type B (φ_{bn})	type C (φ_{bn})	share (s_{bn})	appeal (A_{bn})	type B (φ_{bn})	type C (φ_{bn})
Beer								
brand market share	1.257							
brand appeal	0.756	1.392						
brand type B	0.988	0.745	1.340					
brand type C	0.980	0.747	0.998	1.290				
firm market share	-0.059	-0.101	-0.048	-0.048	0.038			
firm appeal	-0.056	-0.182	-0.044	-0.051	0.848	0.065		
firm type B	-0.044	-0.081	-0.031	-0.031	0.972	0.820	0.039	
firm type C	-0.027	-0.053	-0.013	-0.011	0.923	0.767	0.984	0.041
Spirits								
brand market share	0.643							
brand appeal	0.738	0.619						
brand type B	0.999	0.737	0.652					
brand type C	0.997	0.736	1.000	0.641				
firm market share	-0.048	0.102	-0.049	-0.049	0.058			
firm appeal	-0.132	-0.056	-0.148	-0.158	0.611	0.040		
firm type B	-0.061	0.094	-0.060	-0.058	0.989	0.609	0.066	
firm type C	-0.066	0.092	-0.063	-0.060	0.971	0.605	0.996	0.071

Diagonal: ratio of FE variances to variance of the dependent variable. **Off-diagonal:** correlation between fixed effects from regressions on samples limited to the largest connected set, brands that changed ownership, and firms with 10+ moving brands.

Table C.7: The explanatory power of owner fixed effects: Cournot conduct

Type of FE	# of FE	λ_2	R^2 FE	ΔR^2 FE	Varshr	FE Corr
			Beer			
Firms	464	0.000	0.176	0.007	NA	NA
Firms	90	0.013	0.048	0.009	0.499	-0.507
Firms	22	0.171	0.043	0.005	0.041	-0.011
Clusters	15	0.461	0.112	0.001	0.041	0.097
Clusters	10	0.548	0.107	0.001	0.049	0.126
Clusters	5	0.618	0.102	0.001	0.044	0.126
			Spirits			
Firms	849	0.000	0.172	0.007	NA	NA
Firms	93	0.013	0.060	0.007	0.421	-0.444
Firms	18	0.071	0.065	0.007	0.071	-0.060
Clusters	15	0.426	0.099	0.002	0.082	0.127
Clusters	10	0.436	0.098	0.002	0.089	0.124
Clusters	5	0.904	0.086	0.001	0.041	0.261

Notes: # of FE is either number of firms or clusters. λ_2 measures network connectivity. R^2 FE is the share of variance explained by the firm/cluster FEs only. Varshr is the ratio of the variance of firm/cluster FEs to the total variance of brand type ($\ln \varphi_{bn}$, conduct =Cournot). FE corr is the correlation between brand and firm/cluster FEs.

Table C.8: Friction estimates, alternative heterogeneity assumptions: Cournot conduct

	Beer			Spirits		
Fixed effects:	$b+f$	$b+k$	bf	$b+f$	$b+k$	bf
home	0.469^a	0.497^a	0.477^a	0.281^a	0.273^a	0.279^a
	(0.057)	(0.056)	(0.058)	(0.068)	(0.066)	(0.069)
distance	-0.077^a	-0.068^a	-0.086^a	-0.032^c	-0.031^c	-0.032^c
	(0.019)	(0.018)	(0.020)	(0.019)	(0.019)	(0.019)
common language	0.092^b	0.109^a	0.086^b	-0.019	-0.018	-0.020
	(0.042)	(0.041)	(0.042)	(0.040)	(0.039)	(0.040)
home (HQ)	0.136^b	0.082^c	0.128^b	0.232^a	0.219^a	0.248^a
	(0.056)	(0.047)	(0.059)	(0.058)	(0.053)	(0.061)
distance (HQ)	-0.038^b	-0.037^a	-0.037^c	0.030^c	0.029^c	0.031^c
	(0.017)	(0.013)	(0.020)	(0.017)	(0.015)	(0.018)
com. lang. (HQ)	-0.022	-0.038	-0.011	0.079^b	0.072^b	0.079^b
	(0.038)	(0.035)	(0.041)	(0.031)	(0.030)	(0.032)
Observations	34,675	34,675	34,675	60,624	60,624	60,624
R^2	0.744	0.737	0.756	0.553	0.547	0.557
RMSE	0.245	0.246	0.241	0.388	0.387	0.385

