Advertising, Habit Formation, and U.S. Tobacco Product Demand

Yuqing Zheng, Chen Zhen, James Nonnemaker, and Daniel Dench

The U.S. tobacco market has experienced a shift toward noncigarette tobacco products. We examined the degree of habit formation and the role of advertising for cigarettes, little cigars/cigarillos, large cigars, e-cigarettes, and smokeless tobacco using market-level scanner data for convenience stores from 2009 to 2013. Results based on a dynamic demand system show that while all tobacco products are habitual, e-cigarettes are the most habitual product. More choices of flavors, less restrictions on its use in public places, less documented harmful effects, and a higher upfront cost might explain the higher degree of habit formation for e-cigarettes. We also find that e-cigarettes did not substitute for or complement cigarettes. The results imply that e-cigarettes may serve as a gateway to nicotine addiction but not necessarily to cigarette smoking. Regarding advertising, cigarette magazine advertising did not affect cigarette demand, while e-cigarette TV advertising increased e-cigarette demand with a positive spillover to cigarette demand. Such results may help explain e-cigarettes' recent success in sales and imply that e-cigarette TV advertising might undermine efforts to reduce cigarette smoking. Advertising was also found to affect the degree of habit formation for cigarettes, large cigars, and e-cigarettes.

Key words: Advertising, cigar, cigarette, cigarillo, e-cigarette, electronic cigarette, electronic nicotine delivery system, habit formation, smokeless tobacco.

JEL codes: D12, I18, M37.

The U.S. tobacco market has experienced a shift toward noncigarette tobacco products in the most recent decade. The introduction of e-cigarettes (also called electronic cigarettes or electronic nicotine delivery systems) may further accelerate this shift. Figure 1 presents the value of shipments for cigarettes versus noncigarette tobacco products—including cigars, cigarillos, chewing tobacco, snuff, dissolvables, pipe tobacco, roll-your-own tobacco, and e-cigarettes—for 2000 through 2013. During this period, the value of shipments for cigarettes declined from $41.6 billion to $31.4 billion. However, the value of shipments for noncigarette tobacco products increased from $4 billion to $7.7 billion, mainly driven by larger shipments in chewing and smoking tobacco, and in the most recent years by the introduction of e-cigarettes. As a result, the market share of noncigarette tobacco products has increased from 9% to 20%.

E-cigarettes deliver nicotine-containing aerosol and are rapidly gaining in popularity (Pepper and Brewer 2014), but are also encountering more controversies over their health effects, relationship to smoking, and regulation. E-cigarettes are marketed as healthier alternatives to tobacco smoking. However, very little is known about the potential health benefits or harms of e-cigarettes (Benowitz and Goniewicz 2013). Some recent research shows that e-cigarette emissions are not merely harmless water vapor and can cause and/or worsen respiratory diseases (Grana, Benowitz, and Glantz 2014). To further increase the urgency of the issue,

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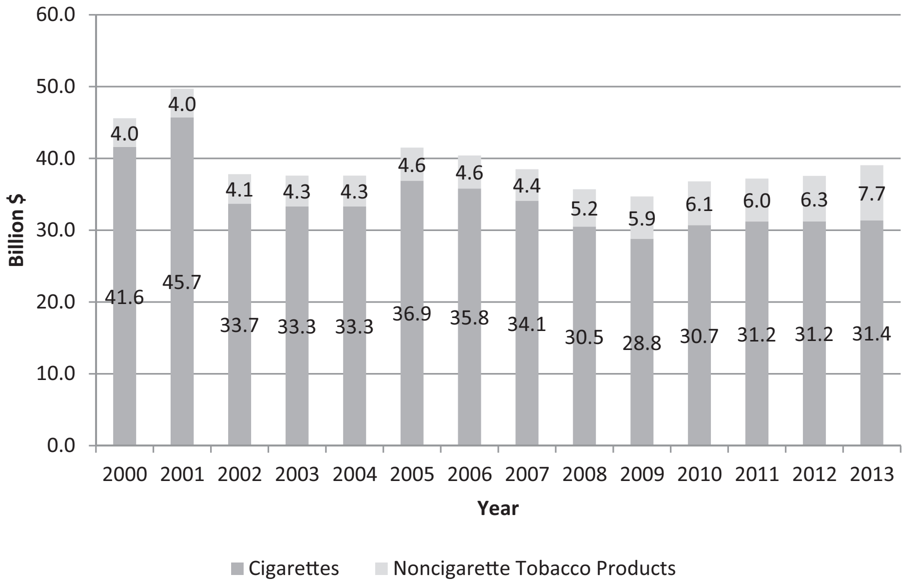


Figure 1. Tobacco products by value of shipments, 2000-2013

Source: 2000–2013 Annual Survey of Manufactures data.
Note: The value of shipments is defined by the Department of Commerce's Annual Survey of Manufactures as the total value of all products shipped by all producers for both domestic and export markets.

rates of e-cigarette use have increased quickly among U.S. adults, from 2.7% in 2010 to 3.4% in 2012 (Adkison et al. 2013; Lee et al. 2014) and youth, from 3.3% in 2011 to 6.8% in 2012 (Corey et al. 2013), who are predominantly current smokers, raising concerns that e-cigarettes will lead to dual use of cigarettes and e-cigarettes (Dutra and Glantz 2014). In addition, e-cigarettes and smokeless tobacco may serve as a gateway to nicotine addiction and cigarette smoking, particularly for youth (O'Connor 2012; Grana 2013). In other words, e-cigarettes may complement rather than substitute for cigarette smoking. Finally, e-cigarette advertising is not regulated. In the absence of regulation, advertising expenditures for these products have increased dramatically (Kim, Arnold, and Makarenko 2014), and tobacco companies are marketing these products online, in print, and, for the first time in decades, on television (Kim et al. 2015). In April 2014, the Food and Drug Administration (FDA 2014) proposed regulating e-cigarettes as tobacco products. Under the proposed regulation, e-cigarette manufacturers would be prohibited from making health-related claims without scientific evidence but still can advertise them on television.

This study attempts to shed light on three unaddressed questions related to e-cigarettes that have important policy implications. First, we estimate the full substitution/complementarity relationships between e-cigarettes and other tobacco products, especially cigarettes. Second, we quantify the impacts that e-cigarette advertising, especially TV advertising, has on tobacco product sales. Third, we measure the degree of habits of e-cigarettes relative to other tobacco products. If e-cigarettes serve as a gateway to cigarette smoking, e-cigarettes may substitute for cigarettes in the short run but complement them in the long run. Two states currently tax e-cigarettes, both in the form of an excise tax, with North Carolina having a 5 cent-per-milliliter tax to the nicotine mixture used in e-cigarettes, and Minnesota taxing e-cigarettes at a rate of 95% of the wholesale cost (Tobacco E-News 2015). Many other states and local governments are considering taxing e-cigarettes, for example Washington State's proposal in 2015 to levy a 95% sales tax on e-cigarettes (Tobacco E-News 2015). Understanding the degree of habit formation for e-cigarettes will help predict the impacts of such tax hikes on consumption and tax revenue in the short run versus in the long run.

