Advertising Spillovers and Consumer Awareness in the Craft Beer Market

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Abstract

This paper studies how firms' advertising decisions depend on the spillovers generated by the competitors' advertising decisions in the U.S. craft brewing industry. By leveraging the discontinuity in advertising across market borders, we find that firms spend less on advertising when facing more competitors, suggesting that advertising spillovers exist. We estimate that advertising spillovers are more pronounced in markets hosting a larger number of craft breweries, as the increase in advertising spending in response to rivals' advertising is smaller in these markets. We also find the elasticity estimates to be smaller for the time periods after the Brewers Association launched a generic advertising campaign, which likely increased consumer awareness of craft beer products. We discuss these findings using a simple limited information discrete choice model of consumer demand, incorporating both persuasive and informative advertising approaches, and analyze the competitive landscape of the craft beer market.

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. Researchers' own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

1 Introduction

How does a firm's advertising decision depend on how much its competitors spend? Does a firm's advertisement induce consumers to learn about the entire product category, benefiting the competitors? We study these questions in the context of the U.S. craft brewing industry, where sellers of a relatively new product category advertise to compete for market shares.

The persistence of cooperative behavior in nascent market organizations beyond their emergent phases leads them as a collective identity to share the belief that *a rising tide lifts all boats* (Mathias et al. (2018)). One of the main drivers of the success of the craft beer industry is the insights of its early brewers, who recognized the importance of promoting the industry collectively as an emerging oppositional identity against their contending identities, the nationally prominent mass-producers. In 2017, the Brewers Association (BA) - a not-for-profit trade association of U.S. craft brewers launched the Independent Craft Brewer Seal as a mark of distinction for craft beers. The Independent Seal, coupled with the satirical crowdfunding Take Craft Back movement from the same year, helped popularize craft beers on a national level. Does this increased level of consumer awareness influence individual brewers' advertising choices?

Higher consumer awareness could encourage brewers to increase their advertising efforts to compete with rivals and capture a larger market share. Alternatively, it might lead some brewers to reduce their advertising spend, taking advantage of the decreased need for informative advertising and relying on consumer knowledge to drive demand. The advertising outcomes in the craft beer market will ultimately depend on the balance between informative and persuasive advertising approaches, as well as the competitive landscape of the industry. There are two effects of advertising by a craft brewer on the market share of other competing firms. The first effect raises consumer awareness about craft beers in general and creates advertising spillovers that benefit the entire industry. The second is the pure business-stealing effect of ad-spending, which increases the market share of the advertising firm at the expense of others. The overall impact of advertising in the craft beer market will be determined by the interplay of these spillover and business-stealing effects.

We use data on weekly brand-level advertising expenditures for 154 craft breweries from 2016 to 2019 to assess the differential impacts of rivals' advertising on a craft brewer's own advertising expenditure. By exploiting advertising discontinuities at designated market area (DMA) borders, we estimate the elasticity of a craft brewer's advertising in response to that of its rival brewers. We compare adjacent markets located on opposite sides of a DMA border to use local advertising differences to trace out existence of spillovers. We examine breweries near the borders to see how their ad spending across DMAs correlates with the number and ad spending of rival breweries in those areas We leverage this spatial heterogeneity to identify the effect of rival advertising. We find lower elasticity estimates for the time periods marked by heightened consumer awareness, particularly in the years following 2017. We also find that in markets with a higher number of competing craft breweries, advertising elasticities—defined as the increase in advertising spending in response to rivals' advertising—are smaller. This suggests the presence of advertising spillovers.

This research makes three contributions to the existing literature. First, using the discontinuity in advertising markets, we find empirical evidence of advertising spillovers in the craft beer market. Specifically, we show that in markets with a higher number of craft breweries, individual craft brewers tend to spend less on advertising in response to rivals' advertising. Additionally, we find that a higher level of consumer awareness is associated with lower cross-advertising elasticity. Second, for the empirical exercises, we construct a comprehensive brand-brewery-week-market level dataset, combing the production data from the Brewers' Association (BA) and the Nielson Ad Intel data. We hand-coded brewery characteristics, such as BA membership, address, and possession of the Independent Craft Brewer Seal. We also construct a sub-sample that consists of breweries located in counties at the DMA borders. Third, we explain the advertising mechanics behind this empirical finding using a model of equilibrium supply and demand in a differentiated products market where consumers have limited information and firms, both craft and mass-producer macro brewers, engage in persuasive and informative advertising. Persuasive advertising enters consumers' utility as a complement to the advertised product. It is important to emphasize the different returns on persuasive advertising for macro and craft brewers, and how this difference translates into the model's utility functions, consideration sets, and the probability of awareness. Consumers are consistently aware of macro brewers, as they have a pervasive presence in the market and successfully utilize persuasive advertising to maintain their visibility. However, due to the limited reach of craft brewers, consumer awareness of craft brewers is less certain. Considering advertising dynamics and consumer awareness when analyzing the competitive landscape of the craft brewing industry is essential. Macro beers exist in the consideration set of every consumer. To account for the varying levels of consumer awareness of craft beers, our model formulates the probability of a craft beer being included in a consumer's consideration set as a function of advertising. The consideration probabilities are formed using the informative advertising by craft brewers and the overall consumer awareness about craft beers. We compute the purchase probability for each product using the discrete choice model of consumer demand. Firms in this model compete in a simultaneous Bertrand Nash game. We simulate this model and find that higher consumer awareness levels are associated with lower advertising elasticities, leading to decreased advertising spending when the return on consumer awareness is positive for firms. Craft brewers' market shares are more responsive to changes in advertising expenditures when consumers have a greater awareness of their products. When the return on a firm's informative advertising is greater than the return on its rivals' informative advertising, the difference between scenarios with higher and lower consumer awareness narrows. Additionally, as the return on persuasive advertising increases, advertising expenditures and elasticity rise, leading to a smaller difference between the expenditures in the two scenarios. The main takeaway from our numerical simulation is that in an emerging industry, where firms face competition from mass producers and consumers have limited information, increasing consumer awareness and the subsequent reduction in advertising spending underscore the importance of informative advertising and the reliance of nascent firms on it. This echoes our empirical finding that an increasing number of craft breweries and their cumulative advertising expenditure are associated with a reduction in the advertising spending of an individual brewer.

Our empirical approach for identification is to exploit the discontinuity in advertising exposure that exists across two bordering geographic regions (called designated market areas, or DMAs). The identifying variation in advertising expenditure comes from deviations from the average ad spending by rival brewers over weeks. Intuitively, the research design relies on the assumption that differential trends in advertising between the two opposite sides of a DMA border are the result of differences in exposure to advertising by rivals.

The primary limitation of this research stems from data constraints. While an empirical specification using sales data would have been more insightful, the reality is that a significant portion of craft brewers sell their beers directly at their brewing facilities or taprooms. As a result, we found production data to be a more fitting choice, despite its limited variation over time. Additionally, the border identification strategy we employed restricted the number of breweries we could include in our final dataset, raising concerns about potential omitted variable bias. Another consideration is our reliance on the time periods following the introduction of the independent craft brewer seal and the industry campaigns by the Brewers Association as proxies for consumer awareness. Such an approach might not fully capture the intricacies of consumer perceptions and preferences. It's also noteworthy that our study is squarely focused on the US craft beer industry, which limits the generalizability of our findings to other sectors or international markets. Looking forward, future studies could enhance our understanding by employing more advanced econometric methods to establish causal relationships and by expanding the scope of the research to include other industries. This would provide insights into the wider applicability of our findings. Alternative indicators for consumer awareness that better capture its multifaceted nature could also be explored. A deeper examination of the interplay between advertising expenditures and consumer awareness might reveal strategies firms can employ to optimize their advertising. Moreover, considering the role of factors such as social media engagement and online reviews in influencing consumer perceptions could offer additional layers of understanding of the dynamics between consumer consciousness and corporate advertising decisions.

Related literature

Economic theory provides insights into how consumer awareness can impact advertising strategies and spending by firms (Bagwell, 2007; Becker & Murphy, 1993). As consumers possess a greater understanding of products and services, the dynamics between informative and persuasive advertising may shift, leading to changes in firms' advertising approaches (Vakratsas & Ambler, 1999). Informative advertising, which focuses on educating consumers about product features and benefits, may see a decline in demand as consumers increasingly rely on their own knowledge to make purchasing decisions (Nelson, 1974). On the other hand, persuasive advertising, which aims to influence consumer preferences by leveraging their interests, increasing product differentiation, and creating brand loyalty, might gain traction in response to heightened consumer awareness (Vakratsas & Ambler, 1999; Kirmani & Wright, 1989). As awareness increases, the responsiveness of consumers to advertising changes, leading firms to adjust their advertising behavior. Firms adapt their advertising strategies to differentiate themselves from competitors and gain market share in an increasingly discerning consumer environment (Iyer, Soberman, & Villas-Boas, 2005).

In nascent industries like craft beer, where consumer awareness has been on the rise, it becomes essential for businesses to distinguish themselves from mass producers and foster a sense of unity within the industry (Tremblay & Tremblay, 2005; Swinnen, 2011). By employing targeted marketing efforts, breweries can heighten consumer awareness of the value of their brewing, consequently expanding consideration sets to include craft beer as a viable alternative to mass-produced options (Schnell & Reese, 2003).

Beer is one of the most advertised products in the US (Tremblay and Tremblay, 2005), and a vast literature on advertising has focused on the market structure, consumer choices, advertising spillovers, and firm behavior. Chandra and Weinberg (2018) study the relationship between market concentration and advertising in the beer industry and find a significant positive effect of local market concentration and firms' advertising behavior.

Grossman and Shapiro (1984) examine the role of advertising in signaling product quality in markets with imperfect information. The authors develop a model where firms can use advertising to signal their product quality and show that high-quality products are advertised more heavily than low-quality products. Generic advertising, which is particularly effective in raising consumer awareness about an industry, can use persuasive and informative approaches to help independent producers in nascent industries. Using its persuasive approach, Crespi and Marette (2002) analyze generic advertising and its effects on product differentiation in the U.S. prune industry. Chung and Kaiser (2000) find that generic advertising is more beneficial to small producers than large New York Dairy Industry producers. The spillovers of advertising create free-riding incentives with the possibility of a decline in the total industry advertising expenditure. Chandra and Kaiser (2014) investigate the spillover effects of advertising in the context of the US beer industry. The authors find that advertising by large breweries has positive spillover effects on smaller craft breweries, increasing consumer awareness of the craft beer category as a whole. This suggests that advertising can create positive externalities within an industry. Shapiro (2018) explores free riding in advertising in the context of the pharmaceutical industry and finds evidence for advertising spillovers and free riding. Another study on advertising in the pharmaceutical market by Iizuka (2004) also finds evidence of free riding as the firms advertise less when the number of rivals increases. Sahni (2016), Lewis and Nguyen (2012), and Anderson and Simester (2013) have also found experimental evidence of the existence of free riding in various industries. Ching, Erdem, and Keane (2009) use scanner data to find that advertising by an individual brand has spillover effects for the entire category.

Our empirical strategy relies on the distinct boundaries that exist within local advertising markets. This means that two nearly identical breweries situated on opposite sides of a

DMA boundary will be subjected to a varying number of competing craft breweries and their associated advertising. This methodology resonates with the identification strategy employed by Shapiro (2018) to find evidence for advertising spillovers in the domain of pharmaceuticals. A similar identification strategy was used by Card and Krueger (1994) and Dube, Lester, and Reich (2010) to discern the repercussions of augmented minimum wages, and by Holmes (1998) to recognize the influence of right-to-work legislation. The aforementioned trio of studies anchors their research on state boundaries where laws, market conditions, or public preferences might diverge. Comparable geographical techniques have been championed by Black (1999) and Bayer, Ferreira, and McMillan (2007) with a focus on school district boundaries and by Ito (2014) while examining the demarcations in electricity markets.

This paper is also related to the literature on the discrete choice demand model of limited information. We use a discrete choice demand model where consumers have limited information, and advertising enhances the probability of a product being included in the consumers' consideration sets. Goeree (2008) refers to these probabilities as consideration probabilities and uses them to study a discrete choice model of limited consumer information in the market for personal computers.

The remainder of this paper is organized as follows: Section 2 provides a brief overview of the craft beer industry. Section 3 discusses the data sources and outlines the sample construction. In Section 4, we delve into our empirical strategy and estimation. Section 5 introduces and simulates a theoretical model discussing craft beer advertising. Finally, Section 6 concludes the paper.

2 Industry Background: A Brief Description of the US Craft Beer Market

Craft breweries are small, independent, and traditional operations that stand out from large national corporate beer companies. The craft beer segment began in San Francisco and has spread across the US since 1965 when Fritz Maytag took ownership of Anchor Steam Beer Company and revitalized "a fading company and a dying product" (Elzinga et al. (2015)). By 1985, the industry's growth had accelerated, and the number of craft brewers increased exponentially. As a result, the regional markets for craft beers experienced continued entry and a reduction in overall market concentration (Elzinga et al. (2015)). One of the main drivers of the success of the craft beer industry is the insights of its early brewers, who recognized the importance of promoting the industry collectively as an emerging oppositional identity against their contending identities, the nationally prominent mass producers. Another reason behind the success of craft beers was the homogenization of macro beers. Macro brewers shifted their production towards milder beer categories, which created an opportunity for craft beers, primarily darker lagers and ales. In response to the growth of the craft segment, macro brewers introduced their own craft-style beers, but many consumers did not accept these as legitimate craft beers. Several other factors contributed to the rapid growth of the craft beer industry, including increases in personal income, the legalization of home brewing, and less stringent regulations.

In 2005, the Brewers Association (BA) was founded as a not-for-profit trade association for U.S. craft brewers and brewing enthusiasts. The BA provided a unified voice and self-referential meaning for the craft brewers' identity. In 2007, the BA defined craft breweries as "small" (annual production of 6 million barrels of beer or less) and "independent" (less than 25 percent of the craft brewery is owned or controlled by a beverage alcohol industry member that is not itself a craft brewer) businesses. To strengthen this collective identity, the BA launched the Independent Craft Brewer Seal in 2017, which marked breweries free of corporate influence and meeting the craft definition. This Independent Seal allowed external audiences to perceive craft breweries as authentic, legitimate, and attractive. As a result, member organizations began to develop standards and form professional associations.

