Distribution Agreement

Essays on Counter-Marketing and the Role of Brands

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Doctor of Philosophy

Business

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B.S. Fudan University, China, 2006
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An Abstract of
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Abstract

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By Yanwen Wang

Counter-marketing, such as excise taxes, educational advertising, and distribution restrictions, has been used to reduce the consumption of vice goods such as cigarettes and alcohol. Currently, there is substantial interest in extending counter-marketing efforts to additional categories that may pose health risks such as sugary sodas and high fat fast foods. While a substantial body of economic and public health research has documented the impact of various counter-marketing techniques at the category level, the role of marketing tactics such as branding is seldom considered.

The first essay of my dissertation, "The Unintended Consequences of Counter-Marketing Strategies", examines whether and how various counter-marketing techniques induce brand substitution, especially substitution to more dangerous products. My results show that uniform cigarette taxes designed to reduce cigarette sales have the unintended consequence of switching consumers towards higher nicotine content products. This dangerous switching occurs because a uniform cigarette tax provides an incentive for consumers to lower their price per unit of nicotine. This is a salient set of results because while excise taxes are the most potent counter-marketing tool, these taxes may also cause harm to a segment of consumers.

The second essay of my dissertation, "Does Brand Strength Moderate the Effectiveness of Counter-Marketing Technique," investigates how brand strength may moderate the efficacy of counter-marketing tactics. A notable feature of "vice" categories is the dominance of strong brands such as Coca-Cola, McDonalds, Marlboro, and Budweiser. I find that consumers who are loyal to strong brands such as Marlboro are less responsive to a cigarette excise tax increase and educational anti-smoking campaigns. However, these strong brand loyalists are more susceptible to smoke-free policies that limit smokers' options to publically consume cigarettes. My work extends the branding literature by looking into the role of strong brands in making brand-consumer relationships more resistant to counter-marketing. These results imply that counter-marketing efforts need to overcome not only the physical addiction of nicotine, but also strong psychological relationships between brands and consumers. This is of interest to both policy makers and big brands in targeted industries.

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Life is a journey. It is irreversible. Although there were sadness, disappointments and regrets that I wished that I could have avoided or better dealt with, I am happy with whom I am now. This is more than enough to me. Finally, I cite an ancient Chinese poem herein to conclude:

Listen not to the rain beating against the trees,
In a straw cloak, spend my life in mist and rain;
In front I see the slanting sun atop the hill,
Impervious to wind, rain or shine, I'll have my will.

---- *Su Shi (1037 – 1101; Song Dynasty), China*

Table of Contents

List of Tables

List of Figures

List of Appendices

Chapter 1

Overview

There are few products that have had the impact of tobacco on society. Tobacco is considered by some to be one of the key products that drove colonization and the slave trade. An interesting historical side note is that tobacco was originally considered a medicinal plant with great healing properties. Tobacco and cigarettes also have a rich history in terms of marketing practice.

Tobacco was one of the earliest product categories to adopt modern marketing and branding techniques. Tobacco and cigarette marketing has featured innovative techniques such as trading cards, celebrity endorsements, sports sponsorships and free distribution to military personnel. However, over the last half century the cigarette industry has found itself confronted by another marketing innovation: counter-marketing.

The development of anti-tobacco counter marketing is driven by the dangers and costs associated with tobacco use. The adverse health consequences of tobacco consumption are well known. For example, the Centers for Disease Control and Prevention report that tobacco causes over 90% of all lung cancer deaths and over 80% of all deaths from chronic obstructive pulmonary disease (COPD). In terms of economics, tobacco usage is blamed for $133 billion in direct medical costs and $156 billion in lost productivity each year.

The CDC defines counter-marketing as the use of commercial marketing techniques to reduce the prevalence of tobacco use. This terminology is somewhat vague as it is unclear what the boundaries of "commercial marketing" are. While health oriented advertising is clearly classified as counter-marketing other techniques such as excise taxes are or smoke free restrictions are less easy to classify. For example, an excise tax on tobacco products might not be automatically viewed as a pure marketing technique but since these taxes effectively act as price increases they do have a marketing interpretation. The key point is that counter-marketing is best viewed from the perspective of consumer behaviour. If we adopt the view that counter-marketing consists of activities that influence consumer decision making in regards to tobacco, or other controversial products, then excise taxes that increase prices or smoke free policies that decrease convenience are tools in the counter-marketers arsenal.

Adopting a more holistic or consumer focused view of counter-marketing is an important step for research focused on reducing tobacco consumption. A current limitation of the extant research on reducing smoking is that most disciplines adopt fairly narrow views of the problem. The economics literature has tended to focus on macro level policy changes while neglecting marketing activity and individual level customer traits. The public health literature has emphasized field experiments and self-reported consumption levels. The marketing literature primarily features lab experiments that may lack ecological validity.