Our study attempts to make two important contributions. First, we estimate a system of demand for cigarettes and four other major noncigarette tobacco products—little cigars/cigarillos, large cigars, e-cigarettes, and smokeless tobacco—using market-level scanner data for convenience stores. To our knowledge, no published study has modeled tobacco products in a demand system framework. We also include advertising data collected by Kantar Media, and introduce the concepts of "advertising substitutes" and "advertising complements" based on the estimated advertising elasticities. Our empirical analysis provides useful insight into the relationship between e-cigarettes and cigarettes, and the own- and spillover effects of e-cigarette advertising. Second, building on the work by Muellbauer and Pashardes (1992) and Zhen et al. (2011), we incorporate habit formation into all tobacco categories and provide a ranking of the degree of addiction among them. We further extend the dynamic system to explore whether advertising can influence habit formation. Unlike cigarette addiction, which has been studied extensively, the nature of habits in noncigarette tobacco product demand is largely unknown. In particular, the degree of habit for e-cigarettes compared with that for cigarettes may have important implications to public health.

Though our focus is on e-cigarettes, our system approach contributes to understanding demand for noncigarette tobacco products as well, which have received much less attention in the economics and public health literature compared with cigarettes. Other noncigarette tobacco products also contribute to the burden of tobacco use. The World Health Organization (2006) summarized that cigar smoking causes cancers of the lung, oesophagus, larynx, and oral cavity. Smokeless tobacco products contain addictive levels of nicotine, heavy metals, and typically several carcinogens that cause head, neck, and throat cancers with high rates of premature mortality. Different tobacco products may also appeal to consumers with different characteristics such as age, gender, race, and education level. For example, cigar use is common among youth; cigars were also found to be the most commonly-used tobacco product among African-American high school students; and smokeless tobacco use appears to be concentrated among certain segments of the population, particularly rural residents, males, whites, and less-educated individuals (Dave and Saffer 2013). Additionally, as cigarettes become more expensive and are more regulated compared with other tobacco products, smokers might turn to other products and thus not quit using tobacco, which may hinder smoking cessation or lead to other health problems. Indeed, multiple tobacco product use in adults has become more prevalent, which might suggest that some tobacco products are complements. Based on a U.S. national telephone survey conducted to around 4,000 adults, Lee et al. (2014) reported that 32.1% of adults currently use one or more tobacco products, with 6.9% using cigarettes with another product (i.e., dual use), 1.3% using two noncigarette products, and 2.4% using three or more products (i.e., polytobacco use).

We found that e-cigarettes and cigars are the most price-elastic tobacco products and e-cigarettes do not substitute for or complement cigarettes in the short or long run. E-cigarettes' TV advertising increased both own demand (both conditional and unconditional on tobacco group expenditure) and the unconditional demand for cigarettes. Such a result helps explain e-cigarettes' market success. As to habit formation, we found that e-cigarettes are the most habitual among all tobacco products.

The rest of the paper is organized as follows. The next section provides a literature review of the demand for various tobacco products, while the subsequent section describes our econometric model. The following section describes the data and the product category classification. The next section presents the results, while the final section contains concluding remarks and discussion.

Literature Review

Although there is an extensive body of literature in economics and public health on cigarette demand, there are only a few studies on smokeless tobacco demand, and even fewer studies on the demand for cigars and e-cigarettes. Gallet and List (2003) performed a meta-analysis and reported that across 86 published studies on cigarettes, the average price elasticity and income elasticity are −0.48 and 0.42, respectively. However, some recent studies using retail U.S. scanner data tended to yield more elastic elasticities for cigarette sales, such as the −1 figure reported by Da Pra and Arnade (2009) using supermarket, drug, and convenience store data, and the −0.75 figure reported by Adhikari et al. (2012) using supermarket data. Table 1 provides a brief summary of the literature on the own-price elasticities for tobacco products.

Table 1. Literature on Own-price and Advertising Elasticities for Tobacco Products

Tobacco Products	Own-price Elasticities	Note	Authors	Own-advertising Elasticities
Cigarettes	–0.48	Meta-analysis	Gallet and List (2003)	0.10
	–0.25 to –0.50	High-income countries	Chaloupka et al. (2002)	
	–1.00		Da Pra and Arnade (2009)	
	–0.75		Adhikari et al. (2012)	
Cigars	−0.34	Elasticity of participation	Ringel, Wasserman, and Andreyeva (2005)	
	–0.50		Da Pra and Arnade (2009)	
E-Cigarettes	–1.20 to –1.90	Disposable and reusable	Huang, Tauras, and Chaloupka (2014)	
Smokeless	–0.65	For youth	Chaloupka, Tauras, and Grossman (1997)	
	–0.38		Dave and Saffer (2013)	0.06

For cigars, Ringel, Wasserman, and Andreyeva (2005) estimated, based on survey data, that the price elasticity of participation for youth (how cigar smoking participation responds to cigar price) was −0.34. Da Pra and Arnade (2009) estimated the price elasticity of demand was −0.50 for cigars in the United States. Nguyen and Grootendorst (2015) also found that banning the sale of flavored cigarillos in Canada led to a decline in the use of cigarillos but an increase in the use of large cigars among youth. For smokeless tobacco, studies have consistently found that higher smokeless tobacco taxes and prices reduce demand, with tax elasticity estimates ranging from −0.06 to – 0.19 (Ohsfeldt and Boyle 1994; Chaloupka, Tauras, and Grossman 1997; Ohsfeldt, Boyle, and Capilouto 1997; Tauras et al. 2007). Chaloupka, Tauras, and Grossman (1997) reported a price elasticity of – 0.65 for youth. More recently, Dave and Saffer (2013) found that the price elasticity for all users was −0.38.

Interestingly, researchers have mixed findings about whether smokeless tobacco and cigarettes are substitutes (Adhikari et al. 2012; Adams, Cotti, and Fuhrmann 2013; O'Connor et al. 2014) or complements (Bask and Melkersson 2003; Tauras et al. 2007; Dave and Saffer 2013). Tauras et al. noted that complementarity could be a result of youths experimenting with both cigarettes and smokeless tobacco as part of the tobacco uptake process.

To our knowledge, there is only one study estimating the own-price elasticity for e-cigarettes. Huang, Tauras, and Chaloupka (2014) found a price elasticity of – 1.2 for disposable e-cigarettes and −1.9 for reusable e-cigarettes, using market-level scanner data collected from U.S. food, drug, mass merchandiser, and convenience stores. These authors did not find any consistent cross-price relationship between cigarettes and e-cigarettes. More recently, based on a survey conducted to a small sample of New Zealand smokers, Grace, Kivell, and Laugesen (2015) estimated a cross-price elasticity of 0.16 for e-cigarettes using a simulated demand procedure, indicating that e-cigarettes are substitute for cigarettes.

Regarding advertising elasticity, Gallet and List's (2003) meta-analysis reported an average advertising elasticity of 0.10 for cigarettes (table 1). Dave and Saffer (2013) found that the magazine advertising elasticity on smokeless tobacco was 0.06. There is a gap in the literature on the effect of e-cigarette advertising.

