Product Placement Effects on Store Sales: Evidence from Consumer Packaged Goods*

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Abstract

Product placement provides an alternative way for brands to reach consumers and does so in a more subtle way than through traditional advertising. We use data from both traditional television advertising and product placement on television shows to compare how these marketing instruments affect consumer demand for brands in the soda, diet soda, and coffee categories. Our approach is to estimate a logit demand model using weekly store-level sales data at the UPC (product) level, while accounting for heterogeneity in consumer preferences and response parameters across markets. Estimates from this model indicate that product placement is generally effective, but that the elasticities are small. For the soda and diet soda categories, average short-term elasticities are around 0.08 for the major brands in the data; these estimated elasticities for product placement are generally larger than those for traditional TV advertising, albeit on the same order of magnitude. For the coffee category, product placement elasticities are roughly zero while the advertising elasticities are larger. The results suggest that product placement is overall more effective than traditional TV advertising for the brands in our data; however, there is a significant amount of heterogeneity in elasticities across categories, brands, and geographical areas.

Keywords: Product Placement, Advertising, Media, Demand Estimation

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1 Introduction

The 2012 film *Skyfall* features a scene in which James Bond drinks from a green Heineken bottle while reclining in bed. In another scene from the film, Heineken bottles are noticeable in the background of a scene that takes place in a bar. These beverage choices were not made purely for artistic reasons; instead, they were examples of product placement and were the result of a $45 million deal between Heineken and the film's producers (Russell, 2012). When presented with concerns that the Heineken deal may have compromised the artistic integrity of the movie, lead actor Daniel Craig justified the partnership by pointing to the relatively unobtrusive nature of the Heineken brand mentions and the fact that the movie may not have been funded otherwise: "Heineken gave us a ton of money for there to be Heineken in a shot in a bar. So, how easy is that? Just to say, O.K., there's Heineken. It's there—it's in the back of the shot. Without them, the movie couldn't get sold" (Diehl and Weiner, 2012).

Product placement is notable in that the brand being mentioned or shown is integrated into the media content, in contrast to a traditional interstitial commercial. The Heineken - *Skyfall* partnership was a prominent example of product placement due to its high dollar value and the fact that it affected a popular and longstanding film franchise, but the broader phenomenon is quite common. For example, Coca-Cola had a 13 year partnership with American Idol in which oversized red cups were prominently displayed on the judges' table with Coca-Cola labels purposefully facing the camera (Poggi, 2014). In recent years, the sandwich chain Subway has purchased product placement across a number of network TV shows, including Community, Chuck, Nashville, and Hawaii Five-O (Steinberg, 2013). Many of these product placement deals have been crucial to keeping a show alive, in large part because brands are willing to pay more for a product placement agreement than for traditional advertising – just as Daniel Craig suggests was true in the case of Heineken and *Skyfall*.

Brands' high willingness to pay for product placement has made TV product placement a more pervasive phenomenon in recent years. From 2016 to 2017, TV product placement revenues grew by about 14% in the US. The market size for TV product placement is about 7 billion dollars, which equals roughly 10% of the total TV advertising market in the US (EMarketer, 2018; PQMedia, 2018). Product placement is a commonly used and financially important marketing mix tool for many brands in a broad variety of categories, and the current trends indicate that it will continue to grow in importance.

This research focuses on the efficacy of product placement in driving sales, and our primary goal is to describe how product placement affects consumer demand. As part of this

inquiry, we examine how product placement compares to traditional advertising in terms of efficacy, and how the effect of product placement varies across heterogeneous markets. Our data consists of weekly television advertising and television product placement information for brands in the soda, diet soda, and coffee categories, coupled with weekly store-level sales, pricing, and promotional information for products in those same categories. Linking these datasets allows us to isolate the effect of product placement while also accounting for contemporaneous changes in advertising, prices, in-store marketing; etc.

Despite the popularity of product placement as a marketing tool, prior research has not directly considered its effect on consumers' purchasing behavior. Traditionally, research in this area has used surveys or lab experiments to measure how product placement affects subsequent brand recall or attitudes towards the focal brands (e.g., Babin and Carder 1996; Lee and Faber 2007; Cowley and Barron 2008). Papers in this research stream typically build on theories from cognitive and social psychology, so they provide a set of explanations for how product placement is processed by the viewer. For our purposes, they serve to explain *why* product placement can work, whereas we endeavor to describe the magnitude of its effect size and how it varies across brands and markets.

A separate stream of research quantifies the effect of product placement by measuring abnormal stock returns using an event study approach (Wiles and Danielova, 2009; Karniouchina et al., 2011). These papers rely upon the idea that the value of product placement can be assessed by measuring how the focal brand's stock price changes immediately after the placement activity. Put more precisely, these papers are measuring how product placement affects firm value, and/or how product placement affects stockholders' perceptions of firm value. Conversely, our approach measures how product placement affects consumers and their relative probability of purchasing the focal brand versus other brands that did not use product placement. This is a key difference in focus between our research and the existing empirical work on product placement efficacy: our approach examines how consumers respond to the product placement, whereas the extant literature largely examines how shareholders respond to the product placement.

This research also relates to recent work examining how TV viewers respond when exposed to product placement. Prior research has demonstrated that exposure to product placement can affect viewership immediately after the placement takes place (Schweidel et al., 2014). Furthermore, product placement leads to an increase in social media activity and website traffic for the brands that engage in it (Fossen and Schweidel, 2018). Our research complements this stream of work: we similarly examine how consumers respond to product placement, but we focus on product sales rather than on viewership or social media activity.

More broadly, this research is related to a large stream of literature on measuring advertising effects. Our focus on TV product placement allows us to contribute an additional set of findings to the existing literature on TV advertising, which has thus far focused on traditional interstitial advertising (Lodish et al., 1995; Tellis et al., 2005; Shapiro, 2018a). In recent years, there have also been a number of papers demonstrating that online advertising effects are small and hard to measure (Blake et al., 2015; Lewis and Rao, 2015; Gordon et al., 2017; Johnson et al., 2017). Although our advertising and product placement measures are from TV and not the internet, one of the measurement concerns is similar: the true effects are likely to be small, so it is important to model the consumer's side carefully. These concerns are particularly true for product placement because it is integrated into TV shows more subtly than a standalone advertisement, and also because the length of each brand mention is typically shorter than a standalone advertisement.

In addition to estimating the effect of product placement on consumer's purchasing behavior, we are also interested in comparing its effect size versus traditional advertising. At a broad level, this goal is similar to that of previous work comparing the effectiveness of multiple types of advertising for a given brand (Danaher and Dagger, 2013; Dinner et al., 2014). However, this research is unique in that we are the first to compare television advertising with product placement, while the previous work in this area has compared multiple types of traditional advertising (e.g., display vs. search, television vs. radio; etc.).

Comparing the relative efficacy of television advertising versus product placement is particularly well-suited for empirical analysis because it is not clear from the extant literature which of the two methods should be more effective. Using survey data, Daugherty and Gangadharbatla (2005) find that consumers believe that product placement is more effective than advertising at increasing their purchase intentions, but this consumer belief is not corroborated with sales data. This prediction is supported by applications of the Petty and Cacioppo (1986) elaboration likelihood model suggesting that consumers react negatively to advertisements clearly intended to persuade them, thereby indicating that subtler product placement methods would be more effective than traditional advertising (Babin and Carder, 1996). However, this theory conflicts with findings that product placement has little effect on brand evaluations or purchase intentions (Karrh, 1998; Ong, 1995; Yang et al., 2003). There are also conflicting findings in the literature about whether product placement or traditional advertising is more effective with regards to processing and attitudinal measures. For instance, Bhatnagar et al. (2003) find that consumers remember brands better if they have been exposed to product placement rather than traditional advertising, while Davtyan et al. (2016) find the opposite. Given these conflicting theories and results, our goal is to empirically estimate and compare the effect sizes of product placement and traditional

advertising. Our estimation approach enables us to make a direct comparison because we estimate both effects on the same set of products, brands, stores, and markets.

Our results show that product placement is generally effective at increasing market shares in the soda and diet soda categories, but that these effects are small. For the major soda and diet soda brands, average short-term product placement elasticities are about 0.08. This exceeds the elasticities for traditional TV advertising of around 0.01, thereby indicating that product placement may be underutilized as a marketing tool for those brands. However, these patterns are reversed in the coffee category, where product placement elasticities are roughly zero but advertising elasticities are about 0.05. Across all three categories, there is significant heterogeneity across markets and stores in terms of these elasticities. Recent findings by Shapiro et al. (2018) on the magnitudes of advertising elasticities across a broad range of products and categories provides us with some reassurance regarding the magnitudes of the advertising effects that we find.

The substantive results of this research have important implications for managers, for both the company buying the product placement and the company allowing the product placement to take place. Brand managers for companies like Coca-Cola and Folgers benefit from a better understanding of how effective product placement will be, relative to other potential marketing tools. Similarly, managers at television studios and networks benefit from this information because they set prices for product placement. Being better informed about the effectiveness of product placement will potentially allow studios and networks to receive better pricing terms.

In addition to the managerial implications, this research also has implications for regulators. Since product placement is "hidden" in a way that traditional advertising is not, there have been calls for government agencies to restrict its use. This regulatory decision potentially depends on a number of complex legal, economic, and consumer protection factors. However, one key issue that regulators have not directly considered is the extent to which product placement can change consumers' purchasing behavior. This research helps to clarify this issue, thereby enabling regulatory officials to make better informed decisions in the future.

In the USA, product placement is regulated by both the Federal Trade Commission (FTC) and the Federal Communications Commission (FCC). In 2005, a consumer advocacy group petitioned the FTC to force television programs to superimpose "ADVERTISEMENT" on-screen whenever there was a scene with product placement. This petition was rejected by the commission, in large part because product placement typically does not make any false claims about the product in question; in fact, it usually does not make any objective claims at all (Engle, 2005). The FTC has also recently instituted disclosure rules on social media,

so that people who are paid by brands to promote a product must disclose this fact in their posts or videos. In 2007, the FCC fined Comcast $16,000 for airing a series of "video news releases" without acknowledging that they had been funded by a third-party (Monteith, 2007). These programs were visually similar to traditional news programs, but they were funded by General Mills and were essentially infomercials for the company. In 2008, the FCC also began an inquiry focused on whether TV product placement should be clearly disclosed, but it decided not to take further action (Clifford, 2008). Overall, the American government has shown a willingness to regulate extreme forms of "hidden" advertising, but has generally taken a laissez-faire attitude towards the milder forms of product placement that are more prevalent. Currently, the FCC mandates that TV shows must list the brands that buy product placement in the end credits of the episode, but there are no limitations on the practice otherwise.

In Europe, regulatory bodies have taken a more active approach towards regulating product placement. In the UK, product placement on television was illegal until 2011. Since then, it has been allowed but brands have had to abide by a much stricter set of guidelines than in the USA. Product placement is not permitted on news programs, current events shows, and shows targeted towards children. Furthermore, programs that contain product placement are required to prominently display a special product placement logo at the beginning of the show, the end of the show, and immediately after each commercial break (Robinson, 2010). There are also a number of product categories which are not allowed to be shown, including medicines, "foods that are high in sugar or salt," alcohol, and tobacco. Although the European Union does not have blanket rules on product placement, many of its member countries have similarly banned product placement of alcohol and tobacco brands (STAP, 2007).

