This Craft's For You! Entry and Market(ing) Competition in the U.S. Beer Industry *

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Abstract

This paper studies the advertising response of incumbents to the entry of craft brewers in the U.S. beer industry. Exploiting changes in local beer legislation and spatial variation across TV markets, I document two facts: mass-producing brewers respond by raising local advertising, and this reduces consumers' price sensitivity. I then evaluate the implications for market power, using a structural model with persuasive advertising. The empirical model establishes that mass-producing brewers indeed had a profit incentive to respond to entry by raising advertising. Furthermore, the empirical results imply that (i) own and rival advertising can reduce price sensitivity; (ii) markups for flagship domestic brands increased from 2.6 to 3.4 for 2011-2016; and (iii) about 20% of the rising markups can be attributed to the observed increase in advertising stock.

Keywords: Market power, Advertising, Demand estimation, Brewing industry.

JEL Codes: L13, M37

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1 Introduction

Market entry has been the object of considerable academic and policy debate due to its potential role in promoting competitive markets. In many concentrated markets, incumbents respond to the arrival of new competition not only by changing the prices of existing products but also by adjusting other dimensions such as variety (Seim and Viard, 2011; Fan and Yang, 2022; Hidalgo, 2023), quality (Mazzeo, 2003; Prince and Simon, 2015), investment/innovation (Ellison and Ellison, 2011; Björkegren, 2022; Igami, 2017), and coordinated effects (Bourreau et al., 2021). Though advertising is considered a key strategic decision across many industries, the advertising response to entry has received little empirical attention. As a result, while much is known about the implications of other non-pricing responses, less is known about the effect of advertising response, for instance, on consumers. This paper aims to fill this gap. In particular, I investigate whether incumbents adjust advertising decisions as a response to market entry in the context of the U.S. beer industry.

Over the last two decades, the U.S. beer industry has experienced unprecedented entry of craft brewers. By 2003 there were 1,485 craft manufacturers, a number that grew to 3,162 in 2013 and 9,709 in 2022.[1] For many years, this new craft beer movement was not seen as a direct threat by mass-producing brewers due to the extent of differentiation in beer styles and the marked differences in selling prices. Yet, changing consumer preferences, fueled mainly by generational shifts, have shown that the competitive pressure arising from the craft segment is not a limited, but rather an increasing one (Bronnenberg et al., 2022a). Both national and local market shares have steadily declined for the top domestic brewers, whereas the craft segment share has increased by about 10 percentage points from 2003 to 2021.[2] This change in market shares is especially striking since the total volume of beer sold has been relatively constant or even slightly falling (Beer Institute, 2021).

The mass-producing brewers have adopted a number of measures to stop, or even try to revert, the success of independent craft beers. Academic work and industry analyses have extensively documented and studied some measures including the acquisition of craft breweries, the creation of in-house craft brands, and the implementation of distribution incentive plans.[3]

Given the long-standing importance that advertising has had in the evolution of the U.S. beer industry, it is surprising that the literature has largely overlooked the role of advertising in the last decades, in particular the response in TV advertising efforts to the rise of craft

[1] Source: https://www.brewersassociation.org/statistics-and-data/national-beer-stats/

[2] This information was retrieved from the Brewers Association quarterly reports containing national beer sales and production data. I thank the Brewers Association for giving me access to various online resources.

[3] See for instance Elzinga and McGlothlin (2022), Fan and Yang (2022) and Codog (2019).

beer.[4] Considering the magnitude and recent accelerated growth of advertising expenditures among U.S. companies (Bronnenberg et al., 2022b), including the largest brewers, it is interesting to study the extent to which these mass-producing brewers responded in TV advertising to the entry of craft breweries.[5] This is the main objective of this paper. The analysis becomes even more relevant when taking into account the potential economic implications of such an advertising response, if any. For instance, advertising-driven preferences might change consumers' price sensitivity, facilitating the rise of market power.

The TV advertising response to craft entry and its implications on market power stand at the center of my analysis, which I develop in three steps using data on the U.S. beer industry for 2010-2016.[6] In the first step, I conduct a reduced form analysis to assess the effect of entry on advertising and to evaluate the effect of advertising on demand. More specifically, I use variation across U.S. states in the cumulative number of fixed cost-related beer regulations to identify the impact of local market entry on TV advertising. The main measure of advertising is Gross Rating Points (GRPs), a standard metric in the marketing literature capturing ad effectiveness. I then examine the potential implications of advertising on demand, and especially on price sensitivity, by exploiting spatial discontinuities in advertising along the borders of TV markets.

In the second step, I estimate a differentiated product demand model, where advertising not only shifts demand but can also change how consumers react to price changes. Instead of modeling the dynamic game involving advertising and market entry decisions, I consider an oligopoly setting and use static price first-order conditions, along with observed values of relevant state variables, to identify marginal costs and conduct counterfactual analyses.

In the third step, I compute the counterfactual profit incentives under alternative entry and advertising decisions to assess whether mass-producing brewers had the incentive to react in advertising in response to craft competition. I subsequently examine the advertising implications on market power by holding advertising fixed to various observed levels (e.g., pre-entry levels) and computing the corresponding price equilibrium.

[4]The work by Chandra and Weinberg (2018) is, to the best of my knowledge, the only one exploring this relationship. A big caveat of this work is that their analysis is only descriptive when it comes to the relationship between craft entry and advertising.

[5]I provide more details of the upward trend of advertising in Section 2.3.

[6]The focus of my research is on TV advertising and, due to data limitations, I abstract from the role of online advertising. Digital advertising is expected to become the main media channel in the coming years, but this transformation in the media industry occurs at a different pace across industries. While for some industries digital ad spending is rapidly outpacing TV advertising, for some others the ad spending crossover is still far. For instance, in 2016, the alcohol industry spent around 89% of the advertising budget on TV, devoting only 2% to digital advertising (Business Insider, 2016). More recent data from DCMS (2021) indicates that, despite the growth of digital advertising, it constitutes only 5% of all expenditures in drinks advertising.

The first set of results examines the effect of entry on advertising. I find that (lagged) entry of breweries increased advertising, and this effect is significantly larger for mass-producing domestic breweries than for their foreign counterparts. Overall, I estimate that the entry of 10 breweries increased GRPs in an average local market by 100 units. This is equivalent to exposing all potential viewers to one additional TV commercial in a given month. To put it in perspective, the observed entry of craft breweries across markets resulted, on average, in a 2.8% increase in advertising compared to the pre-entry advertising levels. These results are robust to using different advertising metrics, alternative lags of market entry, as well as exploiting different sources of exogenous variation (i.e., instrumental variables).

The second set of results analyzes the profit incentives to advertise. I find that for each of the mass-producing breweries, the incentives to advertise are higher under craft competition than in the absence of it. Moreover, by exploiting cross-market variation in profit incentives, I estimate a positive and significant correlation between incentives to advertise and the extent of craft competition. This suggests that mass-producing brewers increased local TV advertising the most in local markets with more craft entry. The intuition for this result is straightforward. Prior to the craft competition, the incumbent chooses advertising for each brand so as to compete against rival products. Yet, advertising competition is less intense as the incumbent may want to avoid excessive cannibalization between its own brands. When confronted with craft entry, the incumbent faces additional competitive pressure from rival products, making the cannibalization concerns less relevant. This additional pressure leads to an increase in advertising by the incumbent.

After providing evidence of the advertising reaction due to market entry, the third set of results examines the implications of advertising in terms of market power. Although the demand estimates indicate that the impact of advertising stock on demand expansion is quite limited, they also show that both own and rival advertising can significantly reduce price sensitivity. These results suggest that in mature industries, such as the beer market, advertising might not be very effective at expanding demand, but it can still shield firms from fierce price competition by affecting how consumers react to price changes. Breweries can leverage this and increase market power accordingly.

I use the estimated structural model to analyze the evolution of markups, defined as the price-marginal cost ratio. While the sales-weighted average markup remained relatively stable over the sample period, market power for heavily advertised beer brands exhibits an increased pattern. More specifically, the markups for flagship domestic brands increased from 2.6 in 2011 to 3.4 in 2016. Holding the observed advertising stock fixed at the pre-entry levels, I show that about 20% of this rise of market power can be attributed to the observed increase in advertising stock. This percentage constitutes an upper bound for the markup effects of the advertising reaction to craft entry.[7] Next, I show that the bulk of the upward trend in markups for the flagship domestic brands is due to declining marginal costs. Overall, the importance of my results lies in the fact that advertising can be used as a strategic response to market entry and such a response has implications in terms of market power.

Related Literature. The fact that advertising -seen as an endogenous sunk cost- can have significant effects on market structure and lead to concentration has been widely documented in the economic literature by Kaldor and Silverman (1948), Bain (1956), Comanor and Wilson (1967), Sutton (1991), Scott Morton (2000), Bronnenberg et al. (2009), Bagwell (2007), Doraszelski and Markovich (2007), Ellison and Ellison (2011), Park (2020), and Li (2023). In contrast, evidence of advertising as a strategic response to competition, in particular market entry, is scarce.[8]

There are few studies considering the impact of mergers and competition on advertising. Murry (2018) analyzes intra-brand dealer competition in the U.S. automobile industry and shows that more competition leads to lower advertising both downstream and upstream. Dubois and Majewska (2022) study the impact of mergers on promotional spending in pharmaceutical markets and find that advertising spending decreases after a merger. With respect to the beer market, Chandra and Weinberg (2018) examine how changes in local competition affect advertising decisions. Exploiting the 2008 Miller-Coors joint venture, they show that increased local concentration increases advertising per capita. In the same work, although in a descriptive fashion, Chandra and Weinberg (2018) find a negative correlation between the number of craft brewers and local advertising expenditures. My work complements their analysis in that I establish the causal effect of a change in market structure on advertising, both using reduced-form evidence and a structural model that allows me to understand profit incentives.

This paper also relates to the empirical literature centered around the impact of advertising on demand.[9] A strand of this literature has focused on understanding how advertising affects consumer choices by studying, in particular, the persuasive or informative role of advertising (Ackerberg, 2003; Sovinsky Goeree, 2008) and the existence of spillovers (Rojas and Peterson, 2008; Anderson et al., 2016; Shapiro, 2018). Within this literature, there is a

[7] Notice that, as I explained in detail in Section 2.2, I analyze the advertising response to the entry only into the retail market. I do not measure the extent of the reaction related to on-premise entry (e.g., brewpubs) as I do not have on-sales data. Thus, my results represent a lower bound of the true effect of market entry on advertising.

[8] Earlier empirical work includes Buxton et al. (1984) and Uri (1988).

[9] See Bagwell (2007) for a survey of past work on advertising.

series of papers assessing the effectiveness of advertising (Assmus et al., 1984; Lodish et al., 1995; Sethuraman et al., 2011; Henningsen et al., 2011). More recently, Shapiro et al. (2021) analyze the effectiveness of TV advertising among 288 top U.S. brands, finding a rather small, and insignificant, effect of advertising on demand. These results question the use of advertising and point to a sizeable misallocation of resources by companies. My analysis adds to this literature by showing that, indeed, TV advertising might not expand demand. Yet, my findings suggest that advertising can prevent price competition, and even lead to market power, by reducing how consumers respond to price changes.

My approach to studying the effects of entry on advertising builds on some of the aforementioned empirical work. Based on Shapiro (2018), I use the discontinuity in local advertising at the border of TV markets. As suggested by Li et al. (2019), I estimate a demand model with advertising using supply-side instruments for the identification of advertising effects. Like Dubois et al. (2018), I include advertising in a flexible way, allowing it to be cooperative or predatory and shifting the value that consumers place on different attributes. An important difference between my work and past empirical analyses is that I include and discuss a micro-founded model with persuasive advertising.

This paper also contributes to a growing economic literature on the rise and causes of market power (De Loecker et al., 2020; Autor et al., 2020). Using a structural model of demand with differentiated products together with an oligopoly setting, several papers have analyzed the evolution of markups. Grieco et al. (2023) find that markups of U.S. automobile manufacturers have declined over 1980-2018 due to an increase in competition and car quality. This result contrasts sharply with the findings in Döpper et al. (2023), where markups exhibit an upward trend from 2006 to 2019 for a wide range of product categories. They show that the markup increase can be explained by decreasing marginal costs and a secular decline in price sensitivity. My results for the beer industry are in line with Döpper et al. (2023). I complement this literature by showing that advertising can explain, to some extent, the changes in price sensitivity and the rise of market power.

Finally, my paper also relates to empirical work analyzing various aspects of the beer industry including price coordination (Miller and Weinberg, 2017; Miller et al., 2021), merger effects (Grieco et al., 2018; Fan and Yang, 2022; Azar and Barriola, 2022), consumer preferences (Bronnenberg et al., 2022a), exclusive dealing (Asker, 2016), market power (De Loecker and Scott, 2022), among others.

The remainder of the paper proceeds as follows. The next section presents the data and a series of industry facts related to market structure and advertising. Section 3 analyzes in a reduced-form fashion the effect of entry on advertising and its implications on demand. Section 4 introduces the structural empirical model, and Section 5 discusses identification, estimation and the results. Section 6 presents the results related to profit incentives and the implications of advertising on market power. Section 7 concludes.

2 Industry Background and Data

This section provides the background of the US beer industry for the period 2006-2016. In this overview, three facts are distinguished: changing market concentration, with the gradual decline of domestic companies and the take-off of the craft fringe (Section 2.1); the massive entry of craft breweries across the US (Section 2.2); and the increasing TV advertising driven primarily by macro breweries (Section 2.3). The interrelations among these facts are examined in Section 3. The data sources are briefly described in Section 2.4.

2.1 Market Shares and Concentration

The US brewing industry has been traditionally deemed as one with very high levels of national concentration. The predominant market structure, with few large firms and high market shares, is the result of a series of successive, somewhat overlapping, events: i) the preemptive marketing race that took place after the rapid diffusion of network television throughout the 1950s; ii) the technological progress in packaging, brewing and automated brewhouses; iii) the successful introduction of heavily-advertised light beer in the early 1970s; and iv) a myriad of (global and local) mergers and acquisitions. By the end of the 20th century, over 80% of the US beer market was dominated by five large breweries: Anheuser-Busch, SAB Miller, Molson Coors, Heineken and Grupo Modelo.

This market structure has been challenged over the last two decades. Figure 1 shows the evolution of the US market shares by breweries over the 2006-2016 period. Three patterns stand out. First, despite the mergers of multinational breweries, the market shares of the largest domestic breweries have been steadily declining.[10] Relative to the market in mid-2008, the market shares of ABI and Millercoors are about 5 percentage points lower in 2016.

The second pattern is the rise in popularity of imported beers which has threatened the dominance of established national brands and has reshuffled market shares at the top of the industry. In the last decade, the Mexican lager-style brand Modelo Especial, owned by Constellation Brands, has been constantly outperforming the US beer industry so much so

[10]The joint venture between Molson Coors Brewing and SABMiller PLC in 2008 increased the national Herfindahl-Hirschman Index (HHI) by 27%, from 1,853 in 2007 to 2,350 in 2009 (Miller & Weinberg, 2007). The AB InBev-Grupo Modelo acquisition in 2013 and AB InBev-SABMiller PLC merger in 2016 would have also changed substantially the industry concentration, had the competition authority not required numerous divestiture packages.

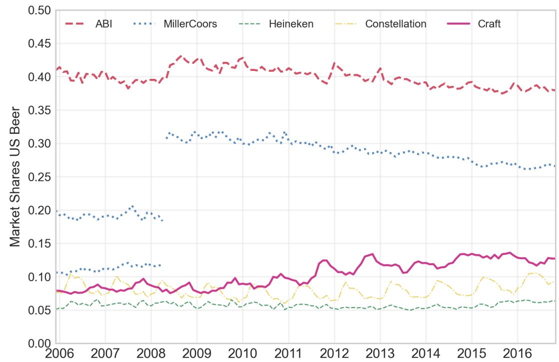


Figure 1: US Market Shares

that it is second only to Bud Light in sales nationwide in 2022.[11]

The third pattern shows that the market share of the craft fringe has taken off, especially after 2010. By the end of 2016, the market share of the craft beer segment is about 13% and, according to Bronnenberg et al. (2022a), it is expected to reach 27.8% by 2030. An important observation is that the period of changing market structure came about while the industry as a whole remained relatively stable. Since 2010, beer manufacturers have sold annually on average 260 million 144-ounce equivalent units in the retail market (see Figure B1). Put differently, the change in market shares seems to be related to substitution between brands rather than expansion or contraction of the market.

The analysis of the change in local market concentration reveals similar patterns to the dynamics of the national market shares: Local concentration has decreased consistently since mid-2008. Figure 2 displays the distribution of the change in concentration for geographic areas defined by Designated Market Areas (DMA).[12]

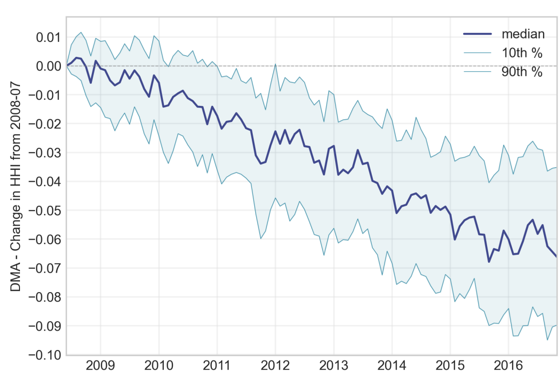


Figure 2: Local concentration trend

[11] Forbes (2022). Retrieved from https://www.forbes.com on September 22th 2022.

[12] Designated Market Areas are geographies set by Nielsen to define media markets.

The median market shows a reduction of concentration by 0.065 over the sample period. Interestingly, the decline in concentration exhibits substantial (increasing) dispersion across local markets. For the 90th percentile, market concentration has fallen by about 0.035. The decrease is more pronounced for the bottom 10th percentile where concentration has declined by 0.09. This downward trend in local concentration is in line with recent evidence showing that average local market concentration has been falling across US industries in the last decades (Rossi-Hansberg et al., 2021). Yet, the underlying mechanism behind falling market concentration is not the expansion into local markets by large breweries, but the increasing local competitive pressure.

2.2 Entry of Craft Breweries

The 2010s witnessed an unprecedented entry of craft breweries.[13] Lower barriers to entry together with demand-side factors fueled the proliferation of new breweries. Figure 3, Panel A plots the number of craft breweries over time. The dashed line represents all types of craft breweries, including brewpubs, microbreweries, and regional breweries. At the beginning of the sample period, the number of craft breweries experienced a slight increase, rising from 1,409 in 2006 to 1,758 in 2010. Since 2011, however, there has been a steep increase, reaching 5,622 operating craft breweries in 2016.

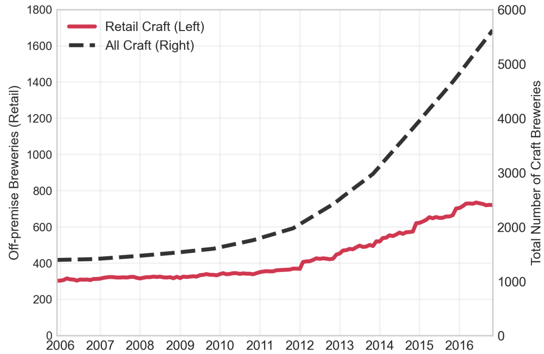
Over 75% of the beer sales (by volume) take place off-premises.[14] In Figure 3, Panel A, the solid line depicts the changing number of breweries in the retail market. While the retail pattern is similar to that of the overall sector, the level is substantially lower. In 2016, just over 700 breweries were competing at retail stores. The bulk of entry into the retail market is largely due to microbreweries.[15]

The surge of craft breweries in the retail market is heterogeneous across locations (Figure 3, Panel B). While few states show limited variation in the number of breweries between 2010 and 2016, the majority experienced a sizeable increase in the presence of competing breweries. The rise in the number of breweries seems to be positively correlated with sales. In California, for instance, the number of breweries in the retail market in 2016 is twice as high as that in 2010. The change in market structure in low- and mid-sales states is less

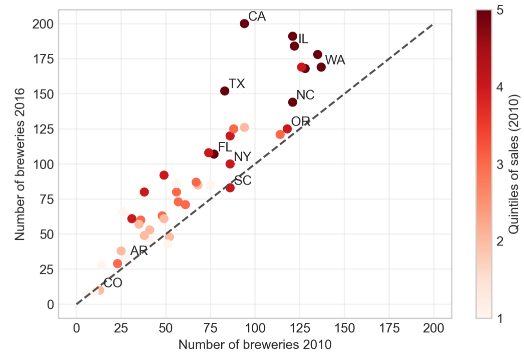
[13] The craft beer movement dates back to the late 1970s. Several factors have contributed to the start and piece-meal growth of the craft segment (e.g. the legalization of home brewing, the legalization of commercial sales in brewpubs, reduced excise taxes, the formation of brewers guilds and associations, among others). See Garavaglia and Swinnen (2017) and Elzinga et al. (2015) for further insights into the history of the US craft beer revolution.

[14] Beverage Information Group. (September 30, 2022). Off-premise beer case sales in the United States from 2006 to 2021** (in 1000 2.25 gallon cases). In Statista. Retrieved July 07, 2023.

[15] See Figures (B2) and (B3) in the appendix for additional details regarding the number of breweries and brands in the retail market over time.



Panel A: US Breweries



Panel B: Retail Breweries by State

Figure 3: Evolution of Breweries

pronounced but still evident.

