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Show and Sell: Studying the Effects of Branded Cigarette Product Placement in TV Shows on Cigarette Sales

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Abstract. We evaluate whether and how branded TV product placement affects sales for cigarette brands. We use data on product placement from TV shows and data on retail sales of cigarettes to estimate a demand model that incorporates the level of product placement exposure for each cigarette brand. We find that product placement has a small yet positive and statistically significant effect on both own-brand sales and competitor-brand sales: Both these elasticities are roughly 0.02. These results indicate that cigarette product placement affects demand for individual cigarette brands and that it also leads to greater overall cigarette use. This issue is of particular importance to policymakers because product placement is one of the few remaining ways that cigarette brands can reach a mass audience. To illustrate how these results could be used by policymakers, we use our model estimates to evaluate how cigarette sales would be affected by two hypothetical kinds of regulations. Limiting brands' ability to be displayed on TV and forcing TV networks to instead use generic, unbranded cigarettes on screen would reduce total retail cigarette sales by only about 2%, whereas forcing TV networks to eliminate all on-screen smoking activity would reduce it by about 7%.

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1. Introduction

Tobacco use is still common today: roughly 10% of all Americans smoke cigarettes regularly, and half a million Americans die every year from tobacco-related illnesses. Unlike many other vice goods, tobacco products can affect the health of people who do not even purchase or use them; more than 40,000 Americans die each year from exposure to secondhand smoke (Centers for Disease Control and Prevention 2021). The prevalence of smoking and its effect on the community have given rise to decades of antismoking public health initiatives in the United States. One of the ways in which organizations such as the Centers for Disease Control (CDC) and the Food and Drug Administration (FDA) have tried to reduce smoking rates is by restricting tobacco brands' ability to reach mass audiences. Most advertising and sponsorship activities have been banned, so one of the only remaining options for reaching a wide audience is product placement on American TV shows and movies.

A notable instance of this phenomenon is the television show "Mad Men," which begins with a scene of its protagonist Don Draper sitting in a bar as he tries to develop an advertising slogan for Lucky Strike cigarettes. Lucky Strike would go on to be a regular presence on "Mad Men" over the eight-year run of the series. Draper's fictional advertising agency interacted with Lucky Strike and its executives on many occasions in plot lines that spanned both professional and personal settings. This resulted in a significant amount of brand exposure for Lucky Strike: its logo was shown on cigarette packets, its cigarettes were smoked by multiple key characters, its brand name and taglines appeared on chalkboards during advertising brainstorm sessions, and its brand name was repeatedly mentioned out loud.[1]

There are varied opinions as to how much this product placement affected sales of Lucky Strike cigarettes. Antismoking advocates and marketing consultants have provided back-of-the-envelope estimates that indicate that

"Mad Men" caused Lucky Strike sales to rise by 43% (Pow 2013, Boluk 2014). Conversely, trade groups representing TV and film producers have argued that this posited causal relationship in which on-screen smoking intensified real-world smoking behavior is "speculative" and that "human behavior is far too complex" to measure the influence of product placement on subsequent smoking behavior (O'Connell 2004, Barnes 2016, Gardner 2016).

Despite the competing narratives regarding these prominent examples of product placement, there have not been any large-scale investigations to quantify how TV product placement affects sales of cigarettes. In this research, our goal is to fill this gap in the academic literature. To quantify the effect of product placement, we use a database comprising all instances of branded cigarette product placement on American network TV from December 2003 to July 2006. We merge this with data on cigarette sales from more than 2,000 stores, and we estimate a demand model that allows us to separately measure how product placement affects sales both for the brand that was shown on-screen and for its competitors.

Product placement is common in many other product categories, and brands like Coca-Cola and General Mills typically pay for TV product placement. However, *product placement for cigarettes is specially regulated: companies that sell cigarettes in the United States are not permitted to pay for product placement on American TV or movies* (National Association of Attorneys General 1998, Morgenstern et al. 2017). Despite this regulation, researchers have identified a few different avenues through which cigarette product placement continues to take place, each of which would allow cigarette brands to receive the possible consumer benefits of product placement while remaining within the bounds of the law (Polansky and Glantz 2016):

1. Product placement can be funded either by an overseas affiliate of a tobacco company or by a foreign advertising agency acting on behalf of a foreign client.

2. Tobacco companies can provide TV producers with in-kind donations of goods and services rather than a financial contribution.

3. TV producers can decide to use a brand on-screen purely for artistic reasons, without any financial benefit from doing so and without receiving formal permission from the cigarette brand. Despite the fact that this would typically constitute a copyright violation, the cigarette brand may choose to allow this to happen rather than protecting its copyright; this leads to a situation described as "don't ask, don't refuse."

In response to these loopholes, advocacy groups have called for further limitation of cigarette product placement on TV and movies, such as a blanket ban on cigarette brand names and logos (Glantz 2021). However, additional regulation may be unnecessary and unhelpful if product placement has no tangible effect on consumers' smoking behavior. Therefore, knowing about the effectiveness of product placement can provide policymakers such as the Federal Trade Commission (FTC) and the Federal Communications Commission (FCC) with valuable information as they continue to evaluate whether additional regulations on tobacco companies and TV producers may be required. Existing regulations in the United States focus on the former group: tobacco companies are held responsible for their brands being portrayed on screen (O'Connell 2004). However, this does not address the larger issue of smoking being depicted on television, which is a potential avenue for regulation that could be imposed directly on the TV producers.

To address these questions, we estimate a demand model that quantifies the effect of branded TV product placement on store-level sales for 15 cigarette brands. Our main finding is that TV product placement has an own-brand elasticity of about 0.02 for the cigarette brands in our data. This estimate is statistically significant and in line with recent elasticity estimates for conventional (interstitial) TV advertising among nontobacco consumer packaged goods (CPG) brands (Shapiro et al. 2021). Our second notable finding is that the competitor-brand elasticity is also about 0.02; this implies that Marlboro product placement helps increase Marlboro sales but also helps its competitors by roughly the same amount. Both the elasticity estimates are robust to alternative assumptions regarding the identification strategy and functional form assumptions regarding the week-to-week carryover of advertising goodwill.

These substantive results yield two main implications for policymakers that are interested in decreasing tobacco use. First, we demonstrate that TV product placement of cigarettes does affect sales and by roughly the same magnitude as regular TV advertising; this provides a potential justification for regulating TV product placement of cigarettes as strictly as TV advertising of cigarettes. Second, the fact that the benefits of product placement spill over to direct competitors by expanding demand for the product category indicates that a blanket ban on cigarette brand names and logos would have very limited effect on cigarette purchases on its own. For instance, if all branded cigarettes displayed in TV product placement were replaced by generic unbranded cigarettes on screen, our back-of-the-envelope calculations suggest that overall cigarette sales would be reduced by less than 2%. Conversely, a stronger measure such as a ban on all on-screen smoking activity would be about four times more effective. This comparison of effect sizes suggests that regulators would benefit from shifting their focus from cigarette brands to TV producers, because the latter group could serve as a conduit for restrictions on tobacco product placement as a whole rather than restrictions on individual brands.

Despite efforts by policymakers, tobacco product placement is still frequent in TV shows and movies, both in the United States and abroad. Overall spending on TV product placement continues to rise at a faster rate than

spending on TV advertising (PQMedia 2015, Barnard 2021), and the prevalence of cigarette product placement in films has been relatively stable for the last 20 years (UCSF Smoke Free Media 2021). A 2012 report from the Surgeon General points out that "entertainment media are among the few remaining channels for transmission of aspirational images of smoking to large audiences," which underlines the importance of product placement for cigarette brands and their promotional activity (U.S. Department of Health and Human Services 2012, p. 564). For instance, Narkar et al. (2019) report that during the 2002–2018 period, an estimated 12.8 billion in-theater cigarette product placement impressions were shown to moviegoers in Ontario, Canada. High levels of impressions are also documented for TV shows in the United Kingdom and for movies in the United States (Barker et al. 2019, Tynan et al. 2019). A recent study revealed that more than 90% of French films between 2015 and 2019 depicted smoking on screen (Hunter 2021), and regulators in Italy have recently criticized cigarette brands for using product placement as "hidden advertising" to circumvent government regulation (Agence France Press 2021). Depictions of tobacco use are also common on streaming platforms, including the majority of shows that are popular among teenagers (Truth Initiative 2022). The relevance of our substantive results and their potential policy implications is underlined by the fact that product placement for cigarettes is both widespread around the globe and the subject of widespread regulatory scrutiny.