By the end of 2018, 4000 craft breweries had adopted the seal, accounting for about eighty percent of the total volume of craft-brewed beer. Early adopters saw it as a symbol of distinction, differentiation, and certification. The "Take Craft Back" campaign, launched in October 2017, was the first to feature the seal's likeness. The Take Craft Back Campaign was a satirical crowdfunding and marketing initiative. It proposed raising $213 billion to acquire Anheuser-Busch InBev (AB InBev), which had purchased 10 independent U.S. breweries since 2011. The campaign ultimately garnered over $3.8 million in pledges from nearly 12,000 supporters.

According to the B.A.'s Chief Economist, Bart Watson, a substantial bulk of the growth of craft beers is driven by microbreweries, brewpubs, and new entrants rather than the regional craft brewers (Annual Growth Report, 2018). In figure 1, we present the growth of the number of craft breweries in the U.S. since 1972 using the BA's historical brewery count data. The total number of operating craft breweries has been growing steadily since 1986 when the U.S. beer market experienced a parallel transforming event of introducing light beer and homogenizing national beers towards this category. This transformation created a sound increase in the demand for craft beers, especially among consumers who preferred darker beers. Following this trend, producers started rushing to enter the craft beer market and initiated a gradual decline in craft brewing quality (Tremblay and Tremblay (2011)). As a result, the remarkable growth rate faced a slack around the late 1990s and early 2000s. The number of brewpubs and microbreweries grew following a similar trend, except in 2019, when microbreweries experienced a considerable lack of growth following the Coronavirus pandemic.

Figure2 compares the historical production of craft beers with that of the non-craft and imported beers by comparing their volume shares during 1998-2020. Craft beers' volume share has increased just about monotonically. The share of imported beers has also increased but somewhat slackened off starting 2007-2008, following the economic recession, and picked up the growth again from 2013-2014. Non-craft beers or macro beers, on the other hand, have been experiencing a gradual decline in their volume shares.

The incredible growth of the craft beer industry attracted many producers causing continued entry with a reduction of overall market concentration. The market structure and concentration of craft brewers have a significant geographical variation as shown in table1.

Table 1 presents the geographical variation in the number of operating craft breweries across the U.S. in 2020. It provides a comprehensive summary of the number of craft breweries in each state of the United States, along with their respective ranks. It also offers a comparative analysis of the concentration of craft breweries by calculating the number of craft breweries per 100,000 adults aged 21 or older, as well as the ranking of each state based on this concentration.

California leads with the highest number of craft breweries, followed by New York, which has about half as many breweries. On the other hand, Mississippi has the lowest number of craft breweries. However, when considering population, Vermont tops the list in craft breweries per capita, followed by Maine and Montana. Notably, California and New York rank lower on this list, at 29th and 31st, respectively. Additionally, Colorado, the home state of the Brewers Association, ranks fourth in the number of craft breweries and sixth when considering craft breweries per capita.

States such as Vermont, Maine, and Montana have the highest concentration of craft breweries per capita, whereas states like Mississippi, Louisiana, and Alabama have the lowest. Overall, the total number of craft breweries in the United States is 8,764, with an average concentration of 3.60 breweries per 100,000 adults aged 21 or older.

By incorporating these insights, table 1 allows for a comprehensive understanding of the craft brewery landscape across the United States, highlighting regional differences in the presence and concentration of these establishments and emphasizing the importance of considering both absolute numbers and per capita figures when analyzing the industry's landscape.

Table 2 illustrates the fluctuations in the growth rate and production of craft breweries over the years. It presents the growth rate (in %), the change in production (in barrels), the number of craft breweries, and the change in production per brewer for each year from 2010 to 2021. The growth rate of craft breweries increased steadily from 2010 to 2014, reaching a peak of 17.8% in 2014. However, the growth rate started declining after 2014, with the lowest growth rate of 2.7% in 2018. 2020 saw a negative growth rate of -10.1%, potentially due to the COVID-19 pandemic. In 2021, the growth rate rebounded to 8.1%. The number of craft breweries consistently increased from 2010 to 2021.

Independent Craft Brewer Seal and Consumer Awareness

The introduction of the Independent Craft Brewer Seal, followed by events similar to "Take Craft Back" campaign raised consumer awareness about the industry. The seal can directly increase a craft brewer's advertising elasticity by enhancing perceived quality, authenticity, and credibility. Indirectly, the seal can affect the advertising elasticities of competing craft brewers through spillover effects, as it raises overall consumer awareness regarding craft beer quality and authenticity. Additionally, the seal may impact the competitive dynamics between craft and macro brewers, potentially resulting in differing advertising elasticities between the two groups. To summarize, the seal's impact on advertising elasticities is multifaceted, affecting individual brewers' advertising effectiveness, the elasticities of competitors, and the competitive landscape. Understanding these effects can support craft brewers in making data-driven decisions about advertising strategies and incorporating the seal into marketing efforts.

3 Data Sources and Sample Construction

3.1 Data Sources

Our production data is sourced from the Brewers Association, while the Nielsen Ad Intel data provides information on advertising expenditures. Here are brief descriptions of these datasets.

Brewers Association Database

By subscribing to the Brewers Association, we gained access to their comprehensive production database and brewery statistics, which provide an elaborate, in-depth, and inclusive description of the craft beer market and its historical growth. In our analysis, we use the time periods 2016-2019. As shown in Table 2, a compelling reason to focus on 2016-2019 is the stabilization in growth rates and the positive, yet moderate, changes in production during this period. This time frame represents a more mature and stable phase in the craft brewing industry compared to the earlier rapid growth observed from 2010-2014. During 2016-2019, the growth rate was relatively steady, ranging from 2.7% to 5.9%. Moreover, these years saw consistent positive changes in production, indicating a stable increase in craft brewery outputs. By analyzing this period, we can gain valuable insights into the industry's performance during a more settled phase, which could provide a better understanding of the underlying factors influencing craft brewery growth and production. The Brewers Association (BA) provides production data at the Brewery-City-State level. In order to make the most effective use of this detailed information, it is reasonable to define a market at the city level. Analyzing markets at the city level provides a granular understanding of consumer preferences and competition within these local markets. However, for our main empirical analysis, we hand-coded zip codes. These were then used to link counties and subsequently aggregate the variables at the DMA level.

According to the Brewers Association's 2019 production data, Boston Beer Co in Boston

(M.A.) is the largest craft beer producer in the U.S., and Sierra Nevada Brewing Co. in Chico (C.A.) is the second in production. Both of them have more than 90% shares in their corresponding markets. The third highest production is by Spoetzl Brewery in Shiner (TX). It has the entire market to itself. With a total of 71 breweries, Portland is the city with the highest number of craft breweries in the U.S. Denver, the city where the BA is situated, ranks second with 67 craft breweries. San Diego, Seattle, and Chicago have, respectively, 56, 55, and 54 craft breweries. No other U.S. cities have over 50 craft breweries in total.

Figure 3 and 4 use, respectively, boxplots and histograms of the Herfindahl-Hirschman Index (HHI) to illustrate the changes in craft beer market concentration during 2016-2019. These HHIs are computed at the city level using the Brewers Association's (BA) production data. The average HHIs across markets have experienced a gradual decline over the years. This growing competition is attributed to the rapid growth in the number of breweries, declining market shares of individual breweries, and the overall growth in production and sales.

Nielson Ad Intel Data

The ad spending data in this paper comes from the Nielsen Ad Intel Database provided by the Kilts Center for Marketing at the University of Chicago Booth School of Business. This dataset consists of brand-level advertising expenditures. First, we extract the data for all beer categories to compare the trends. Figure 5 shows the advertising spending for National (Domestic Macro beers), Craft, and Imported beers during 2016-2019 using two-year averages. The expenditures for both national and imported beers have gone up in 2018-2019, whereas for craft beers, they have gone down. Macro breweries, such as Anheuser-Busch InBev and MillerCoors, typically have larger budgets and are known for their extensive advertising campaigns across various media platforms, including television, print, digital, and event sponsorships. Their advertising spending is generally higher than that of craft breweries, as they aim to maintain and expand their market share. On the other hand, craft breweries usually have smaller budgets and rely more on grassroots marketing strategies, such as social media, local events, and word-of-mouth promotion. Craft breweries often focus on building a strong presence within their local communities, targeting niche markets, and emphasizing their unique offerings and brand identity. As a result, their advertising spending tends to be lower than that of macro breweries. Imported beers spend more on advertising than craft breweries but less than domestic macro brewers in the US.

Figure 6 and 7 further break down craft beer advertising across brewery types and years. Advertising spending follows a highly unequal distribution in the craft beer market, with regional breweries spending significantly more than the rest. As a result, the declines in expenditures over the duration of 2018-2019 for regional and microbreweries have brought down the advertising expenditures of the entire craft beer industry.

Figure 8 displays visualizations of log-transformed weekly ad spending for craft breweries during 2016-2019, along with four-week moving averages. The dashed vertical line indicates when the independent craft brewer seal was introduced. The plot exhibits significant fluctuations. There are periods during 2016-2017 where ad spending appears to be relatively stable, followed by intervals of sharp fluctuations. This pattern suggests that advertising expenditures are subject to short-term factors or events that impact spending decisions. Furthermore, we can identify a general downward direction for the trend over time. When analyzing weekly spending data exhibiting frequent fluctuations, it is essential to account for various factors contributing to these variations. Some potential explanations for such up-and-down patterns include seasonality, promotions and marketing campaigns, and various external factors, such as economic conditions or market trends.

Using the brand-level ad intel spending data, we hand-coded to distinguish the craft, national (domestic macro), and imported beers separately. We also hand-coded the brewery-level information for craft breweries, including location (city, state), brewery type, BA membership, and possession of the independent craft brewer seal before joining these brand-level ad occurrences with the craft breweries available in the BA's production data. We use ad spending at a weekly level over the four years.

Figure 9 provides a detailed overview of the two-year averages of advertising expenditures during 2016-2019, illustrating changes in spending for breweries in terms of their BA membership status and possession of the independent craft beer seal. We observe a declining trend in ad spending across all categories.

3.2 Sample Construction

We construct two distinct samples: a sample of all breweries and a sample of breweries located near DMA borders. The rationale behind the latter sample is elaborated upon in our empirical specification. Advertising can be purchased both locally and nationally. However, our full and border samples consist only of local advertising by breweries, thereby excluding national advertising. The full sample comprises 142 breweries located across 114 counties. To create the border sample, we begin by listing the neighboring counties of the counties in the full sample using the 2010 County Adjacency File from the Census Bureau. Subsequently, we retain the neighboring counties that are situated on opposite sides of a DMA border. This narrows the sample down to 86 breweries located across 74 counties, advertising across 205 distinct DMAs. For each brewery, we analyze the variation in their weekly advertising expenditures across DMAs. It's worth noting that the bordering market samples could repeatedly include data for counties neighboring multiple others. As highlighted by Dube, Lester, and Reich (2010), such repetitive observations could reduce standard errors for estimates, giving an illusion of enhanced precision. To counter this bias in standard errors, following the methodology of Dube, Lester, and Reich (2010), we adopt a two-way clustering approach on the DMA and border. Each combination of border-DMA-week represents a local market and is treated as an independent local experiment. Adjacent border markets located across different DMAs serve as effective control groups for estimating the impacts of rival advertising. This is particularly true when there are marked differences in treatment intensity within these cross-DMA markets and when a market is more akin to its cross-DMA counterpart than to a randomly selected market elsewhere. In stark contrast, the full sample specification operates on an implicit assumption: any given market in the United States can serve as a suitable control for another, irrespective of its location or characteristics. Figure 10 presents the resident counties of the breweries constituting our border sample.

4 Reduced-Form Evidence: Empirical Strategy and Estimation

In this section, we explore the data to see if spillover effects of rival advertising exist.

Baseline Specification Using All-County Sample

We start by estimating rival advertising effects using the full sample, including county and period fixed effects:

$$\begin{aligned}\log(a_{kjt}) = \beta_0 + \beta_1 \log\left(\sum a_{-kjt}\right) + \beta_2 \text{PostSeal} + \beta_3 K_j + \beta_4 (\log\left(\sum a_{-kjt}\right) \times \text{PostSeal}) + \\ \beta_5 (\log\left(\sum a_{-kjt}\right) \times K_j) + \boldsymbol{\beta_6 X_{jt}} + \alpha_j + \gamma_t + \epsilon_{jt}\end{aligned} \tag{1}$$

where a_{kjt} denotes the weekly advertising expenditure of craft brewer k at week t in advertising market j, $PostSeal$ denotes the time after the introduction of the seal when consumer awareness about the industry heightened, (X_{kj}) captures other brewery and market-level factors, K_j is the number of breweries in the advertising market, j, α_k and γ_t are county and time (season) fixed effects, respectively, which control for unobserved heterogeneity across markets and time periods. We measure the number of craft breweries from the Brewers Association database, which consists of all the operating craft breweries.

Empirical Identification Strategy: Border Strategy

The challenges in causally estimating the effect of rival advertising on a brewery's own advertising arise from endogenous advertising choices and the absence of reliable instrumental variables. To navigate these challenges, we exploit the discrete nature of local advertising markets. That is, two very similar markets that are located directly across the DMA border from one another will have exposure to a different number of competing craft breweries and their corresponding advertisement exposures. This differential exposure forms the basis of our analytical comparison. The amount a brewery, located at the border of two DMAs spends in each DMA will be influenced by the competition and rival advertising it encounters in those DMAs. For breweries situated in the interior of a DMA, their advertising expenditures within their own DMA and neighboring DMAs are influenced by various factors, including their distance from the market located on the opposite side of the DMA and their market size. For instance, a small craft brewery near the center of a DMA might opt to advertise solely within its own DMA, foregoing the neighboring ones. Consequently, several confounding variables come into play when analyzing the relationship between a brewery's advertising and that of its rivals within the interior of a DMA. Conversely, for breweries straddling the borders of two DMAs, owing to their equidistant location relative to markets in both DMAs, their advertising outlays are predominantly modulated by DMA-centric attributes, such as the intensity of competition and the prevalence of breweries within that DMA. It's pertinent to note that adjacent DMAs, by virtue of their contiguity, often manifest overlapping geographical and demographic attributes. Consequently, for breweries proximate to such borders, advertising allocations across these DMAs are chiefly contingent upon competitive pressures from adversary brewers. This implies that the interrelationship between a given brewery's advertising strategy and that of its competitors is comparatively insulated from confounding influences for breweries at DMA borders, as opposed to their counterparts situated deeper within a DMA. Consider, for instance, a border county from our sample. Figure 11 showcases the map of Grayson County, located between two distinct DMAs: Sherman-

Ada and Dallas-Ft. Worth. One of the breweries in our sample, located within Grayson County, advertises in both DMAs. Notably, this brewery finds itself equidistant from the central markets of these DMAs. Despite this geographic symmetry, the brewery confronts varying degrees of competitive pressure in each DMA. Specifically, Sherman-Ada features far fewer craft breweries advertising than Dallas-Ft. Worth. Such disparities in exposure to rival advertising are instrumental in elucidating the differential advertising expenditures of the brewery across these two DMAs.

