A Fixed Effects Regressions using All Counties

As a comparison to the border strategy results, in this appendix I estimate regressions using data from all counties (border and non-border) in the top 100 DMAs. The unit of observation in this analysis is a county-week, and I include county fixed effects and common week fixed effects. If firms target advertising as a function of market and time varying unobservables, these regressions could suffer from an endogeniety bias. Comparing the border strategy ad elasticities in Table 4 with the fixed effects elasticities in Table A1, the elasticities from the fixed effects regressions appear to have a slight positive bias. Relative to the border strategy analysis, the fixed effects regressions estimate a larger positive effect of e-cigarette advertising on e-cigarette demand and a positive but not statistically significant effect of e-cigarette ads on cigarette demand. These patterns are consistent with firms advertising more in markets during periods of relatively high demand.

Table A1: Fixed Effects Regression Results

	(1) E-Cig Cartridges	(2) Cigarette Packs	(3) Nicotine Patches	(4) Nicotine Gum
E-Cigarette Log Ads	15.49*	39.60	-3.893**	-16.23
	(8.835)	(58.15)	(1.916)	(25.44)
Smoking Cessation Log Ads	-4.594**	26.15	-	-
	(1.868)	(19.58)	-	-
Nicotine Patch Log Ads	-	-	-0.224	-44.27
	-	-	(1.948)	(28.59)
Nicotine Gum Log Ads	-	-	1.088	-20.81
	-	-	(0.835)	(16.89)
Price E-Cigarette Cartridge	-5.273***	16.37*	-0.159	1.265
	(0.968)	(8.342)	(0.106)	(3.028)
Price Cigarette Pack	1.271	-2,225**	5.730***	-217.7
	(37.83)	(941.2)	(1.603)	(140.2)
Price Nicotine Patch	-5.559***	4.302	-14.89***	-119.6***
	(1.647)	(14.57)	(2.296)	(20.44)
Price Nicotine Gum	-44.71***	163.1	-18.42***	-1,068***
	(12.04)	(114.7)	(5.638)	(123.8)
County FE	Y	Y	Y	Y
Week FE	Y	Y	Y	Y
N Obs	324,865	324,865	324,865	324,865
E-Cigarette Ad Elasticity	0.09	0.003	-0.04	-0.004

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B Common Trends Sensitivities

Recall that the difference-in-differences identification strategy relies on the assumption that sales in bordering markets would follow a parallel trend in the absence of differences in treatment. In this section, I re-estimate the descriptive difference-in-differences regressions, restricting to the subsample of markets that have a correlation in weekly cigarette sales in 2010 above $\rho = 0.5$. This is the set of border markets that most closely satisfy the parallel trends assumption in the year before e-cigarettes were first advertised on TV. As shown in Table A2, the effect of e-cigarette advertising is directionally consistent and the magnitude of the effect increases relative to the estimates for the full sample.

Table A2: Difference in Differences Regression Results for the Restricted Sample

	(1) E-Cig Cartridges	(2) Cigarette Packs
E-Cigarette Log Ads	85.40***	-1,546***
	(13.50)	(387.6)
Smoking Cessation Log Ads	-12.27*	-90.92
	(6.253)	(111.9)
Price Controls	Y	Y
DMA-Border FE	Y	Y
Week-Border FE	Y	Y
N Obs	32,222	32,222
E-Cigarette Ad Elasticity	0.16	-0.04

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Price controls include prices of e-cigarettes, tobacco cigarettes, and smoking cessation products.

C Placebo Test

As an additional robustness check, I conduct a placebo test where I regress e-cigarette and tobacco cigarette sales on TV advertising GRPs for Angel Soft toilet paper.[1] As expected, I find no economically or statistically significant relationship between cigarette sales and advertising for this seemingly unrelated product.

Table A3: Placebo Difference in Differences Regression Results

	(1) E-Cig Cartridges	(2) Cigarette Packs
Angel Soft Log Ads	-4.68	59.9
	(5.11)	(105.7)
Price Controls	Y	Y
DMA-Border FE	Y	Y
Week-Border FE	Y	Y
N Obs	48,968	48,968

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Price controls include prices of e-cigarettes, tobacco cigarettes, and smoking cessation products.