2 Data

Our sales data is at the store-level, and we focus on three product categories: soda, diet soda, and ground coffee. While one might argue that all soda and diet soda products belong in a single "category," research has shown that consumers view them as being distinct (see e.g., DeSarbo and Wu, 2001; Bollinger and Sexton, 2018). In all three categories, each observation in the data is a product-store-week combination, where products are defined at the UPC level. Each of these categories has two dominant focal brands and a number of smaller brands. To aid in computation, we aggregate all these smaller brands into a composite "other" brand separately for each category, thereby yielding three brands (but still a large number of products) in total per category. The categories cover different DMAs,

Table 1: Summary of store-level variables

	Soda	Diet Soda	Coffee
Num. DMAs	35	35	14
Num. brands	3	3	3
Focal brands	Coca-Cola Pepsi	Diet Coca-Cola Diet Pepsi	Folgers Maxwell House
Num. products (UPCs)	3331	1120	765
Num. stores	1317	1317	598
Num. weeks	80	80	80
Num. product-stores	316,274	184,693	42,089
Num. product-store-weeks	10,100,750	6,266,364	1,562,897

but each has 80 weeks of data from December 2003 to July 2005. In sum, we have nearly 18 million observations across the three categories. See table 1 for a summary of the store-level data, broken by category.

Apart from the sales information, our data includes information on general marketing activity, product placement, and advertising. These data come from AC Nielsen. The first group consists of basic variables such as price, as well as in-store promotional variables for feature and display. We also construct an interaction variable between feature and display that we label feature*display. Price is measured in dollars, and the others are indicator variables.

For product placement, we observe the brand in question, as well as the duration and rating for a given product placement incident. The duration refers to how many seconds the brand was mentioned or displayed on screen during the TV show, while the rating measures how many people viewed the TV show r in a specific designated market area (DMA) d in week t:

$$\text{placement rating}_{rdt} = 100 \left(\frac{\text{number of viewers}_{rdt}}{\text{market population}_d} \right)$$

We combine the two placement measures into one: weighted gross rating points (wGRP). Traditional gross rating points (GRPs) are typically measured by 30-second base timings, and we use the same standard here. This yields a standardized measure of a placement's rating, weighted by the number of seconds it was shown:

$$\text{placement wGRP}_{rdt} = \text{placement rating}_{rdt} \left(\frac{\text{placement seconds}_{rdt}}{30} \right)$$

Finally, we create a goodwill variable for product placement by using the past 26 weeks

and creating a decayed stock variable:

$$\text{placement goodwill}_{rdt} = \sum_{l=0}^{26} \left[0.9^l \times \text{placement wGRP}_{rd,t-l}\right]$$

The benefit of this goodwill variable it accounts for both the duration of product placement and the number of people who viewed it, while also allowing for the fact that product placement may affect sales for a given brand many weeks after the consumer was initially exposed to it. Furthermore, this specification is aligned with previous work that uses goodwill variables to measure advertising effects (Horsky, 1977; Chintagunta and Vilcassim, 1992; Rutz and Bucklin, 2011; Braun and Moe, 2013).

A limitation of our data is that the product placement variables are limited in breadth for the smaller brands. For each of the categories, we observe full coverage for the two large focal brands, but only partial coverage for the composite "other" brand. This data limitation means that we are unable to make specific predictions about how effective product placement might be for the smaller brands in the data. However, our estimates and predictions for the main brands in the data would remain econometrically valid, as long as brands are not specifically trying to match each others' product placement during the same weeks (i.e., as long as placement values are not correlated across brands within the same week). Figure 1 below indicates that this concern is not a problem in our setting.

For advertising, we focus specifically on spot television advertising (national advertising effects are absorbed into the brand-week fixed effects that we include in our analysis - this is discussed below). Our advertising variables are similar to the product placement ones: we observe the DMA, the brand that the advertisement was for, the duration of each advertisement, and the DMA-specific rating for the TV show during which the ad was shown. This allows us to create rating, wGRP, and goodwill variables that are analogous to the placement variables:

$$\text{ad rating}_{rdt} = 100\left(\frac{\text{number of viewers}_{rdt}}{\text{market population}_d}\right)$$
$$\text{ad wGRP}_{rdt} = \text{ad rating}_{rdt}\left(\frac{\text{ad seconds}_{rdt}}{30}\right)$$
$$\text{ad goodwill}_{rdt} = \sum_{l=0}^{26} \left[0.9^l \times \text{ad wGRP}_{rd,t-l}\right]$$

Properly identifying the key parameters for advertising and product placement requires two patterns to hold true in the raw data: usage of advertising and product placement

Table 2: Frequency of advertising and product placement usage

		Num. weeks with advertising	Num. weeks with product placement
Soda	Coca-Cola	38	80
	Pepsi	42	73
	Other	3	2
Diet Soda	Diet Coca-Cola	3	75
	Diet Pepsi	22	61
	Other	1	4
Coffee	Folgers	27	47
	Maxwell House	31	9
	Other	1	1

must be frequent enough, and there must be sufficient variation in advertising and product placement exposure across markets and across weeks. We find that both these conditions are met in our data for the major brands that are our primary focus. Table 2 displays the frequency with which the major brands engage in advertising and product placement in the data. Both tools are in fact used, and product placement seems to be more common than spot TV advertising.

The level of weekly variation in advertising and product placement can be seen in figure 1, which displays the total duration of advertising and product placement for each brand. The key brands do in fact show variation in advertising and product placement from week to week, thus creating variation that allows us to identify the key parameters of interest.

Figure 2 displays the correlation between advertising wGRPs and product placement wGRPs, by brand and DMA. Strong positive correlations would mean that brands use high levels of both advertising and product placement in some weeks, and low levels of both advertising and product placement in other weeks. This might imply that brands are using these two marketing tools as complements. On the other hand, strong negative correlations might imply that advertising and product placement are substitutes. In our data, the magnitudes of these correlations are overall quite low, thereby suggesting that brands treat them as independent tools that are neither complements not substitutes. Furthermore, there do not appear to be systematic patterns in these correlation coefficients across brands.

The final set of variables we include in our analysis are demographic variables. These are defined at the store level, and represent the demographics for a 2-mile radius around each store. We include the following variables:

Age: Percentage of population aged 21 to 54, percentage of population aged 55 to 84, and percentage of population aged 85+

Figure 1: Weekly variation in advertising and product placement duration, by brand

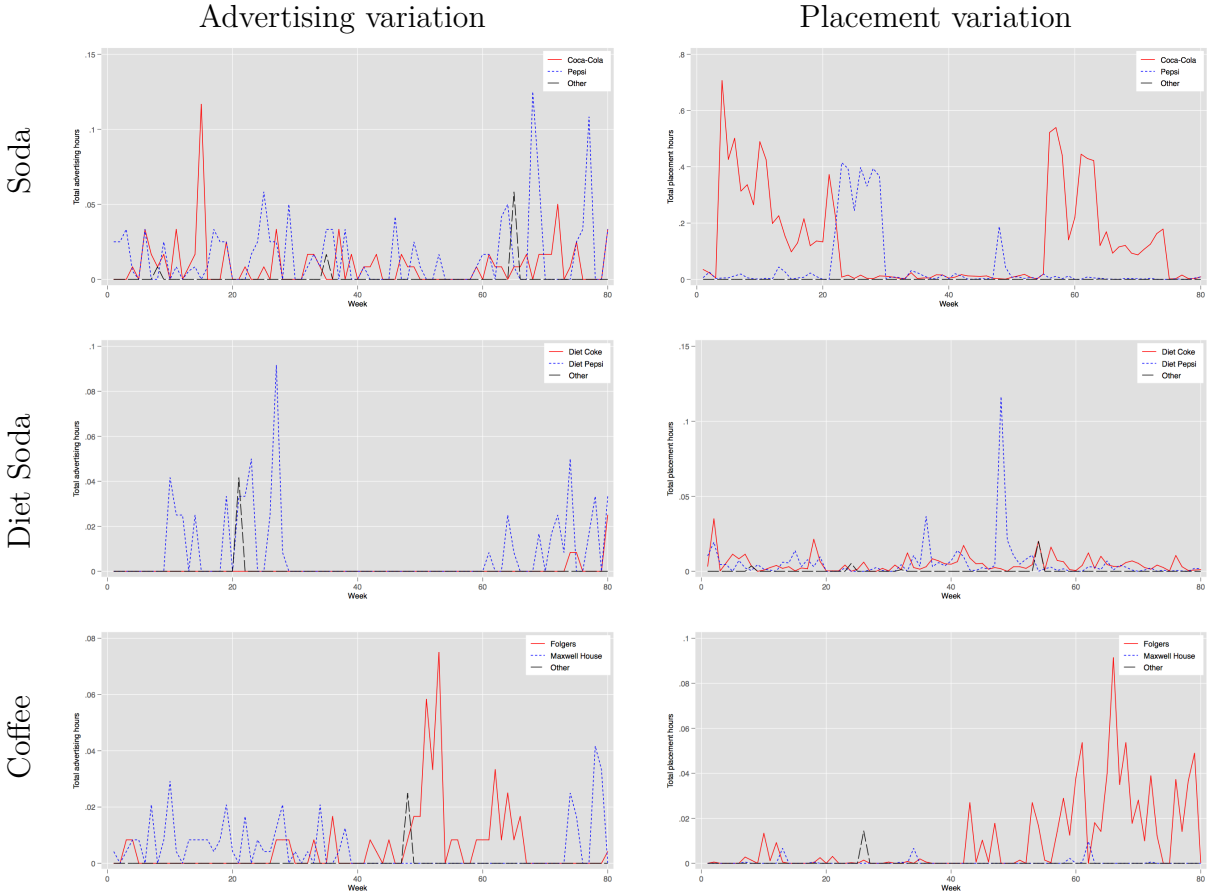
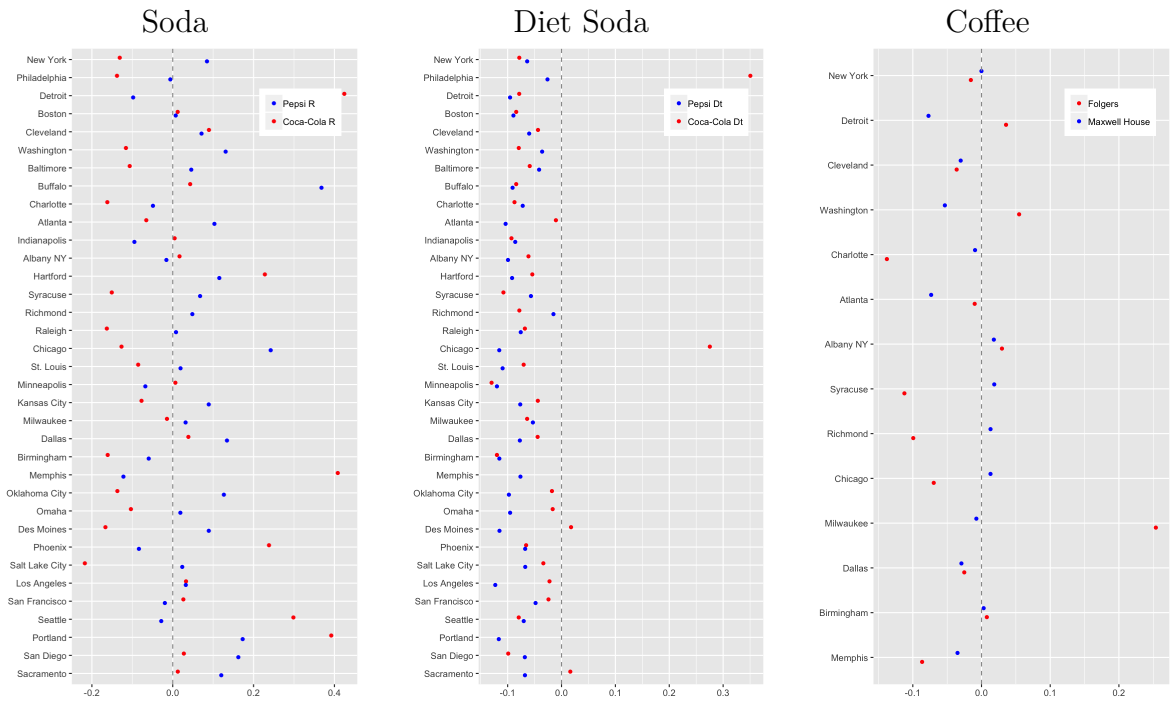


Figure 2: Correlation coefficients between advertising and product placement wGRPs, by brand and DMA



Income: Income per capita

Race: Percentage Native American, percentage Asian, percentage black, percentage Hispanic, and percentage white

Employment: Unemployment percentage

All of the data in this research are at the aggregate level – we do not have any individual- or household-level data on purchasing, exposure to advertising, exposure to product placement, or demographics. However, brands engaging in product placement must purchase each placement at the show-week level, which means that they cannot target their efforts to specific individuals or households. As a result, our data limitation corresponds well to the managerial problem faced by the advertiser.

