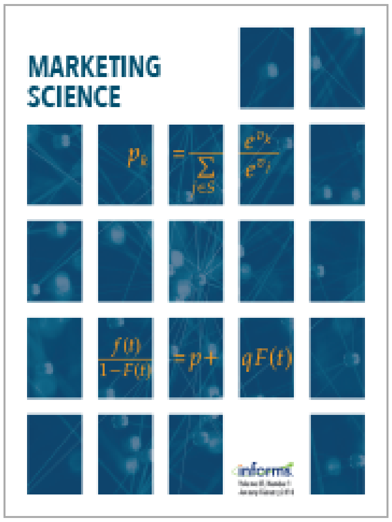

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The Unintended Consequences of Countermarketing Strategies: How Particular Antismoking Measures May Shift Consumers to More Dangerous Cigarettes

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Countermarketing, or efforts to reduce consumption of certain products, has become common in categories such as tobacco, junk food, fossil fuels, and furs. Countermarketing has a particularly long history in the tobacco industry. Efforts to reduce smoking have included excise taxes that increase the cost of consumption, smoke-free restrictions that make consumption less convenient, and antismoking advertising campaigns that highlight the dangers of tobacco use. This article presents an analysis of the relative effectiveness of these different strategies. We find that cigarette excise taxes are the most effective tool for reducing overall cigarette sales, followed by antismoking advertising. Smoke-free restrictions are not found to have a significant effect on cigarette sales. We also investigate how these various policy tools induce product substitution. This issue is of considerable importance because some countermarketing techniques may potentially shift consumers to more dangerous, higher nicotine and tar cigarettes. Specifically, we find that excise taxes levied on a per pack basis rather than based on nicotine levels often shift consumers to more dangerous products.

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1. Introduction

Countermarketing, or efforts to reduce consumption of some specified product, has become common in categories ranging from cigarettes to furs. For the most part, countermarketing activities have focused on goods such as cigarettes, alcohol, and sugary, high fat foods that pose health risks (Cohen 2000). Countermarketing activities are probably most associated with the tobacco industry and these activities are typically justified by the economic and health consequences of tobacco usage. Cigarette smoking has been estimated to cause 443,000 premature deaths each year in the United States and imposes healthcare costs and productivity losses of $193 billion each year (CDC 2011). As a result, government regulators and advocacy groups have used a variety of countermarketing strategies to reduce tobacco consumption.

Our research is focused on the tobacco industry and investigates the extent to which countermarketing strategies can change overall cigarette consumption and shift market shares across products with different nicotine levels. First, we investigate the efficacy of various countermarketing activities on cigarette category sales. This is an important topic because antismoking organizations tend to have limited resources and must therefore identify the most effective interventions. Countermarketing efforts in tobacco may be broadly categorized as price interventions, educational campaigns, and localized smoking bans. These three categories are interesting because they each use different mechanisms to reduce smoking. Price interventions typically involve the implementation of excise taxes that increase the economic cost of being a smoker. Educational campaigns consist of advertising that emphasizes the health consequences and risks associated with smoking. Localized smoking restrictions involve practices such as smoking bans at restaurants and campus smoking prohibitions that make smoking less convenient and increase the time cost of smoking.

Second, we investigate how countermarketing activities change patterns of consumption. The consumption patterns that are of specific interest are potential shifts to higher nicotine cigarettes. Because tobacco taxes are uniformly applied across nicotine levels, as tobacco taxes increase, consumers may shift to products that have higher nicotine content in order to lower their cost per unit of nicotine. Smoke-free restrictions might also cause smokers to switch to higher nicotine brands to alleviate the imposed inconvenience and opportunity cost of smoking (i.e., time). Higher nicotine cigarettes do not only induce stronger addiction but also contain higher tar content, which is directly linked to lung cancer (Denissenko et al. 1996). Hence the health benefits of countermarketing strategies may be mitigated by unintended changes in consumption patterns. Furthermore, we also consider the possibility that shifts in consumption differentially affect various segments of society. In particular, we investigate whether less affluent members of society are more likely to switch to more dangerous products.

The foundational data for our empirical work is a store-level scanner data set. These data include seven years (2001–2007) of store-level cigarette sales and marketing mix activities across a broad cross section of U.S. markets. We supplement these data with extensive information on cigarette excise tax records, smoke-free restriction levels, and antismoking advertising gross ratings points over time and markets. In addition, we collected detailed information on cigarette attributes such as variations in nicotine and tar content across brands and strength levels (regular/lights/ultra lights). Finally, although our research focuses on countermarketing tactics, we also evaluate the effectiveness of the tobacco industry's marketing activities. Countermarketing does not occur in a vacuum, so it is imperative to control for the marketing efforts of the tobacco industry when studying countermarketing effectiveness.

The data used in our research possess several characteristics that facilitate the identification of the effectiveness of the various countermarketing tactics. In our data we observe meaningful intertemporal and cross-sectional variation in antismoking policies. Cigarette excise taxes include a varying state component in addition to a common federal component. Typically, the federal tax is much smaller than the state tax and the only variation in the federal tax during the observation window from 2001 to 2007 was a five-cent increase. In contrast, taxes range considerably across states. Similarly, the majority of antismoking advertising is sponsored by each state's health and human services department. The delegation of policy decisions to the states results in significant differences across states. In addition, as tax rates, smoke-free restrictions, and state budgets for antismoking advertising campaigns are set at the state level, these variables are exogenous to local store-level demand. Collectively the exogenous nature of the policies and the variation of levels across states facilitate the identification of the effects of the various countermarketing techniques. We also use zip code level demographics to examine whether effectiveness varies across socioeconomic groups.

Our empirical analysis involves simultaneously estimating a market-share and a category sales model as a function of pro-smoking marketing mix and the three antismoking tactics. Furthermore, the antismoking policy environment includes factors that may dynamically impact cigarette consumption. The equations are estimated using a Kalman filter (Harvey 1994; Naik et al. 1998, 2005; Sriram et al. 2006; Zhao et al. 2009; Liu and Shankar 2015) with price and advertising endogeneity treated with a control function approach (Petrin and Train 2010).

We find that cigarette excise taxes are the most effective tool for reducing overall cigarette sales, followed by antismoking advertising. Smoke-free restrictions are found to have a nonsignificant effect on cigarette sales. However, cigarette excise taxes and smoke-free restrictions are both associated with the unintended consequence of leading smokers to switch to higher nicotine cigarettes to seek nicotine and time cost savings. For example, although a 10% increase in cigarette excise taxes results in a 1.6% reduction in category sales over a seven-year period, this level of tax increase also causes a 0.7% increase in the market share of regular cigarettes and a 0.9% reduction in the market share of ultra light cigarettes. Antismoking advertising is the only technique that successfully reduces category sales without shifting share to higher nicotine variants. It is interesting to note that antismoking advertising also reduces the effectiveness of pro-cigarette advertising.

To further evaluate these "unintended consequences," we decomposed the net nicotine intake changes into those due to changes in category sales and market share shifts across different nicotine level cigarettes. Our results suggest that a 10% increase in excise taxes (relative to the values observed in the data) results in an overall reduction in category sales of about 1%, but only a net decrease in nicotine consumption of 0.7%. Nicotine reduction is less than category shrinkage because there is a significant shift toward high nicotine cigarettes. This adverse effect is particularly relevant for lower socioeconomic classes. Our findings therefore suggest that uniform cigarette excise taxes should be considered with caution as these flat taxes also increase addiction levels for many smokers. Policy makers should consider the adoption of a nicotine-based tax structure.

The paper is organized as follows: Section 2 frames our contribution in terms of the economic, public health, and marketing literatures. We then provide background on countermarketing efforts and tobacco industry marketing. Section 3 describes the data sources used in our analysis. Next, we present our modeling approach and estimation results in §4. We then use our model results to conduct a simulation study that examines how taxes simultaneously reduce category consumption while shifting consumers to higher nicotine products. We conclude with a discussion of key issues, limitations, and areas for further inquiry in §5.

2. Literature Review

The literature concerned with smoking cessation spans multiple academic disciplines including economics, public health, and marketing. In this review, we begin with the economics and public health literatures that explicitly focus on the effectiveness of antismoking strategies. We then shift to marketing research concerned with tobacco marketing. Our goal in this review is not to exhaustively survey these literatures but to highlight the need for a study of the simultaneous impact of antismoking and pro-smoking tactics on cigarette category sales and market shares of cigarettes with different nicotine content.

2.1. Economic Literature on Antismoking Strategies and Category Sales

Antismoking organizations have employed a variety of techniques including cigarette excise taxes, smoke-free restrictions, and educational antismoking advertising campaigns. Of all of the various countermarketing instruments, cigarette taxes are often viewed as the most important countermarketing technique. Cigarette excise taxes have traditionally been specified per 20-cigarette pack and are included in posted retail prices (Chetty et al. 2009). These taxes typically include a federal and state component.[1] During our observation window the federal tax was constant except for a five-cent increase from 34 cents to 39 cents on January 1, 2002. However, substantial variations in the state tax component are observed across states and over time. For example, in 2005 the cigarette excise tax per package varied from a low of \$1.18 in Missouri to a high of \$6.86 in New York City. Temporal variation is illustrated by the case of the state of Washington. Washington's cigarette tax rate was \$1.17 in 2000 and had increased to \$4.04 in 2011. There have been multiple studies that have examined the relationship between prices and cigarette demand. A majority of these studies have used annual or monthly state level cigarette purchases as the dependent variable and have found that the price elasticity of cigarette demand is about −0.4 (see Chaloupka and Warner 2000 for a review).

[1] A few local governments have their own local cigarette tax—e.g., in 2002 New York City raised its cigarette tax by \$1.42 to \$1.50 per pack; Cook County, Illinois, which includes Chicago, increased its cigarette tax from 18 cents to \$1.00 per pack in 2004, and then by an additional \$1.00 in 2006, bringing its tax rate to \$2.00.

A parallel stream of research in the economics literature has focused on usage restrictions implemented via "smoke-free air policies." The idea behind these restrictions is to increase time and effort costs by forcing smokers outdoors to smoke. Smoke-free restrictions affected approximately 50% of the population before the year 2000 and were steadily expanded to the point where over 70% of the population was affected by 2008. Smoke-free air policies have been found to have mixed results. For example, Evans et al. (1999) find that voluntary workplace smoke-free air laws reduce smoking prevalence by five percentage points and daily consumption by 10 percentage points. However, Bitler et al. (2010) and Adda and Cornaglia (2010) find no effect of smoke-free air laws on smoking behavior.