2. Literature Review

Our paper contributes to three areas: tobacco promotion, product placement, and the measurement of TV advertising effects. In this section, we summarize some of the key literature on these topics.

2.1. Tobacco Promotion

Since the early 2000s, cigarette companies have had limited ability to promote their brands in the United States because of changes in federal tobacco law and the 1998 Master Settlement Agreement with state governments (National Association of Attorneys General 1998, Jones and Silvestri 2010). TV advertising, paid product placement, billboard advertising, and sports sponsorship (especially in motorsports like NASCAR and IndyCar) used to be major promotional tools for cigarette brands, but these have all been largely phased out. Most research using data before these legal changes has mostly shown that TV advertising and sports sponsorship were effective at increasing sales for cigarette brands, although there have been dissenting findings as well (Porter 1986, Tye et al. 1987, Roberts and Samuelson 1988, Vaidya et al. 1996, Saffer and Chaloupka 2000, Siegel 2001, Thomas 2019). E-cigarette brands are currently able to engage in advertising and sports sponsorship, and Tuchman (2019) shows that this advertising is effective at increasing sales. Our contribution to this literature on tobacco promotion is to quantify the effect of product placement on retail cigarette sales, which is a topic of interest for policymakers and other stakeholders.

2.2. Product Placement

Despite the popularity of product placement as a marketing tool, prior research has not considered its direct effect on real-world sales. Traditionally, research in this area has used surveys or laboratory experiments to measure how product placement affects subsequent brand recall or attitudes toward the focal brands (Babin and Carder 1996, Lee and Faber 2007, Cowley and Barron 2008). A separate stream of research quantifies the brand-building effect of product placement by measuring abnormal stock returns using an event study approach (Wiles and Danielova 2009, Karniouchina et al. 2011).

Prior research has demonstrated that exposure to product placement can affect TV 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 2019). Our research complements this stream of work: we similarly examine how consumers respond to a particular form of product placement, but we focus on retail sales rather than on viewership or social media activity.

Although this paper is the first to link branded cigarette product placement to real-world sales, there has been research that examines related effects in the laboratory. Viewing movie scenes featuring smoking activity has been shown to increase people's stated urge to smoke and their actual smoking incidence (Sargent et al. 2009, Shmueli et al. 2010). Wagner et al. (2011) show that watching these kinds of scenes activates neural activity in some of the same parts of the brain that are also activated when smoking. In a report focusing on youth smoking, the Surgeon General summarizes the public health literature by saying that "The evidence is sufficient to conclude that there is a causal relationship between depictions of smoking in the movies and the initiation of smoking among young people" (U.S. Department of Health and Human Services 2012, p. 602). None of these research papers examine brand-level sales; instead, they show more broadly that there may be a category-expansion effect of cigarette product placement in which viewing scenes of people smoking encourages more real-world smoking activity. Accordingly, our model includes the possibility that cigarette product placement from any particular brand may have spillover effects onto its direct competitors and the product category as a whole.

2.3. Measuring TV Advertising Effects

There is a substantial stream of papers that focuses on how TV advertising affects a wide variety of metrics such as short-run TV viewership, online searches for

the focal brand, immediate online shopping behavior, and online word of mouth (Joo et al. 2014, Liaukonyte et al. 2015, Fossen and Schweidel 2017, Du et al. 2019). Our research is more closely related to a separate literature that directly measures how advertising affects sales. Our focus on TV product placement allows us to contribute an additional set of findings to the existing literature on TV advertising effects, which has thus far focused on traditional interstitial advertising (Lodish et al. 1995, Tellis et al. 2005, Shapiro et al. 2021).

Recent papers in this area have focused on methodological advancements around dealing with the endogeneity of TV ads. One proposed method to deal with this issue is a "border strategy" that relies on discontinuities across designated market area (DMA) borders. Local (spot) TV advertising is typically sold at the DMA level, and brands cannot target TV ads to individual counties within the DMA. The premise of the border strategy is that two adjacent counties will receive different advertising exposures if they happen to lie in two different DMAs, and that any targeting that occurs at the DMA level is because of broader demand differences in the nonborder counties within the DMA and not because the brand wants to target people within a specific border county. Therefore, focusing on counties that are on a DMA border and including a border-time fixed effect should account for any DMA-level demand shocks and any demand shocks that are shared by border counties. This method was popularized by Shapiro (2018) and has since been used more widely by researchers working with TV advertising data (Spenkuch and Toniatti 2018, Wang et al. 2018, Tuchman 2019, Kim and KC 2020, Shapiro 2020, Yang et al. 2021).

A separate approach for dealing with the endogeneity of TV advertising is to use high-dimensional fixed effects that substantially reduce the level of unexplained variation in the data (Dubé et al. 2005, Rossi 2014). The justification for this approach is that the fixed effects mean that there is very limited scope for correlation between the advertising levels and the unobservable econometric error term in a regression. This approach also comports well to the rules-of-thumb behind how advertising decisions are oftentimes made. For instance, if a particular brand generally advertises heavily in a particular DMA where it has historically been successful, then a brand-DMA fixed effect will fully account for that issue. One benefit of this approach is that it yields more observations relative to the border strategy, because it allows the researcher to retain all the sales data that they have rather than only keeping observations from DMA border counties. Li et al. (2019) and Thomas (2020) demonstrate that using fixed effects seems to provide improvements over the border strategy when analyzing seasonal products or when border counties are very different from other counties in their DMA. Meanwhile, Shapiro et al. (2021) show that estimated advertising effects for packaged goods are similar regardless of whether one relies on a fixed effects approach or a border strategy approach.

Like Li et al. (2019), Thomas (2020), and Shapiro et al. (2021), our approach is to estimate multiple models that rely on different approaches to dealing with the endogeneity problem and to see whether the results vary based on the assumptions required. We first estimate a set of regressions that rely on high-dimensional fixed effects, and we then estimate a set of border strategy regressions that focus only on border counties. We find similar results in both settings.

3. Data

To study the impact of cigarette product placement on sales, we need to collect data on weekly store sales, product placement instances, and impressions (viewership) across different DMAs. We use IRI store scanner data, Nielsen PlaceViews data, and Nielsen AdIntel data for these three tasks, respectively. In the following sections, we discuss each data set in more detail.

3.1. Sales Data

We use weekly IRI store sales data from December 2003 to July 2006 to study the impact of branded cigarette product placement on sales. The data set contains average weekly prices, quantity, feature, and display instances at the UPC-store level for a subset of categories including cigarettes. For more information about the data set, see Bronnenberg et al. (2008). IRI collects scanner data from 2,717 grocery stores and drugstores that are dispersed across 41 states and 92 DMAs. A subset of 2,078 stores in 91 DMAs sell cigarettes in the period between 2003 and 2006 and are therefore included in our analysis. Table 1 provides more information about the stores, markets, brands, and the length of this study. The "all markets" column summarizes the entire data set, whereas the "border markets" column summarizes the subset of observations from counties that are on a DMA border.

Figure 1 displays which DMAs are present in our data and how many stores are included from each DMA. DMAs in white are ones that are not included in our data, and darker versus lighter shades of color indicate that we observe more stores in that particular DMA. These data include most of the heavily populated DMAs (New York, Los Angeles, Chicago, Houston, etc.) and misses many of the sparsely populated ones.

Sales data are reported at the UPC level, but product placement typically takes place at the brand level rather than the UPC level. For instance, a character might mention the brand Marlboro, or the Marlboro logo might appear in the background. To align the granularity of the sales data and the product placement data, we aggregate the sales data to the set of brands

Table 1. Summary of Store-Level Variables

	All markets	Border markets
No. of brands	15	15
List of brands	Basic, Benson & Hedges, Camel, Chesterfield, Doral, GPC, Kent, Kool, Lucky Strike, Marlboro, Newport, Parliament, Salem, Virginia Slims, Winston	Basic, Benson & Hedges, Camel, Chesterfield, Doral, GPC, Kent, Kool, Lucky Strike, Marlboro, Newport, Parliament, Salem, Virginia Slims, Winston
No. of weeks	133	133
Start week	December 29, 2003	December 29, 2003
End week	July 10, 2006	July 10, 2006
No. of DMAs	91	69
No. of states	41	33
No. of stores	2,078	588
No. of brand-stores	25,620	7,292
No. of brand-store-weeks	2,740,781	778,360

listed in Table 1. Each observation of our aggregated data represents a particular brand-store-week combination, and our sales measure is the total number of cigarette packs[2] that were sold in that brand, store, and week. Shapiro et al. (2021) use a similar aggregation strategy to study the effect of TV advertising on CPG brand sales.

