Online Appendices

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A Building the Data

In this section, we discuss the details of cleaning and preprocessing data sources employed in this project.

A.1 Nielsen AdIntel

Nielsen AdIntel covers TV advertising occurrences and impression instances. The dataset comprises four types of TV advertising occurrences: Cable, Network, Syndicated, and Spot. Cable, Network, and Syndicated ads are purchased and aired nationally. For Cable ads, the dataset has their viewership data only at the national level. Network and syndicated ads contain national records of occurrences, but these occurrences can be merged with local measures of viewership. The dataset also records Spot ads, which are bought locally and have viewership data measured locally for each market. We use data for Spot, Network, and Syndicated ads that have impression data records at the market level.

There is one data recording issue regarding network and syndicated ad types, which we discuss and address here. These ads are purchased nationally, but broadcast and measured locally, and the data records them at both the national and local occurrence levels. These two occurrence instances are meant to represent exactly the same ad occurrence. However, Shapiro, Hitsch, and Tuchman (2021) points out that sometimes, possibly due to problems with local measurement devices, these occurrences do not match perfectly. The instances where National occurrences do not have corresponding occurrences at the local level are referred to as "Missing Network Discrepancy". The missing occurrences could happen either because of measurement errors or because the local station overrides the national ad occurrence. The general procedure to resolve this discrepancy is to reconstruct the TV schedules at national and local levels, and if there is a time period that has no local advertising occurrence but a national occurrence, mark it as an unexpected missing. The complete procedure requires taking care of details about timezone differences and month changes. We follow the same steps as Shapiro, Hitsch, and Tuchman (2021) to address this issue.

Using each market's impression data and population estimates, we calculate the gross rating points (GRP) for each ad occurrence. Specifically, we construct our GRP measure by dividing the number of households who watched the program where an ad was aired by the estimated total households in that market multiplied by one hundred. Hence, GRPs measure the reach of each ad occurrence. We aggregate the GRPs to the category-DMA-week level to have estimates of impressions for each category of advertising in each market during each week. Nielsen partitions the DMAs into 131 Full Discovery Markets (FDMs), where all commercial activity is captured and identified, and 79 Automated Discovery Markets (ADMs) where only the commercials that can be matched to a commercial in any of the FDMs or on National TV are recorded.[12] The ADMs are usually DMAs that are smaller in market size than FDMs. Following Shapiro, Hitsch, and Tuchman (2021), we also focus our analysis on the FDM markets that are less noisy in their measurements. The data covers 522 weeks from January 2010 to December 2019 for these 131 FDMs, totaling 68,382 records for each category. Since we use an advertising goodwill variable (ad stock) in our demand model, the first year of data (2010) is used to initialize the ad stock variables, and the study is performed for the 2011-2019 period.

We collect advertising for the smoking cessation prescription drug Chantix by collecting advertising information from records that have Chantix in their brand title. Both NRTs and e-cigarettes, which are OTC products related to cessation, include the string "SMOKING DETERRENT" within

[12]This means that ADM markets could be missing ads by entities like local car dealerships and law firms and any ads that are designed specifically for those markets that do not also run in national media.

their "brand variant" field. We filter these brands and use brand titles to classify each advertising entity into NRT and e-cigarette categories. Finally, we collect data for public service announcements. There are two types of PSA advertising in the Nielsen data. Some have the string "PSA," and some have "ADV-CITY-STATE" inside their "brand variant" field. While PSAs could be purchased nationally, the "ADV-CITY-STATE" is advertising purchased by local city or state governments. We filter the PSAs ads that are related to tobacco/smoking.

The advertising GRPs for each of these categories exhibit a significant variation throughout the study period, as illustrated in Figure A1. There is a downward trend in the data for PSAs, as shown in Figure A1b, indicating that the GRPs for PSAs have declined in recent years compared to the early years of the 2010s. In the panel for e-cigarettes, different brands exhibit peaks of advertising at different times. The first spike is for the EZSmoker brand, which experienced a significant amount of GRPs in 2011. JUUL also had a spike in advertising GRPs in 2019, followed by a rapid decline towards 2020 following controversies and lawsuits against JUUL for illegal advertising and targeted advertising towards youth (Kaplan, 2021).

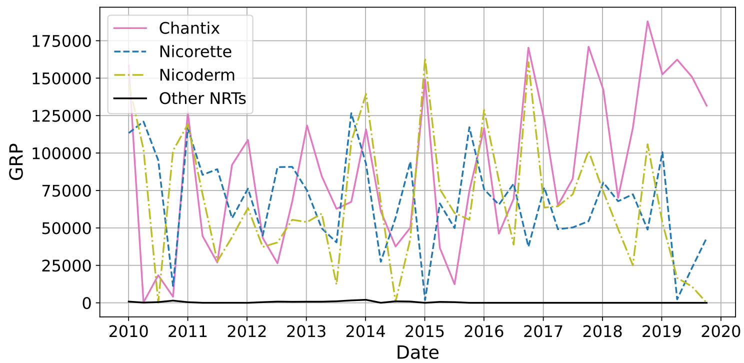
For our analysis, we aggregate the GRPs of each category, namely, PSAs, NRTs, e-cigarettes, and Chantix (DTCA). Specifically, for NRTs and e-cigarettes, we combine advertising across all brands. Additionally, we merge the two educational anti-smoking ad types, PSAs, and City/State ads, to create a unified measure of PSA advertising. There is no need for aggregation for Chantix, as it is only one entity/brand.

To demonstrate how advertising patterns vary geographically, we examine gross rating points for different advertising types across DMAs. Figure A2 presents GRPs for the three most populated DMAs: New York, Los Angeles, and Chicago. The first two panels (A2a and A2b) show GRPs for Chantix DTCA and NRTs in these areas, revealing generally similar patterns across DMAs. This consistency stems from the fact that most ads in these categories are purchased at the national level—only 4.1% of combined GRPs for Chantix and NRTs come from local spot buys. As a result, the variation between DMAs primarily comes from differences in viewership or local TV programming changes. In contrast, panels A2c and A2d illustrate GRPs for PSAs and e-cigarette ads, which exhibit distinct spikes and more variability across DMAs. This pattern is driven by a higher proportion of local advertising: 45.4% of GRPs for PSAs and e-cigarettes come from spot market purchases.

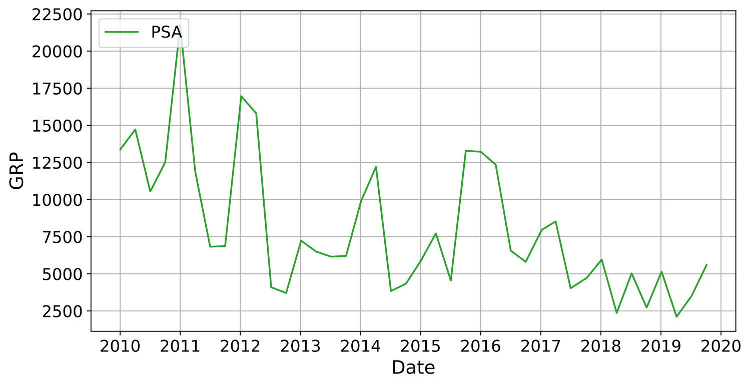
A.2 MarketScan Commercial Database

MarketScan Commercial Database contains individual-level prescription data. The data includes the type of drug and the date the prescription was filled. We focus on prescriptions that are the first usage of the drug to measure the impact of advertising on drug usage initiations. To determine whether a prescription is an initial issuance or a refill, we examine the individual's prescription history. A prescription is classified as a refill if the record comes within thirty days after the end of the supply of a previous prescription of the same drug substance. Moreover, to account for instances where MarketScan begins data collection midstream in an individual's treatment plan, we consider prescription data only for individuals who have been present in the data collection effort for at least one month before the prescription date.

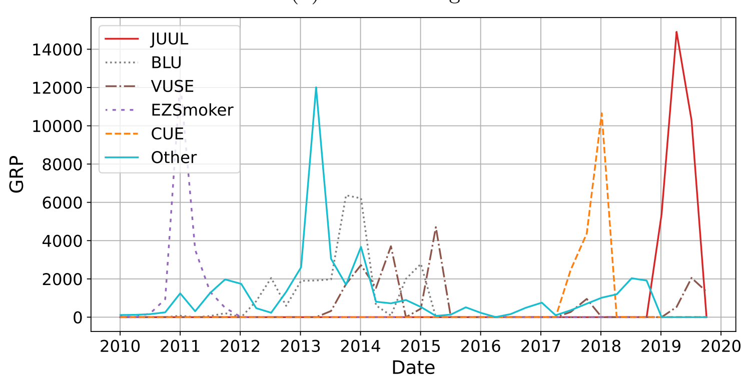
A challenge in merging MarketScan data with Nielsen AdIntel is the difference in geographic information levels. Nielsen AdIntel reports viewership at the DMA level, while MarketScan reports patient locations at the MSA level. The discrepancy arises because DMAs from AdIntel and MSAs from MarketScan, both composite geographic areas combining counties, do not perfectly align geographically. To address this misalignment, we focus our analysis on MSAs that fall entirely within a single DMA, ensuring a consistent geographical framework and that the data can be



(a) NRTs and Chantix

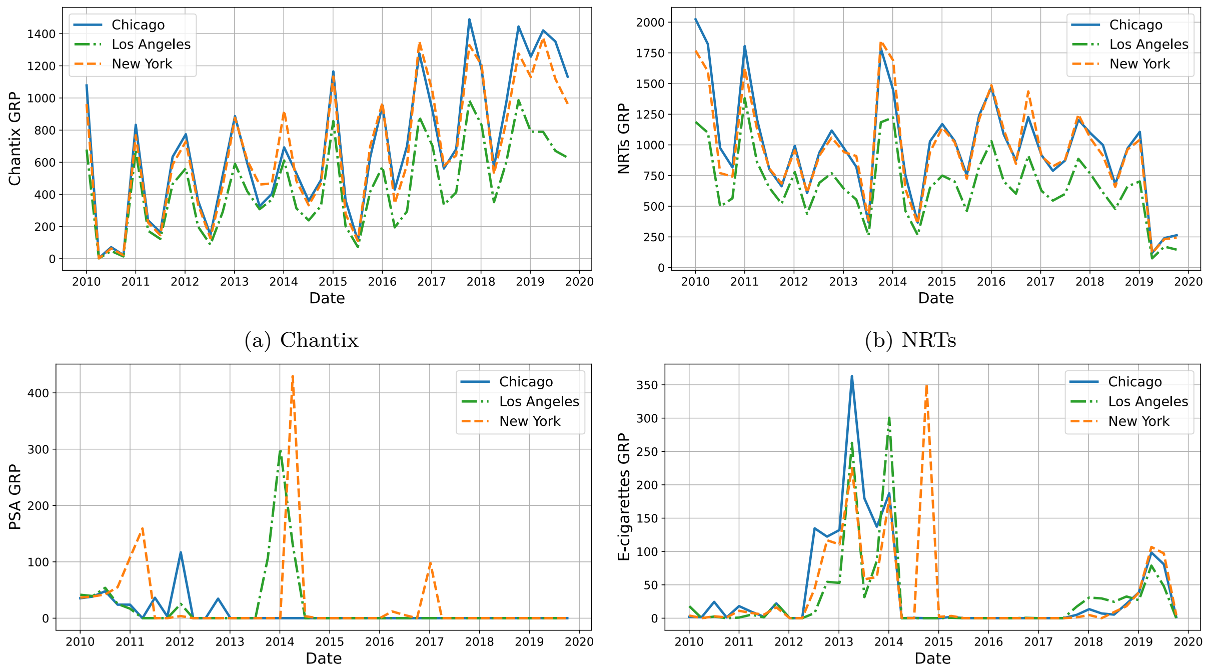


(b) Anti-smoking



(c) E-Cigarettes

Figure A1: Quarterly advertising gross rating points for different types of advertising



(a) Chantix (b) NRTs

(c) PSA (d) E-cigarettes

Figure A2: Quarterly advertising gross rating points for different product categories across Chicago, New York, and Los Angeles DMAs.

merged properly. Out of 410 MSAs covered by MarketScan, 379 meet this criterion, lying entirely within one DMA without extending beyond its borders. Each MSA consists of a collection of one or more counties. Out of the 379 MSAs that we consider, the average number of counties covered by each MSA is 2.90. We aggregate the outcomes at the MSA-week level, calculating the number of prescriptions or number of visits within that MSA for a specific week. When a specific MSA has no outcome records in a week, we add a zero data point for points in time that are within the interval where the MSA has non-zero outcomes.

A.3 NielsenIQ Retail Measurement Service (RMS)

The RMS data records prices and quantities sold for products at the store-UPC-week level. It covers a wide variety of products, but in this research, we are focused on product categories related to smoking, which are over-the-counter NRTs, e-cigarettes, and cigarettes, and are all stored under the "TOBACCO & ACCESSORIES" product group. We use module codes to group the product categories. We use three modules for our study: anti-smoking products, electronic cigarettes, and cigarettes. The electronic cigarette module was added in 2012, and prior to that, electronic cigarette products were grouped under the anti-smoking module. To resolve this, we selected UPCs that were in the e-cigarette module after 2012 and moved them from anti-smoking products to the e-cigarette module in the years before 2012. Table A1 presents the total revenues and market shares of each brand within these categories throughout our study period (2011-2019).

To construct an aggregate measure of demand for over-the-counter NRTs, we need to aggregate the amounts across different products. We use their milligrams of nicotine content because not all of them have the same levels of nicotine. Nicotine gums mainly have 2 or 4 milligrams of nicotine and help individuals get past their nicotine cravings, while nicotine patches have more nicotine

Type	Brand	Revenue	Market Share
NRTs	Private Label Gums	$1645.5M	46.84%
	Nicorette	$1235.8M	35.18%
	Private Label Patches	$335.6M	9.55%
	Nicoderm	$271.9M	7.74%
	Other	$24.2M	0.69%
E-Cigs	JUUL	$757.6M	41.26%
	BLU	$349.4M	19.03%
	NJOY	$249.1M	13.57%
	VUSE	$188.8M	10.28%
	Logic	$78.2M	4.26%
	Markten	$56.4M	3.07%
	Other	$156.4M	8.52%
Cigarettes	Marlboro	$31414.9M	47.79%
	Newport	$6719.5M	10.22%
	Camel	$4740.0M	7.21%
	Pall Mall	$4519.2M	6.88%
	L & M	$2030.3M	3.09%
	Virginia Slims	$1796.6M	2.73%
	Winston	$1633.8M	2.49%
	KOOL	$1327.5M	2.02%
	Misty	$1186.0M	1.80%
	Other	$10365.1M	15.77%

Table A1: Top brands for each type of product with their total revenues in the 2011-2019 time period and relative market shares.

content (7, 14, or 21 mg) and are suitable for daily usage. We focus on the RMS products in the anti-smoking category that have nicotine milligrams information and have 2, 4, 7, 14, or 21 mg of nicotine per unit, which comprises 99.7% of the total revenue in the category. We use the milligrams of nicotine to construct a measure of demand for NRTs.