In this dissertation, I present two essays that examine the interplay between tobacco company marketing activities, counter-marketing activities such as excise taxes, educational advertising and distribution restrictions, and consumer decisions. The first essay is title “The Unintended Consequences of Counter-Marketing Strategies” and it uses store level data to examine how counter-marketing activities can change consumer preferences. In particular, this study examines the question of whether per pack excise taxes may shift consumers towards higher nicotine products. This is an important question since higher nicotine is associated with greater physical dependence. If per cigarette taxes shift some consumers to these more dangerous products then these policies must balance the benefits of reduced overall smoking with the costs of increasing nicotine dependence in certain segments. Specifically, this analysis also investigates whether shifts towards higher nicotine products are more likely for lower socio-economic groups.

The second essay is titled “Does Brand Strength Moderate the Effectiveness of Counter-Marketing Strategies?” This study focuses on the relationship between counter-marketing instrument effectiveness and cigarette brand strength. This essay asks the question of whether counter-marketing instruments have asymmetric effects across cigarette brands that vary in terms of brand equity. This analysis is executed using individual level data on cigarette purchases and longitudinal data on excise taxes, smoke free restrictions and health oriented advertising. In particular, the individual level data is used to construct measures of brand preference.

Chapter 2

Essay 1: The Unintended Consequences of Counter-Marketing Strategies

2.1 Introduction

Counter-marketing, or efforts to reduce consumption of certain products, has become common in categories ranging from cigarettes to furs. For the most part, counter-marketing activities have been concentrated on vice goods such as cigarettes, alcohol, and sugary, high fat foods that pose health risks (Cohen 2000). Counter marketing 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 U.S., 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 counter-marketing strategies to reduce tobacco consumption.

Our research is focused on the tobacco industry and investigates the extent to which counter-marketing strategies can change overall cigarette consumption and shift market shares across products with different nicotine levels. First, we investigate the efficacy of various counter-marketing activities on cigarette category sales. This is an important topic because anti-smoking organizations tend to have limited resources and must therefore identify the most effective interventions. Counter-marketing efforts in tobacco may be broadly categorized as price interventions, educational campaigns, and localized smoking bans. These three categories are interesting as 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 counter-marketing 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. It is also possible to investigate whether smoke-free restrictions may switch smokers 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 counter-marketing 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. This data includes seven years (2001-2007) of store-level cigarette sales and marketing mix activities across a broad cross-section of US markets. We supplement this data with extensive information on cigarette excise tax records, smoke-free restriction levels, and anti-smoking advertising gross ratings points over time and markets. In addition, we collected detailed information on cigarette attributes such as variation in nicotine and tar content across brands and strength levels (Regular/Lights/Ultra-lights). Finally, while our research focuses on counter-marketing tactics, we also evaluate the effectiveness of the tobacco industry's marketing mix. Counter-marketing does not occur in a vacuum, so it is imperative to control for the marketing efforts of the tobacco industry when studying counter-marketing effectiveness.

The data used in our research possesses several characteristics that facilitate the identification of the relative effectiveness of the various counter-marketing tactics. In our data we observe large inter-temporal and cross-sectional variation in anti-smoking policies. Cigarette excise taxes include a varying state component in addition to a common federal component. Usually, 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 5 cent increase. In contrast, taxes range considerably across the states. Similarly, the majority of anti-smoking 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 anti-smoking 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 counter-marketing techniques. We also use zip code level demographic profiles to examine whether effectiveness varies across socio-economic groups.

Given the data described above, our empirical strategy involves simultaneously estimating a market-share and a category sales model as a function of pro-smoking marketing mix and a time-varying anti-smoking policy environment. The anti-smoking policy environment includes factors that dynamically impact cigarette consumption. The two sets of equations are estimated simultaneously using a Kalman filter (Harvey 1994; Naik, Mantrala and Sawyer 1998; Naik, Raman and Winer 2005; Sriram, Chintagunta and Neelamegham 2006; Zhao, Zhao and Song 2009; Liu and Shankar 2012) with price endogeneity treated with a control function approach (Petrin and Train 2010).

We find that cigarette excise taxes and anti-smoking advertising are statistically equally effective in reducing overall cigarette sales. Smoke-free restrictions are found to have no effect on cigarette sales reduction. 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. While a 100% increase in cigarette excise taxes results in a long-term (infinite horizon) in a substantial reduction in category sales, this level of tax increase also causes a 14% increase in the market share of regular cigarettes and a 19% reduction in the market share of ultra-light cigarettes. Anti-smoking advertising is the only technique that is successful at reducing category sales without shifting share to higher nicotine variants. It is interesting to note that anti-smoking advertising also reduces the effectiveness of pro-cigarette advertising.

To further evaluate the unintended consequences, we decomposed the net nicotine intake changes into those due to changes in category sales and those due to market share shifts across different nicotine level cigarettes. For example, during the seven-year data period we find that while a 100% increase in excise taxes (relative to the values observed in the data) results in a reduction in category sales of 11% but only a net decrease in nicotine consumption of 8.5%. Nicotine reduction is less than category shrinkage because there is a significant shift towards high nicotine cigarettes (about 3%). This adverse effect is particularly relevant for lower social-economic classes. Our findings therefore suggest that uniform cigarette excise taxes should be considered with caution as uniform taxes are likely to increase addiction levels for many smokers. Policy makers should consider the adoption of nicotine based tax structures.