3 Model

Our goal is to estimate how product placement activity affects demand in three categories:

soda, diet soda, and coffee. To accomplish this, we model demand for products in these categories using our information on promotional activity and TV product placement. Our approach is to model products' market shares with a logit model that uses weekly store-level data.

Our data contains information on q_{jmt}, the number of units sold of product j in store m in week t. Market demand is defined as the sum of units sold in a specific week in a specific store, across all products within the category. If we denote the store-specific market size for a given category as M_m, this allows us to define the no-purchase quantity q_{0mt} and the market share s_{jmt} as follows:

$$\begin{aligned}
\text{market size}_m &= M_m \\
\text{market demand}_{mt} &= \sum_{j=1}^{J} q_{jmt} \\
q_{0mt} = \text{no purchase}_{mt} &= \text{market size}_m - \text{market demand}_{mt} \\
&= M_m - \sum_{j=1}^{J} q_{jmt} \\
s_{jmt} = \text{market share}_{jmt} &= \frac{\text{units sold}_{jmt}}{\text{market size}_m} \\
&= \frac{q_{jmt}}{M_m}
\end{aligned}$$

Consumers derive the following utility from a given product$j$ in store m in week t:

$$u_{jmt} = \alpha_{jm} + X_{jmt}\beta + \epsilon_{jmt}$$

where α_{jm} is the baseline utility that the consumer receives from a given product-store pair and X_{jmt} is a vector of price, advertising, placement, and promotion variables. These variables vary on two dimensions: store level m vs. DMA d, and product j vs. brand b. Assuming that ϵ_{jmt} is distributed Type 1 extreme value yields a standard logit representation for consumers' choice probabilities. Fixing the utility of the outside option at zero implies that the consumer's choice probabilities are:

$$P_{jmt} = \frac{\exp\left(\alpha_{jm} + X_{jmt}\beta\right)}{1 + \sum_{j=1}^{J} \exp\left(\alpha_{jm} + X_{jmt}\beta\right)}$$

Aggregating across consumers allows us to convert individual consumers' choice proba-

bilities P to market shares s_{jmt}. This yields the following equation (see Berry, 1994):

$$\begin{aligned}\ln(s_{jmt}) - \ln(s_{0mt}) &= \alpha_{jm} + X_{jmt}\beta + \varepsilon_{jmt} \\ &= \alpha_{jm} + \beta_1 \text{ price}_{jmt} + \beta_2 \text{ ads}_{bdt} + \beta_3 \text{ plmt}_{bdt} \\ &\quad + \beta_4 \text{ feat}_{jmt} + \beta_5 \text{ disp}_{jmt} + \beta_6 \left(\text{feat*disp}\right)_{jmt} + \varepsilon_{jmt}\end{aligned} \tag{1}$$

3.1 Identification

The key parameters $\beta_1, \beta_2, \beta_3$ in equation 1 are identified based on variation in prices, advertising, and product placement. This variation is caused by decisions made by the retail stores, the brands, and consumers. The specific identification arguments are as follows:

Price: The price coefficients β_1 are identified through variation in retail prices across weeks for the same product-store combination. We do not specify a model for how retail stores and brands decide upon retail prices for each product, and as described in section 3.3, we account for the possibility that prices may be endogenously chosen in response to local demand shocks.

Advertising: The advertising coefficients β_2 are identified through variation in advertising exposure across markets and weeks. Brands choose how much advertising (in seconds) to buy in each DMA and in each week, so the fact that we focus on spot TV advertising provides natural variation in advertising exposure across markets. Brands can potentially specify the TV shows during which they want their ads to be shown, but they cannot directly control the viewership numbers – therefore, the level of advertising exposure depends on both the brands' advertising decisions and the consumers' TV viewing behavior. We discuss the possibility that advertising decisions may be endogenously chosen in response to local demand shocks, and explain our approach in section 3.3.

Placement: The product placement coefficients β_3 are identified through variation in placement exposure across markets and weeks. Brands can choose advertising at the DMA level within a specific week, but the same is not true for product placement. Because the placement is integrated into the TV content, brands do not have the ability to restrict their product placement so that it only gets viewed in specific DMAs. Instead, brands only choose their product placement at the program/episode level. The exposure to product placement varies across DMAs because TV episodes are viewed differently across DMAs: markets with higher viewership numbers will have higher

levels of exposure to the product placement.

3.2 Heterogeneity

3.2.1 Fixed effects

The panel nature of our data means that we observe sales data for many of the same products in the same stores over time (weeks). To account for taste differences across stores, we included the product-store fixed effect a_{jm} in equation 1. We now include two additional fixed effects: a brand-week fixed effect that accounts for any national advertising or other promotional activity that a brand may be using, and a zip3-week fixed effect that accounts for any local demand shocks. Zip3 refers to the first 3 digits of the store's zip code, so this is a more granular measure than the DMA.

The inclusion of these fixed effects enables us to more carefully isolate the effect of prices, advertising, and product placement from other factors that might affect demand in a systematic way. Denoting b as the brand and z as the zip3 allows us to update our model specification:

$$\begin{aligned}\ln(s_{jmt}) - \ln(s_{0mt}) &= \alpha_{1jm} + \alpha_{2bt} + \alpha_{3zt} + X_{jmt}\beta + \varepsilon_{jmt} \\ &= \alpha_{1jm} + \alpha_{2bt} + \alpha_{3zt} \\ &\quad + \beta_1 \text{ price}_{jmt} + \beta_2 \text{ ads}_{bdt} + \beta_3 \text{ plmt}_{bdt} \\ &\quad + \beta_4 \text{ feat}_{jmt} + \beta_5 \text{ disp}_{jmt} + \beta_6 \left(\text{feat*disp}\right)_{jmt} + \varepsilon_{jmt}\end{aligned} \tag{2}$$

3.2.2 Market-specific coefficients

We allow the coefficients for price, advertising, and product placement to vary across DMAs d. This allows us to rewrite our model specification as:

$$\begin{aligned}\ln(s_{jmt}) - \ln(s_{0mt}) &= \alpha_{1jm} + \alpha_{2bt} + \alpha_{3zt} + X_{jmt}\beta_d + \varepsilon_{jmt} \\ &= \alpha_{1jm} + \alpha_{2bt} + \alpha_{3zt} \\ &\quad + \beta_{1d} \text{ price}_{jmt} + \beta_{2d} \text{ ads}_{bdt} + \beta_{3d} \text{ plmt}_{bdt} \\ &\quad + \beta_4 \text{ feat}_{jmt} + \beta_5 \text{ disp}_{jmt} + \beta_6 \left(\text{feat*disp}\right)_{jmt} + \varepsilon_{jmt}\end{aligned} \tag{3}$$

This approach yields separate price, advertising, and placement coefficients for each DMA,

thereby accounting for the fact that consumers in different areas may respond differently to brands' marketing activity.

3.2.3 Demographic variables

Equation 3 allows for across-market heterogeneity in the price, advertising, and placement coefficients. We now build on this by allowing for within-market heterogeneity using demographic data. Let D_{md} be a vector of demographic variables representing the local area around a given store m, with the variables mean-centered by DMA d. In other words, D_{md} represents how the consumer demographics near a particular store m differ from other consumers in the same DMA d. The inclusion of these demographic variables D_{md} in our logit model allows the various demand coefficients to vary within-market in a parsimonious and easily interpretable fashion. The updated specification is now:

$$\begin{aligned}\ln(s_{jmt}) - \ln(s_{0mt}) &= \alpha_{1jm} + \alpha_{2bt} + \alpha_{3zt} + X_{jmt}\left(D_{md}\gamma + \beta_d\right) + \varepsilon_{jmt} \qquad (4)\\ &= \alpha_{1jm} + \alpha_{2bt} + \alpha_{3zt}\\ &\quad + \left(D_{md}\gamma_1 + \beta_{1d}\right)\ \text{price}_{jmt} + \left(D_{md}\gamma_2 + \beta_{2d}\right)\ \text{ads}_{bdt} + \left(D_{md}\gamma_3 + \beta_{3d}\right)\ \text{plmt}_{bdt}\\ &\quad + \beta_4\ \text{feat}_{jmt} + \beta_5\ \text{disp}_{jmt} + \beta_6\left(\text{feat*disp}\right)_{jmt} + \varepsilon_{jmt}\end{aligned}$$

Note that the above approach to accounting for heterogeneity in preferences and responses is via the use of fixed effects and interactions with demographic characteristics. As we will see below this results in the inclusion of, in some cases, tens of thousands of fixed effects. This allows us to account for rich patterns of heterogeneity consistent with the granularity of our data. We are able to do this without imposing functional form assumptions as in random coefficients models or without being able to pick up heterogeneity in the tails of the distributions as in latent-class type models. Further, controlling for unobservable heterogeneity as in Berry et al. (1995) is difficult in this context due to the granularity of the data: computational feasibility is only plausible if we aggregate across products, across stores, or across weeks – this in turn would result in an unnecessary loss of important variation in the data. We recognize that there could be some incremental heterogeneity in preferences within a product-store or heterogeneity in responsiveness within market beyond the demographics we include but we feel that this is likely to be small compared to all the variation we are able to account for via the inclusion of the large set of fixed effects in the model.

3.3 Endogeneity

A common concern with consumer demand models is that many of the observed variables

are determined by the brand and are not randomly assigned. Brands choose what prices to set and how much advertising to allocate for a particular market, which indicates that these variables may be correlated with variables that are unobserved to the researcher. Dealing with this type of price endogeneity is a standard problem in the literature, and more recent work has suggested that dealing with advertising endogeneity may be similarly important (Chintagunta et al., 2006; Bruce, 2008; Danaher et al., 2008; Petrin and Train, 2010; Rossi, 2014; Dinner et al., 2014; Ebbes et al., 2016; Danaher and van Heerde, 2018). Concerns about advertising endogeneity are particularly strong with online ads because they can be highly targeted at the individual level. TV advertising cannot typically be targeted to a particular viewer, but endogeneity concerns may still be present (albeit to a lesser degree) for TV ads that are targeted to a particular audience or a particular market.