2.3 Strategic Response to the Increasing Craft Fringe

How did the largest breweries handle the rise of craft brewing? The incumbents' response to the entry of craft breweries has been many-fold, namely: (i) the organic introduction of in-house craft brands; (ii) the acquisition of independent craft breweries; (iii) the implementation of wholesaler incentive plans to hinder craft beer distribution; and (iv) the increasing advertising efforts. The analysis of each of these strategic responses (or the joint response) is interesting in itself but lies beyond the scope of this work.[16] However, some of these strategies did not prove successful or had a limited duration, which suggests that their impact might be of second order in this setting. Given the importance of television advertising in the beer industry, the focus of this paper is on the television advertising response of large breweries to the massive entry of craft breweries.

Figure 4 depicts trends in television advertising, as measured by the brand-level average number of TV occurrences. Two trends emerge: First, there is a strong and persistent increase in ad occurrences, particularly after 2011, for both domestic and imported brands. Note that the difference between these two groups remains relatively equal over the sample period. Second, the average number of ad occurrences for craft brands is flat or only slightly increasing. Given the surge in craft breweries, this pattern suggests that craft brands rely very little on TV advertising and might employ other marketing practices.[17]

Apart from the changes over time, there is substantial variation in advertising across

[16]The acquisition of craft breweries and its effects on different economic outcomes has been the focus of recent work. See, for example, Fan and Yang (2022) and Elzinga and McGlothlin (2022).

[17]The evolution of TV advertising is similar when using other metrics such as Gross Rating Points. See Figure (B4) in the appendix.

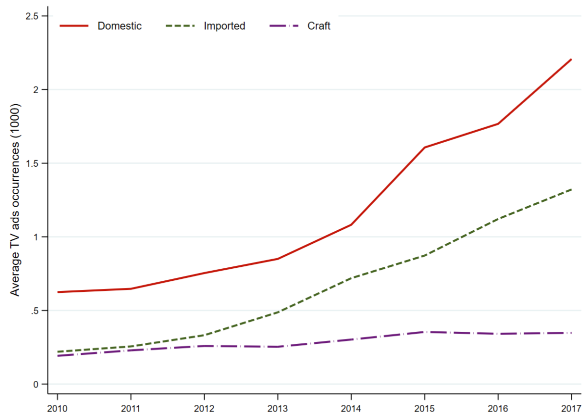


Figure 4: TV Ads Occurrences

TV markets. Figure (B7) in the appendix provides a map that shows the local GRPs for a particular flagship brand in 2016. The objective is to use the large variation in local advertising to see whether it is related to the variation in the number of breweries across TV markets.

Despite the growth of digital media, TV advertising is still an important channel to promote beer brands and reach different parts of the population. In the appendix, Figures (B5) and (B6) show the evolution of gross rating points (GRPs), a measure of advertising exposure, by bins of audience age. The evidence shows a clear relationship between GRP and age. Younger viewers are less exposed to TV advertising than older viewers. This difference has become more marked over time mainly due to the increasing exposure of older audiences.

2.4 Data

This paper uses data from two primary sources. To capture prices and quantities, I use scanner-level data provided by Nielsen. For advertising, I use the Nielsen Ad Intel data with information on various advertising metrics for the period 2010-2016. These data sources are supplemented by several additional datasets involving brand ownership, demographics, state laws, among others. Summary statistics for the main datasets are provided in Appendix A.

Retail sales data The first primary source is the Nielsen Retail Scanner (RMS) data provided by the Kilts Center at the University of Chicago. The scanner data record weekly transactions of all beer products across a sample of retail stores in the US. Every transaction identifies products at Universal Product Code (UPC) level and contains information on unit sales, revenue, and product attributes (package size, ounces per unit, and brand name).

I restrict attention to the set of conventional stores that appear every year during 2006-

2016.[18] Note that I only have access to (a sample of) retail information and do not cover on-premise sales. Hence, the analysis focuses only on retail competition, defining entry as instances of breweries entering the retail market.

Beer products exhibit multiple package sizes.[19] To adjust for differences in package size, I measure quantity in 144-ounce equivalent units. The average price is then computed as the ratio of revenue to equivalent unit sales.

To ease the computational burden, I aggregate the data at the brand-market-year-month level.[20] A market is defined by the Designated Market Area (DMA) which is an exclusive geographic area used by Nielsen Corporation for gauging media consumption. I restrict attention to 90 beer brands, comprising 30 popular brands and 60 aggregated single-brand breweries.[21]

Advertising data The second primary source is Nielsen Ad Intel Data spanning 2010-2016. The advertising data includes brand-level ad occurrences, expenditures, and impressions of different media channels in the US.[22] The data show the date, time, and duration of each occurrence. I measure occurrences and ad prices in 30-second-spot equivalent. I focus on television media which includes Cable, Network, Syndicated, and Spot. The TV advertisements might be aired and viewed at national (Cable ads) or local level (Spot ads). In the case of Syndicated and Network media, the ads are purchased at a national level but broadcast on local TV stations.[23] Thus, variation in TV advertising exposure across TV markets arises from both variation in the number of ads aired and variation in impressions across markets.

[18] Conventional stores are those labeled as "Food Stores" within the Nielsen RMS dataset.

[19] For this analysis, I focus on the most popular package sizes, namely: 6, 12, 18, 24, and 30 packs. In addition, I restrict the sample to container types (e.g. cans or bottles) containing between 11 and 22 ounces per unit.

[20] This data description primarily corresponds to the dataset employed for the structural model analysis. For the descriptive analysis used in the industry background and for the reduced form evidence, I employ the data at different levels of granularity according to the respective analysis. For instance, in Section 3.2, I use the borders of the DMAs as the relevant markets.

[21] The popular brands are (1) Blue Moon Belgian White Ale; (2) Bud Light; (3) Budweiser; (4) Busch; (5) Busch Light; (6) Coors Banquet; (7) Coors Light; (8) Corona Extra; (9) Corona Light; (10) Dos Equis Amber Lager; (11) Dos Equis Especial Lager; (12) Heineken; (13) Heineken Light; (14) Keystone Light; (15) Michelob Ultra Light; (16) Miller Genuine Draft; (17) Miller High Life; (18) Miller Lite; (19) Modelo Especial; (20) Natural Light; (21) New Belgium Fat Tire Amber Ale; (22) Pabst Blue Ribbon; (23) Pacifico; (24) Samuel Adams Boston Lager; (25) Shock Top Wheat Belgian Ale; (26) Sierra Nevada Pale Ale; (27) Stella Artois; (28) Tecate; (29) Tecate Light; (30) Yuengling Amber Lager. There are a couple of aggregated fringes representing different types of breweries. For instance, there is one "brand" for microbreweries, one for small regional breweries, and another for imported breweries.

[22] Advertisements with zero duration or ad price are excluded from the analysis.

[23] Nielsen reports both national and local occurrences for Network TV and Syndicated TV. They represent the same occurrence. The main difference is that the national reports contain information on the cost of the ad.

The construction of the advertising data follows closely the procedure proposed by Shapiro et al. (2021). There are two issues that merit attention. First, the ad impressions provide an estimate of the number of households that were exposed to each occurrence. Nielsen populates this variable every month for the top 25 DMAs using set-top box recording devices. In contrast, the impressions for all other markets are reported only during sweeps months (February, May, July, and November). Following Shapiro, Hitsch and Tuchman (2021), I impute the impressions for the non-top 25 DMAs for all other months using a weighted average of the impressions in the two nearest sweeps months. Using the resulting impressions variable, I compute the gross rating points (GRPs) variable which is defined as the number of impressions divided by the potential number of TV-viewing households within a given DMA.[24] Second, the nationwide purchase of a Network (Syndicated) TV ad must coincide with the local realization. This is not always the case as TV ads that were scheduled to be broadcast simultaneously across the US might not be aired (or recorded) in some local markets. This mismatch might lead to local measurement error. To the extent that this discrepancy is due to a local displacement of the ad to a different time slot, the aggregation of the advertising data to the month level (see below) sorts out this issue. The mismatch might also arise from a local recording device failure. Any resulting measurement error, if any, is assumed to be exogenous.

To match the granularity of the sales data, for each beer brand, I aggregate the advertising data from the occurrence-media-market-date-time level to the market-month level. To do so, I calculate the sum of all occurrences, impressions and GRPs for a brand in a given month in the DMA. I merge the sales and advertising data at the market-brand-month level using the Ad Intel and RMS brand names which are quite consistent for the most popular beer brands. For the less popular brands, I assume that all advertising metrics are equal to zero.[25]

Additional data I supplement the main data sources with various datasets. The details are given in Appendix A. First, I augment the retail scanner data with hand-collected data on the identities of breweries and corporate owners as well as the location of the brewery for all beer products. Using the location of the production facility, I compute the distance between the market and the nearest brewery. Second, I obtain the distribution of consumer demographics by sampling households from the annual Public Use Microdata Sample (PUMS) of the American Community Survey. Third, I gather data on beer state laws from the publication of the magazine "The New Brewer - The Journal of the Brewers Association".[26] Fourth,

[24]The GRP is a metric measuring advertising intensity and is scaled between o and 100

[25]Even the majority of popular brands show little or no TV advertising over time. Hence, it is reasonable to assume that advertising for less popular brands is null.

[26]I thank the Brewers Association for giving me access to various online resources, including the bi-monthly publication of the magazine and data on the craft beer sector.

I collect data on global input prices (e.g., barley) as a measure of cost shock. Fifth, I obtain diesel fuel prices from the U.S. Energy Information Administration of the US Department of Energy. Finally, excise taxes on beer are obtained from the Tax Policy Center.[27]

3 Reduced Form Evidence

This section provides evidence of advertising responses to market entry and the impact of advertising on demand. First, I investigate the degree to which the entry of craft breweries into the retail market prompts large incumbents to change advertising decisions (section 3.1). Second, I quantify the impact of (own and rival) advertising on demand, emphasizing the effect on price elasticity (section 3.2).

3.1 The Advertising Response to Craft Entry

The traditional flagship beers are in the midst of a long steady sales decline, fueled by the increasing rise of craft breweries. Anecdotal evidence strongly suggests that flagship brands have devoted substantial marketing efforts to downplay the role of craft beers and stop (or even revert) the declining sales. Consider, for example, the Budweiser 2015 SuperBowl Ad "Brewed the Hard Way". In this TV commercial, AB Inbev portrays a certain craft-drinker demographic (e.g., millennials with an avid interest in taste) as pretentious, while casting Budweiser as the real beer for everyday American people.[28] The purpose of anti-craft TV ads was primarily to increase product differentiation and retain the appeal of flagship brands among the traditional customer base. Next, I turn to more systematic empirical evidence.

Specification Let d index DMAs and t index time periods (year and month combinations). I model the outcome of interest a_{dt} as the TV advertising metric which can be the number of ad occurrences or the measure of advertising intensity (gross rating points). The key independent variable of interest is n_{dt} which denotes the number of breweries competing in the retail market in DMA d at time period t. To quantify the effects of the number of breweries on advertising, I estimate the following regression:

$$a_{dt} \; = \; \rho_d + \beta n_{d(t-12)} + \gamma_t^1 + \gamma_{dm}^2 + \boldsymbol{\delta}\boldsymbol{x}_{dt} + \varepsilon_{dt}, \tag{1}$$

where ρ_d is a DMA effect, γ_t^1 is a time effect, γ_{dm}^2 is a DMA-month effect, $\boldsymbol{x}_{dt}$ is a vector of observable characteristics, $\boldsymbol{\delta}$ is a vector of parameters, and ε_{dt} is a DMA-time shock.

[27] Retrieved from https://www.taxpolicycenter.org/statistics/state-alcohol-excise-tax-rates

[28] Another example is the 2017 Bud Light TV commercial "Complex" in which AB Inbev mocks the number of different ingredients that craft beer may have while drawing attention to the simplicity of Bud Light.

Note that, for the baseline specification, the advertising response to entry is not immediate but occurs with a 12-month delay.[29] This assumption is in line with the institutions of the market for TV advertising. Most TV ads are purchased well in advance in an upfront market (80%), while the remaining advertising inventory is divided between bulk purchases by ad agencies and last-minute scatter market purchases.[30]

The vector of controls $\boldsymbol{x}_{dt}$ includes demographics related to income, the share of the DMA population that is millennial, the share of the population that is Hispanic, and the number of brewers' permits (proxy for number of brewers manufacturers).[31] The set of fixed effects controls for systematic differences in demand across local markets (ρ_d), general changes over time (γ_t^1), and market-specific seasonal factors (γ_{dm}^2).

Identification The parameter β in equation (1) captures the effect of $n_{d(t-12)}$ on a_{dt}. The OLS estimate of β is likely to be biased due to two reasons. First, the variable $n_{d(t-12)}$ denotes a sample of the number of breweries competing in the retail market (off-premise), disregarding on-premise competitors (e.g., taprooms or restaurants).[32] This source of measurement errors might lead to attenuation bias provided the on-premise competition matters for advertising decisions. Second, the main explanatory variable $n_{d(t-12)}$ may still be correlated with unobserved DMA-level variables that also affect advertising decisions. The entry of breweries is associated with certain demographic characteristics, such as age or income, that influence also advertising decisions. For instance, DMAs with a large share of millennial and high-income households might be appealing to the craft beer market and induce entry of new breweries. At the same time, these demographic groups spend less time watching traditional TV than older generations, reducing the incentives to advertise.[33] Any unobservable demographic characteristic (or shock) may confound the interpretation of the OLS estimates. Despite the inclusion of a full set of DMA- and time-fixed effects, these two endogeneity concerns (measurement error and unobservable demand shocks) exert a downward

[29] As a robustness check (Appendix C), I estimate the model using different time lags.

[30] For more information on the institutional details of the TV advertising market, see Hristakeva and Mortimer (2023) and Shapiro et al. (2021).

[31] The number of active brewers permits in the US is different from the number of breweries as some permitted brewers do not own physical breweries. This information comes from the Alcohol and Tobacco Tax and Trade Bureau (TTB).

[32] The scanner data is provided from a partnership between Nielsen and the Kilts Center for Marketing at the Chicago Booth School of Business. Nielsen has information on the universe of retail stores in the U.S. However, not every retail store has agreed to share the scanner data with the Kilts Center. Hence, I only have access to the sample of retail stores available for research purposes at the Kilts Center.

[33] According to Gentzkow et al. (2022), the increasing share of a less active group of TV viewers (e.g., millennials) commands a larger price premium to reach this group. This result, all else equal, must reduce advertising activity. The information on viewers' habits by groups of consumers was retrieved from `https://www.forbes.com/sites/tonifitzgerald/2018/11/28/wow-millennials-watch-more-online-video-than-traditional-television/?sh=df367c84138b`.

bias in the estimate of the effect of breweries on advertising.

To address the endogeneity issues, it is critical to understand the forces driving advertising decisions and the entry of craft breweries into the retail market. On the one hand, the advertiser's problem is such that the firm chooses the optimal advertising based on product-specific variables (attributes, prices, and marginal cost), determinants of advertising exposure (e.g., geographic characteristics and demographics), demand shocks, and the price of advertising.[34] On the other hand, entry decisions are based on (a subset of) the same profit determinants as in the advertising problem, the potential market size, and fixed costs variables. Since the determinants of fixed costs are relevant to the entry decisions but do not directly impact advertising, they serve as natural exclusion restrictions to identify the effect of entry on advertising.

I take advantage of the state-level legislation of the beer industry and use changes in local laws related to fixed costs as instrumental variables. The rationale behind the instruments is that once these laws become effective, they change the fixed costs that breweries must incur to enter the retail market. In practice, I use the cumulative number of statutory provisions concerning contracting brewing, wholesaler franchising, and self-distribution.[35] First, contracting brewing is an arrangement in which a brewery outsources the production and packaging to another brewery. In doing so, the contracting brewery starts producing without the overhead required to setting up a full-scale brewery (e.g., purchasing and maintenance of equipment). Second, wholesaler franchising refers to all legal provisions governing brewer-wholesaler relations. These laws aim at balancing the bargaining power between both parties by setting conditions primarily related to termination conditions, exclusive sales territories and wholesaler obligations. These laws could change the fixed cost associated with entry to retail markets through third parties. For instance, in the state of New York, small brewers can terminate a franchising agreement without good cause, increasing their bargaining power during negotiations with wholesalers.[36] Finally, the self-distribution provisions set the rights and production caps under which breweries can self-distribute beer, avoiding the costs concerning franchising agreements.[37]

[34]This brief characterization of the advertiser's problem is based on the work by Gordon and Hartmann (2016) and Li et al. (2019).

[35]To be consistent with the timing of entry, I use the lag of the cumulative number of statutory provisions. See Appendix A for details of the construction of the data.

[36]Retrieved from the Beer Franchise Law Summary available on https://www.brewersassociation.org/wp-content/uploads/2015/06/Beer-Franchise-Law-Summary.pdf.

[37]A concern with the identification strategy is the potential correlation of the changes in statutory provisions with unobserved demand shocks. Lobbying practices by the macro brewers, for instance, could delay the approval of local laws and be related to the unobserved characteristics of the constituents. The timing and the institutions of the legislative process deal with this concern and limit the bias, if any. The approval of a bill can take over a year after the idea was developed, drafted and introduced. This means that the (lag

Results Table (1) shows the estimates of regression (1). Columns (1) and (2) show the extent to which OLS estimates exhibit a downward bias and how this issue is addressed by using the above-mentioned instrumental variables. The weak IV statistic on the excluded instruments and the Hansen J test indicate that the instruments are not weak and there are no overidentification concerns.[38] The findings reveal that the entry of breweries leads to a positive and statistically significant increase in advertising intensity. The point estimates indicate that the entry of 10 breweries results in an increase in the monthly GRP of around 100 units. This is equivalent to exposing all potential viewers within a DMA to one additional TV commercial.[39]

Table 1: The Effect of Breweries Entry on Advertising (Gross Rating Points)

	All		Breweries		
	(1) OLS	(2) IV	(3) Domestic	(4) Imported	(5) Regional
Breweries_{t-12}	2.827	10.001	7.931	3.243	-0.301
	(0.469)	(2.497)	(2.036)	(0.689)	(0.625)
Weak IV		111.84	111.84	111.84	111.84
J-stat (pval)		0.12	0.79	0.08	0.00

Notes: The unit of observation is the DMA-year-month combination. The sample consists of 172 DMAs and 72 month-year periods for a total of 12384 observations. All specifications include DMA, DMAxMonth and YearxMonth fixed effects. The dependent variable is the gross rating points (GRPs). The parameters are estimated using two-step feasible GMM. The IV is the cumulative sum of statutory provisions related to contracting and franchising (see text for more information). All specifications include control variables for demographics and the number of TTB permits. The weak IV test corresponds to the Kleibergen-Paap F-statistic and the p-value of the J-stat is the p-value of the Hansen tests for over-identifying restrictions. Robust standard errors are in parentheses.

The advertising response to craft entry is heterogeneous across breweries. Columns (3)-(5) show the estimates for three groups of breweries: domestic, imported and regional breweries. The results suggest that the large domestic breweries are the ones with the strongest reaction. The imported breweries also increase advertising but the magnitude is less than half of the one estimated for the domestic breweries. Not surprisingly given the low engagement in TV advertising, there is no reaction by the regional craft breweries.

The results suggest a negative relationship between concentration and advertising. This is in line with the work by Dubois and Majewska (2022) on mergers in the pharmaceutical

of) changes in legal provisions and lobbying practices depend on past unobserved shocks ($\varepsilon_{d(t-s)}$, $s >= 24$) which are unlikely to be correlated with current ones. Any legal or lobbying decisions based on systematic (long-term) demand unobservables are controlled using fixed effects.

[38] Specifically, the P-value associated with the Hansen J-test indicates the no rejection of the null hypothesis that the overidentifying restrictions are valid. The first stage estimates are reported in Appendix C, table C6.

[39] Recall that Gross Rating Point is computed as exposures per capita times 100.

industry and in contrast with the analysis by Chandra and Weinberg (2018) on mergers and craft entry in the US beer industry.[40] Intuitively, suppose that there is a share of consumers of traditional beer (domestic and imported) who might consider switching to a (high-price) craft entrant due to its taste, independence from large companies, and/or local identity. The fact that they are willing to switch to more expensive products implies low price sensitivity and hence limited room for price competition. The large breweries can then resort to advertising to prevent losing sales to craft entrants. As a robustness check in Appendix C, I have also estimated specifications with another advertising variable, alternative lags of entry, and different combinations of instruments. These specifications generate estimates similar to the ones discussed in this section.

3.2 Advertising Effects on Demand

To quantify the effects of advertising on demand, I rely on the quasi-random variation in advertising arising along the borders of television markets (DMAs) in the US. The intuition behind this design is that similar households residing on either side of the border face different levels of advertising exposure due to factors specific to non-border areas. This spatial strategy is similar to Card and Krueger (1994) and has been used to study the effectiveness of TV advertising (Shapiro et al., 2021), issues in the pharmaceutical market (Shapiro, 2022, 2018), political advertising (Spenkuch and Toniatti, 2018), and the e-cigarette market (Tuchman, 2019). In addition, I show that advertising not only has a direct effect on demand expansion but also changes price sensitivity. This latter effect can have relevant implications in terms of elasticities and market power.

The spatial strategy requires the use of areas that lie on the borders between DMAs. For this preliminary analysis, I constructed a sample of areas located along the borders using the county-border mapping provided by Shapiro et al. (2021).[41] The resulting unit of observation is the product-border-DMA-time combination. Empirically, the idea is to use various (multiplicative) fixed effects to isolate each border experiment, and then compare a market (or products thereof) on one side of the DMA border with its adjacent counterpart.

Specification Let j index products, m index TV markets (i.e., DMA), b index borders, and t index time periods. The demand model for product j in market m at border b in time

[40] Chandra and Weinberg (2018) show that changes in market structure - related to the entry of breweries- are negatively correlated with local advertising expenditures by macro breweries. This finding is, however, descriptive as they do not address the endogeneity concerns which, as discussed in the text, might lead to downward biased OLS estimates.