A Dynamic Demand System with Habit Formation

We use the dynamic Almost Ideal Demand System (AIDS) model in Zhen et al.'s (2011) beverage study to model habit formation, but our study design differs in two respects. First, we do not incorporate durability. Muellbauer and Pashardes (1992) suggest that a specification with only one dynamic parameter per product would probably suffice because both the habit formation and durability parameters are capable of capturing habituation and durability. Second, unlike Zhen et al.'s (2011) study, which aims to compare habit formation under rational addiction and myopia, we utilize a (numerically simpler) myopic version of the model in order to include market-specific fixed effects and focus on the advertising effects. The model starts with specifying a utility-generating stock of service

$$(1) \quad Z_{imt} = q_{imt} - \phi_i q_{imt-1}$$

where i indexes five tobacco product categories in the order of cigarettes, little cigars/cigarillos, large cigars, e-cigarettes, and smokeless tobacco; m and t index market and time period, respectively; q_{imt} is the per capita quantity of product category i sold in market m in period t; and ϕ_i is the habit formation parameter that captures the degree of habits. The ϕ_i term normally is bounded between zero (inclusive) and one (exclusive); a larger ϕ_i means a larger degree of habits.

Assuming weakly separable preferences between tobacco products and an outside good (a *numéraire* all other goods combined), we estimated tobacco category choices using a two-stage budgeting model. In the first stage of our model, the smoker allots total income among tobacco products as a group and the outside good. The second stage is the choice on the five categories of tobacco products given the group expenditure on tobacco. The budget share equation of the dynamic AIDS at the second stage of budgeting is

$$(2) \quad w_{imt} = \alpha_i + \sum_{j=1}^{5} \gamma_{ij} \ln p_{jmt} + \beta_i (\ln \bar{x}_{mt} - \ln p_{mt})$$

where p_{jmt} is a panel rolling-window GEKS (named after Gini 1931; Eltetö and Köves 1964; and Szulc 1964) price index of category j in market m and period t.[1] In equation (2), conditional budget shares (within the tobacco products group), per capita expenditures on tobacco products, and log of the group price index are defined, respectively, as

$$(3) \quad w_{imt} = \frac{p_{imt} Z_{imt}}{\bar{x}_{mt}}$$

$$(4) \quad \bar{x}_{mt} = \sum_{i=1}^{5} p_{imt} Z_{imt}$$

and

$$(5) \quad \ln p_{mt} = \alpha_0 + \sum_{i=1}^{5} \alpha_i \ln p_{imt} + 0.5 \sum_{i=1}^{5} \sum_{j=1}^{5} \gamma_{ij} \ln p_{imt} \ln p_{jmt}$$

where α, β, and γ are parameters. Theoretical restrictions on long-run demand were imposed, including adding up $\sum_{i=1}^{5} \alpha_i = 1$, and $\sum_{i=1}^{5} \beta_i = \sum_{i=1}^{5} \gamma_{ij} = 0$ for all j, homogeneity $\sum_{j=1}^{5} \gamma_{ij} = 0$ for all i, and symmetry $\gamma_{ij} = \gamma_{ji}$ for all i, j. Following Zhen et al. (2011), we substituted the service stock equation (1) into the budget share equation (2), multiplied both sides by $\bar{x}_{mt}/p_{imt}$, and rearranged terms. This generated the following second-stage quantity demand estimating equation:[2]

$$(6) \quad q_{imt} = \left\{ \alpha_i + \sum_{j=1}^{5} \gamma_{ij} \ln p_{jmt} + \beta_i (\ln \bar{x}_{mt} - \ln p_{mt}) \right\} \times \left(\bar{x}_{mt}/p_{imt} \right) + \phi_i q_{imt-1}.$$

Denoting per capita income as *Inc*, we specify the first-stage equation similar to Zhen et al. (2011) to close the system:

[1] The panel rolling-window GEKS price index is a panel price index we constructed following the procedure in Zhen et al. (2016); it is based on the multilateral GEKS index and the time-series GEKS adapted by Ivancic, Diewert, and Fox (2011) and De Haan and van der Grient (2011), both of which eliminate chain drift in high- and medium-frequency scanner data. The panel index allows the simultaneous comparison of prices across space and time. The reason for using price indices rather than unit values (i.e., costs per unit) to represent category-level prices is to reduce the simultaneity bias arising from any within-category quality-quantity trade-off that consumers may pursue (Deaton 1988). For example, as cigarette prices increase, consumers may economize by switching from premium brands to discount brands. A price index is a simple way of accounting for this type of within-category substitution without explicitly modeling brand-level demand.

[2] As in Zhen et al. (2011), we used the quantity demand rather than a budget share demand to facilitate full information maximum likelihood estimation of the nonlinear system. A significant source of nonlinearity comes from the dynamic budget share of equation (3) being a function of the ϕ parameters. One reviewer pointed out that by estimating a quantity demand model, we can no longer assume that the errors have a constant variance-covariance matrix (Pollak and Wales 1969, footnote 11). In static demand, the standard solution is to estimate the budget share equations (Fry, Fry, and McLaren 1996). However, this is not computationally feasible in our dynamic model. Because of the extra nonlinearity associated with estimating the service stocks Z, we could not achieve convergence when estimating the dynamic budge share equation (2). In addition, even presenting demand as budget shares may not render the error terms truly homoscedastic (Chavas and Segerson 1987). In other words, estimating the quantity demand does not introduce the problem of non-homoscedastic errors, it just translates it into a different form. Another potential solution is to use limited information estimators such as three-stage least squares or generalized method of moments that are free of residual distribution assumptions. However, the model failed to converge using these alternative estimators. Therefore, estimating the quantity demand appears to be the most practical approach.

Table 2. Nielsen Convenience Channel Markets

Atlanta	Little Rock	Philadelphia
Birmingham	Los Angeles	Phoenix
Boston	Louisville	Portland
Chicago	Miami	Raleigh/Durham
Cincinnati	Minneapolis	Richmond/Norfolk
Cleveland	Nashville	San Antonio
Dallas/Ft. Worth	New Orleans/Mobile	San Francisco
Denver	New York	Seattle
Detroit	Oklahoma City/Tulsa	St. Louis
Houston	Orlando	Tampa

$$(7) \quad \ln \bar{x}_{mt} = \alpha_m + \beta_m \ln (Inc_{mt}) + \gamma_m \ln p_{mt}.$$