In conjunction with these tax hikes and usage restrictions, antismoking ad campaigns have been rolled out by the states' departments of health and human services with the goals of preventing youth smoking and reducing adult smoking rates. During the period from 2001 to 2007 the majority of antismoking advertising campaigns were planned at the state level. Antismoking advertising has been found to reduce smoking rates. For example, Hu et al. (1995) found the antismoking advertising elasticity to be significant at −0.07 using data from California. Studies in the public health literature have often evaluated the effectiveness of antismoking advertising campaigns using field studies and self-reported usage measures (see NCI 2008 for a review).

2.2. Marketing Literature on Pro-Smoking Strategies, Market Shares, and Category Sales

The extant economic literature on smoking has largely ignored the interactions between antismoking and pro-smoking marketing strategies. This is a significant omission as it is imperative to control for the marketing efforts of the tobacco industry when studying countermarketing effectiveness. Although cigarette advertising is restricted to newspapers and magazines with target audiences above the age of 18, recent research indicates that even minimal exposure to advertising (100 milliseconds) can be effective. Research from marketing studies supports the premise that cigarette brand advertising is very effective. For example, Pollay et al. (1996) found cigarette advertising elasticity with regard to brand shares to be 0.28. Furthermore, Leeflang and Reuijl (1985) provide evidence that cigarette advertising also significantly expands category sales. Several marketing studies also provide lab-based experimental evidence on the relationship between ad content (i.e., peer effects) and ad effectiveness (Pechmann and Knight 2002). This experimental literature has tended to focus on adolescent smoking with self-reported intention data (Pechmann and Shih 1999, Pechmann et al. 2003, Andrews et al. 2004).

The marketing literature also includes two studies that utilize scanner data. These papers involve dynamic models of purchase and inventory decisions and are focused on the impact of temporary versus permanent price adjustments (Gordon and Sun 2015, Chen et al. 2009). Chen et al. (2009) build a dynamic structural brand choice model to investigate the effect of Marlboro's one-time permanent price cut in 1993 on smokers' brand switching. Gordon and Sun (2015) also use a dynamic structural model to investigate the impact of tobacco companies' temporary versus permanent price adjustments on cigarette consumption. Although these studies illustrate the roles of pricing and promotion on brand tier choice and incidence, these studies do not consider the role of all three countermarketing activities or switching between nicotine-based subcategories.

2.3. Antismoking Strategies and Market Shares

Few studies investigate whether and how antismoking activities change the patterns of consumption across cigarette types. For instance, there is an open question as to whether cigarette taxes, smoke-free restrictions, and antismoking advertising lead to market share shifts toward higher nicotine content cigarettes. Studies by Adda and Cornaglia (2006) and Evans and Farrelly (1998) do partially address the issue. Adda and Cornaglia (2006) investigate whether smokers extract more nicotine per cigarette by varying the number of puffs. Using a biomarker measure of cotinine concentration in saliva, they find that tax hikes induce nicotine intake compensating behavior. Evans and Farrelly (1998) supplement self-reported cigarette brand purchases in the National Health Interview Survey with state tax data, and find that smokers in high-tax states are more likely to smoke higher nicotine cigarettes than those in low-tax states. Given the cross-sectional nature of the two waves of surveys in 1979 and 1987, their results are subject to survival bias since smokers who prefer high nicotine cigarettes may be more or less likely to be left in the population. Apart from the aforementioned studies, there is no evidence on how the present practice of uniform cigarette excise taxes may lead smokers to switch to higher nicotine content brands to obtain nicotine per dollar cost savings. In addition, it is unknown whether smoke-free restrictions may switch smokers to higher nicotine brands to alleviate the imposed inconvenience and opportunity cost of smoking (i.e., time), or whether health-warning messages carried in antismoking advertising may switch smokers toward lighter brands. Our study attempts to fill this gap by examining the full consequences of antismoking tactics.

2.4. Summary and Outstanding Issues

The preceding discussion highlights a lack of empirical research that simultaneously considers the impact of antismoking and pro-smoking strategies on both category sales and market shares of cigarettes with different nicotine contents. For example, the use of cigarette taxes that are independent of nicotine content may have unintended effects on consumer's choices. Although the taxes themselves may reduce consumption, the possibility exists that consumers might switch to higher nicotine brands in order to lower the cost per unit of nicotine. Similarly, educational advertising and usage restrictions may also have multidimensional effects on consumer behavior. There is a need for studies that consider the unintended consequences of antismoking policies.

3. Data

The cigarette category has been a source of controversy for at least the past half century. Cigarette marketing has been regulated, restrictions that limit distribution and public consumption have been imposed, governments have levied taxes, and public health organizations have conducted educational campaigns. Simultaneously, cigarette companies have developed strong brands, and used a variety of pricing and promotional strategies. The complexity of this environment presents several challenges for analyses of consumer behavior. To address our research questions, it is necessary to assemble and combine multiple data sets. The data sources include a seven-year U.S. store-level cigarette sales data set covering January 2001 to December 2007, cigarette excise tax records, smoke-free policies, antismoking advertising, cigarette brand advertising, and cigarette attributes such as nicotine and tar content.

3.1. Scanner Store Data

Our data source for cigarette sales is a comprehensive scanner data panel provided by IRI (Bronnenberg et al. 2008). The data spans seven years from 2001 to 2007 and covers a large cross section of markets across the United States. The units of analysis are overall category sales and the market shares of regular, light, and ultra light cigarettes at each retail store. Because Marlboro is a clear market leader, we add in a brand component and focus on seven cigarette products including Marlboro regular, Marlboro lights, Marlboro ultra lights, other regular, other lights, other ultra lights, and other mild.[2] We restricted the analyses to 645 stores with complete seven-year records. These stores span 38 states, 52 designated media areas (DMAs), 196 counties, and 592 zip codes.

[2] The three major flavor versions are regular, lights, and ultra lights. There are a few exceptions such as mild flavor. The mild category is included to insure that we cover 100% of the category sales.

The store-level scanner data records detailed information on weekly volumes, dollars, and promotional activities at the universal product code (UPC) level. We use three steps to recover the tax-exclusive cigarette shelf (regular) price per pack. First, we calculate the regular cigarette price per pack as dollars divided by packs for each stock keeping unit (SKU), and tax-exclusive cigarette price per pack as cigarette price per pack minus tax per pack. Second, we identify and remove cigarette prices when (i) there is missing dollars or volume information; (ii) there is a feature, display, and/or price reduction in that week; (iii) the prices are outliers in the top and bottom 1%. We then estimate the tax-exclusive cigarette price per pack for the removed store/week/SKU as the most recent tax-exclusive cigarette price per pack within the eight weeks before and afterward (Abraham and Lodish 1993). The tax-exclusive brand price is an SKU-share weighted average. A brand is said to be on promotion if any of its SKUs are on feature, display, or temporary price reduction.

As we are interested in how antismoking policies may lead to potential shifts to higher nicotine products, we collected attribute information on nicotine content from Federal Trade Commission Reports. The annual reports provide machine-tested nicotine content of sampled SKUs with various design features (e.g., flavors, filters, menthols, and lengths) from major cigarette brands. We matched the nicotine content per cigarette to every cigarette SKU in the IRI data by brand, year, and the four attributes of flavors, filters, menthols, and lengths. An SKU-share weighted average is used to measure brand nicotine content as milligrams of nicotine content per cigarette.

Table 1 provides descriptive statistics for the seven cigarette products' marketing mixes. The three Marlboro products account for more than 40% market share. It is important to note that cigarette prices within a brand are constant across products with various nicotine contents. For example, Marlboro ultra lights, which have less than half the nicotine content of Marlboro regular, sells at approximately the same retail price ($3.80 per pack) as Marlboro regular. Therefore a smoker who is unconcerned with health outcomes can derive higher levels of nicotine per dollar by switching to regular cigarettes.

3.2. Brand Advertising

Monthly brand and corporate advertising expenditures in thousands of dollars were obtained from Kantar Media CMAG. Cigarette brand advertising has only been allowed in newspapers and magazines since the 1998 Master Settlement Agreement and it is reported as national expenditures. We use DMA-level population to proxy newspaper and magazine circulation, and obtain monthly DMA-level brand advertising expenditures in thousand dollars. Corporate advertising, which features health messages and youth smoking prevention efforts by tobacco companies such as Philip Morris and Lorillard, is allowed on television and radio. In Table 1, we report the combined brand and corporate advertising expenditures in thousands of dollars at the monthly DMA level.

3.3. Countermarketing Strategies

We supplement the store category sales and market shares with data on three countermarketing strategies. The data are collected from several sources and include cigarette excise taxes, smoke-free restrictions, and antismoking advertising rating points. Cigarette excise taxes are obtained from the Tax Burden on Tobacco report that provides detailed information on federal, state, and local tax rates and effective dates. To quantify smoke-free restrictions, we collect CDC (Centers for Disease Control and Prevention) reported annual smoke-free restriction levels for each state. The CDC categorizes smoking restrictions on a zero to five scale (whole numbers) for 12 common areas including government worksites, private worksites, restaurants, healthcare facilities, public transportation, shopping

Table 1 Summary Statistics of the Seven Cigarette Brands' Marketing Mix

	Marlboro regular	Marlboro lights	Marlboro ultra lights	Other regular	Other lights	Other ultra lights	Other medium
Market share (%)	14.446	22.666	5.563	21.765	20.868	11.143	3.548
	(6.385)	(6.924)	(2.498)	(7.705)	(5.899)	(5.547)	(1.738)
Price/pack (tax inclusive)	3.800	3.840	3.876	3.871	3.743	3.870	3.713
	(0.834)	(0.847)	(0.851)	(0.887)	(0.867)	(0.903)	(0.822)
Promotion frequency	0.362	0.357	0.274	0.530	0.513	0.336	0.337
	(0.481)	(0.479)	(0.446)	(0.499)	(0.500)	(0.472)	(0.473)
Nicotine (mg/piece)	1.090	0.808	0.505	1.221	0.808	0.403	0.840
	(0.021)	(0.009)	(0.021)	(0.541)	(0.115)	(0.094)	(0.143)
Monthly brand ads spend ($1,000)	31.987	33.582	31.987	210.367	239.540	167.639	179.784
	(78.131)	(80.184)	(78.131)	(237.897)	(280.992)	(204.382)	(207.070)

malls, bars, recreational facilities, cultural facilities, public schools, private schools, and child care centers. We conducted a principal component analysis using the ratings on the 12 areas and extracted the first principal component (see Appendix A) for use in subsequent modeling. To measure antismoking advertising, we obtained antismoking advertising gross rating points from A.C. Nielsen. The monthly DMA-level gross rating points measure all televised antismoking advertisements produced by each state's department of health.