[41] Specifically, I constructed a sample of counties located at the borders of the TV markets and aggregated them up. The aggregation is not relevant as all the counties belonging to the same border area are exposed to the same level of advertising. For further information about the data construction and border selection, see the supplementary material of Shapiro et al. (2021).

t is the following:

$$\begin{aligned}\log(Q_{jmbt}) \; &= \boldsymbol{\beta}^T \boldsymbol{A}_{jmt} + \boldsymbol{\alpha}^T \log(\boldsymbol{p}_{jmbt}) + \boldsymbol{\varrho}^T [\log(p^{own}_{jmbt}) \boldsymbol{A}_{jmt}] \\ &+ \gamma_{jbt} + \gamma_{jbm} + \epsilon_{jmbt}, \end{aligned} \tag{2}$$

where $\boldsymbol{p}_{jmbt}$ is a vector of own and competitor prices, $\boldsymbol{A}_{jmt}$ is a vector of own and competitor advertising stock, γ_{jbt} is a product-border-time fixed effect, γ_{jmb} is a product-border-market fixed effect, and ϵ_{jmbt} is an unobserved demand shock.[42] This estimation provides insights into the existence of advertising spillovers, the effect of advertising stock on demand expansion, and how advertising might change price sensitivity. When the coefficient associated with the interaction between price and advertising is zero, the model collapses to the constant elasticity model.

The vector of advertising stock captures dynamic advertising effects, including the carryover effect. Specifically, I define the advertising stock as the lag of a nonlinear function of current advertising:

$$\boldsymbol{A}_{jmt} \;=\; \sum_{\tau=t-L}^{t} \delta^{t-\tau} \log(1 + \mathfrak{a}_{jmt}),$$

where δ is the carryover parameter, $\mathfrak{a}_{jmt}$ (also a vector) is the flow of own and competitor advertising, and L is the number of lags in which advertising has an effect on current demand. For the purposes of estimation, I set $\delta = 0.8$ and $L = 12$ which implies that advertising has a persistent effect over one year.[43]

The equation (2) allows advertising to have a direct effect on price elasticities. For product j, the own price elasticity is given by[44]

$$\frac{\partial Q_j}{\partial p_j} \frac{p_j}{Q_j} \;=\; \alpha + \boldsymbol{\varrho}^T \boldsymbol{A}_j.$$

Given that the direct effect of price on demand is negative ($\alpha < 0$), the effect of advertising stock on price elasticity will depend on the relative signs and magnitudes of the coefficients of the interactions between price and (own and competitor) advertising. For example, if $\boldsymbol{\varrho} > 0$, consumer responsiveness to price changes decreases with advertising stock.

Identification Advertising is an endogenous decision as it can be targeted based on un-

[42]For the competitor prices, I include the sales-weighted average price within the same border-DMA area. As for competitor advertising, I use the sum of advertising across competitors within the same border-DMA and segment (i.e., flagship domestic, flagship imported, and non-flagship brands). The idea is that advertising spillovers affect brands with similar characteristics.

[43]In the empirical application, I used different functional forms for the advertising stock and experimented with various carry-over rates. The results are qualitatively similar.

[44]For simplicity, I focus only on one component of $\boldsymbol{p}_{jmbt}$ and drop the indices of border, DMA and time.

observed demand factors. To identify the causal effect of advertising on demand, I implement the modified difference-in-differences estimator proposed by Shapiro (2018). Specifically, I include various fixed effects in equation (2). First, γ_{jbt} captures border-specific seasonal patterns and allows for within-border spatial heterogeneity. This fixed effect allows to analyze separately each border and focus on the spatial variation arising between contiguos DMAs. Second, γ_{jmb} controls for time-invariant unobserved heterogeneity across markets. This multiplicative fixed effect captures systematic differences in demand on either side of the DMA border.

The identifying assumption is that along the border of two DMAs, any differential trends in demand between the two sides of the DMA border are primarily caused by differences in advertising. In turn, conditional on the set of fixed effects, advertising is exogenous when evaluated at the DMA border. The idea is that border areas are exposed to more (or less) advertising than they would because the DMA advertising decisions are driven mainly by the audience living in densely populated non-border areas. If firms could target ads at a more granular level, in equilibrium, they would choose different advertising levels for border and non-border areas. In this hypothetical case, one could expect to see similar advertising exposure across the borders of a DMA, which is not what is observed in reality.[45]

The border strategy helps to address the identification of advertising effects but might not completely deal with the potential identification issues related to prices. The reason is that, unlike advertising, firms can set prices based on local unobserved demand shocks, leading to endogeneity concerns. In addition, in the empirical application I use quarters as the time period in equation (2). Since the dataset is at the month-level, there is still price variation within quarters that could show some correlation between unobserved local shocks and prices. To account for endogeneity of prices, I use instrumental variables related to

[45]There are various scenarios under which this identification strategy might fail. First, the relevance of the estimated effect can be undermined if the findings cannot be generalized to the population living in non-border areas. The existing literature provides evidence suggesting that border counties resemble typical non-border county in terms observable characteristics at the county-level, and that estimating advertising effects using the border areas tend to yield results consistent with those from the entire population (Shapiro, 2022). Second, the identification strategy relies on local variation in advertising as opposed to national variation. According to the institutional features of the TV advertising market, local variation is the remnant of the upfront market and might exhibit limited variation. Figure (D1) in the appendix shows a histogram of advertising net of the fixed effects. The distribution of the remaining variation in advertising has a mean of zero and a standard deviation of 0.82 which implies substantial variation for identification. Third, it might be the case that the border areas are the ones influencing advertising decisions within the DMA (e.g., they represent a large drinking population). In this case, advertising decisions represent some local preferences and are not exogenous. Fourth, another potential issues is that consumers might be exposed to advertising on one side of the border but choose to make their beer purchases on the other side. Existing empirical work suggests that this scenario is unlikely. For instance, Tuchman (2019) shows that a very small fraction (3%) of the (e-)cigarette transactions were made outside the Nielsen panelist household's DMA. This type of measurement error, if any, would attenuate the estimated effect towards zero.

cost shifters. In particular, I use Hausman-type instruments and the interactions between product ownership variables and a proxy for distribution costs.

For the Hausman instrument, I use the sales-weighted average of prices of the same product in different geographic markets. This variable can serve as a proxy of costs as long as the demand shocks are not correlated across markets. The common source of such cross-market correlation is national advertising campaigns which I explicitly control for in the empirical analysis. As for the second source of exogenous variation, I interact the distance to the nearest brewery (a proxy for shipping costs) with indicator variables representing the owner of the products.[46] Conditional on the fixed effects, the distance variable exhibits no variation whereas the ownership variable can change due to various factors such as acquisitions, mergers, divestitures, and changes in production rights. The logic behind this instrument is that ownership changes might lead to changes in distribution cost (e.g., the use of a broad distribution network). These cost changes, in turn, can be different depending on the owner.

Results Table (2) shows the estimation results for the demand model. Column (1) shows the estimates of the specification accounting for advertising endogeneity (through fixed effects) but without addressing price endogeneity. The price coefficient is significant and negative but the magnitude is small. The own ads effect is positive and significant yet its magnitude is smaller compared to that of rival advertising. As discussed below, the specification with interaction terms exhibits heterogeneity in advertising effects across brands which shifts the relative magnitude between own and rival effects. With the interaction terms, the rival advertising effect is no longer greater than the own effect and can even take on negative values.[47]

Column (2) shows the estimates when using instruments for the endogenous price variable. As expected, the price coefficient increases in absolute value from -1.91 to -5.14 and the rival price coefficient becomes significant and positive.

Columns (3)-(5) incorporate the interaction terms of price and advertising variables and include observed heterogeneity related to the valuation of price. The sign of the heterogeneity parameter implies that high-income consumers have a low price sensitivity. As for the interaction of price and advertising, the results suggest that own and rival advertising have the potential to decrease the reaction of consumers to price changes. The effect on price sensitivity of own advertising is 54% greater than the effect of rival advertising.

[46]Specifically, I use the interaction of distance with indicator variables for beer produced by ABI, Heineken and Constellation Brands.

[47]Recall that rival advertising stock is the total advertising within a given market segment, rather than the advertising of selected competitors (e.g., only top rival) which is the standard measure used in the literature. The underlying assumption is that advertising spillovers arise from the exposure to all beer advertising in the market. Alternative specifications include different variables of rival advertising (e.g., top competitor). The estimation results, as expected, show that own advertising effect is greater than the spillover effect.

Table 2: The Effect of Advertising on Demand

	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV
log(price)	-1.919	-5.146	-5.519	-5.536	-8.021
	(0.043)	(0.221)	(0.236)	(0.237)	(0.635)
log(price) × GRP Stock$_{own}$			0.093	0.093	0.105
			(0.009)	(0.009)	(0.010)
log(price) × Income				0.044	0.050
				(0.027)	(0.028)
log(price) × GRP Stock$_{rival}$					0.069
					(0.016)
GRP Stock$_{rival}$	0.032	0.032	0.031	0.031	-0.158
	(0.001)	(0.001)	(0.001)	(0.001)	(0.044)
GRP Stock$_{own}$	0.010	0.009	-0.212	-0.212	-0.239
	(0.001)	(0.001)	(0.023)	(0.023)	(0.023)
log(price$_{rival}$)	-0.037	0.512	0.384	0.385	0.352
	(0.033)	(0.051)	(0.053)	(0.053)	(0.054)
Price Elasticity non-top		-5.15	-5.28	-5.44	-5.24
Price Elasticity top		-5.15	-3.35	-3.35	-3.07
Ad Elasticity		0.01	0.01	0.01	0.01
Weak IV		115.23	98.11	81.77	66.56

Notes: The unit of observation is the brand-border-DMA-year-month combination. The sample consists of 307 border-DMAs, 72 month-year periods, and on average 55 brands in each market for a total of 1182459 observations. All specifications include brand-border-DMA and brand-border-year-quarter fixed effects. The parameters in columns (2)-(5) are estimated using two-step feasible GMM. The IVs are Hausman prices and the interaction of distance and brewery (see text for more information). The weak IV test corresponds to the Kleibergen-Paap F-statistic. The (sales-weighted) average elasticities are computed using the estimated parameters. Standard errors clustered at the product-DMA level are reported in parenthesis.

The findings pose interesting implications in terms of substitution patterns. As shown in the bottom rows of Table (2), the constant elasticity model (column (2)) implies an own-price elasticity of -4.9, whereas the model with all interaction terms implies that own-price elasticities vary, on average, by an order of magnitude from -2.86 to -5.1. The variation in price elasticity across products relies on the advertising intensity. Thus, the most popular brands (e.g., Bud Light) exhibit lower price sensitivity than less popular (e.g. craft) brands. With respect to the advertising elasticities, the estimates show very small positive own-ad effects and negative competitor effects. For a beer brand priced at \$10, the average own and competitor ad elasticity is 0.005 and -0.001, respectively.

The estimates of the substitution patterns are broadly in line with other empirical findings. The own-price elasticities for the top brands are in the same order of magnitude as Shapiro et al. (2021). They estimate a constant elasticity model using several specifications and find an average own-price elasticity of -2.78 among popular beer brands. For advertising elasticities, the authors find that the average own-advertising elasticity is 0.002.[48] My estimates are also in line with the ad elasticities of Rojas and Peterson (2008) and smaller in size than the structural-based own-price elasticities of Asker (2016), Miller and Weinberg (2017) and Fan and Yang (2022).[49] As a robustness check, I have also estimated additional analysis: specifications with different carry-over rates; different instrumental variables; use of occurrences as advertising metric; analysis of fixed effects; and multiple specifications including further interaction terms with demographics. These analyses yield comparable parameter estimates and are reported in Appendix D.

3.3 Summary Reduced Form Evidence

The reduced form evidence suggests that the massive entry of craft breweries led to a surge in advertising across markets in the US beer industry. This strategic response in advertising was more pronounced among large domestic breweries compared to their imported counterparts. There is no evidence of a response among already established craft breweries. When analyzing the effect of advertising on demand, the estimates show that TV advertising has a limited impact on demand expansion. The findings show, however, that advertising has the potential to influence how consumers react to price changes. In the next sections, I evaluate the extent of strategic advertising response due to market entry and investigate the implications of such response with respect to market power.

4 The Empirical Model

4.1 Demand

4.1.1 Random Utility Model with Advertising

Advertising has been extensively studied in modern industrial organization literature, specifically in the context of discrete choice demand systems (e.g., Dubé et al., 2005; Sovinsky Goeree, 2008; Doraszelski and Markovich, 2007). To analyze the non-informative role of advertising (i.e. goodwill), the literature relies on a demand model where advertising not only affects linearly consumer choices but can also directly impact how consumers react to price changes (e.g., Erdem et al., 2008; Dubois et al., 2018). Although this relationship be-

[48] Shapiro et al. (2021) provide an interactive web application where I have retrieved the estimates for the most popular beer brands. The web application is available at https://advertising-effects.chicagobooth.edu/.

[49] More specifically, the own-price elasticity of Asker (2016) is around -3.4, it is in the range of -3.4 and -5.9 in Miller and Weinberg (2017), and around -5.8 for main brands in Fan and Yang (2022).

tween advertising and price sensitivity might have interesting economic implications, it lacks micro-foundation support. This section briefly discusses this issue and introduces a random utility model that incorporates non-informative advertising. I provide the full derivation of the underlying choice model with advertising in Appendix E.

The model assumes that consumer i derives utility from two components: (i) the consumption of a product among the set of J products available in the market m during a given month t, and (ii) the consumption of the composite good. I omit the market (m) and time (t) indices to ease the exposition of the model. The utility of consuming product j is given by the following expression

$$U_{ij} \;=\; u(C, \boldsymbol{A}_j) + V(\mathbf{X}_j, \boldsymbol{A}_j, \xi_j, \varepsilon_{ij}). \tag{3}$$

The function $u(\cdot)$ denotes the utility derived from the consumption of the composite good C, which can be affected by the level of exposure to total (own and rival) advertising stock $\boldsymbol{A}_j$. The second term of equation (3) denotes the valuation of product j which depends on both observable attributes ($\mathbf{X}_j$) and unobserved (by the researcher) attributes (ξ_{jt}). This valuation can also be affected by the total advertising stock and depends on the idiosyncratic unobserved taste shock ε_{ij}.

The impact of advertising on utility is twofold. On the one hand, it increases the utility that the consumer derives from purchasing the product. This is attributed to the fact that advertising has the potential to enhance the valuation of the product, for instance, by augmenting the perceived quality or by acting as a complement to other product characteristics (Bagwell, 2007). On the other hand, advertising might reduce the utility derived from the composite good. Beyond promoting a specific product, advertising often portrays an unrealistic reality, which can lead to consumer dissatisfaction. Specifically, advertising sets a standard of qualitative conventions for individual behavior and consumption patterns, prompting individuals to compare themselves against an idealized reality that cannot be achieved.[50] As such, advertising collectively might reduce the utility that consumers derive from the consumption of the composite good.

The main implication of advertising in this model is that all else equal, it not only increases the utility that the consumer receives from consuming the product itself but it also increases this utility relative to the consumption of the composite good. When solving the utility maximization problem with discrete choices, I show that this setup leads to a model

[50]The link between advertising and the representation (and misconception) of social reality has been investigated in several papers (e.g., Giaccardi, 1995; Sherry, 1987). Michel et al. (2019) provide empirical evidence of the negative relationship between advertising expenditure and life satisfaction across multiple European countries.

in which advertising not only affects the valuation of the product but may also change price sensitivity. The resulting demand model is presented in the next section.[51]

4.1.2 Demand Model

To model the demand for beer, I employ the discrete choice framework proposed by Berry et al. (1995, henceforth BLP). Consider the choice problem of consumer i in market m at time t. This consumer faces $J_{mt}+1$ alternatives: J competing beer products offered at time t in market m, plus the outside option ($j=0$). The indirect utility consumer i obtains from j is

$$U_{ijmt} \;=\; \delta_{jmt} + \mu_{ijmt} + \varepsilon_{ijmt}. \tag{4}$$

The first term of equation (4) is the mean utility δ_{jmt} which all consumers agree on. For a given market and time period, the mean utility depends on a vector of observed ($\mathbf{X}_j$) and unobserved (ξ_j) product characteristics, price of the product p_j and advertising stock variables. The latter variables include own advertising $\boldsymbol{A}_j$ and rival's advertising which is the sum of the rival's advertising stock in the market $\sum_{b=1,b\neq j}^{J}\boldsymbol{A}_b$.[52] The mean utility takes the following linear form:

[51]There is an alternative model in which advertising may affect price sensitivity. This micro-foundation portrays a model of consumer decision where advertising plays two roles: (i) it can reinforce the valuation of all attributes (observed and unobserved), and (ii) it changes the variance of the distribution of the idiosyncratic unobserved taste shocks (i.e., the logit error). In the literature on discrete choice demand models, these logit errors represent unobserved symmetric product differentiation. Assuming that these errors are independent and identically distributed and follow an extreme value type I distribution, one can allow the variance of the logit error to depend positively on total advertising stock. That is, the logit error is distributed with the variance scale parameter $h(\boldsymbol{A};\boldsymbol{\lambda})$, where $\boldsymbol{A}$ represents the total advertising stock in the market in a given time period. This micro-foundation leads to a demand model where price sensitivity can change due to total advertising stock, up to the parameter $\boldsymbol{\lambda}$. This model is similar to the multiplicative adjustment introduced by Ackerberg and Rysman (2002) when modeling unobserved product differentiation in discrete choice models. In Appendix E.2, I introduce this simple model and estimate the demand parameters. In particular, I assume that $\boldsymbol{\lambda}=1$ and estimate a standard logit model. Despite the restrictive assumption on the variance of the logit error, I show that this alternative, and more structural, micro-foundation yields similar substitution patterns as the model discussed in the text. Incorporating a parametric specification of the scale parameter and allowing for heteroskedastic errors are extensions worth investigating in the future.

[52]Advertising stock is defined similarly as in the reduced form evidence. Specifically, I define the advertising stock as the lag of a nonlinear function of current advertising:

$$\boldsymbol{A}_{jmt} \;=\; \sum_{\tau=t-L}^{t} \delta^{t-\tau}\log(1+\mathfrak{a}_{jmt}),$$

where δ is the carryover parameter, $\mathfrak{a}_{jmt}$ (also a vector) is the flow of own and competitor advertising, and L is the number of lags in which advertising has an effect on current demand. For the purposes of estimation, I set $\delta=0.8$ and $L=12$ which implies that advertising has a persistent effect over one year.

$$\delta_j(\Gamma) = -\alpha p_j + \lambda_1 p_j \boldsymbol{A}_j + \lambda_2 p_j \left(\sum_{b=1, b\neq j}^{J} \boldsymbol{A}_b \right) + \gamma_1 \boldsymbol{A}_j + \gamma_2 \left(\sum_{b=1, b\neq j}^{J} \boldsymbol{A}_b \right) + \mathbf{X}_j \beta + \xi_j,$$

where the parameters $\Gamma = \{\alpha, \lambda_1, \lambda_2, \gamma_1, \gamma_2, \beta\}$ are to be estimated. Of special interest for the interpretation of the results are the parameters associated with advertising. The first ones, λ_1 and λ_2 represent the impact of own advertising on the indirect utility; the second pair of parameters, γ_1 and γ_2 govern the existence and magnitude of spillover effects. Notice that own advertising stock enters the expression as a stand-alone term and as an interaction with price. Because of this, advertising has the potential to affect the mean utility in two ways: directly and by changing price sensitivity. For instance, if $\lambda_1 > 0$, own advertising can make consumers less responsive to price changes. The same analysis applies to rival advertising.

The second and third terms of equation (4) denote the consumer-specific taste shock μ_{ij} and the idiosyncratic valuation ε_{ij}, respectively. The μ_{ij} term includes interactions between observed (demeaned) consumer demographics (D_i) and product attributes, including price and advertising. Specifically,

$$\mu_{ij}(D_i; \Pi) \; = \; [p_j, \mathbf{X}_j, \boldsymbol{A}_j, p_j \boldsymbol{A}_j] \cdot (\Pi D_i).$$

The matrix Π represents the parameters of interactions between demographic draws and characteristics.[53] I allow for heterogeneous preferences related to prices, a subset of product characteristics and variables related to advertising stock. Consumers can also opt for the outside option which includes a collection of other alternatives that range from the non-purchasing decision to the purchasing of another alcoholic product (e.g., spirits). The indirect utility from the outside option is assumed to be $U_{i0} \; = \; \varepsilon_{i0}$.

A consumer chooses the option j if and only if $U_{ij} > U_{ij'} \;\; \forall j' \neq j$. Under the assumption that ε_{ij} is i.i.d and drawn from a type I extreme value distribution, the probability that consumer i purchases product j is:

$$s_{ij}(\Gamma, \Pi) \; = \; \frac{\exp(\delta_j(\Gamma) + \mu_{ij}(D_i; \Pi))}{1 + \sum_k^J \exp(\delta_k(\Gamma) + \mu_{ik}(D_i; \Pi))}$$

and the aggregate market share of product j is given by

$$s_j(\Gamma, \Pi) \; = \; \int s_{ij}(\Gamma, \Pi) dP_D(D)$$

[53] I use $[p_j, \mathbf{X}_j, \boldsymbol{A}_j, p_j \boldsymbol{A}_j]$ to denote a row vector of appropriate dimension.

where $P_D(D)$ is the probability density function of D_i. For a given market and time period, the demand for product j is $\mathcal{M}s_j$, where $\mathcal{M}$ is the market size which is assumed to be 50% greater than the maximum observed unit sales within each market (Miller and Weinberg, 2017).