As mentioned in the body, to capture the usage levels for e-cigs, we focus on refill cartridges and disposable e-cigarettes and filter out starter packs. To do so, we use the following filtering criteria:

- We filter out UPCs with "S-K" in their description, which stands for Starter Kit.
- We also filter out JUUL electronic cigarette devices, which are the devices that the user must purchase first and then can use refill cartridges to supply e-liquids to the device.
- Lastly, we filter out all the UPCs that have an average unit price higher than $22. This criterion was based on the gap in unit prices and the fact that most of the products above this price point are starter kits or devices.

Using this filtering, the remaining products, which are refills and disposable e-cigarettes, account for 90.66% of the revenue.

Lastly, for cigarettes, we use the number of cigarette sticks.[13] Specifically, we incorporate data for products that have units measured in "count," which represents the number of sticks. Fortunately, all of the cigarette records in the RMS data have this particular unit measurement, so we do not need to perform any further data cleaning before aggregating the data for cigarettes at the store-week level.

[13] Each pack of cigarettes typically consists of 20 cigarette sticks.

These procedures yield aggregate-level quantities sold at the store-week level for each of the categories studied. RMS records price, feature, and display at the UPC level. To aggregate these at the category level; we should create an index for each. We follow the averaging process used in Dubé, Hitsch, and Rossi (2018) to construct a price index, and a category-level measure of display and feature. To do this, we first construct yearly weights based on the revenue share of each UPC in a given year and construct the geometric average price index using these weights. For feature and display, which are dummies, we use the same weights but perform an arithmetic weighted average.

There are periods in the data when a store does not have any sales records for a product category. For each category, we remove all periods with zero sales of any products in that category at the beginning or at the end of the panel, as well as periods with eight or more consecutive weeks with zero sales.[14] We use the last price index associated with a nonzero sales week for weeks for which we do not have any sales records. This backfilling process for the price index is performed for any week where there are no sales records. Since this can introduce noise and the actual price might be different, we only use stores that have zero sales for less than 5% of weeks in their records.[15]

A.4 Insurance Coverage

To obtain estimates of insurance coverage, we use the American Community Survey (ACS) Public Use Microdata Sample (PUMS). This dataset records the number of individuals covered by seven insurance types: coverage through current or former employers, directly purchased insurance, Medicare, Medicaid, Tricare or Military healthcare, VA healthcare, and Indian Health Services. In this section, we discuss how we use this data to obtain yearly estimates of access to Chantix through insurance in each DMA.

Among the insurance types available in the data, Medicare, VA, and private insurance types have been covering smoking cessation prescription drugs throughout the study period. In August 2003, the VA removed previous restrictions on prescribing smoking cessation medication, allowing prescriptions for all patients who wished to quit, regardless of their willingness to attend a smoking cessation clinic (Smith et al., 2010). Medicare also includes prescription drug benefits for FDA-approved cessation medications since January 2006 (CMS, 2024). Subsequently, regarding private insurance types (directly purchased and employer-sponsored), the Affordable Care Act has mandated all new plans to cover tobacco cessation since 2010 (ALA, 2024). Because of this requirement, we consider that all individuals with private insurance have access to cessation medication.

TRICARE, a health care program serving uniformed service members, retirees, and their families, expanded its benefits to cover smoking cessation products in March 2013 (Lugo, Allerman, and Trice, 2019). To reflect this expansion, we incorporate TRICARE into our coverage measure for the years 2013 and beyond. For the Indian Health Service, which covers about 0.5% of individuals in our study period, we did not find specific data detailing the coverage of cessation medication. We assume that this insurance provided coverage for smoking cessation medication throughout the study period.

The final insurance category we examine in the PUMS data is Medicaid. Throughout our study period, the coverage of smoking cessation medications under Medicaid has evolved significantly. Starting in January 2014, the Affordable Care Act (ACA) mandated that state Medicaid programs must cover all seven FDA-approved tobacco cessation medications. This expanded coverage includes a range of Nicotine Replacement Therapies (NRTs), Zyban (Bupropion), and our primary focus,

[14] These are likely periods where either the store was closed or that category was not carried, so the zeros are different from a case where the product was available but no sales took place.

[15] This means that after removing streaks of zeros that are 8 weeks or longer, less than 5% of the remaining periods have non-zero sales.

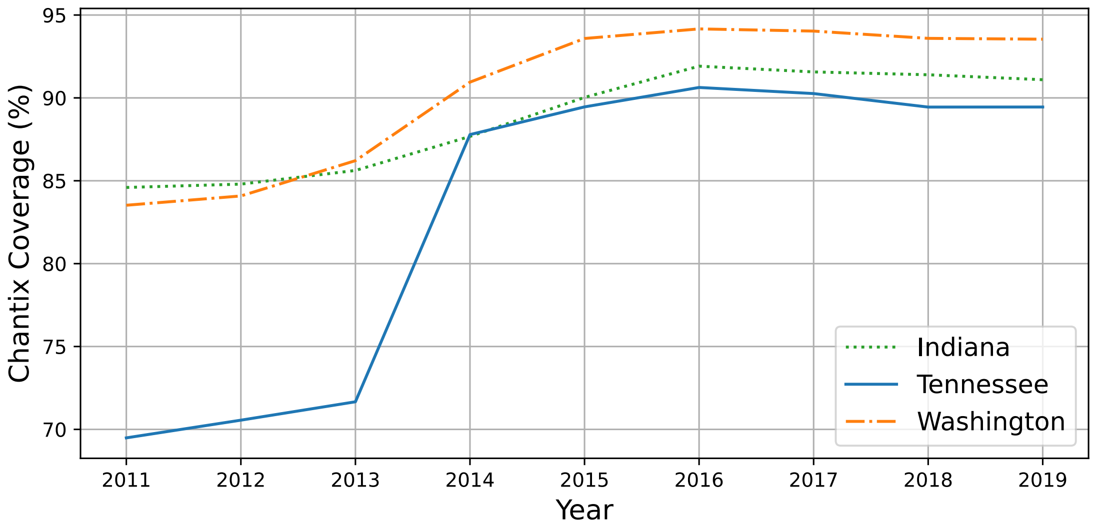


Figure A3: Estimate of the percentage of the population with access to Chantix through insurance for three states, Tennessee, Indiana, and Washington, from 2011 to 2019. The sudden increase in Chantix coverage in Tennessee in 2014 is attributed to the modification in the state's Medicaid coverage, which expanded to include Chantix that year, driven by the Affordable Care Act (ACA). The variation between the trendlines of Washington and Indiana during the 2014-2020 period is attributed to Washington's enrollment in Medicaid expansion in 2014 and Indiana's enrollment in 2015.

Chantix (Varenicline). Given that a majority of states incorporated these medications into their coverage even before the ACA enactment, we use sources that report the coverage status of cessation medications in each state. Specifically, we rely on tables from Singleterry et al. (2014) and DiGiulio et al. (2018), offering snapshots of medications covered by each state in the years 2008, 2014, 2015, 2017, and 2018, and include Medicaid enrollees in our measure when these sources do not label the state as not covering the Chantix or only covering pregnant women. To fill in the missing years between these snapshots, we use the last year for which data is available.

To illustrate how these policy changes translate into observable variation in insurance coverage over time, we provide an example in Figure A3. This figure depicts the variation in coverage levels for tobacco cessation medications in Tennessee, Indiana, and Washington. Prior to 2014, Tennessee's Medicaid program did not cover Chantix. However, the enactment of the Affordable Care Act in January 2014 mandated that all Medicaid programs must cover tobacco cessation medications, leading to a substantial increase in Chantix accessibility in the state. Another source of variation comes from Medicaid expansion. The ACA permits states to expand their Medicaid coverage to individuals earning up to 138% of the Federal poverty level. The timing of Medicaid expansion's adoption, though, varied by state, with some states yet to adopt the expansion (KFF, 2024).

While Medicaid programs in both Washington and Indiana provided Chantix coverage before the ACA's mandate, the extent and timing of Medicaid expansion differed between the two, affecting the trajectory of Chantix coverage. Washington adopted the expansion in 2014, resulting in a noticeable uptick in coverage, as displayed in Figure A3. In contrast, Indiana's adoption in 2015 led to a more gradual increase in its coverage trendline, also presented in Figure A3. The top panel of Table 4 presents summary statistics of Chantix insurance coverage at the county-year level. A comparison of average insurance coverage between the first and last years of the panel indicates that Chantix coverage increased by about 9 percentage points over the period. In summary, differential insurance coverage for tobacco cessation is driven by two primary factors: (a) the timing of tobacco cessation coverage inclusion and expansion by insurance programs (such as Medicaid and TRICARE), and (b) the proportion of individuals within different counties relying on various types of insurance coverage.

B Derivative of Demand in Conceptual Model

This section outlines the derivation of the demand derivative with respect to DTCA for cessation prescription drugs. In our illustrative example, we consider one type of advertising and three product categories: Cessation prescription drugs, cigarettes, and e-cigarettes. Given a set of parameters for the demand model, the utility functions for each category can be expressed as:

$$\begin{aligned} U_{drug} &= \delta_{drug} + \alpha_{drug} p_{drug} + \beta_{drug,DTCA} A_{DTCA} + \epsilon_{drug}, \\ U_{ecig} &= \delta_{ecig} + \alpha_{ecig} p_{ecig} + \beta_{ecig,DTCA} A_{DTCA} + \epsilon_{ecig}, \\ U_{cig} &= \delta_{cig} + \alpha_{cig} p_{cig} + \beta_{cig,DTCA} A_{DTCA} + \epsilon_{cig}, \end{aligned}$$

based on these utility functions and the properties of the logistic demand model, the market share of e-cigarettes, denoted as s_{ecig}, can be calculated as:

$$s_{ecig} = \frac{e^{U_{ecig}}}{1 + e^{U_{ecig}} + e^{U_{cig}} + e^{U_{drug}}}.$$

To find the impact of DTCA on the share of e-cigarettes, we must take the derivative of the market share with respect to the advertising variable A_{DTCA}, which yields to:

$$\begin{aligned} \frac{\partial s_{ecig}}{\partial A_{DTCA}} &= \frac{\partial \frac{e^{U_{ecig}}}{1+e^{U_{ecig}}+e^{U_{cig}}+e^{U_{drug}}}}{\partial A_{DTCA}} \\ &= \frac{\beta_{ecig,DTCA} e^{U_{ecig}}}{1 + e^{U_{ecig}} + e^{U_{cig}} + e^{U_{drug}}} \\ &\quad - \frac{(\beta_{ecig,DTCA} e^{U_{ecig}} + \beta_{cig,DTCA} e^{U_{cig}} + \beta_{drug,DTCA} e^{U_{drug}}) e^{U_{ecig}}}{(1 + e^{U_{ecig}} + e^{U_{cig}} + e^{U_{drug}})^2} \\ &= \frac{\beta_{ecig,DTCA} e^{U_{ecig}}}{1 + e^{U_{ecig}} + e^{U_{cig}} + e^{U_{drug}}} - \frac{\beta_{ecig,DTCA} e^{U_{ecig}} e^{U_{ecig}}}{(1 + e^{U_{ecig}} + e^{U_{cig}} + e^{U_{drug}})^2} \\ &\quad - \frac{\beta_{cig,DTCA} e^{U_{cig}} e^{U_{ecig}}}{(1 + e^{U_{ecig}} + e^{U_{cig}} + e^{U_{drug}})^2} - \frac{\beta_{drug,DTCA} e^{U_{drug}} e^{U_{ecig}}}{(1 + e^{U_{ecig}} + e^{U_{cig}} + e^{U_{drug}})^2} \\ &= \beta_{ecig,DTCA}(s_{ecig} - s_{ecig}^2) - (\beta_{cig,DTCA} s_{cig} + \beta_{drug,DTCA} s_{drug}) s_{ecig}. \end{aligned}$$

C Controlling for Detailing

One potential concern for our advertising estimates is that detailing activities might be systematically correlated with advertising decisions, potentially confounding our results. In this section, we investigate these concerns by controlling for detailing activities.

C.1 Detailing Data

Detailing is a form of promotion employed by pharmaceutical manufacturers, which involves visits by pharmaceutical sales representatives to healthcare providers, primarily physicians, to provide information about specific drugs. These visits may be accompanied by payments or gifts. To account for this type of promotion, we use the Open Payments Database from the Centers for Medicare and Medicaid Services (CMS), which provides information on transfers of value between drug manufacturers and physicians. The database, established under the Physician Payments Sunshine Act of 2010, is a comprehensive resource for capturing detailing activities. Our analysis focuses on data from August 2013, the start date of the database, through December 2019.

Our focus is on smoking cessation medications, specifically Varenicline (brand name Chantix) and Bupropion (brand name Zyban), two prescription medications approved by the FDA for this purpose. We consider a detailing record to be associated with a medication if it is reported as one of the drugs detailed during the visit. The Open Payments Database classifies detailing visits into 15 categories based on the type of value transfer. Following Lawler and Skira (2022), we include payments classified as food and beverages, which account for more than 98% of Chantix detailing activities. This yields over 751,000 detailing records for Chantix, while Zyban has only three reported instances. The stark difference in detailing efforts between Zyban and Chantix, also noted in prior research (Lawler and Skira, 2022), led us to focus on constructing a detailing measure only for Chantix.