Store zip codes are used to match the countermarketing information. For antismoking advertising, we first match each store to a specific DMA based on county according to Nielsen's DMA map. Based on the DMA we then determine the exposure to antismoking gross rating points. Web Appendix A (available as supplemental material at http://dx.doi.org/10.1287/mksc.2015.0910) shows large variations in the three countermarketing tactics across states and over time. Web Appendix B reports demographic variables using zip code level data from the 2000 U.S. Census.

3.4. Model-Free Analyses

Before introducing the formal model, we present several model-free analyses of countermarketing tactics on cigarette consumption. In Figures 1 and 2 we plot the geographical and temporal distributions of cigarette excise taxes, smoke-free restriction levels, and antismoking advertising ratings. Figure 3(a) plots a three-month moving average of cigarette category sales in a typical store. The figure shows a significant declining pattern, which is consistent with the growing popularity of cigarette excise taxes, smoke-free restrictions, and antismoking ad campaigns.

Our first objective is to examine cross-sectional evidence on the relationship between countermarketing strategies and category sales and cigarette market

Figure 1 **Geographical Variation in Countermarketing Policies**

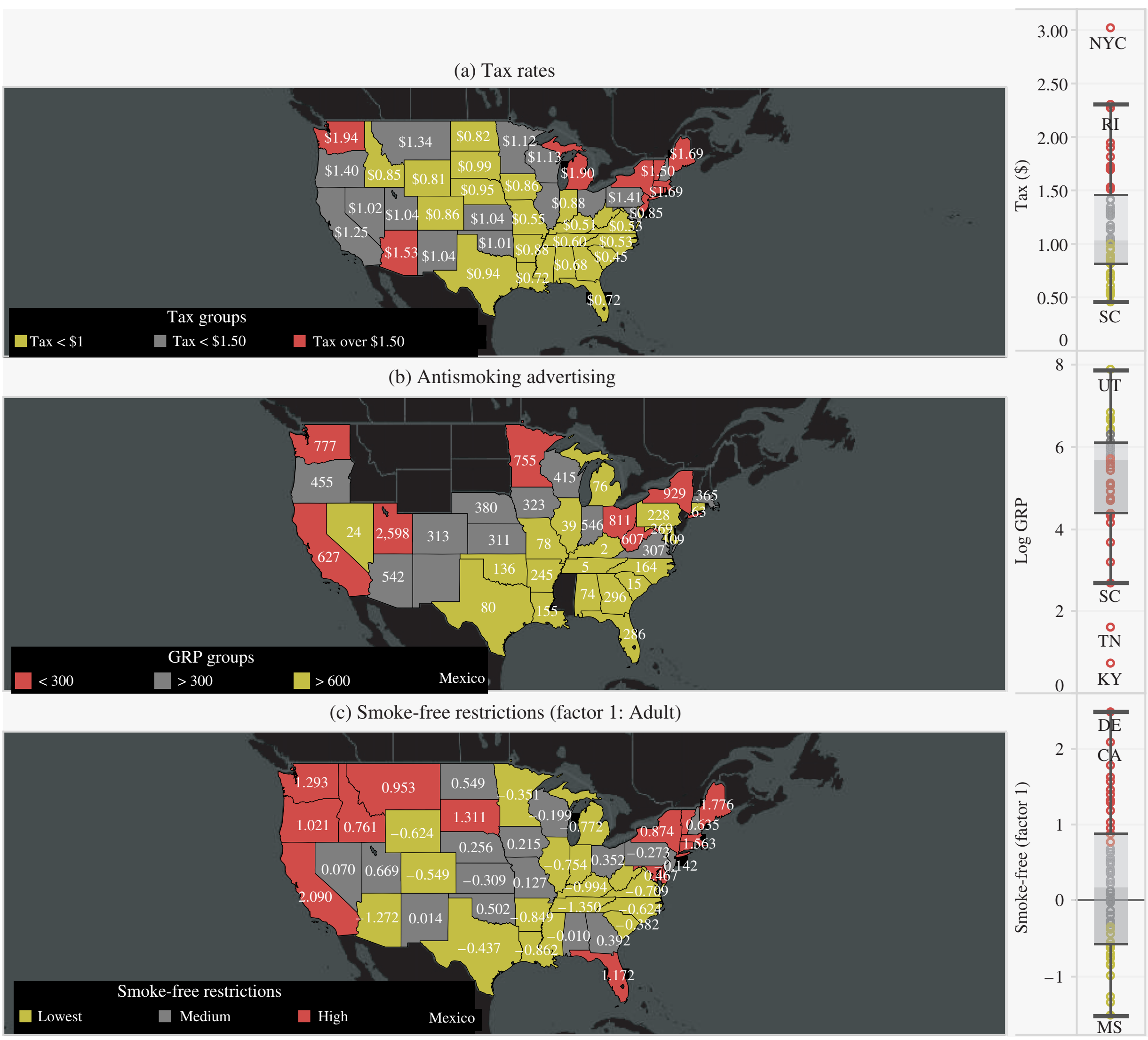


Figure 2 **Temporal Variation in Countermarketing Policies**

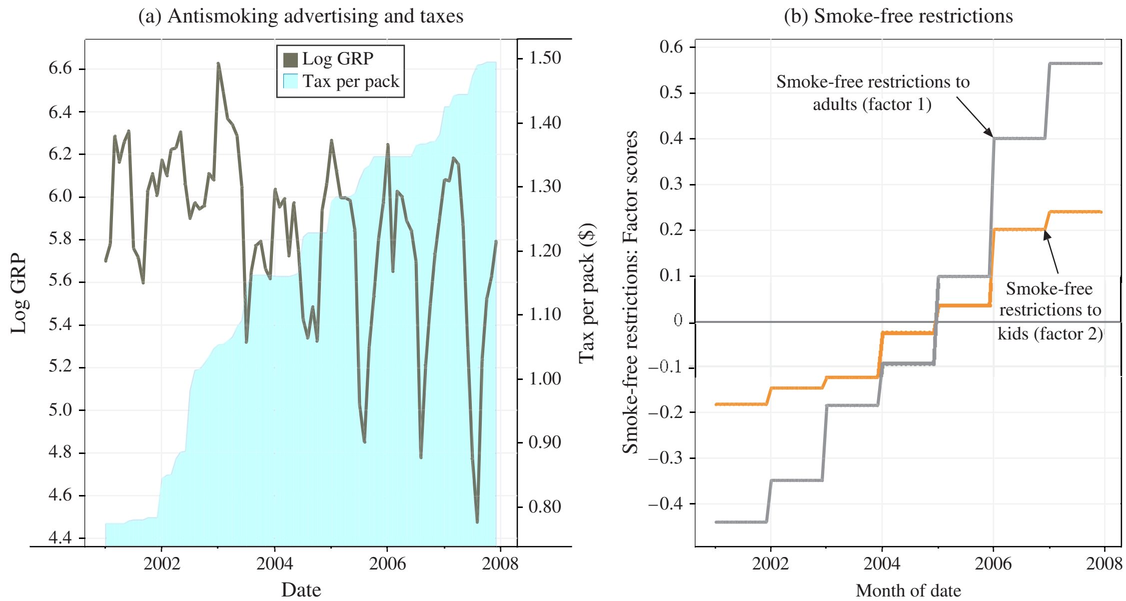
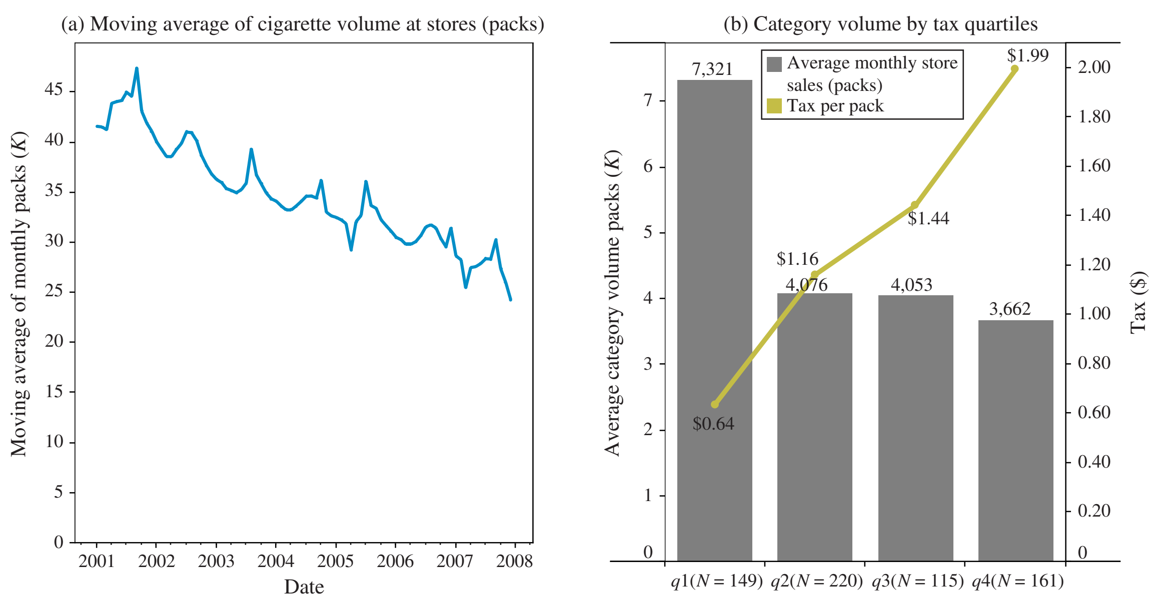