The remainder of the paper is organized as follows: The next section frames our contribution in terms of the economic, public health, and marketing literatures. We then provide background on counter-marketing efforts and tobacco industry marketing. This section also describes the data sources used in our analysis. Next, we present our modeling approach and estimation results. 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.

2.2 Literature Review

The literature concerned with smoking cessation has spanned multiple academic disciplines including economics, public health and marketing. In this review, we begin with the economics and public health literature that explicitly focuses on the effectiveness of anti-smoking 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 anti- and pro-smoking tactics on both cigarette category sales and market shares of cigarettes with different nicotine contents.

2.2.1 Economic Literature on Anti-Smoking Strategies and Category Sales

Anti-smoking organizations have employed a variety of techniques including cigarette excise taxes, smoke-free restrictions and educational anti-smoking advertising campaigns. Of all the various counter-marketing instruments, cigarette taxes are often viewed as the most important counter-marketing technique. Cigarette excise taxes are specified per twenty-cigarette pack and are included in posted retail prices (Chetty, Looney and Kroft 2009). These taxes typically include a federal and state component.[1] During our observation window the federal tax was constant except for a minimal 5-cent increase from 34 cents to 39 cents on January 1st 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 -.4 (see Chaloupka and Warner 2000 for a review).

[1] A few local governments have their own local cigarette tax—e.g., in 2002 NYC raised its cigarette tax by $1.42 to $1.50 per pack; Cook County, IL, 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 of these restrictions is to increase time and effort costs by forcing smokers outdoors to smoke. Smoke-free restrictions affected approximately 50 percent of the population before the year 2000 and were rapidly expanded to the point where over 70% of the population was affected by 2008. The smoke-free air policies have been found to have mixed results. For example, Evans, Farrelly and Montgomery (1999) find that voluntary workplace smoke-free air laws reduce smoking prevalence by 5 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, anti-smoking 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 anti-smoking advertising campaigns were planned at the state level. Anti-smoking advertising has been found to reduce smoking rates. For example, Hu, Sung and Keeler (1995) found the anti-smoking advertising elasticity to be significant at -.07 using data from California. In addition, studies in the public health literature have often evaluated the effectiveness of anti-smoking advertising campaigns using field studies and self-reported usage measures (see NCI 2008 for a review).

2.2.2 Marketing Literature on Pro-Smoking Strategies and Category Sales

The extant economic literature on smoking has largely ignored the interactions between anti- 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 counter-marketing 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 (in the tune of 100 milliseconds) can be quite effective (Pieters and Wedel 2011). Research from marketing studies supports the premise that cigarette brand advertising is very effective. For example, Pollay et al. (1996) found that cigarette advertising elasticity with regard to brand shares is .28. Furthermore, Leeflang and Reuijl (1985) provided 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 2012; Chen, Sun and Singh 2009). Chen, Sun and Singh (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, while Gordon and Sun (2012) investigate the dynamic impact of tobacco companies' temporary versus permanent price adjustments on cigarette consumption. While these studies illustrate the roles of pricing and promotion on brand tier choice and incidence, these studies do not consider the role of counter-marketing activities or switching between nicotine based sub-categories.

2.2.3 Anti-Smoking Strategies and Market Shares

Few studies investigate whether and how anti-smoking activities change patterns of consumption across cigarette types. Specifically, there is an open question as to whether cigarette taxes, smoke-free restrictions, and anti-smoking advertising lead to market share shifts towards 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 (NHIS) 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 anti-smoking advertising may switch smokers toward lighter brands. Our study attempts to fill this gap in the literature by examining the unintended consequences of anti-smoking strategies.

2.2.4 Summary and Outstanding Issues

The preceding discussion highlights a lack of empirical research that simultaneously considers the impact of anti- and pro-smoking strategies on both category sales and market shares of cigarettes of different nicotine contents. For example, the use of cigarette taxes that are independent of nicotine content may have unintended effects on consumer’s choices. While 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. In sum there is a critical need for studies that consider the unintended consequences of anti-smoking policies.

2.3 Data

The cigarette category has been a source of controversy for 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 the cigarette companies have developed strong brands, and used a variety of pricing and promotions 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 dataset covering from January 2001 to December 2007, cigarette excise tax records, smoke-free policies, anti-smoking advertising, cigarette brand advertising, and cigarette attributes such as nicotine and tar content.

2.3.1 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 7 years from 2001 to 2007 and covers a large cross-section of markets across the US. The units of analysis are overall category sales and the market shares of regular, light and ultra-light cigarettes at each retail store. As Marlboro is a clear market leader, we add in a brand component and focus on 7 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 the 645 stores with complete seven-year records. These stores span 38 states, 52 designated media areas (DMAs), 196 counties and 592 zip codes.

The store level scanner data records detailed information on weekly volumes, dollars, and promotional activities at the 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 SKU, and tax-exclusive cigarette price per pack as cigarette price per pack minus tax per pack. Second, we identify and remove the cigarette prices when: (i) there is missing dollars or volume information; (ii) there is a feature, a display, and/or a price reduction in that week; (iii) the prices are outliers in the top and bottom one per cent. 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 afterwards (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 SKU is on feature, display, or temporary price reduction.