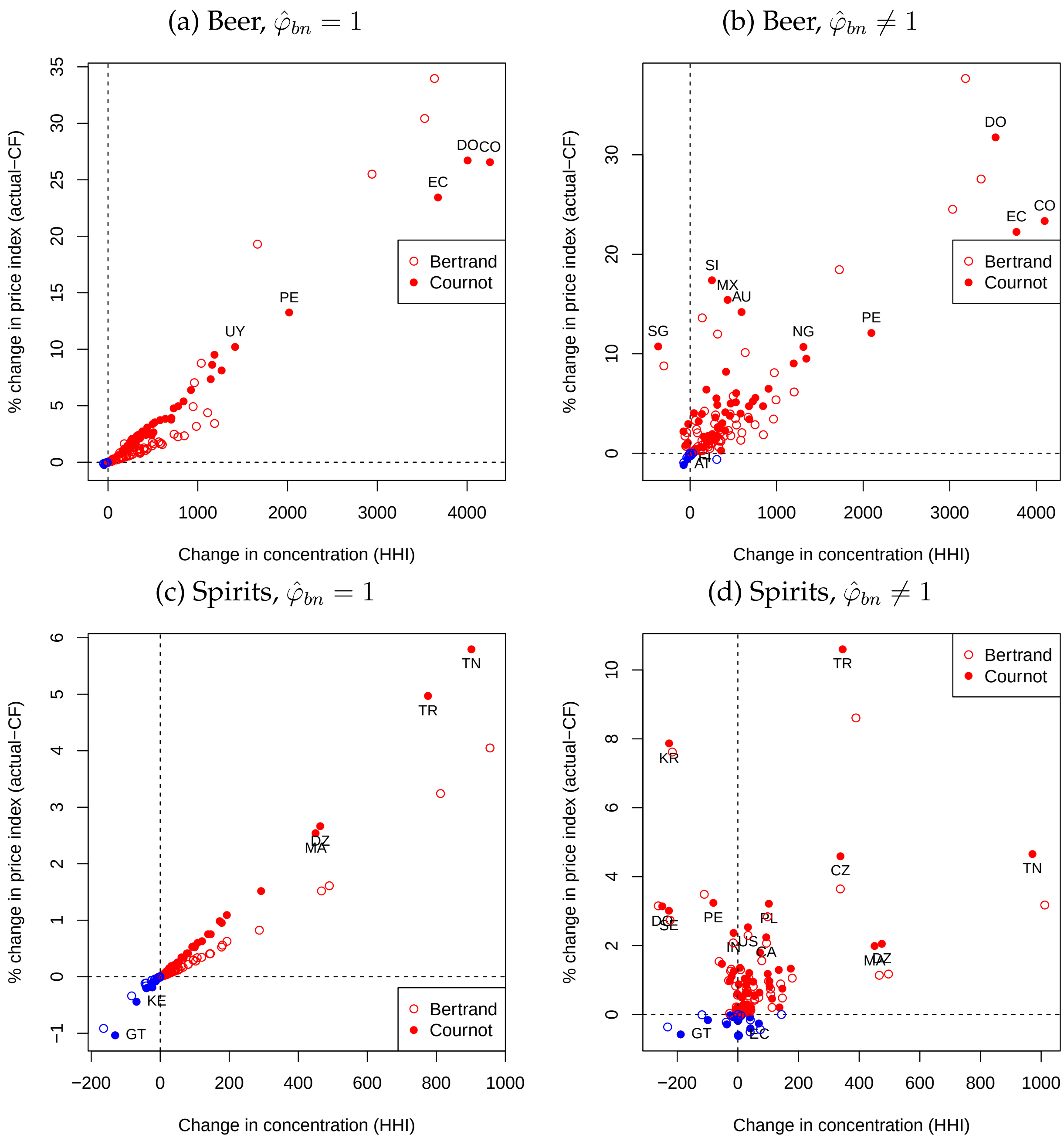
Standard errors in (), clustered by origin-market dyads. Dependent variable: $\ln \varphi_{bn}$. Market-year-product fixed effects in each regression. HQ variables determined by brand owner's headquarter country. Significance levels: 1% (a), 5% (b), and 10% (c).

D Restoring 2007 owners: concentration and price indexes

Figure D.1 illustrates the model-based quantification of the impact of mergers and acquisitions occurring over the decade after 2007. The graphs in the left column hold φ_{bn} constant wheres the graphs on the right use our HQ friction estimates and group fixed effect to capture changes in φ_{bn}. The vertical axes display changes in the price index attributed to the 2007–2018 ownership changes. The horizontal axes show changes in the Herfindahl concentration: $\Delta H = H_{2018} - H'_{2007}$. The upper two panels show results for beer and the lower two panels show the spirits results.