[1] I was able to obtain data on Angel Soft advertising from 2011–2014, so this regression is on a slightly smaller sample.

D Sensitivity to Changes in Cigarette Excise Taxes

The identification section discussed the fact that changes to cigarette excise taxes could pose a threat to my identification strategy. To check the sensitivity of the results to this potential omitted variable, I tried dropping observations for DMA borders located in states that increased their cigarette excise tax during the period 2011–2015 (Campaign for Tobacco-Free Kids (2017)). I consider two procedures. First, I drop observations for border-weeks corresponding to years and states with excise tax changes. Specifically, I drop all observations for the year in which the border's tax change occurred. Almost all tax changes occurred in June, July, or August, so this procedure would take care of any correlations between advertising and sales leading up to and following the tax change. In the event of a tax change in January, I drop observations for the preceding year too. These results are shown in columns 1 and 2 in Table A4. Second, I drop all observations for all borders that are located within a state that ever changed its cigarette excise tax between 2011–2015. The results are presented in columns 3 and 4. The estimates are consistent with the full sample results shown in Table 4 and if anything, the ad effects are larger in this restricted sample. These results indicate that the estimates for the full sample do not seem to be driven by changes in excise taxes.

Table A4: Sensitivity to Excise Tax Changes

	(1)	(2)	(3)	(4)
	E-Cig Cartridges	Cigarette Packs	E-Cig Cartridges	Cigarette Packs
E-Cigarette Log Ads	34.08***	-647.1***	56.77***	-1,021***
	(6.063)	(246.8)	(7.921)	(317.1)
Smoking Cessation Log Ads	-0.183	38.84	-4.374	72.64
	(3.935)	(61.95)	(4.598)	(73.87)
Price Controls	Y	Y	Y	Y
DMA-Border FE	Y	Y	Y	Y
Week-Border FE	Y	Y	Y	Y
N Obs	54,850	54,850	36,151	36,151
E-Cig Ad Elasticity	0.09	-0.03	0.15	-0.04

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

E Border Sample Demographics

Two questions arise with respect to the profile of border markets. First, are bordering markets similar on observed demographics? Market fixed effects in the model control for any time invariant differences across bordering markets, but to the extent that ad-sensitivity could be a function of demographics, it is informative to compare demographics for bordering markets. Second, how do border counties compare to the larger DMAs in which they are located? This second question relates to the generalizability or external validity of the estimates. If the demographics of the individuals living in border markets are similar to the general population, then it may be reasonable to think that the causal effect of e-cigarette advertising estimated on the border sample can be extrapolated when making policy decisions.

E.1 Comparison of Bordering Markets

In order to check whether neighboring markets are similar on observed demographics, I calculate border market level demographics by taking the population-weighted average of county-level U.S. census data. For each characteristic I calculate the absolute deviation for each pair of bordering markets and normalize this statistic by the standard deviation of that characteristic across all 282 border markets.[2] The resulting statistic measures the distance in standard deviations between bordering markets. The distributions of these statistics are reported in Table A5. The median pair of bordering markets is within less than half of a standard deviation of each other for most characteristics.

Table A5: Normalized Absolute Deviations in Demographics Across Bordering Markets

	N	Min	Median	Mean	Max
Percent Female	141	0.00	0.71	0.92	5.08
Percent Population Under 18	141	0.00	0.60	0.81	3.63
Percent HS Diploma	141	0.01	0.43	0.60	3.42
Percent White	141	0.00	0.34	0.52	2.74
Percent Black	141	0.01	0.18	0.38	2.60
Per Capita Income	141	0.00	0.41	0.65	4.47
Population Per Square Mile	141	0.00	0.17	0.48	8.06

[2] Absolute deviation in characteristic x for markets i and $j = |x_i - x_j|$. Normalized absolute deviation calculated as $\frac{|x_i - x_j|}{\sigma_x}$.