Figure 3 **Category Volume Overall and by Tax Quartiles**



shares. As noted, the three antismoking countermarketing strategies are all planned at the state level. As a result, we have quasi-experiment data from retail stores across various states. Figure 3(b) compares the monthly category volumes across stores based on tax quartiles. It shows that category sales in the high-tax stores are about half that of the low-tax stores. Similarly, the cross-sectional variation facilitates the identification of how the three countermarketing tactics may induce potential shifts to cigarette products with higher nicotine contents. In Figure 4(a), we compare market shares of regular, light, and ultra light cigarettes across stores based on tax quartiles. The figure shows that the market share of regular cigarettes in high-tax stores is 12% larger than that in low-tax stores, whereas the market share of ultra light cigarettes in high-tax stores is 16% smaller than that in low-tax stores. Similar patterns can be found in Figures 4(b) and 4(c), which provide a comparison of market shares across stores based on smoke-free restrictions and antismoking advertising quartiles. These figures suggest that smokers are more likely to purchase regular cigarettes in states with high levels of countermarketing tactics (i.e., taxes and smoke-free restrictions) to compensate for both the increasing

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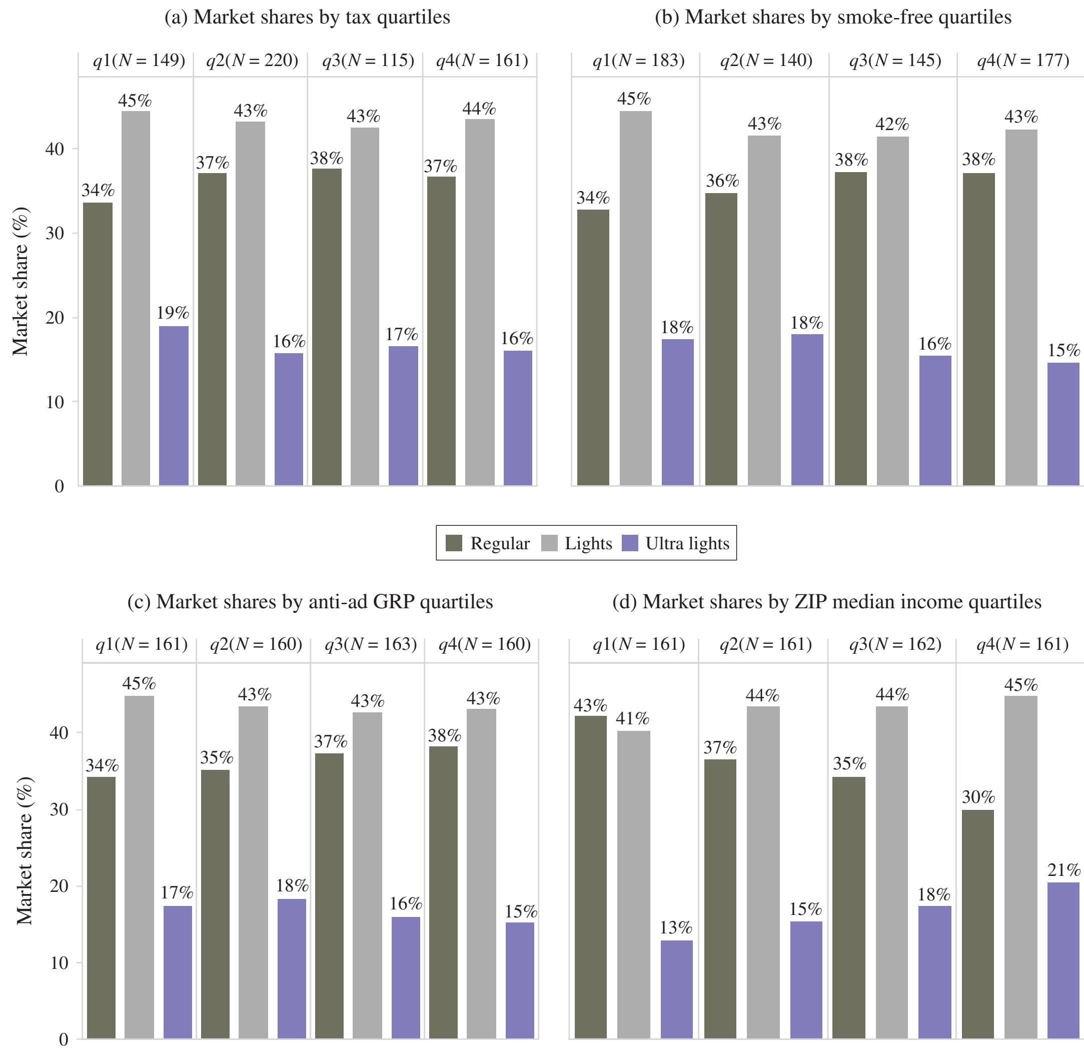
Figure 4 **(Color online) Marketing Shares of Regular, Light, and Ultra Light by Tax (a), Smoke-free (b), Antismoking Ad (c), and Median Income (d)**



Note. The correlation between regular cigarette and median income is −0.49 (p-value < 0.05).

per-nicotine economic costs and smoking-associated opportunity costs (time).

In Figure 4(d) we show the correlations between market shares of regular, light, and ultra light cigarettes and the median household income in a store's zip code. Previous literature has noted that smoking rates in the United States are significantly higher among lower socioeconomic status households (CDC 2011). Interestingly, we find that smokers with relatively lower socioeconomic status purchase a substantially higher proportion of regular cigarettes than smokers of higher socioeconomic status (43% versus 32% in the top and bottom quartile of household median income).

Next, we take a difference-in-difference approach to explore the reaction to within-state tax variations. As a benchmark, California (CA) went through no (state) tax hikes during our observation window. Its tax rate was set at \$1.20. We also notice that four states, Massachusetts (MA), Maryland (MD), Michigan (MI), and New Jersey (NJ), that had about the same tax level as California at the beginning of our observation period in 2001, all increased cigarette taxes in July 2002. This creates a quasi-field experiment setting such that there are 118 stores in the control group in California and 108 stores in the other four states (see details in Table 2). We look at the category volumes and market shares 12-months before and after the tax hike. Table 3 reports the difference-in-difference regression results of category volumes as a function of cigarette excise taxes. Both the intercept and the coefficient associated with tax differences are significantly negative ($p < 0.001$). This suggests that the four states in the treatment conditions had a larger reduction in cigarette volumes than the control group in California, and that the larger the tax hikes, the more the reduction in category volume. Table 4 reports the difference-in-difference regression results of market

Table 2 Difference-in-Difference Regression Setting

State	Tax hike date	Tax rates before ($)	Tax rates after ($)	No. of stores
CA	None	1.21	1.26	118
MA	07/25/2002	1.15	1.90	35
MD	07/01/2002	1.05	1.39	20
MI	08/01/2002	1.14	1.64	24
NJ	07/01/2002	1.19	1.89	29

Table 3 Difference-in-Difference Regression on Cigarette Category Volumes

	Estimate	SE	p-value
Intercept	−4,951	1,041	<0.001***
Tax difference	−15,499	2,426	<0.001***

***Significance level < 0.01.

Table 4 Difference-in-Difference Regression on Market Shares of Full, Lights, and Ultra Lights Cigarettes

	Estimate	SE	p-value
Intercept	−0.433	0.208	0.038**
Regular	−0.144	0.295	0.625
Lights	1.237	0.295	<0.001***
Tax diff	−0.775	0.486	0.111
Tax diff × Regular	1.008	0.687	0.143
Tax diff × Lights	1.598	0.687	0.020**

**Significance level <0.05; ***significance level < 0.01.

shares of full, lights, and ultra lights on cigarette excise taxes. The intercepts show that the states with tax hikes saw a significant reduction in the market shares of ultra light cigarettes ($p = 0.038$) compared to the control group. At the same time, the market shares of light cigarettes in the four states increased ($p < 0.001$) compared to the control group. Furthermore, as a state implemented a larger tax hike, the market shares of light cigarettes increases ($p = 0.020$). The coefficient associated with regular cigarettes is positive but statistically nonsignificant ($p = 0.143$).

4. Econometric Analysis

In this section we use our insights from the preceding model-free analyses to specify our model. The model focuses on two dependent variables: *market shares of cigarettes of different nicotine contents* and *category sales*. It serves two purposes. First, it allows us to assess the extent to which countermarketing strategies can change cigarette category sales and/or affect market shares of different nicotine content cigarettes. Second, it lets us decompose overall nicotine intake changes into changes due to category sales and shifts in market shares of cigarettes of different nicotine contents.

4.1. Setup

We employ an attraction model wherein a product's market share is equal to its attraction relative to all others. More formally, the market share MS_{jst} for product $j = 1, 2, \ldots, 7$ in month t at a store s is given by $\mathrm{MS}_{jst} = A_{jst}/\sum_k A_{kst}$, where A_{jst} is the attraction of product j in month t in store s. The formulation is similar in spirit to research in marketing that satisfies the logical-consistency requirements of market share models (e.g., Cooper and Nakanishi 1988; Naik et al. 1998, 2005). We specify attraction as $A_{jst} = \exp(H_{jst} + X_{1jst}\alpha + \varepsilon_{jst})$, where H_{jst} indicates the time-varying attractiveness intercept of cigarette product j in month t at store s. Variables X_{1jst} includes product j's tax-exclusive cigarette price per pack P_{jst}, promotion dummy Pr_{jst}, and nicotine content Nico_{jst}. After applying a log-centering transformation the market share can be specified as

$$\mathrm{MS}^*_{jst} = H^*_{jst} + \alpha_1 P^*_{jst} + \alpha_2 \mathrm{Pr}^*_{jst} + \alpha_3 \mathrm{Nico}^*_{jst} + \sum \alpha_k D_{kt} + \varepsilon^*_{1jst}, \tag{1}$$

where $\mathrm{MS}^*_{jst} = \log(\mathrm{MS}_{jst}/\widetilde{\mathrm{MS}}_{st})$; $\widetilde{\mathrm{MS}}_{st}$ is the geometric mean of MS_{jst}. Let $P^*_{jst} = P_{jst} - \bar{P}_{st}$, and $\bar{P}_{st}$ is the arithmetic mean of P_{jst}. Similarly, H^*_{jst}, Pr^*_{jst}, Nico^*_{jst}, and ε^*_{1jst} are centered to their arithmetic means. We also include monthly dummies D_{kt}.