4.1.3 Substitution Patterns

The demand system with advertising has implications for product-level substitution patterns. The own- and cross-price elasticities for the demand model are given by

$$\begin{aligned} \frac{\partial s_j p_j}{\partial p_j s_j} &= \frac{p_j}{s_j} \int \tilde{\alpha} s_{ij}(1 - s_{ij}) dP_D(D) \\ \frac{\partial s_{j'} p_j}{\partial p_j s_{j'}} &= -\frac{p_j}{s_{j'}} \int \tilde{\alpha} s_{ij} s_{ij'} dP_D(D) \quad \forall j' \neq j, \end{aligned} \tag{5}$$

where $\tilde{\alpha} = -\alpha_i + \lambda_1 \boldsymbol{A}_j + \lambda_2 \big(\sum_{b=1, b\neq j}^{J} \boldsymbol{A}_b \big)$ is the marginal utility from price. The model allows for flexible substitution patterns that depend on the level of own- and competitor advertising. If λ_1 and λ_2 are positive, consumers become less price sensitive as they are more exposed to advertising.

The marginal effect of a change in advertising state variable (i.e. current and past advertising exposures) on individual-level choice probabilities is:

$$\begin{aligned} \frac{\partial s_{ij}}{\partial \boldsymbol{A}_j} &= s_{ij} \left[\tilde{\gamma}_j (1 - s_{ij}) + \sum_{l \neq j} s_{il} \tilde{\lambda}_l \right] \\ \frac{\partial s_{ij'}}{\partial \boldsymbol{A}_j} &= s_{ij'} \left[\tilde{\lambda}_j (1 - s_{ij}) - s_{ij} \tilde{\gamma}_j + \sum_{j} s_{ij} \tilde{\lambda}_j \right] \\ \frac{\partial s_{i0}}{\partial \boldsymbol{A}_j} &= -s_{i0} \left[s_{ij} \tilde{\gamma}_j + \sum_{l \neq j} s_{il} \tilde{\lambda}_l \right], \end{aligned} \tag{6}$$

where $\tilde{\gamma}_j = \gamma_1 + \lambda_1 p_j$ and $\tilde{\lambda} = \gamma_2 + \lambda_2 p_j$. The interaction of advertising with price and the presence of advertising spillovers have important implications for market shares. If there are no spillovers ($\tilde{\lambda} = 0$) and $\tilde{\gamma}_j > 0$, own advertising has a positive impact on own shares. This is due to both the predatory effect of advertising on rival's shares and the market expansion effect. Under the presence of advertising spillovers, however, the sign of the own advertising effect does not necessarily dictate the implication of advertising in the market. In this particular case, depending on the magnitude of the parameters, advertising may be predatory or cooperative and it may lead to an expansion or contraction of the market.

4.2 Supply

The US beer market is modeled as an oligopoly with multiproduct breweries that sell their products to consumers through retailers. For a given brewer, market and time period, the per-period profit function is

$$\Pi_b = \sum_{j \in J_b} (p_j^b - c_j^b - c_{b(j)}^w - \tau) \mathcal{M} s_j (\mathbf{P}^b + \mathbf{c^r}, \boldsymbol{A}) - c^{ad}(\mathfrak{a}), \tag{7}$$

where b denotes the brewer, r the retailer, and j the product. J_b is a list of offered products in a given market with corresponding wholesale prices p_j^b and the marginal cost of production c_j^b. The variable $c_{b(j)}^w$ represents distribution costs that are computed using diesel prices, wages and distance from the market to the brewery.[54] The constant τ denotes the excise taxes that are state-specific and $\mathcal{M}$ is the potential size of the market.

The product market share s_j depends on (own and rival) retail prices as well as advertising stock $\boldsymbol{A}$. The vectors $\mathbf{P}^b$ and $\boldsymbol{A}$ can be split into elements related to product j and those corresponding to competitors: $\mathbf{P}^b = (P_j^b, \mathbf{P}_{-j}^b)$ and $\boldsymbol{A} = (\boldsymbol{A}_j, \boldsymbol{A}_{-j})$. De Loecker and Scott(2023) find that retail competition is passive. Accordingly, I assume that retailers set the price for product j using the formula $p_j^r = p_j^b + c^r$, where c^r is the exogenous retailing cost.[55] The cost of current advertising decisions is denoted by $c^{ad}(\mathfrak{a})$, where $\mathfrak{a} = (\mathfrak{a}_1, ..., \mathfrak{a}_{J_b})$. Note that the dependence of profits on $\boldsymbol{A_j}$ means that the current choice of advertising $\mathfrak{a}$ will affect future advertising stock.

Brewers play a dynamic oligopoly game in which they choose the optimal prices and advertising levels to maximize the expected present discounted value of profits. The dynamics of the model arise from the long-term effects of advertising on demand. Specifically, current advertising decisions $\mathfrak{a}_\mathrm{j}$ have the potential to affect not only current profits but also future demand. I formalize this intertemporal dependence using the advertising stock variable $\boldsymbol{A}_j = \sum_{\tau=t-L}^{t} \delta^{t-\tau} \log(1 + \mathfrak{a}_j)$. Another potential dynamic strategic decision might involve market structure and the entry decisions of craft breweries.

[54]Based on De Loecker and Scott (2022), I assume that a truck can transport 900 cases (equivalent to 1800 12 packs) and gets 6 miles per gallon. In turn, truck drivers earn \$35/hour and are assumed to travel 60 miles per hour. The distribution and wholesaling costs per 12 pack are then given by the following expression:

$$c_{bmt}^w = (p_{mt}^{diesel} \cdot distance_{bmt}/6 + distance_{bmt} \cdot 25/60)/1800,$$

where p_{mt}^{diesel} is the regional price for diesel at time t and $distance_{bmt}$ captures the distance between the market m and the nearest plant of brewer b. In the text, I suppress the market and time subscripts for brevity.

[55]Similar to De Loecker and Scott (2022), I use Dominick's data and set the retail cost equal to the (quantity-weighted) average difference between retail and wholesale prices in the Chicago area in 1994.

To solve such a dynamic problem, I could capture the strategic decisions using the solution concept related to Markov Perfect Equilibrium (Maskin and Tirole, 1988; Ericson and Pakes, 1995). To do this, however, I need to specify a large space of actions and states taking into account complex dynamic strategic decisions. Instead of dealing with the additional structure and complications of the dynamic setting, I focus only on pricing decisions that become static after conditioning on the observed advertising state variables and market structure. I use these static optimality decisions to identify marginal costs and conduct counterfactual analyses.[56]

Conditional on the advertising stock variables and the observed market structure, the brewer b maximizes per period profits. In particular, the pure-strategy Bertrand-Nash equilibrium assumes that brewer b sets prices to maximize profits, taking as given the prices set by competing brewers.[57] For a given market with a list of J different beer products and B brewers, let θ^B denote the product ownership matrix, $\mathbf{\Delta}(\mathbf{p}, \mathbf{A})$ denote the $|J| \times |J|$ jacobian matrix of first derivatives, and $\odot$ the Hadamard product operator.[58] The system of first-order conditions for a given market, in matrix form, can be written as

$$\mathbf{s}(\mathbf{p}, \mathbf{A}) + \Big(\theta^B \odot \mathbf{\Delta}(\mathbf{p}, \mathbf{A})\Big)(\mathbf{P} - \mathbf{c} - \mathbf{c^w} - \tau) \;=\; 0, \tag{8}$$

where $\mathbf{s}$, $\mathbf{P}$, $\mathbf{c}$, $\mathbf{c^w}$, and τ are all $|J| \times 1$ vectors. In a given market, τ is a constant vector, with all elements equal to τ. I use the set of first-order conditions (8) for each market (DMA-month) to back out current marginal costs. The first-order conditions, information on the shape of demand, and observations on advertising and prices are sufficient conditions for marginal cost identification.

4.3 Counterfactual

The main goal of this paper is to study the advertising response to craft beer entry and evaluate the implications in terms of market power. After the entry of craft brewers, the incumbents face higher competitive pressure than in the absence of entry, leading potentially

[56] This approach has been used by Dubois et al. (2018) to study advertising restrictions in the potato chips market, and by Dubois and Majewska (2022) to analyze the advertising effects of mergers in the pharmaceutical market in the US.

[57] I assume the existence and uniqueness of pure-strategy Bertrand-Nash equilibrium. The literature related to proving the existence and uniqueness of oligopoly equilibrium in games with firm and product heterogeneity remains relatively small. Caplin and Nalebuff (1991) provide the conditions for the existence and uniqueness of an oligopoly equilibrium with single-product firms. More recently, Nocke and Schutz (2018) provide a unified approach to show the existence and uniqueness of multi-product oligopoly equilibrium in an aggregative approach without random coefficients but for a wide range of demand systems.

[58] The ownership matrix is a block-diagonal matrix with elements equal to one for products offered by the same brewer and zeros otherwise.

to a price equilibrium change. As I have shown and discussed in Section 3.1, advertising strategies can be affected by such a change in market structure, leading also to a change in price equilibrium. Thus, the counterfactual analysis essentially consists of the simulation of price equilibrium at different levels of advertising and in the absence/presence of craft beer entry.

Since I observe the pre and post-entry levels of advertising stock, I simulate the counterfactual price equilibrium with both scenarios of market structure (Craft and No Craft) at pre and post-entry observed levels of advertising stock (Advertising Before and After). With this approach, I cannot specifically determine the effect of craft entry on advertising strategies. Yet, under the assumption that advertising stock is either the one observed pre-entry or post-entry, I can elicit realistic counterfactual predictions of the short-term effects on prices. I use these predictions to analyze the profit incentives for advertising under craft competition and to assess the implications with respect to market power.

More formally, the craft competition status is defined as a change in the ownership matrix θ^B. The market scenario with and without craft entry is denoted by the ownership matrices θ^B_{Craft} and $\theta^B_{NoCraft}$, respectively. Using the system of first-order conditions (8) and each of the ownership matrices, I solve for the equilibrium price at pre-entry (A_{Before}) and post-entry (A_{After}) observed levels of advertising.

For a given craft entry scenario and each brewer, I consider the price effects of a unilateral move from, for instance, pre-entry observed advertising level to post-entry advertising decisions. I compare the resulting variable profits to draw implications on individual profit incentives to advertise.

In addition, I use the new price equilibrium to analyze the impact of advertising changes on markups, measured as the ratio of the brewer's price to its marginal cost of production. Following De Loecker and Scott (2022), markup for product j can be computed as follows:

$$\mu_j = \frac{p^r_j - c^r - c^w_b - \tau}{c^b_j}. \tag{9}$$

5 Empirical Results

This section presents the empirical results from the demand model. I start discussing the specification, estimation, and identification of the model. Next, I present the main estimation results and discuss the corresponding substitution patterns. I use the parameter estimates to calculate the price elasticities and diversion ratios. The aim is to understand how consumers make choices in the US beer market and to study the extent of substitution between craft beer and flagship brands.

5.1 Specification and Estimation

The econometric model is based on the utility specification of Section 4. For market m and time period t, consumers make decisions based on prices (p_{jmt}), own advertising stock ($\mathbf{A_{jmt}}$), the sum of rival's advertising stock ($\sum_{b=1,b\neq j}^{J} \mathbf{A_{jmt}}$), a vector of product attributes ($\mathbf{X_{jmt}}$), and unobserved characteristics (ξ_{jmt}). The vector $\mathbf{X_{jmt}}$ consists of a series of dummy variables related to the type of beer (i.e., lager, light and other types as the base), craft beer status, and Mexican brands. It also contains a proxy variable capturing how local the brand is with respect to the respective market. The localness attribute is computed by taking the distance from the market to the nearest brewery.

The unobserved attribute can be specified as $\xi_{jmt} = \xi_j + \xi_m + \xi_t + \Delta\xi_{jmt}$. The ξ_j are product fixed effects that account for time-invariant unobserved attributes for the beer brand j. The ξ_m are market fixed effects, capturing all systematic heterogeneity across markets. The ξ_t are the time-fixed effects that control for time-specific macroeconomic shocks affecting all beer brands. Finally, the remaining unobserved demand shocks are captured by $\Delta\xi_{jmt}$.

To account for consumer heterogeneity, I include interactions between consumer demographics and product attributes. More specifically, the random coefficient for the characteristic k is specified as $\beta_{ik} = \beta_k + \pi_k D_i$, where π_k is a row vector of parameters measuring how valuation for characteristic k varies with demographics D_i. For the empirical application, the demographics include income (Income), a dummy variable indicating whether the individual belongs to either the Millennial or Gen Z generation (Millennial), and a dummy variable indicating whether the individual self-identifies as being of Hispanic ethnicity (Hispanic).

To estimate the demand parameters $\Theta = \{\Gamma, \Pi\}$, I use the generalized method of moments (GMM) following the literature (Berry et al., 1995). The overall idea is to search for the parameters of the model that allow the predicted market shares to match the observed ones. For this purpose, I proceed in two steps.

First, I use the contraction mapping proposed by BLP to solve the system $s = s(\delta; \Pi)$ for the mean utility δ in each market. Once I retrieve the vector of mean utilities, I infer $\Delta\xi_{jmt}$ using the equation for the mean utility. Second, I interact the structural error term with a vector of instrumental variables Z_{jmt} to construct the moment condition of the form $g(\Theta) \equiv E[\Delta\xi_{jmt}(\Theta) Z_{jmt}]$. This moment restriction is equal to zero when evaluated at the true value of the parameters Θ_0. I estimate the model by minimizing the GMM objective function:

$$\min_{\Theta} g(\Theta)' W g(\Theta),$$

where W is a weighting matrix. I estimate the demand model using pyblp (Conlon and Gortmaker, 2020). In particular, I employ the two-step GMM procedure with a derivativebased optimization algorithm. I approximate the market share function using 500 draws on individuals per market-year and use an error tolerance of 10^{-14} for the contraction mapping. To accelerate the convergence of the contraction mapping, I use the SQUAREM algorithm proposed by Varadhan and Roland (2008).

5.2 Identification

Regarding the identification of the parameters of demand, the identifying assumption is that the structural error term is orthogonal to the vector of observable product characteristics. This assumption seems reasonable in the beer industry, particularly for the top brands, as there are not too many characteristics that can be adjusted without changing substantially the product's taste. Hence, the attributes are rather fixed over time.[59] For the least popular brands, on the other hand, product reformulation can happen in the long run. However, reformulation often comes together with rebranding which, in my analysis, is seen as a new product.

The primitives of the structural model include unobservable characteristics (or shocks) that are taken into account by consumers when choosing the product, and by firms when setting the price and advertising thereof. The endogeneity concern arises due to the fact that these unobserved factors are taken into account by market participants but remain unobserved by the econometrician.

To account for the potential endogeneity of prices, I use instrumental variables consisting of interactions of beer types with input prices and excise taxes. More specifically, I use the global prices of barley and malt, key ingredients in beer production. Since the proportion of these ingredients varies by the type of beer (e.g., lager, ale, light, among others), one could expect changes in input prices to affect differently the retail price. Although the global prices have the same value across markets and products, they exhibit substantial monthly variation in the time series. The use of excise taxes has a similar explanation. The interaction between beer types and taxes captures the extent to which different brewers pass on the tax burden to consumers. This is especially prominent for the craft segment, which predominantly consists of ale beers.

To identify the parameters governing the preferences related to advertising, I employ the price of TV advertising as an instrument. The model of advertising decisions proposed by Li (2023) shows how advertisers incorporate this variable into their advertising decisions. The main issue with this instrumental variable is that ad prices tend to be correlated with

[59]The package of the product is perhaps the only characteristic that brewers may change over time. I do not take these changes into account in my analysis and focus only on the standard and most popular packages, i.e., 6, 12, and 24 packs.

the characteristics of the consumers. For example, Gentzkow et al. (2022) show that TV advertisers pay varying prices based on the characteristics of the target audience. The existence of such a correlation calls into question the validity of the exclusion restriction.

The identification of the advertising parameters relies on the institutional features of the market for TV advertising (Shapiro et al., 2021). About 80% of the TV ads are purchased well in advance in the upfront market. During these negotiations, the ad price is mostly related to broad characteristics of the future audience (e.g., age, income, gender, ethnicity), seasonal factors and trends. I control for these broad characteristics using demographics and multiple fixed effects. The remaining 20% of the TV ads can be purchased in the short term in the so-called scatter market. These advertising decisions may be strongly correlated with unobserved demand shocks, raising concerns about the validity of my instrumental variable. However, the bulk of these last-minute local TV ads are purchased by national networks which, in turn, sell them in bundles. These bundles contain several ad slots, whose price is less likely to be related to specific demand shocks. Overall, these features of the ad buying process make targeting cumbersome which can be reflected in a low correlation between ad prices and demand shocks. With respect to the parameters associated with competitors' advertising, I use a set of instruments that are in the spirit of the characteristic-based instruments (BLP, 1995). More specifically, I employ the sum of advertising expenditure of rival products.

One issue merits discussion. The identification strategy used in Section 3.2 employs the discontinuity in advertising arising at the borders of the TV markets in the U.S. This approach relies on the use of a battery of multiplicative fixed effects, making the model quite flexible. The downside of this strategy is that it captures substantial variation that is needed to estimate a demand model with flexible substitution patterns. For this reason, in this section, I choose to employ instrumental variables instead of employing the border strategy.

Finally, the parameters governing consumer heterogeneity in preferences are identified by the correlation between local demographics and market shares. To identify these parameters, I use the average of the demographic variables interacted with the observed product attributes. This set of instruments has been used by Romeo (2010) and Miller and Weinberg (2017).

5.3 Demand Estimates

Table (3) reports the demand estimation results. Panel A shows the parameter estimates for the mean valuation. Price has a significant and negative impact on mean utility. This average disutility for price decreases in both own and rival advertising. The effect is particularly twice as large for own advertising than for the one of rival brands. Taken together, these estimates imply that price sensitivity can be lower (in absolute value) for heavily advertised brands compared to brands that are not involved in TV advertising (e.g., microbreweries). Accordingly, the implied average own-price elasticity is -3.4 and -8.3 for flagship and craft brands, respectively.

	Parameter	Coefficient	Std. Err.
Panel A. Mean Valuations			
Price	α	-0.652	0.0210
Price $\times$ Ad_{own}	λ_1	0.007	0.0005
Price $\times$ Ad_{rival}	λ_2	0.003	0.0006
Ad_{own}	γ_1	-0.058	0.0058
Ad_{rival}	γ_2	-0.082	0.0063
Distance	β_1	-0.234	0.0061
Distance $\times$Craft	β_2	-0.247	0.0068
Panel B. Observed Heterogeneity			
Income $\times$ Price	Π_1	0.051	0.0070
Income $\times$ (Price $\times$ Ad_{own})	Π_2	-0.004	0.0003
Income $\times$ Mexican Beer	Π_3	0.282	0.0851
Millennial $\times$ Price	Π_4	-0.109	0.0104
Millennial $\times$ (Price $\times$ Ad_{own})	Π_5	0.002	0.0003
Millennial $\times$ Craft Beer	Π_6	2.814	0.1207
Hispanic $\times$ Price	Π_7	-0.128	0.0156
Hispanic $\times$ (Price $\times$ Ad_{own})	Π_8	0.002	0.0002
Hispanic $\times$ Mexican Beer	Π_9	3.281	0.0875

Notes: Product, market and month FEs are included. The local variable denotes the distance to the nearest brewery and it is scaled as distance/1000. The number of observations is 617,140 .

Table 3: Demand Estimates

To analyze the mean valuation for advertising stock, we need to account for the interactions as well. For brands that advertise, the results indicate that consumers place a positive valuation on their own advertising. The stand-alone advertising coefficient is negative but it is outweighed by the positive estimate associated with the interaction term (price and own advertising). Thus, the average own-advertising elasticity for the flagship brands is 0.03. This result is in line with Shapiro et al. (2021). In contrast, the coefficient associated with rival advertising is negative across brands.

The distance has a significantly negative impact on mean utility. This may, at least, partially reflect the preference for products that are brewed locally, supporting the local economy and having less environmental impact. The interaction with the craft dummy indicates that have a particular distaste for beer brands that tend to be unknown, both because they are produced far from the local market and because they are produced by relatively small craft companies.

Panel B shows the observed consumer heterogeneity related to the valuation of product characteristics. There is considerable heterogeneity in the valuation of beer characteristics across consumers. High-income consumers tend to be less price-sensitive. Their price sensitivity, in turn, can be less affected by changes in own advertising, possibly because they face less exposure to TV ads or tend to be less persuaded by the content. High-income consumers also slightly prefer Mexican brands.

Millennial and Hispanic consumers tend to exhibit higher price sensitivity than older non-Hispanic consumers. This price sensitivity, however, can be more affected by changes in advertising stock. In other words, millennial and Hispanic population decisions can be more affected by TV advertising. Although these consumers are, on average, less exposed to TV advertising, the ad content might be more effective at conveying the message, and it may even propagate to other media (e.g., it may become viral on social media).

The estimates also imply that millennial and Hispanic consumers show strong preferences for craft and Mexican brands, respectively. This has several possible interpretations. It may reflect a high valuation for different tastes as this group of beers may have a different flavor compared to regular beers (e.g., flagship domestic brands). For craft beer, this strong preference may also reflect a valuation for the independent status of craft breweries, i.e., the fact that they are not owned by mass-producing and multinational companies. For the Mexican beers, it can also reflect a connection between the Hispanic population and the Hispanic/Latino culture.