E.2 Comparison of Border Markets to Non-Border Markets

I compare county-level demographics for border counties to the demographics of non-border counties. The results in Table A6 show that the population of border counties is on average slightly older, less educated, and lower income. Border counties have a lower share of black residents and a lower population density than non-border counties.

Table A6: Average Characteristics in Border and Non-Border Markets

	Border Counties	Non-Border Counties	*p* value
Percent Female	50.18	50.07	0.217
Percent Population Under 18	22.11	22.82	0.000
Percent HS Diploma	83.25	85.35	0.000
Percent White	86.32	84.91	0.037
Percent Black	8.95	10.17	0.056
Per Capita Income	23,085	24,582	0.000
Population Per Square Mile	167.0	524.1	0.000
N Counties	847	1,130	

F Sensitivities to Advertising Stock Carry-Over Rate

This appendix considers the robustness of the results to allowing for the effect of past advertising on current sales. Specifically, I replace current period advertising a_{mt} in equation 1 with a discounted cumulative stock of advertising $A_{mt} = \sum_{\tau=t-52}^{t} \delta^{t-\tau} a_{m\tau}$. Tables A7 and A8 report results for various advertising carry-over parameters δ. Note, column 1 with $\delta = 0$ corresponds to the specification reported in Table 4. For both e-cigarettes and tobacco cigarettes, the implied elasticities are quite consistent across specifications for the models with $\delta \leq 0.6$. The models with $\delta = 0.9$ differ, though the models with $\delta = 0.9$ have a higher root-mean squared error, indicating worse model fit. Based on these analyses, the estimated elasticities reported in Table 4 appear robust to allowing for the effect of past advertising on current sales.

An alternative approach to modeling past ad effects would be to include current and lagged advertising separately. The correlation between current and lagged e-cigarette advertising is high ($\rho = 0.89$), making it hard to separately identify the effects of current and lagged ads. The ad stock model shown in this appendix is frequently used in the literature because it serves as a parsimonious way to capture the combined effect of current and past advertising.

Table A7: E-Cigarette Regressions by Ad Stock Carry-Over Rate δ

	(1) E-Cigarette Cartridges ($\delta = 0$)	(2) E-Cigarette Cartridges ($\delta = 0.3$)	(3) E-Cigarette Cartridges ($\delta = 0.6$)	(4) E-Cigarette Cartridges ($\delta = 0.9$)
E-Cigarette Log Ad Stock	29.77**	37.05***	32.82***	1.162
	(5.644)	(6.072)	(5.593)	(7.147)
Smoking Cessation Log Ad Stock	-6.005	-3.976	-6.406	-20.54
	(4.473)	(5.615)	(8.759)	(23.13)
Price E-Cigarette Cartridge	-8.166***	-8.166***	-8.138***	-8.131***
	(0.988)	(0.988)	(0.987)	(0.985)
Price Cigarette Pack	86.98***	87.35***	87.57***	87.25***
	(12.24)	(12.24)	(12.24)	(12.18)
Price Nicotine Patch	7.013***	6.979***	6.944***	7.043***
	(1.980)	(1.981)	(1.982)	(1.982)
Price Nicotine Gum	-25.23**	-24.96**	-25.14**	-26.53**
	(12.12)	(12.12)	(12.11)	(12.09)
Observations	63,952	63,952	63,952	63,952
RMSE	213.18	213.16	213.17	213.26
Market FE	Y	Y	Y	Y
Week-Border FE	Y	Y	Y	Y
E-Cigarette Ad Elasticity	0.08	0.10	0.09	0.003

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A8: Cigarette Regressions by Ad Stock Carry-Over Rate δ