As we are interested in how anti-smoking policies may lead to potential shifts to higher nicotine products, we collected attribute information on nicotine content from the 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

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

SKU-share weighted average is used to measure brand nicotine content as milligrams nicotine content per cigarette.

Table 1 provides descriptive statistics for the 7 cigarette products' marketing mixes. The three Marlboro products account for more than 40 per cent 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 has less than half the nicotine content of Marlboro Regular sells at approximately the same retail price of $3.8 per pack as Marlboro Regular. Therefore a smoker who is unconcerned with health outcomes can derive higher levels of nicotine per dollar savings by switching to regular cigarettes.

2.3.2 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.

2.3.3 Counter-Marketing Strategies

We supplement the store category sales and market shares with data on three counter-marketing strategies. The data are collected from several sources and include cigarette excise taxes, smoke-free restrictions, and anti-smoking advertising rating points. Cigarette excise taxes are obtained from the Tax Burden on Tobacco report (2011) that provides detailed information on federal, state, and local tax rates and effective dates. To measure smoke-free restrictions, we collect CDC-reported annual smoke-free restriction level for each state from zero to five on 12 common areas including government worksites, private worksites, restaurants, healthcare facilities, public transportation, shopping malls, bars, recreational facilities, cultural facilities, private schools, child care centers and public schools. We then conducted a principal component analysis and extracted the first principal component (see Appendix 1) for use in subsequent modeling. To measure anti-smoking advertising, we obtained anti-smoking advertising gross rating points from A.C. Nielsen. The monthly DMA-level gross rating points measure all televised anti-smoking advertisements produced by each state's department of health and human services.

Store zip codes are used to match the counter-marketing information. For anti-smoking advertising, we first match each store to a specific DMA based on the county according to Nielsen's DMA map. Based on the DMA we then determine the exposure to anti-smoking gross rating points. Table 2 shows large variations in the three counter-marketing tactics across states and over time. Table 3 reports demographic variables using zip code information from the 2000 US Census.

2.4 Model-Free Analyses

Before introducing the formal model, we conduct several model-free analyses of the three counter-marketing strategies on cigarette consumption. In Figure 1 we plot the geographical and temporal distribution of cigarette excise taxes, smoke-free restriction levels, and anti-smoking advertising ratings. First, we examine the cigarette category sales trend. Figure 2 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 anti-smoking advertising campaigns.

As noted, the three anti-smoking counter-marketing strategies are all planned at the state level. As a result, we have quasi-experiment data from retail stores across various states. This facilitates the identification of how the three counter-marketing tactics may induce potential shifts to cigarette products with higher nicotine contents. In Figure 3a, we compare market shares of regular, light and ultralight 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, while the market share of ultra-light cigarettes in high-tax states is 16% smaller than that in low-tax stores. Similar patterns can be found in Figures 3b and 3c which provide a comparison of market shares across stores based on smoke-free restrictions and anti-smoking advertising quartiles. These figures suggest that smokers are more likely to purchase regular cigarettes in states with high levels of counter-marketing tactics (i.e. tax and smoke-free restriction) to compensate for both the increasing per-nicotine economic costs and smoking-associated opportunity costs (time).

In Figure 3d we further 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 U.S. are significantly higher among lower socio-economic 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% vs. 32% in top and bottom quartile of household median income, respectively).

2.5 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 counter-marketing strategies can change cigarette category sales and/or affect market shares of different nicotine content cigarettes. Second, it lets us decompose the overall nicotine intake changes as a result of the changes in category sales and that of the shifts in market shares of cigarettes of different nicotine contents.

2.5.1 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 $j = 1, 2, \dots, 7$ in month t at a store s is given by $MS_{jst} = \frac{A_{jst}}{\sum_k A_{kst}}$, where A_{jst} is the attraction of product j in month t store s. The formulation is similar in spirit to a long line of research in marketing that satisfies the logical-consistency requirements of market share models (e.g. Cooper and Nakanishi 1988, Naik, Mantrala and Sawyer 1998; Naik, Raman and Winer 2005). We specify the attraction as $A_{jst} = Exp(H_{jst} + X_{1jst}\alpha + \varepsilon_{jst})$, where H_{jst} indicates the policy environment against cigarette product j in month t store s. X_{1jst} includes product j's pro-smoking marketing mix, specifically, P_{jst}, tax-exclusive cigarette price per pack, and, Pr_{jst}, a promotion dummy. After applying a log-centering transformation the market share can be specified as:

(1) $$MS^*_{jst} = H^*_{jst} + \alpha_1 P^*_{jst} + \alpha_2 Pr^*_{jst} + \varepsilon^*_{1jst}$$

where $MS^*_{jst} = \log\frac{MS_{jst}}{\widetilde{MS}_{st}}$; $\widetilde{MS}_{st}$ is the geometric mean of MS_{jst}. $P^*_{jst} = P_{jst} - \bar{P}_{st}$, and $\bar{P}_{st}$ is the arithmetic mean of P_{jst}. Similarly, H^*_{jst}, Pr^*_{jst} and ε^*_{1jst} are centered to their arithmetic means.