Our methodology echoes the approach adopted by Shapiro (2018) to identify advertising spillovers in the pharmaceutical market, as well as the strategies of Card and Krueger (1994), and Dube, Lester, and Reich (2010) in studying the implications of the increase in the minimum wage. A unique aspect of DMA or TV market boundaries is their origin, specifically tailored for broadcasting, making them largely uncorrelated with other external factors. Hence, DMA boundaries might be perceived as independent of consumer traits. Advertising can be procured at both the national and local levels. The DMA assigned to a brewery's county, as delineated by AC Nielsen, influences the cumulative advertising presented in its locale. Nielsen groups counties based on anticipated viewer preferences for local stations, often gravitating around urban hubs. We treat each DMA border as a distinct case study. The intensity of the investigative focus is dictated by the concurrent rival advertising within each DMA at a given time. Only adjacent markets act as mutual controls, isolating local influences impacting both border sides. Observations are structured as brewery-border-DMA-week. Intuitively, firms make different advertising decisions for different DMAs, which creates useful variation in advertising between the opposite sides of bordering DMAs. More specifically, we trace out the variation in own ad spending generated by brewers who advertise on opposite sides of a DMA border over time and measure how that variation relates to the variation in advertisements by their rivals in those DMAs. Importantly, these breweries in the bordering markets are exposed to the same business cycles, economic conditions, and unobserved local demand shocks that are correlated with firms' advertising decisions. As a result, our research design leaves only the level of rival advertising exposure to explain the differences in own spending between neighboring DMAs. To deduce advertising effects within this framework, we employ a tailored difference-in-differences estimator. The key identifying assumption is that advertising trends diverging across DMA borders are predominantly influenced by variations in rival advertising exposure. Our analysis incorporates border-DMA-season and City-State-Season fixed effects, ensuring that the shared trend premise is locally applied, allowing for regional and seasonal variations.

Therefore, our preferred identification strategy exploits variation between contiguous DMAs and uses the sample with all such adjacent border county pairs. This strategy involves a change in samples as well as a change in specification. The identifying variation comes from the three dimensions in our data: brewery, DMA, and time. The baseline regression equation is as follows:

$$\log(a_{kbt}) = \gamma_0 + \gamma_1 \log\left(\sum a_{-kbt}\right) + \gamma_2\text{PostSeal} + \gamma_3 K_b + \gamma_4(\log\left(\sum a_{-kbt}\right) \times \text{PostSeal}) + \gamma_5(\log\left(\sum a_{-kbt}\right) \times K_b) + \boldsymbol{\gamma_6 X_{kj}} + \alpha_j + \phi_{bds} + \epsilon_{kjbt} \tag{2}$$

where a_{kbt} denotes the weekly advertising expenditure of craft brewer k at week t in border region b, and ϕ_{bds} represents the border-DMA-season fixed effects that absorb common trends on opposite sides of a DMA border. The equation is an interactive model. Our identifying assumption is that the differences in exposure to rival advertising are uncorrelated with the differences in residual own advertising, i.e., $E\left(\log(\sum a_{-kbt}), \epsilon_{kjbt}\right) = 0$. Note that equation 2 is not identified using the full sample specification.

Potential Threats to Our Identification Strategy

The primary constraint of the border approach mirrors the inherent limitation found in typical regression discontinuity designs: treatment effects are pinpointed at the border but might not be universally applicable elsewhere. It is conceivable that the effect within the interior of the DMA varies from the effect observed at its edge. Another potential concern with the border strategy is that limited variation might exist, net of the fixed effects. This could occur if most of the advertising was national, leaving little room for local advertising. However, this concern is mitigated for craft brewers who predominantly operate in and rely on local markets. Additionally, very large regional breweries like Boston Beer Co., which engage in nationwide advertising, are not present in our border sample. There is also potential for measurement error. Some breweries engage in both local and national advertising. By excluding national advertising from our analysis, we could inadvertently violate our exogeneity assumption, especially if a brewery's choice of local advertising is influenced by its choice of national advertising. To determine if this is the case, we exclude all breweries that engage in national advertising and repeat the analysis. Our main coefficient estimates remain similar but with smaller magnitudes (see Table 5). Another concern is the potential for various policies or cost inputs to change discontinuously at the DMA border, influencing breweries to locate on one side of the DMA border over the other. As Shapiro (2018) points out, DMAs are generally only relevant to television markets, it is challenging to conceive why tax or other regulations would systematically vary across DMA borders. Most business tax policies are set at the state or potentially large city levels. Thus, being on the border of a DMA usually exempts those counties from significant city-specific taxes. However, since many DMA borders align with state borders, state tax policies could pose an issue. Another issue is the potential for selection bias across the border. For instance, breweries might select counties with specific attributes, such as lower corporate rental rates. If these breweries inherently respond differently to rival advertising compared to those in areas with higher rents, it could bias our results. Lastly, the identifying assumption of the difference-in-differences could be at risk. If the difference-in-differences model doesn't meet the parallel trends assumption, it could invalidate the research design. To address this, we conducted a placebo test using DMA-level local advertising data for imported beers as a placebo treatment. The results did not show any significant effects (see Table 6). However, since this regression was performed solely based on the AdIntel dataset, we could not include all our covariates.

4.1 Empirical Findings

Table 3 presents the results derived from the specification detailed in equation (2), with controls applied at the border-DMA-season level. All coefficients are significant at the 1% level, with the advertising elasticity — the responsiveness of a brewer's own advertising to changes in rival advertising — being 0.448. The interaction terms play a critical role in deciphering the mechanisms of advertising spillovers. As the number of breweries in a DMA increases by one unit, the advertising elasticity decreases by 0.002. This indicates that in denser markets, brewers are capturing positive spillovers from rival advertising, thereby tempering their own advertising spend. In the period following 2017, denoted by the *post_seal* variable, which highlights increased consumer awareness of craft beers, the advertising elasticity decreases further by 0.098. This period also sees an increased effect of the number of breweries in a DMA on the dependent variable, with an increase of 0.003, suggesting a heightened response to rival advertising spillovers post-2017. Additionally, as competition in the craft beer sector intensifies, indicated by the increase in breweries, the natural logarithm of a brewer's own advertising decreases by 0.019. This is consistent with the existence of ad spillovers that lead to a reduction in individual advertising efforts. The post-2017 period also sees a substantial increase in the dependent variable by 0.502, underscoring the significant effect of heightened consumer awareness, which is explained in detail in our theoretical model. Overall, our results show evidence of advertising spillovers in the craft brewing industry. Table 4 compares the full model using the specification in equation (1) to our preferred specification using equation (2). Most coefficients remain similar in signs across these two specifications, but the full sample specification overstates all these estimates. However, the coefficient estimates for the number of breweries vary substantially across these two specifications by both sign and magnitude.

4.2 Robustness Checks

We acknowledge the complexities in identifying the effects of rival advertising on a brewer's own advertising decisions. Since advertising is an endogenous decision for brewers, it might be swayed by factors that aren't immediately observable. It is thus crucial to examine the robustness of our estimates and our identification strategy that hinges on the advertising discontinuity at DMA borders. We begin by analyzing the relationships between the key outcome variable, the log of own advertising spending, and the main treatment variable, the log of rival ad spending, using our border sample. As we see in figure 12, the former is an increasing function of the latter, as our estimates indicate. Second, we employ the Frisch-Waugh-Lowell (FWL) theorem and plot the reduced-form figure with residuals, i.e., with the impacts of other experiment-related controls removed. The revised figure in figure 13 follows a similar upward-rising pattern as our original reduced-form figure, supporting our assessment that our initial estimates were not severely biased by excluding the relevant controls from the model. As we discussed earlier, there is a potential for measurement error. Some breweries engage in both local and national advertising. By excluding national advertising from our analysis, we could inadvertently violate our exogeneity assumption, especially if a brewery's choice of local advertising is influenced by its choice of national advertising. To determine if this is the case, we exclude all breweries that engage in national advertising and repeat the analysis. Our coefficient estimates remain similar but with smaller magnitudes (see Table 5). Another concern is that if the difference-in-differences model doesn't meet the parallel trends assumption, it could invalidate the research design. To address this, we conducted a placebo test using DMA-level local advertising data for imported beers as a placebo treatment. The results did not show any significant effects (see Table 6). However, since this regression was performed solely based on the AdIntel dataset, we could not include all our covariates. Our primary result does not use any outlier trimming. By experimenting with outlier trimming thresholds for our dependent variable, including 95% and 99%, we find that our results remain fairly robust. The estimates are presented in Figure

7. We also examine whether introducing a triple interaction term in our preferred border sample specification has an impact on the estimates. Specifically, we estimate the following equation:

$$\log(a_{kbt}) = \gamma_0 + \gamma_1 \log\left(\sum a_{-kbt}\right) + \gamma_2 \text{PostSeal} + \gamma_3 K_b + \gamma_4 (\log\left(\sum a_{-kbt}\right) \times \text{PostSeal}) + \boldsymbol{\gamma_5 X_{kj}} + \gamma_6 (\log\left(\sum a_{-kbt}\right) \times K_b) + \gamma_7 (\log\left(\sum a_{-kbt}\right) \times \text{PostSeal} \times K_b) + \alpha_j + \phi_{bds} + \epsilon_{kjbt} \tag{3}$$

Results are presented in Table 8. We observe that our coefficients are largely consistent. Nonetheless, the triple interaction term is both negative and statistically significant. This suggests that, in the period after 2017, advertising elasticity estimates are reduced even more in markets with a higher number of breweries, underscoring a positive correlation between advertising spillovers and consumer awareness.

Finally, we conduct a data-driven check to ensure the robustness of our specification and estimate using the double/debiased machine learning (DML) method as discussed below.

Effects of Rival Advertising on Own using Double/Debiased Machine Learning (DML)Method

Double/Debiased Machine Learning (DML) refers to a method that employs machine learning techniques to estimate causal effects in the presence of high-dimensional controls. It is designed to obtain valid statistical inference even when high-dimensional nuisance parameters are estimated non-parametrically using machine learning algorithms. The "double" in its name comes from the fact that it employs two separate machine learning predictions - one for the treatment and one for the outcome - and then combines them to derive causal estimates. In the context of our study on advertising expenditures of breweries, DML can be used as a robustness check by first employing machine learning algorithms to non-parametrically predict the "treatment" (exposure to rival advertising) and the "outcome" (a brewery's own ad spending); and then by using the machine learning predictions to get residuals for both treatment and outcome, which are essentially the parts of treatment and outcome that cannot be predicted by the controls. DML algorithm then regresses the outcome residuals on the treatment residuals to obtain the causal effect of the treatment on the outcome. By employing DML as a robustness check, we are essentially verifying that the causal relationship we observe between advertising exposures and ad spending is not driven by confounding factors or omitted variables, even in high-dimensional settings. This can bolster confidence in our findings, showing they are not artifacts of model specification or standard regression techniques. We use the DML algorithm in conjunction with a predefined model selection, namely the Partially Linear Regression Model (PLR), which we briefly discuss below.

Key Causal Model: Partially Linear Regression Model (PLR): Partially linear regression models (PLR), which encompass the standard linear regression model, play an important role in data analysis (Robinson (1988)). Partially linear regression models take the form:

$$Y = D\theta_0 + g_0(X) + \zeta, \quad E(\zeta|D, X) = 0, \tag{4}$$

$$D = m_0(X) + V, \quad E(V|X) = 0, \tag{5}$$

where Y is the outcome variable and D is the treatment variable of interest. The high-dimensional vector $X = (X_1, \ldots, X_p)$ consists of other confounding covariates, and ζ and V are stochastic errors. Equation (1) is the equation of interest, and θ_0 is the main regression coefficient that we would like to infer. If D is conditionally exogenous (randomly assigned conditional on X), θ_0 has the interpretation of a structural or causal parameter. The second equation keeps track of confounding, namely the dependence of D on covariates/controls. The characteristics X affect the treatment variable D via the function $m_0(X)$ and the outcome variable via the function $g_0(X)$. The partially linear model generalizes both linear regression models, where functions g_0 and m_0 are linear with respect to a dictionary of basis functions with respect to X and approximately linear models. We use this DML specification, with $Y = \log(a_{kjt})$, and $D = \log(\sum a_{-kjt})$ on our full sample and border sample to see if it produces similar advertising elasticity estimates as our baseline and border specifications. X includes all location-market-brewery-time-season-DMA level controls. In Table 9, Panel A presents the DML estimates. Panel B contrasts the advertising elasticity estimates from the DML with those from our baseline and border identification specifications. Interestingly, the Border strategy estimate aligns more closely with the DML results—both for the full sample and the border sample—than the baseline specification estimate. Such congruence between the DML and the Border strategy bolsters the argument that our identification strategy and interactive modified difference-in-difference specification are fairly robust.

To sum up, the empirical findings delineated in this section offer valuable insights into the dynamics of advertising spillovers in the craft brewing domain. The evidence, particularly from Table 3, reveals statistically significant coefficients at the 1% level, with the advertising elasticity being notably responsive at 0.448. A denser market landscape, characterized by an increased number of breweries, seems to temper this elasticity, suggesting that breweries in such markets draw tangible benefits from their rivals' advertising spillovers, leading to moderated advertising expenditures on their end. The post-2017 era, marked by burgeoning consumer awareness of craft beers, only intensifies this trend. As the industry becomes increasingly competitive, there's a palpable decline in individual advertising initiatives. This is further substantiated by Table 4, where, despite most coefficients retaining consistent directional tendencies, the number of breweries showcases divergent estimates in terms of magnitude and direction. The robustness of these findings is cemented by the application of the Double/Debiased Machine Learning (DML) method, as presented in Table 9. This comprehensive analysis unequivocally underscores the pervasive influence of advertising spillovers in the craft brewing sector, with factors like market density and enhanced consumer cognizance playing pivotal roles in shaping advertising strategies among brewers.