	(1) Cigarette Packs ($\delta = 0$)	(2) Cigarette Packs ($\delta = 0.3$)	(3) Cigarette Packs ($\delta = 0.6$)	(4) Cigarette Packs ($\delta = 0.9$)
E-Cigarette Log Ad Stock	-631.7***	-791.9***	-773.5***	101.3
	(217.4)	(245.9)	(238.6)	(198.9)
Smoking Cessation Log Ad Stock	-28.19	167.8	416.6*	285.9
	(83.81)	(132.7)	(238.8)	(649.1)
Price E-Cigarette Cartridge	68.48***	68.28***	67.58***	68.10***
	(10.89)	(10.89)	(10.88)	(10.85)
Price Cigarette Pack	-10,128***	-10,134***	-10,140***	-10,124***
	(826.5)	(826.6)	(826.8)	(828.3)
Price Nicotine Patch	-47.87	-47.48	-46.94	-48.88
	(38.28)	(38.31)	(38.32)	(38.20)
Price Nicotine Gum	87.47	83.29	84.30	118.8
	(255.2)	(255.5)	(255.5)	(254.6)
Observations	63,952	63,952	63,952	63,952
RMSE	5207.68	5207.09	5207.03	5209.06
Market FE	Y	Y	Y	Y
Week-Border FE	Y	Y	Y	Y
E-Cigarette Ad Elasticity	-0.02	-0.03	-0.03	0.004

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

G Household-Level Regressions with Prices and Advertising

This appendix explores the robustness of the household-level regressions to including controls for current prices and advertising. Because I only observe prices paid by households when they make a purchase and I don't have any household-level ad exposure data, I bring in price and advertising data from the aggregate data by merging on average prices in each household's county and ad GRPs for each household's DMA. The results are shown in Table A9. Notably, the coefficients on the lagged purchase dummies are very consistent with the coefficients in the more parsimonious model reported in Table 5.

Table A9: Household Addiction and Substitution Patterns Between Cigarettes and E-Cigarettes

	Cig Purchase Incidence	E-Cig Purchase Incidence
Cigarette Purchase in Previous Week	0.080***	-0.001***
	(0.003)	(0.0002)
E-Cig Purchase in Previous Week	-0.034***	0.140***
	(0.008)	(0.012)
Nicotine Gum Purchase in Previous Week	-0.033***	0.002
	(0.010)	(0.003)
Nicotine Patch Purchase in Previous Week	-0.053***	-0.001
	(0.013)	(0.002)
E-Cigarette Log Ads	0.0002	0.0003*
	(0.001)	(0.0002)
Smoking Cessation Log Ads	-0.002	2.92e-05
	(0.001)	(0.0002)
Price Cigarette Pack	-0.005***	-0.0003
	(0.002)	(0.0002)
Price E-Cigarette Cartridge	0.0002	3.6e-05
	(0.0002)	(2.7e-05)
Price Nicotine Gum	-0.002	-0.0003
	(0.006)	(0.0009)
Price Nicotine Patch	0.0005	7.36e-05
	(0.0006)	(9.79e-05)
HH FE	Y	Y
Week FE	Y	Y
N Observations	3,261,333	3,261,333
N HHs	21,808	21,808
N E-Cigarette HHs	2,145	2,145
Mean DV	0.132	0.002
Mean DV if E-Cig Buyer	0.242	0.019
Last Week Cig as % of DV	60.5%	-51.3%
Last Week E-Cig as % of DV for E-Cig Buyers	-13.8%	738.9%

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Magnitude of change post e-cigarette reported as percent of average DV for those households who ever purchase an e-cigarette. E-cigarette users are on average heavier smokers than non e-cigarette users. The average weekly cigarette purchase incidence for e-cigarette users is 0.24 and for non e-cigarette users is 0.12. Standard errors clustered at the household level.

H Model Simulations

I carry out a simulation exercise to illustrate the model's ability to recover the parameters of interest. The steps of the simulation are described below.