The time-varying attractiveness of product j in month t at store s, H^*_{jst}, is specified as[3]

$$\begin{aligned} H^*_{jst} = {} & \delta_1 H^*_{jst-1} + \gamma_{1s} \mathrm{Tax}_{st} \times \mathrm{Nico}^*_{jst} + \gamma_{2s} \mathrm{SF}_{st} \times \mathrm{Nico}^*_{jst} \\ & + \gamma_{3s} \log \mathrm{Anti}_{st} \times \mathrm{Nico}^*_{jst} + \gamma_4 \log \mathrm{Ads}^*_{jst} \\ & + \gamma_5 \log \mathrm{Anti}_{st} \times \log \mathrm{Ads}^*_{jst} + v_{1jst}, \end{aligned} \tag{2}$$

where Tax_{st}, SF_{st}, and Anti_{st} are cigarette excise taxes, smoke-free restriction level, and antismoking gross rating points at store s during time t, and Ads_{jst} is the cigarette brand advertising dollars for product j in store s during month t.[4] The above equation captures the influence of antismoking policies on the market shares of cigarettes of different nicotine content. For example, a positive coefficient γ_{1s} suggests that preference for higher nicotine content cigarettes gets stronger as cigarette excise taxes increase, and vice versa. The interpretation of γ_{2s} and γ_{3s} is similar. Furthermore, we allow the parameters to differ across socioeconomic status as $\gamma_s = \gamma + \rho \times (I_{s,\,income\_q1} = 1)$, where $I_{s,\,income\_q1}$ is an indicator for stores in the bottom quartile of median household income. The ρ

[3] Note that we assume common parameters for the main effects of the antismoking policies across products in the market share Equation (1). As a result, after applying a log-centering transformation of Equation (1), the main effects of the policy variables that are common across products drop out of the attraction model.

[4] Note that H^*_{jst} is arithmetic mean centered. Therefore, the product-varying attributes enter as $\mathrm{Nico}^*_{jst} = \mathrm{Nico}_{jst} - \overline{\mathrm{Nico}}_{st}$, where $\overline{\mathrm{Nico}}_{st}$ is the arithmetic mean; $\log \mathrm{Ads}^*_{jst} = \log \mathrm{Ads}_{jst}/\widetilde{\mathrm{Ads}}_{st}$, where $\widetilde{\mathrm{Ads}}_{st}$ is the geometric mean.

term will be positive if lower income smokers are more likely to engage in tax-induced nicotine compensating behaviors. Equation (2) also captures how cigarette brand advertising may counter the effect of antismoking advertising, and the extent to which antismoking advertising may reduce the effectiveness of cigarette brand advertising. To achieve this, we include an interaction between antismoking advertising and cigarette brand advertising. The dynamic influence of the antismoking policies and cigarette brand advertising is captured through a monthly carryover parameter δ_1. A higher value of δ_1 implies a higher level of carryover and persistence.

Cigarette category sales, Sales_{st}, in month t at store s are specified as follows:

$$\log \text{Sales}_{st} = Q_{st} + \beta_1 \log P_{st} + \sum \beta_k D_{kt} + \varepsilon_{2st}, \qquad (3)$$

where Q_{st} is the time-varying category sales intercept in month t at store s. Term P_{st} is the category-level tax-exclusive cigarette price per pack in month t in store s. The D_{kt} terms are monthly dummies. The time-varying category sales intercept Q_{st} is parameterized as

$$\begin{aligned} Q_{st} = {} & \delta_2 Q_{st-1} + \theta_{1s} \log \text{Tax}_{st} + \theta_2 \,\text{SF}_{st} \\ & + \theta_3 \log \text{Anti}_{st} + \theta_4 \log \text{Ads}_{st} \\ & + \theta_5 \log \text{Anti}_{st} \times \log \text{Ads}_{st} + v_{2st}, \end{aligned} \qquad (4)$$

where Tax_{st}, SF_{st}, and Anti_{st} are cigarette excise taxes, smoke-free restriction levels, and antismoking gross rating points at store s in time t, whereas Ads_{st} is the cigarette category advertising spending dollars at store s in time t. Equation (4) captures the dynamic influence of the three antismoking policies on overall cigarette category sales. Term δ_2 is a monthly carryover rate with a higher value implying persistence.

We rewrite Equations (1) and (3) in the following matrix form:

$$\begin{bmatrix} \text{MS}^*_{st} \\ \log \text{Sales}_{st} \end{bmatrix} = \begin{bmatrix} H^*_{st} \\ Q_{st} \end{bmatrix} + \begin{bmatrix} X^*_{1st} & 0 \\ 0 & X_{2st} \end{bmatrix} \cdot \begin{bmatrix} \alpha \\ \beta \end{bmatrix} + \begin{bmatrix} \varepsilon^*_{1st} \\ \varepsilon_{2st} \end{bmatrix},$$
$$\text{where } \begin{bmatrix} \varepsilon^*_{1st} \\ \varepsilon_{2st} \end{bmatrix} \sim N(0, V). \qquad (5)$$

In the above equation, the dependent variable is an 8×1 vector. Equations (2) and (4) can be written in matrix form as

$$\begin{bmatrix} H^*_{st} \\ Q_{st} \end{bmatrix} = \begin{bmatrix} \delta_1 & 0 \\ 0 & \delta_2 \end{bmatrix} \begin{bmatrix} H^*_{st-1} \\ Q_{st-1} \end{bmatrix} + \begin{bmatrix} W^*_{1st} & 0 \\ 0 & W_{2st} \end{bmatrix} \cdot \begin{bmatrix} \gamma \\ \theta \end{bmatrix}$$
$$+ \begin{bmatrix} v_{1st} \\ v_{2st} \end{bmatrix}, \quad \text{where } \begin{bmatrix} v_{1st} \\ v_{2st} \end{bmatrix} \sim N(0, F). \qquad (6)$$

Similarly, $[H^{*'}_{st}\ Q'_{st}]$ is an 8×1 vector. The initial means of the transition vector, $[H^{*'}_{s0}\ Q'_{s0}]$, are analogous to regression intercepts, and are estimated from the data.

4.2. Estimation

We estimate model parameters using Kalman filtering (see Harvey 1994). The Kalman filter has been used to estimate continuous unobserved state variables such as advertising awareness and quality (Naik et al. 1998, 2005), brand equity (Sriram et al. 2006, Liu and Shankar 2015), and time-varying parameters (Zhao et al. 2009). The approach is recursive in nature and obtains efficient estimates of the time-varying unobservables based on the observed market shares and category sales in month t. It is well suited for the dynamic model specified in Equations (5) and (6), where Equation (5) is an observation equation and Equation (6) is a transition equation.

In the first step, we write the state space Equation (6) in vector form as $H_t = \delta H_{t-1} + W_t \mathbf{g} + v_t$, where $v_t \sim N(0, F)$. A potential concern is that the mean zero normally distributed error term v_t is likely to be correlated with cigarette advertising $\log \text{Ads}_t$. We account for advertising endogeneity through a control function approach (see Petrin and Train 2010). We decompose the error term v_t and rewrite the equation as $H_t = \delta H_{t-1} + W_t \mathbf{g} + \vartheta_t + \tilde{v}_t$, where ϑ_t is the unobserved factor that may be correlated with $\log \text{Ads}_t$, and $\tilde{v}_t$ is the random shock. The control function method alleviates endogeneity bias by including a proxy to condition out the variation in the error term, ϑ_t, that is not independent of the endogenous variables. The proxy is the residual from a regression of endogenous cigarette advertising on a set of instruments Z_{1t}: $\log \text{Ads}_t = Z_{1t}\omega_1 + \mu_{1t}$, such that

$$E(\mu_{1t} \mid \log \text{Ads}_t) = 0 \quad \text{and} \quad E(\vartheta_t \mid Z_{1t}, \mu_{1t}) = \tau_1 \mu_{1t}. \qquad (7)$$

We use monthly producer price indices for newspapers and general consumer periodicals from the Bureau of Labor Statistics as instruments.[5] We take the residual from the regression and include the estimated residual in the equation $H_t = \delta H_{t-1} + W_t \mathbf{g} + \tau_1 \hat{\mu}_{1t} + \tilde{v}_t$, where $\tilde{v}_t \sim N(0, \tilde{F})$. Furthermore, we assume the prior for the initial advertising stock to be $H'_o \sim N(H_0 F_0)$ with F_0 being a large number in order to begin with a diffuse prior. Given all information up to time $t-1$, we obtain the predicted advertising stock, $\hat{H}_{t|t-1} = \delta \hat{H}_{t-1|t-1} + W_t \hat{\mathbf{g}} + \hat{\tau}_1 \hat{\mu}_{1t}$ and the estimated variance in month t as $\hat{B}_{t|t-1} = \delta \hat{B}_{t-1|t-1} \delta' + \tilde{F}$.

In the second step, we observe market shares and category sales in month t, and attempt to obtain the prediction error $\tilde{Y}_{t|t-1}$ and variance $S_{t|t-1}$. We rewrite the observation Equation (5) in vector form as $Y_t = H_t + X_t \mathbf{a} + \varepsilon_t$. The mean zero normally distributed

[5] We ran a regression of cigarette brand advertising on two producer price indices along with DMA dummies, and exogenous variables. The two instruments are both statistically significant at 0.01 (see Web Appendix C).