In the following section, we explain the advertising mechanics of the craft beer market using a simple discrete choice model of limited information.

5 Modeling Craft Beer Advertising: Theoretical Insights

We specify a consumer and firm behavior model that includes a finite number, N, of macro beers, and a finite number, K, of craft beers. Our model incorporates consumer consideration sets that represent a consumer's awareness of the existing firms in the market. The macro beers are nationally known and exist in the consideration set of each consumer. On the other hand, craft brewers operate at relatively smaller scales and may or may not appear in the consumers' consideration sets. Consumer awareness of craft beers is captured by a binary variable, M. We consider two timeframes: period 1 ($M = 0$), when consumer awareness about craft beers is negligible and does not impact the consideration probabilities, and period 2 ($M = 1$), when consumer awareness of the craft beer industry is heightened and influences the consideration probabilities of craft beers.

5.1 Consumer Choice and Consideration Probabilities

We model demand as the aggregated discrete choice model of individual consumer behavior. Consumers purchase the product that gives them the highest level of indirect utility. Consumer i's indirect utility from purchasing from firm j in market t is given by:

$$u_{ijt} = \delta_{jt} + \epsilon_{ijt}, \quad j = 1, 2, ..., N + K \tag{6}$$

where δ_{jt} is the mean utility of product j in market t, and ϵ_{ijt} is the random idiosyncratic taste shock. The probability that a consumer i chooses product j over all other available products in the market is given by

$$\text{Prob}(jt) = \text{Prob}(u_{ijt} \geq u_{ilt}), \text{ for all } j \neq l \tag{7}$$

δ_{jt} depends on the type of beer the consumer buys. For a national macro beer, n,

$$\delta_{nt} = \beta_n X_{nt} - \alpha_n p_{nt} + \gamma_n a_{nt}, \quad n = 1, 2, ..., N \tag{8}$$

and, for a craft beer k,

$$\delta_{kt} = \beta_k X_{kt} - \alpha_k p_{kt} + \eta_k a_{kt}, \quad k = 1, 2, ..., K \tag{9}$$

where, X_{jt} and p_{jt} denote respectively, the product characteristics and price of product $j = \{n, k\}$ and a_{jt} represents the advertising by the producer of beer j in market t. Macro brewers typically have larger advertising budgets and wider reach, enabling them to effectively use persuasive advertising to influence consumer preferences and enhance their brand awareness. $\gamma_n a_n$ captures this impact of advertising on a consumer's utility for macro brewers. On the other hand, craft brewers face a more challenging environment in terms of advertising due to their smaller scale, limited resources, and niche market focus. The return to persuasive advertising is higher for macro brewers than for craft brewers.

To account for the varying levels of consumer awareness of craft beers, we consider the binary variable M. Even when the overall level of awareness about craft beers is high, consumers may not be aware of all operating craft breweries in the market. The probability function ϕ_{kt} models the probability that a consumer in market t is aware of a craft brewer, k. The probability that consumer i purchases from firm j depends on the probability of her knowledge about the existence of firm j and that of the other firms in the market. Let ϕ_{kt} denote the probability that a consumer in market t is aware of a craft brewer, k. We assume these probabilities do not vary across consumers. Intuitively, the probability that a consumer is aware of the existence of craft beer k depends on the overall level of awareness about craft beers (M) and how the brewers in the market are advertising and promoting their products: $\phi_{kt} = f\left(M, a_k, a_{-k}\right)$. We model these probabilities in the following way:

$$\phi_k = \frac{\exp\left(\rho_k M + \gamma_k a_k + \sum_l \gamma_l a_l\right)}{1 + \exp\left(\rho_k M + \gamma_k a_k + \sum_l \gamma_l a_l\right)};\ k \neq l \text{ and } \gamma_k \geq \gamma_l \tag{10}$$

The purchase probability of a product accounts for all possible consideration sets. The unconditional purchase probabilities are the weighted averages of the conditional probabilities, with the consideration probabilities as the weights. Assuming a Logit specification, and a Type-1 Extreme Value distribution for ϵ_{ijt}, we can write the probability that a consumer in market t buys from a national brewer n, $s_{nt}, n = 1, 2, .., N$ as:

$$s_{nt} = \prod_{k=1}^{K}(1 - \phi_{kt}) \frac{\exp(\delta_{nt})}{\sum_{n=1}^{N} \exp(\delta_{nt})} + \left[\sum_{S \in C_k} \prod_{l \in S} \phi_{lt} \prod_{r \notin S} (1 - \phi_{rt}) \frac{\exp(\delta_{nt})}{\sum_{n \in N} \exp(\delta_{nt}) + \sum_{l \in S} \exp(\delta_{lt})}\right] \tag{11}$$

where C_k is the set of all consideration sets that include craft beer k. The purchase probability of craft beer k in market t, $s_{kt}, k = 1, 2, .., K$ is:

$$s_{kt} = \left[\sum_{S \in C_k} \prod_{l \in S} \phi_{lt} \prod_{r \notin S} (1 - \phi_{rt}) \frac{\exp(\delta_{kt})}{\sum_{n \in N} \exp(\delta_{nt}) + \sum_{l \in S} \exp(\delta_{lt})}\right] \tag{12}$$

Equations (11) and (12) give us our predicted market shares, which are formed based on the distributional assumptions on the uncertainty over consumer preferences stemming from the heterogeneous taste shocks, ϵ_{ijt}. Equation (11) describes the purchase probability of a consumer in market t buying from a national brewer n, s_{nt}. The product of (1-ϕ_{kt}) across all craft brewers captures the probability of the consumer not being aware of any of the craft brewers. It also takes into account all the possible consideration sets, denoted by C_k, that include craft beer k. The equation effectively captures the different scenarios of awareness and consideration sets contributing to the purchase probability of a national brewer's product. Equation (12) represents the purchase probability of a craft beer k in market t, s_{kt}. It considers all possible consideration sets that include craft beer k, denoted by C_k, and incorporates the probabilities of awareness (ϕ_{lt}) and non-awareness ($1-\phi_{rt}$) for each craft brewer l and r. This equation reflects the different scenarios of awareness and consideration sets that contribute to the purchase probability of a craft brewer's product. These share functions capture the relevant dynamics of consumer choice and awareness in the craft beer market and provide a solid foundation for analyzing their impacts, advertising, and other factors on the purchase probabilities of both national and craft brewers' products.

5.2 Firm Behavior

Each firm in this model produces a single product and competes in a simultaneous Bertrand Nash game. We assume the brewers can adjust their capacity and output. The most common model under this setup involves Bertrand–Nash price competition with differentiated products. These equilibrium conditions allow a researcher who has obtained estimates of consumer demand and firm costs to compute equilibrium prices or test hypotheses about non-cooperative pricing behavior, perhaps against alternative behavioral assumptions such as collusive pricing.

A brewer j (craft or national) in market t chooses $\{a^*_{jt}, p^*_{jt}\}$ to maximize its profit, π_{jt}:

$$\pi_{jt} = (p_{jt} - c_{jt})M_t s_{jt}(p,a) - c^a_{jt} a_{jt}, \quad j = 1, 2, ..., N+K \tag{13}$$

where c_{jt} and c^a_{jt} are, respectively, the marginal costs of production and advertising, and M_t is the market size.

At equilibrium, the following first-order conditions are satisfied:

$$\frac{\partial \pi_j}{\partial p_j} = (p_j - c_j)\frac{\partial s_j(p,a)}{\partial p_j} + s_j(p,a) = 0 \tag{14}$$

$$\frac{\partial \pi_j}{\partial a_j} = (p_j - c_j)M\frac{\partial s_j(p,a)}{\partial a_j} - c^a_j = 0 \tag{15}$$

We suppress the t subscripts here to simplify the notations.

5.3 Advertising Elasticities

In the competitive craft beer market, advertising is crucial in promoting awareness and influencing consumer preferences. With a growing number of craft brewers entering the market, it becomes increasingly important for individual brewers to differentiate themselves from their competitors and appeal to a wider audience. One way to achieve this is through effective advertising strategies that not only showcase the unique attributes of their products but also convey a sense of authenticity and craftsmanship to potential consumers.

Consumer awareness can influence the spillover effects of advertising across different craft breweries. As more consumers become aware of craft beers through advertising by one craft brewer, they may also become more inclined to consider other craft beers, resulting in a positive impact on the entire category. This can result in a positive externality for the entire industry, further emphasizing the importance of advertising in this market and the role of consumer awareness in shaping advertising outcomes.

To see how the ad spillovers work, consider the effects of individual advertising by brewer k and l. Advertising by a craft brewer has two effects. First, it increases the probability that a consumer considers craft beers as a category. Second, it induces a pure business-stealing effect by lowering the market shares of the competing craft beers while raising its own. Using the Logit structures, our specifications in equation (12), and the independent and identically distributed taste shocks, we get the following share derivatives of brewer k with respect to own and brewer l's advertising:

$$\begin{aligned}\frac{\partial s_k(p,a)}{\partial a_k} = \frac{1}{\phi_k}\frac{\partial \phi_k}{\partial a_k}s_k + \phi_k\Bigg[&\sum_{S\in C_k}\prod_{\substack{l\in S\\ l\neq k}}(-\frac{\partial \phi_l}{\partial a_k})\frac{\exp(\eta_k a_k)}{\sum\limits_{n\in N}\exp(\delta_n)+\exp(\delta_k)}+\\ &+\sum_{S\in C_k}\prod_{\substack{l\in S\\ l\neq k}}\phi_l\prod_{r\notin S}\frac{\partial \phi_r}{\partial a_k}\frac{\exp(\eta_k a_k)}{\sum\limits_{n\in N}\exp(\delta_n)+\sum\limits_{l\in S}\exp(\delta_l)}\Bigg]\end{aligned} \tag{16}$$

$$
\begin{aligned}
\frac{\partial s_k(p,a)}{\partial a_l} = \frac{1}{\phi_k}\frac{\partial \phi_k}{\partial a_l}s_k + \phi_k \Bigg[& \sum_{S \in C_k} \prod_{\substack{m \in S \\ m \neq l}} (-\frac{\partial \phi_m}{\partial a_l}) \frac{\exp(\eta_k a_k - \eta_l a_l)}{\sum\limits_{n \in N} \exp(\delta_n) + \exp(\delta_l)} + \\
& + \sum_{S \in C_k} \prod_{\substack{m \in S \\ m \neq l}} \phi_m \prod_{r \notin S} \frac{\partial \phi_r}{\partial a_l} \frac{\exp(\eta_k a_k - \eta_l a_l)}{\sum\limits_{n \in N} \exp(\delta_n) + \sum\limits_{m \in S} \exp(\delta_m)} \Bigg]
\end{aligned}
\tag{17}
$$

and the advertising elasticities:

$$
\begin{aligned}
e_{kk} = \frac{1}{\phi_k}\frac{\partial \phi_k}{\partial a_k}a_k + \phi_k \frac{a_k}{s_k} \Bigg[& \sum_{S \in C_k} \prod_{\substack{l \in S \\ l \neq k}} (-\frac{\partial \phi_l}{\partial a_k}) \frac{\exp(\eta_k a_k)}{\sum\limits_{n \in N} \exp(\delta_n) + \exp(\delta_k)} + \\
& + \sum_{S \in C_k} \prod_{\substack{l \in S \\ l \neq k}} \phi_l \prod_{r \notin S} \frac{\partial \phi_r}{\partial a_k} \frac{\exp(\eta_k a_k)}{\sum\limits_{n \in N} \exp(\delta_n) + \sum\limits_{l \in S} \exp(\delta_l)} \Bigg]
\end{aligned}
\tag{18}
$$

$$
\begin{aligned}
e_{kl} = \frac{1}{\phi_k}\frac{\partial \phi_k}{\partial a_l}a_l + \phi_k \frac{a_l}{s_l} \Bigg[& \sum_{S \in C_k} \prod_{\substack{m \in S \\ m \neq l}} (-\frac{\partial \phi_m}{\partial a_l}) \frac{\exp(\eta_k a_k - \eta_l a_l)}{\sum\limits_{n \in N} \exp(\delta_n) + \exp(\delta_l)} + \\
& + \sum_{S \in C_k} \prod_{\substack{m \in S \\ m \neq l}} \phi_m \prod_{r \notin S} \frac{\partial \phi_r}{\partial a_l} \frac{\exp(\eta_k a_k - \eta_l a_l)}{\sum\limits_{n \in N} \exp(\delta_n) + \sum\limits_{m \in S} \exp(\delta_m)} \Bigg]
\end{aligned}
\tag{19}
$$

Equations (16) and (17) show the changes in market share for craft beer k, in response to changes in own and rival advertising spending. There are two key effects captured in these derivatives. The first terms in both equations account for the impact of advertising on the consideration probability of craft beer k, which is the probability that a consumer will consider buying the product. If advertising by either brewer increases, the consideration probability is expected to rise, increasing market share for craft beer k. This term in equation (17) represents the ad spillover effect of rival brewer's spending on brewer k. The second term represents the business-stealing effects of advertising on competing craft beers. Advertising by brewer l may decrease market shares for other craft beers as consumers shift their preferences. Equation (18) and (19) measures the responsiveness of the market share for craft beer k to changes in its own and brewer l's advertising spending respectively. In other words, it shows the percentage change in market share resulting from a 1% change in advertising spending. The interpretation of the components in this elasticity equation is similar to the share derivative equation. The first term captures the effects of own and rival's advertising on the consideration probability of craft beer k. A positive elasticity value indicates that increased advertising spending will lead to a higher market share for craft beer k. The second term captures the business-stealing effects of advertising on competing craft beers. A positive elasticity value in this component suggests that increasing advertising spending by brewer k will increase the market share for craft beer k at the expense of other craft beers.

The cross elasticity, e_{kl} measures the effect of advertising by brewer l on the market share of brewer k. The cross elasticity e_{kl} can be obtained by computing the derivative of the market share of brewer k with respect to the advertising of brewer l. The first term reflects the change in the probability of awareness of brewer k with respect to the advertising of brewer l, while the second term captures the business stealing effect, in which advertising by brewer l affects the market shares of other craft brewers in the consideration set.