The tobacco literature has shown that many factors other than price and income, such as socioeconomic characteristics and advertising, could affect demand for tobacco products (e.g., Farrelly, Pechacek, and Chaloupka 2003). We adopted a demographic translation procedure to introduce such variables into the demand system (Pollak and Wales 1981). Specifically, the parameter α_i in equations (5) and (6) was augmented into a linear function in the following form:

$$(8) \quad \alpha_i = \alpha_{i0} + \sum_{j=1}^{5} \alpha_{ij} Adv_{jmt} + \alpha_{i6} Black_{mt} + \alpha_{i7} Hisp_{mt} + \alpha_{i8} Asian_{mt} + \alpha_{i9} UI_{mt} + \alpha_{i10} Trend_t + \boldsymbol{\alpha_{i,D} QtrMktDummy_{mt}}$$

where Adv_{jmt} is the real advertising expenditure on cigarettes, cigars (we combine cigar advertising because we could not break it down by little cigars/cigarillos versus large cigars), e-cigarettes on TV, e-cigarettes in magazines and other media, and smokeless tobacco. Moreover, $Black_{mt}$, $Hisp_{mt}$, and $Asian_{mt}$ are the percentages of the population that are black, Hispanic, and Asian in market m and period t, respectively; UI stands for the unemployment rate; $Trend$ is a yearly linear trend that takes on the value 1 for the first year of the sample, which intends to capture some unobservable factors that contributed to the overall decline of cigarette demand (e.g., tobacco control programs and smoking bans) and the explosive sales increase in e-cigarettes during this data period; $\boldsymbol{QtrMktDummy_{mt}}$ is a vector of dummy variables for quarters and Nielsen markets; α_{i0} through α_{i10} and vector $\boldsymbol{\alpha_{i,D}}$ are parameters to be estimated. The α_m term in the first stage budgeting (equation [7]) follows the same specification except total advertising expenditures on all five tobacco categories are used instead.

Data Descriptions

Our data on purchase quantities and dollar sales came from Nielsen ScanTrack, which collects observations of data purchases at the point of sale from convenience stores, food stores, drug stores, and mass merchandisers across the United States. We used data for the 30 convenience channel markets because a majority of sales of tobacco products occur in convenience stores (table 2 lists the detailed convenience channel markets. Note that the number of Nielsen convenience channel markets is less than the number of Nielsen supermarket channel markets). We used four-weekly data for the period from November 2009 through April 2013, resulting in a sample size of 1,284 markets and four-weekly period combinations for each product category. The definitions and summary statistics for the variables used in this study are reported in table 3. We excluded nicotine replacement therapy products in the demand system because there are limited sales of them in convenience stores. We also excluded loose smoking tobacco (roll-your-own and pipe tobacco) because the market share of loose smoking tobacco was negligible (around 0.2%) during the sample period.

Figure 2 provides a breakdown of the five tobacco categories used in this study. The first category, cigarettes, includes all cigarettes sold in convenience stores with varying characteristics such as brand, strength, tar level, package type (pack, carton, half carton, canister, tray), box type (hard, soft, round corner box, flask, other), menthol and nonmenthol,

Table 3. Variable Definitions and Summary Statistics (*N* = 1,284 Unless Otherwise Noted)

Variable	Description	Mean	Min.	Max.	S.D.
Second-stage variables (budget shares and expenditures are calculated assuming $\phi_i = 0$)					
w_{1mt}	Budget share for cigarettes	0.885	0.812	0.947	0.030
w_{2mt}	Budget share for little cigars/cigarillos	0.023	0.007	0.042	0.006
w_{3mt}	Budget share for large cigars	0.018	0.006	0.045	0.009
w_{4mt}	Budget share for e-cigarettes	0.003	0.000	0.018	0.003
w_{5mt}	Budget share for smokeless tobacco	0.071	0.020	0.147	0.028
p_{1mt}	GEKS price index for cigarettes	1.029	0.789	1.596	0.166
p_{2mt}	GEKS price index for little cigars/ cigarillos	1.054	0.787	1.578	0.161
p_{3mt}	GEKS price index for large cigars	1.025	0.776	1.481	0.151
p_{4mt}	GEKS price index for e-cigarettes	0.822	0.488	1.644	0.165
p_{5mt}	GEKS price index for smokeless tobacco	1.060	0.713	1.670	0.215
Adv_{1mt}	Real (2013$) advertising expenditures for cigarettes per thousand people	$15.540	$1.153	$32.005	$6.657
Adv_{2mt}	Real advertising expenditures for cigars per thousand people	$2.200	$0.098	$6.732	$1.398
Adv_{3mt}	Real advertising expenditures for e-cigarettes on TV per thousand people	$0.727	$0.000	$6.263	$1.457
Adv_{4mt}	Real advertising expenditures for e-cigarettes in other media (mainly magazine) per thousand people	1.953	0	14.342	2.733
Adv_{5mt}	Real advertising expenditures for smokeless tobacco per thousand people	$9.463	$0.054	$29.135	$8.260
First-Stage Variables					
Adv_{mt}	Per capita real advertising expenditures on tobacco products	$29.00	$10.39	$54.24	$9.14
Inc_{mt}	Per capita four-week income	$1,301	$1,035	$1,929	$194
Variables Shared by Both Stages					
$\bar{x}_{mt}$	Per capita expenditures on tobacco products	$17.532	$6.074	$35.977	$6.178
$Black_{mt}$	Percentage of population that is black	0.137	0.019	0.305	0.077
$Hisp_{mt}$	Percentage of population that is Hispanic	0.154	0.024	0.460	0.127
$Asian_{mt}$	Percentage of population that is Asian	0.045	0.011	0.238	0.044
UI_{mt}	Unemployment rate	0.086	0.049	0.147	0.016

and filtered or not filtered. The second category, little cigars/cigarillos, includes all cigars labeled as little cigars, cigarillos, small cigars, or any other label indicative of a smaller than normal cigar size.[3] The third category, large cigars, includes any cigars that are labeled large or not otherwise labeled to indicate a smaller than normal cigar size. Both sizes of cigars are differentiated by their brand, cigar size, number of cigars within a pack, style (filter tip, versus nontip), and flavor. Our e-cigarette category includes disposables, starter kits, and replacement cartridges. At this time, e-liquid was not sold in any substantial amount in convenience stores. The same is true of e-hookah and e-cigars. The defining characteristics include brand, flavor, and milligrams of nicotine where specified. Although the model does not differentiate within product categories, the defining characteristics above are used to define a unique product when calculating the price indices. Smokeless includes various types of noncombustible tobacco including moist snuff, dry snuff, loose leaf, plug, twists, and dissolvable tobacco, sold in ounces. The defining characteristics include brand, cut (long, regular, fine, thick, etc.), and flavor.

County-level demographic and economic data were aggregated to the Nielsen market level and used as covariates in the demand model. Race category percentages in each market were derived from the 2010 census (U.S. Census Bureau 2010) at the county

[3] This is based on the product string that Nielsen derived from product packaging, which is updated every few years. New product categories such as electronic cigarettes are updated more frequently. Our classification of cigars does not match the federal tax definition of little vs. large cigars, which are solely based on weight.