There is no standard instrumental variable for TV advertising endogeneity in the literature, and finding an instrument that represents common cost shocks but not demand is challenging in this context. A recent stream of papers has used discontinuities across DMA borders to estimate TV advertising effects, but this approach is infeasible in our context because we have store-level sales data as opposed to consumer-level sales data (Shapiro, 2018a,b; Tuchman, 2018). Further, restricting our data to border counties would further reduce the amount of variation we can leverage for our analysis (see Li et al., 2018).

Our approach for dealing with advertising endogeneity is to use fixed effects to soak up much of the variation in the data, as recommended by Rossi (2014) and Li et al. (2018). The worry with advertising endogeneity is that advertising decisions ads_{jmt} may be correlated with the unobservable term ε_{jmt}. Including high-dimensional fixed effects dramatically reduces ε_{jmt}, the unexplained variation in the model that would otherwise be attributed to unobserved demand shocks. We find that there is no additional variation that can be explained by allowing advertising to be targeted at the brand-DMA-week level, which in turn implies that the endogeneity problem has been minimized by the fixed effects in the model. Our approach is similar to previous papers that also use fixed effects to minimize the level of unexplained variation in the data (Dubé et al., 2005; Thomas, 2018). This approach has been demonstrated to be successful in other contexts: in particular, Thomas (2018) suggests that it leads to significant improvements over the regular OLS results.

Our approach for dealing with price endogeneity is to use standard "Hausman instruments" that instrument for price by using the average price in other markets for the same week (Hausman, 1996; Nevo, 2001). A necessary assumption for the validity of these instruments is that the unobserved demand shocks ε_{jmt} are independent across markets – this is a reasonable assumption in our context after including the fixed effects described above. Furthermore, instead of using the average price in all other markets for which we have data,

we instead only take the average in markets that do not share a border with the focal market. This ensures that our instrumental variable approach remains valid even if two neighboring markets were to have highly correlated demand shocks.

We do not include an instrumental variable for product placement. Unlike spot TV advertising, product placement decisions must typically be made far in advance so that the brands can be integrated into the creative content of the show during the production process. Furthermore, brands cannot specifically choose to display product placement in particular DMAs. As a result, it is unlikely that product placement would be chosen in accordance with local demand shocks in the way that advertising and prices can. Furthermore, even if brands were to do so, this potential source of endogeneity would also be minimized by the fixed effects approach we describe above.

We provide diagnostics for our approaches to these endogeneity concerns. Section 4.2 contains first-stage regressions that show that our price instruments are valid and strong. Section 4.3 estimates alternative versions of our main regression model and demonstrates that the potential correlation between advertising and the unobservable term ε_{jmt} is minimized by the high-dimensional fixed effects, thereby indicating that the advertising variable is unlikely to be endogenous conditional upon these fixed effects.

4 Estimation results

To allow the strongest amount of flexibility in coefficient estimates, we estimate separate regressions for each of the three categories: soda, diet soda, and coffee. For each category, we provide estimates from three different models:

1. An OLS regression corresponding to equation 2 that provides a baseline set of estimates but does not include instrumental variables, DMA-specific coefficients, or demographic-based heterogeneity.

2. A 2SLS regression corresponding to equation 2 but with the inclusion of price instruments. However, this does not include DMA-specific coefficients or demographic-based heterogeneity. This model is easily estimated due to the relatively small number of coefficients, but it is limited by its lack of heterogeneity.

3. A 2SLS regression corresponding to equation 4 that includes price instruments, DMA-specific coefficients, and demographics-based heterogeneity. This is the main specification that we focus on, because it allows for greater heterogeneity across consumers.

All three of the models include fixed effects by product-store, zip3-week, and brand-week. For models that include such high-dimensional fixed effects, de-meaning the outcome variables can lead to inconsistent estimates (Gormley and Matsa, 2014). Rather than de-meaning the data multiple times, we instead rely on recent methods that directly and efficiently estimate the fixed effects and properly adjust the standard errors (Correia, 2016).

For the purposes of estimation, we use ln(price) as our "price" variable. We also use ln(placement goodwill) and ln(ad goodwill) as our placement ("plmt") and advertising ("ads") variables, respectively. We define the weekly market size for a particular category at a given store (M_m) as 500% of the highest observed weekly sales volume for that store. In keeping with the prior literature, this assumption is chosen to allow for the possibility that a significant portion of shoppers may choose not to buy soda, diet soda, or coffee product in any given week (e.g., Nevo, 2000; Jiang et al., 2009). Finally, the demographic variables D_{md} are mean-centered by DMA so that the demographic effects are relative to the particular market.

4.1 OLS and 2SLS regression results

Estimation results from the three models described above are displayed in table 3. All three models include fixed effects by product-store, brand-week, and zip3-week.

Models 3, 6, and 9 are our main specifications for each of the three categories. These models include heterogeneity in two ways: DMA-specific coefficients for placement, price, and advertising, and demographic-based effects for those same three variables. As a result, the placement, price, and advertising estimates and standard errors presented in table 3 for models 3, 6, and 9 correspond to the imputed pooled values – these estimates are in italics.

For models 3, 6, and 9, the full set of DMA-specific coefficients are displayed in figure 3, which show how the coefficients vary across DMAs and categories. Each dot corresponds to the point estimate, and each bar corresponds to the corresponding 95% confidence interval. Figure 4 displays a similar coefficient plot for the demographic variables.

From table 3, we can see that advertising consistently has a statistically significant positive effect on demand and price consistently has a statistically significant negative effect on demand. The effect of product placement is positive and significant for the soda and diet soda categories but is statistically insignificant for the coffee category. For soda and diet soda, the effect of product placement is much larger than the effect of advertising. Figure 3 demonstrates that there is substantial heterogeneity across DMAs in placement and price coefficients, but that the advertising coefficients tend to be more tightly clustered.

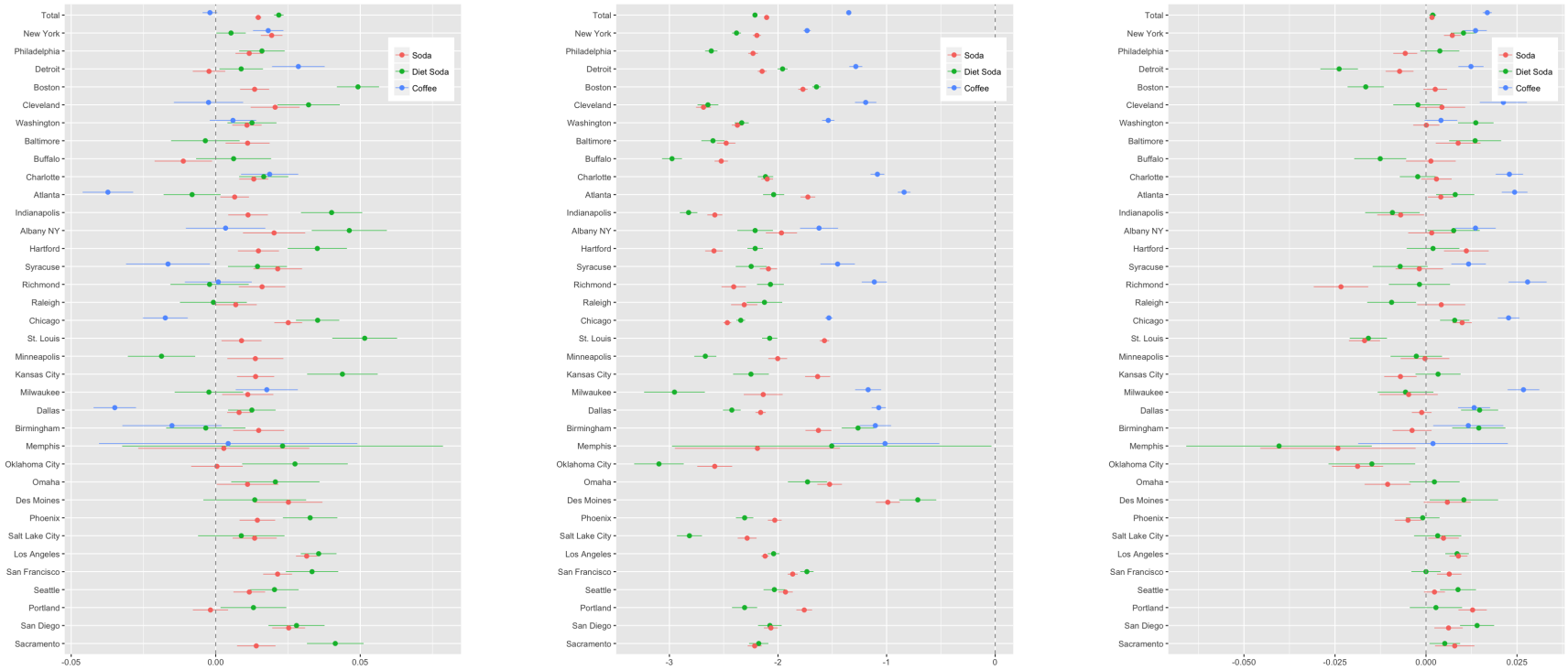
Table 3: OLS and 2SLS logit estimates (eqs. 2 and 4)

	(1) Soda OLS	(2) Soda 2SLS	(3) Soda 2SLS	(4) Diet Soda OLS	(5) Diet Soda 2SLS	(6) Diet Soda 2SLS	(7) Coffee OLS	(8) Coffee 2SLS	(9) Coffee 2SLS
placement	0.0132***	0.0134***	*0.0147****	0.0185***	0.0188***	*0.0218****	-0.00297	-0.000683	*-0.00200*
	(0.000915)	(0.000916)	*(0.000535)*	(0.00112)	(0.00112)	*(0.00085)*	(0.00212)	(0.00213)	*(0.00130)*
feature	0.193***	0.181***	0.180***	0.172***	0.150***	0.141***	0.519***	0.642***	0.634***
	(0.000807)	(0.00117)	(0.00123)	(0.000911)	(0.00146)	(0.00158)	(0.00241)	(0.00371)	(0.00395)
display	0.460***	0.456***	0.450***	0.367***	0.358***	0.351***	0.456***	0.492***	0.489***
	(0.000840)	(0.000902)	(0.000919)	(0.00101)	(0.00110)	(0.00114)	(0.00344)	(0.00355)	(0.00355)
feature × display	0.0548***	0.0549***	0.0548***	0.0525***	0.0526***	0.0540***	0.273***	0.272***	0.270***
	(0.00134)	(0.00134)	(0.00135)	(0.00153)	(0.00153)	(0.00157)	(0.00558)	(0.00561)	(0.00570)
price	-2.022***	-2.107***	*-2.105****	-2.040***	-2.184***	*-2.212****	-1.834***	-1.402***	*-1.348****
	(0.00146)	(0.00586)	*(0.00572)*	(0.00175)	(0.00769)	*(0.00780)*	(0.00376)	(0.0105)	*(0.00937)*
advertising	0.00211***	0.00214***	*0.00164****	0.00280***	0.00295***	*0.00185****	0.0227***	0.0193***	*0.0168****
	(0.000369)	(0.000369)	*(0.000368)*	(0.000657)	(0.000657)	*(0.000500)*	(0.000788)	(0.000795)	*(0.000628)*
DMA and demographic heterogeneity	No	No	Yes	No	No	Yes	No	No	Yes
Product-Store FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip3-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Brand-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.815	0.815	0.815	0.782	0.782	0.782	0.783	0.781	0.782
Adjusted R^2	0.809	0.808	0.809	0.775	0.775	0.775	0.776	0.775	0.775
F-statistic	543510.3	246032.8	10831.2	369771.3	155512.1	6836.6	109485.7	72151.9	5841.5
Cragg-Donald Wald F-statistic		646642.7	4605.9		329544.3	1499.6		222934.4	3837.6
Centered R^2		0.815	0.815		0.782	0.782		0.781	0.782

Note: Standard errors in parentheses. Models, 3, 6, and 9 include DMA and demographic heterogeneity, corresponding to equation 4. The italicized values for placement, price, and advertising in models 3, 6, and 9 represent pooled values across all DMAs. The 2SLS specifications include price instruments, while the OLS specifications do not.