The advertising elasticities provide valuable insights into the effectiveness of advertising spending in influencing market shares while accounting for the direct and indirect effects of advertising on the overall craft beer market.

6 A Numerical Simulation with Two Symmetric Craft Breweries

In order to provide a simple example of how advertising in the craft beer market changes with varying levels of consumer awareness, we demonstrate the following case. This example shows two craft brewers and one national brewer in a market. Let k_2 and k_3 denote the two craft brewers, and n represent the national brewer. A consumer i's awareness of the available products in this market is represented by her consideration set, which may be any one of the four possible sets: $\{(n,k_2,k_3),(n,k_2),(n,k_3),(n)\}$. That is, the consumer is, in all cases, fully aware of the existence of the national brewer, but she may or may not know of any or both of the craft brewers. Let us call the national and the craft brewers, respectively, firms 1,2 and 3. The indirect utility of consumer i for buying product j is given by, $u_{ij} = \delta_j + \epsilon_{ij}$, where $\delta_1 = \beta x_1 - \alpha p_1 + \gamma_1 a_1$, and $\delta_k = \beta x_k - \alpha p_k + \eta_k a_k$, for $k = 2, 3$. With ϕ_k as the probability that consumer i is aware of craft brewer k, and a Type-1 Extreme Value distribution for ϵ_{ij}, we can write the purchase probability for product j, $s_j, j = 1, 2, 3$ as:

$$s_1 = (1-\phi_2)(1-\phi_3) + \left(\phi_2(1-\phi_3)\frac{e^{\delta_1}}{e^{\delta_1}+e^{\delta_2}} + (1-\phi_2)\phi_3\frac{e^{\delta_1}}{e^{\delta_1}+e^{\delta_3}} + \phi_2\phi_3\frac{e^{\delta_1}}{e^{\delta_1}+e^{\delta_2}+e^{\delta_3}}\right)$$

$$s_2 = \left(\phi_2(1-\phi_3)\frac{e^{\delta_2}}{e^{\delta_1}+e^{\delta_2}} + \phi_2\phi_3\frac{e^{\delta_2}}{e^{\delta_1}+e^{\delta_2}+e^{\delta_3}}\right); s_3 = \left(\phi_3(1-\phi_2)\frac{e^{\delta_3}}{e^{\delta_1}+e^{\delta_3}} + \phi_2\phi_3\frac{e^{\delta_3}}{e^{\delta_1}+e^{\delta_2}+e^{\delta_3}}\right)$$

Let

$$\phi_k = \frac{\exp\left(\rho_k M + \gamma_k a_k + \gamma_l a_l\right)}{1+\exp\left(\rho_k M + \gamma_k a_k + \gamma_l a_l\right)};\ k \neq l$$

where M is a binary variable representing consumer awareness. We consider two timeframes: period 1 ($M = 0$), when consumer awareness about craft beers is negligible and does not impact the consideration probabilities, and period 2 ($M = 1$) when consumer awareness of the craft beer industry is heightened and influences the consideration probabilities of craft beers. Let's assume that the craft brewers are symmetric. The profit maximization exercises of the brewers follow the first-order conditions in equations (9)-(10). The data-generating process for this simulation exercise is as follows. The variables, x_j, a_j, c_j, and c_j^a, are all created as independent standard normal random variables with $a_1 > a_k$, $k = 2, 3$. The initial chosen values of our parameters are $\alpha = 1$, $\beta = 2$, $\gamma_1 = 1$, $\gamma_2 = \gamma_3 = 1$, $\rho_2 = \rho_3 = \rho = 1$, $\eta_2 = \eta_3 = \eta = 1$. We compute the equilibrium values for $M = 1$ and $M = 0$, and compare the advertising expenditures and elasticities for a representative craft brewer in this market in table 10 and 11. We also perform sensitivity tests to understand the effects of varying the parameters ρ, η, γ_2, and γ_3 on the advertising expenditure (a_k^*) and elasticity (e_{kk}). Advertising elasticity measures the percentage change in market shares due to a 1% change in advertising expenditure. By comparing the advertising elasticities, we can understand how consumer awareness affects the responsiveness of market shares to changes in advertising spending.

Advertising levels are generally lower with higher consumer awareness. As is apparent from table11, according to our model, advertising elasticity is higher when the effect of own spending is higher in both informative and persuasive channels in both scenarios. However, when the return to consumer awareness (ρ) is zero, brewers tend to spend more with a higher elasticity of market share with respect to advertising than when the return is positive. In most cases shown in table11, the craft brewers' market shares are more responsive to changes in advertising expenditure when consumers are more aware of their products. This necessitates higher advertising efforts by craft brewers to influence consumer decisions.

γ_k represents the return to informative advertising by brewer k. When the return to the brewer's own informative advertising (γ_2) is higher than her return to informative advertising by the other craft brewer ($\gamma = \frac{\gamma_2}{\gamma_3} > 1$), the difference in advertising levels between the two scenarios of consumer awareness decreases, and the advertising elasticities go up in both scenarios. An increasing return to persuasive advertising (η) in a product's mean utility also results in higher spending and lower differences between the expenditures in the two different levels of consumer awareness. This implies that the effects of consumer awareness in reducing advertising levels and expanding consideration sets are less evident when brewers are more confident in the efficiency of their own advertising. An increase in the return to consumer awareness (ρ) leads to a larger difference in advertising between two different levels of consumer awareness. This suggests that when the impact of consumer awareness on consideration sets is higher, the difference between advertising levels in the two cases becomes more significant. In summary, these implications emphasize the role of consumer awareness in shaping the optimal advertising levels for craft brewers. Increasing consumer awareness generally reduces the need for advertising, as it affects the responsiveness of market shares to changes in advertising expenditure. However, the extent of this reduction depends on the specific market conditions and the relative impacts of advertising efforts on consumer consideration sets.

7 Concluding Remarks

Drawing from data in the craft beer market, this paper offers novel insights into the complexities of advertising dynamics, particularly concerning spillover effects. The importance of understanding these spillovers goes beyond the brewing sector; it touches upon the intricate fabric of competitive markets and how firms strategize their advertising endeavors. Using the unique discontinuity presented by DMA borders, our empirical findings robustly indicate significant spillover effects from competitor advertising. Critically, this analysis shows that the advertising elasticity — reflecting how a brewer's advertising responds to rival advertising — diminishes in denser markets, a manifestation of positive reactions to competitor advertising. Moreover, in the period post-2017, denoted by increased consumer awareness of craft beers, this elasticity experienced a further decline. The results from the Double/Debiased Machine Learning (DML) method further reinforce the robustness of these findings.

Complementing our empirical findings, our theoretical exploration via a discrete choice model of limited information elucidates the systematic ad spending decisions of firms, suggesting that rising consumer awareness affects the sensitivity of market shares to shifts in advertising.

These insights bear significant implications. Brewers and other firms might find value in collaborative advertising endeavors, potentially enjoying benefits from positive spillovers. Regulators should be attuned to these dynamics, ensuring a competitive yet cooperative market landscape. For econometricians and marketers, understanding these spillovers is crucial for accurately capturing advertising's influence on demand and supply.

The current investigation does come with certain limitations, offering avenues for future exploration. A primary constraint is data availability. Procuring weekly sales data for breweries would not only enhance our ability to gauge the impact of rival advertising on a brewer's market share but also allow us to refine the discrete choice model we've established amidst limited information. Such an estimation could shed light on the intricate dynamics of the craft beer market. Additionally, while the data indicate firm behavior aligns with advertising spillovers, it doesn't negate other plausible narratives wherein own and rival advertising act as strategic substitutes. A more rigorous exploration to determine firm interactions within this market would be enlightening. Lastly, all results hinge on the presumption that all overlooked variables, including those from national magazines and newspapers, maintain consistent trends at DMA borders. Given the unavailability of these data in the present study, this assumption remains unverifiable. In future research, more detailed datasets, perhaps inclusive of weekly sales figures or national advertising metrics, could further refine our understanding of the craft beer market's advertising dynamics. Additionally, exploring other methodologies that can dissect the nuances of firm interactions will be invaluable.