Table 5 Model Comparisons

	Category equation	Market share equation	LL	No. of parameters	BIC	AIC
Model 1	Antismoking variables	Pro-smoking variables	−259,320	36	519,106	518,711
Model 2	Anti and pro	Pro	−257,498	40	515,514	515,075
Model 3	Anti and pro	Anti and pro	−257,316	48	515,254	514,727
Model 4	Anti, pro, and their interactions	Anti, pro, and their interactions	−256,969	50	514,586	514,037
Model 5	Anti, pro, interaction, monthly dummies	Anti, pro, interaction, monthly dummies	−254,940	72	510,814	510,023
Model 6	Anti, pro, interaction, monthly dummies, and different decay parameters	Anti, pro, interaction, monthly dummies, and different decay parameters	−254,558	73	510,063	509,261
Model 7	Drop the nonsignificant smoke-free component	Drop the nonsignificant smoke-free component	−254,561	70	510,030	509,261

error term, ε_t, is likely correlated with cigarette prices, P_t. We account for price endogeneity through a control function approach (see Petrin and Train 2010). We also decompose the error term ε_t and rewrite the equation as $Y_t = H_t + X_t\mathbf{a} + \epsilon_t + \tilde{\varepsilon}_t$, where ϵ_t is the unobserved factor that may be correlated with P_t and $\tilde{\varepsilon}_t$ is the random shock. The proxy is the residual from a regression of cigarette prices P_t on a set of instruments Z_{2t}: $P_t = Z_{2t}\omega_2 + \mu_{2t}$ with the following assumptions:[6]

$$E(\mu_{2t} \mid P_t) = 0 \quad \text{and} \quad E(\epsilon_t \mid Z_{2t}, \mu_{2t}) = \tau_2\mu_{2t}. \tag{8}$$

The assumption in Equation (8) implies that μ_{2t} has a conditional mean of zero and the unobserved factor ϵ_t is linear in μ_{2t}. We obtained monthly tobacco production costs, raw agriculture material costs, and crude oil prices from the U.S. Department of Agriculture as instruments for the tax-exclusive cigarette price per pack P_t.[7]

The residuals from the regressions and the estimated residuals $\hat{\mu}_{2t}$ are included in the observation equation as $Y_t = H_t + X_t\mathbf{a} + \tau_2\hat{\mu}_{2t} + \tilde{\varepsilon}_t$, where $\tilde{\varepsilon}_t \sim N(0, \tilde{V})$. The prediction error is $\tilde{Y}_{t|t-1} = Y_t - \hat{H}_{t|t-1} - X_t\hat{a} - \hat{\tau}_2\hat{\mu}_{2t}$ and the prediction variance is $S_{t|t-1} = \operatorname{cov}(\tilde{Y}_{t|t-1}) = \hat{B}_{t|t-1} + \tilde{V}$.

Next, we update the posterior of the state variable $\hat{H}_{t|t}$ by multiplying by a Kalman gain factor $\hat{H}_{t|t} = \hat{H}_{t|t-1} + K_t\tilde{Y}_{t|t-1}$, where $K_t = \hat{B}_{t|t-1}S^{-1}_{t|t-1}$. The posterior variance is $\hat{B}_{t|t} = \hat{B}_{t|t-1} - K_t\hat{B}_{t|t-1}$. The estimation proceeds as a recursive loop with the updated posterior state variable $\hat{H}_{t|t}$ serving as input data for step one described above. We let $\theta = \{\mathbf{a}, \mathbf{g}, \delta, \tau, \tilde{V}, \tilde{F}\}$ denote the sets of parameters to estimate and write the conditional log-likelihood function of the probability of observing the cigarette market shares and category sales Y_t, given the information set T_{t-1} as

$$\mathrm{LL} = \sum_{t=1}^{T} \ln[p(Y_t \mid T_{t-1})]. \tag{9}$$

Parameters are then recovered by maximizing the conditional log-likelihood function in Equation (9). Further details on the estimation procedure are provided in Appendix B.

5. Results and Discussions

5.1. Model Comparisons

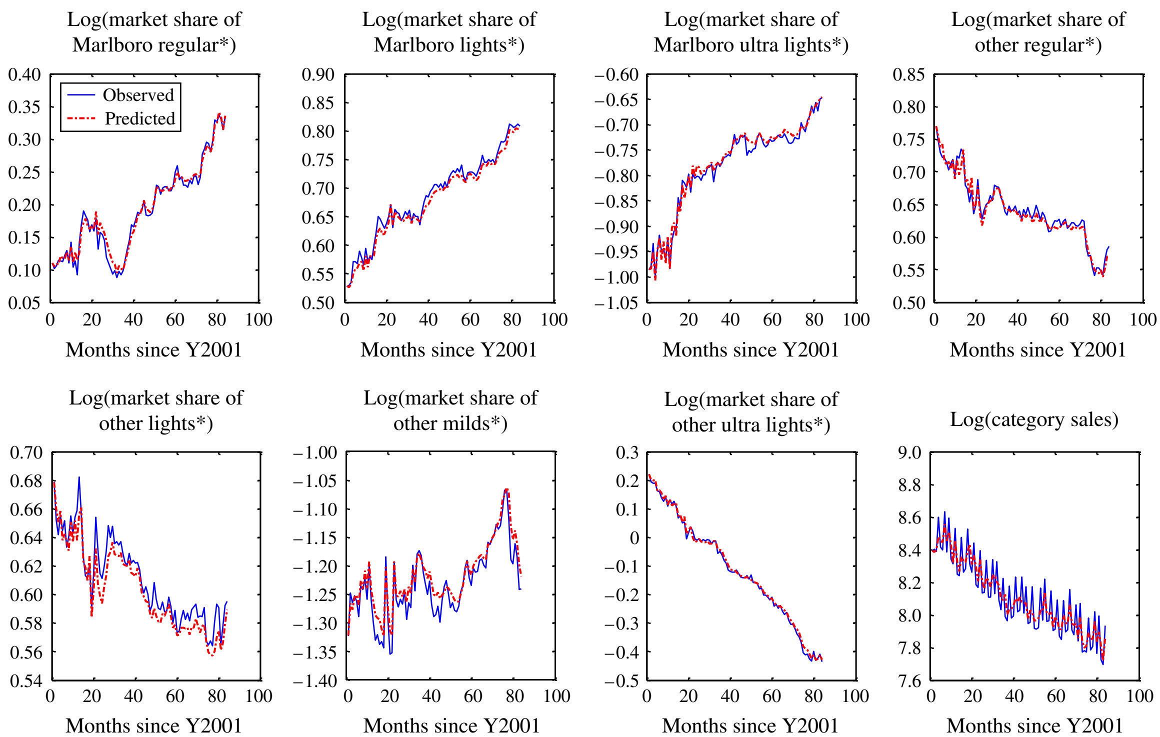
In this section we compare several alternative model specifications and present the estimation results of our proposed model. Model 1 is structured so that only marketing variables impact market shares and only antismoking policies influence category sales. Model 2 adds marketing variables to the category equation. Model 3 allows antismoking policies to affect market shares. Model 4 includes an interaction between antismoking and pro-smoking variables in both market share and category sales. Model 5 adds monthly dummies to both market shares and category sales. Model 6 allows for separate carryover rates for market shares and category sales. As mentioned previously, the factor analysis of the smoke-free regulations reveals two factors, one aimed at adults and the other related to efforts to create a smoke-free environment for children. Model 6 suggests that the children-targeted smoke-free restriction is nonsignificant in either market shares or category sales.[8] In model 7 we test a parsimonious model that only includes the adult-targeted smoke-free restriction levels. Table 5 lists the log-likelihood values and the number of

[6] We also make the assumption that $\operatorname{cov}(H_{t|t-1}, \mu_{1t}) = 0$. This implies that the unobserved factor μ_{1t} that may be correlated with cigarette brand prices are uncorrelated with $H_{t|t-1}$. To verify this assumption, we recovered the estimated $\hat{H}_{t|t-1}$ and $\hat{H}_{t|t}$ in the Kalman filter estimation. We then estimated the correlation $\mathrm{rho}(\hat{H}_{t|t-1}, \hat{\mu}_{1t}) = 0.0002$ and $\mathrm{rho}(\hat{H}_{t|t}, \hat{\mu}_{1t}) = 0.0022$. We find both correlations to be insignificant ($p = 0.91$ and $p = 0.15$, respectively).

[7] We ran a regression of the tax-exclusive cigarette price per pack on the three instruments along with store dummies, and other exogenous variables. The three price instruments are all statistically significant at 0.01 (see Web Appendix D).

[8] This is primarily due to a limited variation in the factor score of "smoke-free environment for children," as can be seen in Figure 2(b).

Figure 5 (Color online) Observed vs. Predicted Market Shares and Category Sales in Equations (1) and (3)



parameters of each model. To compare models, we use the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) metrics. Model 7 is superior to all of the other models. This result suggests that both antismoking and pro-smoking marketing strategies play a role in driving total cigarette category sales and market shares of different nicotine cigarettes. Figure 5 visually demonstrates a model fit for both category sales and market shares.

5.2. Results

5.2.1. Antismoking Policies on Cigarettes' Market Shares. We first discuss the estimates for the antismoking instruments on the market shares of cigarettes with different nicotine contents (Table 6). We find that the interaction between cigarette excise taxes and a product's nicotine content is significantly positive. This implies that an increase in cigarette excise taxes will lead to greater preferences for higher nicotine content cigarettes. Furthermore, the tax-induced nicotine compensating pattern is significantly more salient for stores located in the bottom quartile of median household income. These results confirm our speculation that the current uniform cigarette excise taxes leads smokers to switch to higher nicotine cigarettes to seek nicotine cost savings. This effect is more pronounced for low income smokers.

Regarding smoke-free restrictions, we find that an increase in the level of smoke-free restrictions leads to significantly greater preferences for higher nicotine content cigarettes as well. This result supports our speculation that smoke-free restrictions lead to a shift in preferences toward higher nicotine cigarettes to alleviate the imposed inconvenience and opportunity cost of smoking (i.e., time). However, the interaction is significantly weaker for stores in the bottom quartile of median household income.

When it comes to antismoking advertising, we find no significant role for antismoking advertising in altering the market shares of cigarettes of different nicotine contents. However, antismoking advertising does have a significant effect of mitigating the cigarette advertising by tobacco companies.