Figure 3: Coefficient plots by category and DMA

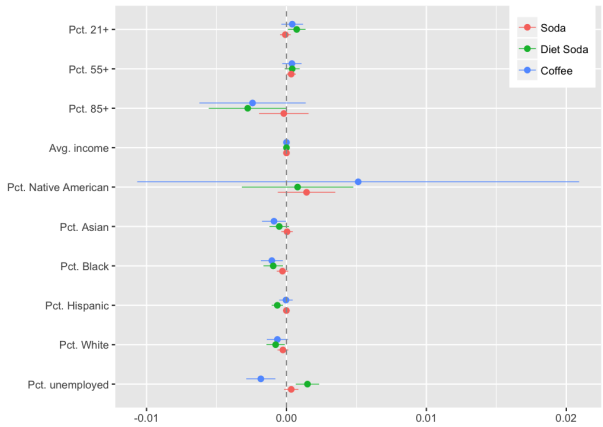
(a) Placement coefficients (b) Price coefficients (c) Advertising coefficients



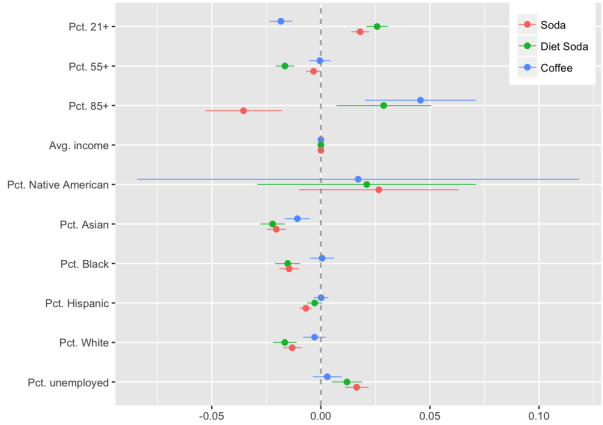
Note: each dot represents a point estimate, and each bar is the corresponding 95% confidence interval. Estimates are derived from models 3, 6, and 9 in table 3. The "Total" row represents the pooled estimates across all DMAs.

Figure 4: Coefficient plots by category and demographic variable

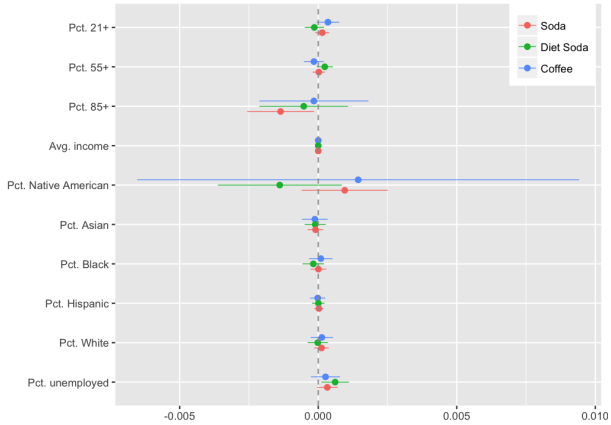
(a) Placement coefficients



(b) Price coefficients



(c) Advertising coefficients



Note: each dot represents a point estimate, and each bar is the corresponding 95% confidence interval. Estimates are derived from models 3, 6, and 9 in table 3.

Table 4: First-stage OLS regressions for price, by category

	Soda	Diet Soda	Coffee
price instrument	0.6870	0.7448	0.8321
	(0.0009)	(0.0013)	(0.0018)
placement	0.0009	0.0015	-0.0007
	(0.0002)	(0.0003)	(0.0004)
ads	0.0003	0.0003	0.0002
	(0.0001)	(0.0001)	(0.0002)
feature	-0.1402	-0.1447	-0.2607
	(0.0002)	(0.0002)	(0.0004)
display	-0.0529	-0.0535	-0.0740
	(0.0002)	(0.0002)	(0.0007)
feature × display	-0.0020	-0.0023	-0.0022
	(0.0003)	(0.0003)	(0.0011)
First stage F-statistic	325646	209237	133052

Note: These estimates represent the first-stage regressions with price as the left-hand-side variable. The price instrument variable corresponds to the Hausman instruments as explained in section 3.3.

Finally, figure 4 demonstrates that the demographic coefficients are generally small and statistically insignificant, particularly for advertising and placement. For price, many of the demographic coefficients are statistically significant, but there is no strong pattern that can be drawn. Overall, the demographic-level coefficients seem to be of limited additional benefit relative to the DMA-level coefficient estimates.

The various R^2 metrics are consistently very high, thereby indicating that our model explains most of the variation in the data. Furthermore, the Cragg-Donald statistics are very high, thereby indicating that the Hausman instruments are strong and warrant inclusion in our model.

4.2 First-stage regressions for price endogeneity

To ensure that the Hausman-style price instruments are well-behaved, we check the first-stage regressions. These OLS regressions have price as the dependent variable, with the price instrument and the various covariates on the right-hand side. Results are in table 4.

The first-stage results indicate that our price instrument is valid: regressing price on our explanatory variables yields a statistically significant positive coefficient for the price instrument variable. The first-stage F-statistics in table 4 coupled with the Cragg-Donald statistics from table 3 indicate that our price instruments are both valid and strong.

4.3 Endogeneity checks for advertising

Our approach to dealing with advertising endogeneity is to include high-dimensional fixed effects so that the unobservable term is minimized. By doing so, we hope to minimize the possibility of any correlation between the unobservable term and advertising. To validate this approach, we check whether our model explains as much of the data as alternative versions of the model where we fully account for potential advertising effects through fixed effects. In particular, we estimate alternative models where the brand-week and zip3-week two-way fixed effects are replaced by a three-way fixed effect: either brand-week-DMA or brand-week-zip3.

Spot TV ads are chosen and viewed at the brand-week-DMA level, and product placement is also viewed at the brand-week-DMA level. Therefore, the inclusion of either of these three-way fixed effects should perfectly subsume both local ads and local product placement. Our comparison of interest is between (a) our focal specification and (b) alternative specifications that drop advertising, placement, and the brand-week and zip3-week fixed effects and instead include a three-way fixed effect. If the latter specification has a substantially higher R^2 and adjusted R^2 and if it changes the other estimated model parameters, this implies that perfectly accounting for potential advertising endogeneity has a big effect on our model estimates. If both specifications have similar R^2 values, then this implies that our model estimates are less likely to be biased. In particular, it indicates that our advertising and placement variables fully account for the three-way interaction effect between brand, week, and zip3, thereby lowering the possibility of unobservable factors that would then be absorbed into the error term and cause the endogeneity problem. Specifically, in the estimation we replace the model in equation 4 with the equation below:

$$\begin{aligned}\ln(s_{jmt}) - \ln(s_{0mt}) &= \alpha_{1jm} + \alpha_{2bz(or\,d)t} + X_{jmt}\left(D_{md}\gamma + \beta_d\right) + \varepsilon_{jmt} \\ &= \alpha_{1jm} + \alpha_{2bz(or\,d)t} \\ &\quad + \left(D_{md}\gamma_1 + \beta_{1d}\right)\ \text{price}_{jmt} + \\ &\quad + \beta_4\ \text{feat}_{jmt} + \beta_5\ \text{disp}_{jmt} + \beta_6\left(\text{feat*disp}\right)_{jmt} + \varepsilon_{jmt}\end{aligned} \tag{5}$$

where $\alpha_{2bz(or\,d)t}$ represents the fixed effects for the 3-way interaction between brand-zip3 (or DMA) - week. An R^2 comparison between various models is in table 5. Model 1 is our standard approach, with placement and advertising variables as well as three two-way fixed effects: product-store, zip3-week, and brand-week. Model 2 includes the product-store fixed effect but replaces the latter two fixed effects by a three-way fixed effect at the brand-week-

Table 5: R^2 values across alternative model specifications

		(1)	(2)	(3)	(4)	(5)
Soda	R^2	0.815	0.814	0.303	0.815	0.815
	Adjusted R^2	0.808	0.808	0.302	0.808	0.808
	Num. observations	10,073,743	10,073,743	10,085,903	10,073,743	10,073,657
	Num. coefficients and FEs	321,903	312,511	8,404	321,901	356,682
Diet Soda	R^2	0.782	0.780	0.297	0.782	0.783
	Adjusted R^2	0.775	0.774	0.296	0.775	0.775
	Num. observations	6,252,500	6,252,500	6,258,635	6,252,500	6,252,391
	Num. coefficients and FEs	196,047	186,655	8,404	196,045	230,792
Coffee	R^2	0.781	0.780	0.272	0.781	0.785
	Adjusted R^2	0.775	0.774	0.270	0.774	0.776
	Num. observations	1,561,282	1,561,286	1,562,879	1,561,282	1,561,033
	Num. coefficients and FEs	47,930	43,804	3,364	47,928	61,975
	Placement and ad variables	Yes	No	No	No	No
	Product-Store FE	Yes	Yes	No	Yes	Yes
	Zip3-Week FE	Yes	No	No	Yes	No
	Brand-Week FE	Yes	No	No	Yes	No
	Brand-Week-DMA FE	No	Yes	Yes	No	No
	Brand-Week-Zip3 FE	No	No	No	No	Yes

DMA level. Model 3 is similar to model 2, except without the product-store fixed effect. Model 4 is similar to model 1 in that it includes all three two-way fixed effects, but it differs in that it does not include the placement or advertising variables. Finally, model 5 is similar to model 2: it includes the product-store fixed effect and also includes a three-way fixed effect at the brand-week-zip3 level.

When comparing the results from table 5, our preferred specification without three-way fixed effects (model 1) does just as well as the other models in the soda and diet soda categories, and nearly as well in the coffee category. Including three-way fixed effects does not seem to dramatically improve model fit, which indicates that our preferred specification is appropriately modeling the advertising and product placement variables.

Prior research has suggested that not controlling for advertising endogeneity will lead to overestimating the effect of advertising (Shapiro, 2018a; Thomas, 2018). Given the diagnostic measures presented in table 5, we believe that we have adequately controlled for the possibility that advertising might be endogenous. However, if we have not done so fully, this implies that our advertising effects might be slightly over-estimated.

5 Elasticity estimates

Our estimation procedure yields a large number of coefficients that need to be estimated,

particularly in the preferred specification with heterogeneity by DMA and demographics. For ease of comparison, we now describe the estimated elasticities that come from our regression results. For each product j, brand b, store m, DMA d, and week t, we can estimate the short-term own-elasticities as follows:

$$\begin{aligned}
\text{price elasticity}_{jmt} &= \left(D_{md}\hat{\gamma}_1 + \hat{\beta}_{1d}\right)\left(\text{price}_{jmt}\right)(1 - s_{jmt}) \\
\text{ad elasticity}_{jmt} &= \left(D_{md}\hat{\gamma}_2 + \hat{\beta}_{2d}\right)(\text{ads}_{bdt})(1 - s_{jmt}) \\
\text{placement elasticity}_{jmt} &= \left(D_{md}\hat{\gamma}_3 + \hat{\beta}_{3d}\right)(\text{plmt}_{bdt})(1 - s_{jmt})
\end{aligned}$$

We estimate a separate price, advertising, and placement elasticity for each of the 18 million product-store-week observations in our data. Standard errors corresponding to each of these elasticity estimates are calculated using the delta method.