Figures and Tables

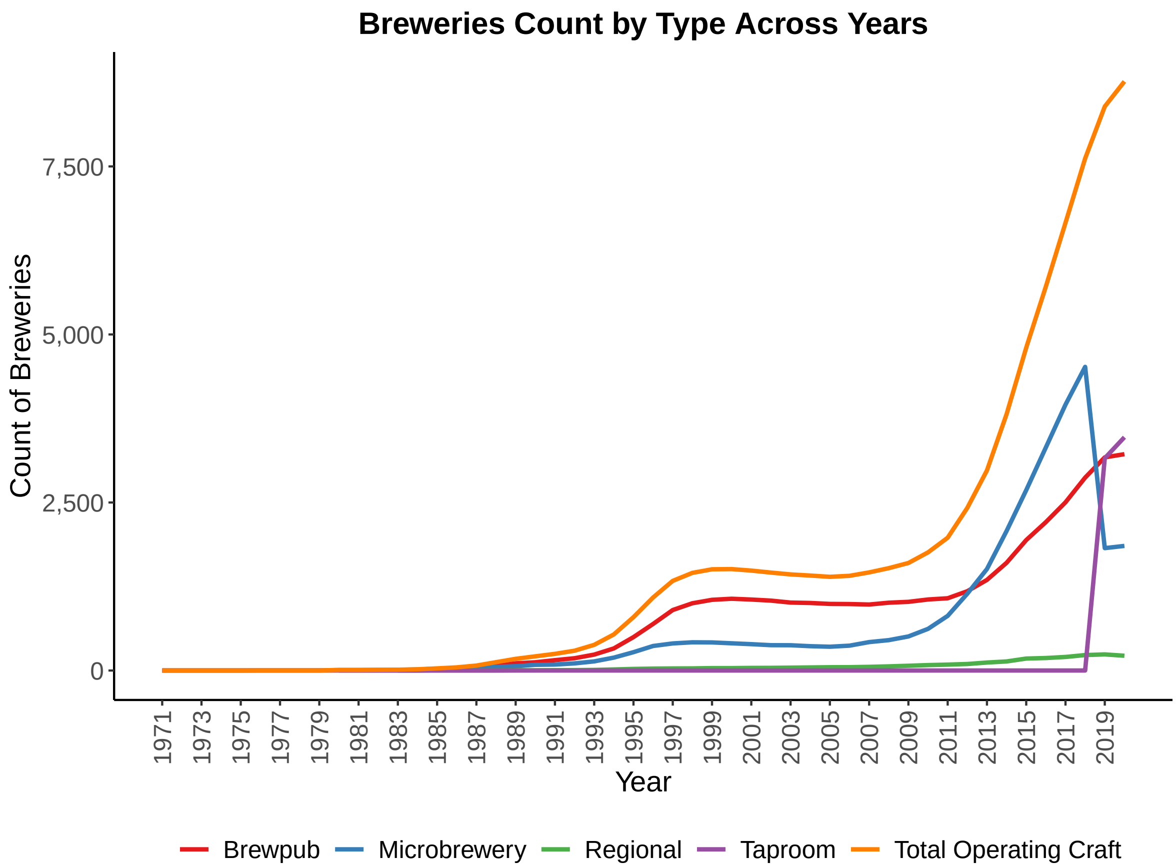

Figure 1: Growth of the Number of Operating Craft Breweries Across Years

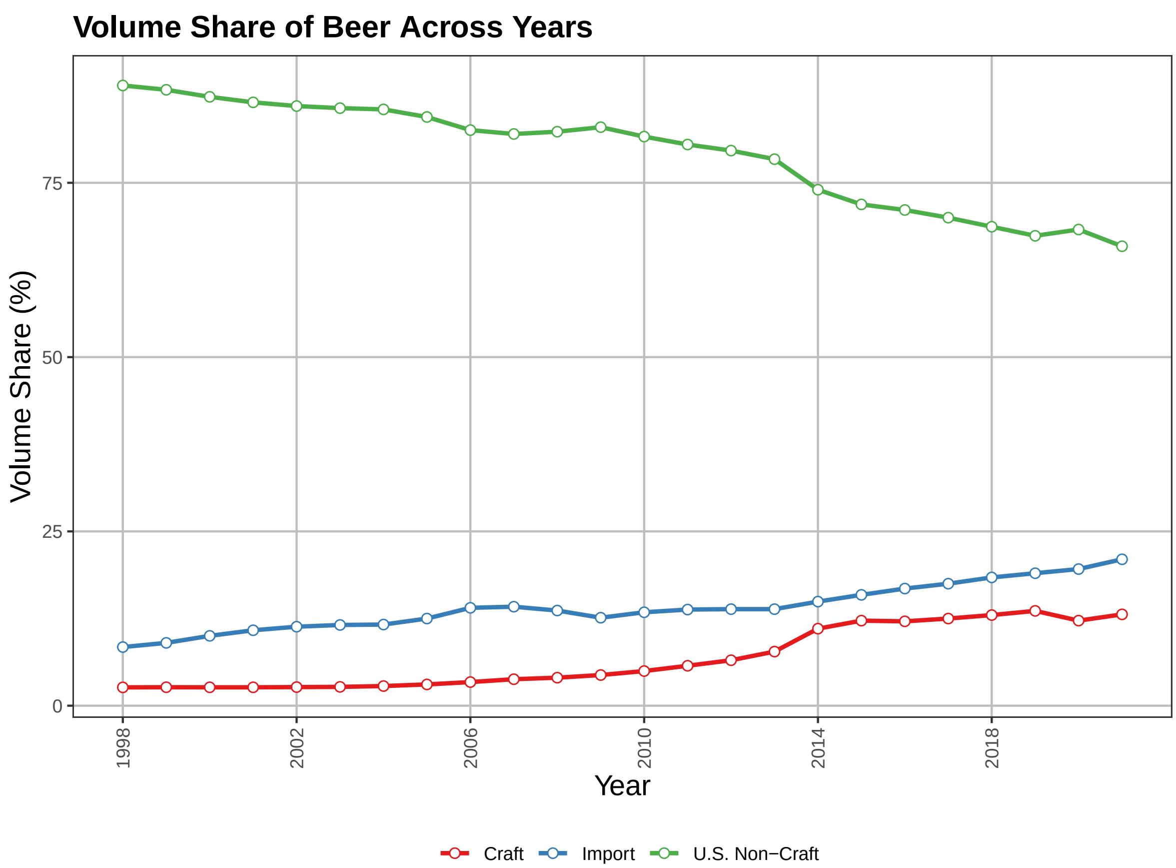

Figure 2: Changes in Volume Shares Across Years

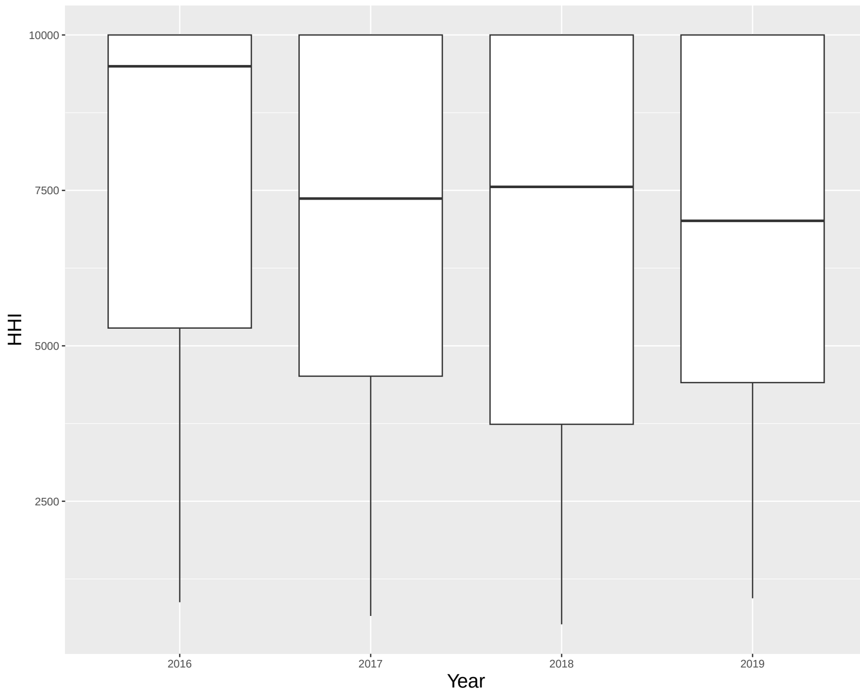

Figure 3: Boxplot of HHI in Craft Beer Market across Years

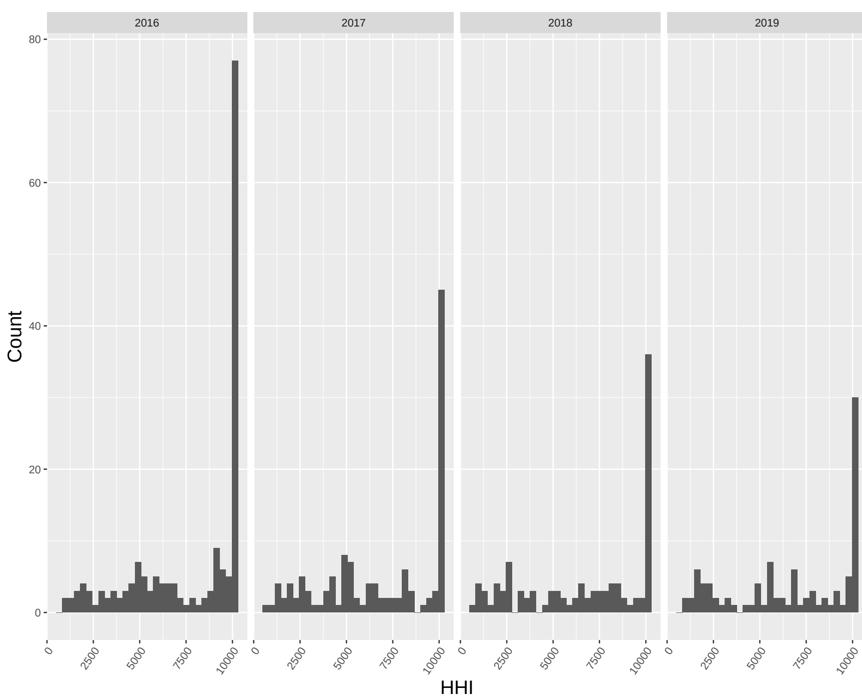

Figure 4: Histogram of HHI in Craft Beer Market across Years

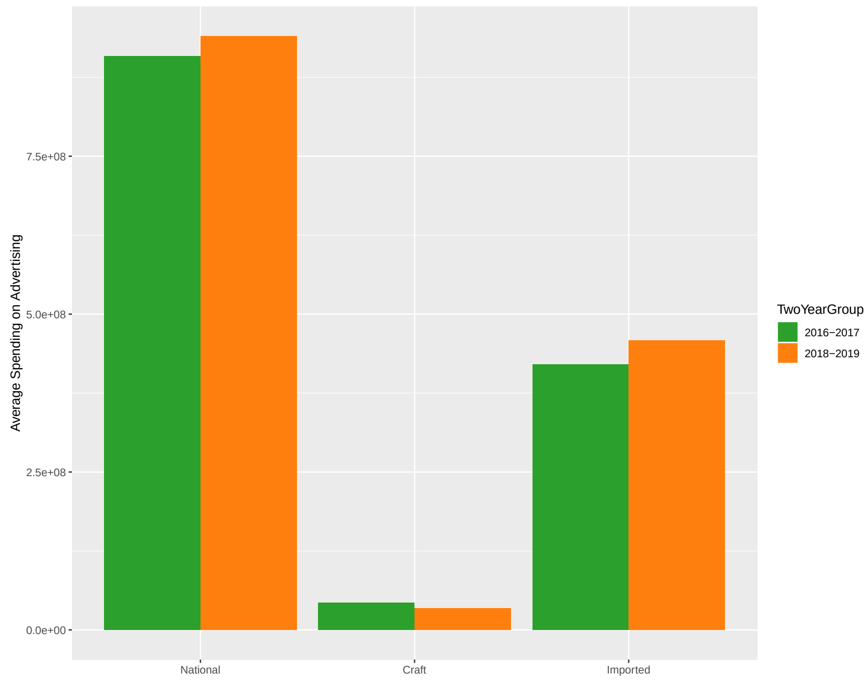

Figure 5: Ad Spending Across Beer Industry

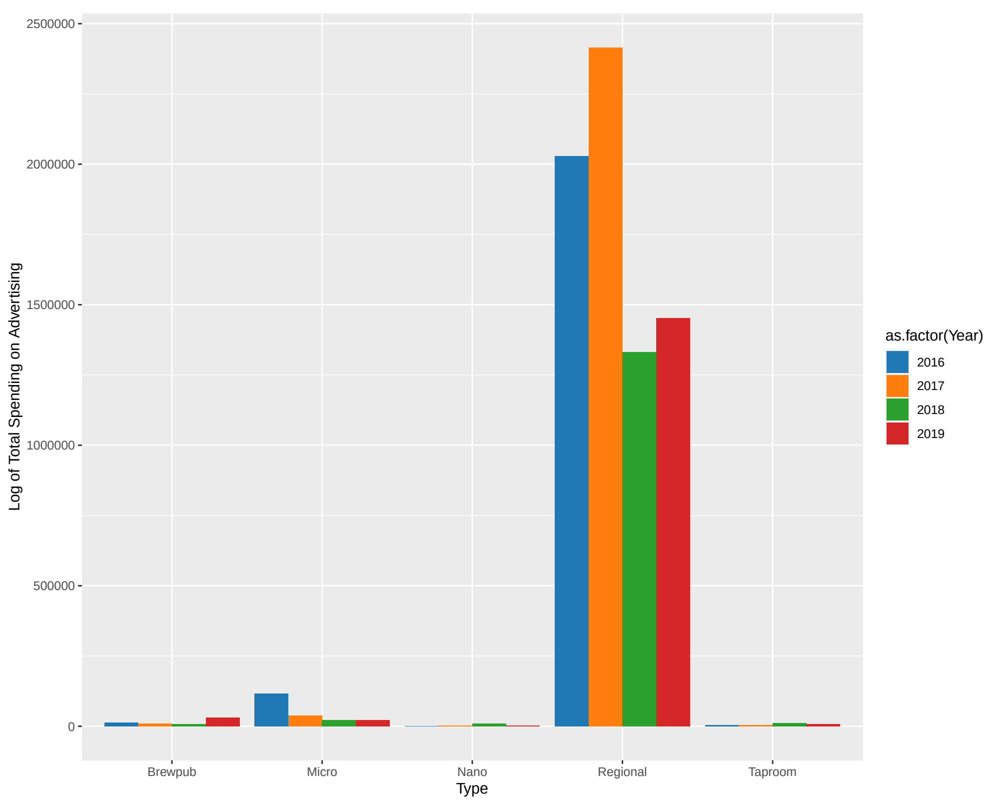

Figure 6: Total Spending Across Craft Brewery Types Across Years

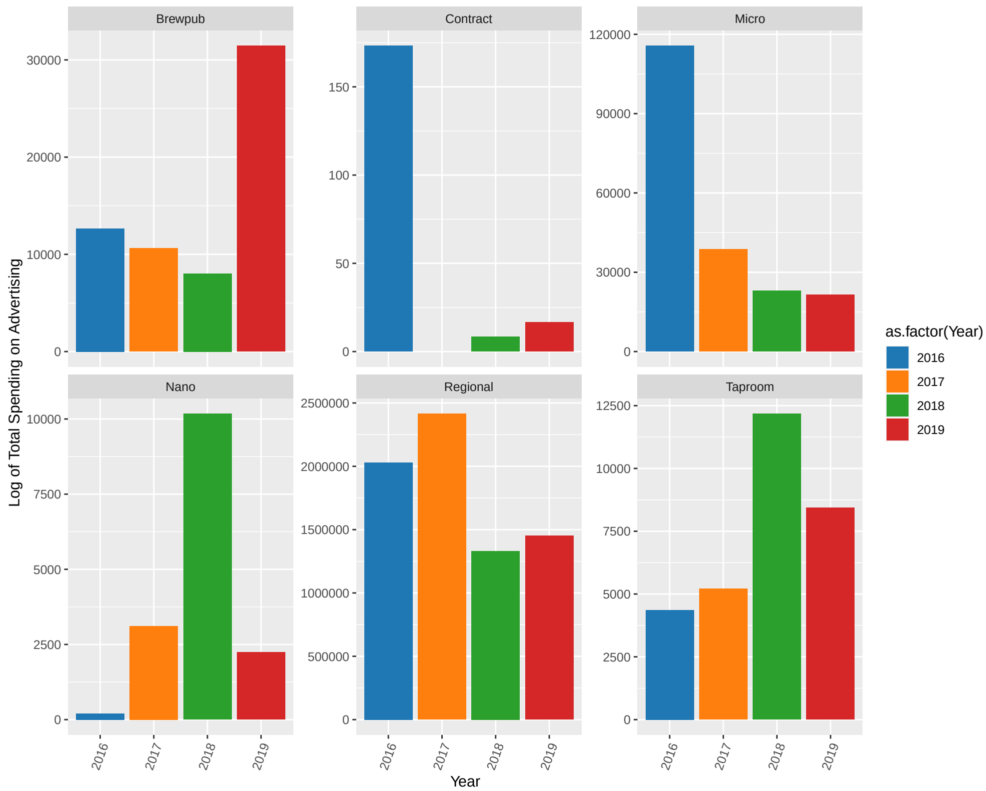

Figure 7: Total Spending Across Craft Brewery Types Across Years

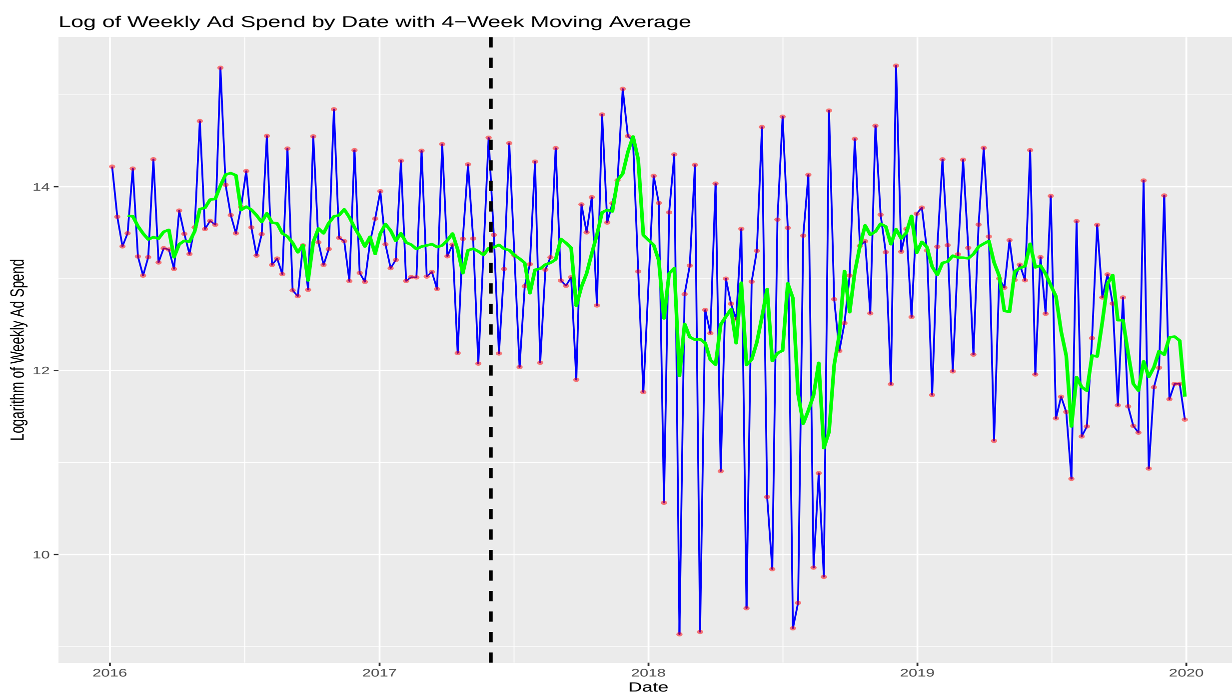