5.2.2. Pro-Smoking Marketing Mix on Cigarettes' Market Shares. As expected, the tax-exclusive cigarette price has a significant negative effect on a product's market share. Price promotions are found to have a significant positive effect. The price endogeneity correction residuals enter significantly and with the expected sign. In particular, a positive residual occurs when the price of the product is higher than can be explained by observed attributes. A positive residual suggests that the product possesses desirable attributes that are not included in the analysis (Petrin and Train 2010). The significant positive effect of cigarette advertising on market share is consistent with the findings from Pollay et al. (1996). The cigarette advertising endogeneity correction residuals are significantly negative. It suggests that there

Table 6 **Model Estimation Results**

Market share			Category sales		
Estimates in the observation Equation (1)			Estimates in the observation Equation (3)		
Price P^*_{jst}	−0.407	(0.003)***	Price $\log P_{st}$	−0.987	(0.058)***
Price endogeneity correction	0.014	(0.002)***	Price endogeneity correction	0.601	(0.057)***
Promotion Pr^*_{jst}	0.011	(0.001)***	Monthly dummies	Yes	
Nicotine	−0.015	(0.002)***			
Monthly dummies	Yes				
Estimates in the transition Equation (2)			Estimates in the transition Equation (4)		
$\text{Tax}_{st} \times \text{Nico}^*_{jst}$	0.004	(0.0005)***	$\log \text{Tax}_{st}$	−0.002	(0.001)***
$\text{Tax}_{st} \times \text{Nico}^*_{jst} \times I_{s,\,income\_q1}$	0.005	(0.001)***	$\log \text{Tax}_{st} \times I_{s,\,income\_q1}$	−0.003	(0.001)***
$\text{SF}_{st} \times \text{Nico}^*_{jst}$	0.002	(0.0003)***	SF_{st}	0.0002	(0.0002)
$\text{SF}_{st} \times \text{Nico}^*_{jst} \times I_{s,\,income\_q1}$	−0.003	(0.0006)***	$\log \text{Anti}_{st}$	−0.001	(0.0001)***
$\log \text{Anti}_{st} \times \text{Nico}^*_{jst}$	0.0001	(0.0001)	$\log \text{Ads}_{st}$	0.003	(0.0003)***
$\log \text{Anti}_{st} \times \text{Nico}^*_{jst} \times I_{s,\,income\_q1}$	−0.0004	(0.0003)	$\log \text{Anti}_{st} \times \log \text{Ads}_{st}$	−0.002	(0.0002)***
$\log \text{Ads}^*_{jst}$	0.0008	(0.0001)***	Ads endogeneity correction	−0.014	(0.001)***
$\log \text{Anti}_{st} \times \log \text{Ads}^*_{jst}$	−0.0004	(0.0001)***			
Ads endogeneity correction	−0.0008	(0.0001)***			
Carryover δ_1	0.992	(0.016)***	Carryover δ_2	0.997	(0.055)***
Initial $H^{*\prime}_{s0}$			Initial Q'_{s0}		
Marlboro regular	0.098	(0.019)***	Category sales	9.397	(0.061)***
Marlboro lights	0.541	(0.017)***			
Marlboro ultra lights	−0.978	(0.025)***			
Other regular	0.788	(0.020)***			
Other lights	0.657	(0.018)***			
Other mild	−1.318	(0.029)***			
Other ultra lights	0.217	(0.027)***			

***p-value < 0.01.

are negative unobservables that tend toward lower cigarette advertising levels.

Our estimates of $H^{*\prime}_{s0}$, product attractiveness at the initial period $t = 0$ in Table 6, are all significantly different from zero. The magnitude of the estimates is consistent with the market share sizes in Table 1. The carryover parameter δ_1 that captures the dynamic impact of antismoking policies on market shares from month to month is 0.992. It implies that the tax- and smoke-free-restrictions need to be evaluated over an extended time horizon. Note that the monthly carryover rate translates to about an annual carryover rate of 0.91, which is close in magnitude to what was used in Hu et al. (1995).

5.2.3. Antismoking Policies on Cigarette Category Sales. We find that an increase in cigarette excise taxes leads to a significant reduction in category sales. As expected, the effect of cigarette excise taxes on category sales is significantly stronger for stores in the bottom quartile of median household income. Similar to Bitler et al. (2010) and Adda and Cornaglia (2010), our results suggest that smoke-free restrictions do not impact overall cigarette consumption. In addition, we find that antismoking advertising significantly reduces cigarette category sales. In particular, antismoking advertising weakens the effectiveness of pro-smoking advertising by the tobacco industries.

5.2.4. Prosmoking Marketing Mix on Cigarette Category Sales. The estimate of tax-exclusive cigarette prices per pack is significant and negative. The endogeneity correction residuals also enter significantly and with the expected positive sign. It is important to note that the estimate of cigarette advertising on category sales is significant and positive. This is not a trivial finding. A key argument used by the tobacco industry in its defense testimony is that tobacco advertising does not expand markets but only influences market share (Goldberg et al. 2006). Our results, on the contrary, provide evidence to counter the assertions by the tobacco industry. We also find that advertising endogeneity correction terms are significantly negative. Variance parameters for both observed and transition equations are reported in Web Appendix E.

5.3. Elasticity

The relative effectiveness of the three countermarketing tactics is best illustrated through a comparison of elasticities. For the specification in the attraction model of market shares, the expressions for elasticity are given by $\gamma \times (1 - \text{MS}) \times \text{Tax} \times (1 - \delta^n)/(1 - \delta)$ for cigarette excise taxes, $\gamma \times (1 - \text{MS}) \times \text{SF} \times (1 - \delta^n)/(1 - \delta)$ for smoke-free restrictions, and $\gamma \times (1 - \text{MS}) \times (1 - \delta^n)/(1 - \delta)$ for antismoking advertising. The elasticity of category sales is given by $(\theta \times (1 - \delta^n))/(1 - \delta)$ for cigarette excise taxes, $(\theta \times \text{SF} \times (1 - \delta^n))/(1 - \delta)$ for smoke-free restrictions, and $(\theta \times (1 - \delta^n))/(1 - \delta)$ for antismoking advertising (see Web Appendix F). In Table 7, we report the elasticity of response to the three antismoking policies for a

Table 7 Seven Year Elasticity of the Three Antismoking Policies

	Cigarette excise taxes	Smoke-free restriction	Antismoking ads
Category sales	−0.162	0.001	−0.104
	(−0.272, −0.053)	(−0.001, 0.003)	(−0.124, −0.085)
Market shares of			
Regular cigarettes	0.066	0.014	0.003
	(0.047, 0.085)	(0.009, 0.019)	(−0.001, 0.007)
Light cigarettes	−0.0002	−0.0001	0.0001
	(−0.0003, −0.0002)	(−0.0001, −0.0001)	(−0.0001, 0.0001)
Ultra light cigarettes	−0.090	−0.020	−0.004
	(−0.053, −0.115)	(−0.027, −0.013)	(−0.010, 0.085)

Notes. (a) The point elasticity is calculated at the average market share of regular, light, and ultra light cigarettes, respectively; (b) 95% confidence interval in parentheses.

seven-year time period. Cigarette excise taxes are significantly more effective than antismoking advertising in reducing overall cigarette sales (elasticity of −0.162 and −0.104, respectively). Smoke-free restrictions are not found to reduce cigarette sales.

However, cigarette excise taxes and smoke-free restrictions are both associated with the unintended consequences of leading smokers to switch to higher nicotine cigarettes to seek nicotine and time cost savings. For example, over a seven-year period a 10% increase in cigarette excise taxes (relative to the tax levels in our data) results in a 1.6% reduction in category sales. Although this is a positive public health outcome, the tax increase also leads to a 0.7% increase in the market share of regular cigarettes and a 0.9% reduction in the market share of ultra light cigarettes. A 10% increase in smoke-free restrictions results in approximately a 0.1% increase in market share of regular cigarettes and 0.2% reduction in market share of ultra light cigarettes. Antismoking advertising is the only technique that successfully decreases category sales reduction without shifting market share toward high nicotine cigarettes. Over a seven-year period a 10% increase in antismoking advertising will lead to a 1% reduction in category sales.

5.4. Policy Simulations

Because nicotine is the major addictive agent in cigarettes, the diverse effects of the antismoking policies on category sales and market shares raise important questions. What is the effect of the three antismoking policies on overall nicotine intake and how does the reduction in nicotine consumption from category shrinkage compare to the increase due to brand switching? To answer these questions, we performed a series of simulations.

We first computed the level of nicotine intake (measure 1) for some level of antismoking policies observed in the data over the entire seven-year period. We then computed category sales, market shares, and the corresponding level of nicotine intake (measure 2) for an alternative antismoking policy. The difference (diff 1) is the net effect of the antismoking policy on nicotine intake. Next, we calculated another level of nicotine intake (measure 3) under an assumption that the antismoking policy only had an effect on category sales but not market shares. The difference (diff 2) between measures 1 and 3 is the nicotine intake change due to category sales reduction. The difference between diff 1 and diff 2 is a measure of the extra nicotine intake that can be attributed to market share shifts to high nicotine cigarettes. A positive value of this measure implies an unintended nicotine compensation effect.

In Table 8, we show the decomposition of nicotine consumption changes. In Table 9, we show the decomposition for the bottom quartile of median household income. During a seven-year period, when there is a 10% increase in cigarette excise taxes, the overall category shrinks by 1.06%. However, the net

Table 8 Policy Simulations on Nicotine Intake Levels Over the Seven-Year Data Period

	10% tax hike	10% increase in the 12 smoke-free restriction items	10% antismoking GRP increase
Net nicotine intake change (%)	−0.76	0.69	−1.48
	(−1.31, −0.30)	(−0.15, 1.54)	(−1.60, −1.35)
Because of market share shifts	0.30	0.37	0.02
	(0.24, 0.38)	(0.20, 0.56)	(−0.01, 0.04)
Because of category sales reduction	−1.06	0.32	−1.50
	(−1.59, −0.63)	(−0.53, 1.06)	(−1.63, −1.38)

Note. 95% confidence interval in parentheses.

Table 9 Policy Simulations on Nicotine Intake Levels Among Bottom Income Quartile Over the Seven-Year Data Period

	10% tax hike	10% increase in the 12 smoke-free restriction items	10% antismoking GRP increase
Net nicotine intake change (%)	−1.43 (−2.45, −0.45)	0.12 (−0.75, 1.12)	−1.28 (−1.39, −1.16)
Because of market share shifts	0.54 (0.42, 0.69)	−0.21 (−0.56, 0.01)	0.03 (−0.01, 0.05)
Because of category sales reduction	−1.97 (−2.92, −1.02)	0.32 (−0.55, 1.08)	−1.31 (−1.42, −1.21)

Note. 95% confidence interval in parentheses.

impact of the tax hike on nicotine intake is just 0.76% because it is mitigated by the shift toward high nicotine cigarettes (which drives a 0.30% increase in nicotine consumption). In addition, lower income smokers are more sensitive to cigarette excise taxes and also more likely to engage in tax-induced nicotine compensating. We find that a 10% increase in cigarette excise taxes leads to a larger reduction in category sales (−1.97%) for this subgroup. However, this segment also exhibits a larger unintended shift (0.54%) toward high nicotine cigarettes. Hence we find a net effect of a 1.43% nicotine intake reduction for the bottom income quartile.