5.1 Mean elasticities

Table 6 displays the mean elasticity values for brands in each of the three categories, after trimming the top and bottom one percent for each elasticity type to control for potential outliers. The signs of the elasticities have face validity: increasing price reduces consumer demand, while increasing advertising and product placement will increase consumer demand. The advertising elasticities are generally lower and oftentimes statistically insignificant, while the product placement elasticities are noticeably larger. The only exception to this pattern is in the coffee category, where the reverse occurs: advertising elasticities in this category are substantially higher than the product placement elasticities, and the product placement elasticities are typically insignificant.

The advertising and placement elasticities are consistently lower for the "other" brand than for the focal brands in the data. Part of this is attributable to our data limitations for this composite brand (see section 2), but it also indicates that smaller brands may not benefit as much from advertising and product placement as their larger, more well-known competitors.

For the focal brands in the data, our average estimates for price and advertising elasticities are broadly in line with previous meta-analyses by Bijmolt et al. (2005) and Sethuraman et al. (2011). In both cases, our average elasticities are on the low end relative to the meta-analytic findings, but this may be explained by the fact that we have stronger fixed effects and controls for endogeneity compared to most papers that are included in those meta-analyses. As a consequence, our estimated elasticities are less likely to be inflated due to model misspecification issues. Our estimated advertising elasticities do correspond very

Table 6: Summary of trimmed mean elasticities, by category and brand

		Elasticity type		
		Price	Ads	Plmt
Soda	Coca-Cola	-1.78	0.011	0.098
		(0.03)	(0.007)	(0.026)
	Pepsi	-1.62	0.011	0.076
		(0.03)	(0.011)	(0.016)
	Other	-1.07	0.001	0.002
		(0.02)	(0.001)	(0.000)
Diet Soda	Diet Coca-Cola	-1.79	0.002	0.077
		(0.04)	(0.001)	(0.018)
	Diet Pepsi	-1.71	0.015	0.081
		(0.04)	(0.010)	(0.019)
	Other	-1.30	0.000	0.003
		(0.03)	(0.000)	(0.001)
Coffee	Folgers	-1.81	0.050	-0.002
		(0.06)	(0.009)	(0.015)
	Maxwell House	-1.78	0.060	0.002
		(0.05)	(0.010)	(0.007)
	Other	-1.77	0.001	0.002
		(0.05)	(0.000)	(0.000)

Note: Standard errors in parentheses. The displayed values are means after trimming the top and bottom 1%.

closely with more recent work by Shapiro et al. (2018) who estimate advertising effects across a large number of packaged goods categories, using a different econometric methodology than ours.

Overall, we find that product placement has a small, positive effect on consumer demand. The placement elasticities are overall larger than the advertising elasticities, but of the same order of magnitude: for the focal brands, roughly 0.08 compared to 0.01. The exception to this pattern is in the coffee category, where the average product placement elasticity is roughly zero but the advertising elasticity is substantially higher. In the aggregate, the fact that placement elasticities tend to exceed advertising elasticities suggest that product placement may be an underutilized tool (relative to traditional TV advertising) for brands in the soda and diet soda categories, while the reverse holds true in the coffee category.

5.2 Elasticity heterogeneity

Table 6 displays average elasticities for each brand, across all products, stores, and weeks. We now display the heterogeneity of these elasticities in figure 5, which shows brand-level

trimmed histograms for the estimated elasticities.

Figure 5 indicates that there is significant variance in the price and placement elasticities, but that the advertising elasticities are less dispersed. For price elasticities, the soda and diet soda categories seem to be bimodal: there is one cluster around -0.5 and another around -2.5. This pattern does not hold true for the coffee category, where the price elasticities are distributed more smoothly around -1.5. For advertising elasticities, all three categories display a significant spike at zero. The advertising elasticities for soda and diet soda are sometimes negative, but the majority of the elasticities are still positive. Finally, the placement elasticities are quite different across categories: the soda elasticities display the highest level of variance, followed by the diet soda category and then the coffee category. The coffee elasticities are frequently negative, but this is rarely the case in the other two categories.

5.3 Cross-market differences in elasticities

The histograms in figure 5 display the level of variation in the elasticity estimates across observations; however, they do not specifically address to what extent that variation is across products, across stores, or across time. In figure 6, we now calculate the average price elasticity for the focal brands by DMA and display these averages spatially. Given the negative sign of the price elasticities, darker values on the map represent DMAs that are less price-elastic (i.e., with price elasticities closer to zero).

Figure 6 demonstrates that there is considerable heterogeneity across markets in terms of their average price elasticities. Across all three categories, DMAs in the south tend to be less price elastic than DMAs in the Great Lakes region.

Figures 7 provides similar spatial maps for advertising elasticities. Darker values on the map represent DMAs with higher ad elasticities. The New York DMA consistently has high elasticities in all three categories, but otherwise there are few generalizable patterns across categories.

Finally, figure 8 provides spatial maps for placement elasticities. Darker values on the map represent DMAs with higher placement elasticities. Generally speaking, product placement elasticities tend to be higher on the coasts relative to the Midwest and the plains states. The soda and diet soda elasticity maps are broadly similar, but those similarities do not carry over to the coffee elasticity map.

5.4 Connections between the estimated elasticities

The previous sections have displayed the heterogeneity in elasticities, both across observations and across markets. In this section, we examine the relationship between the price, advertising, and placement elasticities for each DMA. The premise behind this exercise is

Figure 5: Elasticity histograms, by brand

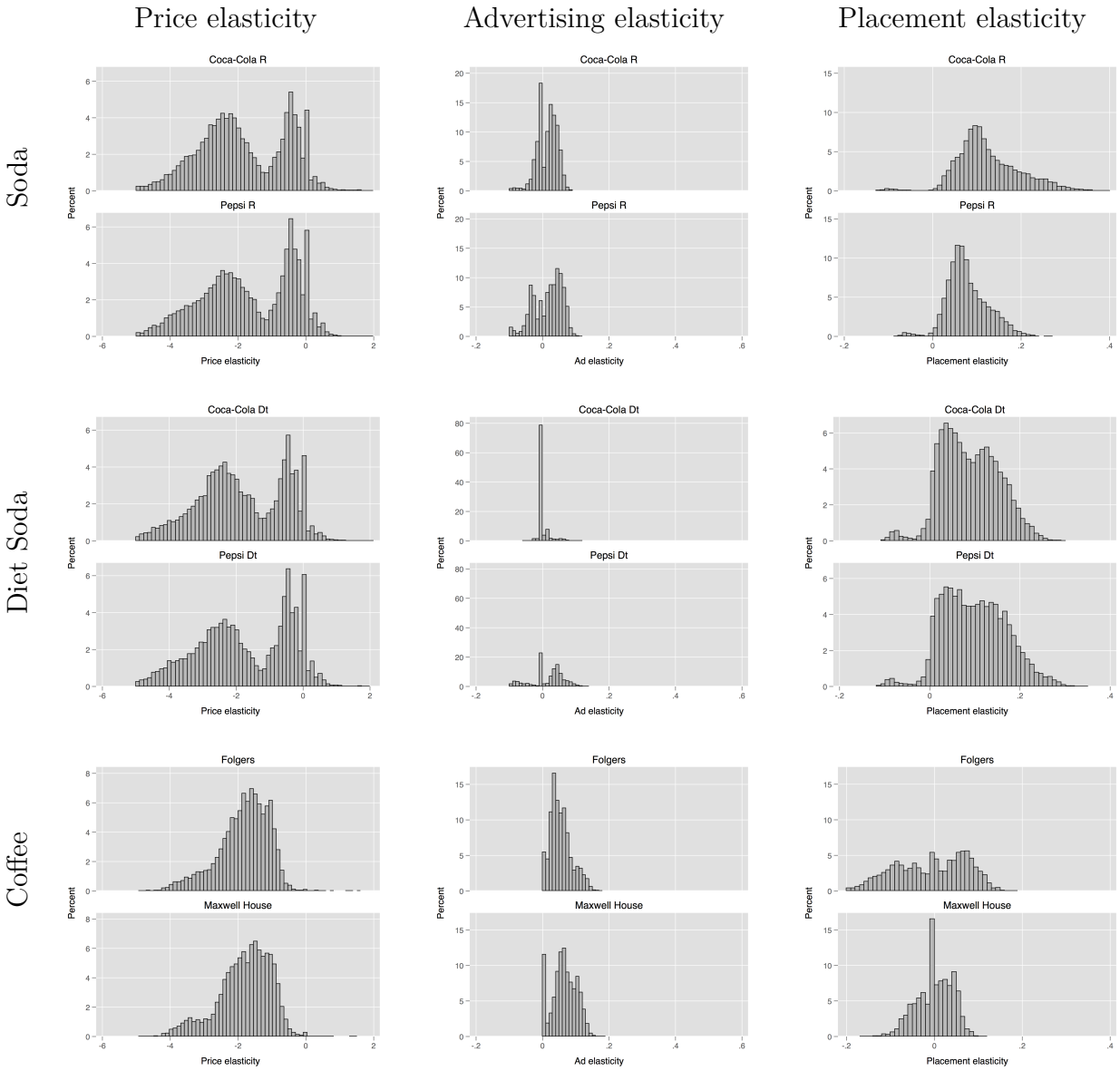
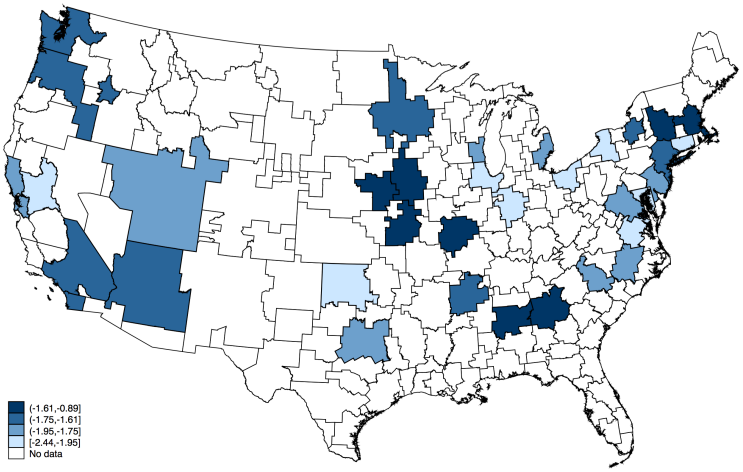
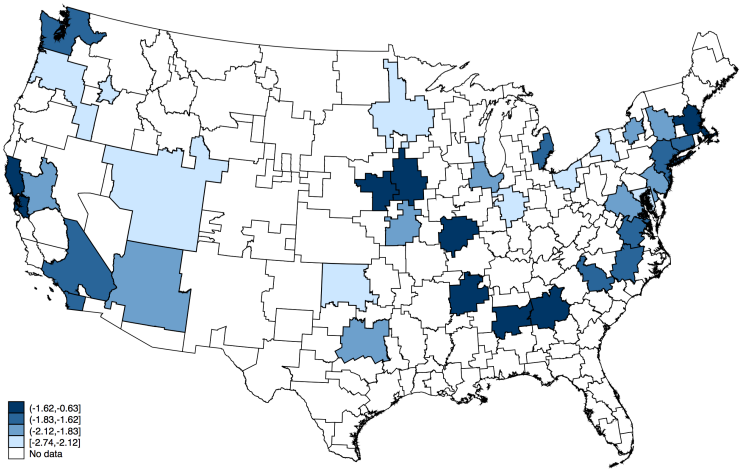