To integrate detailing data with Nielsen Ad Intel advertising data, we aggregate detailing visits at the DMA-week level. This process involves several steps. First, we use the zip codes of prescribers provided in the detailing data. We then map these zip codes to US counties using HUD-USPS ZIP Crosswalk Files (*HUD ZIP Crosswalk* 2024) for the first quarter of each year. In cases where a zip code is associated with more than one county, we distribute each detailing visit across counties using residential population ratios. Finally, we aggregate this county-level data to DMAs as reported in Nielsen data. Across the sample that includes detailing data (August 2013–December 2019), there are, on average, 15.8 Chantix detailing occurrences in each DMA-week.

C.2 Econometric Specification

We now discuss the econometric specification used to control for detailing. To obtain a similar measure of detailing as we do for advertising, we construct detailing stock variables to allow detailing to have longer-term effects, a technique also used to account for carry-over effects of detailing activities in previous literature like Narayanan, Desiraju, and Chintagunta (2004). We consider:

$$D_{\mathcal{D}t} = \sum_{\tau=t-L}^{t} \delta^{t-\tau} d_{\mathcal{D}\tau}, \tag{A1}$$

where $d_{\mathcal{D}\tau}$ is the number of Chantix detailing visits in DMA $\mathcal{D}$ and week τ, and $D_{\mathcal{D}t}$ is the detailing stock for that DMA in week t. We use the same δ and L values as for advertising stock. Note that detailing data are not available from the beginning of our panel. The Open Payments Database collection effort, our source for detailing data, began in August 2013. Due to the 52-week lookback period for initialization, our analysis, including detailing variables, starts from August 2014. This limited availability of detailing data results in a different sample span compared to our original panel.

We build our econometric specification by extending our base specification (5) to include a term for detailing as follows:

$$\log(O_{mt}+1) = \boldsymbol{\beta}^\top \log(\boldsymbol{A}_{\mathcal{D}_m t}+1)+\gamma_{Chantix\ Detailing}\cdot\log(D_{\mathcal{D}_m t}+1)+\gamma_{mY(t)}+\gamma_{\mathcal{S}(t)}+\gamma_{\mathcal{T}(t)}+\epsilon_{mt}. \quad \text{(A2)}$$

C.3 Results with Detailing

Using the econometric specification discussed above for the healthcare data, and a similar extension for our specification using retail demand, we estimate the models with detailing measures as controls. Table A2 shows the results for the effect of advertising on new Chantix and Bupropion prescriptions on the full sample and the sample with detailing. Notably, the key finding regarding the direct effect of Chantix advertising on Chantix prescriptions remain consistent when controlling for detailing, across both Log-Log and Poisson specifications. In the subsample where detailing data are available, we also observe a positive association between Chantix detailing and prescriptions, although this effect is only marginally statistically significant ($P < 0.1$). Note that we include detailing as a control and we remain cautious about interpreting its coefficient causally. Our data are sampled weekly, while Manchanda, Rossi, and Chintagunta (2004) show detailing strategies are typically planned at quarterly or annual frequencies. This difference in periodicity (sampling frequency), combined with our fixed effects structure, likely absorbs most endogeneity concerns (Rossi, 2018).

Furthermore, our results showing the business-stealing effect of NRT advertising on both Chantix and Bupropion prescriptions are consistent across the two samples. The coefficients for NRT ads are not statistically different ($P < 0.05$) between the full sample results and the results with detailing. Lastly, in the full sample, we see a positive effect of Chantix advertising on Bupropion prescriptions, indicating category expansion role of DTCA. However, in the subsample with detailing data (post-August 2014), the effect of Chantix ads on Bupropion prescriptions becomes statistically insignificant. This change aligns with the documented decline in Bupropion's popularity as a smoking cessation aid over time (Zhu et al., 2015). In Section C.4, we show that these differences stem from temporal changes in the sample period rather than the inclusion of the detailing control.

We now turn to the results on the effects of advertising on retail demand. Table A3 displays the ad elasticity estimates for the full sample period (2011-2019) and the sample of the data with detailing information (Aug 2014 - Dec 2019). The direction (sign) and statistical significance of the estimates are generally consistent across the two specifications, with one exception: the effect of PSA advertising on NRT demand. For this particular estimate, while the sign and magnitude are similar between the two samples ($\beta = 0.0045$, $p < 0.05$ in the full sample; $\beta = 0.0050$, $p > 0.05$ in the detailing sample), it is statistically significant in the full sample but not in the sample with detailing. However, these estimates are not statistically distinguishable from each other ($p > 0.05$). This consistency across samples underscores the robustness of our findings.

C.4 Discussion regarding Further Endogeneity Concerns

Our results in the previous section highlight the robustness of our main findings to controlling for detailing activities. However, there could still be concerns regarding the endogeneity of detailing and advertising activities, affecting our advertising estimations. Based on the institutional details of pharmaceutical marketing, this is likely not a significant concern since detailing strategies are typically planned at quarterly or annual frequencies (Manchanda, Rossi, and Chintagunta, 2004),

Table A2: The effect of advertising on new Varenicline (Chantix) and Bupropion prescriptions. The full sample covers January 2011 to December 2019. The subsample with detailing data covers August 2014 to December 2019. Detailing is measured using a stock variable with the same construction as the advertising stock.

	Full Sample				With Detailing			
	Varenicline (Chantix)		Bupropion		Varenicline (Chantix)		Bupropion	
	Log-Log	Poisson	Log-Log	Poisson	Log-Log	Poisson	Log-Log	Poisson
$\beta_{Chantix\ Ads}$	**0.0564*****	**0.0735*****	**0.0357*****	**0.0360*****	**0.0403****	**0.0480****	0.0006	0.0086
	(0.0123)	(0.0152)	(0.0106)	(0.0097)	(0.0170)	(0.0212)	(0.0161)	(0.0126)
$\beta_{NRT\ Ads}$	-0.0159	**-0.0444*****	**-0.0281****	**-0.0476*****	-0.0189	**-0.0499****	-0.0174	**-0.0501*****
	(0.0116)	(0.0148)	(0.0113)	(0.0100)	(0.0148)	(0.0208)	(0.0142)	(0.0136)
$\beta_{PSA\ Ads}$	0.0037	0.0050	0.0028	0.0021	0.0071*	0.0076	0.0029	0.0020
	(0.0032)	(0.0035)	(0.0030)	(0.0023)	(0.0041)	(0.0064)	(0.0047)	(0.0043)
$\beta_{E-Cig\ Ads}$	0.0030	0.0031	0.0019	0.0029*	-0.0022	-0.0013	0.0024	0.0023
	(0.0022)	(0.0029)	(0.0017)	(0.0016)	(0.0026)	(0.0034)	(0.0020)	(0.0014)
$\gamma_{ChantixDetailing}$					0.0180*	0.0258*	0.0079	0.0146
					(0.0097)	(0.0142)	(0.0086)	(0.0098)
Observations	143,469	143,365	143,705	143,705	88,866	88,762	89,039	89,039
(Pseudo) R^2	0.8260	0.6897	0.9197	0.8728	0.8216	0.6718	0.9173	0.8686
Adjusted (Ps.) R^2	0.8224	0.6862	0.9181	0.8718	0.8174	0.6673	0.9153	0.8674
Residual Std. Dev.	0.4288	1.0546	0.3681	1.1755	0.4237	1.0348	0.3765	1.0898
Residual DF	143,305	143,201	143,541	143,541	88,744	88,640	88,917	88,917

Note. – Each column represents the results of estimating a specific specification for the number of new prescriptions for either Varenicline (Chantix) or Bupropion as outcomes.
Standard errors are two-way clustered at MSA and DMA-year.
All specifications include MSA-Year, Month, and week-of-year fixed effects.
For the Poisson models the reported R^2 and Adjusted R^2 are Pseudo R^2 and Adjusted Pseudo R^2.
Advertising and detailing carry-over (δ) is set to 0.9.
$^{*}: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$

Table A3: The effect of different forms of advertising on demand for cigarettes, e-cigarettes, and NRTs, using the national specification for all data and subset of data where detailing information is available. The number of detailing occurrences is used as a measure of detailing.

	Full Sample			With Detailing		
	Cigarettes	E-Cigs	OTC NRTs	Cigarettes	E-Cigs	OTC NRTs
$\beta_{Chantix\ Ads}$	**-0.0220*****	**0.0514****	-0.0046	**-0.0242*****	**0.1374*****	0.0078
	(0.0054)	(0.0257)	(0.0077)	(0.0086)	(0.0357)	(0.0095)
$\beta_{NRT\ Ads}$	-0.0008	-0.0173	**0.0166*****	0.0044	-0.0348	**0.0269*****
	(0.0039)	(0.0195)	(0.0056)	(0.0055)	(0.0246)	(0.0076)
$\beta_{PSA\ Ads}$	0.0019	**0.0145****	**0.0045****	0.0036	**0.0167****	0.0050
	(0.0017)	(0.0060)	(0.0018)	(0.0030)	(0.0071)	(0.0038)
$\beta_{E-Cig\ Ads}$	-0.0005	0.0084*	-0.0017*	0.0008	0.0062	-0.0019
	(0.0012)	(0.0051)	(0.0010)	(0.0017)	(0.0053)	(0.0013)
$\gamma_{ChantixDetailing}$				0.0026	0.0036	0.0057
				(0.0046)	(0.0270)	(0.0057)
α_{Price}	**-0.9497*****	**-0.1367****	**-1.3858*****	**-0.8391*****	-0.0967	**-1.7368*****
	(0.1310)	(0.0617)	(0.1302)	(0.1047)	(0.0839)	(0.2284)
$\eta_{Feature}$	**0.0541*****	0.3744	**0.9602*****	**0.0461*****	**0.2421*****	**0.8581*****
	(0.0092)	(0.2870)	(0.0388)	(0.0163)	(0.0799)	(0.0410)
$\eta_{Display}$	**0.1304*****	0.4196	**0.6904*****	**0.1286*****	**-5.2673*****	**0.7701*****
	(0.0270)	(0.3556)	(0.0701)	(0.0247)	(0.1928)	(0.0920)
Observations	13,992,417	4,235,960	5,625,872	9,043,362	3,163,724	3,421,246
R^2	0.9616	0.7968	0.6705	0.9586	0.8084	0.7073
Adjusted R^2	0.9608	0.7925	0.6640	0.9577	0.8043	0.7008
Residual Std. Dev.	0.2397	0.5662	0.6629	0.2481	0.5456	0.5963
Residual DF	13,992,250	4,235,793	5,625,705	9,043,237	3,163,599	3,421,121

Note. – Each column represents the results of estimating a specific log-log specification (full sample or sample with detailing) for the demand of a particular category of products as the outcome variable.
Standard errors are two-way clustered at the DMA-year and store level.
All specifications include store-year, month, and week-of-year fixed effects.
Advertising and detailing carry-over (δ) is set to 0.9.
* : $p < 0.1$, ** : $p < 0.05$, *** : $p < 0.01$

while our high-dimensional fixed effects structure should absorb most of this strategic allocation. Additionally, as shown in Online Appendix E, the residual variation in advertising after including our fixed effects shows minimal correlation with detailing activities, suggesting effective isolation of quasi-random variation in advertising exposure.

Nevertheless, we formally assess whether the inclusion of detailing controls affects our advertising coefficient estimates. We reanalyze the healthcare and retail outcomes from Sections 5 and 6 using the subsample with available detailing data (August 2014 to December 2019), estimating models both with and without detailing controls to determine if advertising coefficient estimates are sensitive to their inclusion.

Table A4 presents the results for the prescription drugs Varenicline (Chantix) and Bupropion. The left panel displays the results without including the Chantix detailing coefficient, while the right panel includes it. The comparison between the two panels shows that the advertising coefficients remain consistent in magnitude and statistical significance, indicating minimal impact from the inclusion of the detailing coefficient.

These findings suggest that our advertising estimates remain stable regardless of whether detailing controls are included, implying that our fixed effects adequately account for potential adjustments in detailing and advertising strategies. Similar analyses for the retail sales are provided in Table A5. Comparisons across all retail categories confirm the stability of advertising effects.

Table A4: The effect of advertising on new Varenicline (Chantix) and Bupropion prescriptions, comparing models without detailing controls (left columns) and with detailing controls (right columns). Analysis uses subsample with available detailing data (August 2014 to December 2019).

	Varenicline (Chantix)		Bupropion		Varenicline (Chantix)		Bupropion	
	Log-Log	Poisson	Log-Log	Poisson	Log-Log	Poisson	Log-Log	Poisson
$\beta_{Chantix\ Ads}$	**0.0405****	**0.0487****	0.0007	0.0092	**0.0403****	**0.0480****	0.0006	0.0086
	(0.0169)	(0.0212)	(0.0161)	(0.0125)	(0.0170)	(0.0212)	(0.0161)	(0.0126)
$\beta_{NRT\ Ads}$	-0.0181	**-0.0489****	-0.0170	**-0.0496*****	-0.0189	**-0.0499****	-0.0174	**-0.0501*****
	(0.0148)	(0.0209)	(0.0142)	(0.0137)	(0.0148)	(0.0208)	(0.0142)	(0.0136)
$\beta_{PSA\ Ads}$	0.0069*	0.0074	0.0028	0.0019	0.0071*	0.0076	0.0029	0.0020
	(0.0041)	(0.0064)	(0.0047)	(0.0042)	(0.0041)	(0.0064)	(0.0047)	(0.0043)
$\beta_{E-Cig\ Ads}$	-0.0022	-0.0012	0.0024	0.0023	-0.0022	-0.0013	0.0024	0.0023
	(0.0026)	(0.0034)	(0.0020)	(0.0014)	(0.0026)	(0.0034)	(0.0020)	(0.0014)
$\gamma_{ChantixDetailing}$					0.0180*	0.0258*	0.0079	0.0146
					(0.0097)	(0.0142)	(0.0086)	(0.0098)
Observations	88,866	88,762	89,039	89,039	88,866	88,762	89,039	89,039
R^2	0.8216	0.6718	0.9173	0.8686	0.8216	0.6718	0.9173	0.8686
Adjusted R^2	0.8174	0.6673	0.9153	0.8674	0.8174	0.6673	0.9153	0.8674
Residual Std. Dev.	0.4237	1.0348	0.3765	1.0899	0.4237	1.0348	0.3765	1.0898
Residual DF	88,745	88,641	88,918	88,918	88,744	88,640	88,917	88,917

Note. – Each column represents the results of estimating a specific specification for the number of new prescriptions for either Varenicline (Chantix) or Bupropion as outcomes.
Standard errors are two-way clustered at MSA and DMA-year.
All specifications include MSA-Year, Month, and week-of-year fixed effects.
For the Poisson models the reported R^2 and Adjusted R^2 are Pseudo R^2 and Adjusted Pseudo R^2.
Advertising and detailing carry-over (δ) is set to 0.9.
$^{*}: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$

Table A5: The effect of advertising on demand for cigarettes, e-cigarettes, and NRTs, comparing models without detailing controls (left columns) and with detailing controls (right columns). Analysis uses subsample with available detailing data (August 2014 to December 2019).