In sum, these findings on the importance of non-traditional beer for younger generations indicate the source of competitive pressure on mass-producing breweries. As these demographics are becoming important and are projected to keep on growing, large companies need to strategically react. Even though millennials tend to be more price sensitive, this valuation for price changes is conditional on purchasing a craft beer - for which millennials have sizeable a premium. This suggests that there is little room for price competition between, for instance, flagship and craft brands. In light of this, mass-producing breweries can recur to advertising which, according to the estimates, has the potential to attract consumers.

5.4 Substitution Patterns

I use the estimated coefficient to compute implied elasticities and diversion ratios. I report detailed results of these economic outcomes in Appendix F. In this section, I focus on discussing the specific substitution patterns related to diversion ratios. More specifically, I compute the diversion ratio to craft beer which is defined as follows. After a price increase for a particular non-craft brand, some consumers decide to switch to a substitute product. The diversion ratio to craft measures the fraction of those consumers who switch to any beer in the craft segment.

Figure (5) shows the evolution of diversion ratios for flagship brands to the craft segment (i.e., any craft brand). In 2011, the diversion to craft shows that following a price increase of the domestic brands, about 15% of their sales would be captured by the craft segment. This share is 9% for the flagship imported brands. It is interesting to see that while the diversion ratios are increasing over time, there is a clear difference between domestic and imported flagship brands. For domestic brands, the diversion ratio increased on average 20 percentage points, reaching a maximum of 34% in 2016. On the other hand, over the sample period, the diversion ratio surged about 10 percentage points for Mexican brands and 15 percentage points for other imported brands. Table F1 in Appendix F shows the diversion ratios by brands to different groups of beers. Although both craft and imported brands draw an increasing share of consumers from the main domestic brands, the domestic flagship brands still constitute the bulk of diversion patterns. The substitution to domestic brands is, however, declining over time.

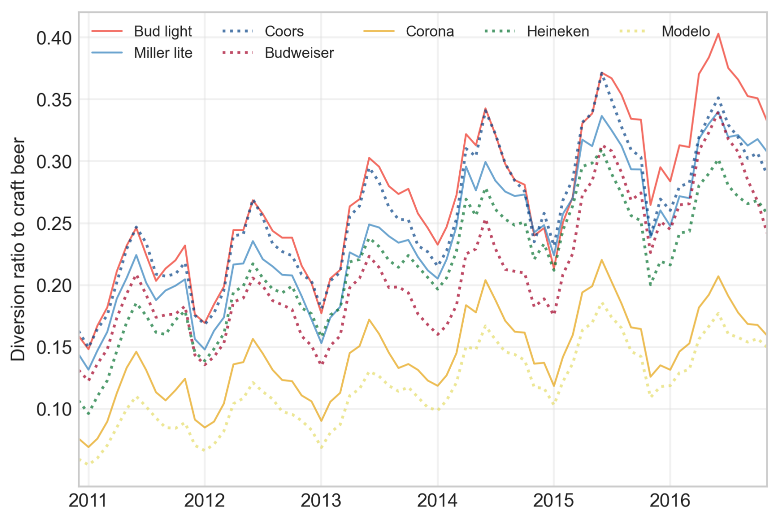


Figure 5: Diversion to Craft Beer

In sum, the diversion ratios are in line with the reduced form evidence in section 3.1. The craft segment creates competitive pressure for flagship brands, and this pressure is larger for domestic than for imported brands. In general, the craft segment steals business from the incumbents' flagship brands and this pattern has become more important over time. These substitution patterns, and the evolution of thereof, can have interesting implications for the profit incentives to advertise and market power. I evaluate these implications in the next section.

6 Counterfactual Analysis

In this section, I use the estimated demand system and equilibrium conditions to identify marginal costs and conduct counterfactual analyses. Conditional on the advertising state variable, I compute the price equilibrium in each of these scenarios. First, I examine the profit incentives to advertise (section 6.1). Next, I study the implications of changes in advertising on market power (section 6.2).

In this analysis, I consider the static pricing game, conditional on the distribution of advertising stocks. In other words, I solve the firms' optimal pricing strategies for different levels of observed advertising. This approach has been used by Dubois et al. (2018) and Dubois and Majewska (2022) to analyze merger effects on advertising and advertising bans.

In contrast, Abi-Rafeh et al. (2023) solve the full dynamic model with advertising choices to analyze the impact of taxes on consumption in the UK cola market. In their framework, they leverage the role of advertising agencies to link a firm's advertising expenditure to the multi-dimensional decision related to advertising exposure. In doing so, they simplify the dynamic competition between firms. Their setting is different from the one analyzed in this paper in several ways. First, unlike cola manufacturers who employ one agency in the UK, the mass-producing breweries work with multiple ad agencies in the U.S., including in-house agencies.[60] In addition, the beer advertising data do not provide information on these relationships, making it difficult to model the advertising agency's problem. Second, Abi-Rafeh et al. (2023) employ the national nature of both pricing and advertising choices to analyze the cola market. In contrast, I rely on local variation to estimate well-established regional preferences in the U.S. beer market and to examine the extent of advertising responses to craft entry. In terms of advertising choices, the beer setting involves decisions both at a national and local level, adding complexities to the dynamic problem. Finally, Abi-Rafeh et al. (2023) consider the advertising decisions of 3 different cola brands, resulting in a discretized state space of 9,261 points. Using the same setting to examine the advertising decisions of (at least) 13 heavily advertised beer brands, I may end up with 1.54×10^{17} points in the discretized state space.

All the above-mentioned issues render the dynamic oligopoly game in the U.S. beer industry computationally intractable. Instead of dealing with the additional structure and complications of the dynamic setting, I focus only on pricing decisions that become static

[60]For instance, Ab Inbev works with over 50 advertising agencies. https://www.inside.beer/news/detail/usa-ab-inbev-to-launch-own-advertising-agency/

after conditioning on the observed advertising state variables.

6.1 Profit Incentives for Advertising

To assess the profit incentives to advertise, I compute the counterfactual profit incentives under alternative entry and advertising decisions. For this analysis, I use a sharp increase in the number of breweries in 2012 to define the pre- and post-entry period. The reason is that the advertising decisions during this time period are more likely to be only related to the massive entry of craft breweries. For later time periods (e.g., 2014-2016), mass-producing breweries may have chosen advertising outlays as a function of many contemporaneous events including the acquisition of craft breweries, implementation of incentive plans, the merger between Ab Inbev and SABMiller, the entry of craft breweries, among others.

Using this setting, I analyze four hypothetical scenarios for each mass-producing brewer. Each scenario is characterized by an entry status (*Craft or No Craft*) and by individual advertising decisions. As discussed in Section 4.3, a shift in the craft entry status can be modeled as a change in the ownership matrix. As for advertising decisions, advertising before entry (*Before*) is given by the observed advertising stock in 2011, whereas advertising after entry (*After*) corresponds to the one observed in 2013.

I carry out this analysis for two large domestic breweries (Ab Inbev and MillerCoors) and two large foreign breweries (Constellation Brands and Heineken), resulting in sixteen hypothetical counterfactual scenarios.[61] In practice, the analysis is as follows. Holding the rival advertising fixed to the post-entry levels, I compute the price equilibrium with pre- and post-entry advertising for each brewer.[62] I use the resulting equilibrium to compute variable profits, and focus on comparing the analysis with and without craft competition.

Table (4) shows the variable profits for the counterfactual scenarios. The first two columns report the variable profits for each of the brewers without craft competition. For instance, the variable profits of Ab Inbev go up by 4.1% when the company unilaterally decides to increase advertising to the post-entry levels. The next two columns report the variable profits under craft competition. In this case, the profits of Ab Inbev increase by 5% when increasing advertising to the post-entry levels. A similar pattern can be seen for the remaining large breweries.

The last three columns of Table (4) show the analysis corresponding to the incentives to advertise. For Ab Inbev, the profit incentives to advertise without craft competition amount

[61] Four out of the sixteen scenarios are actually the observed scenarios so I do not conduct any simulation analysis.

[62] In Appendix G.1, I do the same exercise holding the rival advertising fixed to the pre-entry level of advertising. I obtain identical results.

Entry:	No Craft		Craft		Incentives to Advertise		
Advertising:	Before	After	Before	After	No Craft	Craft	Δ
Ab Inbev	574.5	597.8	567.2	595.3	23.3	28.1	4.8
MillerCoors	309.0	319.8	304.2	318.2	10.8	14.0	3.3
Constellation	121.4	138.4	118.3	138.0	17.0	19.7	2.6
Heineken	32.9	35.4	31.9	35.3	2.5	3.4	0.9

Notes: The table reports for each of the sixteen scenarios: the current variable profits (USD million) without craft competition (columns 1 and 2) and the variable profits with craft competition (columns 3 and 4). The last three columns show the profit incentives to advertise under each competition scenario.

Table 4: Individual Profit Incentives (USD million)

to 23.3 USD million. This value increases to 28.1 USD million with competition, showing that the profit incentives to advertise are higher in the presence of craft competition than in the absence of it. The intuition for this result is straightforward. Prior to the craft competition, the incumbent chooses advertising for each brand so as to compete against rival products. Yet, advertising competition is less intense as the incumbent may want to avoid excessive cannibalization between its own brands. When confronted with craft entry, the incumbent faces additional competitive pressure from rival products, making the cannibalization concerns less relevant. This additional pressure, as depicted by the increasing diversion to craft (Figure 5), leads to an increase in advertising by the incumbent. Taken together, these results show that mass-producing breweries have positive incentives to advertise and that such incentives are greater under craft competition. These results validate the reduced-form evidence discussed in Section 3.1.

The difference in profit incentives between the scenario with and without craft competition seems rather small. For instance, the difference for Ab Inbev is only 4.8 USD million. One potential explanation for why the incentives to advertising under craft competition are relatively small is that I only consider a sample of retail stores in the U.S. market and I abstract from on-premise competition. First, the sample of retail stores can be around 50% of the universe of stores, and this sample does not include big-box stores such as Walmart and Costco. Second, craft brewers constitute a threat to large breweries in the on-premise market as they not only produce their own beer but also have massively entered the hospitality industry. To the extent that competition between mass-producing and craft brewers is intense in the unobserved retail market and in the on-premise sector, the computed incentives to advertise under craft competitions represent a lower bound.

Another explanation is that the small profit incentive may reflect the fact that not all local markets experienced craft entry during the period of analysis. If this is the case, one would expect then the profit incentives to be greater in those markets where the craft competition is more intense.

To further explore this, I analyze the correlation between incentives to advertise and the extent of craft competition (Table 5). More specifically, for each brewer and local market, I compute the difference in incentives between the craft and no-craft scenarios. Next, I project this variable on different measures related to craft brewers. Column (1) of Table (5) shows that there is a positive and significant correlation between the number of breweries and the incentives to advertise. In column (2), I show that this correlation is higher for the domestic brewers than for their foreign counterparts. Columns (3) and (4) report similar findings using the market share of the craft segment as independent variable.

	$\text{Incentive}_{Craft} - \text{Incentive}_{NoCraft}$			
	(1)	(2)	(3)	(4)
# Breweries	40.90	25.01		
	(1.34)	(1.76)		
# Breweries × Domestic Brewer		31.78		
		(2.81)		
Market Share Craft			61.92	33.71
			(9.49)	(10.97)
Market Share Craft × Domestic Brewer				56.41
				(16.36)
R-Squared	0.39	0.42	0.23	0.23
Observations	7200	7200	7200	7200

Notes: The unit of observation is at the Brewer-DMA-year-month level for 2013. The sample consists of observations for the largest breweries: Ab Inbev, MillerCoors, Heineken and Constellation Brands. All specifications include month and brewer fixed effects. All specifications include control variables for demographics and the number of TTB permits. Robust standard errors are in parentheses.

Table 5: Correlation Between Profit Incentives and Craft Competition

In sum, the analysis of the individual profit incentives validates the reduced-form evidence shown in Section 3.1. More specifically, I show that the largest breweries have a positive strategic incentive to advertise, which is greater under craft competition than in the absence of it. Moreover, exploiting cross-market variation in profit incentives, I estimate a positive and significant correlation between incentives to advertise and the extent of craft competition. This suggests that mass-producing brewers increased local TV advertising the most in local markets with more craft entry.

6.2 Implications of Advertising on Market Power

What are the implications of the advertising response? To address this question, I use the estimated model to assess to what extent the advertising reaction affects market power in the U.S. beer industry. Before I do this analysis, I show the implied markups, defined as the price-marginal cost ratio. Figure (6) shows the evolution of markups for 2011-2016.

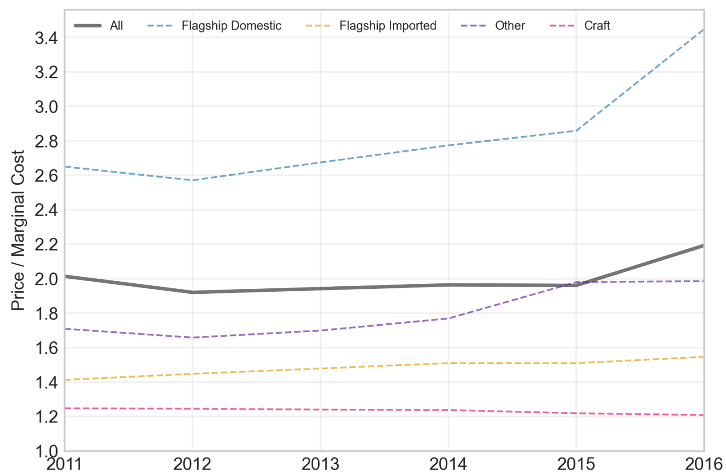


Figure 6: Evolution of Markups

While the sales-weighted average markup remained relatively stable over the sample period, the evolution of market power for heavily advertised beer brands exhibits a different pattern. More specifically, for imported brands markups rose from 1.4 to just under 1.6, whereas the markups for flagship domestic brands increased from 2.6 in 2011 to 3.4 in 2016. In contrast, the craft segment exhibits a modest average markup which slightly declines over the sample period.

As a way to validate the results, it is instructive to compare them with other estimates in the literature on the demand for beer. First, the estimated markups for both domestic and imported flagship brands are identical to the ones estimated by Miller and Weinberg (2017) and De Loecker and Scott (2022). To be more precise, I calibrate the conduct parameter using the estimates of Miller and Weinberg (2017) and compute markups under this adjustment. The results, shown in Appendix G.2, are in line with these two papers. Regarding the craft segment, industry sources (Satran, 2014) put the craft brewer's margin at 8% of the retail price. This margin amounts to \$1.4. Fan and Yang (2022) estimated average margin is in the range between \$1.3 and \$2.1. For an average price of \$17, these margins imply a markup between 1.08 and 1.14, which is broadly in line with my findings.

The reduced-form evidence (Section 3.2) along with the demand estimates (Section 5.3) show that advertising stock can affect how consumers react to price changes. This has relevant implications for price elasticity and, ultimately, for market power. To assess the implications of advertising on markups, I conduct two counterfactual predictions. First, I introduce a ban on advertising. This is a very extreme case but it can be informative with respect to the long-term effect that advertising has had in the beer industry. Second, I hold the advertising stock fixed to the observed level in 2011. The aim is to see what would have been the evolution of markups without any reaction in advertising. Figure (7) shows the counterfactual markups under the advertising ban (dashed line) and in the absence of any changes in advertising (red line).

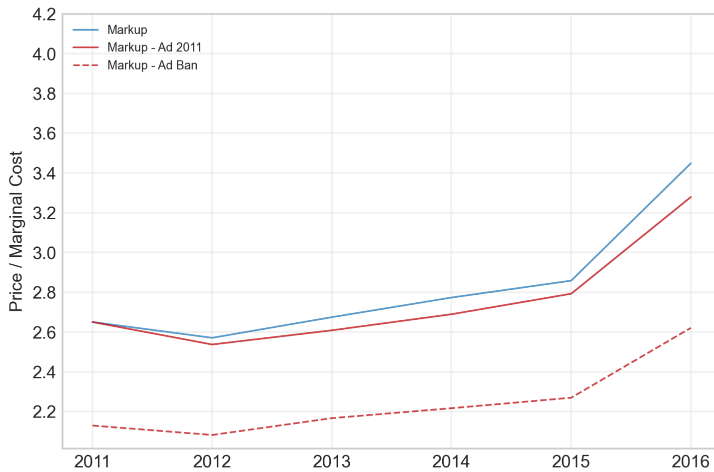


Figure 7: Counterfactual Markups (Flagship Domestic)

The ban on advertising (dashed line) leads to a substantial reduction in market power. On average, markups fell by 0.5 points from 2011 to 2016, with a major decline of 0.8 points in 2016. This finding indicates the role of advertising for mass-producing brewers. TV advertising may not be effective at expanding demand in this mature industry but rather shields brewers from price competition. Once the ban is in place, there is a sizeable reduction in product differentiation along with an increase in price sensitivity. All else equal, these two effects intensify price competition among brewers.

Holding the observed advertising stock fixed at the pre-entry levels, I show that, in 2016, about 20% of this rise of market power can be attributed to the observed increase in advertising stock. This percentage constitutes an upper bound for the markup effects of the advertising reaction to craft entry.[63] The remaining surge in market power (80%) can be explained by declining marginal costs. Figure (8) shows the additional counterfactual analysis in which I hold both advertising and marginal cost fixed at the pre-entry levels.

In the absence of any marginal cost and advertising changes, market power would have remained relatively stable over the period. In Appendix G.3, I show that the bulk of in-

[63]Notice that, as I explained in detail in Section 2.2, I analyze the advertising response to the entry only into the retail market. I do not measure the extent of the reaction related to on-premise entry (e.g., brewpubs) as I do not have on-sales data. Thus, my results represent a lower bound of the true effect of market entry on advertising.

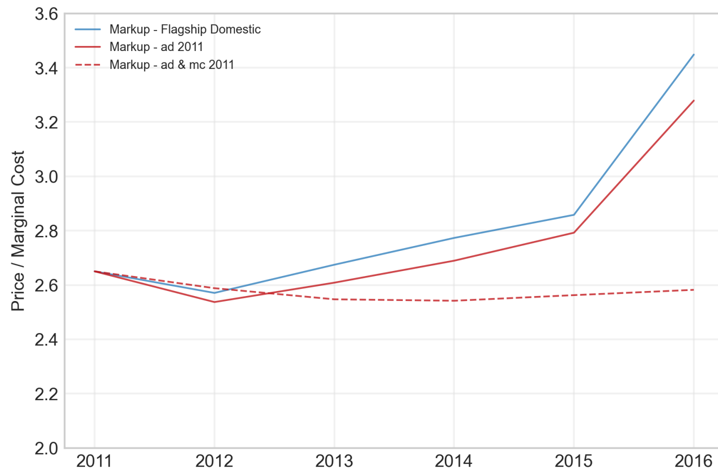


Figure 8: Markups Decomposition

creasing market power can be attributed to changes in marginal cost and not to changes in prices. These results are in line with Döpper et al. (2023). Overall, the importance of my results lies in the fact that advertising can be used as a strategic response to market entry and such a response has implications in terms of market power.

7 Concluding Remarks

Mass-producing breweries have had a long-standing dominance in the U.S. beer industry for decades. This paradigm is, however, changing with the emergence of craft breweries which are characterized by increasingly valued attributes such as taste, brewer independence, and localness. In light of this, the mass-producing brewers must respond to the entry of craft breweries.

In this paper, I empirically analyze the response in advertising to the massive entry of craft brewers. Exploiting variations in local beer laws, I established a causal relationship between craft entry and TV advertising across U.S. local markets. Next, I estimate a differentiated product demand model with persuasive advertising to estimate rich substitution patterns. I use these estimates, along with an oligopoly model of price competition, to infer marginal costs and conduct counterfactual predictions. These predictions allow me to evaluate the mass-producing brewers' profit incentives to advertise and to examine the implications of advertising on market power.

The empirical results from my reduced-form evidence show, among other things, that (lagged) entry of breweries increased advertising, and this effect is significantly larger for mass-producing domestic breweries than for their foreign counterparts. Next, I develop a framework to understand the profit incentives to advertise under craft competition. I show that the largest breweries have a positive strategic incentive to advertise, which is greater under craft competition than in the absence of it. Moreover, exploiting cross-market variation in profit incentives, I estimate a positive and significant correlation between incentives to advertise and the extent of craft competition. This suggests that mass-producing brewers increased local TV advertising the most in local markets with more craft entry.

What are the implications of the advertising response to market entry? to address this question by analyzing markups and conducting several counterfactual analyses. Although the findings show that the impact of advertising stock on demand is quite limited, I show that both own and rival advertising can significantly reduce price sensitivity. Taken together, these results suggest that in mature industries, such as the beer market, advertising might not be very effective at expanding demand, but it can still shield firms from fierce price competition by decreasing price sensitivity. Breweries can leverage this and increase market power accordingly.

Overall, my findings are relevant to policy issues in that they create the following trade-off regarding market entry. On the one hand, entry increases the competitive pressure, leading to a price reduction and benefiting consumers. This positive effect is reinforced by the variety that comes together with market entry. On the other hand, as I have shown in this paper, market entry may trigger a strategic reaction in advertising by incumbents. This reaction can reduce price sensitivity, increase market power, and potentially affect consumers. The final outcome related to market entry is then ambiguous and hinges on the interplay of these opposing effects. In future research, it would be interesting to analyze the relevance of each element to see to what extent and how consumers are affected by entry in markets where advertising plays a major role in competition.