Figure 6: Average price elasticities by DMA

(a) Soda



(b) Diet Soda



(c) Coffee

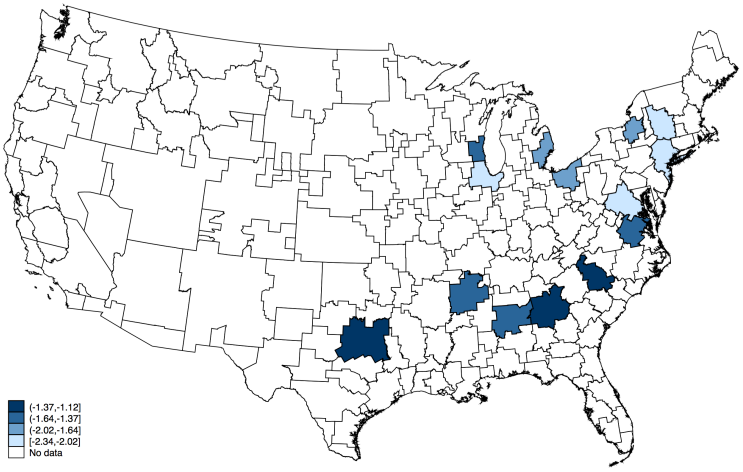
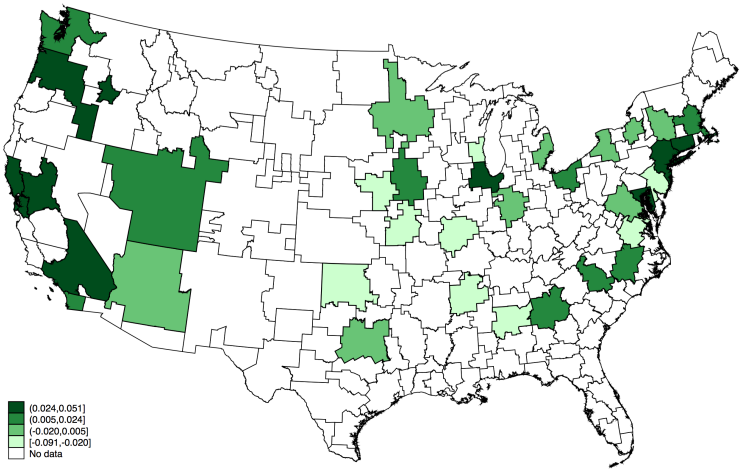
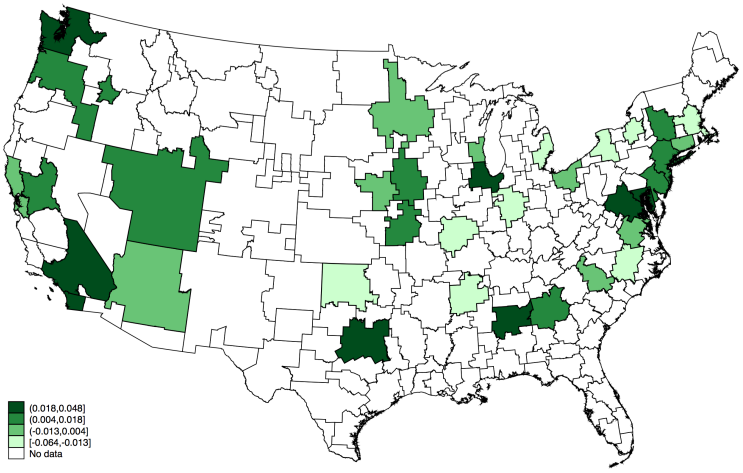


Figure 7: Average advertising elasticities by DMA

(a) Soda



(b) Diet Soda



(c) Coffee

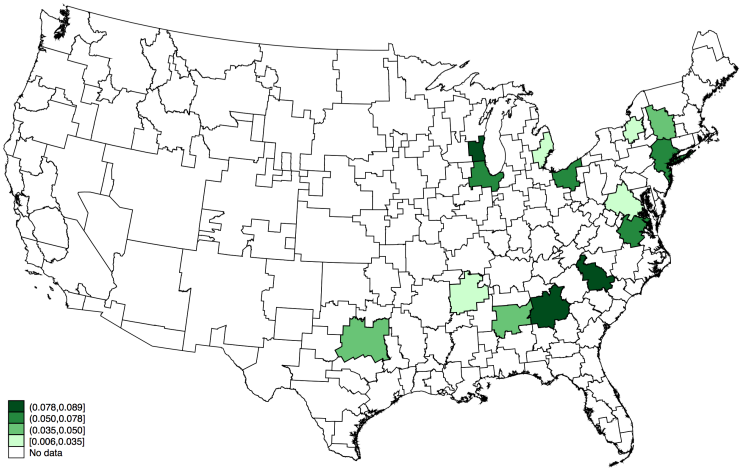
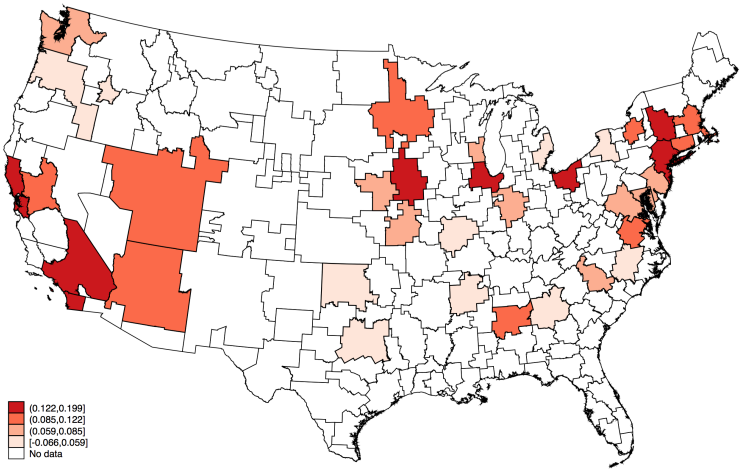
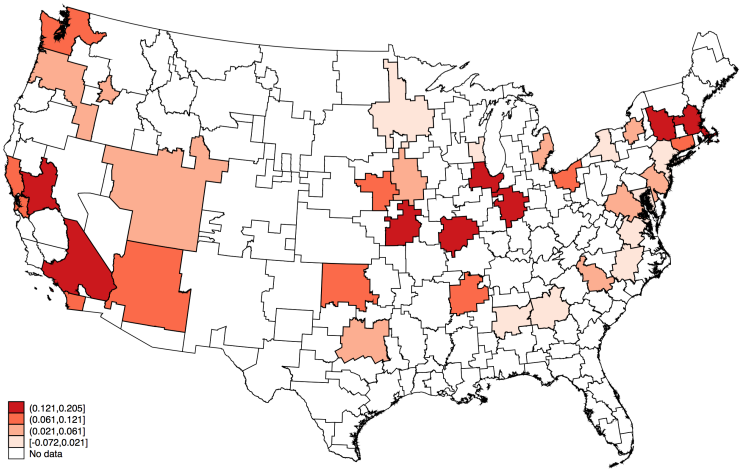


Figure 8: Average placement elasticities by DMA

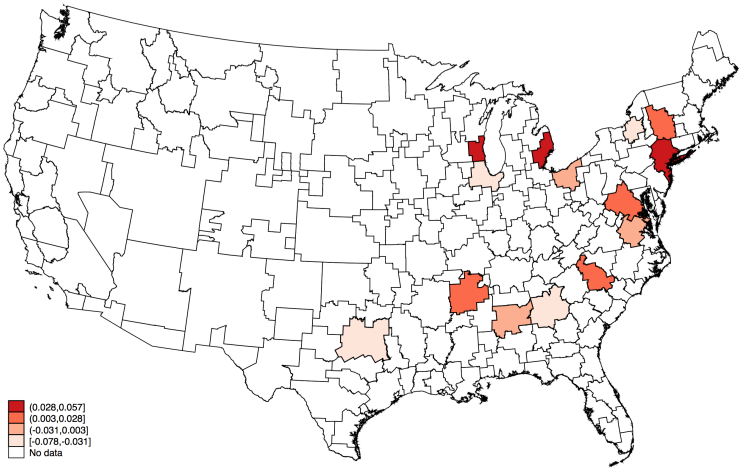
(a) Soda



(b) Diet Soda



(c) Coffee



there there may certain underlying characteristics that affect consumers' responses to both price changes and advertising changes – if that is the case, then we should observe a relationship between the price elasticity and the advertising elasticity across DMAs. Similarly, it may be the case that the same types of customers who respond strongly to advertising are also the same customers who respond most strongly to product placement – if that is the case, then we should observe a positive relationship between the advertising elasticity and the placement elasticity across DMAs.

We have three comparisons that we would like to examine: whether the advertising and placement elasticities are related, whether the price and advertising elasticities are related, and whether the price and placement elasticities are related. Figure 9 displays the first comparison: whether advertising and placement elasticities are related, for focal brands in each of the three categories.

The findings in figure 9 are quite different across categories. In the soda category, there seems to be a noisy yet positive correlation between the average advertising elasticity and the average placement elasticity across DMAs. If the placement elasticity is high, then the advertising elasticity tends to be high as well. For diet soda and coffee, there appears to be no strong correlational relationship along these lines. These results yield two important substantive conclusions for brands that buy product placement: product placement and advertising do not necessarily work on the the same kinds of customers, and knowing the ad responsiveness in a particular market may not provide much indication about what the product placement responsiveness will be in that same market.

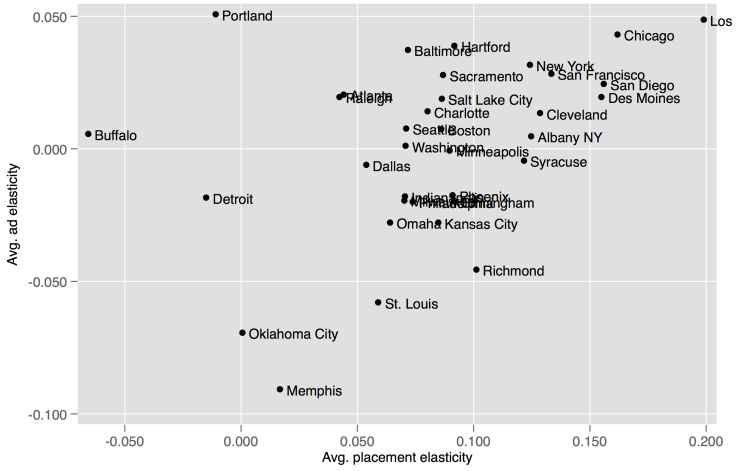
Figure 10 shows similar scatter plots comparing whether price and advertising elasticities are related, for focal brands in each of the three categories. Figure 11 does the same for price and placement elasticities. In both cases, there seem to be no real patterns in the data: DMA-level price elasticities seem to be generally uncorrelated with that same DMA's advertising and placement elasticities.