In each period consumers decide whether to smoke cigarettes ($c = 1$) or not ($c = 0$). Addiction is captured by allowing today's consumption decision to be related to the consumption state in the previous period through the parameter γ. I assume the following data generating process at the individual level.

$$u_{ict} = \beta_i + \alpha p_t + \phi a_t^e + \gamma \mathbb{I}(c_{it-1} = 1) + \xi_t + \varepsilon_{ict} \tag{1}$$

$$u_{i0t} = 0 + \varepsilon_{i0t} \tag{2}$$

Consumers are assumed to be heterogenous in their preference for cigarettes. The distribution of product intercepts β_i is assumed to be normal, with mean $\bar{\beta}$ and variance σ^2. The parameters of interest are the "linear" parameters $\theta_1 = (\bar{\beta}, \alpha, \phi)$ and "non-linear" parameters $\theta_2 = (\sigma, \gamma)$. Consistent with the full model, I include unobserved aggregate demand shocks in the simulation. In a first simulation, I assume that ξ_t is normally distributed and e-cigarette advertising is uncorrelated with the aggregate demand shocks. In a second simulation, I assume $\xi_t = \beta_t + \eta_t$ can be decomposed into a component β_t that varies systematically over time and a component η_t that is normally distributed. In order to illustrate the joint model's ability to account for endogeneity using the aggregate data, I assume that demand for cigarettes is decreasing over time ($\beta_t \geq \beta_{t+1}$) and advertising is increasing over time such that $Corr(a_t^e, \xi_t) < 0$, making advertising endogenous. Finally, I assume the ε shocks are distributed type 1 extreme value. The model-predicted aggregate market share of cigarettes is given by equation 3.

$$s_{ct} = \int_{\Theta \times \{0,1\}} \pi_{it}(c \mid k) dF_t(\theta, k) \tag{3}$$

In estimation, I approximate the distribution of heterogeneity with $R = 100$ draws from the standard normal distribution $\nu_r \sim N(0, 1)$ s.t. $\beta_r = \bar{\beta} + \sigma \nu_r \sim N(\bar{\beta}, \sigma^2)$ and evaluate the integral in equation 3 using Monte Carlo integration.

I simulate purchase decisions for 10,000 consumers in each of $T = 150$ periods. Aggregate market shares in each period are calculated using the full set of households. A 1% random sample of households makes up the household-level dataset used for estimation. I estimate the model parameters (i) via maximum likelihood using only the household data and (ii) using the joint estimation procedure and both the aggregate and household datasets. I include time fixed effects that control for the endogeneity of advertising in the final linear regression step in the joint estimation procedure. Because of the parameter proliferation problem, including these fixed effects in the household model is intractable. I carry out the simulation $NS = 1,000$ times and compare the results across models.

As shown in Table A10 and Figures A1 and A2, both estimation procedures perform quite well in recovering the “non-linear" model parameters $\theta_2 = (\sigma, \gamma)$. In the simulation with exogenous advertising, the joint procedure is more efficient in recovering the “linear" model parameters $\theta_1 = (\bar{\beta}, \alpha, \phi)$ because it incorporates the full information contained in the aggregate data. In the simulation with endogenous advertising, the joint procedure recovers an unbiased estimate of the advertising coefficient, while the model using only household data recovers biased estimates because of the persisting advertising endogeneity.

Table A10: Model Simulation Results

		Exogenous Ads		Endogenous Ads	
	True Values	HH ML	Joint Est	HH ML	Joint Est
$\bar{\beta}$	-0.5	-0.4844	-0.4999	-0.6968	-0.4967
		(0.2941)	(0.1810)	(0.3206)	(0.1819)
α	-0.6	-0.5982	-0.6009	-0.6358	-0.6012
		(0.0957)	(0.0536)	(0.1054)	(0.0538)
ϕ	-0.02	-0.0200	-0.0201	-0.0212	-0.0201
		(0.0020)	(0.0010)	(0.0022)	(0.0010)
σ	0.2	0.1881	0.1927	0.1763	0.1899
		(0.0488)	(0.0495)	(0.0656)	(0.0624)
γ	1.75	1.7428	1.7562	1.8073	1.7554
		(0.0653)	(0.0724)	(0.0819)	(0.0905)