At the same time, the cigarette category sales $Sales_{st}$ in month t in store s are as follows:

(2) $$\log Sales_{st} = Q_{st} + \beta_1 \log P_{st} + \sum \beta_k D_{kt} + \varepsilon_{2st}$$

where Q_{st} is the anti-smoking policy environment in month t at store s. P_{st} is the category-level tax-exclusive cigarette price per pack in month t store s. D_{kt} are monthly dummies.

We can rewrite our two focal outcomes in the following matrix form:

(3) $$\begin{vmatrix} MS^*_{st} \\ \log Sales_{st} \end{vmatrix} = \begin{vmatrix} H^*_{st} \\ Q_{st} \end{vmatrix} + \begin{vmatrix} X^*_{1st} & 0 \\ 0 & X_{2st} \end{vmatrix} * \begin{vmatrix} \alpha \\ \beta \end{vmatrix} + \begin{vmatrix} \varepsilon^*_{1st} \\ \varepsilon_{2st} \end{vmatrix}, \quad \text{where} \begin{vmatrix} \varepsilon^*_{1st} \\ \varepsilon_{2st} \end{vmatrix} \sim N(0, V)$$

In the above equation, the dependent variable is an 8 ×1vector. $X^*_{1,st}$ is an 8× 2 matrix and α is a 2 × 1 vector. $X_{2,st}$is an 1× 12 matrix and β is a 12 × 1 vector.We allow for a correlated error structure such that a category shock might affect market share shocks.

We now turn to the dynamics in the vector $|H^{*\prime}_{st} \quad Q_{st}{}'|$. The time-varying anti-tobacco policy environment against a product j in month t in store s, H^*_{jst}, is specified as:

(4) $$H^*_{jst} = \delta H^*_{jst-1} + \gamma_{1s} Tax_{st} \times Nico^*_{jst} + \gamma_{2s} SF_{st} \times Nico^*_{jst} + \gamma_{3s} \log Anti_{st} \times Nico^*_{jst} + \gamma_4 \log Ads^*_{jst} + \gamma_5 \log Anti_{st} \times \log Ads^*_{jst} + v_{1jst}.$$

The above equation captures the dynamic influence of anti-smoking policies on the market shares of cigarettes of different nicotine contents[3]. For example, a positive coefficient γ_{1s} would suggest that the preference for higher nicotine content cigarettes gets stronger as cigarette excise

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

taxes increase, and vice versa. This is the same with γ_{2s} and γ_{3s} on the influence of smoke-free restriction and anti-smoking advertising on cigarette products' market shares. Furthermore, we allow the influence to differ among socio-economic status as $\gamma_s = \gamma + \delta \times (I_{s,income\_q1} = 1)$. $I_{s,income\_q1}$ is an indicator for stores in the bottom quartile of median household income. We expect δ to be positive if lower income smokers are more likely to engage in tax-induced nicotine compensating behaviors. Equation (4) also captures how cigarette brand advertising may counter the effect of anti-smoking advertising, and the extent to which anti-smoking advertising may reduce the effectiveness of cigarette brand advertising. To achieve this, we include interaction between anti-smoking advertising and cigarette brand advertising.

The time-varying policy environment against smoking Q_{st} takes the form of:

$$(5) \qquad Q_{st} = \delta Q_{st-1} + \theta_{1s} \log Tax_{st} + \theta_2 SF_{st} + \theta_3 \, log\, Anti_{st} + \theta_4 \log Ads_{st} + \theta_5 \, log\, Anti_{st} \times \log Ads_{st} + v_{2st}$$

Equation (5) captures the dynamic influence of the three anti-smoking policies on overall cigarette category sales reduction. We also allow for the interaction between anti- and pro-smoking advertising to impact category sales. Equations (4) and (5) can be written in matrix form as:

$$(6) \qquad \begin{vmatrix} H_{st}^* \\ Q_{st} \end{vmatrix} = \begin{vmatrix} \delta & 0 \\ 0 & \delta \end{vmatrix} \begin{vmatrix} H_{st-1}^* \\ Q_{st-1} \end{vmatrix} + \begin{vmatrix} W_{1st}^* & 0 \\ 0 & W_{2st} \end{vmatrix} * \begin{vmatrix} \gamma \\ \theta \end{vmatrix} + \begin{vmatrix} v_{1st} \\ v_{2st} \end{vmatrix}, \quad \text{where} \begin{vmatrix} v_{1st} \\ v_{2st} \end{vmatrix} \sim N(0, F)$$

In the above equation, δ is the carryover rate of the policy environment against smoking, with a higher value of δ implying higher level of carryover and persistence. $|H_{st}^{*\prime} \quad Q_{st}{}'|$ is an 8×1vector. $W_{1,st}^*$ is a 7× 8 matrix and γ is a 8×1 vector. $W_{2,st}$is an 1× 5 matrix and θ is a 5×1 vector.We allow for a correlated error structure in F such that a category shock might affect market share shocks. The initial means of the transition vector, $|H_{s0}^{*\prime} \quad Q_{s0}{}'|$, are analogous to regression intercepts, and are estimated from the data.