The feature, display, and price variables are reported at the UPC level only during weeks where at least one unit of that UPC was sold in a given store. Aggregating these UPC-level observations to the brand level requires a three-step process similar to the one used by Dubé et al. (2018).

Step 1: Fill in missing observations. Because the IRI data only contains observations for weeks in which sales occurred, this means that weeks with zero sales for a particular UPC-store are not visible. We fill in these observations and impute the price, feature, and display variables for each of these UPC-store-week observations that had zero sales. For each brand-store pair, we consider UPCs that had positive sales for at least five different weeks in the time period we examine. For weeks where prices are missing, we fill up the prices with the most recent nonpromoted price.[3] We also assume that during weeks with zero sales, the product was not featured or displayed at the store.

Step 2: Create UPC weights. Prices are originally listed at the UPC-store-week level, but we need to aggregate across products to the brand-store-week level. First, to account for the fact that some UPCs

Figure 1. (Color online) Number of Stores in Each DMA

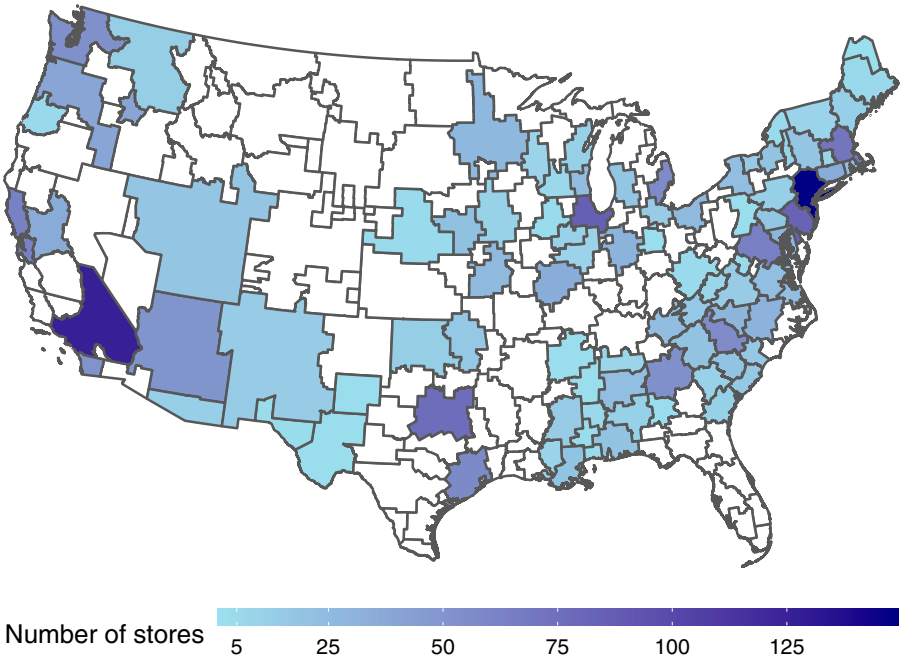
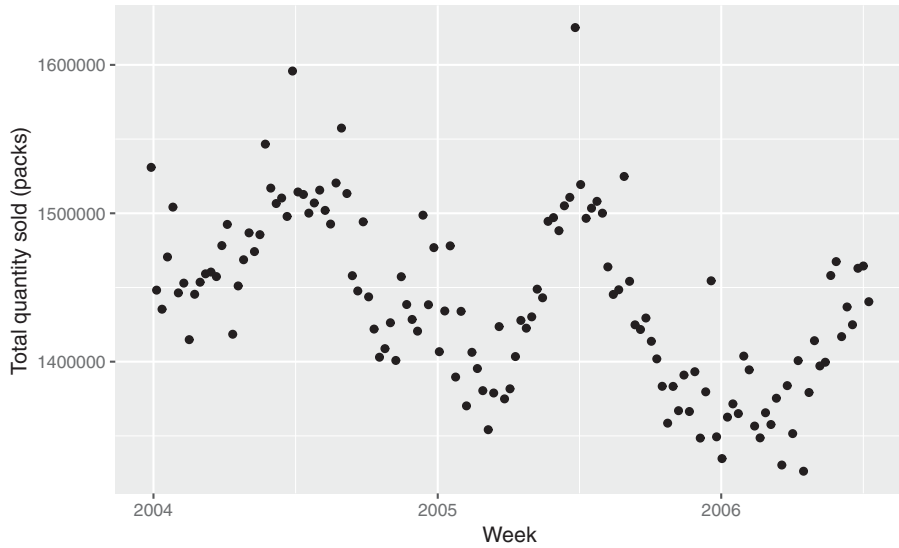


Figure 2. Total Weekly Cigarette Sales Measured in Packs (20 Sticks)



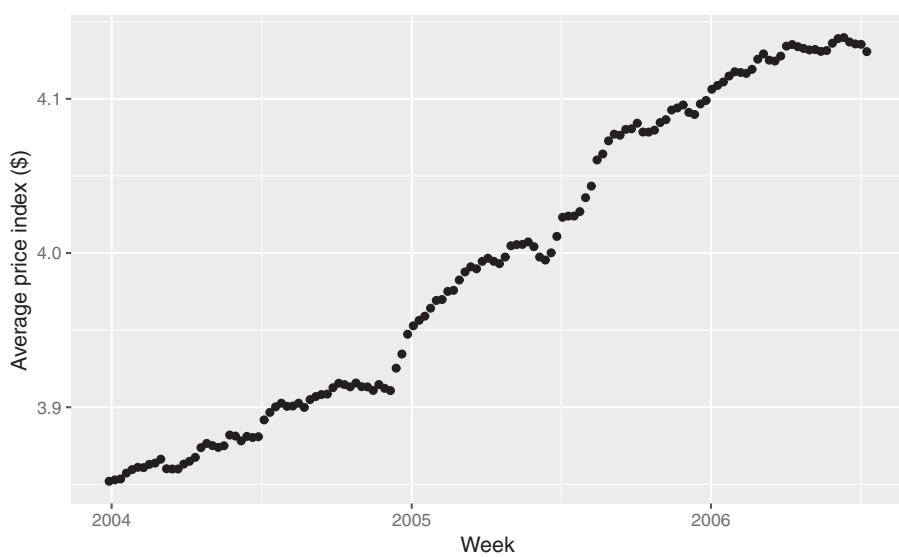
represent multipack boxes while others represent single packs of cigarettes, we standardize the sales and price units for each UPC to the pack level. Next, for each brand-store combination we calculate the total volume proportion (of brand sales) that each individual UPC represents across the entire time period we examine. These UPC weights represent how much a particular UPC contributes to brand sales for each particular brand-store. The values sum to one for each brand-store and they are fixed over time.[4]

Step 3: Aggregate to the brand-store-week level. Using the weights from the previous step, we aggregate the UPC-store-week observations to the brand-store-week level. The weights allow us to construct a price index that is a weighted average of the individual UPC prices. We also use a similar approach to construct feature and display variables at the brand-store-week level as well.

Figure 2 displays the total quantity of cigarettes sold (in packs) over time. This demonstrates the seasonality of tobacco sales: sales are higher in the summer than they are in the winter. This seasonal pattern has also been found in other studies (Chandra and Chaloupka 2003, Momperousse et al. 2007).

Figure 3 shows weekly changes in the price index (in dollars), averaged across all stores and brands. We see that average prices have risen steadily over time, although the magnitude of the price increase has been relatively low and roughly in line with inflation rates.

Figure 3. Average Weekly Price Index ($ per Pack)



3.2. Product Placement Instances

The product placement instances are collected from Nielsen PlaceViews, which is a proprietary data set that gathers information on branded product placement on television. Our sample of the PlaceViews data starts in December 2003 and ends in July 2006, and it contains all cigarette brand product placement that occurred on network television (ABC, CBS, FOX, and NBC) in the United States during that time period.[5] Each observation in the data set is a unique placement instance and includes information about the show, the episode, the network, the date and air time, the duration of the product placement, the product placement type, and a brief description of the placement instance. For instance, one of the observations provides the following details: episode 102 of "The Simple Life" aired on FOX from 8:30 p.m. to 9:00 p.m. Eastern on December 30, 2003, and there was an eight-second product placement instance in which Paris Hilton held a pack of Marlboro cigarettes. There are four types of product placement in our data: foreground (31% of the instances), background (41%), prop (13%), and dialogue mention (15%). Figure 4 presents examples of each of these product placement types.