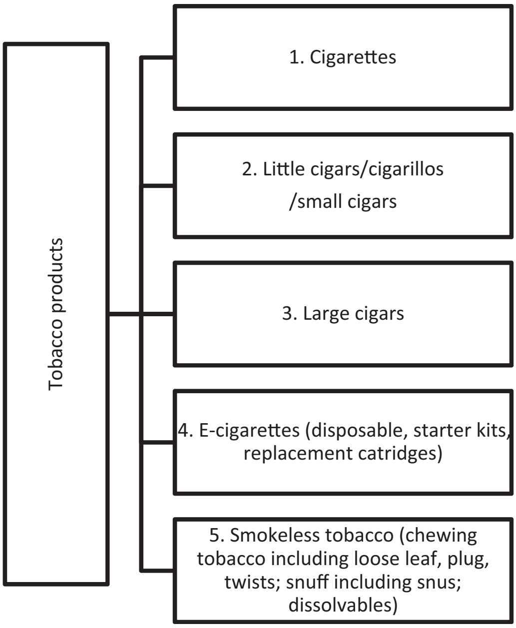


Figure 2. A breakdown of the five tobacco categories used in this study

level. We summed the population totals and subpopulation totals across each county and divided each market's subpopulation for race (white [base group in the model], black, Hispanic, and Asian) by the total population to obtain the percentage from each demographic category. All non-Hispanic race categories exclude Hispanic from their definition.

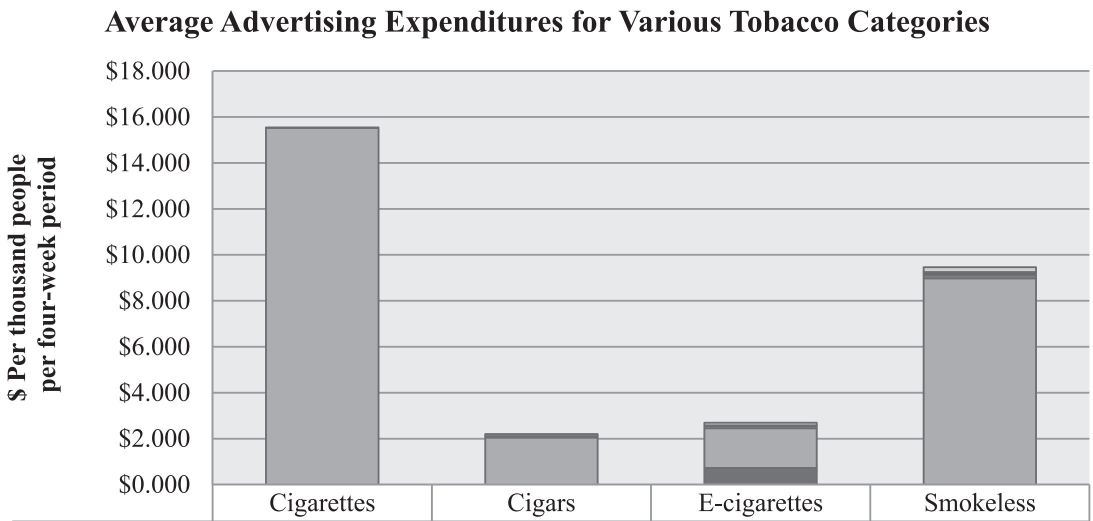
Per capita income is available from the Bureau of Economic Analysis for the years 2009 to 2013 by county. We took the population-weighted average of income across counties to aggregate to Nielsen scanner markets. Unemployment data are available from the Bureau of Labor Statistics on a monthly by county basis. For a more stable estimate, we took the quarterly average of unemployed persons summed across counties within markets, not seasonally adjusted, and divided it by the quarterly average of people in the labor force summed across counties within markets, again not seasonally adjusted.

Advertising data (excluding point-of-sale advertising) on tobacco products came from Kantar Media's Stradegy database (http://www.kantarmedia.com/us/our-solutions/advertising-monitoring-and-evaluation). Kantar Media tracks advertisements placed in over 400 consumer magazines, 100 U.S. markets for outdoor media, 6,000 Web sites, 90 television networks, 200 newspapers, and 4,000 radio stations. The database provides access to detailed information on product advertising such as type and brand of product advertised, placement of advertisements (e.g., specific magazine issue and page number), date of publication, and cost of the advertisement, as well as copies of actual advertisements available for download (magazines only). For each media channel we extracted information from Stradegy on the frequency of and expenditures on tobacco product advertisements by brand, market, and media channel-specific information (e.g., publication name, television program name, Internet site category). Nielsen advertising markets and Kantar Media Stradegy's advertising markets are largely congruent. Nielsen provides a county-to-advertising market identifier that we used to link file advertising expenditures to counties. We divided each market's advertising expenditure on each product by the total population in that advertising market. We then took the weighted per capita advertising expenditure for each ScanTrack market aggregated by county.

Figure 3 shows the average advertising expenditures across all markets for various tobacco categories studied in this research, broken down by eight media channels. It is important to note that we do not have data on point-of-sale advertising, which is where most cigarette (and potentially other tobacco products) advertising expenditures occur. Figure 3 illustrates that cigarettes still outspent cigars, e-cigarettes, and smokeless tobacco on advertising by a large margin. Magazine advertising was the lion's share of the advertising expenditures spent by each of the four tobacco categories. Though cigarette advertising on television has been banned and cigar companies spent little on television advertising, e-cigarettes companies have become the biggest spender on television advertising, reaching \$0.73 per 1,000 people in a 4-week period.

Estimation and Results

The second and first-stage equations, specified in equations (6) and (7), were jointly estimated using the PROC MODEL procedure in SAS 9.3. Following Zhen et al. (2011), we used the full information maximum likelihood (FIML) for the system to account for endogeneity $\bar{x}_{mt}$ (see footnote 2 for a discussion of the choice of functional form and estimator).



	Cigarettes	Cigars	E-cigarettes	Smokeless
Internet	$0.010	$0.084	$0.115	$0.212
Outdoor		$0.002	$0.002	$0.001
Spot radio		$0.004	$0.005	
Net radio		$0.007	$0.006	
Newspaper	$0.001	$0.006	$0.010	$0.143
News magazine		$0.051	$0.097	$0.131
Magazine	$15.529	$2.046	$1.730	$8.977
Television		$0.001	$0.727	

Figure 3. Average advertising expenditures (excluding point-of-sale advertising) for various tobacco categories

The Godfrey's serial autocorrelation test indicated the existence of autocorrelation for the second-stage demand equations; we therefore estimated the second-stage demand model with an AR (1) and MA (1) process, which resulted in satisfactory Durbin–Watson statistics centering around two for all equations. Adding up restrictions were placed on the demand shift variables.

Barnett and Serletis (2008) note that demand functions that do not satisfy both curvature (concavity of the expenditure function) and monotonicity (indirect utility decreases in income normalized price) will fail duality theory. The AIDS model does not impose the curvature property or monotonicity on the model. We examined whether the curvature property holds following Moschini (1998). Specifically, the Slutsky substitution matrix, defined in equation (3) of Moschini (1998), have to be negative semidefinite to satisfy the curvature property.[4] The monotonicity is rarely mentioned in the literature. We therefore derive and provide the formula in a supplementary online appendix on how to check monotonicity for the AIDS model, following Barnett and Serletis' guideline (2008). Based on our estimated parameters for the dynamic AIDS, we found that 93.3% and 65.3% of the observations satisfy the curvature condition and monotonicity condition, respectively. Overall, we found that these two regularity conditions are satisfied within our data sample.