2.5.2 Estimation

We estimated the 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, Mantrala and Sawyer 1998; Naik, Raman and Winer 2005), brand equity (Sriram, Chintagunta, and Neelamegham 2006; Liu and Shankar 2012), and time varying parameters (Zhao, Zhao and Song 2009). This approach is recursive in nature and obtains efficient estimates of the unobserved policy environment against smoking in month *t* based on the observed market shares and category sales in month *t*. It is well suited for the dynamic model specified in equation (3) and (6) where equation (3) 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 $H_t = \delta \mathrm{H}_{t-1} + W_t\boldsymbol{g} + v_t$, where $v_t \sim \mathrm{N}(0, \mathrm{F})$. We assume the prior for the initial advertising stock to be $H_o' \sim \mathrm{N}(H_0, \mathrm{F}_0)$ 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, $\widehat{\mathrm{H}}_{\mathrm{t|t-1}} = \delta\widehat{H}_{t-1|t-1} + W_t\widehat{\boldsymbol{g}}$ and the estimated variance in month t as $\widehat{B}_{t|t-1} = \delta\widehat{B}_{t-1|t-1}\delta + F$.

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 (3) in vector form as $Y_t = H_t + X_t\boldsymbol{a} + \varepsilon_t$. The mean zero normally distributed error term ε_t is likely to be 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 $Y_t = H_t + X_t\boldsymbol{a} + \epsilon_t + \tilde{\varepsilon}_t$, where ϵ_t is the unobserved factor that maybe correlated with P_t and $\tilde{\varepsilon}_t$ is the random shock. The control function method alleviates endogeneity bias by including a proxy to condition out the variation in the error term, ϵ_t, that is not independent of the endogenous cigarette price P_t. The proxy is the residual from a regression of cigarette prices P_t on a set of instruments Z_t: $P_t = Z_t\omega + \mu_t$ with the following assumptions[4]:

(7) $E(\mu_t|P_t) = 0$ and $E(\epsilon_t|Z_t, \mu_t) = \tau\mu_t$

The assumption in equation (7) implies that μ_t has a conditional mean of zero and the unobserved factor ϵ_t is linear in μ_t. We obtained monthly tobacco production costs, raw agriculture material cost and crude oil prices from the U.S. Department of Agriculture as instruments for the tax-exclusive cigarette price per pack P_t. We take the residual from the regression of cigarette price on the instruments[5] and include the estimated residual in the observation equation as: $Y_t = H_t + X_t\boldsymbol{a} + \tau\hat{\mu}_t + \tilde{\varepsilon}_t$, where $\tilde{\varepsilon}_t \sim N(0, \tilde{V})$. The prediction error is $\tilde{Y}_{t|t-1} = Y_t - \hat{H}_{t|t-1} - X_t\hat{\boldsymbol{a}} - \hat{\tau}\hat{\mu}_t$, while the prediction variance is $S_{t|t-1} = \mathrm{cov}(\tilde{Y}_{t|t-1}) = \hat{B}_{t|t-1} + \tilde{V}$.

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 $K_t = \hat{B}_{t|t-1}S_{t|t-1}^{-1}$. The posterior variance follows 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 $\theta = \{\boldsymbol{a}, \boldsymbol{g}, \delta, \tau, V, F\}$ denote the sets of parameters to estimate and write the conditional log-

[4] We also make the assumption that $cov(H_{t|t-1}, \mu_t) = 0$. It suggests that the unobserved factor μ_t that may be correlated with cigarette brand prices are uncorrelated with $H_{t|t-1}$, the state-level policy environment against smoking. 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 empirically estimated the correlation $\mathrm{rho}(\hat{H}_{t|t-1}, \hat{\mu}_t)$ =-.0004 and $\mathrm{rho}(\hat{H}_{t|t}, \hat{\mu}_t)$ =.0003. We find both correlations to be insignificant (p=.81 and p=.82, respectively).

[5] We ran a regression of the tax-exclusive cigarette price per pack on the three instruments. We also included store and brand dummies, and the exogenous variables in equation (1) and (4). The three price instruments are all statistically significant at .01 (see appendix 2 for details).

likelihood function of the probability of observing the cigarette market shares and category sales Y_t, given the information set $\mathcal{T}_{t-1}$ as:

$$(8) \qquad LL = \sum_{t=1}^{T} Ln[p(Y_t|\mathcal{T}_{t-1})]$$

Parameters are then recovered by maximizing the conditional log-likelihood function in equation (8). Further details on the estimation procedure are provided in Appendix 3.