3.3. Network Viewership

Product placement instances for each brand are identical across the country in any particular week because the product placement occurs at the show level, and network TV shows are shown throughout the entire country. However, product placement impressions vary across different DMAs because of differences in viewership. One reason for this is that people living in different parts of the country have different preferences for watching TV shows. However, there are other contributing reasons as well. Simonov et al. (2022) and Martin and Yurukoglu (2017) show that the position of TV channels varies across DMAs and that this affects viewership patterns. Furthermore, viewership can be affected by changes in the broadcast schedule, perhaps because of the airing of live events that take longer than expected. A TV show that is aired on WABC-TV (ABC's New York affiliate) at 8 p.m. local time (EST) may air at 7 p.m. local time (PST) on KABC-TV (ABC's Los Angeles affiliate), and that can alter the exposure intensity to the product placement instance because the viewership of the show will be affected.

We use the Nielsen AdIntel data to construct the number of impressions, or views, for each product placement instance across the DMAs. The Nielsen AdIntel data focuses on traditional (interstitial) TV advertising, and it reports how many impressions each advertising occurrence received across different DMAs. For each local affiliate station, we calculate the viewership for the shows in each time slot by calculating the average viewership of

Figure 4. (Color online) Examples of Cigarette Product Placement Instances from Our Data

Notes. (a) *Prop:* Abby holds Marlboro cigarettes on "ER" (source: NBC). (b) *Dialogue mention:* Berta mentions the Camel brand on "Two and a Half Men" (source: CBS). (c) *Background:* Marlboro and Virginia Slims are visible on store shelves in "Law and Order" (source: NBC). (d) *Foreground:* A pack of GPC cigarettes is visible on the table in "King of Queens" (source: CBS).

the ads that were aired in that time slot using the Nielsen AdIntel data. This yields a show-viewership table that measures how many people were watching each of the four major TV networks in each DMA and in each time slot. We also match each slot of the local affiliate station schedule with the national schedule to understand how schedules are shifted when one moves across different DMAs. This process is similar to the process used by Shapiro et al. (2021) to match the local TV schedule with the national TV schedule within a ±4-hour window.

We then merge the show viewership and the product placement tables to calculate measures of product placement exposure. First, we measure the placement rating for each placement instance i aired during show r_i, which reflects how many people viewed the TV show r_i in a specific designated market area (DMA) d in week t. The placement rating is defined as

$$\text{placement rating}_{r_i dt} = 100\left(\frac{\text{number of viewing households}_{r_i dt}}{\text{total number of households with TV}_{dt}}\right).$$

In the PlaceViews data set, we observe the brand and the duration for each product placement instance. The duration refers to how many seconds the brand was mentioned or displayed on screen during the TV show. We combine the duration and placement rating into one measure: weighted gross rating points (wGRPs). 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:

$$\text{placement wGRP}_{r_i dt} = \text{placement rating}_{r_i dt}\left(\frac{\text{placement seconds}_{r_i t}}{30}\right).$$

For example, we can calculate these measures for episode 102 of "The Simple Life," which was mentioned earlier, as an example of Marlboro product placement in our data. This episode aired on December 30, 2003, and in the Chicago DMA, it was watched by 260,140 of 3,475,220 households that had TVs. Therefore, the placement rating for this show-market-week is

$$\begin{aligned}\text{placement rating} &= 100\left(\frac{\text{number of viewing households}}{\text{total number of households with TV}}\right)\\ &= 100\left(\frac{260,140}{3,475,220}\right)\\ &= 7.486.\end{aligned}$$

This episode had one eight-second instance of product placement. Therefore, the weighted gross rating points are

$$\begin{aligned}&\text{placement wGRP}\\ &\quad = \text{placement rating}\left(\frac{\text{placement seconds}}{30}\right)\\ &\quad = 7.486\left(\frac{8}{30}\right)\\ &\quad = 1.996.\end{aligned}$$

Recall that the number of placement instances and the duration (placement seconds) are both constant across DMAs, which means that any wGRP variation across DMAs must be caused by changes in viewership (placement rating). Figure 5 shows how the total placement wGRP measure (summed across all instances, brands, and weeks) varies across DMAs. We see that there is substantial variation across DMAs. Notably, there does not appear to be any connection between product placement wGRPs and the size of the DMAs: The areas with the highest total wGRPs are moderately sized DMAs: St. Louis, Oklahoma City, Providence, and Buffalo. This suggests that brands are not using product placement specifically to target people living in larger, more financially important markets; instead, they are likely using it to improve outcomes across the board without much focus on specific DMAs.

The wGRP measure is defined above at the level of a particular product placement instance. Because brands can have multiple product placement instances over the course of the week, we aggregate the wGRPs by summing over the placement instances $\mathcal{I}_{bt}$ for brand b in week t:

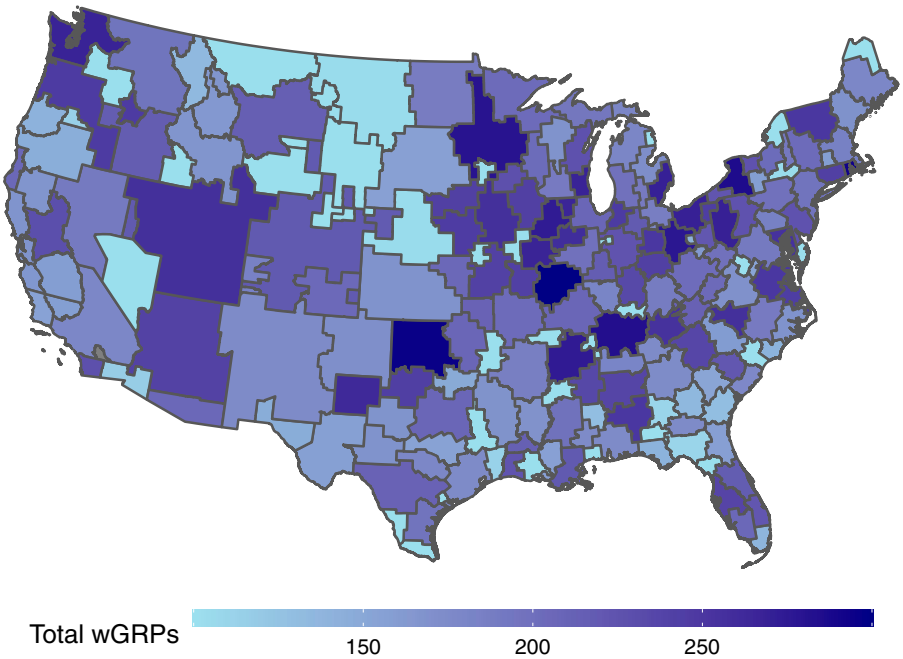
$$\mathcal{P}_{bdt} = \sum_{r_i \in \mathcal{I}_{bt}} \text{placement wGRP}_{r_i dt}.$$

Finally, we create a goodwill variable for product placement by using a cumulative discounted sum of weekly wGRPs:

$$\mathcal{G}_{bdt} = \sum_{l=0}^{\infty}[\delta^l \times \mathcal{P}_{bd(t-l)}]. \tag{1}$$

The benefit of this goodwill variable is that 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. 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). Our initial estimation results are based on a

Figure 5. (Color online) Total Weighted GRPs by DMA



carry-over parameter $\delta = 0.9$ to be consistent with the previous literature (Dubé et al. 2005, Shapiro et al. 2021). In subsequent sections, we also show that the results remain consistent once we calibrate the carry-over on our data.

Figure 6 shows the weekly placement goodwill for each brand, averaged over the DMAs. Benson & Hedges is the only brand that does not have any product placement over the course of our data, whereas Marlboro and Camel are the brands with the most product placement overall. With the exception of Benson & Hedges, all the other brands have substantial variation in their goodwill measure over time.

To show how the goodwill measure varies both across DMAs and over time, Figure 7 displays placement log-goodwill for two brands (Marlboro and Camel) across four DMAs (New York, Chicago, Houston, and Los Angeles). The bottom panels of Figure 7 demonstrate that even though the placement instances do not vary across DMAs, the placement goodwill for the same brand varies across DMAs because of difference in viewership; that is, the lines for different DMAs do not always move in parallel to each other. This type of variation is important for our estimation, because we partially rely on differences in product placement across DMAs (within a particular brand-month) to identify our effects.