My analysis is based on a series of assumptions and settings that may be generalized in future work. First, the structural model with persuasive advertising is static. A full setting of multi-product firms with dynamic advertising decisions can improve our understanding of why and how firms spend resources on advertising efforts. Second, digital media has become one of the most important channels for advertising. Further work could include these decisions to examine not only the advertising response of incumbents but also the extent of advertising by craft breweries. Finally, the literature related to the welfare effects of advertising has not delivered conclusive results. This issue is even more unclear for the beer industry. For this analysis, one needs to take a stand on how advertising affects consumers' choices and one needs to take the externalities arising from the industry seriously.

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Appendix

A Data Description and Summary Statistics

Demographics The distribution of demographics was obtained by sampling households from the annual Public Use Microdata Sample (PUMS) of the American Community Survey. I restrict the demographic information to the period 2010-2016. There are 500 draws on individuals per DMA-year.[64] Income is obtained by dividing the total household income by the size of the household. The variables millennial and Hispanic are dummy variables that equal one if the individual was born after 1981 and the individual reports Hispanic origin, respectively.[65]

Beer state laws The database of beer state laws comes from the publication of the magazine The New Brewer - The Journal of the Brewers Association.[66] Every two months, the brewers association documents policy issues and tracks the legislative progress of state bills related to the beer industry. Using this source, I hand-collected approved bills (i.e. bills becoming law) across states between 2008 and 2019. There might be a time gap between bill approval and reporting. I address this issue by assigning the approval month to each bill using state-specific legislative tracking tools. Each bill might add (or amend) several statutory provisions. I classify these provisions into different categories according to the description provided by the Brewers Association.[67] I use the resulting dataset to construct a panel of states containing the total number of statutory provisions by category.

Input prices The source for the input prices is the Federal Reserve Economic Data (FRED). For barley, I use the global monthly price (PBARLUSDM).

Ownership, breweries and production facility location To collect information on brand ownership, I use the repository of the website BeerAdvocate. This website consists of beer reviews for the universe of products in the US. For each brand, the repository provides

[64] The demographics are obtained at the DMA level by matching the counties that compose the DMAs to the PUMS areas.

[65] The income variable is top-coded at the 95th percentile. The millennial indicator variable captures two generation cohorts: millennials (born between 1981 and 1996) and Generation Z (born between 1997 and 2012). For the sake of brevity, the term millennials encompasses both cohorts throughout the text.

[66] I thank the Brewers Association for giving me access to various online resources, including the bi-monthly publication of the magazine and data on the craft beer sector.

[67] The categories are related to (1) small brewer definition (microbreweries, brewpubs, and taprooms); (2) brewer categories and production caps; (3) use of local agricultural products; (4) taprooms; (5) contract and alternating proprietorship; (6) beer definition (ABV); (7) beer license and/or permits; (8) multiple licenses; (9) multiple business locations; (10) self-distribution; (11) franchise laws; (12) beer containers; (13) Sample and/or tasting rooms; (14) events; (15) donation and tourism; (16) home and farm brewery; (17) on/off-premise sales; (18) promotional advertising (e.g. coupons); (19) day/time sales (e.g. Sunday sales); (20) taxes; (21) related alcoholic products; (22) label; and (23) other.

information on the owner of the brand and whether the owner is the same as the manufacturer (brewery). As for the location of the production facility, I use the brewery directory provided by the Brewers Association. For the foreign breweries, I assume that the location of the brewery is the same as the location of Heineken's primary ports. For the Mexican brands, the shipping distance is computed as the distance from each market to the US-Mexico border (Miller and Weinberg, 2017).

Diesel fuel prices The diesel information is retrieved from the US Energy Information Administration (EIA). In particular, I employ the monthly diesel prices (all types) by region.

Beer taxes I obtain the federal and state beer tax rates by state from the Tax Policy Center (TPC).

Summary Statistics The tables below show the summary statistics. Table (A1) presents the descriptive statistics for the sales data by group of breweries. Overall, the beer price for the large breweries is on average smaller than for the imported and craft breweries. The market shares show the opposite relation in that the large breweries hoard, on average, a larger market share than their competitors. Note that there are not too many large breweries, whereas the craft segment contains on average 17 competing breweries.

Table A1: Summary Statistics Sales Data

	Mean	Std. Dev.	p10	p50	p90
Large Breweries					
Price	9.7	2.5	7	9.5	13.1
Rev. share	4.4	3.7	0.6	2.9	10.3
Distance	1181.5	454.3	369.7	1307.6	1307.6
Breweries	3.8	0.9	3	3	5
Brands	17.7	14.7	2	13	38
Imported Breweries					
Price	14.7	2.2	13.4	14.5	16.1
Rev. share	2.1	1.9	0.2	1.5	4.9
Distance	1886.6	1015.9	369.7	1307.6	1307.6
Breweries	15.1	10.7	5	12	30
Brands	3	3.5	1	1	7
Craft Breweries					
Price	16.4	8	12.8	14.7	20.2
Rev. share	0.6	0.4	0.1	0.6	1.2
Distance	1044.7	964.3	368.8	454.8	2809.4
Breweries	17.2	12.5	4	14	34
Brands	3.4	2.9	1	3	7

Notes:number of observations is 5,165,772 which correspond to 175 TV markets during the 2010-2016 period. Prices are in 12 pack equivalent units and in 2010 dollars. The statistics for prices, revenue shares and distance are weighted by sales. Distance is in kilometers and denotes the minimum distance from each TV market to the nearest brewery. Breweries and brands correspond to the number of breweries in each market and the total number of brands offered per brewery, respectively.

With respect to the distance from the market to the nearest brewery, imported breweries face the longest distances compared to their competitors. This is due to the fact that the distance for these breweries is measured as the shipping distance from each local market to the nearest port or border. On average, craft breweries show shorter distances relative to large breweries. This difference is, however, modest. The reason is that large breweries have multiple production locations across the countries so they can reduce the shipping costs (and distance) by producing beer at nearby breweries. The analysis of the distribution of distance shows that craft breweries tend to be located closer to local markets.

Table (A2) presents the summary statistics for brands that advertise at least once within my sample. As expected, the bulk of advertising outlays are linked to national advertising. Yet, the breweries also incur in local TV advertising. In particular, the descriptive statistics show that there is substantial variation in local advertising across TV markets.

Table A2: Summary Statistics Advertising Data

	Mean	Std. Dev.	Min	Max
Local				
# Ads	9.2	31.2	0	1579
GRP	28.3	109.4	0	5735.9
Spending (1000)	6.9	36.1	0	1445.4
Spending per GRP (1000)	0.3	0.8	0	66
Price Ad (1000)	0.7	3.3	0	227.2
National				
# Ads	702	1240.9	0	11966
GRP	373.9	743	0	7613.7
Spending (1000)	3790.8	3990.9	0	29331.2
Spending per GRP (1000)	6	3.6	1.4	46.5
Price Ad (1000)	3.3	5.9	0	181.6
Total				
# Ads	711.2	1255.4	0	12626
GRP	402.2	796.5	0	10982.1

Notes: The number of observations is 584,640 which correspond to 29 brands in 210 TV markets during the 2010-2017 period. Advertising spending is thousands and in 2010 dollars. The local advertising spending corresponds only to TV spot. Gross Rating Points (GRP) denotes the number of impressions as a percentage of all the potential viewers in a TV market (local or national).

Table (A3) shows the statistics for the demographics. Three facts stand out. First, average income has increased over time. Second, there is a clear trend aging population and, accordingly, the younger generation is gaining more importance across local markets. By 2018, 25.7% of the population belonged to either the Millennial or the Gen Z generation, representing a 12 percentage point increase since 2010. Third, the Hispanic population is also, on average, growing but at a lower pace. It is important to notice that there is a large cross-market variation in terms of population composition and demographics. There are some local markets exhibiting wealthier individuals, with younger populations, and a higher proportion of Hispanic residents. This is expected to have considerable implications on preferences and consumption of beer.

Table A3: Demographics

	2010	2012	2014	2016	2018
Income	33.9	35.7	37	39.1	40.1
	[26.5,44.5]	[27.7,47.5]	[28,50.9]	[30.2,53.1]	[30.5,52.2]
Age	50.8	51.3	51.5	51.7	52.1
	[48.1,53.4]	[48.5,53.9]	[48.6,54.3]	[49.3,54.5]	[49.3,55.2]
% Millenials	13.5	16.6	19.7	22.7	25.7
	[9.6,18]	[12,22]	[14.8,25]	[17.4,28.4]	[19.2,32]
% Hispanic	7.47	7.66	7.79	7.97	8.16
	[0.8,33]	[0.8,33.2]	[0.8,32.6]	[1,32.6]	[1,34]

Notes: The DMA level socio-demographic characteristics come from the American Community Survey Public Use Microdata Sample (PUMS). The table reports the means, and percentiles (5th and 95th) in square brackets. Income is in 2010 dollars and denotes the US household income per capita.

B Industry Background

Figure B1: Total Beer Volume

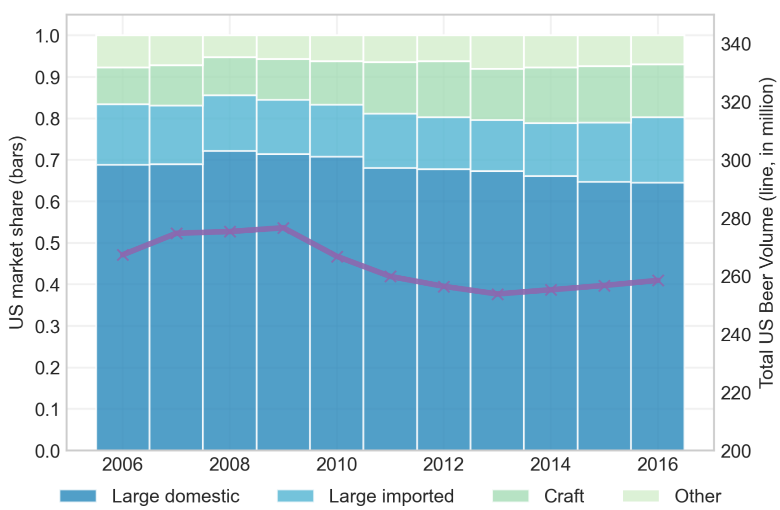


Figure B2: US Breweries by Category

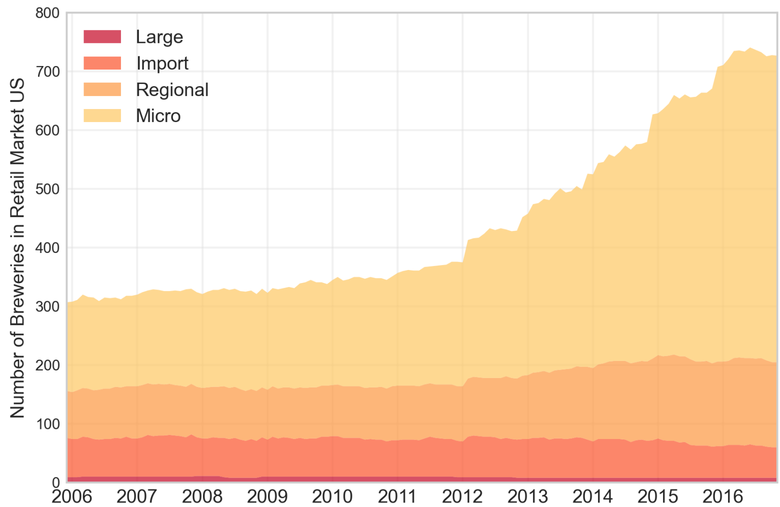


Figure B3: US Beer Brands by Category

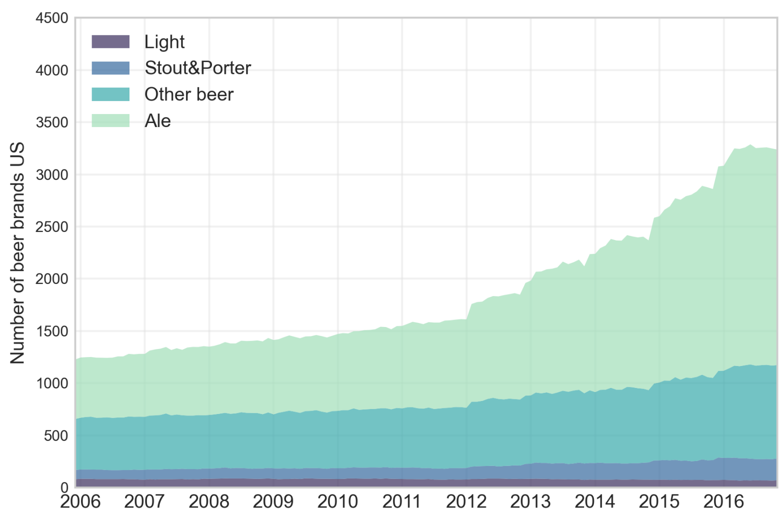


Figure B4: Evolution GRPs over time

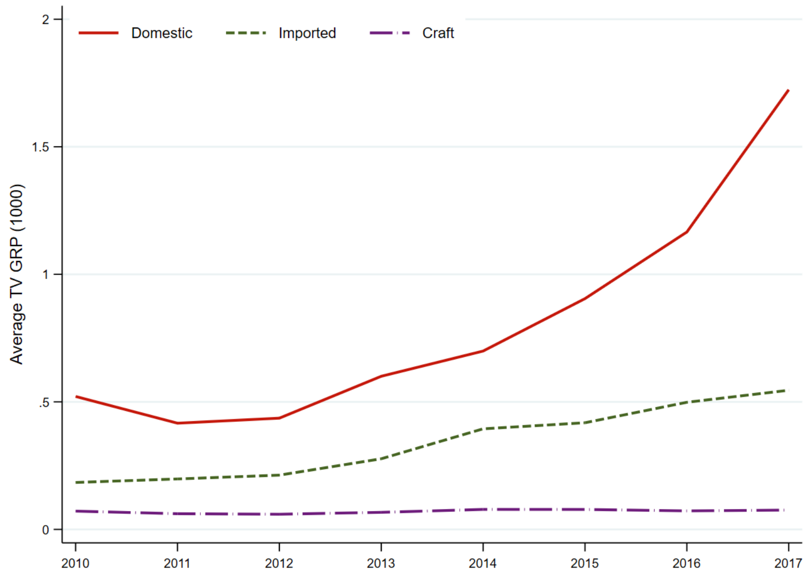


Figure B5: Local Advertising by Age (GRP)

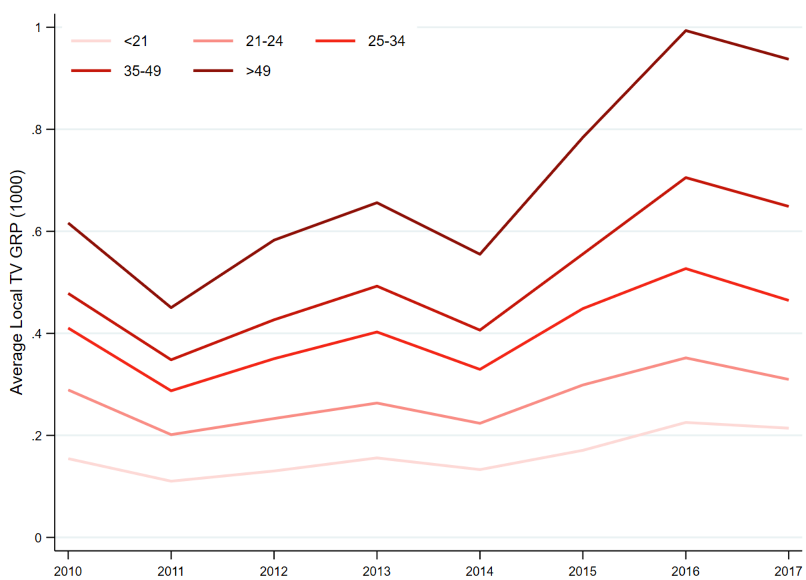


Figure B6: National Advertising by Age (GRP)

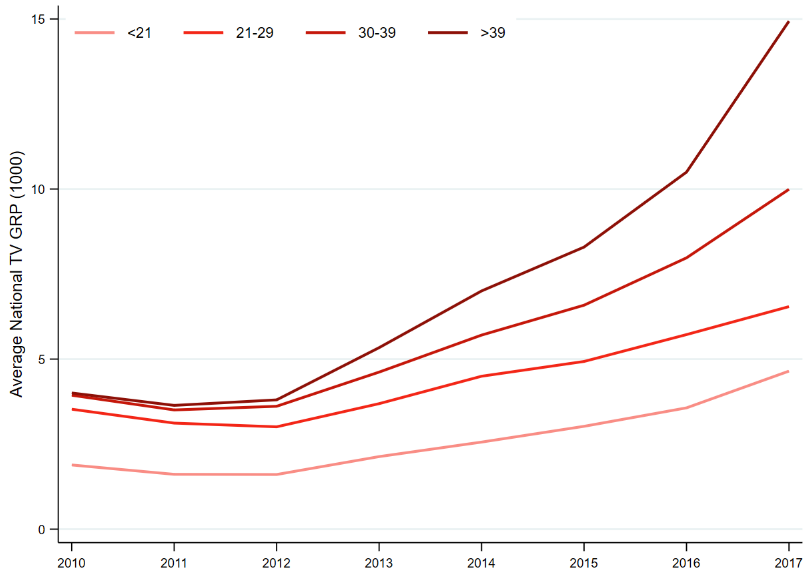
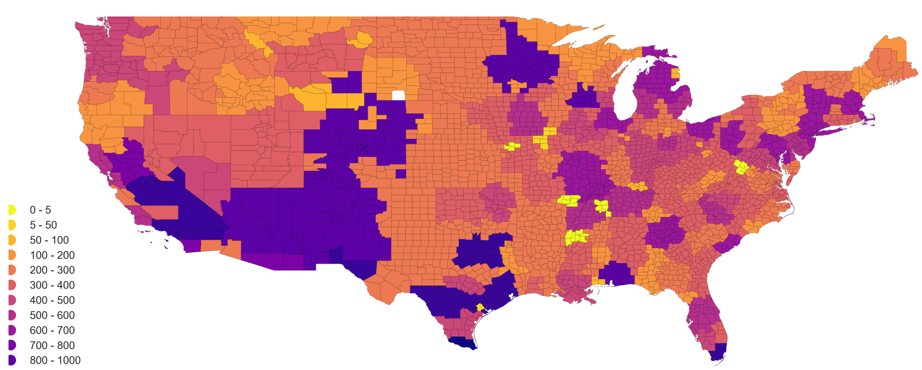


Figure B7: Advertising variation across TV markets (GRP)



C Advertising Response to Craft Entry

Table C1: The Effect of Breweries Entry on Advertising (Gross Rating Points)

	All		Breweries		
	(1) OLS	(2) IV	(3) Domestic	(4) Imported	(5) Regional
Breweries_{t-12}	2.827	10.001	7.931	3.243	-0.301
	(0.469)	(2.497)	(2.036)	(0.689)	(0.625)
TBB Permits	0.797	0.520	0.451	0.135	-0.099
	(0.098)	(0.142)	(0.111)	(0.040)	(0.030)
Income	-23.992	-17.840	-15.107	-4.093	2.336
	(8.231)	(8.153)	(5.530)	(1.750)	(4.895)
Income sqr	0.286	0.203	0.189	0.046	-0.052
	(0.102)	(0.100)	(0.066)	(0.020)	(0.065)
Mid-millennial	-74.573	-78.260	-52.558	-17.302	-3.681
	(9.279)	(9.752)	(7.113)	(2.170)	(4.976)
High-millennial	-55.744	-67.951	-55.366	-17.355	9.500
	(14.501)	(15.415)	(10.882)	(3.453)	(8.493)
Mid-hispanic	20.485	15.659	-0.371	-1.715	15.187
	(8.974)	(9.485)	(6.952)	(1.962)	(5.043)
High-hispanic	-10.320	-14.512	-7.470	-14.914	2.764
	(19.886)	(20.093)	(15.764)	(4.449)	(9.024)
Weak IV		111.84	111.84	111.84	111.84
J-stat (pval)		0.12	0.79	0.08	0.00

Notes: The unit of observation is the DMA-year-month combination. The sample consists of 172 DMAs and 72 month-year periods for a total of 12384 observations. All specifications include DMA, DMAxMonth and YearxMonth fixed effects. The dependent variable is the gross rating points (GRPs). The parameters are estimated using two-step feasible GMM. The IV is the cumulative sum of statutory provisions related to contracting and franchising (see text for more information). All specifications include control variables for demographics and the number of TTB permits. The weak IV test corresponds to the Kleibergen-Paap F-statistic and the p-value of the J-stat is the p-value of the Hansen tests for over-identifying restrictions. Robust standard errors are in parentheses.

Table C2: The Effect of Breweries Entry on Advertising (Occurrences)

	All		Breweries		
	(1) OLS	(2) IV	(3) Domestic	(4) Imported	(5) Regional
Breweries_{t-12}	2.423	12.910	7.518	5.504	0.027
	(0.212)	(1.588)	(0.988)	(0.704)	(0.182)
Weak IV		111.84	111.84	111.84	111.84
J-stat (pval)		0.25	0.79	0.06	0.00

Notes: The unit of observation is the DMA-year-month combination. The sample consists of 172 DMAs and 72 month-year periods for a total of 12384 observations. All specifications include DMA, DMAxMonth and YearxMonth fixed effects. The dependent variable is the number of advertising occurrences. The parameters are estimated using two-step feasible GMM. The IV is the cumulative sum of statutory provisions related to contracting and franchising (see text for more information). All specifications include control variables for demographics and the number of TTB permits. The weak IV test corresponds to the Kleibergen-Paap F-statistic and the p-value of the J-stat is the p-value of the Hansen tests for over-identifying restrictions. Robust standard errors are in parentheses.