	Cigarettes	E-Cigs	OTC NRTs	Cigarettes	E-Cigs	OTC NRTs
$\beta_{Chantix\ Ads}$	**-0.0241*****	**0.1375*****	0.0080	**-0.0242*****	**0.1374*****	0.0078
	(0.0085)	(0.0357)	(0.0095)	(0.0086)	(0.0357)	(0.0095)
$\beta_{NRT\ Ads}$	0.0044	-0.0349	**0.0270*****	0.0044	-0.0348	**0.0269*****
	(0.0055)	(0.0247)	(0.0076)	(0.0055)	(0.0246)	(0.0076)
$\beta_{PSA\ Ads}$	0.0036	**0.0167****	0.0049	0.0036	**0.0167****	0.0050
	(0.0030)	(0.0071)	(0.0038)	(0.0030)	(0.0071)	(0.0038)
$\beta_{E-Cig\ Ads}$	0.0008	0.0062	-0.0019	0.0008	0.0062	-0.0019
	(0.0017)	(0.0053)	(0.0013)	(0.0017)	(0.0053)	(0.0013)
$\gamma_{ChantixDetailing}$				0.0026	0.0036	0.0057
				(0.0046)	(0.0270)	(0.0057)
α_{price}	**-0.8392*****	-0.0965	**-1.7367*****	**-0.8391*****	-0.0967	**-1.7368*****
	(0.1047)	(0.0839)	(0.2284)	(0.1047)	(0.0839)	(0.2284)
$\eta_{Feature}$	**0.0461*****	**0.2426*****	**0.8581*****	**0.0461*****	**0.2421*****	**0.8581*****
	(0.0163)	(0.0797)	(0.0410)	(0.0163)	(0.0799)	(0.0410)
$\eta_{Display}$	**0.1290*****	**-5.2705*****	**0.7700*****	**0.1286*****	**-5.2673*****	**0.7701*****
	(0.0247)	(0.1896)	(0.0920)	(0.0247)	(0.1928)	(0.0920)
Observations	9,043,362	3,163,724	3,421,246	9,043,362	3,163,724	3,421,246
R^2	0.9586	0.8084	0.7073	0.9586	0.8084	0.7073
Adjusted R^2	0.9577	0.8043	0.7008	0.9577	0.8043	0.7008
Residual Std. Dev.	0.2481	0.5456	0.5963	0.2481	0.5456	0.5963
Residual DF	9,043,238	3,163,600	3,421,122	9,043,237	3,163,599	3,421,121

Note. – Each column represents the results of estimating a specific log-log specification (full sample or sample with detailing) for the demand of a particular category of products as the outcome variable.
Standard errors are two-way clustered at the DMA-year and store level.
All specifications include store-year, month, and week-of-year fixed effects.
Advertising and detailing carry-over (δ) is set to 0.9.
* : $p < 0.1$, ** : $p < 0.05$, *** : $p < 0.01$

D Advertising Stock Carry-over Parameter

In our analysis throughout the paper, we use a carry-over parameter of $\delta = 0.9$ to construct our advertising stock variables. While this choice is consistent with previous literature Dubé, Hitsch, and Manchanda (2005) and Shapiro, Hitsch, and Tuchman (2021), in this section, we investigate this choice to show the robustness of our findings. We calibrate the carry-over parameter using grid search by maximizing the average fit across our models. Below, we discuss this process in detail.

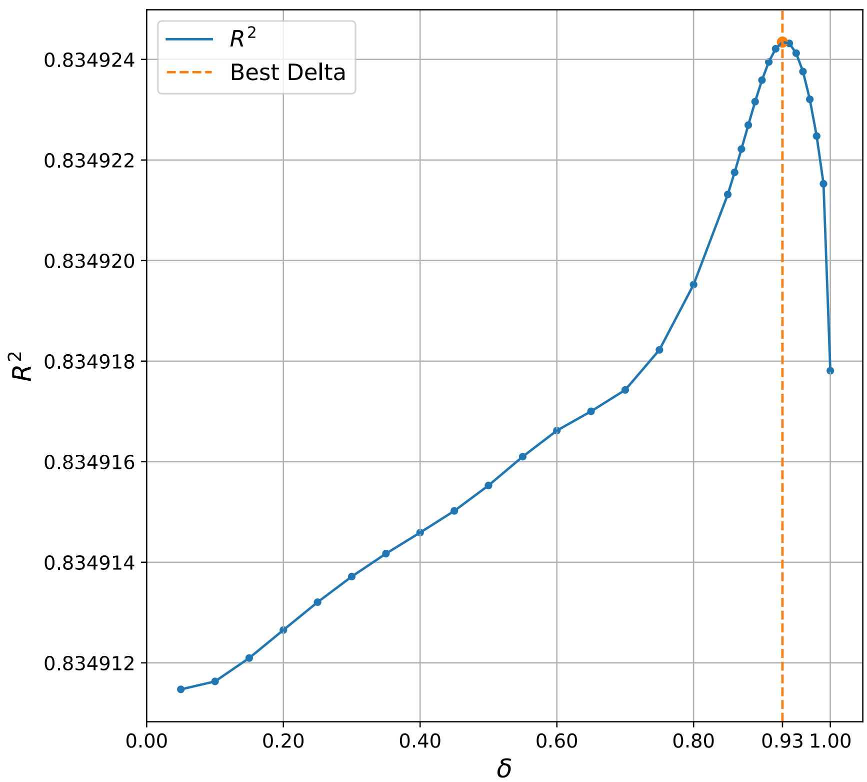


Figure A4: Average Model Fit R^2 for different values of carry-over parameter δ. We use the average R^2 across our main five product categories (Varenicline (Chantix), Bupropion, cigarettes, e-cigarettes, and over-the-counter NRTs) and find the maximum R^2 at $\delta = 0.93$

We calibrate the carry-over parameter δ by evaluating the model fit across different values in the range [0, 1]. For this process, we use increments of 0.05 when $0 < \delta \leq 0.85$ and finer increments of 0.01 for $0.85 < \delta \leq 1$. For each δ value, we estimate the demand model for five product categories: Bupropion, Chantix, cigarettes, e-cigarettes, and over-the-counter NRTs. We use Equation (5) for Merative data and Equation (6) for retail products. To assess model fit, we use the R^2 of each estimation. We then calculate the average R^2 across all five product categories for each δ value. Figure A4 illustrates the relationship between the average R^2 and different δ values. The maximum average R^2 is attained at $\delta = 0.93$, which is close to the 0.9 value used in our main analysis.

To demonstrate the robustness of our main results, we replicate our estimations using the calibrated carry-over parameter $\delta = 0.93$. The results are presented in Tables A6 and A7.

Table A6 validates our primary findings regarding prescription medications. The effect of Chantix advertising remains positive for both Chantix and Bupropion demand. Additionally, the coefficient for NRT advertisements continues to be negative for Chantix and Bupropion demand. For retail categories (Table A7), we observe that the negative effect of Chantix advertising on cigarette consumption remains statistically significant. The estimate for the impact of Chantix advertising on e-cigarette demand remains similar in size (0.0588 compared to 0.0514 in the main analysis) but is not statistically significant. These results largely align with our original findings using $\delta = 0.9$, underlining the consistency of our conclusions across different carry-over parameters.

Table A6: The effect of advertising on new Varenicline (Chantix) and Bupropion prescriptions using the calibrated carry-over parameter $\delta = 0.93$.

	Varenicline (Chantix)		Bupropion	
	Log-Log	Poisson	Log-Log	Poisson
$\beta_{Chantix\ Ads}$	**0.0691*****	**0.0881*****	**0.0465*****	**0.0482*****
	(0.0164)	(0.0208)	(0.0143)	(0.0135)
$\beta_{NRT\ Ads}$	-0.0320*	**-0.0745*****	**-0.0478*****	**-0.0739*****
	(0.0163)	(0.0216)	(0.0158)	(0.0149)
$\beta_{PSA\ Ads}$	0.0039	0.0053	0.0026	0.0033
	(0.0034)	(0.0036)	(0.0031)	(0.0026)
$\beta_{E-Cig\ Ads}$	0.0032	0.0033	0.0011	0.0024
	(0.0024)	(0.0030)	(0.0018)	(0.0015)
Observations	143,469	143,365	143,705	143,705
(Pseudo) R^2	0.8260	0.6897	0.9197	0.8728
Adjusted (Ps.) R^2	0.8224	0.6862	0.9181	0.8718
Residual Std. Dev.	0.4288	1.0546	0.3681	1.1755
Residual DF	143,305	143,201	143,541	143,541

Note. – Each column represents the results of estimating a specific specification for the number of new prescriptions for either Varenicline (Chantix) or Bupropion as outcomes.
Standard errors are two-way clustered at MSA and DMA-year.
All specifications include MSA-Year, Month, and week-of-year fixed effects.
For the Poisson models the reported R^2 and Adjusted R^2 are Pseudo R^2 and Adjusted Pseudo R^2.
Advertising carry-over (δ) is set to 0.93.
$^{\star}: p < 0.1$, $^{\star\star}: p < 0.05$, $^{\star\star\star}: p < 0.01$

Table A7: The effect of different forms of advertising on demand for cigarettes, e-cigarettes, and NRTs, using the calibrated carry-over parameter $\delta = 0.93$.

	Cigarettes	E-Cigs	OTC NRTs
$\beta_{Chantix\ Ads}$	**-0.0307*****	0.0588	-0.0089
	(0.0078)	(0.0384)	(0.0110)
$\beta_{NRT\ Ads}$	-0.0017	-0.0190	**0.0198****
	(0.0060)	(0.0323)	(0.0086)
$\beta_{PSA\ Ads}$	0.0030	**0.0159*****	**0.0042****
	(0.0019)	(0.0057)	(0.0019)
$\beta_{E-Cig\ Ads}$	-0.0005	0.0094*	-0.0019*
	(0.0012)	(0.0054)	(0.0011)
α_{price}	**-0.9495*****	**-0.1366****	**-1.3858*****
	(0.1308)	(0.0617)	(0.1302)
$\eta_{Feature}$	**0.0539*****	0.3763	**0.9603*****
	(0.0091)	(0.2867)	(0.0388)
$\eta_{Display}$	**0.1299*****	0.4182	**0.6904*****
	(0.0271)	(0.3543)	(0.0701)
Observations	13,992,417	4,235,960	5,625,872
R^2	0.9616	0.7968	0.6705
Adjusted R^2	0.9608	0.7925	0.6640
Residual Std. Dev.	0.2397	0.5662	0.6629
Residual DF	13,992,250	4,235,793	5,625,705

Note. – Each column represents the results of estimating the full sample specification for the demand of a particular category of products as the outcome variable. Standard errors are two-way clustered at the DMA-year and store level. All specifications include store-year, month, and week-of-year fixed effects. Advertising carry-over (δ) is set to 0.93.
$^{*}: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$

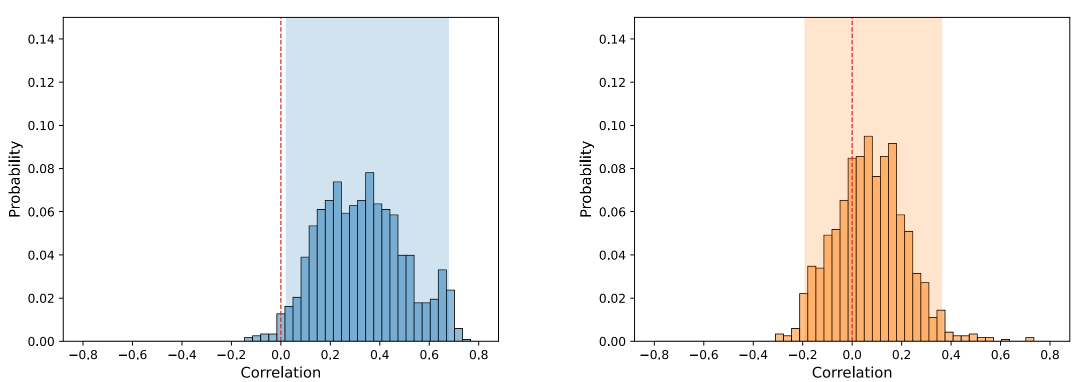
E Effectiveness of the Fixed Effects

Our identification strategy (see Equation 5) uses high-dimensional fixed effects to isolate quasi-random variation in advertising exposure. However, this approach requires that the residual variation in advertising, after accounting for fixed effects, be plausibly exogenous. This appendix provides empirical evidence supporting the effectiveness of our approach.

The institutional details of television advertising markets discussed in Section 5.1 suggest that targeting typically occurs at broader time scales than weeks. Advertisers may plan their allocations seasonally or target predictable patterns (like New Year's resolution periods), but fine-grained week-to-week targeting is constrained by the structure of ad-buying markets. To empirically verify this, we examine correlations between advertising patterns for related product categories.

Among the product categories we study, NRTs and Chantix categories are the two that are most closely related to each other. Both are FDA-approved cessation therapies that are allowed to be advertised, and their manufacturers likely employ similar targeting techniques in their advertising efforts. This means that to the extent possible, they will allocate their advertising dollars in periods where they expect positive demand shocks or when advertising is likely to be more effective (for example, they might air more ads early in the year when people are more likely to attempt quitting). However, given the institutional constraints of TV advertising markets discussed in Section 5.1, this strategic allocation is likely only feasible at a coarse level, such as allocating more advertising to certain quarters or targeting based on predictable demand shocks that occur at fixed times across all years (first week of January), rather than responding to demand patterns in a specific time.