The model provides a satisfactory fit for the data in that the adjusted R^2's ranged from 0.966 for the e-cigarette equation to 0.990 for the cigarette equation. We provided the estimated parameters in the supplementary appendix and focus on the discussion of elasticities, which were calculated based on the formulas used in Zhen et al. (2011). Taking advantage of the joint estimation of both stages, SAS uses the Estimate Statement to calculate the standard errors for elasticities

[4] This condition will be satisfied if all the eigenvalues of the matrix are not positive.

Table 4. Unconditional Own-price Elasticities (Uncompensated Elasticities, $N = 1{,}194$, FIML Used)

	Static AIDS (all $\phi_i = 0$)	Dynamic AIDS with habit formation			Dynamic AIDS with habit formation			
		Baseline Model			$\phi_i = \phi_{i0} + \phi_{i,Adv} * Adv_{imt}$			
	Elasticities	ϕ_i	Long-run elasticities	Short-run elasticities	ϕ_{i0}	$\phi_{i,Adv}$	Long-run elasticities	Short-run elasticities
Cigarettes	–0.962***	0.681***	–0.495***	–0.402***	0.660***	1.247***	–0.446***	–0.361***
	(0.105)	(0.014)	(0.151)	(0.123)	(0.014)	(0.141)	(0.142)	(0.115)
Little Cigars/Cigarillos	–0.886***	0.738***	–2.788***	–1.545***	0.731***	–5.408	–2.679***	–1.567***
	(0.096)	(0.017)	(0.399)	(0.204)	(0.018)	(3.179)	(0.388)	(0.207)
Large Cigars	–1.108***	0.894***	–2.787***	–0.699***	0.861***	12.397***	–2.588***	–0.762***
	(0.052)	(0.015)	(0.360)	(0.071)	(0.017)	(2.559)	(0.302)	(0.072)
E-Cigarettes	–1.126***	0.930***	–2.769***	–0.508***	0.951***	–3.331**	–2.474***	–0.568***
	(0.109)	(0.013)	(0.738)	(0.135)	(0.015)	(1.418)	(0.600)	(0.134)
Smokeless	–0.405***	0.711***	–2.074***	–1.750***	0.698***	0.399	–1.934***	–1.715***
	(0.086)	(0.017)	(0.613)	(0.537)	(0.017)	(0.462)	(0.586)	(0.542)

Note: Asterisks indicate **$p < 0.05$, and ***$p < 0.01$. Standard errors appear in parentheses.

involving more than one parameter, given the covariance matrix of the jointly estimated parameters. Elasticities were evaluated at the means of the right-hand side variables involved.[5]

Degree of Habit Formation

Table 4 reports the estimated unconditional (uncompensated) own-price elasticities and habit formation parameters (ϕ_i). The results in the middle panel (under the heading of baseline model and corresponding to our system of equations [6] and [7]) show that all the habit formation parameters are statistically significant at the 1% level, indicating that all five tobacco categories display some degree of habit formation. A comparison of the size of habit formation parameters show that e-cigarettes are the most habit forming category, followed by large cigars, little cigars/cigarillos, smokeless tobacco, and cigarettes. It may be surprising that e-cigarettes, advertised as smoking alternatives, were found to be the most habitual category, though the difference in the two habit formation parameters (0.93 vs. 0.681) is not large. The first possible explanation for this ordering is that although cigarettes and most e-cigarettes contain nicotine, many e-cigarettes are flavored, while cigarette flavoring aside from menthol has been banned by the FDA since 2009. If the consumption of flavored tobacco is more habit-forming than unflavored tobacco (flavoring may enhance the addictive potential of nicotine; flavorings themselves, apart from nicotine, may result in some degree of habit formation), we could find a higher degree of habit formation in e-cigarettes than in traditional cigarettes. Second, e-cigarettes can be "grazed"—vaped almost continuously throughout the day—and used in places that cigarettes cannot be used. This might lead to high degree of habit formation regardless of nicotine content. Third, in contrast to the well-documented harmful effects of cigarettes and other conventional tobacco product use, there has been little information on the health effects of e-cigarette smoking. If e-cigarettes are perceived to be less harmful than other tobacco products, forward-looking smokers could develop stronger habits in e-cigarette use than in other tobacco products. Fourth, e-cigarettes can be classified into starter kits, disposables, and refill cartridges. Starter kits have a higher upfront cost but can be refilled, thus having a lower nicotine delivery cost than disposable e-cigarettes and conventional cigarettes in the long run. The nontrivial cost of starter kits can be considered as investment in consumption capital, which is not required for cigarette

[5] We also compared with the means of elasticities calculated at the individual observation level. In that case, the e-cigarettes tend to be more elastic, probably due to the large variation of e-cigarette budget shares across observations, while other results are very comparable.

smoking. In the rational addiction model of Becker and Murphy (1988), this implies that e-cigarettes have a higher degree of addiction than cigarettes. Finally, smokers may be more ready to develop habits on the new and emerging e-cigarette category compared with other tobacco categories that have been in the market much longer.

The long-run unconditional own-price elasticities for cigarettes, little cigars/cigarillos, large cigars, e-cigarettes, and smokeless tobacco are −0.495, −2.788, −2.787, −2.769, and −2.074 respectively. They are all statistically significant at the 1% level. The unconditional own-price elasticity for cigarettes is within the −0.25 to − 0.50 range summarized by Chaloupka et al. (2002). With respect to e-cigarettes, our estimated own-price elasticity of –2.769 (which is an overall elasticity for reusable and disposable e-cigarettes) is more elastic than the one reported by Huang, Tauras, and Chaloupka (2014) on reusable e-cigarettes (−1.90) and the one on disposable e-cigarettes (−1.20). We also report in the next column the short-run elasticities. Because of habit formation, the long-run elasticities are larger in magnitude than the short-run ones, especially for the more habitual categories. In the left panel in table 4, we report the own-price elasticities using a static AIDS by setting all ϕ_i equal to zero. Compared with the static model, cigarettes become less price elastic with habit formation incorporated while all the other products become much more elastic in the long run.

Based on the dynamic AIDS, we further investigated the possibility that advertising affects the degree of habit formation. Specifically, we allow the habit formation parameter to depend on own advertising as follows:

$$(9) \qquad \phi_i = \phi_{i0} + \phi_{i,Adv} * Adv_{imt}$$

where $\phi_{i,Adv}$ is the new parameter to be estimated that captures how habit formation varies with own advertising. The right panel of table 4 reports the findings. We found that all ϕ_{i0} terms continue to be positive and significant, and three of the newly-introduced $\phi_{i,Adv}$ terms are statistically significant at the 5% level or better. On one hand, the signs of $\phi_{i,Adv}$ indicate that cigarette magazine advertising made cigarettes more habitual and so did cigar advertising for large cigars. On the other hand, e-cigarette advertising made e-cigarettes less habitual, probably because the degree of habit formation for e-cigarettes is already very high.