Table C3: The Effect of Breweries Entry on Advertising (GRPs) - Different Fixed Effects

	GRP			# Ads		
	(1)	(2)	(3)	(4)	(5)	(6)
Breweries_{t-12}	20.704	13.000	10.001	19.238	14.072	12.910
	(12.568)	(3.136)	(2.497)	(21.401)	(1.796)	(1.588)
Year FE	Yes	No	No	Yes	No	No
Month FE	Yes	No	No	Yes	No	No
DMA FE	Yes	Yes	Yes	Yes	Yes	Yes
YearxMonth FE	No	Yes	Yes	No	Yes	Yes
DMAxMonth FE	No	No	Yes	No	No	Yes
Weak IV	124.75	125.95	111.84	124.75	125.95	111.84
J-stat (pval)	0.49	0.40	0.12	0.93	0.32	0.25

Notes: The unit of observation is the DMA-year-month combination. The sample consists of 172 DMAs and 72 month-year periods for a total of 12384 observations. All specifications include DMA, DMAxMonth and YearxMonth fixed effects. The dependent variable is the gross rating points (GRPs). The parameters are estimated using two-step feasible GMM. Each specification uses different (combinations of) IVs. The row Sum IVs indicates that the IV used is the sum of the respective variables. Hence, these specifications are exactly identified. All specifications include control variables for demographics and the number of TTB permits. The weak IV test corresponds to the Kleibergen-Paap F-statistic and the p-value of the J-stat is the p-value of the Hansen tests for over-identifying restrictions. Robust standard errors are in parentheses.

Table C4: The Effect of Breweries Entry on Advertising (GRPs) - Different Lags of Entry

	(1)	(2)	(3)	(4)
Breweries_{t-3}	9.448			
	(1.952)			
Breweries_{t-6}		11.019		
		(2.217)		
Breweries_{t-9}			10.029	
			(2.356)	
Breweries_{t-12}				10.001
				(2.497)
Weak IV	182.92	159.60	135.75	111.84
J-stat (pval)	0.70	0.20	0.12	0.12

Notes: The unit of observation is the DMA-year-month combination. The sample consists of 172 DMAs and 72 month-year periods for a total of 12384 observations. All specifications include DMA, DMAxMonth and YearxMonth fixed effects. The dependent variable is the gross rating points (GRPs). The parameters are estimated using two-step feasible GMM. Each specification uses different (combinations of) IVs. The row Sum IVs indicates that the IV used is the sum of the respective variables. Hence, these specifications are exactly identified. All specifications include control variables for demographics and the number of TTB permits. The weak IV test corresponds to the Kleibergen-Paap F-statistic and the p-value of the J-stat is the p-value of the Hansen tests for over-identifying restrictions. Robust standard errors are in parentheses.

Table C5: The Effect of Breweries Entry on Advertising (GRPs) - Different IVs

	(1)	(2)	(3)	(4)	(5)	(6)
Breweries$_{t-12}$	11.479	16.257	12.928	23.597	10.001	9.319
	(2.570)	(2.826)	(3.016)	(4.097)	(2.497)	(2.524)
Franchise	Yes	Yes	No	Yes	Yes	Yes
Contract	Yes	Yes	Yes	No	Yes	Yes
Self-distribution	Yes	Yes	Yes	Yes	No	No
Sum IVs	No	Yes	No	No	No	Yes
Weak IV	84.12	214.12	114.86	43.45	111.84	227.87
J-stat (pval)	0.00		0.00	0.01	0.12	

Notes: The unit of observation is the DMA-year-month combination. The sample consists of 172 DMAs and 72 month-year periods for a total of 12384 observations. All specifications include DMA, DMAxMonth and YearxMonth fixed effects. The dependent variable is the gross rating points (GRPs). The parameters are estimated using two-step feasible GMM. Each specification uses different (combinations of) IVs. The row Sum IVs indicates that the IV used is the sum of the respective variables. Hence, these specifications are exactly identified. All specifications include control variables for demographics and the number of TTB permits. The weak IV test corresponds to the Kleibergen-Paap F-statistic and the p-value of the J-stat is the p-value of the Hansen tests for over-identifying restrictions. Robust standard errors are in parentheses.

Table C6: The Effect of Breweries Entry on Advertising (GRPs) - First-Stage

	Dep. Var: Breweries$_{t-12}$		
	(1)	(2)	(3)
L12.Laws:Contr./Alter. Prop	0.410	0.410	0.415
	(0.029)	(0.029)	(0.031)
L12.Laws:Franchise	0.800	0.808	0.831
	(0.100)	(0.100)	(0.110)
Year FE	Yes	No	No
Month FE	Yes	No	No
DMA FE	Yes	Yes	Yes
YearxMonth FE	No	Yes	Yes
DMAxMonth FE	No	No	Yes
F-test	125	126	112

Notes: The unit of observation is the DMA-year-month combination. The sample consists of 172 DMAs and 72 month-year periods for a total of 12384 observations. All specifications include DMA, DMAx-Month and YearxMonth fixed effects. The dependent variable is lag of the number of breweries. The parameters are estimated using OLS. All specifications include control variables for demographics and the number of TTB permits. Robust standard errors are in parentheses.

D Advertising Effects on Demand

Figure D1: Variation in Advertising Net of Fixed Effects

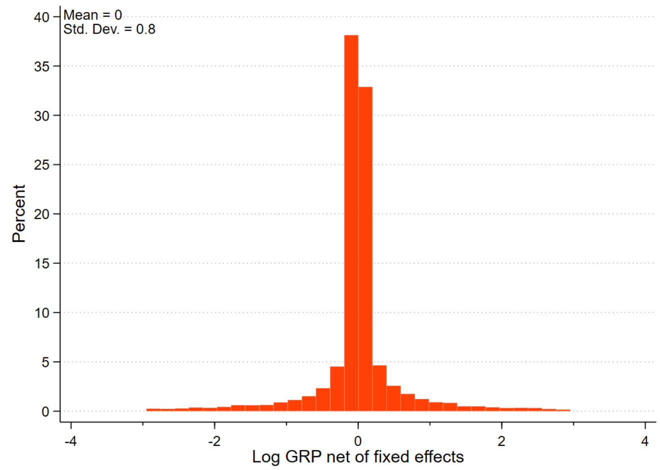


Table D1: The Effect of Advertising on Demand: Carry-over rates

	(1)	(2)	(3)	(4)
log(price)	-4.484	-7.916	-7.593	-8.021
	(0.826)	(0.811)	(0.620)	(0.635)
log(price) $\times$ GRP Stock$_{own}$	0.176	0.222	0.177	0.105
	(0.022)	(0.019)	(0.013)	(0.010)
log(price) $\times$ Income	0.032	0.043	0.047	0.050
	(0.026)	(0.027)	(0.027)	(0.028)
log(price) $\times$ GRP Stock$_{rival}$	0.006	0.245	0.122	0.069
	(0.083)	(0.059)	(0.030)	(0.016)
GRP Stock$_{own}$	-0.411	-0.515	-0.405	-0.239
	(0.055)	(0.046)	(0.033)	(0.023)
GRP Stock$_{rival}$	0.144	-0.512	-0.251	-0.158
	(0.212)	(0.158)	(0.080)	(0.044)
log(price$_{rival}$)	0.355	0.333	0.359	0.352
	(0.051)	(0.052)	(0.053)	(0.054)
Carryover parameter	0.2	0.4	0.6	0.8
Weak IV (F-test)	28.16	27.79	61.82	66.56

Notes: The unit of observation is the brand-border-DMA-year-month combination. The sample consists of 307 border-DMAs, 72 month-year periods, and on average 55 brands in each market for a total of 1182459 observations. All specifications include brand-border-DMA and brand-border-year-quarter fixed effects. The parameters are estimated using two-step feasible GMM. The IVs are Hausman prices and the interaction of distance and brewery (see text for more information). The weak IV test corresponds to the Kleibergen-Paap F-statistic. Standard errors clustered at the product-DMA level are reported in parenthesis.

Table D2: The Effect of Advertising on Demand: GRP vs Occurrences

	(1)	(2)	(3)	(4)
log(price)	-5.146	-5.519	-5.132	-5.562
	(0.221)	(0.236)	(0.221)	(0.239)
log(price) × Ad_{own}		0.093		0.094
		(0.009)		(0.009)
Ad_{rival}	0.032	0.031	0.029	0.029
	(0.001)	(0.001)	(0.001)	(0.001)
log(price_{rival})	0.512	0.384	0.506	0.365
	(0.051)	(0.053)	(0.051)	(0.053)
Ad_{own}	0.009	-0.212	0.009	-0.215
	(0.001)	(0.023)	(0.001)	(0.021)
Ad variable	GRP	GRP	Count	Count
Weak IV (F-test)	115.23	98.11	115.26	102.88

Notes: The unit of observation is the brand-border-DMA-year-month combination. The sample consists of 307 border-DMAs, 72 month-year periods, and on average 55 brands in each market for a total of 1182459 observations. All specifications include brand-border-DMA and brand-border-year-quarter fixed effects. The parameters are estimated using two-step feasible GMM. The IVs are Hausman prices and the interaction of distance and brewery (see text for more information). The weak IV test corresponds to the Kleibergen-Paap F-statistic. Standard errors clustered at the product-DMA level are reported in parenthesis.

Table D3: The Effect of Advertising on Demand: Different IVs

	(1) ols	(2) iv1	(3) iv2	(4) iv3	(5) iv4	(6) iv5	(7) iv6
log(price)	-1.919	-5.019	-5.547	-5.331	-4.972	-5.146	-6.638
	(0.043)	(0.231)	(0.197)	(0.217)	(0.229)	(0.221)	(0.737)
GRP Stock_{own}	0.010	0.009	0.009	0.009	0.009	0.009	0.009
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GRP Stock_{rival}	0.032	0.032	0.032	0.032	0.032	0.032	0.032
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(price_{rival})	-0.037	0.500	0.590	0.542	0.498	0.512	0.784
	(0.033)	(0.052)	(0.049)	(0.051)	(0.052)	(0.051)	(0.135)
Weak IV		347.32	269.87	120.99	117.59	115.23	25.01
J-stat (pval)			0.00	0.00	0.03	0.00	0.00

Note: The IVs specifications show the parameters estimated using two-step efficient GMM. The instrumental variables used are: (iv1) $p_{Hausman}$; (iv2) iv1 + $p^2_{Hausman}$; (iv3) iv1 + interaction between $p_{Hausman}$ and brewers dummy variables; (iv4) iv1 + interaction between distance and brewers dummy (abi and coors); (iv5) iv1 + interaction between distance and brewers dummy (abi, heineken and constellation brands); and (iv6) interaction between distance and brewers dummy (abi, coors, heineken, and constellation brands). Brand-border-DMA and brand-border-time fixed effects are included. The number of observations is 1182459. The number of observations is 1182459. Standard errors clustered at the product-DMA level are reported in parenthesis.

Table D4: The Effect of Advertising on Demand: First-Stage

	(1) iv1	(2) iv2	(3) iv3	(4) iv4	(5) iv5	(6) iv6
log(price$_{hausman}$)	0.027	0.078	0.026	0.027	0.026	
	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	
log(price$_{hausman}$) × log(price$_{hausman}$)		-0.001				
		(0.000)				
abi × log(price$_{hausman}$)			0.001			
			(0.001)			
mcoors × log(price$_{hausman}$)			0.005			
			(0.002)			
distance × abi				-0.002	-0.002	-0.018
				(0.027)	(0.027)	(0.028)
distance × mcoors				0.090		0.068
				(0.041)		(0.042)
distance × heineken					-0.083	-0.112
					(0.011)	(0.012)
distance × constellation					-0.005	-0.029
					(0.010)	(0.010)
Constant	1.779	1.349	1.772	1.772	1.786	2.113
	(0.021)	(0.038)	(0.021)	(0.021)	(0.021)	(0.013)
F-test IVs	347.3	269.9	121	117.6	115.2	25
R^2	0.98	0.98	0.98	0.98	0.98	0.98

Note: The dependent variable is the (log of) price. The specifications include (not reported) own and rival (log of) GRP stock, and (log of) rival price. The reported distance variables are rescaled by 10^4. Brand-border-DMA and brand-border-time fixed effects are included. The number of observations is 1182459. Standard errors clustered at the product-DMA level are reported in parenthesis.

Table D5: The Effect of Advertising on Demand: Various fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GRP Stock$_{own}$	0.040	0.039	0.043	0.012	0.010	0.010	0.010
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time	No	Yes	Yes	Yes	Yes	No	No
BorderxDMA	No	No	Yes	Yes	No	No	No
Brand	No	No	No	Yes	No	No	No
BorderxDMAxBrand	No	No	No	No	Yes	Yes	Yes
BorderxTime	No	No	No	No	No	Yes	No
BrandxBorderxTime	No	No	No	No	No	No	Yes
R^2	0.36	0.37	0.59	0.79	0.94	0.94	0.98

Notes: This table shows the estimated advertising stock parameters (OLS) of the demand model. The specifications also include (not reported) the (log of) own and rival price, and the stock of rivals advertising. The unit of observation is the brand-border-DMA-year-month combination. The sample consists of 307 border-DMAs, 72 month-year periods, and on average 55 brands in each market for a total of 1182459 observations. Standard errors clustered at the product-DMA level are reported in parenthesis.

E Random Utility Model

E.1 Random Utility Model with Advertising

This appendix describes the parametric utility specification used to formulate the discrete choice demand model. This model elaborates on the insights discussed in the main text (Section 4.1.1).

Let $j = 0, 1, ..., J$ be the index of all goods available to consumers, where $j > 0$ represents any inside good and $j = 0$ is the outside alternative. Consumer i has preferences defined over a bundle of characteristics.[68] For product j, the consumer values observable ($\mathbf{X}_j$) and unobservable (by the researcher) attributes (ξ_j). The valuation of product j can also be affected by the own and competitors' advertising levels $\boldsymbol{A} = (\boldsymbol{A}_1, ..., \boldsymbol{A}_J)$. The utility for product j is given by

$$V(\mathbf{X}_j, \boldsymbol{A}, \xi_j, \varepsilon_{ij}) = \mathbf{X}_j\beta + g(\boldsymbol{A}; \boldsymbol{\gamma}) + \xi_j + \varepsilon_{ij},$$

where ε_{ij} is the idiosyncratic unobserved taste shock by consumer i for product j and is assumed to follow an i.i.d extreme value type I distribution.

The vector of preference parameters $\boldsymbol{\gamma}$ measures how much own and competitor advertising affects the valuation consumer places on the unobserved product attributes. Competitor advertising enters also the valuation for product j which allows for the possibility that advertising may be cooperative or predatory.

The utility of consuming the composite good takes the functional form:

$$u(C, \boldsymbol{A}) = \Big[\alpha_i - h(\boldsymbol{A}; \boldsymbol{\lambda})\Big] C,$$

where the term in squared brackets is the marginal utility of consumption of the composite good C, which can vary with the exposure to own and competitor advertising. Assuming that the total utility is additively separable, it is specified for product j as follows:

$$U_{ij} \;=\; u(C, \boldsymbol{A}) + V(\mathbf{X}_j, \boldsymbol{A}, \xi_j, \varepsilon_{ij}).$$

The impact of advertising on utility is twofold. On the one hand, it increases the utility that the consumer derives from purchasing the product ($\partial V(\cdot)/\partial \boldsymbol{A} > 0$). This is attributed to the fact that advertising has the potential to enhance the valuation of the product, for instance, by augmenting the perceived quality or by acting as a complement to other product characteristics (Bagwell, 2007). On the other hand, advertising reduces the utility derived

[68] To simplify the exposition, I omit the market and time indices.

from the composite good ($\partial u(\cdot)/\partial \boldsymbol{A} < 0$). Beyond promoting a specific product, advertising often portrays an unrealistic reality, which can lead to consumer dissatisfaction. Specifically, advertising sets a standard of qualitative conventions for individual behavior and consumption patterns, prompting individuals to compare themselves against an idealized reality that cannot be achieved.[69] As such, advertising collectively reduces the utility that consumers derive from the consumption of the composite good. The main implication of advertising in this model is that, all else equal, it ultimately provides an advantage to the purchasing option over the non-purchasing alternative.

The decision problem of consumer i is

$$\begin{aligned} \max_{\{d_{i0}, d_{i1}, \ldots, d_{iJ}\}} \quad & U_i \;=\; u(C, \boldsymbol{A}) \;+\; \sum_{j=0}^{J} d_{ij} V(\mathbf{X}_j, \boldsymbol{A}, \xi_j, \varepsilon_{ij}) \\ \text{s.t.} \quad & C \;+\; \sum_{j=1}^{J} d_{ij}\; p_j \;\leq\; y_i \\ & d_{ij} \in \{0, 1\} \\ & \sum_{j=0}^{J} d_{ij} = 1 \end{aligned} \tag{10}$$

Substituting the budget constraint, the choice-specific indirect utility of product j is

$$\begin{aligned} U_{ij} \;&=\; \Big[\alpha_i - h(\boldsymbol{A}; \boldsymbol{\lambda})\Big](y_i - p_j) \;+\; \mathbf{X}_j\beta + g(\boldsymbol{A}; \boldsymbol{\gamma}) + \xi_j + \varepsilon_{ij} \\ &=\; -\,\alpha_i p_j + h(\boldsymbol{A}; \boldsymbol{\lambda}) p_j + g(\boldsymbol{A}; \boldsymbol{\gamma}) + G_{ij} + \varepsilon_{ij}, \end{aligned} \tag{11}$$

where $G_{ij} \;=\; \big[\alpha_i - h(\boldsymbol{A}; \boldsymbol{\lambda})\big] y_i + \mathbf{X}_j\beta + \xi_j$. The first two terms of equation (**??**) show the price valuation which depends on the exposure to own and competitor advertising. The random coefficient for price is given by $\alpha_i \;=\; \alpha + \sigma v_i$, where v_i is a random variable with zero mean and unit variance so that α represents the mean valuation for price and σ is its standard deviation across consumers.

In this model, advertising can change how consumers react to price changes. If the coefficients associated with the interaction between price and advertising are positive, a larger advertising exposure implies lower price sensitivity. The third term of equation (15) shows the effect of advertising on the utility. Depending on the nature of the competitor's

[69]The link between advertising and the representation (and misconception) of social reality has been investigated in several papers (e.g., Giaccardi, 1995; Sherry, 1987). Michel et al. (2019) provide empirical evidence of the negative relationship between advertising expenditure and life satisfaction across multiple European countries.

advertising, it can increase (cooperative) or decrease (predatory) the utility consumer receives from product j.

The indirect utility can be decomposed into the sum of three terms: mean utility $\delta_j = \mathbf{X}_j\beta - \alpha p_j + h(\boldsymbol{A};\boldsymbol{\lambda})p_j + g(\boldsymbol{A};\boldsymbol{\gamma}) + \xi_j$ which is common to all consumers; an individual-specific term $\mu_{ij}(v_i) = \sigma v_i$; and an idiosyncratic error term ε_{ij}. If $\sigma = 0$, the demand model collapses to the standard logit model. The demand model is completed with the inclusion of the outside good whose normalized indirect utility is $U_{i0} = \varepsilon_{i0}$.

A consumer chooses the option j if and only if $U_{ij} > U_{ij'} \;\; \forall j' \neq j$. Under the assumption that ε_{ijt} is i.i.d and drawn from a type I extreme value distribution, the probability that consumer i purchases product j is:

$$s_{ij}(\boldsymbol{A},\mathbf{p}) \;=\; \frac{\exp(\delta_j + \mu_{ij}(v_i))}{1 + \sum_k^J \exp(\delta_k + \mu_{ik}(v_i))}$$

and the aggregate market share of product j is given by

$$s_j(\delta,\sigma) \;=\; \int s_{ij}(\boldsymbol{A},\mathbf{p})dP_v(v)$$

where the probability density function of α_i is assumed to be the normal distribution $\mathcal{N}(\alpha,\sigma)$.

Functional Form of Advertising. I assume that own and competitor advertising have, potentially, different effects on utility. Own advertising has a direct impact on utility, whereas competitor advertising collectively affects utility. The following is the functional form for the advertising preferences that enter the product-specific utility:

$$g(\boldsymbol{A};\boldsymbol{\gamma}) = \gamma_1\boldsymbol{A}_j + \gamma_2\bigg(\sum_{b=1,b\neq j}^{J}\boldsymbol{A}_b\bigg). \tag{12}$$

The coefficient γ_1 measures how much own advertising stock affects the valuation consumer places on the unobserved product attributes. Competitor advertising stock enters also the valuation for product j which allows for the possibility that advertising may be cooperative or predatory. The coefficient γ_2 captures the extent to which exposure to competitor advertising affects the valuation consumer places on the unobserved attributes.

The functional form for the advertising affecting the marginal utility of the composite good is:

$$h(\boldsymbol{A};\boldsymbol{\lambda}) = \lambda_1\boldsymbol{A}_j + \lambda_2\bigg(\sum_{b=1,b\neq j}^{J}\boldsymbol{A}_b\bigg) \tag{13}$$

The coefficients λ_1 and λ_2 capture the impact of own and competitor advertising on the utility of the composite good. Substituting equations 12 and 13 into the mean utility, we obtain the following expression

$$\delta_j = -\alpha p_j + \lambda_1 p_j \boldsymbol{A}_j + \lambda_2 p_j \left(\sum_{b=1, b \neq j}^{J} \boldsymbol{A}_b \right) + \gamma_1 \boldsymbol{A}_j + \gamma_2 \left(\sum_{b=1, b \neq j}^{J} \boldsymbol{A}_b \right) + \mathbf{X}_j \beta + \xi_j$$

Substitution Patterns. The demand system with advertising has implications for product-level substitution patterns. The own- and cross-price elasticities for the demand model are given by

$$\begin{aligned} \frac{\partial s_j p_j}{\partial p_j s_j} &= \frac{p_j}{s_j} \int \tilde{\alpha} s_{ij}(1 - s_{ij}) dP_v(v) \\ \frac{\partial s_{j'} p_j}{\partial p_j s_{j'}} &= -\frac{p_j}{s_{j'}} \int \tilde{\alpha} s_{ij} s_{ij'} dP_v(v) \quad \forall j' \neq j, \end{aligned} \tag{14}$$

where $\tilde{\alpha} = -\alpha_i + \lambda_1 \boldsymbol{A}_j + \lambda_2 \big(\sum_{b=1, b \neq j}^{J} \boldsymbol{A}_b \big)$ is the marginal utility from price. The model allows for flexible substitution patterns that depend on the level of own- and competitor advertising. If λ_1 and λ_2 are positive, consumers become less price sensitive as they are more exposed to advertising.