This type of coarse targeting is quite different from being able to adjust advertising at a fine weekly level. To further clarify this distinction, while advertisers might believe advertising in the first week of January is generally more effective (which would be absorbed by our week-of-year fixed effects), a potential concern would be valid if advertisers could predict that advertising in, say, the first week of January 2015 would have better returns than the first week of January 2016. Such a level of granular forecasting is unlikely given both the institutional constraints of TV advertising markets and the difficulty in predicting advertising returns at such a granular level.



(a) Without Fixed Effects

(b) With Fixed Effects

Figure A5: Comparison of the distribution of correlations between advertising GRPs for NRT and Chantix at different DMA-years. The shaded area shows the 95% band for each distribution, and the dashed red line indicates zero on the x-axis.

To provide empirical evidence for this phenomenon, we analyzed the time series of advertising at each DMA-year and calculated the correlation between the Gross Rating Points (GRPs) for NRTs and Chantix in each DMA-year. If advertisers are able to target based on demand shocks in general (at either coarse or fine level), then we should see positive correlations between advertising intensity of Chantix and NRTs across the weeks. Figure A5a illustrates the distribution of these correlations, with the shaded area representing 95% band for the distribution. As anticipated, advertising for these two categories is skewed toward positive values, with a mean correlation of 0.329, indicating strategic allocation across time periods.

However, when we apply the fixed effects used in our study (DMA-year, year-month, and week-of-year) and examine the residuals of GRPs for NRTs and Chantix, these correlations disappear. The new distribution, displayed in Figure A5b shifts to the left and includes zero within its 95% band. This evidence suggests that while firms do strategically allocate advertising based on predictable demand patterns at a coarse level, our fixed effects adequately account for this type of endogeneity and the residuals become largely uncorrelated. This indicates that NRTs and Chantix advertisers are not able to target at a very fine level (week-to-week) – if they could, we would still observe substantial correlation in the residuals. Instead, the bulk of the endogeneity appears to be absorbed by our fixed effects.

This analysis provides additional methodological validation that may be useful in similar research contexts. We also performed the same analysis to examine the correlation between Chantix and NRT advertising GRPs and other relevant variables, including Chantix detailing, retail category prices for cigarettes, e-cigarettes, and OTC-NRTs, across different DMA-years. Figures A6 and A7 illustrate the distribution of these correlations. Similar to our previous analysis, we observe that before accounting for fixed effects, some of these distributions are not centered at zero, suggesting that these variables share common time-variant components with advertising measures. However, after applying our fixed effects (DMA-year, year-month, and week-of-year), the distributions become centered around zero, demonstrating that our fixed effects effectively absorb the systematic variation in advertising that might be driven by predictable demand patterns. This further supports the validity of our identification strategy and highlights the robustness of our approach in mitigating endogeneity concerns.

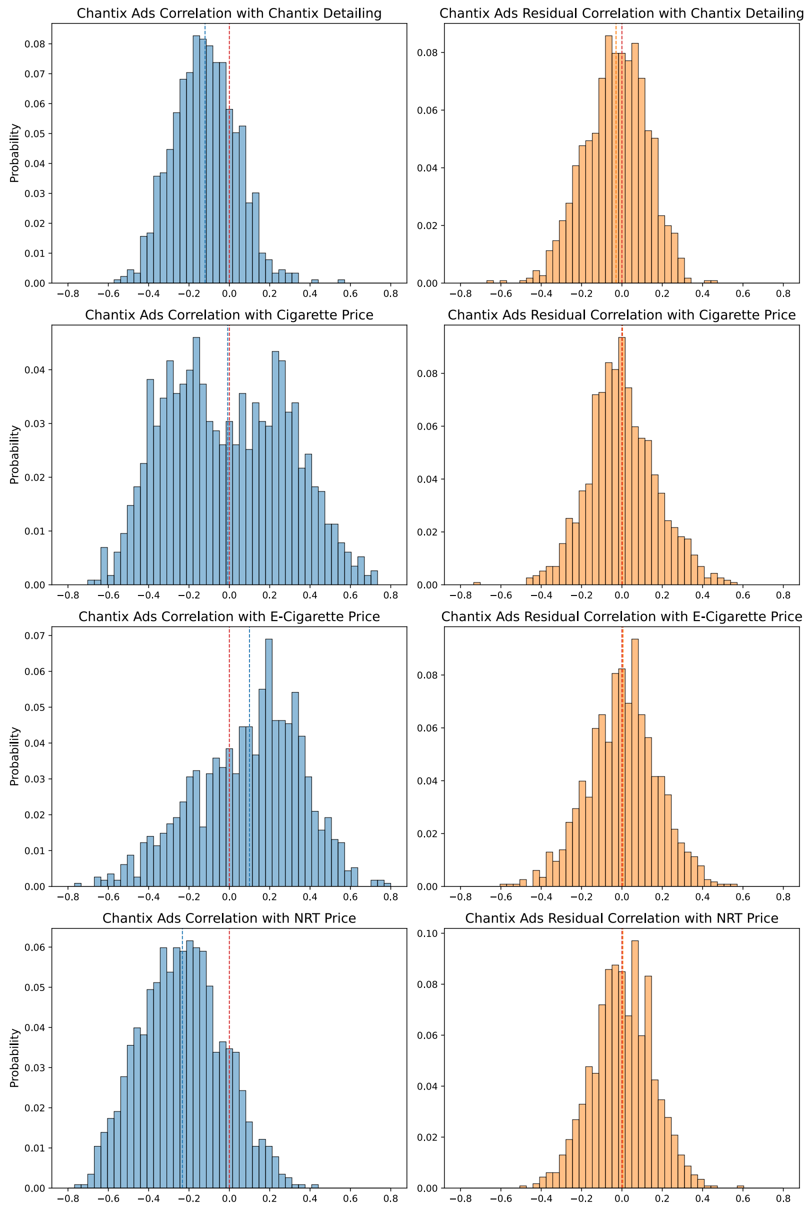


Figure A6: Comparison of the distribution of correlations (before and after residualization using fixed effects) between Chantix advertising GRPs and Chantix detailing as well as retail category prices for cigarettes, e-cigarettes, and OTC-NRTs across different DMA-years.

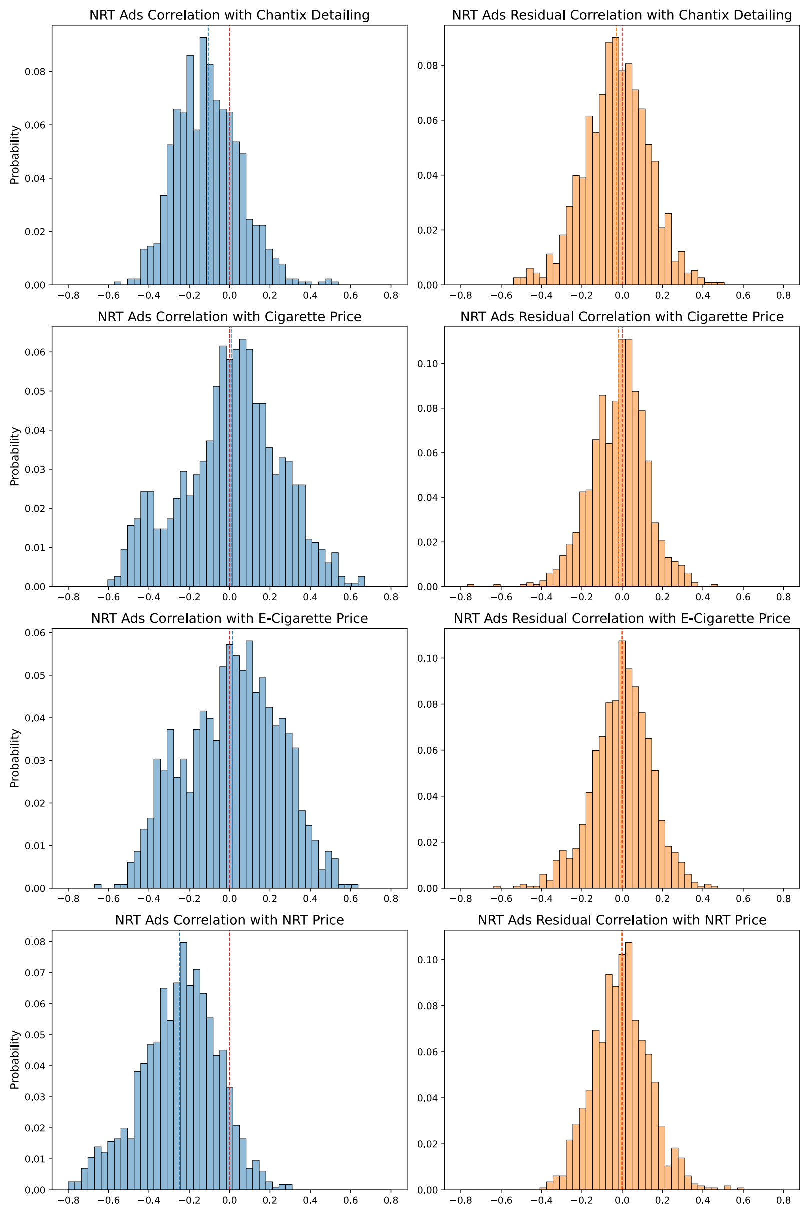


Figure A7: Comparison of the distribution of correlations (before and after residualization using fixed effects) between NRT advertising GRPs and Chantix detailing as well as retail category prices for cigarettes, e-cigarettes, and OTC-NRTs across different DMA-years.

F Prescription NRTs

While our main analysis focuses on OTC NRTs purchased in stores, the Marketscan claims data also includes information on prescribed NRTs. For completeness, we analyze the effect of advertising on new NRT prescriptions in this section, though we interpret these results with caution due to data limitations. The number of NRT prescriptions in our dataset is considerably lower than other prescriptions, with approximately one-fifth of the volume of Chantix prescriptions. This smaller sample size results in a high rate of zero outcomes (60.5%) in the weekly aggregated NRT prescription data, which may affect the reliability of our estimates for the log-log model given that we have a log(1+y) transformation. To allay these concerns, we also present the results using Poisson regressions (Chen and Roth, 2024).

Table A8 below is the counterpart to Table 5 for prescription NRTs. Given the high number of zeros in the panel, we consider the Poisson results more reliable; nevertheless, both the Log-Log and Poisson specifications show a positive and significant effect of Chantix advertising on NRT prescriptions.

This positive effect of Chantix advertising on NRT prescriptions aligns with our earlier findings of its positive effect on Bupropion demand. Several factors could explain this: Chantix ads may prompt more doctor visits for smoking cessation consultations, leading to increased NRT prescriptions, and the advertising may raise general awareness about smoking cessation treatments. Furthermore, some providers may also recommend combination therapy using both Chantix and NRTs, as some studies suggest improved efficacy (Koegelenberg et al., 2014).

Interestingly, we find no significant effects of NRT advertising on prescription NRT rates across both specifications, contrasting with our findings in Section 6.2 where NRT advertising increased OTC NRT sales. Moreover, the effect of NRT advertising on prescription NRTs, while not statistically significant, is directionally negative across both specifications. This pattern aligns with our earlier finding that NRT ads reduce Chantix prescriptions. Together, these results suggest that NRT advertising may encourage consumers to bypass healthcare professionals and opt for OTC alternatives, potentially reducing the number of NRT prescriptions.

These findings highlight the complex relationship between pharmaceutical advertising and consumer behavior in the smoking cessation market. Chantix advertising appears to have broader impacts, potentially driving individuals to consult healthcare providers and increasing prescriptions for various cessation aids. In contrast, NRT advertising seems to primarily influence OTC purchasing behavior, possibly at the expense of prescription options and reduced engagement with healthcare professionals. This analysis complements our main findings on OTC NRTs, providing a more comprehensive picture of how advertising affects different NRT acquisition channels. However, due to the data limitations mentioned earlier, we present these results as supplementary rather than core findings.

Table A8: The effect of advertising on the number of new NRT prescriptions.

	Log-Log	Poisson
$\beta_{Chantix\ Ads}$	$\mathbf{0.0212}^{**}$	$\mathbf{0.1012}^{***}$
	(0.0093)	(0.0310)
$\beta_{NRT\ Ads}$	-0.0048	-0.0232
	(0.0097)	(0.0302)
$\beta_{PSA\ Ads}$	$\mathbf{0.0056}^{**}$	0.0102
	(0.0025)	(0.0079)
$\beta_{E-Cig\ Ads}$	-0.0005	-0.0029
	(0.0019)	(0.0054)
Observations	142,949	138,980
(Pseudo) R^2	0.6984	0.5372
Adjusted (Ps.) R^2	0.6922	0.5272
Residual Std. Dev.	0.3662	0.9143
Residual DF	142,785	138,816

Note. – Each column represents the results of estimating a specific specification for the number of prescription NRTs as the outcome.
Standard errors are two-way clustered at MSA and DMA-year.
All specifications include MSA-Year, Month, and week-of-year fixed effects.
For the Poisson models the reported R^2 and Adjusted R^2 are Pseudo R^2 and Adjusted Pseudo R^2.
Advertising carry-over (δ) is set to 0.9.
$^{\star}: p < 0.1$, $^{\star\star}: p < 0.05$, $^{\star\star\star}: p < 0.01$

G Effect of Advertising on Prescription Adherence Duration

In our main analysis, we found that Chantix advertising increases new prescriptions for Chantix and Bupropion, while advertising for NRTs leads to a reduction in prescriptions for smoking cessation drugs. In this section, we explore whether these ads are converting different potential users. Specifically, we examine whether the individuals who initiate Chantix treatment in response to its advertising, or those who forgo the treatment when exposed to NRT ads, differ in their prescription usage patterns. We do this by analyzing the average duration of prescription usage for new users on a weekly basis and its association with advertising exposures.

This analysis helps us understand the characteristics of "compliers" – those individuals whose treatment decisions are influenced by advertising. By examining how the average prescription adherence shifts as a function of advertising, we can assess whether the types of individuals who start or forgo Chantix treatment due to ads differ from the average user.