Figure 8: Log-transformed Weekly Ad Spend of Craft Beer Across Years

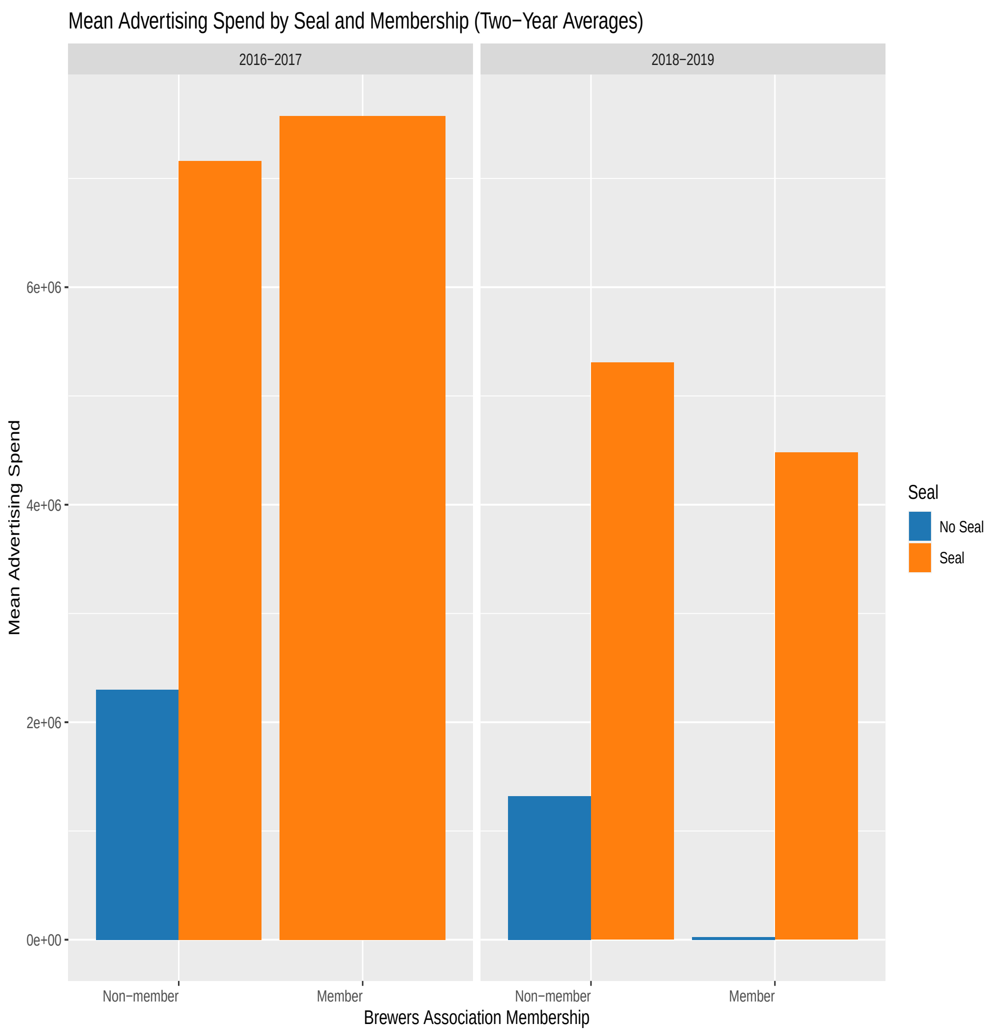

Figure 9: Total Spending Across Craft Brewery Types Across Years

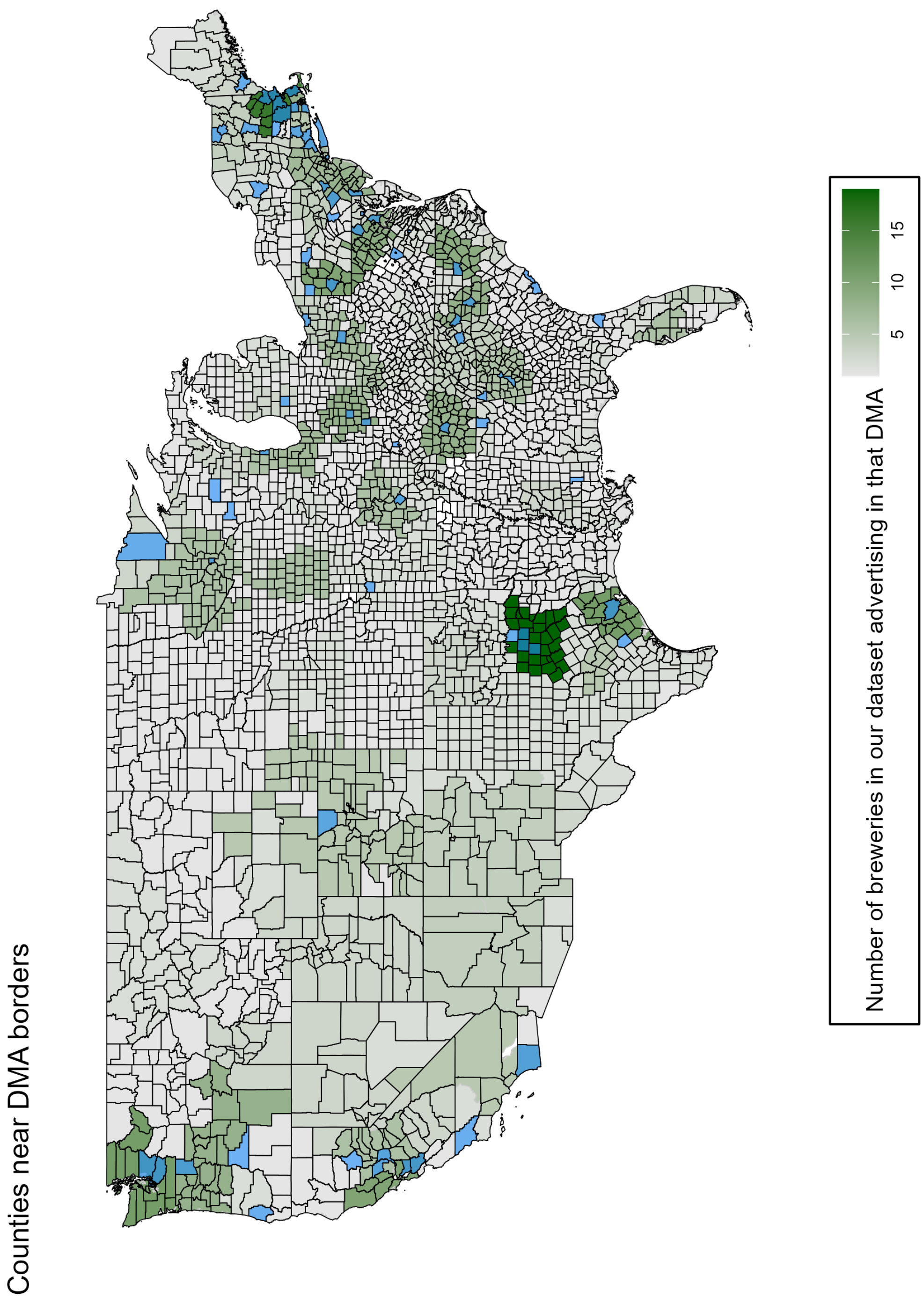
Counties near DMA borders
Number of breweries in our dataset advertising in that DMA
5
10
15

Figure 10

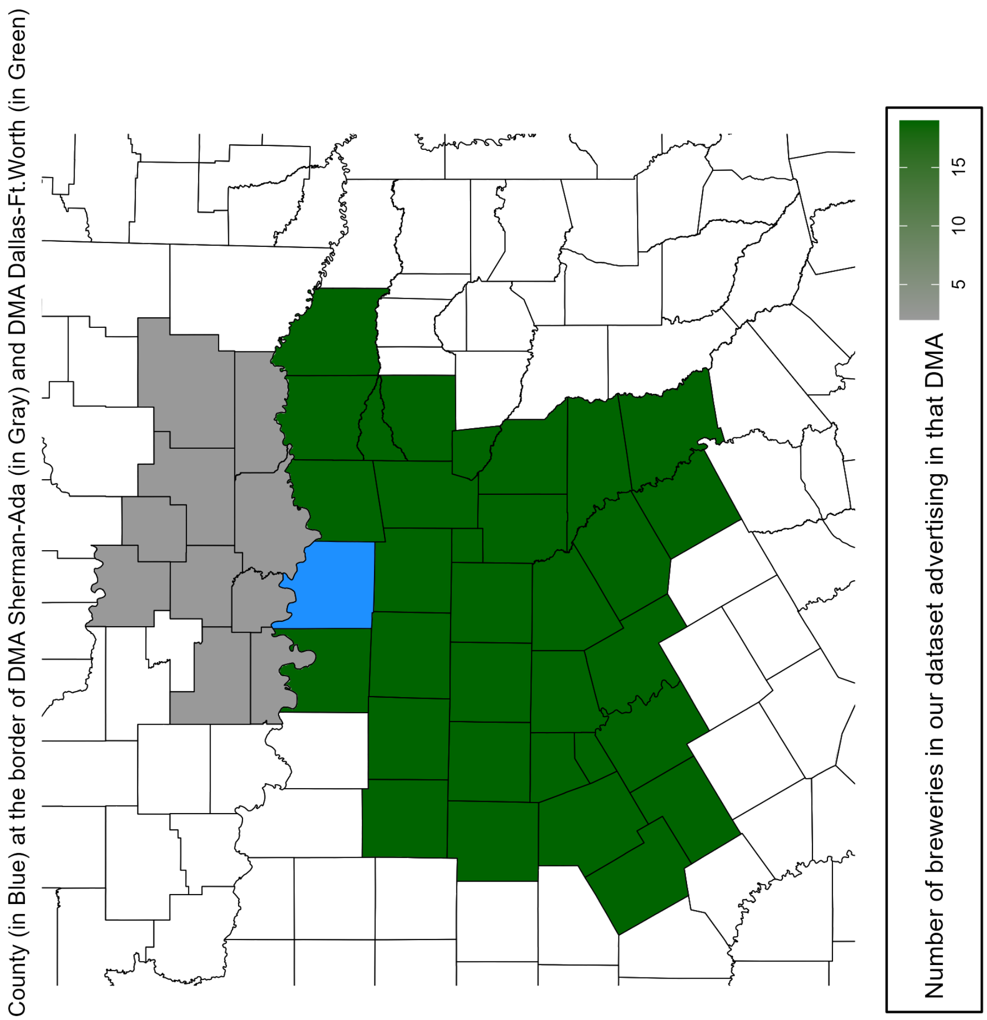
Grayson County (in Blue) at the border of DMA Sherman-Ada (in Gray) and DMA Dallas-Ft.Worth (in Green)
Number of breweries in our dataset advertising in that DMA
5
10
15

Figure 11

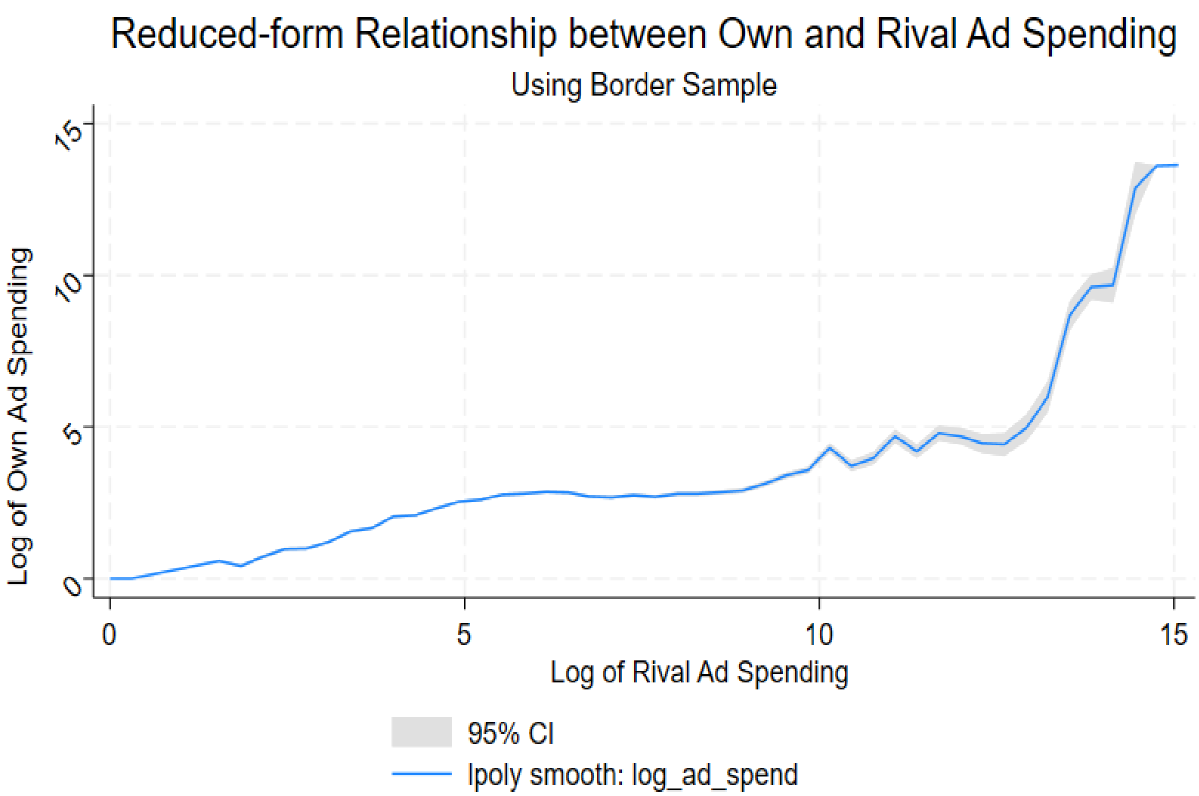
Reduced-form Relationship between Own and Rival Ad Spending
Using Border Sample
Log of Own Ad Spending
0
5
10
15
Log of Rival Ad Spending
0
5
10
15
95% CI
lpoly smooth: log_ad_spend