As we described before, tar content and nicotine content are highly correlated. In Web Appendix G, we conducted the same evaluation using tar intake as the metric. The results show that market share shifts toward high nicotine content also significantly mitigates the health benefits of cigarette excise taxes created by category sales reductions. Given that tar content is directly linked to lung cancer, this finding has important public health implications.

Since antismoking advertising does not drive market shares, over a seven-year period a 10% increase in antismoking advertising leads to a 1.48% net reduction in nicotine intake based entirely on lower category sales. The effect of smoke-free restrictions on nicotine intake is not significant.[9] Our results reveal the overall benefits of antismoking advertising and highlight a potential downside associated with cigarette excise taxes.

6. Discussion

Over the last several decades, there has been a concerted effort by government and nonprofit organizations to reduce cigarette consumption. These organizations have used a variety of methods such as tax hikes, smoking restrictions, and educational campaigns that can collectively be classified as countermarketing. Given that these organizations have limited resources and lobbying power, a critical issue in public health is determining the relative effectiveness of these different countermarketing tools. Furthermore, the general issue of countermarketing effectiveness is growing in importance as governments and public health organizations have begun to target other categories such as soda and fast food.

Of the three countermarketing strategies evaluated in our study, cigarette excise taxes are found to be the most effective in reducing cigarette category sales, followed by antismoking advertising. We find that smoke-free restrictions are ineffective in reducing overall cigarette demand. However, cigarette excise taxes and smoke-free restrictions are both associated with an unfortunate consequence of causing smokers to switch to higher nicotine cigarettes to seek nicotine and time cost savings. This dangerous side effect occurs because a uniform cigarette tax provides an incentive for consumers, particularly in lower income brackets, to minimize their price per unit of nicotine. The health benefits of a tax-based countermarketing strategy may therefore be mitigated by the substitution of higher nicotine and higher tar cigarette brands by some consumers. Our results and policy experiments suggest that a cigarette tax that varies based on nicotine levels would be more effective in delivering health benefits.

Critically, given that we do not see a drop in category consumption associated with smoke-free restrictions but do observe that these policies shift consumption toward more dangerous products, smoke free policies seem particularly problematic. However, it is important to recognize that smoke-free restrictions are also intended to alleviate the negative effects associated with second-hand smoking. Antismoking advertising on the other hand, is the only technique found to successfully reduce category sales without shifting demand toward higher nicotine cigarettes. It is also worth highlighting the interaction between antismoking and pro-smoking advertising campaigns. Apart from its main effect in reducing cigarette category sales, we find that antismoking advertising is also effective in reducing the effectiveness of pro-smoking advertising on total cigarette

[9] Regarding the counterfactual of smoke-free restriction, we first find out what a 10% increase in the 12 smoke-free restriction items (see Appendix A) translates to in terms of the change in the factor score of component 1, and then assess the counterfactual.

market expansion. Hence, educational antismoking campaigns deserve an increased emphasis.

It is also important to note that the coefficient associated with cigarette advertising on category sales is significant and positive. This is not a trivial finding. A key argument used by the tobacco industry in defense testimony has been that tobacco advertising does not expand markets but focuses on gaining market share. Our results provide evidence to counter these assertions.

There are several limitations of the paper that deserve mention. First, as in any empirical analysis, we are limited by the data available. Although we have detailed point of sale data on quantity, price, and promotions, our advertising variables (both pro and anti) are observed at an aggregate level. Even within the point of sale (POS) scanner data, our database does not include sales from gas stations that account for slightly larger volumes of tobacco sales than supermarkets (37% versus 36%, Tauras et al. 2006). Second, large tax increases in certain states/cities (e.g., New York) have created black market activities that our analysis does not account for.[10] There are several other countermarketing tactics (e.g., dramatic images or messages on cigarette packs) that our analysis does not consider.

The topic of our analysis may also be studied using alternative data sources and modeling methodologies. For example, cigarette consumption features addiction and self-control (Gordon and Sun 2015). These behavioral traits suggest an opportunity to study consumer response to countermarketing and cessation at the individual level (Wang et al. 2014). Furthermore, use of structural models of smoker response to cigarettes can allow evaluation of how consumers respond to long-term price changes (Gordon and Sun 2015, Chen et al. 2009) or how brand strength moderates the impact of countermarketing at the level of the individual smoker (Wang et al. 2014). Such individual level models that can capture the dynamic structure of consumer decision making are of significant value and complement the current study, which relies on aggregate data. An obvious trade-off is that unlike the current paper, the papers mentioned above rely on purchase data from small samples of consumer panelists, short time frames, and usually single markets with limited exogenous variation in tax policies.

Finally, the analysis presented in the paper is also important because such antitobacco programs are increasingly used as models for newer efforts to improve public health. For example, there is currently a great deal of interest in antiobesity programs. These programs have been justified using similar arguments regarding medical costs, as the estimated annual medical costs due to obesity exceed $150 billion.[11] Similar to antitobacco campaigns, antiobesity organizations have advocated for taxes on high fat products,[12] educational campaigns, and efforts to ban products such as large sizes of sugary beverages.[13] The extension of countermarketing efforts to these less controversial categories also highlights the need for firms to investigate the proper marketing response to countermarketing tactics. Fast food companies and soft drink manufacturers may benefit from further research into the ideal responses to countermarketing activities.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0910.

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Appendix A. Standardized Scoring Coefficients of the Factor Analysis of the Smoke-Free Restrictions on 12 Areas

	Component 1	Component 2
Shopping malls	0.261	−0.182
Bars	0.242	−0.208
Restaurants	0.198	−0.083
Recreational facilities	0.184	−0.059
Healthcare facilities	0.175	−0.072
Private work sites	0.147	−0.002
Cultural facilities	0.123	0.021
Government work sites	0.095	0.064
Public transportation	0.095	0.015
Public schools	−0.319	0.659
Private schools	−0.206	0.494
Child care centers	−0.083	0.288

Note. The raw data are CDC-reported smoke-free restriction levels from zero to five on 12 areas including government work sites, private work sites, restaurants, healthcare facilities, public transportation, shopping malls, bars, recreational facilities, cultural facilities, private schools, child care centers, and public schools.

Appendix B. Steps in Kalman Filter Estimation

(a) We estimate the parameters $\theta = \{\mathbf{a}, \mathbf{g}, \delta, \tau, \tilde{V}, \tilde{F}\}$ through a Kalman filtering process. The observation and transition equation in (5) and (6) can be rewritten in a vector form as

[10] In fact a law (labeled "Stop Tobacco Smuggling in the Territories Act of 2013") is currently being discussed in Congress on precisely this issue.

[11] http://www.obesitycampaign.org.

[12] http://abcnews.go.com/Health/Wellness/fat-tax-lower-obesity/story?id=16353067#.UGBoy41lTng.

[13] http://www.nytimes.com/2012/09/14/nyregion/health-board-approves-bloombergs-soda-ban.html?_r=0.

follows: recall the observation and transition equation in (5) and (6) as

$$Y_t = H_t + X_t \mathbf{a} + \tau_2 \hat{\mu}_{2t} + \tilde{\varepsilon}_t \quad \text{where } \tilde{\varepsilon}_t \sim N(0, \tilde{V}), \tag{B1}$$

$$H_t = \delta H_{t-1} + W_t \mathbf{g} + \tau_1 \hat{\mu}_{1t} + \tilde{v}_t \quad \text{where } \tilde{v}_t \sim N(0, \tilde{F}). \tag{B2}$$

(b) We assume that the prior of state variable H_t at time 0 is $H_o' \sim N(H_0, F_0)$. Moreover, F_0 are assumed to be a large number as a diffuse prior.

(c) We let $\hat{H}_{t|t-1}$ denote the estimates of state variables at time t and $\hat{B}_{t|t-1}$ denote variance at time t, given all of the information up to time $t-1$. Therefore, our knowledge of $\hat{H}_{t|t-1}$ and $\hat{B}_{t|t-1}$ is

$$\hat{H}_{t|t-1} = \delta \hat{H}_{t-1|t-1} + W_t \hat{\mathbf{g}} + \hat{\tau}_1 \hat{\mu}_{1t}, \tag{B3}$$

$$\hat{B}_{t|t-1} = \delta \hat{B}_{t-1|t-1} \delta' + \tilde{F}. \tag{B4}$$

(d) We then obtain the prediction error and the variance of this prediction error as

$$\tilde{Y}_{t|t-1} = Y_t - \hat{H}_{t|t-1} - X_t \hat{\alpha} - \tau_2 \hat{\mu}_{2t}, \tag{B5}$$

$$S_{t|t-1} = \operatorname{cov}(\tilde{Y}_{t|t-1}) = \hat{B}_{t|t-1} + \tilde{V}. \tag{B6}$$

(e) We now update the posterior of state variable and associated variance-covariance matrix (see Harvey 1994 for details of derivation)

$$\hat{H}_{t|t} = \hat{H}_{t|t-1} + K_t \tilde{Y}_{t|t-1}, \tag{B7}$$

$$\hat{B}_{t|t} = \hat{B}_{t|t-1} - K_t \hat{B}_{t|t-1}, \quad \text{where } K_t = \hat{B}_{t|t-1} S_{t|t-1}^{-1}. \tag{B8}$$

(f) Iterate step (b) to step (d) and obtain for each $t = 1, \ldots, T$.

(g) We write the conditional log-likelihood function $\sum_{t=1}^{T} \ln[p(Y_t \mid \mathcal{T}_{t-1})]$ as follows (see Naik et al. 1998 for details):

$$\mathrm{LL} = \sum_{t=1}^{T} \sum_{j=1}^{J} \sum_{s=1}^{S} \left[-\frac{1}{2} \log(2\pi) - \frac{1}{2} \log |S_{jst|t-1}| - \frac{1}{2} \tilde{Y}'_{jst|t-1} S_{jst|t-1}^{-1} \tilde{Y}_{jst|t-1} \right]. \tag{B9}$$

(h) Given the above log-likelihood function, we use maximum likelihood estimation to obtain the estimates.

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