6 Conclusion

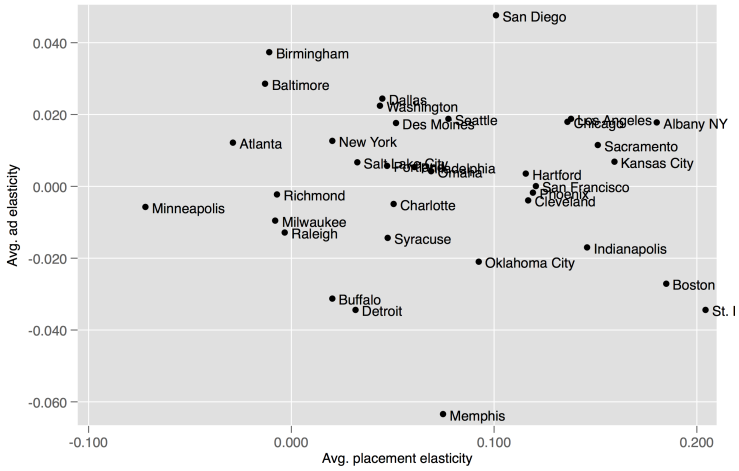
Our results offer three main substantive findings: (1) product placement overall has a small, positive effect on consumer demand, (2) product placement seems to be more effective at driving sales than traditional TV advertising for soda and diet soda but not for coffee, and (3) the magnitude of the placement elasticities can vary significantly across brands and DMAs. This has important implications for brands that are interested in using product placement as a marketing tool, as it can potentially allow them to compare the effectiveness of product placement versus more traditional forms of advertising.

Figure 9: Average advertising vs. placement elasticities, by DMA

(a) Soda



(b) Diet Soda



(c) Coffee

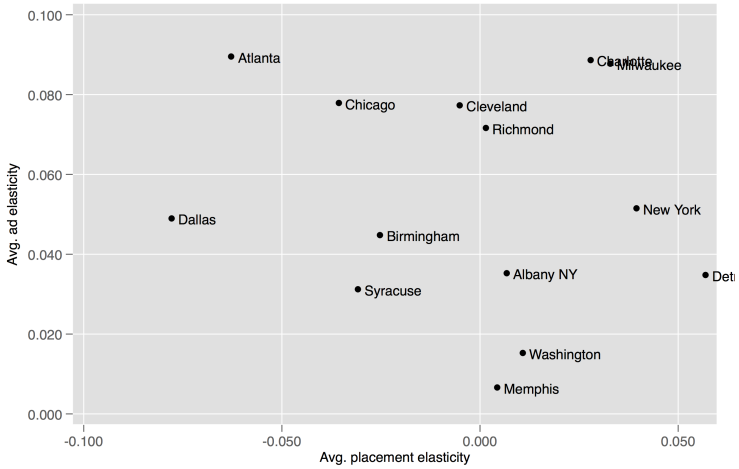
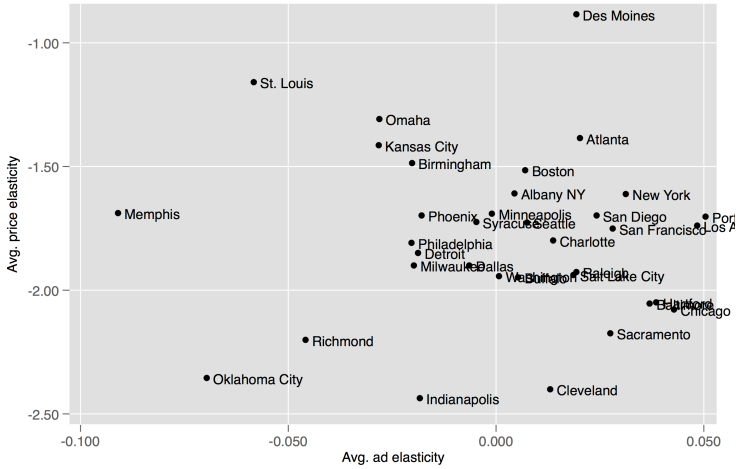
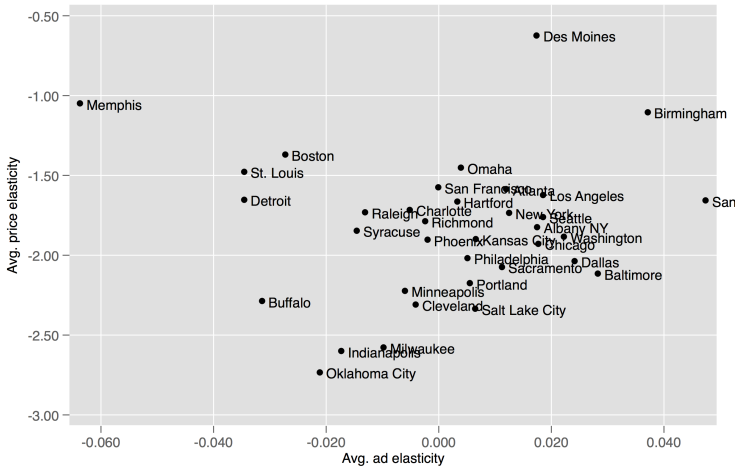


Figure 10: Average price vs. advertising elasticities, by DMA

(a) Soda



(b) Diet Soda



(c) Coffee

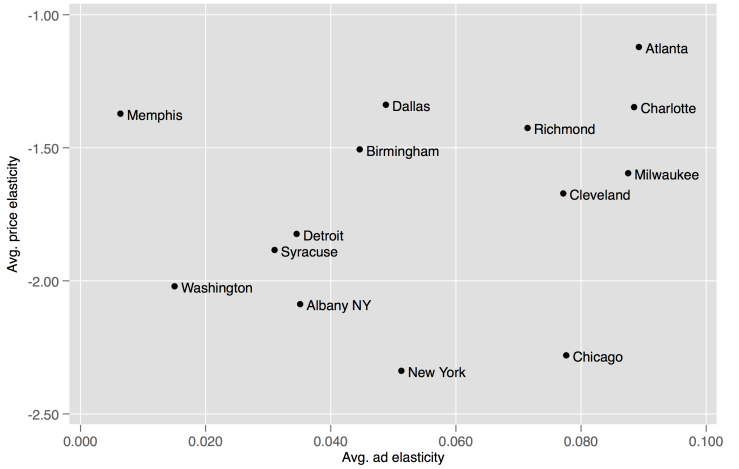
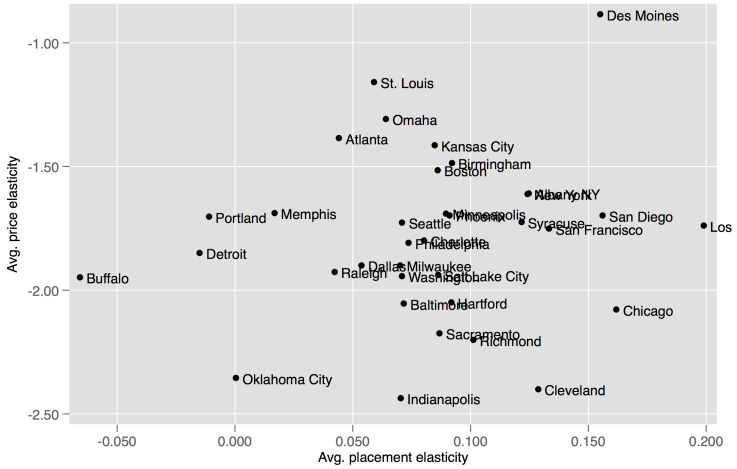
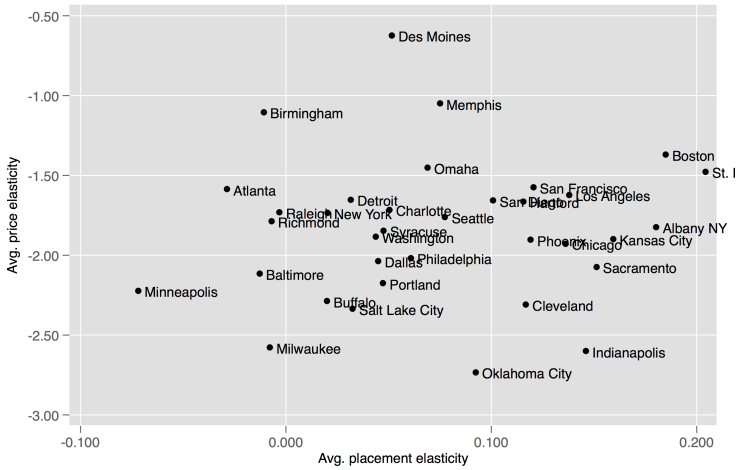


Figure 11: Average price vs. placement elasticities, by DMA

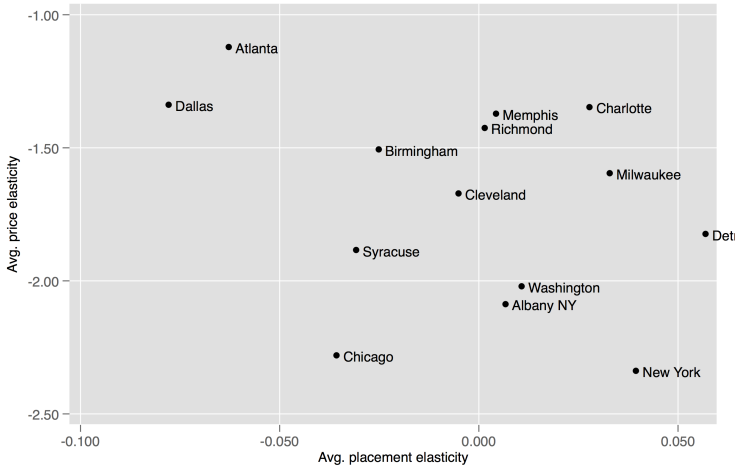
(a) Soda



(b) Diet Soda



(c) Coffee



This research is the first attempt to quantify how product placement affects consumer demand, and there are a number of related questions that arise afterwards. For instance, future research could attempt to address whether product placement or traditional advertising yields a higher return on investment. This would require the researcher to have data on how much product placement costs per exposure and how these costs vary across shows and networks. Such data would also allow researchers to more carefully examine how brands should allocate a fixed budget across advertising and product placement. Our results suggest that major brands in the soda and diet soda categories are receiving roughly 8 times higher lift from product placement than advertising, so their willingness-to-pay for additional media should similarly be higher for product placement than for advertising.

The nature of our product placement data limits our ability to estimate product placement effects for the small brands in each category. Extending the analysis to other brands in these categories as well as to other categories where product placement may be prevalent would also be worthwhile. Another area of potential research would be considering alternative demand systems and ways of dealing with the endogeneity issue.

In addition to providing valuable guidance to advertisers and TV networks, our results also enable regulatory bodies to make better-informed decisions. In the US, both the FCC and FTC have the ability to regulate TV product placement but have thus far chosen to allow it to continue. One key question for regulators is the extent to which product placement affects consumers and their purchasing decisions, and this research provides an answer to that.

Product placement is already a common marketing tool, but it may become increasingly prevalent in the future. In recent years, technological advancements such as television DVRs and internet ad blockers have decreased the effectiveness of traditional advertising by limiting the number of ad exposures and the level of attention that consumers spend on a particular ad. If these broad patterns continue, alternative methods such as product placement may become more popular, because product placement's integration within the creative content means that it cannot be skipped, fast-forwarded, or blanked out as easily as traditional ads can.

More broadly, other industries have begun to incorporate strategies similar to that of product placement. Print and online media have, in recent years, begun to rely upon "sponsored content" and minimally-labeled advertorials as an additional income source. These articles are oftentimes intended to seamlessly blend in with the rest of the linked articles on a given web page, despite the fact that they are funded by (and function as advertisements for) a third-party company. The seamless nature of sponsored content means that this type of integrated advertising is conceptually similar to the TV product placement that we study

in this research. As traditional media companies continue to seek out new opportunities for earning revenue, product placement and similar approaches are likely to be increasingly prevalent in the near future.

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