4. Model Specification

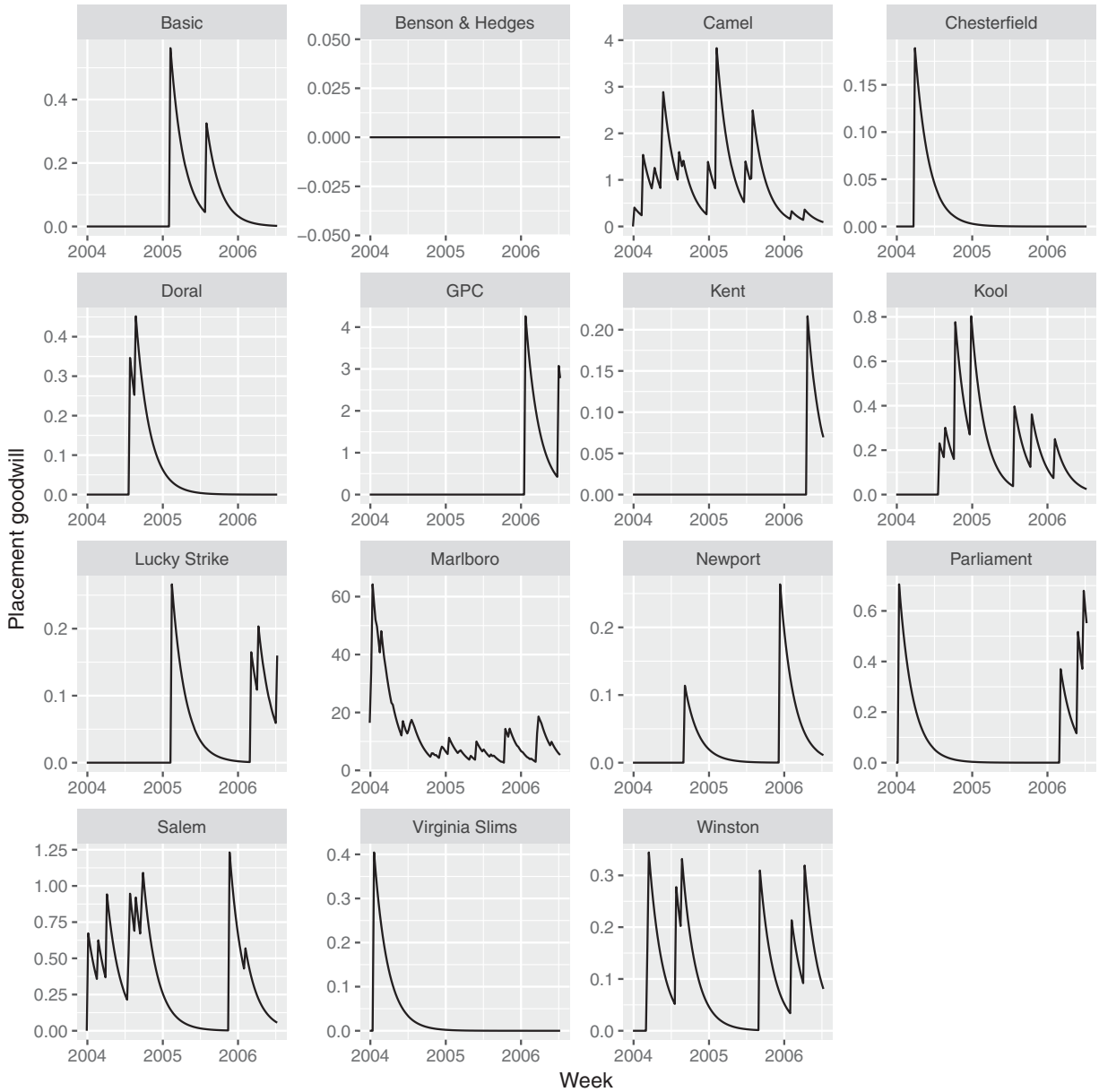
To study the impact of branded cigarette product placement on sales, we study how sales respond to changes in own and competitor placement goodwill. The placement goodwill constructs that we use here are akin to the advertising goodwill variables used by Dubé et al. (2005), Thomas (2020), and Shapiro et al. (2021) for measuring TV ad effects. The inclusion of both own and competitor placement variables allows us to account for the possibility that cigarette product placement may yield brand-specific sales gains and category-expansion effects (Sahni 2016, Shapiro 2018). We consider the following specification based on a standard log-log demand model:

$$\begin{aligned}&\log(1+Q_{bst})\\&=\beta\log(P_{bst})+\gamma\log(1+\mathcal{G}_{bd_st})+\gamma_c\log(1+\mathcal{G}_{\text{-}bd_st})\\&\quad+\xi f_{bst}+\kappa d_{bst}+\eta_{sw_t}+\eta_{bm_t}+\eta_{sby_t}+\epsilon_{bst},\end{aligned}\tag{2}$$

where b, s, and t index brands, stores, and weeks, respectively. Q_{bst}, P_{bst}, f_{bst}, and d_{bst} are the number of cigarette packs sold, the price index, the feature, and display of brand b during week t at store s, respectively.[6] Each store s is located within a DMA d_s, and the variables $\mathcal{G}_{bd_st}$, and $\mathcal{G}_{\text{-}bd_st}$ are the product placement goodwill for brand b and its competitors during week t at DMA d_s. Finally, η_{sw_t}, η_{bm_t}, and η_{sby_t} are store-week-of-year, brand-month, and store-brand-year fixed effects, respectively.

The typical endogeneity concern with TV ads is that brands may be selectively using advertising: either by targeting it to populations that would have bought the product anyway or by targeting it to populations that are most likely to be responsive to the advertising. If that is the case, then a naive analysis of TV advertising data would yield inflated estimates of how effective

Figure 6. Placement Goodwill by Brand and Week (Average Across DMAs)



advertising is. In the context of TV product placement, this concern is mitigated for three main reasons.