2.6 Results and Discussions

2.6.1 Model Comparisons

In this section we compare several alternative model specifications and present the estimation results of our proposed model. The objective is to assess how anti- and pro-smoking strategies influence category sales and market shares. Model 1 is structured so that marketing variables impact market shares and anti-smoking policies drive category sales. Model 2 adds marketing variables to category equation. Model 3 allows anti-smoking policies to affect market shares. Model 4 allows for the interaction between anti- and pro-smoking variables in both market share and category sales, as proposed in the preceding section. Table 4 lists the maximized log-likelihood values and the number of parameters of each model. To compare models, we use the AIC (Akaike Information Criterion) and BIC (Bayes Information Criterion) metrics. Our proposed model, model 4, is superior to the other three models. This result suggests that both anti- and pro-smoking marketing strategies play a role in driving total cigarette category sales and market shares of different nicotine cigarettes. Figure 4 visually demonstrates model fit for both category sales and market shares.

2.6.2 Results

Anti-smoking policies on cigarettes' market shares. We first discuss the estimates for the anti-smoking instruments on the market shares of cigarettes with different nicotine contents. 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 lead smokers to switch to higher nicotine cigarettes to seek nicotine cost savings. And that 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 anti-smoking advertising, we find no significant role for anti-smoking advertising in altering the market shares of cigarettes of different nicotine contents. However, anti-smoking advertising does have a significant effect of mitigating the cigarette advertising by tobacco companies.

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 also found to have a significant positive effect. The endogeneity correction residuals, $\hat{\mu}_t$, 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 finding by Pollay et al. (1996).

Our estimates of the effects of initial anti-smoking policy environment are all significantly different from zero. The magnitude of the estimates is consistent with the market share sizes in Table 1. The parameter δ that captures the carryover of the anti-smoking policy environment from month to month is .994. This is consistent with our expectation that the anti-smoking policy environment should be highly persistent and should hence have a positive and high (close to 1) carryover. It implies that the tax- and smoke-free-restrictions need to be evaluated over an extended time horizon.

Anti-smoking 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, Carpenter and Zavodny (2010) and Adda and Cornaglia (2010), our results suggest that smoke-free restrictions do not impact overall cigarette consumption. In addition, we find that anti-smoking advertising significantly reduces cigarette category sales. In particular anti-smoking advertising weakens the effectiveness of pro-smoking advertising by the tobacco industries.

Pro-smoking marketing mix on cigarette category sales. The estimate of tax-exclusive cigarette prices per pack is significant and negative. The endogeneity correction residuals, $\hat{\mu}_t$, 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 defense testimony is that tobacco advertising does not expand markets but only influences market share (Goldberg, Davis, and O'Keefe 2006). Our results, on the contrary, provide evidence to counter the assertions by the tobacco industry. Variance and covariance parameters for both the observed and transition equations are reported in Appendix 4 and 5.

2.6.3 Elasticity

The relative effectiveness of the three counter-marketing tactics is best illustrated through a comparison of elasticities. For the specification used in our attraction model of market shares, the expressions for elasticity with respect to anti-smoking policies are given by $e_{ms} = \frac{\gamma(1-MS)X}{(1-\delta)}$ and the elasticity of category sales with respect to anti-smoking policies are given by $e_{cat} = \frac{\theta}{(1-\delta)}$. In Table 6, we report the long-term elasticity of the three anti-smoking policies. Cigarette excise taxes and anti-smoking advertising are statistically equally effective in reducing overall cigarette sales (elasticity of -.667 and -.610, respectively). Smoke-free restrictions are not found to reduce cigarette sales.

However, cigarette excise taxes and smoke-free restriction are both associated with the unintended consequences of leading smokers to switch to higher nicotine cigarettes to seek nicotine and time cost savings, respectively. For example, over an infinite horizon a 100% increase in cigarette excise taxes (relative to the tax levels in our data) results in approximately 67% reduction in category sales. While this is a positive public health outcome, the tax increase also leads to 14% increase in the market share of regular cigarettes and 19% reduction in the market share of ultra-light cigarettes. A 100% increase in smoke-free restrictions results in approximately a 3% increase in the market share of regular cigarettes and 5% reduction in the market share of ultra-light cigarettes. Anti-smoking advertising is the only technique that successfully decreases category sales reduction without shifting market share towards high nicotine cigarettes.

2.6.4 Counterfactuals

As nicotine is the major addictive agent in cigarettes, the diverse effects of the anti-smoking policies on the category sales and market shares raise important questions. What is the effect of the three anti-smoking 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 set of counterfactual studies.

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

In Table 7, we show the decomposition of nicotine consumption changes. In Table 8, we show the decomposition among the bottom quartiles of median household income. During a seven-year period, when there is 100% increase in cigarette excise taxes, the overall category shrinks by 11.4%. However, the net impact of the tax hike on nicotine intakes is just -8.5% as it is mitigated by the unintended side effect of market share shifts toward high nicotine cigarettes (which drives a 2.9% increase in 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 100% increase in cigarette excise taxes leads to a larger reduction in category sales (-18%) for this subgroup. However, this segment also exhibits a larger unintended shift (5.3%) towards high nicotine cigarettes. Hence we find a net effect of a 12.7% nicotine intake reduction for the bottom income quartile.