Figure A1: Distribution of Estimates in Simulation w/ Exogenous Ads

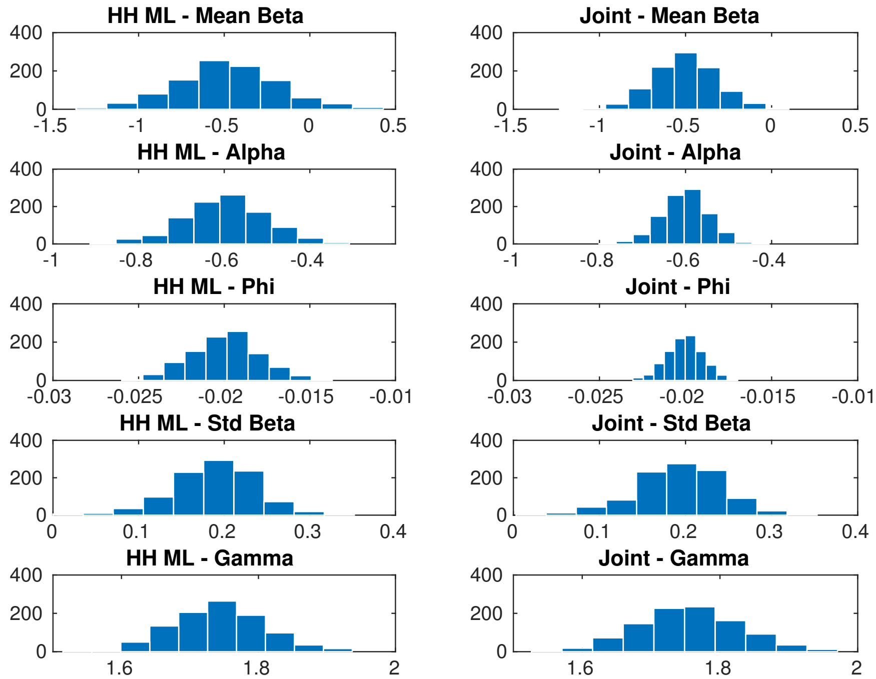
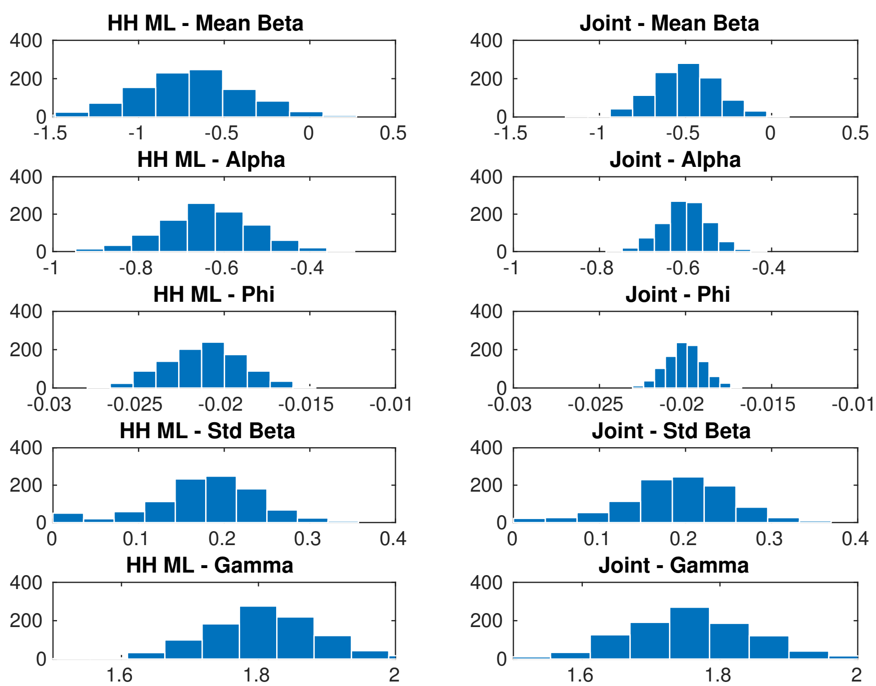


Figure A2: Distribution of Estimates in Simulation w/ Endogenous Ads



I Data Appendix

I.1 Aggregate Price Series Construction

A market-level price series is constructed for packs of cigarettes, refill cartridges / disposable e-cigarettes, and smoking cessation products. In each case, the price is constructed on a per unit basis, where a unit is a pack of cigarettes, a single cartridge / disposable e-cigarette, and a single piece of nicotine gum or a single nicotine patch. The price series is calculated as the quantity-weighted price of products across all UPCs and stores in a given market.