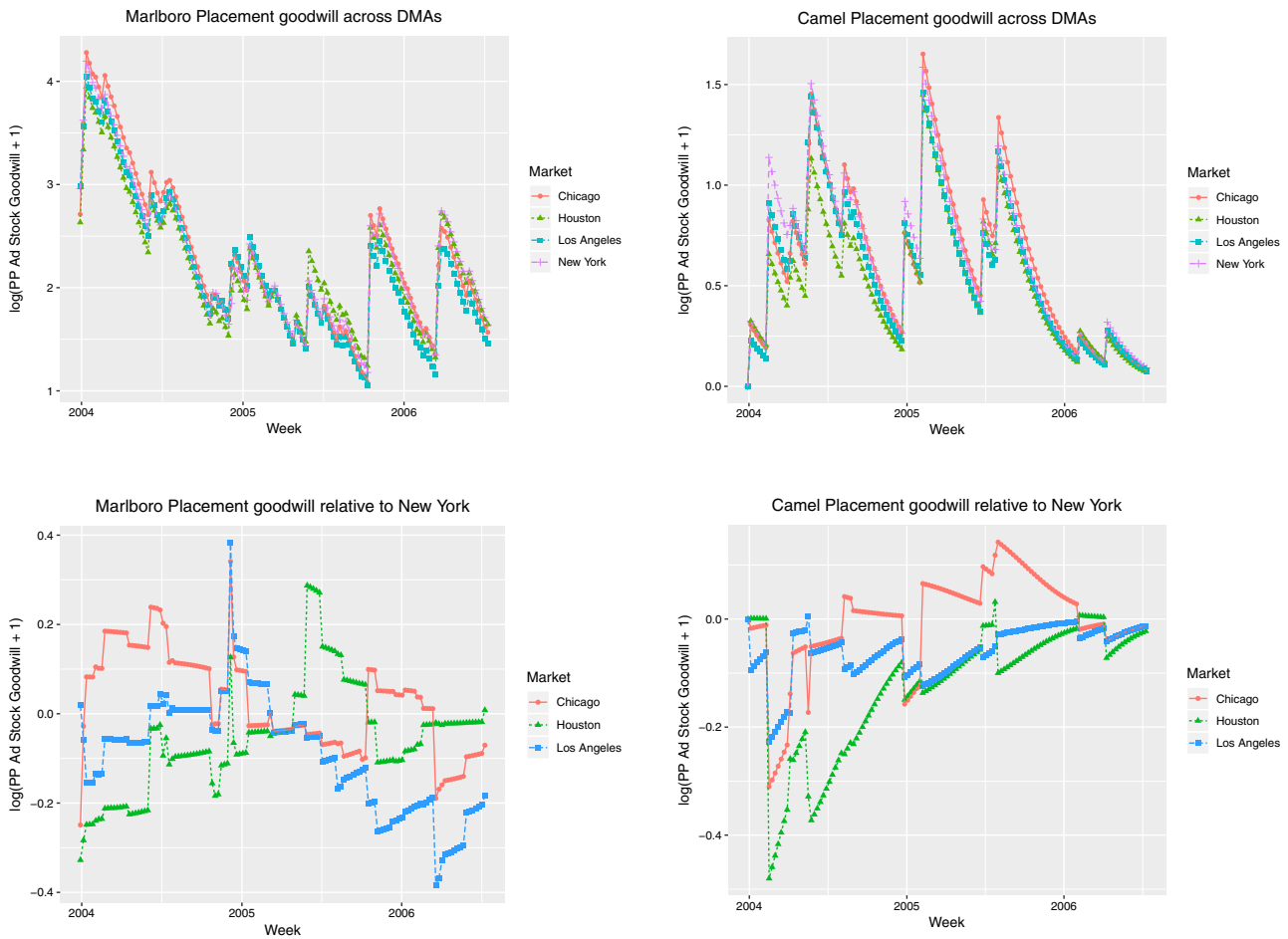
4.1. Nonpaid Instances

As discussed previously, paid cigarette product placement in American movies and TV shows has been illegal after the 1998 Master Settlement Agreement (National Association of Attorneys General 1998). Although there are loopholes through which brands can indirectly pay for product placement, there are also nonpaid instances that occur when a TV show decides to display a specific cigarette brand on-screen without receiving any benefits from the brand. This phenomenon of nonpaid instances is unique to product placement and does not occur with TV ads. If a TV show is choosing to display a specific cigarette brand on the show without receiving any compensation, then this decision is presumably being made for artistic reasons that benefit the show; that lies in contrast to paid product placement, which is used by brands to directly improve their outcomes. This difference in focus suggests that TV product placement is less likely to be made explicitly with the goal of improving brand outcomes, relative to traditional TV advertising.

4.2. Limited Targeting

TV ads can be bought at either the national level or the spot level, the latter of which is targeted to a specific DMA. Conversely, TV product placement occurs at the show-episode level so it cannot be targeted to an individual person or even an individual DMA. If

Figure 7. (Color online) Variation in Product Placement Log-Goodwill Across the New York, Chicago, Los Angeles, and Houston DMAs for Marlboro (Left) and Camel (Right)



Note. The top panels show all four DMAs simultaneously, whereas the bottom panels shows the goodwill for Chicago, Houston, and Los Angeles relative to New York.

product placement appears on a particular episode, all viewers of that episode will see the product placement. The fact that product placement cannot be targeted at a granular level implies that there is less possibility for placement endogeneity to be a serious concern.[7] If brands wanted to focus their marketing dollars only on specific markets where they are likely to be successful, product placement would be a worse choice than local TV ads or other promotional tools that could be more granularly targeted.

4.3. Advance Purchasing

TV ads can be purchased close to the airdate, which allows brands to purchase ads in response to observed (and unexpected) demand shocks. Conversely, TV product placement typically needs to be decided on far in advance of the airdate because it needs to be incorporated into the script before filming. As a result, brands cannot use product placement in a nimble way to respond to current demand conditions.

The combination of nonpaid instances, limited targeting, and advance purchasing suggest that TV product placement is less likely to suffer from endogeneity than TV advertising. Nevertheless, we use a rich set of fixed effects to further alleviate potential endogeneity concerns, as well as to control for confounds or spurious correlations that could potentially affect our analysis. We use store-week-of-year fixed effects to control for local seasonality in cigarette consumption (see Figure 2, which shows clear seasonal trends in cigarette sales). Product placement instances are placed in national shows, and the inclusion of brand-month fixed effects constrains the model to use the variation in product placement goodwill across DMAs that are because of differences in viewership rather than instances. Finally, we use store-brand-year fixed effects to absorb changes in assortments or brands at the store level, as well as changes in local tobacco taxes.[8]

Our main specification corresponds to Equation (2) and estimates from this model are reported in Table 2. Results in column (1) display the estimates without any fixed effects. In column (2), we add store-brand

Table 2. Effect of Own and Competitor Product Placement Using the Full Set of Stores

	Dependent variable: *log(Quantity + 1)*			
	(1)	(2)	(3)	(4)
Log own placement goodwill	0.987***	−0.006	0.042***	0.026***
	(0.045)	(0.007)	(0.014)	(0.008)
Log competitor placement goodwill	−0.121***	0.050***	0.026***	0.020***
	(0.030)	(0.006)	(0.007)	(0.004)
Feature	2.185***	0.401***	0.418***	0.446***
	(0.116)	(0.036)	(0.036)	(0.038)
Display	3.213*	1.019	1.118*	0.816
	(1.655)	(0.626)	(0.640)	(0.646)
Log price index	−1.617***	−1.271***	−1.299***	−1.424***
	(0.142)	(0.047)	(0.053)	(0.047)
Constant	4.839***			
	(0.207)			
Store-brand		X	X	
Store-week of year		X	X	X
Brand-month			X	X
Store-brand-year				X
Observations	2,740,781	2,740,781	2,740,781	2,740,781
R^2	0.309	0.868	0.869	0.891
Adjusted R^2	0.309	0.862	0.863	0.883
Residual standard error	1.457 (df = 2740775)	0.651 (df = 2616251)	0.648 (df = 2615791)	0.598 (df = 2553836)

Notes. We control for a wide variety of fixed effects to absorb the effect of potential confounds such as persistent differences in brand shares across regions, seasonal shocks in cigarette consumption, changes in the overall placement instances that could be correlated with seasonal shocks, and changes in assortments or excise taxes across different stores. All standard errors are two-way clustered at the DMA-brand and brand-week level.

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

and store-week-of-year fixed effects to control for persistent differences in brand preferences across different regions and to control for seasonality in cigarette consumption. In column (3), we add brand-month fixed effects that account for other contemporaneous promotional activity that the brand may be doing, and this yields positive and statistically significant coefficients for both own and competitor product placement. The coefficient of own and competitor placement effects in columns (1) and (2) are identified based on both the variation in placement instances over time and variation in impressions across DMAs. However, the coefficient estimates in column (3) are identified based on changes in impressions across DMAs as brand-month fixed absorb the variation in placement instances that vary at the national level. The inclusion of brand-month fixed effects allays concerns regarding seasonal targeting of product placement. Finally, to ensure that confounds such as concurrent changes in product assortments or changes in excise taxes are controlled for, we include store-brand-year fixed effects in column (4). All standard errors in our analyses are two-way clustered by DMA-brand and brand-week, because the variation in product placement wGRPs is at the DMA-brand and brand-week level (Shapiro 2020). The results in column (4) show a positive and statistically significant ($p < 0.01$) effect for both own and competitive product placement.

Given the setup of this model, the coefficients γ and γ_c can be interpreted as the approximate long-run (goodwill) elasticities of own-brand product placement and competitor-brand product placement.[9] In column (4) of Table 2, these values are 0.026 and 0.02, respectively. Although the own-brand placement elasticity is slightly larger in magnitude than the competitor-brand placement elasticity, the estimates are statistically indistinguishable. This similarity in the magnitude of the effects suggests that cigarette product placement on TV has a category expansion role and that a blanket ban on branded cigarette product placement may not be very effective in reducing tobacco consumption.[10]

5. Robustness Checks

We verify the robustness of our findings across a few different dimensions. For each of these robustness checks, we summarize the main results here and present the full details in the online appendix.

5.1. Border Strategy

We use another approach for dealing with potential endogeneity by estimating regressions that use the border strategy (Shapiro 2018). The premise behind this approach is that discontinuities across DMA borders create plausibly exogenous variation in TV viewership, which in turn could be used to identify the effect of product placement. We find that this approach yields very similar estimates as our main results: both own-brand

and competitor-brand elasticities are statistically significant, with values around 0.018.

5.2. Calibration of the Carry-Over Parameter

We evaluate whether our results are sensitive to the choice of the carry-over parameter δ, and we examine how the elasticities change when we calibrate this parameter to each model rather than setting it to a default value of $\delta = 0.9$. The main results are similar to what we report in Table 2, with elasticities in the range of 0.020–0.030.