To measure prescription adherence, we use the time duration between the start date of each new prescription and the last day of supply from the final refill, using the same labeling method for new and refill prescriptions we used in the main analysis. We find an average adherence duration of approximately 50.56 days across all new Chantix prescriptions in the data. We then conducted a regression analysis to assess the impact of advertising on this adherence duration using the following specification:

$$\log(H_{mt}) = \boldsymbol{\beta}^\top \log(\boldsymbol{A}_{\mathcal{D}_m t} + 1) + \gamma_{mY(t)} + \gamma_{\mathcal{S}(t)} + \gamma_{\mathcal{T}(t)} + \epsilon_{mt}, \tag{A3}$$

where H_{mt} represents the average days of adherence for new Chantix users in MSA m in week t. The model controls for the same fixed effects as in our main analysis.

The regression results, presented in Table A9, indicate that Chantix DTCA does not have a statistically significant effect on prescription adherence duration. This suggests that marginal users who initiate Chantix due to advertising are neither more nor less likely to adhere to the medication compared to other users. However, we observe a positive effect of NRT advertising on Chantix adherence duration. This finding is particularly noteworthy in light of our main results, which demonstrate that NRT advertising is associated with a reduction in new Chantix prescriptions. This positive effect suggests that NRT ads may discourage potential users who would have had shorter usage periods with Chantix from initiating the treatment. Consequently, this switch leads to an increase in the average adherence duration among the remaining Chantix users.

Table A9: The effect of advertising on the average duration of prescription adherence for Varenicline (Chantix) prescriptions in each MSA-week.

	Log-Log
$\beta_{Chantix\ Ads}$	-0.0049
	(0.0126)
$\beta_{NRT\ Ads}$	**0.0413*****
	(0.0142)
$\beta_{PSA\ Ads}$	0.0012
	(0.0025)
$\beta_{E-Cig\ Ads}$	0.0021
	(0.0020)
Observations	108,788
R^2	0.0759
Adjusted R^2	0.0505
Residual Std. Dev.	0.4382
Residual DF	108,624

Note. – Standard errors are two-way clustered at MSA and DMA-year.
The specification includes MSA-Year, Month, and week-of-year fixed effects.
Advertising carry-over (δ) is set to 0.9.
$^{\star}: p < 0.1$, $^{\star\star}: p < 0.05$, $^{\star\star\star}: p < 0.01$

H Border Method

In this study, we employ two distinct identification strategies. Our primary approach, which we term 'national' identification, uses the full dataset at our disposal and aims to account for potential confounds through high-dimensional fixed effects and a reduced-form demand model. This national strategy forms the core of our analysis in the main body of the paper. For robustness, we also implement a secondary approach known as the 'border method', which compares stores on different sides of Designated Market Area (DMA) borders. This method, originally developed by Shapiro (2018), relies on narrower comparisons of stores in regionally similar areas but with different advertising exposures due to their location in distinct DMAs. While our main results are based on the national identification strategy, in this appendix, we present the findings from the border method to demonstrate the robustness of our conclusions.

The border method requires identifying geographic areas that share a border but are in two different advertising markets. We use county-level adjacency data from the US Census (Bureau, 2019) to identify such borders. During this process, we only consider counties in the Nielsen data that have been consistently assigned to the same DMA throughout our study period. In the following two sections, we present the implementation details of the border method and the results of the robustness check on healthcare outcomes and retail products.

H.1 Results for Prescriptions

We employ the border method to identify the effect of advertising on new prescriptions for Chantix, Bupropion, and prescription NRTs. To implement this approach, we identify pairs of MSAs situated along the borders of DMAs, with each MSA residing on opposite sides of the border. We consider the following specification for the border method:

$$\log(O_{bmt} + 1) = \boldsymbol{\beta}^\top \log(\boldsymbol{A}_{\mathcal{D}_m t} + 1) + \gamma_{mY(t)} + \gamma_{\mathcal{S}(t)} + \gamma_{\mathcal{T}(t)} + \gamma_{bq_t} + \epsilon_{bmt}, \tag{A4}$$

where, b denotes the border, and γ_{bq_t} denotes the border-quarter fixed effects. Note that in addition to the fixed effects included in specification (5), this specification also includes border-quarter fixed effects. Including border-quarter fixed effects γ_{bq_t} controls for time-varying demand shocks or confounds at the border level. These fixed effects account for quarterly shifts in demand on both sides of the border, thereby isolating the changes that are more likely attributable to differences in advertising levels on different sides of the border.

We present the findings from 'national' and 'border method' identification strategies in Tables A10, A11, A12 for new Chantix prescriptions, new Bupropion prescriptions, and new NRT prescriptions, respectively. In each table, the first two columns display results from national-level data using the Log-Log and Poisson specifications, while the subsequent two columns present the border method results for both specifications.

For new Chantix prescriptions, across all specifications in Table A10, we find a positive and statistically significant own advertising elasticity for Chantix, supporting the robustness of the effect to the identification strategy. Examining the NRT advertising coefficient, we observe that while the signs are consistent across Log-Log and Poisson specifications, the magnitudes of the effects differ. Importantly, the results of the same specification across different identification strategies (national and border method) remain similar. Furthermore, all other advertising estimates are not statistically different across the specifications ($P < 0.05$). Given the non-trivial proportion of zeros at the MSA-week level for prescriptions, we consider the Poisson specification to be more reliable than the log(1+y) transformation (Chen and Roth, 2024).

For new Bupropion prescriptions, estimated elasticities are not statistically different for each advertising type across different specifications in Table A11 at the $P < 0.05$ level. Lastly, the results for new NRT prescriptions are shown in Table A12. Consistent with the Chantix results, we observe that the effect of NRT advertising in the Log-Log model appears to be systematically smaller than in the Poisson model. However, the signs of the coefficients remain consistent across both specifications. Importantly, for each type of specification (Log-Log or Poisson), the coefficients are not statistically different at the $P < 0.05$ level across national and border method identification strategies. This consistency demonstrates the robustness of our national estimates and supports the validity of our findings across different methodological approaches.

The border strategy, as employed by Shapiro (2018) and Shapiro, Hitsch, and Tuchman (2021), relies on comparing bordering counties, which represent small portions of a DMA. This approach exploits quasi-random variation in advertising exposure, as advertisers optimize for the entire DMA rather than just its borders. However, in our Marketscan data, the smallest geographic unit available is the MSA, which may encompass multiple counties and represent a larger portion of a DMA's population. Using MSAs instead of counties could reintroduce endogeneity concerns, as these larger geographic units might influence advertising decisions and create a correlation between advertising levels and unobserved area characteristics. To mitigate this concern, we refined our analysis following an approach similar to Li, Hartmann, and Amano (2024). We analyzed the population sizes of MSAs residing on advertising borders, calculating the total population for each border with MSAs on both sides. We then focused on smaller borders by performing a median split on total population, excluding borders with large population centers that might be more likely to influence advertising decisions directly.

Table A13 displays the results of this refined border-method strategy for Chantix and Bupropion. Despite the sample sizes shrinking by more than half, the estimates remain similar and not statistically distinguishable from the results using all borders ($P < 0.05$). This consistency across different border subsamples reinforces the robustness of our main findings, providing additional support for our conclusions regarding the effects of Chantix and NRT advertising on prescription drug usage, even when focusing on areas less likely to drive strategic advertising decisions.

Table A10: Comparison of estimation results using reduced-form specification with the border method for new Varenicline (Chantix) prescriptions.

	National		Border Method	
	Log-Log	Poisson	Log-Log	Poisson
$\beta_{Chantix\ Ads}$	**0.0564*****	**0.0735*****	**0.0744*****	**0.0778*****
	(0.0123)	(0.0152)	(0.0171)	(0.0178)
$\beta_{NRT\ Ads}$	-0.0159	**-0.0444*****	-0.0017	**-0.0515*****
	(0.0116)	(0.0148)	(0.0176)	(0.0186)
$\beta_{PSA\ Ads}$	0.0037	0.0050	**0.0097****	0.0034
	(0.0032)	(0.0035)	(0.0040)	(0.0058)
$\beta_{E-Cig\ Ads}$	0.0030	0.0031	-0.0031	-0.0019
	(0.0022)	(0.0029)	(0.0028)	(0.0036)
Observations	143,469	143,365	114,638	114,638
(Pseudo)R^2	0.8260	0.6897	0.8548	0.6946
Adjusted (Ps.) R^2	0.8224	0.6862	0.8491	0.6890
Residual Std. Dev.	0.4288	1.0546	0.4087	1.0576
Residual DF	143,305	143,201	111,703	111,703

Note. – Each column represents the results of estimating a specific specification for the number of new Varenicline (Chantix) prescriptions as outcomes.
Standard errors are two-way clustered at MSA and DMA-year for the national specification and at border-DMA-year and MSA for the border method specification.
All specifications include MSA-year, month, and week-of-year fixed effects. In addition to these fixed effects, the border method specification also includes border-quarter fixed effects.
For the Poisson models, the reported R^2 and Adjusted R^2 are Pseudo R^2 and Adjusted Pseudo R^2 respectively.
Advertising carry-over (δ) is set to 0.9.
$^{\star}: p < 0.1$, $^{\star\star}: p < 0.05$, $^{\star\star\star}: p < 0.01$

Table A11: Comparison of estimation results using reduced-form specification with the border method for new Bupropion prescriptions.

	National		Border Method	
	Log-Log	Poisson	Log-Log	Poisson
$\beta_{Chantix\ Ads}$	**0.0357*****	**0.0360*****	**0.0314****	0.0202*
	(0.0106)	(0.0097)	(0.0128)	(0.0118)
$\beta_{NRT\ Ads}$	**-0.0281****	**-0.0476*****	**-0.0360*****	**-0.0605*****
	(0.0113)	(0.0100)	(0.0131)	(0.0090)
$\beta_{PSA\ Ads}$	0.0028	0.0021	**0.0077****	**0.0086*****
	(0.0030)	(0.0023)	(0.0034)	(0.0031)
$\beta_{E-Cig\ Ads}$	0.0019	0.0029*	-0.0019	0.0008
	(0.0017)	(0.0016)	(0.0021)	(0.0031)
Observations	143,705	143,705	114,670	114,670
(Pseudo)R^2	0.9197	0.8728	0.9405	0.8810
Adjusted (Ps.) R^2	0.9181	0.8718	0.9381	0.8795
Residual Std. Dev.	0.3681	1.1755	0.3260	1.2245
Residual DF	143,541	143,541	111,735	111,735

Note. – Each column represents the results of estimating a specific specification for the number of new Bupropion prescriptions as outcomes.
Standard errors are two-way clustered at MSA and DMA-year for the national specification and at border-DMA-year and MSA for the border method specification.
All specifications include MSA-year, month, and week-of-year fixed effects. In addition to these fixed effects, the border method specification also includes border-quarter fixed effects.
For the Poisson models, the reported R^2 and Adjusted R^2 are Pseudo R^2 and Adjusted Pseudo R^2 respectively.
Advertising carry-over (δ) is set to 0.9.
* : $p < 0.1$, ** : $p < 0.05$, *** : $p < 0.01$

Table A12: Comparison of estimation results using reduced-form specification with the border method for new NRT prescriptions.

	National		Border Method	
	Log-Log	Poisson	Log-Log	Poisson
$\beta_{Chantix\ Ads}$	**0.0212****	**0.1012*****	0.0090	0.0764*
	(0.0093)	(0.0310)	(0.0177)	(0.0460)
$\beta_{NRT\ Ads}$	-0.0048	-0.0232	-0.0025	-0.0174
	(0.0097)	(0.0302)	(0.0152)	(0.0358)
$\beta_{PSA\ Ads}$	**0.0056****	0.0102	0.0062	0.0120
	(0.0025)	(0.0079)	(0.0048)	(0.0126)
$\beta_{E-Cig\ Ads}$	-0.0005	-0.0029	-0.0010	-0.0001
	(0.0019)	(0.0054)	(0.0034)	(0.0078)
Observations	142,949	138,980	114,356	112,397
(Pseudo) R^2	0.6984	0.5372	0.7434	0.5689
Adjusted (Ps.) R^2	0.6922	0.5272	0.7334	0.5551
Residual Std. Dev.	0.3662	0.9143	0.3990	0.9661
Residual DF	142,785	138,816	111,421	109,492

Note. – Each column represents the results of estimating a specific specification for the number of new NRT prescriptions as outcomes.
Standard errors are two-way clustered at MSA and DMA-year for the national specification and at border-DMA-year and MSA for the border method specification.
All specifications include MSA-year, month, and week-of-year fixed effects. In addition to these fixed effects, the border method specification also includes border-quarter fixed effects.
For the Poisson models, the reported R^2 and Adjusted R^2 are Pseudo R^2 and Adjusted Pseudo R^2 respectively.
Advertising carry-over (δ) is set to 0.9.
$^{\star}: p < 0.1$, $^{\star\star}: p < 0.05$, $^{\star\star\star}: p < 0.01$

Table A13: Border method estimation results on prescriptions data from smaller borders that have populations less than the median population of advertising borders when using MSA geographies.