Own and Spillover Effects of Advertising

We report in table 5 all long-run unconditional advertising elasticities as well as price elasticities. The own-advertising elasticities are highlighted in the table. Interestingly, we found that e-cigarette TV advertising increased e-cigarette demand with an advertising elasticity of 0.108 (statistically significant), while e-cigarette magazine adverting did not affect own demand. The short-run own-advertising elasticity for e-cigarettes is 0.008, which is much smaller than the long-run own-advertising elasticity because of the large degree of habit formation or demand persistence. Such results highlight the large difference in a sustained advertising campaign versus a short campaign in the presence of habit formation (Zhen et al. 2011). Therefore, the aggressive e-cigarette TV advertising may have partly contributed to e-cigarettes' exponential sales increase in the United States. The other category with a statistically significant (at the 5% level or better) own-advertising elasticity is smokeless tobacco; its advertising elasticity is 0.02 (short-run elasticity is 0.006), which is much smaller than the 0.06 estimated by Dave and Saffer (2013) using a single equation.[6] Finally, the insignificant own effect of cigarette advertising (virtually all in magazines) may not suggest ineffective overall cigarette marketing efforts as our data do not account for point-of-sales marketing (e.g., tobacco displays over the counter).[7]

While the spillover effects of advertising have long been recognized in the literature (e.g., Zheng and Kaiser 2008), the concepts of advertising substitutes and advertising complements have not been formally defined. Following the logic behind price substitute and complement, we define advertising substitute as a negative spillover effect of advertising and define an advertising complement

[6] We also estimated the system trying to incorporate advertising goodwill. We started defining the lag weights as quadratic exponential lag functions following Cox's (1992) specification, allowing for three lagged periods. However the system, already loaded with habit formation parameters, failed to find a solution for the newly-introduced lag weight parameters. We therefore followed Dave and Saffer's (2013) specification to manually set the decay parameter to be 0.8. When advertising good will was included, the own-advertising parameters remained robust for e-cigarettes and smokeless tobacco.

[7] We are not aware of a data source for point-of-sale advertising data that can be used for econometric modeling.

Table 5. Unconditional Price and Advertising Elasticities in the Long Run (FIML Used)

Equations	Price Elasticities					Advertising Elasticities				
	Cigarettes	Little Cigars/ Cigarillos	Large Cigars	E-Cigarettes	Smokeless	Cigarettes	Cigars	E-Cigarettes TV	E-Cigarettes Other (mag.)	Smokeless
Cigarettes	–0.495***	0.019***	–0.001	0.0004	–0.931**	0.011	0.001	0.001**	0.001	0.005
	(0.151)	(0.006)	(0.003)	(0.000)	(0.462)	(0.006)	(0.001)	(0.0003)	(0.001)	(0.003)
Little Cigars/Cigarillos	1.353***	–2.788***	0.984***	0.035	-1.095	0.036**	–0.015	–0.016	–0.018	0.038***
	(0.352)	(0.399)	(0.192)	(0.024)	(0.610)	(0.015)	(0.009)	(0.008)	(0.014)	(0.010)
Large Cigars	0.267	1.876***	–2.787***	–0.039	–0.591	–0.027	0.014	0.001	0.013	–0.003
	(0.382)	(0.384)	(0.360)	(0.028)	(0.419)	(0.023)	(0.016)	(0.013)	(0.022)	(0.018)
E-Cigarettes	2.503	3.585	–2.118	–2.769***	–3.505	–0.115	–0.006	0.108***	–0.066	–0.032
	(2.729)	(2.460)	(1.535)	(0.738)	(2.301)	(0.119)	(0.082)	(0.042)	(0.076)	(0.071)
Smokeless	0.454	0.129	0.028	–0.023	–2.074***	0.008	0.018***	0.001	0.016**	0.020***
	(0.278)	(0.239)	(0.111)	(0.036)	(0.613)	(0.010)	(0.007)	(0.005)	(0.008)	(0.007)

Note: Asterisks indicate **$p < 0.05$, and ***$p < 0.01$. Standard errors appear in parentheses.

as a positive spillover effect of advertising. That is, if product A's advertising positively affects the demand for product B, then product A's advertising is a complement to product B.

In table 6, we present in a 3 x 3 matrix any pair that was found to have a statistically significant cross-product price or advertising relationship. The row corresponds to no advertising spillover, advertising substitute, and advertising complement. The column corresponds to the price dimension.[8] Overall, we found five pairs of advertising complements, no advertising substitute, and the presence of both price substitutes and complements, with one pair of advertising complement overlapping with a price substitute. In particular, we found that e-cigarette TV advertising increased cigarette demand and e-cigarette magazine advertising enhanced smokeless tobacco demand. We further conducted a test to see if advertising spillover effects are symmetric. That is, for any advertising spillover effect that was found to be statistically significant (a total of four pairs shown in table 5), we test if this effect is symmetric. Overall, we failed to reject the symmetric hypothesis for the four pairs mostly because the standard errors for the insignificant advertising parameters tend to be large.

Based on our data, we are interested in whether the effectiveness of cigarette and e-cigarette advertising depends on each other. Therefore, we interacted cigarette advertising with both e-cigarette TV and magazine advertising and included the two interactions in all second-stage equations.[9] The estimated parameters are reported in table 7, where the first row corresponds to the cigarette equation and the last two rows correspond to the e-cigarette equations. For cigarettes, the own advertising parameter was not statistically significant no matter whether interaction was allowed or not. When interaction was allowed, neither interaction effect was statistically significant. For e-cigarette TV advertising, the own advertising parameter was positive and statistically significant no matter whether interaction was allowed or not. The interaction term between cigarette advertising and e-cigarette TV advertising is negative and statistically significant.

[8] Note that because our results are based on uncompensated elasticities, the price substitute or complement relationships we report are a gross substitute or complement, which also reflect the income effect.

[9] The two interactions are included in the equations for cigars and smokeless tobacco to satisfy the adding up requirement.

Table 6. Substitutes and Complements for Price and Advertising

Price / Advertising	Not Price Substitute or Complements	Price Substitutes	Price Complements
Not Advertising Substitute or Complements	–	(Cigarettes, little cigars) (Little cigars, large cigars) (Large cigars, little cigars)	(Cigarettes, smokeless)
Advertising Substitute	–	–	–
Advertising Complements	(Cigarettes, e-cigarettes TV) (Little cigars, smokeless) (Smokeless, cigars) (Smokeless, e-cigarettes other)	(Little cigars, cigarettes)	–

Note: Little cigars include cigarillos. Price substitute: an increase of price in the latter product in the parentheses induces an increase in the demand for the former product in the parentheses. Advertising substitute: an increase of advertising in the latter product in the parentheses induces a decrease in the demand for the former products in the parentheses.

Table 7. Interaction of Cigarette and E-cigarette Advertising (FIML Used)

	No Interaction	With Interaction		
Category	Own-adv. parameter	Own-adv. parameter	Cigarette adv.* E-cigarette TV adv.	Cigarette adv.* E-cigarette other adv.
Cigarettes	–0.003	–0.006	–6.743	4.083
E-cigarettes TV	0.015***	0.085***	–4.551***	–
E-cigarettes Mag.	–0.003	–0.033***	–	2.392***

Notes: Asterisks indicate **p < 0.05, and ***p < 0.01.