In the structural model, I further aggregate the two types of smoking cessation products together because both products have small market shares. Here, I define an equivalent unit for nicotine gum as 10 pieces of gum and for nicotine patches as a single patch because these quantities yield roughly the equivalent nicotine content to a single pack of cigarettes. Thus, I calculate the aggregate market share for smoking cessation products as the total number of nicotine patches sold plus 0.1 times the number of pieces of gum sold, divided by the market size. The aggregated smoking cessation price series is computed as the price for such an equivalent unit, and the aggregation is again carried out using quantity sales as weights.

I.2 Rationalizing Multiple Purchases with Discrete Choice

In some cases, a household will buy multiple different products from the choice set or multiple units of a given product in a given period. The former case happens very infrequently in the household-level data: a purchase of multiple different inside goods occurs in only 0.4% of weeks that have a purchase. In the estimation dataset, I create duplicate entries for those weeks, one for each inside good that was purchased. If both an e-cigarette and a tobacco cigarette were purchased in the same week, I randomly set the state variable to either the e-cigarette or the tobacco cigarette state for the following week's observation, since it is inconsistent for a household to be in both states at once. If a consumer buys both a smoking cessation product and either an e-cigarette or a tobacco cigarette in the same week, I again create duplicate entries for those weeks, one recording each purchase. For the following week's observation, I set the state variable to the cigarette product that was purchased in the previous week.

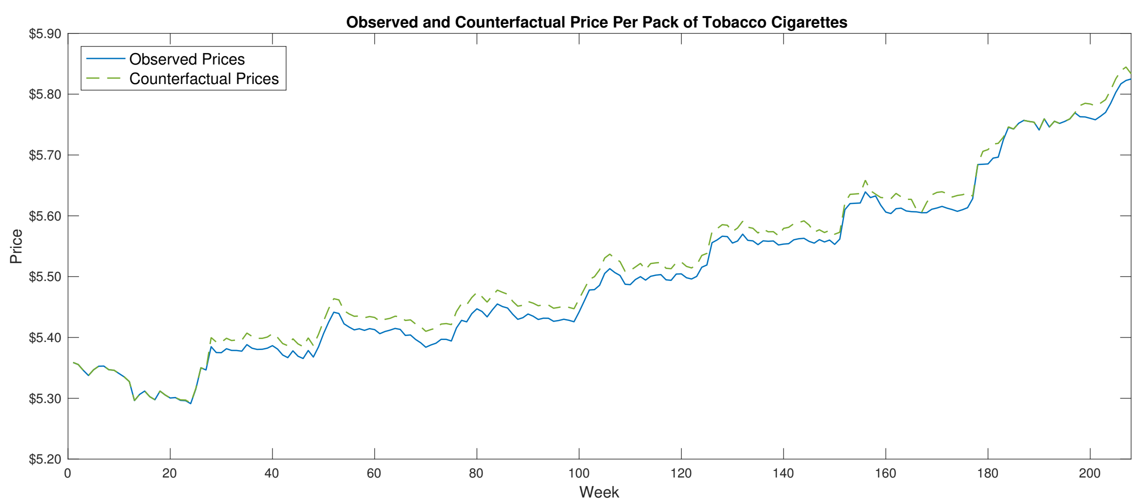
In the weekly household data, a single pack of tobacco cigarettes is purchased in 11% of weeks in which at least one pack was purchased. This suggests that it is common for smokers to purchase more than one pack in a week. In the structural model, I abstract away from quantity and focus on incidence – whether at least one unit was purchased. Thus, a household that buys one or more packs of cigarettes in a given week is recorded as having purchased a tobacco cigarette product that week. In the aggregate data, I cannot observe how many consumers purchased in a given store-week. This is a standard challenge when working with aggregate data. The discrete choice model essentially thinks of each unit in the aggregate data as being purchased by a single consumer. Thus, the sale of 10 packs of cigarettes in a given week would imply that there are 10 "addicted" consumers in that market for the next period. I model households' purchase incidence rather than purchase quantity because the aggregate data is necessary to measure ad effects, but models of purchase quantity require strong assumptions to make the models tractable with aggregate data.