	Varenicline (Chantix)		Bupropion	
	Log-Log	Poisson	Log-Log	Poisson
$\beta_{Chantix\ Ads}$	**0.0809*****	**0.1067*****	0.0353*	**0.0319****
	(0.0212)	(0.0251)	(0.0203)	(0.0137)
$\beta_{NRT\ Ads}$	-0.0100	-0.0509*	-0.0240	**-0.0589*****
	(0.0269)	(0.0293)	(0.0189)	(0.0187)
$\beta_{PSA\ Ads}$	0.0011	0.0038	-0.0055	-0.0109*
	(0.0072)	(0.0080)	(0.0051)	(0.0060)
$\beta_{E-Cig\ Ads}$	-0.0001	-0.0031	-0.0047	-0.0054*
	(0.0039)	(0.0043)	(0.0030)	(0.0029)
Observations	48,078	48,078	48,093	48,093
(Pseudo) R^2	0.7673	0.5618	0.9079	0.8231
Adjusted (Ps.) R^2	0.7559	0.5500	0.9034	0.8198
Residual Std. Dev.	0.4416	1.0503	0.3610	1.1023
Residual DF	46,547	46,547	46,562	46,562

Note. – Each column represents the results of estimating a specific border method specification for one of the outcomes.
Standard errors are two-way clustered at border-DMA-year and MSA.
All specifications include MSA-year, month, week-of-year, and border-quarter fixed effects.
For the Poisson models, the reported R^2 and Adjusted R^2 are Pseudo R^2 and Adjusted Pseudo R^2 respectively.
Advertising carry-over (δ) is set to 0.9.
$^{\star}: p < 0.1$, $^{\star\star}: p < 0.05$, $^{\star\star\star}: p < 0.01$

H.2 Results for Cigarettes, E-Cigarettes, and OTC NRTs

As an alternative to the reduced-form demand model in Equation (6), we estimate the causal effect of advertising using the border method. We implement this method on retail data by focusing on the subset of data from stores reported to be in counties located on the borders between different DMAs throughout the panel, with each border denoted as b. We consider the following specification for this task:

$$\log(Q_{bst} + 1) = \boldsymbol{\beta}^\top \log(\boldsymbol{A}_{\mathcal{D}_s t} + 1) + \alpha \cdot \log(p_{st}) + \gamma_{sY(t)} + \gamma_{\mathcal{S}(t)} + \gamma_{\mathcal{T}(t)} + \gamma_{bq_t} + \boldsymbol{\eta}^\top \boldsymbol{x}_{st} + \epsilon_{bst}. \quad \text{(A5)}$$

Similar to the econometric specification from the previous section on healthcare outcomes, this specification follows its 'national' counterpart (Equation (6)) with the only difference being the introduced border-quarter fixed effects γ_{bq_t}.

The 'national' and 'border method' estimates from this exercise are presented in Table A14 for cigarettes, e-cigarettes, and OTC NRTs. The first column for each product category displays the results of the reduced-form demand specification and the second column showcases the estimated effects from the border method.

Comparing the national estimates to the border method results, we find generally consistent signs across specifications, with most elasticities not statistically different ($P < 0.05$). As we transition from national estimates to border method results, we observe that the effectiveness of Chantix advertising in reducing cigarette sales decreases while its spillover to e-cigarettes and OTC NRTs increases. These changes could be due to differences in the underlying data or the identification strategy. The border method focuses on geographic areas that are at the border of advertising markets, which may have lower insurance coverage or access rates for physicians. Based on our results from Section 7, this could lower the effectiveness of Chantix advertising which is in the same directions as the change we see going from national results to the border method results. Overall, the estimates largely align whether using the reduced-form demand model or the border method, which validates the reliability of our results reported in the main text.

Table A14: Comparison of estimation results using reduced-form specification and border method for cigarette, e-cigarette, and OTC-NRT demand.

	Cigarettes		E-cigarettes		OTC-NRT	
	National	Border Method	National	Border Method	National	Border Method
$\beta_{Chantix\ Ads}$	**-0.0220*****	**-0.0102*****	**0.0514****	**0.0548*****	-0.0046	**0.0147****
	(0.0054)	(0.0027)	(0.0257)	(0.0118)	(0.0077)	(0.0070)
$\beta_{NRT\ Ads}$	-0.0008	-0.0017	-0.0173	**-0.0227****	**0.0166*****	**0.0218*****
	(0.0039)	(0.0023)	(0.0195)	(0.0091)	(0.0056)	(0.0062)
$\beta_{PSA\ Ads}$	0.0019	-0.0018	**0.0145****	0.0050*	**0.0045****	**0.0040****
	(0.0017)	(0.0011)	(0.0060)	(0.0029)	(0.0018)	(0.0017)
$\beta_{E-Cig\ Ads}$	-0.0005	-0.0007	0.0084*	**0.0065****	-0.0017*	0.0002
	(0.0012)	(0.0005)	(0.0051)	(0.0028)	(0.0010)	(0.0014)
α_{price}	**-0.9497*****	**-1.4731*****	**-0.1367****	**-0.1687*****	**-1.3858*****	**-1.2087*****
	(0.1310)	(0.1058)	(0.0617)	(0.0424)	(0.1302)	(0.1937)
$\eta_{Feature}$	**0.0541*****	**0.0508*****	0.3744	0.1135	**0.9602*****	**0.8213*****
	(0.0092)	(0.0124)	(0.2870)	(0.1184)	(0.0388)	(0.0549)
$\eta_{Display}$	**0.1304*****	**0.1059*****	0.4196	**0.8314*****	**0.6904*****	**0.5503*****
	(0.0270)	(0.0124)	(0.3556)	(0.1026)	(0.0701)	(0.0732)
Observations	13,992,417	7,724,855	4,235,960	2,364,919	5,625,872	2,665,664
R^2	0.9616	0.9666	0.7968	0.8107	0.6705	0.6711
Adjusted R^2	0.9608	0.9661	0.7925	0.8071	0.6640	0.6652
Residual Std. Dev.	0.2397	0.2291	0.5662	0.5409	0.6629	0.6539
Residual DF	13,992,250	7,715,995	4,235,793	2,357,950	5,625,705	2,659,694

Note. – Each column represents the results of estimating a specific specification for the demand of a product category.
Standard errors are two-way clustered at DMA-year and store for the national specification and at border-DMA-year and store for the border method specification.
All specifications include store-year, month, and week-of-year fixed effects. In addition to these fixed effects, the border method specification also includes border-quarter fixed effects.
Advertising carry-over (δ) is set to 0.9.
$^{\star}: p < 0.1$, $^{\star\star}: p < 0.05$, $^{\star\star\star}: p < 0.01$

I Placebo Tests for DTCA

One might be concerned that Chantix advertising could be systematically correlated with demographics or insurance coverage at the DMA level, and these confounds could lead to biased coefficients. In this section, we investigate whether Chantix advertising is correlated with demographic variables among individuals taking new Chantix prescriptions or with DMA-level coverage.

To study the correlation with demographic variables, we consider the following specification:

$$X_{pt} = \beta_{ChantixAds} \log(A_{Chantix,\mathcal{D}_{m_p}t} + 1) + \gamma_{m_pY(t)} + \gamma_{\mathcal{S}(t)} + \gamma_{\mathcal{T}(t)} + \epsilon_{pt}, \tag{A6}$$

where X_{pt} is the target variable for prescription record p that happens at time t, which could be the age or sex of the individual taking the prescription or the copayment amount of the transaction. Additionally, the specification has $A_{Chantix,\mathcal{D}_pt}$ the advertising stock measure for Chantix at DMA $\mathcal{D}_p$ in which the prescription is filled and the same set of fixed effects as described in Section 5.

The left panel of Table A15 presents the results of estimating this specification for our target variables age, sex, and copayment. The findings indicate that after controlling for the fixed effects used for our analysis, none of the variables are significantly correlated with the ad stock variable at the $P < 0.05$ level. These results suggest that demographic factors such as age, sex, and copayment are not correlated with changes in advertising exposure.

Table A15: Placebo regressions.

	Prescription level			DMA-year level
	Age	Sex	Copayment	Coverage
$\beta_{\text{Chantix Ads}}$	-0.1850	-0.0029	0.0358	
	(0.1258)	(0.0053)	(0.3735)	
$\beta_{\text{Yearly Chantix Ads}}$				0.0011
				(0.0023)
MSA-year FE	X	X	X	
Monthly FE	X	X	X	
week-of-year FE	X	X	X	
Year FE				X
Observations	786,312	786,312	786,312	1,837
R^2	0.02866	0.01007	0.12669	0.31802
Adjusted R^2	0.02435	0.00567	0.12281	0.31466

Note. – Standard errors are two-way clustered at MSA and DMA-year level for estimations on prescription level data and at DMA level for coverage as the outcome.
Advertising carry-over (δ) is set to 0.9.
$^{\star}: p < 0.1$, $^{\star\star}: p < 0.05$, $^{\star\star\star}: p < 0.01$

Furthermore, our results in Section 7 indicate that the spillover effect of DTCA on product categories varies depending on the accessibility of Chantix through insurance. One concern is that the amount of advertising across different DMAs might be correlated with the portion of the population that has access to the drug through insurance. To test this, we compile data at the DMA-year level, which is the combination of the geographic level at which our advertising data is collected and the temporal level for our measure of access to Chantix through insurance. We then use the following specification to test this:

$$\log(C_{\mathcal{D}Y}) = \beta_{\text{Yearly Chantix Ads}} \log(a_{Chantix,\mathcal{D}Y} + 1) + \gamma_Y + \epsilon_{\mathcal{D}Y}, \tag{A7}$$

where $C_{\mathcal{D}Y}$ is the percentage of individuals who have access to cessation medication through insurance at DMA $\mathcal{D}$ and year Y. For Chantix advertising, we aggregate the GRPs of Chantix at each DMA throughout the year, which we denote as $a_{Chantix,\mathcal{D}Y}$. The specification also includes year fixed effects to absorb the effect of common trends across DMAs throughout the years. The last column of Table A15 presents the estimate for $\beta_{\text{Yearly Chantix Ads}}$. Once again, we do not find any evidence suggesting that Chantix advertising and DMA-level coverage are indeed correlated.

J Effect of Advertising on Mental Health and Substance Abuse Visits

In this section, we examine the impact of advertising on mental health and substance abuse-related outpatient visits and psychotherapy sessions. Our outcome variable captures the number of mental health and substance abuse outpatient office visits and psychotherapy sessions at a specific MSA each week.

The outpatient service data encompasses 25 types of outpatient care received by patients, including office visits, medical tests, diagnostic procedures, surgical interventions, etc. To accurately capture the relevant interactions with healthcare professionals, we focus specifically on outpatient office visits and psychotherapy sessions. To identify individuals with a history of tobacco use, we select those who have ever taken a Chantix or nicotine replacement therapy (NRT) prescription at any point during our study period and analyze outpatient data for this subgroup. However, to avoid counting visits that directly result in cessation medication prescriptions, we exclude visits that were followed by a Chantix prescription record within thirty days after the visit. This procedure leaves us with weekly outpatient visits related to mental health and substance abuse for patients who have a history of tobacco consumption at the MSA level.

The left panel of Table A16 shows the effects of advertising on mental health and substance abuse outpatient visits and psychotherapy sessions. Chantix advertising significantly increases these visits across all specifications, suggesting that DTCA not only affects prescription rates but also encourages individuals to seek professional healthcare services. In contrast, NRT advertising led to a decrease in these visits when using Poisson estimation, indicating that individuals exposed to NRT ads may opt for over-the-counter solutions, bypassing healthcare provider consultations.

J.1 Placebo Test using Emergency Visits

To verify the credibility of our findings regarding office visits, we conducted a placebo test focusing on all emergency visits related to mental health and substance abuse. The rationale behind this test is that emergency visits may not be directly influenced by advertising, as emergency situations arise beyond the control of the patient. Therefore, if we detect any effects, it is indicative that Chantix advertising might be correlated with local shocks or confounds that also lead to higher incidents of issues related to mental health and substance abuse. To measure the outcome of interest, we analyze Marketscan data on mental health and substance abuse MDCs and filter records containing Current Procedure Terminology (CPT) codes for emergency department visits (99281-99285). This filtering yields a dataset comprising more than 2.1 million emergency visits during the study period.

The right panel of Table A16 presents the results of both Log-Log and Poisson specifications. While our primary analysis on office visits related to mental health and substance abuse and psychotherapy sessions indicates a positive and significant effect of Chantix advertising, the results of this placebo test reveal no statistically significant effects on the number of emergency visits for these advertisements. Across both Log-Log and Poisson specifications, the coefficient for Chantix ads fails to reach statistical significance ($P < 0.05$). This finding suggests that Chantix advertising is not likely to be correlated with a confound that is related to the underlying cause or rate at which mental health and substance abuse issues occur.

Table A16: The effect of advertising on visits related to mental health and substance abuse and emergency visits within mental health and substance abuse categories.

	Visits and Psychotherapy Sessions		Emergency Visits	
	Log-Log	Poisson	Log-Log	Poisson
$\beta_{Chantix\ Ads}$	**0.0342****	**0.0362*****	-0.0010	0.0038
	(0.0155)	(0.0112)	(0.0144)	(0.0136)
$\beta_{NRT\ Ads}$	-0.0183	**-0.0257****	0.0081	0.0199
	(0.0138)	(0.0107)	(0.0163)	(0.0132)
$\beta_{PSA\ Ads}$	-0.0018	-0.0017	-0.0057*	-0.0010
	(0.0049)	(0.0026)	(0.0034)	(0.0040)
$\beta_{E-Cig\ Ads}$	-0.0047*	**-0.0046****	-0.0013	0.0017
	(0.0027)	(0.0019)	(0.0022)	(0.0023)
Observations	142,612	142,612	143,151	143,047
(Pseudo) R^2	0.9210	0.8788	0.8209	0.7908
Adjusted (Ps.) R^2	0.9193	0.8777	0.8172	0.7891
Residual Std. Dev.	0.3760	1.0602	0.5307	1.3879
Residual DF	142,448	142,448	142,987	142,883

Note. – Each column represents the results of estimating a specific specification for either the number of mental health and substance abuse visits and psychotherapy sessions or emergency visits as the outcome.
Standard errors are two-way clustered at MSA and DMA-year.
All specifications include MSA-Year, Month, and week-of-year fixed effects.
For the Poisson models the reported R^2 and Adjusted R^2 are Pseudo R^2 and Adjusted Pseudo R^2.
Advertising carry-over (δ) is set to 0.9.
$^{\star}: p < 0.1$, $^{\star\star}: p < 0.05$, $^{\star\star\star}: p < 0.01$

K Controlling for Prices of Adjacent Categories

Another concern is that prices of competing categories might be systematically correlated with promotion strategies and could confound our advertising effects. To address this, we create a price index to control for the prices of adjacent categories when studying the demand for retail products. A challenge in constructing this index is that not all stores sell all three product categories we study: cigarettes, e-cigarettes, and NRTs. To overcome this missing data problem, we develop county-level price indices for each category. We calculate these indexes using the same sample of stores employed in our main regressions. We use revenue-weighted averages to combine store-level price indices into county-level price indices, mirroring the weighting approach used to aggregate prices for products in each category at the store level. For weeks in which none of the stores had any sales in a given category, we used the last available price index for that category to control for its cross-price effect.