5.3. Heterogeneity Across Product Placement Types

We examine whether the effect of product placement varies depending on the product placement type: background, foreground, dialogue mention, and prop. Including a separate coefficient for each type in our demand model yields underpowered and inconclusive results. If we classify the placement types as visually salient versus nonsalient product placement and re-estimate the demand model, we find that visually salient product placement has a higher magnitude (0.024 versus 0.014); however, the two coefficients are not statistically different from each other. Alternatively, if we classify the placement types as verbal versus on-screen product placement, we find that on-screen product placement has an elasticity of 0.026 but verbal product placement is statistically insignificant. We can reject the hypothesis that on-screen product placement is equally effective as verbal product placement. However, given that only about 15% of the product placement instances in our data are verbal, we do not have enough statistical power to conclude whether verbal product placement is broadly ineffective.

5.4. Heterogeneity Across Brands

Marlboro is responsible for most product placement instances in our data (Figure 6). To examine whether the effects of product placement are different for Marlboro versus the other brands, we estimate an alternative demand model specification in which Marlboro has separate product placement coefficients. We find that the effects for Marlboro are not statistically different from the other brands in the data.

5.5. Heterogeneity Across Product Types

In 2021, the Biden administration announced it would pursue a ban on menthol cigarettes. Menthols are believed to be more addictive than nonmenthol cigarettes, and they have also predominantly been marketed toward African Americans (McGinley 2021). For each UPC in our sales data, we observe whether that product is a menthol or a nonmenthol cigarette. We include this information in our demand model to examine whether menthol cigarettes exhibit a different product placement elasticity compared with nonmenthol cigarettes, and we find no significant difference between them.

5.6. Autoregressive Errors

The goodwill variable for product placement in Equation (2) is a discounted sum of previous product placement wGRPs. This introduces the potential for biased coefficients if there were autoregressive errors in this setting. We use the Hildreth-Lu grid search procedure and allow the variables to be serially correlated. Accounting for this potential issue has little effect on our final results, and the estimated elasticities are similar to what we report in Table 2.

5.7. Spurious Correlation and Potential Confounds

The high-dimensional fixed effects in our demand model help to mitigate some possible confounds that might otherwise affect our analysis. To further examine whether our results are truly being driven by exposure to different levels of product placement, we now use two additional tests. First, to examine whether there may be spurious correlation in product placement instances, we construct a permutation test that shuffles product placement goodwill values across DMAs. Second, to examine whether there may be an underlying confound that drives both viewership of shows that depict smoking and demand for cigarette products, we construct time-reversed product placement goodwill values. For each of these tests, we re-estimate the demand model and find that our results cannot be explained by either of these factors.

6. Discussion

A wide variety of tools have been used by policymakers and regulators to curb cigarette consumption, including excise taxes, warning labels, advertising restrictions, and constraints on the number of tobacco sales licenses. Understanding the impact and the underlying mechanisms of these instruments can help policymakers revise their regulations and improve their effectiveness. Although most of these regulatory tools would be expected to reduce sales of cigarettes as a category, it is not clear whether this result also holds for banning advertising and product placement. Some prior research has argued that cigarette advertising is entirely about share stealing: "advertising may be effective in changing market shares between companies but it has little effect on total cigarette demand" (Hamilton 1972, McAuliffe 1988, p. 58). These findings have been publicized by cigarette brands themselves as a way of arguing against further government regulation: They argue that if their promotional activity does not increase overall cigarette sales, then there is not a compelling public health reason for the government to regulate this activity (Wang et al. 2016).

Our results stand in contrast to this argument, because we find that the effect of cigarette product placement is not limited to the focal brand but also extends to the cigarette category more broadly.

In the current regulatory environment, the government regulates branded placement for cigarettes but does not regulate unbranded product placement featuring fake cigarette brands. Authorities have occasionally pressured tobacco companies to monitor the use of their brands in movies and ask for their removal. For instance, under pressure from multiple states' attorneys general, the tobacco manufacturer RJ Reynolds asked Sony studios to remove instances of cigarette placement for Winston and Camel brands in the movie "Mona Lisa Smile." Similarly, executives from tobacco manufacturer Philip Morris argued that movie producers "should voluntarily refrain from portraying or referring to cigarette brands or brand imagery in movies" (O'Connell 2004).

Under the current policy in the United States, using fake cigarette brands is permitted, and there is no legal burden on media companies for doing so. If the cigarette product placement instances act by expanding the category, as our results suggest, this policy would not be effective in controlling cigarette consumption. Instead, stricter measures such as imposing adult ratings on shows or movies with tobacco placement instances or banning all on-screen depictions of smoking or tobacco products could be more effective at reducing cigarette consumption. These actions would serve as a regulation on TV production companies or networks, whereas the current regulations are primarily targeted toward regulating cigarette brands. In the following sections, we discuss the implications of two different policies: a ban on *branded* cigarette placement and a full ban on any cigarette placement instance. Although a full ban on all on-screen depictions of smoking has not been implemented in the United States, other countries such as Montenegro and India have implemented such policies (Prodger 2004, Mudur 2005).

6.1. Business Implications

Our results in Section 4 suggest that cigarette product placement by a focal brand stimulates demand for the brand and their competitors. This would mean that the impact of restrictions on cigarette product placement is not limited to brands with high intensity of product placement like Marlboro and Camel, and in fact, they can even affect brands like Benson & Hedges that have no product placement. We evaluate two policies here: (1) a ban on branded product placement, in which TV shows would be banned from displaying or naming any real-life cigarette brands, and (2) a full ban on any cigarette placement, in which TV shows would be banned from all depictions of smoking.

In the first scenario, we assume that all observed instances of product placement would still take place under this hypothetical ban on branded product placement; the only difference is that all the brand names and logos would get replaced by fake brands. We assume that all these fake brand placement instances would act similarly to competitor product placement. In the second scenario, we assume that all product placement instances disappear, and we set the goodwill variables for both own and competitor placement to zero. In both scenarios, we keep all other factors fixed, and we do not model how cigarette brands might reallocate their promotional budget or their marketing mix variables in response to these regulatory changes. These assumptions are strong, so our discussion here should be regarded as illustrative rather than a formal full-equilibrium counterfactual analysis.

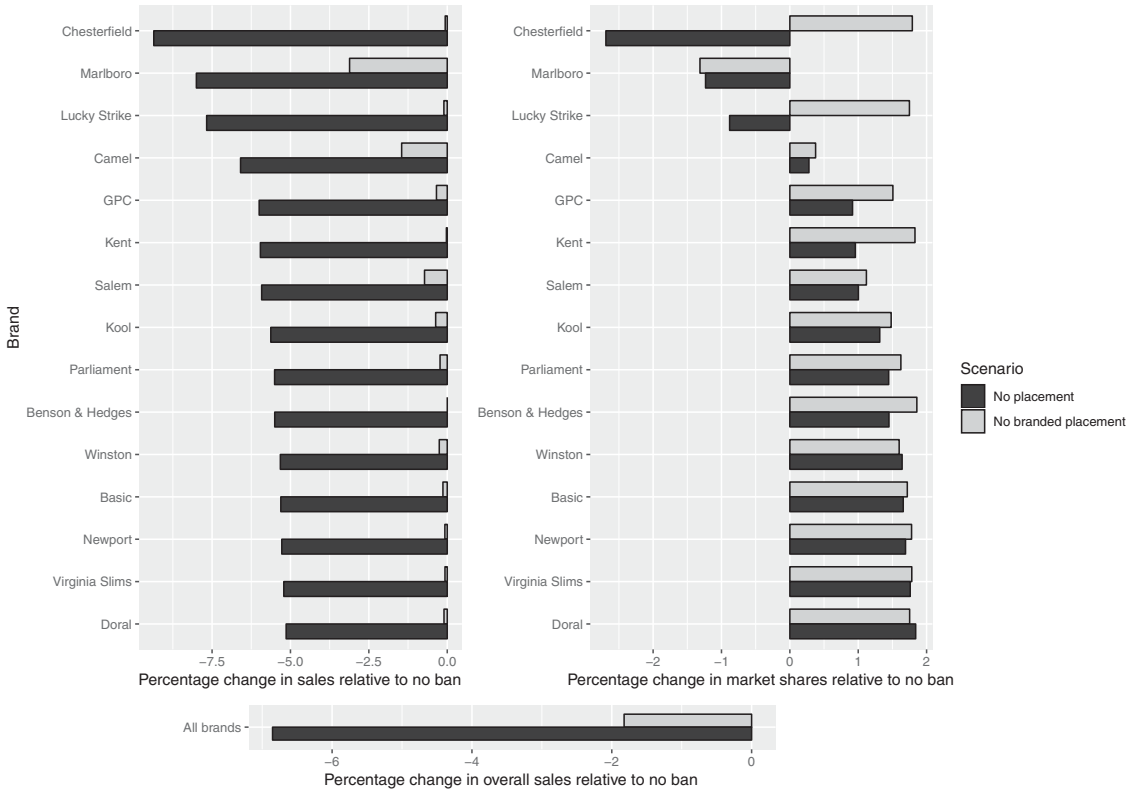
Figure 8 illustrates how different brands are affected under each scenario relative to the status quo. The left panel displays changes in sales, whereas the right panel displays changes in market share. Although all brands lose sales under both scenarios, the market share changes are heterogeneous across different brands and under different scenarios. For instance, although Chesterfield and Lucky Strike would lose market share under a full ban on cigarette product placement, their market share would increase under a ban on branded product placement. In general, the heterogeneous impact of the policies on different brands are because of differences in which geographic markets they are popular in, the timing of their placement instances, and differences in viewership (and therefore placement wGRPs) across different DMAs.