J Counterfactual Prices

This appendix first explains how I predict counterfactual prices and then discusses how reasonable these counterfactual prices are. First, under the assumption that observed prices are set optimally, I infer marginal costs given the observed prices, market shares, and price sensitivity parameter α. A limitation of this analysis is that tobacco cigarette price elasticities are predicted to be inelastic (between -1 and 0) in many markets, which can lead to negative marginal cost estimates. This is a problem that previous researchers have resolved by either i) adding supply-side moments that require marginal costs to be positive and thus force demand to be more elastic or ii) specifying a dynamic model that can justify why firms might set low prices. The first approach is not well-suited to my estimation procedure that utilizes maximum likelihood as opposed to GMM and the latter approach would add significant complexity to this robustness check. Balancing these trade-offs, I move forward with the static supply side model and think of the negative marginal cost estimates as costs that are adjusted for discounted future revenue streams. Given the estimated costs for all three products, I then solve for the new prices that would maximize profits when e-cigarette ads are banned. I compare the resulting counterfactual prices to the observed prices and find that the predicted change in prices is small. Below I discuss how credible the resulting predicted prices are.

Figure A3 plots the observed and counterfactual average price of a pack of cigarettes, where the simple average is taken across all markets. The blue line in the graph shows the observed prices and the dashed green line shows the predicted counterfactual prices.

Figure A3: Observed and Counterfactual Average Price Per Pack of Tobacco Cigarettes



First looking at the observed price series, there are clear price increases that occur roughly twice a year. These correspond to manufacturers' bi-annual changes to wholesale prices. During the four year counterfactual period (2012–2015), Altria increased cigarette list prices 8 times.[3] Each increase was either 6 or 7 cents per pack. When Altria announced list price increases, Reynolds and Lorillard typically responded within a couple of days by raising their wholesale prices by a similar amount. The graph shows that these list price increases were largely passed on to consumers at the point of sale.

Turning to the counterfactual price series in green, the supply-side analysis predicts that the price of cigarettes would have been on average 1.6 cents higher if there were no e-cigarette advertising on TV. In evaluating whether the magnitude of the difference between counterfactual and observed prices seems reasonable, cigarette pricing before e-cigarettes gained popularity can serve as a point of comparison. The observed wholesale price increases in 2010–2011 were 1 to 2 cents larger than the observed wholesale price increases between 2012–2015.[4] The slightly higher counterfactual prices would thus be consistent with the observed pricing behavior in the period before e-cigarette advertising became prevalent. These additional facts suggest that the predicted counterfactual prices are reasonable.

The counterfactual predicts that the average price of smoking cessation products would have been slightly higher in the absence of e-cigarette advertising, but the maximum predicted price increase is less than 0.5 cents per unit. The observed average price for a unit of cessation product (1 patch or 10 pieces of gum) was about 4 cents lower in 2012 (after e-cigarette advertising picked up) compared to an average price of $4.26 in 2010–2011. Thus, the counterfactual suggests that only a small part of the observed price decrease was driven by e-cigarette advertising.

It is harder to evaluate how credible the predicted counterfactual prices are for e-cigarettes because there is very little data on e-cigarette prices in the absence of e-cigarette advertising. However, the directional prediction that counterfactual e-cigarette prices would be lower than observed prices seems credible.

[3] Price increases went into effect on 6/18/2012, 12/3/2012, 6/10/2013, 12/1/2013, 5/11/2014, 11/16/2014, 11/16/2014, 5/17/2015, and 11/15/2015.

[4] Altria increased their list prices by 8 cents on 5/10/2010 and 12/6/10, by 9 cents on 7/8/11, and by 5 cents on 12/12/11. All 8 observed list price increases between 2012–2015 were either 6 cents or 7 cents.

References

Campaign for Tobacco-Free Kids (2017). Cigarette tax increases by state per year 2000-2017.