Such results imply that cigarette magazine advertising may have undermined the effectiveness of e-cigarette TV advertising. Regarding e-cigarette magazine advertising, the own advertising parameter was not significant without including the interaction and turned negative when the interaction term was added. The parameter for cigarette advertising and e-cigarette magazine advertising interaction is positive, indicating that cigarette magazine advertising may have reinforced the effect of e-cigarette magazine advertising.

Overall, our results on advertising in tables 5–7 show that e-cigarette TV advertising increased demand for e-cigarettes and cigarettes, and the own-adverting effect was attenuated by cigarette magazine advertising. Such results may lend support to those who advocate that more regulations on e-cigarette marketing are needed. In the United States, cigarettes, little cigars/cigarillos, and smokeless tobacco have been banned from advertising on TV or radio.[10] Our data in figure 3 shows that large cigars spent close to nothing on TV advertising, leaving e-cigarettes to become the main tobacco product that advertises on TV. If e-cigarette TV advertising complements cigarette demand, then it might undermine the efforts to reduce cigarette smoking.

Can E-cigarettes Complement Cigarettes?

Our results of cross-price elasticities (table 5) show that e-cigarettes do not substitute or complement cigarettes.[11] To further examine the possibility that e-cigarettes serve as a gateway to cigarette smoking, we modified the second-stage equation (equation [6]) by including a lagged quantity of e-cigarettes in each equation.[12] Such a modification allows for the possibility of short-term substitution and long-term complementarity between cigarettes and e-cigarettes. Average e-cigarette prices declined considerably during our sample period.[13] Therefore, if the lagged e-cigarette quantity positively affects cigarette demand, then a decrease in e-cigarette price will increase cigarette demand, making e-cigarettes a price complement to cigarettes. The estimated parameter for lagged e-

[10] Federal Cigarette Labeling and Advertising Act, Little Cigar Act, and Comprehensive Smokeless Tobacco Health Educations Act.

[11] In the static AIDS we estimated, e-cigarettes were found to be a price substitute to cigarettes. As expected, the introduction of habit formation picks up a lot of effects in explaining demand that were attributed to cross-price effects in the static model.

[12] We thank an anonymous reviewer of this journal for making this suggestion.

Table 8. A Summary of Main Empirical Findings

Topics	Main Findings
Habit Formation	All habitual but e-cigarettes most habitual
	Advertising can affect habit formation (cigarettes, large cigars, e-cigarettes)
Own-price Elasticity	E-cigarettes and cigars most elastic while cigarettes and smokeless least elastic
Price Substitute/Complement	E-cigarettes did not substitute or complement cigarettes
Own-Adv. Elasticity	E-cigarettes TV and smokeless tobacco adv. increased demand
	Sustained adv. campaign can be much more effective than short one
Adv. Substitute/Complement	A few complements exist; e-cigarette adv. increased cigarette demand
Adv. Symmetry	Some evidence
Interaction of Adv.	Cigarette magazine adv. affected effectiveness of e-cigarette adv.

cigarette quantity in the cigarette equation is –0.155 and statistically insignificant, rejecting the hypothesis that e-cigarettes may complement cigarette consumption in the longer horizon. This result remains robust when we estimated the specification using a static AIDS. A summary of our main empirical findings are reported in table 8.

Conclusions and Policy Implications

This study aims to provide more insight into consumer demand for tobacco products by adopting a system approach. By using Nielsen ScanTrack market-level data, we examined the degree of habit formation and the role of advertising for cigarettes, little cigars/cigarillos, large cigars, e-cigarettes, and smokeless tobacco. The study findings may have important policy implications. First, we found that while all tobacco products are habitual, e-cigarettes are the most habitual product. Such a result raises concerns about the possibility of strong nicotine addiction for e-cigarettes, though e-cigarettes are frequently advertised as a better alternative to smoking.

Second, there is a public health concern that e-cigarettes may complement cigarettes in the long run by serving as a gateway to cigarette smoking. We found that e-cigarettes did not substitute or complement cigarettes in the short or in the long run. Combined with the first finding, our results imply that e-cigarettes may lead people to nicotine addiction but not necessarily to cigarette smoking.[14]

Third, using data on advertising, we investigated the role of advertising by including the following: advertising's own and spillover effects; whether advertising affects habit formation; whether cigarettes and e-cigarettes advertising affects the effectiveness of each other; and advertising symmetry. We found that cigarette advertising (virtually all in magazines) did not affect cigarette demand, while e-cigarettes' TV advertising increased e-cigarettes demand with a positive spillover to cigarette demand. Such a result indicates the effectiveness of TV advertising and may help explain e-cigarettes' success in the market. If a new policy were to prohibit e-cigarette television ads, similar to what is imposed for cigarettes, the model predicts a small drop in consumer demand for e-cigarettes, and a minor decrease in cigarette demand. We also found evidence that advertising for cigarettes, large cigars, and e-cigarettes affected the respective degree of habit formation.

Finally, our results should be interpreted with the following caveats in mind. First, we excluded nicotine replacement therapy products and loose smoking tobacco products (such as pipe tobacco and roll-your-own tobacco) in the demand system because sales of both products are extremely low in convenience stores. A few studies found that nicotine replacement therapy products are substitutes for cigarettes (e.g., Chaloupka and Tauras 2004). Second and more importantly, our advertising data do not capture point-of-sale marketing. Therefore,

[13] The average price index of e-cigarettes declined from 100 in the November 2009-May 2010 period (i.e., the base period) to 62.3 in April 2013 (i.e.,the end of our sample).

[14] Note that our results do not rule out the possibility of youth starting cigarette smoking with e-cigarettes because of the use of market level data rather than smokers' survey data.

our results do not speak to the overall impacts of tobacco advertising on demand. Third, although convenience stores account for the largest share of the tobacco market among all retail channels, future research should account for potential substitutions between convenience stores and other retailer types to gain a more complete picture of the tobacco retail environment.[15] Fourth, for new and emerging tobacco products such as e-cigarettes, the demand parameters may vary over time as smokers develop experience and habits with these products. The potential parametric instability may bias predictions generated from a model assuming stable preferences such as ours. The emergence of a new tobacco product in the future would likely result in a drop in the degree of habit formation currently exhibited for e-cigarettes. Finally, our estimate of the elasticity for e-cigarettes lumps all types of e-cigarette products together. If a policy differentially affected the price of different types of e-cigarette products, our results would not address the shifts in demand that might result from this. However, our results do speak to shifts in demand that might result from policies that would affect all types of e-cigarette products similarly.

Supplementary Material

Supplementary material is available at http://oxfordjournals.org/our_journals/ajae/.

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[15] Anecdotal evidence suggests that e-cigarette sales may be shifting from convenience stores to the emerging vape shops, where consumers can buy cheaper refillable vaporizers made by smaller manufacturers (Wall Street Journal 2014).

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