Restoring 2007 owners leads to only small changes concentration for the majority of the countries. Some countries, like Canada and Australia, have concentration increases large enough to move them over the EU threshold for highly concentrated markets. Three countries—Colombia, Peru, and the Dominican Republic—that were already highly concentrated, move to near monopoly in 2018 and experience large price index changes.

Figure D.1: Counterfactual results: restoring the 2007 owner in 2018



E Concentration and markups

A classical question in industrial organization is how equilibrium markups and overall welfare vary with respect to market concentration, usually measured as a Herfindahl index, that is the sum of squared market shares. In dataset such as ours, we know the aggregate share of the small firms, but not their individual shares. We assume that there is a very large number of fringe firms, such that we can treat them as massless, and therefore assign them the monopolistically competitive Lerner index of $L_o = 1/\sigma$. The zero mass assumption implies that the Herfindhal index in market n is $H_n = \sum_{f \neq o} S_{fn}^2$.

The literature specifies and aggregates the markup in several different ways. De Loecker et al. (2020) use a market-share-weighted price to cost ratio. Syverson (2019b) also uses weighted arithmetic means but applies it to the Lerner index. Meanwhile Edmond et al. (2015) and Grassi (2017) use the weighted harmonic mean of μ. We find that for Bertrand competition, the weighted harmonic mean Lerner index gives a neat result whereas for Cournot conduct we can obtain useful results for both the arithmetic and harmonic mean μ. The harmonic mean is signaled with a h superscript, the arithmetic mean with a. For Bertrand competition, recalling that S_{on} is the aggregate market share of "other" firms, we have

$$L_n^h \equiv \left(\sigma S_{on} + \sum_{f \neq o} \frac{S_{fn}}{L_{fn}} \right)^{-1} = \frac{1}{\sigma - (\sigma - \eta) H_n}. \tag{31}$$

As $H_n \to 0$ the aggregate markup goes to the monopolistic competition limit of $L_n^h = 1/\sigma$, whereas sector monopolization ($H_n \to 1$) takes the markup to $L_n^h = 1/\eta$ (the same limiting values we obtain for individual firm Lerner indexes).

Under Cournot the arithmetic mean Lerner index is linear in the Herfindahl,

$$L_n^a \equiv \frac{1}{\sigma} S_{on} + \sum_{f \neq o} S_{fn} L_{fn} = \frac{1}{\sigma} + \left(\frac{1}{\eta} - \frac{1}{\sigma} \right) H_n \tag{32}$$

A special case of this result appears in Syverson (2019b) where he assumes homogeneous goods producers (equivalent to $\sigma \to \infty$) and obtains $L_n^a = H_n/\eta$. Applying the Edmond et al. (2015) definition in the Cournot CES case, the harmonic mean markup is

$$\mu_n^h \equiv \left(\frac{\sigma - 1}{\sigma} S_{on} + \sum_{f \neq o} \frac{S_{fn}}{\mu_{fn}} \right)^{-1} = \left[\frac{\sigma - 1}{\sigma} - \left(\frac{1}{\eta} - \frac{1}{\sigma} \right) H_n \right]^{-1} \tag{33}$$

Now the limiting price-cost ratios are $\mu_n^h = \sigma/(\sigma - 1)$ as $H_n \to 0$ and $\mu_n^h = \eta/(\eta - 1)$

as $H_n \to 1$.[41] The general point is that under both types of conduct, aggregate markups are increasing with the Herfindahl, moving from monopolistic competition to monopoly levels.

De Loecker et al. (2020) use a market share weighted price to cost ratio, that is

$$\mu_n^a \equiv \frac{\sigma}{\sigma - 1} S_{on} + \sum_{f \neq o} S_{fn} \mu_{fn}. \tag{34}$$

Nocke and Schutz (2018a) show in propositions 3 and 4 that, for demand in a class that includes our nested CES, the distortion (defined as a reduction in consumer surplus) from oligopoly is linear in the Herfindahl.

[41] Burstein et al. (2019) independently derived this relationship and use the fact that $1/\mu^h$ is linear in the Herfindahl index to estimate $1/\sigma - 1/\eta = -0.444$ as the coefficient in a regression of sectoral markups on sectoral concentration.