We then add these aggregated price indices of categories besides the target category to our main specification as control variables. This allows us to account for potential price-related confounds while estimating the advertising effects. The revised specification is as follows:

$$\begin{aligned}\log(Q_{st}+1) =& \boldsymbol{\beta}^\top \log(\boldsymbol{A}_{\mathcal{D}_s t}+1) + \alpha_{Price} \cdot \log(p_{st}) + \boldsymbol{\alpha}_{Other\ Prices} \cdot \log(\boldsymbol{p}_{Other\ Prices,\mathcal{C}t}) \\ &+ \gamma_{sY(t)} + \gamma_{sY(t)} + \gamma_{\mathcal{S}(t)} + \gamma_{\mathcal{T}(t)} + \boldsymbol{\eta}^\top \boldsymbol{x}_{st} + \epsilon_{st},\end{aligned} \tag{A8}$$

where $\boldsymbol{p}_{Other\ Prices,\mathcal{C}t}$ is a vector of prices containing aggregated prices of the other two categories at county $\mathcal{C}$ and week t, and $\boldsymbol{\alpha}_{Other\ Prices}$ is the vector containing corresponding cross-price elasticities.

Table A17 is the counterpart to Table 6 and displays the estimates for specification (A8). Note that the regressions are estimated on the subsample of data that has aggregated prices of the other two categories available in the same week at the county in which the store resides. The aggregated prices could be missing for a category if the week is outside the date span of store sales data for all of the stores in that county. Hence, the number of observations in these regressions is smaller than the results we showed in Section 6.2. This missing data occurs more frequently for e-cigarettes, especially at the panel's start when they were not yet broadly introduced to the U.S. market. The main results of the effect of advertising on categories of retail products are not affected when price indices for other product categories are included. The only change is a slight reduction in the coefficient for Chantix advertising on e-cigarettes that causes this coefficient to lose its significance at $P < 0.05$ level and become marginally significant at $P < 0.1$. However, the point estimates for this coefficient are pretty close and are not statistically different with and without cross-price controls ($P < 0.05$). This consistency across results shows that our main observations are reliable and are not affected by the prices of alternative categories.

Regarding cross-price elasticities, we can only document a significant cross-price elasticity for the prices of e-cigarettes on cigarette consumption. We see a positive and significant cross-price elasticity of 0.0219 that shows consumers react to changes in e-cigarette prices, and higher e-cigarette prices are associated with higher cigarette consumption. We find no evidence of price effects from other adjacent product categories on demand.

Table A17: The effect of different forms of advertising on demand for cigarettes, e-cigarettes, and NRTs, using the national specification. These specifications also include price indices for adjacent categories. Hence, the estimation uses the sample of data where these price indices are available.

	Cigarettes	E-Cigs	OTC NRTs
$\beta_{Chantix\ Ads}$	**-0.0181*****	0.0473*	0.0026
	(0.0056)	(0.0252)	(0.0062)
$\beta_{NRT\ Ads}$	-0.0011	-0.0217	**0.0223*****
	(0.0039)	(0.0190)	(0.0058)
$\beta_{PSA\ Ads}$	0.0010	**0.0143****	**0.0045****
	(0.0018)	(0.0059)	(0.0018)
$\beta_{E-Cig\ Ads}$	-0.0003	0.0087*	**-0.0028*****
	(0.0012)	(0.0051)	(0.0010)
α_{Price}	**-0.9967*****	**-0.1705*****	**-1.4344*****
	(0.1044)	(0.0591)	(0.1598)
$\alpha_{Cig\ Price}$		-0.0361	0.0386
		(0.1982)	(0.0348)
$\alpha_{E-Cig\ Price}$	**0.0219*****		0.0064
	(0.0080)		(0.0098)
$\alpha_{NRT\ Price}$	0.0169*	0.0357	
	(0.0103)	(0.0297)	
$\eta_{Feature}$	**0.0504*****	0.3744	**0.9287*****
	(0.0092)	(0.2871)	(0.0383)
$\eta_{Display}$	**0.1499*****	0.4254	**0.7051*****
	(0.0565)	(0.3576)	(0.0736)
Observations	12,006,951	4,098,603	5,110,636
R^2	0.9612	0.7966	0.6787
Adjusted R^2	0.9604	0.7923	0.6720
Residual Std. Dev.	0.2385	0.5664	0.6460
Residual DF	12,006,782	4,098,434	5,110,467

Note. – Each column represents the results of estimating the demand of a particular category of products as the outcome variable.
Standard errors are two-way clustered at the store and DMA-year level.
All specifications include store-year, month, and week-of-year fixed effects.
Advertising carry-over (δ) is set to 0.9.
$^{*}: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$

L Model Specification and Results for Heterogeneity Analysis

In Section 7, we analyzed how insurance coverage and healthcare access moderate the impact of DTCA of Chantix on the demand for cigarettes, e-cigarettes, and NRTs. To account for potential confounding factors stemming from geographic differences, we included additional demographic variables in our analysis. These demographic variables are similar to the ones chosen by Shapiro (2018), including income, percentage of males, blacks, Asians, Hispanics, and individuals above 45 years old, that are available in the Public Use Microdata Sample (PUMS) dataset. The estimation specification, including these factors, is:

$$
\begin{aligned}
\log(Q_{st}+1) = {} & \boldsymbol{\beta}^\top \log(\boldsymbol{A}_{\mathcal{D}_s t}+1) \\
& + \beta_{Chantix\ Ads, Coverage} \cdot \log(A_{Chantix, \mathcal{D}_s t}+1) \cdot V_{Coverage, \mathcal{C}_s Y(t)} \\
& + \beta_{Chantix\ Ads, Provider\ per\ Capita} \cdot \log(A_{Chantix, \mathcal{D}_s t}+1) \cdot V_{Provider\ per\ Capita, \mathcal{C}_s Y(t)} \\
& + \beta_{Chantix\ Ads, Income} \cdot \log(A_{Chantix, \mathcal{D}_s t}+1) \cdot V_{Income, \mathcal{C}_s Y(t)} \\
& + \beta_{Chantix\ Ads, PercentMale} \cdot \log(A_{Chantix, \mathcal{D}_s t}+1) \cdot V_{PercentMale, \mathcal{C}_s Y(t)} \\
& + \beta_{Chantix\ Ads, PercentBlack} \cdot \log(A_{Chantix, \mathcal{D}_s t}+1) \cdot V_{PercentBlack, \mathcal{C}_s Y(t)} \\
& + \beta_{Chantix\ Ads, PercentAsian} \cdot \log(A_{Chantix, \mathcal{D}_s t}+1) \cdot V_{PercentAsian, \mathcal{C}_s Y(t)} \\
& + \beta_{Chantix\ Ads, PercentHispanic} \cdot \log(A_{Chantix, \mathcal{D}_s t}+1) \cdot V_{PercentHispanic, \mathcal{C}_s Y(t)} \\
& + \beta_{Chantix\ Ads, PercentAbove45} \cdot \log(A_{Chantix, \mathcal{D}_s t}+1) \cdot V_{PercentAbove45, \mathcal{C}_s Y(t)} \\
& + \alpha_{Price} \cdot \log(p_{st}) + \gamma_{sY(t)} + \gamma_{\mathcal{S}(t)} + \gamma_{\mathcal{T}(t)} + \boldsymbol{\eta}^\top \boldsymbol{x}_{st} + \epsilon_{st},
\end{aligned}
\tag{A9}
$$

where $V_{\cdot, \mathcal{C}_s Y(t)}$ are the z-scored variables for insurance coverage, healthcare providers per capita, and other demographic measures in county $\mathcal{C}_s$ in year $Y(t)$. Additional indexes and parameters in equation (A9) are defined similarly to those in equation (6).

To conserve space in the main text, we focused primarily on insurance coverage and healthcare access. Here, we present the complete regression results, including interaction terms for all demographic variables (Table A18). The results reveal that Chantix advertising is more effective in areas with larger female populations and less effective in areas with higher proportions of black or Hispanic populations. These findings highlight demographic disparities in advertising effectiveness, aligning with previous research on DTCA exposure and effectiveness among racial minorities (Lee and Begley, 2010).

Table A18: Effect of advertising on demand for cigarettes, e-cigarettes, and OTC-NRTs, including interaction terms of Chantix advertising with variables for insurance coverage, healthcare providers per capita, and other demographic measures.

	Cigarettes	E-Cigs	OTC NRTs
$\beta_{Chantix\ Ads}$	**-0.0211*****	0.0281	0.0066
	(0.0060)	(0.0275)	(0.0070)
$\beta_{Chantix\ Ads,Coverage}$	**-0.0124*****	**-0.0232****	**-0.0165*****
	(0.0023)	(0.0093)	(0.0036)
$\beta_{Chantix\ Ads,Provider\ per\ Capita}$	**-0.0031****	0.0095	**-0.0081*****
	(0.0014)	(0.0063)	(0.0024)
$\beta_{Chantix\ Ads,Income}$	-0.0015	0.0108	0.0004
	(0.0019)	(0.0074)	(0.0019)
$\beta_{Chantix\ Ads,PercentMale}$	**-0.0116*****	-0.0163*	**-0.0092*****
	(0.0020)	(0.0086)	(0.0034)
$\beta_{Chantix\ Ads,PercentBlack}$	**0.0057*****	0.0144*	0.0020
	(0.0016)	(0.0087)	(0.0028)
$\beta_{Chantix\ Ads,PercentAsian}$	-0.0005	0.0085*	-0.0024
	(0.0014)	(0.0048)	(0.0015)
$\beta_{Chantix\ Ads,PercentHispanic}$	**0.0074*****	**0.0287*****	**0.0166*****
	(0.0022)	(0.0080)	(0.0032)
$\beta_{Chantix\ Ads,PercentAbove45}$	-0.0004	**0.0187*****	0.0065*
	(0.0021)	(0.0060)	(0.0035)
$\beta_{NRT\ Ads}$	0.0023	-0.0152	**0.0233*****
	(0.0039)	(0.0196)	(0.0057)
$\beta_{PSA\ Ads}$	0.0015	**0.0135****	**0.0037****
	(0.0018)	(0.0062)	(0.0018)
$\beta_{E-Cig\ Ads}$	-0.0005	0.0092*	**-0.0024****
	(0.0012)	(0.0051)	(0.0009)
α_{Price}	**-0.9071*****	**-0.1443****	**-1.3574*****
	(0.1276)	(0.0620)	(0.1387)
$\eta_{Feature}$	**0.0571*****	0.3895	**0.9402*****
	(0.0099)	(0.2921)	(0.0392)
$\eta_{Display}$	**0.1266*****	**1.0541*****	**0.6999*****
	(0.0261)	(0.2828)	(0.0749)
Observations	13,238,144	4,081,884	5,272,118
R^2	0.9609	0.7938	0.6759
Adjusted R^2	0.9602	0.7896	0.6695
Residual Std. Dev.	0.2423	0.5645	0.6534
Residual DF	13,237,969	4,081,709	5,271,943

Note. – Each column represents the results of estimating the effect of advertising on the demand for a particular category of products as the outcome variable.
All standard errors are two-way clustered at the store and DMA-Year level.
All specifications include store-year, month, and week-of-year fixed effects.
Advertising carry-over (δ) is set to 0.9.

* : $p < 0.1$, ** : $p < 0.05$, *** : $p < 0.01$

M Passing Saving on DTCA Limitations as Price Reductions

In this section, we outline the data sources and methodology employed in our back-of-the-envelope analysis comparing the effectiveness of direct-to-consumer advertising (DTCA) and price reductions for the prescription drug Chantix. Our analysis uses Marketscan prescription history records, along with other public records, to assess the impact of these marketing strategies on prescription demand.

We divide the Chantix market into two segments: individuals with insurance coverage for Chantix and those without such coverage. To estimate the total number of Chantix prescriptions in the insured segment, we rely on Marketscan's 2019 prescription data, which includes prescription drug usage for 23,665,354 individuals in the United States. According to the data, a total of 8,225,920 milligrams of Chantix were prescribed to individuals in this dataset.

To generalize this to the broader insured U.S. population, we use our measure of access to Chantix through insurance, constructed from PUMS data. In 2019, 90.7% of the U.S. population (approximately 297.8 million individuals) had access to Chantix through health insurance. Based on this, we estimate that the total volume of Chantix prescriptions for the insured population was approximately 103.5 million milligrams. This estimate assumes that the prescription rate observed in the Marketscan data is representative of the entire insured population. Marketscan also reports the total cost of each Chantix prescription, including copayment and the amount paid by insurance, which in 2019 averaged $8.27 per milligram. To estimate the volume of Chantix purchased by individuals without insurance, we integrate our estimates with quarterly reports from Pfizer, the manufacturer of Chantix (Pfizer, 2021). According to Pfizer's 2019 report, annual sales of Chantix amounted to $899 million. Combining this with the average price of Chantix provides an estimate of 108.7 million milligrams sold, of which 5.19 million milligrams were sold to individuals without insurance.

For the advertising analysis, reports from 2019 (Snyder Bulik, 2020) indicate that Pfizer spent $197.4 million on Chantix advertising. We explore the potential impact on demand if the company reallocated a portion of its advertising budget to price reductions. Specifically, we examine the effect of a hypothetical 10% reduction in the advertising budget. Based on our regression estimates from Table 5, this 10% reduction in advertising would decrease demand for Chantix in the insured segment by at least about 0.5%. However, reallocating this 10% reduction towards lowering the price of the drug could increase the demand. The reallocation result in a 2.2% price reduction, which would primarily impact demand among individuals without insurance, as those with insurance typically face a low copayment for the drug. Assuming a price elasticity of 1 for uninsured individuals, this would lead to a 2.24% increase in demand for uninsured population, equivalent to an additional 116,461 milligrams of Chantix. On the other hand, the reduction in demand from the insured segment would result in a decrease of 522,121 milligrams. Therefore, with a price elasticity of 1, maintaining the advertising expenditure generates higher overall drug usage. To reach a breakeven point where reallocating the advertising budget to price reductions becomes equally effective, the price elasticity would need to exceed 4.3, which represents a high elasticity level for prescription drugs (Duggan and Morton, 2010; Goldman, Joyce, and Zheng, 2007). Note that these calculations do not account for the impact of reduced advertising on uninsured individuals. If advertising affects this group similarly, a decrease in advertising would result in a larger overall reduction in demand. Consequently, the estimated price elasticity of 4.3 should be considered a conservative lower bound.

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