6.2. Policy Implications

Analyzing the impact of different policies on overall cigarette consumption is of interest for policymakers. As discussed previously, the impact tends to be heterogeneous across brands depending on on the product placement exposure levels across different DMAs (Figure 5) and through time (Figure 6). We present the impact of each policy on the total consumption level in the bottom panel of Figure 8. A ban on branded cigarette product placement would yield a small reduction in category sales of about 1.8%, which suggests that this regulation would not be very effective. In comparison, a full ban on all product placement (i.e., a ban on all on-screen cigarette use) would reduce sales by about 6.9%.[11]

This calculation is based on the assumption that the cigarette product placement instances are occurring organically and would be replaced with a fake brand by studios when a ban on branded cigarette placement is imposed.[12] If indeed some of these instances are paid for by tobacco brands, we would expect a reduction in the number of product placement instances, in which case the current estimate would constitute a lower bound for the effectiveness of a ban on

Figure 8. Change in Sales and Market Shares Under Different Scenarios



branded cigarette product placement. Conversely, if all instances are paid for by tobacco brands, then the estimates of the effect under the full ban can be regarded as an upper bound.

One limitation of our data is that we are unable to examine which specific kinds of smokers would be most affected by this kind of regulation—we do not know whether everyone would buy proportionally fewer cigarettes, or whether some individuals would curtail their smoking much more than others. A second limitation of our data are that we are unable to directly quantify how different these policy implications would be if we were using contemporary data rather than data from 2003 to 2006. However, the overall utilization patterns indicate that brands themselves still believe that product placement is an effective marketing tool: product placement remains an important tool for tobacco brands, and overall spending on TV product placement is forecasted to grow at a faster rate than spending on TV advertising (PQMedia 2015, Barnard 2021, UCSF Smoke Free Media 2021).

Overall, our results indicate that policymakers and regulators should be concerned about product placement of cigarettes, because we find evidence that product placement does affect real-world sales of these products. Furthermore, policymakers need to consider the category expansion effects of product placement when they devise potential new regulations that are intended to curb cigarette use. Regulations that limit the exposure of cigarette brand names or logos on TV and regulations that force TV producers to use fake cigarette brands on screen may not do much to reduce overall smoking behavior. Policymakers whose goal is to limit cigarette sales would benefit from trying to reduce the overall number of times that cigarettes are shown on screen rather than focusing on which brand names are on the cigarette packs.

7. Conclusion

Using data from retail cigarette sales, we find that branded product placement in TV shows aired in the United States led to a positive and statistically significant increase in both own-brand sales and competitor-brands' sales. Our results remain consistent when using the full data set with granular fixed effects or when relying on discontinuities at DMA borders (border strategy) to identify the effects. Although we find that the effect of own product placement on own sales is slightly larger in magnitude than that of competitors, the coefficient of own and competitor product placement is statistically indistinguishable across different specifications; both the own-brand and competitor-brand elasticities consistently hover around 0.02. These results suggest that cigarette product placement has a category expansion role, similar to patterns documented in online ads

for restaurants and TV ads for antidepressant medications (Sahni 2016, Shapiro 2018).

Our results are of interest for researchers, policymakers, and companies. In addition to showing that branded product placement leads to a sales increase for the focal brand, our findings highlight the category expansion role of product placement and the importance of modeling competitor advertising decisions on own sales. Our estimates for the effect of own and competitor product placement are almost equal, which suggests that forcing TV producers to use fake cigarette brands on-screen would have a very small impact on overall cigarette sales. To improve the effectiveness of the current policies on branded cigarette placement, policymakers and regulators may want to hold studios accountable for tobacco placement instances and add restrictions that go beyond regulation of brand names and images. Finally, our results underline the importance of category expansion effects, and brands should be aware of how their competitors' product placement could affect their own sales. In this case we show that even brands with no product placement could be dramatically affected by policies that change cigarette placement instances.

To the best of our knowledge, this is the first paper that studies the causal impact of both own and competitor product placement on real-world sales. We focus here on the cigarette category because it is of particular interest to policymakers and has been subject to a wide array of regulations. Product placement is effectively the only remaining channel for tobacco companies to promote their brands on television in the United States, and its prevalence may continue to rise as technology improvements allow brands to target individual viewers with product placement insertions (Hsu 2019). Although our results from this particular category are of interest for policymakers, cigarette brands, and other stakeholders, an interesting avenue for future research would be to study the effect of product placement on sales more broadly in other product categories or to evaluate how product placement and traditional TV ads compare in terms of their effect on own-brand and competitor-brand sales.

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Endnotes

[1] Although Lucky Strike and tobacco use were mostly depicted glamorously in Mad Men, there were some key deviations from this pattern. Later seasons of the show had plotlines that included a Lucky Strike executive behaving unethically, antismoking campaigns that highlighted the adverse health effects of tobacco use, and a major character developing lung cancer after years of smoking.

[2] Each pack consists of 20 cigarette sticks.

[3] For missing observations in the beginning of a panel we back-fill the price with the first nonpromoted observed price. A UPC price at a store is considered promoted if it is at least 15% lower than the median price for that UPC in that store.

[4] For other examples of fixed-weight price indexes, see Dubé et al. (2018) and Chevalier et al. (2003).

[5] Our data do not contain information about whether each product placement instance is paid or unpaid. This is a common limitation even among product placement papers that focus on other product categories (Schweidel et al. 2014, Fossen and Schweidel 2019). In the context of tobacco product placement, distinguishing between paid versus unpaid product placement is even more challenging because the various parties involved have strong legal incentives to obfuscate whether any payments have taken place (UCSF Smoke Free Media 2020).

[6] Display is relatively rare for cigarette products during the time period we study: in most weeks, there is zero total display activity across all of the cigarette brands and all of the stores in our data. Feature ads are more common: in most weeks, about 2%–3% of brand-stores are featured.

[7] Although product placement cannot be targeted to specific individuals or specific DMAs, in theory it could be targeted to shows that smokers are more likely to watch. We cannot examine this issue in our data because we do not have information about which shows are popular with smokers versus nonsmokers, nor can we directly deal with the problem by including fixed effects at the TV show level. However, this potential source of targeting is not a major threat to our identification strategy. Even if certain TV shows were receiving more tobacco product placement because they are popular among smokers, this would lead to increased exposure to tobacco product placement in DMAs with more smokers, which in turn would be absorbed by our store-brand fixed effects.

[8] Tobacco excise taxes typically vary at the state level.

[9] See appendix A of Shapiro et al. (2021) for a derivation of this result.

[10] Our analysis evaluates retail sales of cigarettes, and we are unable to directly measure consumption or usage of cigarettes. Recent research has shown that retail sales and consumption of cigarettes are very highly correlated, which implies that increases in cigarette sales generally correspond to increases in cigarette consumption (Jackson et al. 2019).

[11] We also estimate alternative specifications using a weekly category-level demand model and a monthly category-level demand model to account for potentially biased estimates arising from brand-switching or forward-buying. The policy implications based on these models are very similar to what is presented in Figure 8. Full results from these category-level demand models are presented in the online appendix.

[12] This analysis assumes that product placement depicting a fake cigarette brand would have the same effect on brand sales as product placement for a rival brand.

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