The marginal effect of a change in advertising state variable (i.e. current and past advertising exposures) on individual-level choice probabilities is:

$$\begin{aligned} \frac{\partial s_{ij}}{\partial \boldsymbol{A}_j} &= s_{ij} \left[\tilde{\gamma}_j (1 - s_{ij}) + \sum_{l \neq j} s_{il} \tilde{\lambda}_l \right] \\ \frac{\partial s_{ij'}}{\partial \boldsymbol{A}_j} &= s_{ij'} \left[\tilde{\lambda}_j (1 - s_{ij}) - s_{ij} \tilde{\gamma}_j + \sum_{j} s_{ij} \tilde{\lambda}_j \right] \\ \frac{\partial s_{i0}}{\partial \boldsymbol{A}_j} &= -s_{i0} \left[s_{ij} \tilde{\gamma}_j + \sum_{l \neq j} s_{il} \tilde{\lambda}_l \right], \end{aligned} \tag{15}$$

where $\tilde{\gamma}_j = \gamma_1 + \lambda_1 p_j$ and $\tilde{\lambda} = \gamma_2 + \lambda_2 p_j$. The interaction of advertising with price and the presence of advertising spillovers have important implications for market shares. If there are no spillovers ($\tilde{\lambda} = 0$) and $\tilde{\gamma}_j > 0$, own advertising has a positive impact on own shares. This is due to both the predatory effect of advertising on rival's shares and the market expansion effect. Under the presence of advertising spillovers, however, the sign of the own advertising effect does not necessarily dictate the implication of advertising in the market.

In this particular case, depending on the magnitude of the parameters, advertising may be predatory or cooperative and it may lead to an expansion or contraction of the market.

E.2 Alternative Model

In this alternative primitive model, advertising plays two roles: (i) it can reinforce the valuation of product characteristics (observed and unobserved), and (ii) it changes the variance of the distribution of the idiosyncratic unobserved taste shocks (i.e., the logit error).[70]

The valuation of all attributes can be reinforced by own and competitors' advertising measures:

$$V(\mathbf{X}_j, \boldsymbol{A}, \xi_j, \varepsilon_{ij}) = \Big[\mathbf{X}_j\beta + \xi_j\Big] g(\boldsymbol{A}; \boldsymbol{\gamma}) + \varepsilon_{ij},$$

where ε_{ij} is the idiosyncratic unobserved taste shock by consumer i for product j and is assumed to follow an i.i.d extreme value type I distribution. These logit errors represent unobserved product differentiation that is symmetric across products. I allow the variance of the logit error to depend positively on advertising. That is, the logit error is distributed with the scale parameter $h(\boldsymbol{A}; \boldsymbol{\lambda})$. This adjustment allows products to differentiate more in unobserved dimensions.

The utility of consuming the composite good takes the functional form:

$$u(C) = \alpha C.$$

Assuming that the total utility is additively separable, it is defined for product j as

$$U_{ij} \;=\; u(C) + V(\mathbf{X}_j, \boldsymbol{A}, \xi_j, \varepsilon_{ij}).$$

Solving the choice problem for consumer i, the choice-specific indirect utility of product j is

$$U_{ij} \; = \alpha_i(y_i - p_j) \; + \; \Big[\mathbf{X}_j\beta + \xi_{jt}\Big] g(\boldsymbol{A}; \boldsymbol{\gamma}) + \varepsilon_{ij}. \tag{16}$$

The random coefficient for price is given by $\alpha_i = \alpha + \sigma v_i$, where v_i is a random variable with zero mean and unit variance so that α represents the mean valuation for price and σ is its standard deviation across consumers. A consumer chooses the option j if and only if $U_{ij} > U_{ij'} \;\; \forall j' \neq j$. Under the assumption that ε_{ijt} is i.i.d and drawn from a type I extreme

[70] This model is based on the multiplicative adjustment introduced by Ackerberg and Rysman (2002) when modeling unobserved product differentiation in discrete choice models.

value distribution with scale parameter $h(\boldsymbol{A};\boldsymbol{\lambda})$, the probability that consumer i purchases product j is:

$$s_{ij}(\mathfrak{a},\mathbf{p}) \;=\; \frac{\exp\left(\frac{\left[\mathbf{X}_j\beta+\xi_{jt}\right]g(\boldsymbol{A};\boldsymbol{\gamma})-\alpha p_j}{h(\boldsymbol{A};\boldsymbol{\lambda})}\right)}{1+\sum_k^J \exp\left(\frac{\left[\mathbf{X}_k\beta+\xi_{kt}\right]g(\boldsymbol{A};\boldsymbol{\gamma})-\alpha p_k}{h(\boldsymbol{A};\boldsymbol{\lambda})}\right)}$$

I assume that $g(\boldsymbol{A};\boldsymbol{\gamma}) = h(\boldsymbol{A};\boldsymbol{\lambda})$. The individual choice probability takes the following form:

$$s_{ij}(\mathfrak{a},\mathbf{p}) \;=\; \frac{\exp\left(\mathbf{X}_j\beta+\xi_{jt}-\frac{\alpha p_j}{h(\mathfrak{a}_t;\boldsymbol{\lambda})}\right)}{1+\sum_k^J \exp\left(\mathbf{X}_k\beta+\xi_{kt}-\frac{\alpha p_k}{h(\mathfrak{a}_t;\boldsymbol{\lambda})}\right)} \tag{17}$$

In this model, total advertising can increase the variance of the unobservable part of the utility. When total advertising increases, the variance goes up and products become more differentiated. This rise in differentiation, in turn, makes consumers less price-responsive. This feature is captured by the equation (17).

Functional Form of Advertising. I assume that unobserved differentiation is affected by the total exposure to advertising. This ensures that the logit error is identically distributed within markets. The following is the functional form for the scale parameter of the Type I Extreme Value Distribution:

$$h(\mathfrak{a}_t;\boldsymbol{\lambda}) = \lambda \sum_{b=1}^{J} \mathfrak{a}_b$$

In the next section, I make the restrictive assumption $\lambda = 1$ and let the source of unobserved product differentiation depend directly on total advertising. Incorporating a parametric specification of the scale parameter and allowing for heteroskedastic errors are extensions worth investigating in the future.

E.3 Comparison

I now turn to the estimation of the standard logit model. The goal of this exercise is to see how the standard logit model performs with the specifications obtained from the micro-founded models. In particular, I compare the estimates in terms of the substitution patterns.

I label the main micro-founded model (i.e., the one used in the main analysis) as the "behavioral" model. The reason for this name is the interpretation of the advertising effects from a consumer perspective: advertising can change how consumers perceive a particular product and can also impact how this product is valued relative to other consumption goods. I estimate the demand model using variables related to input prices, taxes and price of advertising, as instrumental variables. I provide further details about identification and estimation in Section 5.2. The alternative micro-founded model is denoted as the "structural" model. The reason for this is the more structural nature of this micro-foundation.

Figure (E1) shows the estimated own-elasticity across beer brands. The dots represent the sales-weighted average elasticities, whereas the vertical bars show the distribution of the elasticity between the 10th and 90th percentiles. The comparison shows that both specifications yield broadly similar substitution patterns. The similarity is particularly noticeable for less elastic brands which tend to be the most popular ones. For instance, for products with own-price elasticity between -2 and -6, the distributions of elasticities overlapped each other. For brands with a high value of price elasticity, the estimated elasticities differ on average and their distribution becomes wide. The variability in the estimates is more pronounced for the structural than for the behavioral specification.

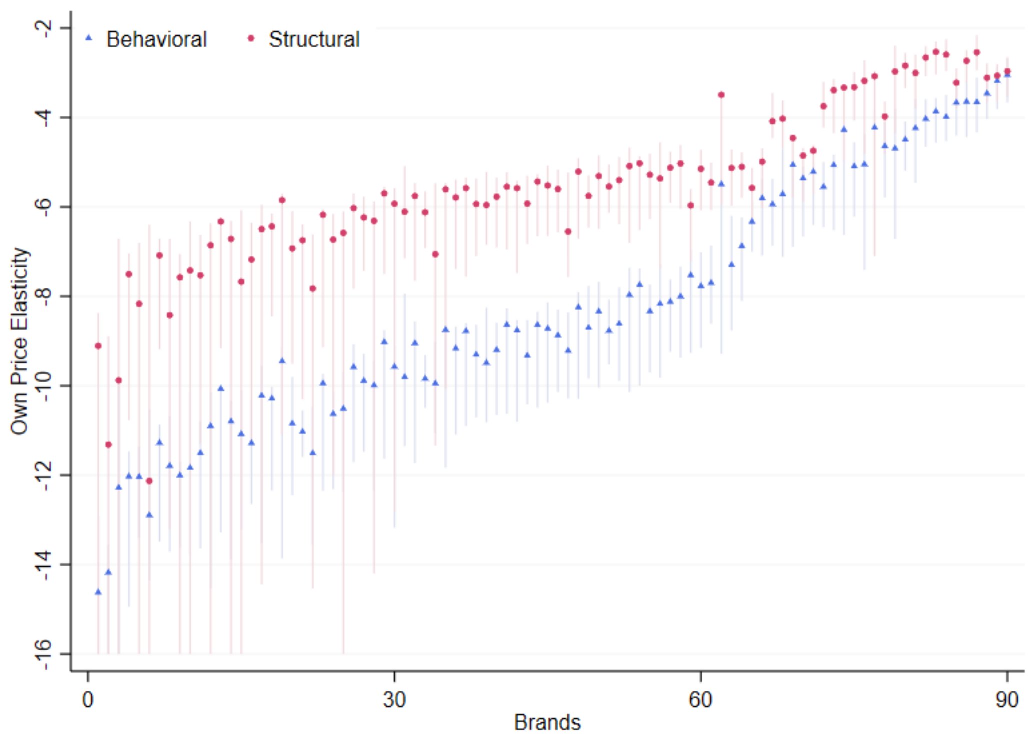


Figure E1: Own-price Elasticity

F Substitution Patterns

Figure F1: Own-price Elasticity

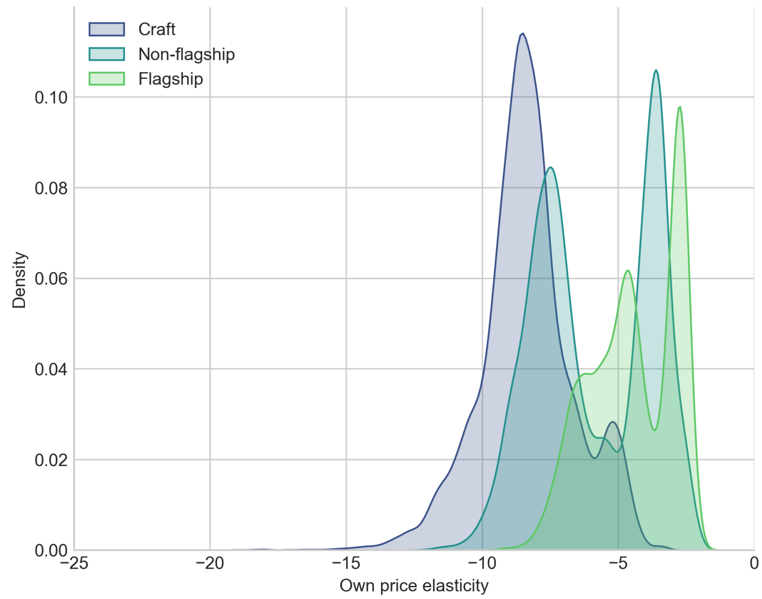


Figure F2: Long-run Advertising Elasticities

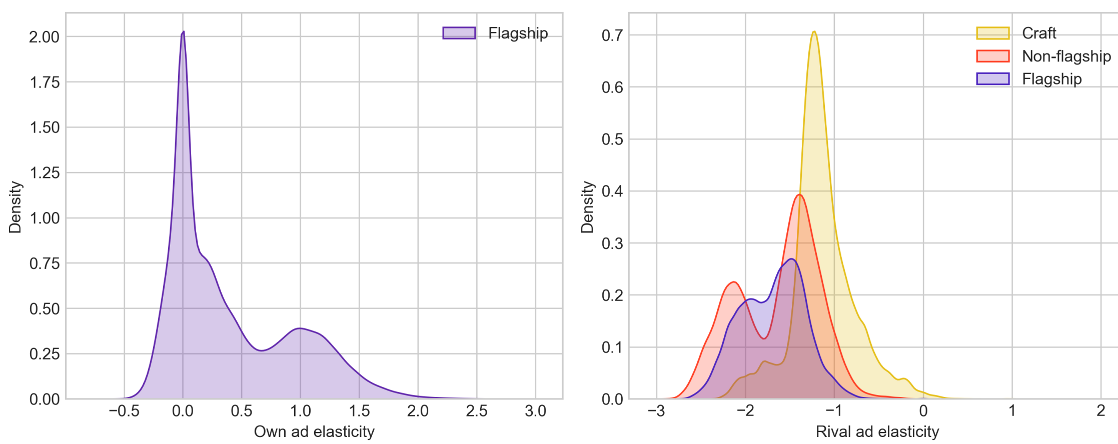


Table F1: Diversion Ratios

	% Substitution 2011	% Substitution 2016		% Substitution 2011	% Substitution 2016
Bud Light ($8.6)			Miller Lite ($8.4)		
Domestic Flagship	36.1	35.9	Domestic Flagship	40.3	37.0
Import Flagship	7.3	8.3	Import Flagship	6.6	7.1
Craft	16.6	27.5	Craft	15.1	23.1
Budweiser ($8.7)			Corona Extra ($13.1)		
Domestic Flagship	36.6	36.5	Domestic Flagship	39.0	36.7
Import Flagship	5.8	6.6	Import Flagship	7.0	9.8
Craft	12.9	21.1	Craft	10.0	16.0
Heineken ($13.5)			Modelo Especial ($12.7)		
Domestic Flagship	39.8	37.8	Domestic Flagship	34.3	32.8
Import Flagship	4.0	4.7	Import Flagship	10.6	13.4
Craft	11.3	18.3	Craft	7.9	14.0
Samuel Adams Boston Lager ($14.1)			Sierra Nevada Pale Ale ($14.9)		
Domestic Flagship	37.9	30.3	Domestic Flagship	23.7	18.2
Import Flagship	4.7	4.8	Import Flagship	2.7	2.5
Craft	30.1	36.8	Craft	12.6	16.9
Shock Top Belgian White ($13.4)			Blue Moon Belgian White ($13.8)		
Domestic Flagship	26.0	20.9	Domestic Flagship	27.4	25.1
Import Flagship	3.1	2.9	Import Flagship	3.2	3.7
Craft	6.2	8.0	Craft	16.8	27.2

Note: This table reports the aggregate diversion ratios for popular beer brands. Substitution to the same(or other) category is driven by the random coefficients incorporated in the demand model. The diversion rates show the median over all markets and correspond to (July) 2011 and 2016.

G Counterfactual Analysis

G.1 Profit Incentives - Full Table

Table G1: Profit Incentives for Advertising (USD Millions)

			Rivals Advertising	
			Before	After
		(A) No Craft		
Brewery Advertising	Before	Ab Inbev	579.5	574.5
		MillerCoors	309.2	309.0
		Constellation	123.4	121.4
		Heineken	34.7	32.9
	After	Ab Inbev	602.8	597.8
		MillerCoors	319.6	319.8
		Constellation	140.7	138.4
		Heineken	37.4	35.4
		(B) Craft		
Brewery Advertising	Before	Ab Inbev	572.1	567.2
		MillerCoors	304.3	304.2
		Constellation	120.3	118.3
		Heineken	33.7	31.9
	After	Ab Inbev	600.2	595.3
		MillerCoors	318.0	318.2
		Constellation	140.3	138.0
		Heineken	37.3	35.3

G.2 Markups

Figure G1: Markups: coordinated effects - All Flagship Brands

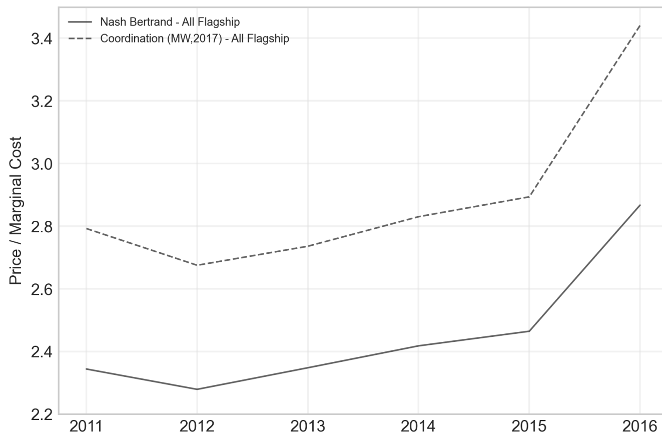
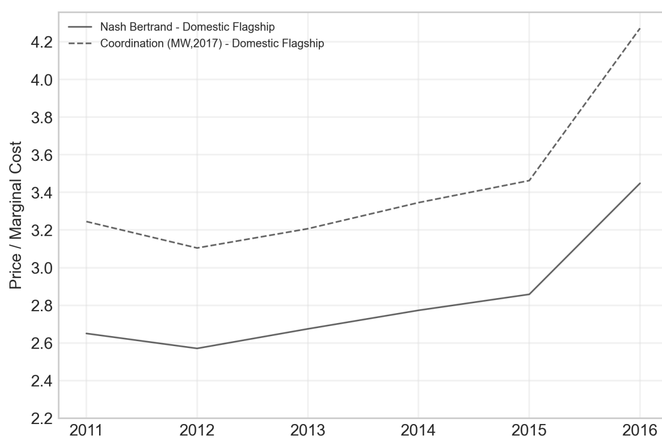


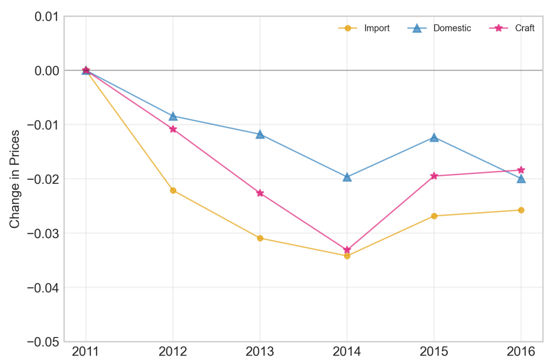
Figure G2: Markups: coordinated effects - Domestic Flagship Brands



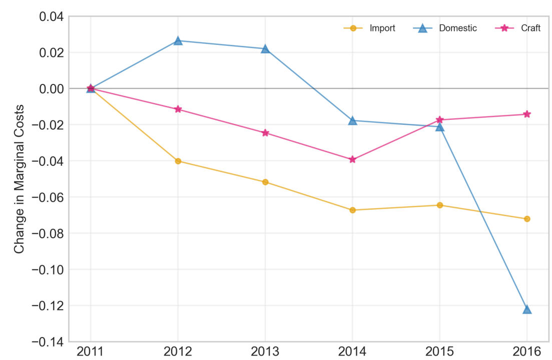
G.3 Changes in Economic Outcomes

These figures show the coefficients of a regression of log of the economic outcome on year dummies controlling for quarter, market and brand fixed effects. The year 2011 is the base category.

Figure G3: Brand-Level Changes in Prices and Marginal Costs

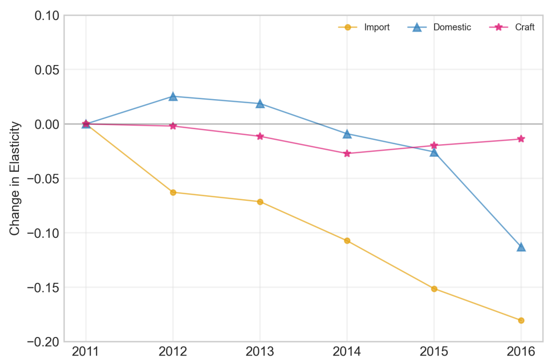


Panel A: Prices

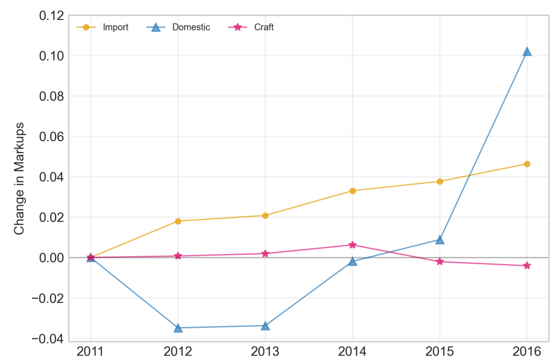


Panel B: Marginal Costs

Figure G4: Brand-Level Changes in Elasticity and Markups



Panel A: Own-price Elasticity



Panel B: Markups