Figure 12

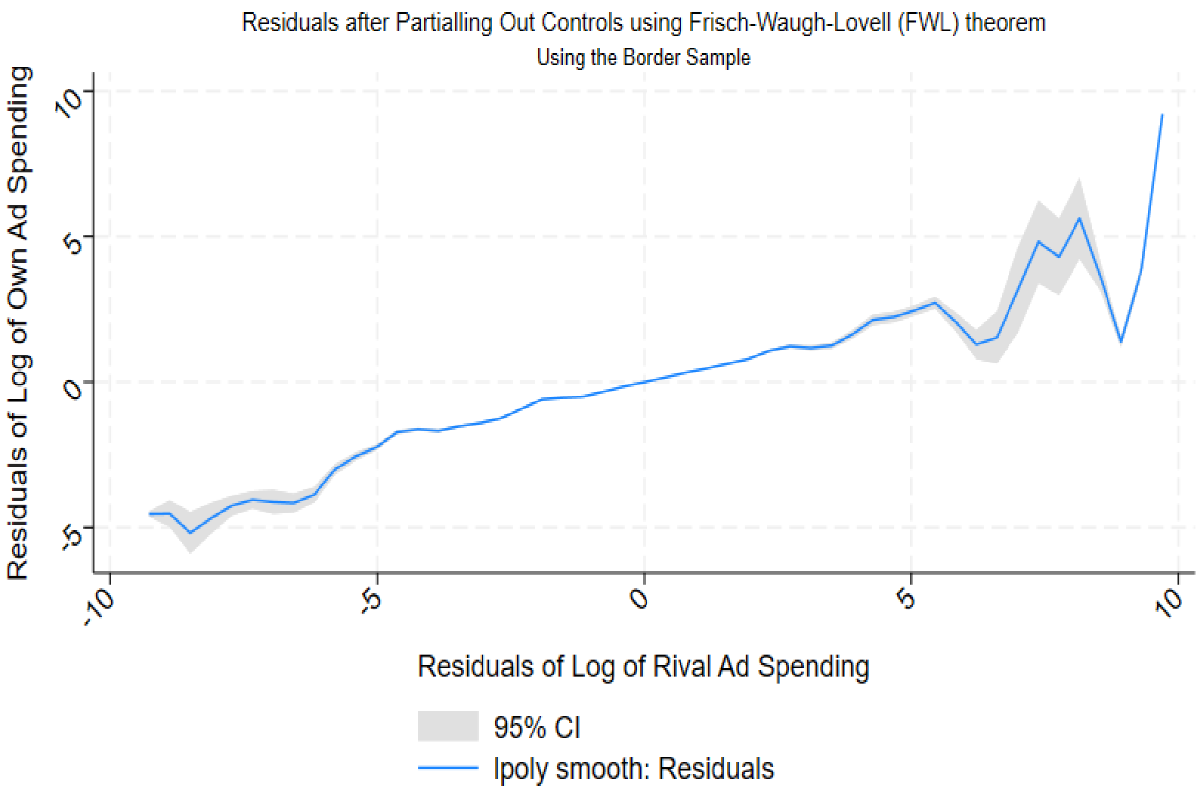
Residuals after Partialling Out Controls using Frisch-Waugh-Lovell (FWL) theorem
Using the Border Sample
Residuals of Log of Own Ad Spending
10
5
0
-5
-10
-5
0
5
10
Residuals of Log of Rival Ad Spending
95% CI
lpoly smooth: Residuals

Figure 13

State	Craft Breweries	Rank	Craft Brewerie--s/100,000 21+ Adults	Craft Brewerie--s/Capita Rank
Alabama	52	37	1.43	49
Alaska	51	38	10.05	5
Arizona	124	22	2.28	40
Arkansas	43	41	1.95	46
California	958	1	3.29	29
Colorado	433	4	10.04	6
Connecticut	112	25	4.18	24
Delaware	32	46	4.33	21
District of Columbia	15	50	2.75	33
Florida	368	7	2.21	41
Georgia	130	21	1.68	48
Hawaii	26	48	2.53	35
Idaho	77	32	5.94	11
Illinois	295	13	3.16	30
Indiana	195	16	3.97	25
Iowa	107	26	4.65	17
Kansas	63	35	3.04	32
Kentucky	79	31	2.40	37
Louisiana	44	40	1.31	50
Maine	136	19	12.91	2
Maryland	121	24	2.71	34
Massachusetts	189	17	3.60	27
Michigan	398	6	5.33	12
Minnesota	217	15	5.22	13
Mississippi	12	51	0.56	51
Missouri	150	18	3.30	28
Montana	100	27	12.42	3
Nebraska	58	36	4.21	23
Nevada	50	39	2.15	42
New Hampshire	93	30	8.79	8
New Jersey	134	20	2.02	44
New Mexico	100	27	6.51	10
New York	460	2	3.14	31
North Carolina	359	9	4.62	18
North Dakota	23	49	4.22	22
Ohio	339	10	3.91	26
Oklahoma	67	34	2.35	39
Oregon	312	11	9.64	7
Pennsylvania	444	3	4.59	19
Rhode Island	35	44	4.36	20
South Carolina	95	29	2.46	36
South Dakota	33	45	5.20	14
Tennessee	122	23	2.39	38
Texas	364	8	1.77	47
Utah	43	41	1.98	45
Vermont	74	33	15.43	1
Virginia	297	12	4.74	16
Washington	428	5	7.48	9
West Virginia	28	47	2.06	43
Wisconsin	224	14	5.16	15
Wyoming	43	41	10.18	4
Total	8,764		3.60	

Table 1: Source: Breweries by State, Brewery Production Data 2020, Brewers Association

Year	Growth Rate (%)	Production Change Barrels	Craft Breweries	Change per Brewer
2010	11.8	1,069,348	1,758	608
2011	13.2	1,333,360	1,976	675
2012	15.4	1,768,580	2,420	731
2013	17.1	2,268,933	2,977	762
2014	17.8	3,327,306	3,814	872
2015	11.3	2,461,409	4,803	512
2016	5.9	1,355,551	5,713	237
2017	4.0	959,154	6,661	144
2018	2.7	659,814	7,618	87
2019	3.5	889,352	8,391	106
2020	-10.1	-2,569,432	8,905	-289
2021	8.1	1,866,722	9,118	205

Table 2: Change in Production and Growth Rate of Craft Breweries Across Years

Table 3: Rival Advertising Effect of Own Ad Spending

	Dependent variable
	$log(a_{kdt})$
log_rival_spend	0.448***
	(0.003)
BreweriesPerDMA	−0.019***
	(0.001)
post_seal	0.502***
	(0.019)
LargeBrewery	−0.400***
	(0.081)
log_Production	0.240***
	(0.014)
log_rival_spend:BreweriesPerDMA	−0.002***
	(0.0001)
log_rival_spend:post_seal	−0.098***
	(0.003)
BreweriesPerDMA:post_seal	0.003***
	(0.0004)
Observations	108,238
R^2	0.736
Adjusted R^2	0.721
Residual Std. Error	1.441 (df = 102768)
Border-DMA-Season FE	Y
City-State-Season FE	Y
Note:	Clustered Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 4: Comparison between the Full Model and the Border DMA model

	Dependent variable: log(a_{kdt})	
	Border Model	Full Model
log_rival_spend	0.448***	0.434***
	(0.003)	(0.002)
BreweriesPerDMA	−0.019***	0.012***
	(0.001)	(0.0004)
post_seal	0.502***	0.971***
	(0.019)	(0.013)
LargeBrewery	−0.400***	−1.076***
	(0.081)	(0.027)
log_Production	0.240***	0.270***
	(0.014)	(0.006)
log_rival_spend:BreweriesPerDMA	−0.002***	−0.002***
	(0.0001)	(0.00004)
log_rival_spend:post_seal	−0.098***	−0.129***
	(0.003)	(0.002)
BreweriesPerDMA:post_seal	0.003***	−0.001***
	(0.0004)	(0.0003)
Observations	108,238	262,432
R^2	0.736	0.563
Adjusted R^2	0.721	0.562
Residual Std. Error	1.441 (df = 102768)	1.632 (df = 261965)
Border-DMA-Season FE	Y	N
City-State-Season FE	Y	Y

Note: Clustered Standard errors in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table 5: Comparison between the border samples with (Model 1) and without (Model 2) breweries enagaged in national advertising

	Dependent variable: log(a_{kdt})	
	Model (1)	Model (2)
log_rival_spend	0.448***	0.137***
	(0.003)	(0.003)
BreweriesPerDMA	−0.019***	0.0005
	(0.001)	(0.001)
post_seal	0.502***	0.201***
	(0.019)	(0.018)
LargeBrewery	−0.400***	−0.246**
	(0.081)	(0.097)
log_Production	0.240***	0.068***
	(0.014)	(0.011)
log_rival_spend:BreweriesPerDMA	−0.002***	−0.001***
	(0.0001)	(0.0001)
log_rival_spend:post_seal	−0.098***	−0.059***
	(0.003)	(0.003)
BreweriesPerDMA:post_seal	0.003***	0.003***
	(0.0004)	(0.0004)
Observations	108,238	43,666
R^2	0.736	0.250
Adjusted R^2	0.721	0.234
Residual Std. Error	1.442 (df = 102563)	1.012 (df = 42708)
Border-DMA-Season FE	Y	Y
City-State-Season FE	Y	Y

Note: Clustered Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 6: OLS estimates using the placebo effects of imported beers on advertising on advertising by a craft brewer

	Dependent variable: log(AdSpend)
log_spend_Imported	0.002
	(0.004)
PostSeal	2.935***
	(0.775)
Market Effects	Y
Time Effects	Y
Market × Time Effects	Y
Observations	32,320
R^2	0.336
Adjusted R^2	0.322
Residual Std. Error	2.431 (df = 31659)
F Statistic	24.289*** (df = 660; 31659)
Note:	Clustered Standard errors in parentheses.
	*p<0.1; **p<0.05; ***p<0.01

Table 7: Comparison of Estimates across Specifications with Different Outlier Trimmings

	Dependent variable: log(a_{kdt})		
	Original	99th Trim	95th Trim
log_rival_spend	0.448***	0.442***	0.380***
	(0.003)	(0.003)	(0.002)
BreweriesPerDMA	−0.019***	−0.018***	−0.021***
	(0.001)	(0.001)	(0.001)
post_seal	0.502***	0.501***	0.346***
	(0.019)	(0.019)	(0.017)
LargeBrewery	−0.400***	−0.389***	−0.805***
	(0.081)	(0.079)	(0.072)
log_Production	0.240***	0.234***	0.220***
	(0.014)	(0.014)	(0.013)
log_rival_spend:BreweriesPerDMA	−0.002***	−0.002***	−0.002***
	(0.0001)	(0.0001)	(0.0001)
log_rival_spend:post_seal	−0.098***	−0.106***	−0.097***
	(0.003)	(0.003)	(0.003)
BreweriesPerDMA:post_seal	0.003***	0.003***	0.003***
	(0.0004)	(0.0004)	(0.0003)
Observations	108,238	107,159	102,827
R^2	0.736	0.724	0.735
Adjusted R^2	0.721	0.709	0.721
Residual Std. Error	1.442 (df = 102563)	1.405 (df = 101625)	1.244 (df = 97666)
Border-DMA-Season FE	Y	Y	Y
City-State-Season FE	Y	Y	Y

Note: Clustered Standard errors in parentheses.
*p<0.1; **p<0.05; ***p<0.01

Table 8: Comparing Specifications with and the triple-interaction term

	Dependent variable:	
	$log(a_{kdt})$	
log_rival_spend	0.442***	0.448***
	(0.003)	(0.003)
BreweriesPerDMA	−0.021***	−0.019***
	(0.001)	(0.001)
post_seal	0.456***	0.502***
	(0.022)	(0.019)
LargeBrewery	−0.400***	−0.400***
	(0.081)	(0.081)
log_Production	0.240***	0.240***
	(0.014)	(0.014)
log_rival_spend:BreweriesPerDMA	−0.002***	−0.002***
	(0.0001)	(0.0001)
log_rival_spend:post_seal	−0.087***	−0.098***
	(0.004)	(0.003)
BreweriesPerDMA:post_seal	0.006***	0.003***
	(0.001)	(0.0004)
log_rival_spend:BreweriesPerDMA:post_seal	−0.0005***	
	(0.0001)	
Observations	108,238	108,238
R^2	0.736	0.736
Adjusted R^2	0.721	0.721
Residual Std. Error	1.442 (df = 102562)	1.442 (df = 102563)
Border-DMA-Season FE	Y	Y
City-State-Season FE	Y	Y
Note:	Clustered Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01	

Table 9: Comparing the advertising elasticity estimates

Panel A: DML Result

DML on full sample

Dependent variable: log(a_{kdt})	Estimate	Std. Error	t value	$Pr(>\|t\|)$
log_rival_spend	0.473	0.002	213.1	0.000

DML on border sample

Dependent variable: log(a_{kdt})	Estimate	Std. Error	t value	$Pr(>\|t\|)$
log_rival_spend	0.452	0.002	187	0.000

Panel B: Comparison between Estimates

Dependent variable *log*(a_{kdt})	Baseline Specification	Border Strategy Specification	DML Model full sample	DML Model border sample
log_rival_spend	0.434***	0.448***	0.473***	0.452***
	(0.002)	(0.003)	(0.002)	(0.002)
Observations	262,432	108,238	262,432	108,238
Location FE	*Y*	*Y*	*Y*	*Y*
Time FE	*Y*	*Y*	*Y*	*Y*

Note: ***p<0.01

Table 10: Numerical simulation : Advertising

	a_k (M=1)	a_k (M=0)	a_k (M=0) - a_k (M=1)
Case-I: $\rho = 0$**;** $\gamma = 2$**;** $\eta = 1$	0.821	0.821	0.000
Case-II: $\rho = 1$**;** $\gamma = 2$**;** $\eta = 1$	0.347	0.821	0.474
Case-III: $\rho = 1$**;** $\gamma = 2$**;** $\eta = 2$	2.337	2.338	0.001
Case-IV: $\rho = 1$**;** $\gamma = 1$**;** $\eta = 2$	2.343	2.354	0.011

Note: γ is the ratio of γ_2 to γ_3.

Table 11: Numerical simulation : Advertising Elasticities

	e_{kk} (M=1)	e_{kk} (M=0)	e_{kk} (M=0) - e_{kk} (M=1)
Case-I: $\rho = 0$; $\gamma = 2$; $\eta = 1$	1.463	1.463	0.000
Case-II: $\rho = 1$; $\gamma = 2$; $\eta = 1$	0.589	1.463	0.874
Case-III: $\rho = 1$; $\gamma = 2$; $\eta = 2$	4.671	4.669	-0.002
Case-IV: $\rho = 1$; $\gamma = 1$; $\eta = 2$	2.328	2.316	-0.012

Note: γ is the ratio of γ_2 to γ_3.

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