As we described before, tar content and nicotine content are highly correlated. In Table 9 and 10, 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 anti-smoking advertising does not drive market shares a 100% increase in anti-smoking advertising leads to a 14% net reduction in nicotine intake based entirely on lower category sales. The effect of smoke-free restrictions on nicotine intakes is at best minimal. In sum our results reveal the overall benefits of anti-smoking advertising and highlight a potential downside associated with cigarette excise taxes.

2.7 Discussion

Over the last several decades there has been a concerted effort by government and non-profit 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 counter-marketing. Given that these organizations have limited resources and lobbying power, a critical issue in public health is determining the relative effectiveness of these different counter-marketing tools. Furthermore, the general issue of counter-marketing effectiveness is growing in importance as governments and public health organizations have begun to target other categories such as soda and fast food.

Out the three counter-marketing strategies evaluated in our study, cigarette excise taxes and anti-smoking advertising are found to be equally effective in reducing cigarette category sales. We find that smoke-free restrictions are ineffective in reducing overall cigarette category consumption. However, cigarette excise taxes and smoke-free restrictions are both associated with unintended consequences of leading 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 counter-marketing 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 which 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 towards more dangerous products, smoke free policies seem problematic. However, it is important to recognize that smoke free restrictions are also intended to alleviate the negative effects associated with second-hand smoking. Anti-smoking advertising on the other hand, is the only technique found to successfully reduce category sales without shifting demand towards higher nicotine cigarettes. It is also worth highlighting the interaction between anti- and pro-smoking advertising campaigns. Apart from its main effect in reducing cigarette category sales, we find that anti-smoking advertising is also effective in reducing the effectiveness of pro-smoking advertising on total cigarette market expansion. Hence, educational anti-smoking campaigns deserve increased emphasis.

It is also 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 the defense testimony is that tobacco advertising does not expand markets but focuses on gaining market share. Our results, on the contrary, provide evidence to counter the assertions made by the tobacco industry.

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 POS scanner data, our database does not include sales from gasoline stores that account for slightly larger volume for tobacco sales than supermarkets (37% versus 36%, Tauras, Peck and Chaloupka 2006). In addition, large tax increases in certain states/cities (e.g. New York) have created significant black market activities that our analysis does not account for[6]. Finally, there are several other counter marketing tactics (e.g. dramatic images or messages on cigarette packs) that our analysis does not consider.

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

The analysis presented in the paper is also important because such anti-tobacco programs are being used as models for newer efforts to improve public health. For example, there is currently a great deal of interest in anti-obesity programs. These programs have been justified using similar arguments regarding medical costs, as the estimated annual medical costs due to obesity exceed $150 billion[7]. Similar to anti-tobacco campaigns, anti-obesity organizations have advocated for taxes on high fat products[8], educational campaigns and efforts to ban products such as large sizes of sugary beverages[9]. Furthermore, the extension of counter-marketing efforts to these less controversial categories highlights the need for firms to investigate the proper marketing response to these tactics. Fast food companies and soft drink manufacturers may benefit from further research into the ideal responses to counter-marketing activities.

[7] www.obesitycampaign.org;
[8] http://abcnews.go.com/Health/Wellness/fat-tax-lower-obesity/story?id=16353067#.UGBoy41lTng
[9] http://www.nytimes.com/2012/09/14/nyregion/health-board-approves-bloombergs-soda-ban.html?_r=0

CHAPTER 3

Essay 2: Does Brand Strength Moderate the Effectiveness of Counter-Marketing Techniques? The Case of Cigarettes

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3.1 Introduction

Over the last 20 years, counter-marketing tactics have been used extensively to reduce the consumption of vice goods such as cigarettes and alcohol. Currently, there is substantial interest in extending these counter-marketing efforts to additional categories that may pose health risks such as sugary sodas and high fat fast food offerings (Cohen 2000). In the cigarette category counter-marketing activities have included tactics such as excise taxes that increase costs to consumers, distribution and usage constraints that make consumption less convenient and educational campaigns that increase awareness of health risks. Cigarette counter-marketing has been very successful as smoking rates have dropped from 44% in 1950 to 19% in 2011 (CDC 2012).

A notable feature of these "vice" categories is that they tend to be dominated by very strong brands. For example, the Interbrand Top 100 brands list includes Coca-Cola, McDonalds, Budweiser, and Marlboro (Interbrand 2010-2012). However, economic and public health oriented research on counter-marketing effectiveness has largely ignored the role of brands. This is a clear oversight in that the perceived importance of branding and marketing is demonstrated by advocacy groups' and regulators' efforts to limit advertising. An interesting example of efforts to reduce brand power is the current effort by the Australian government to mandate plain packaging of tobacco products.

The lack of research on the role of branding on consumers' consumption of vice goods is a significant omission. The marketing literature on branding posits that there are often strong psychological bonds between a brand and its customers (Fournier 1998). Furthermore, strong brands are known to provide benefits to manufacturers in terms of reducing price elasticity, increasing advertising effectiveness and increasing sensitivity to competitors' prices (Hoeffler and Keller 2003; Keller and Lehmann 2006). Although almost all previous branding research has focused on the value of strong brands in forming and maintaining brand-consumer relationships, it is reasonable to speculate that strong brands might also make it more difficult for advocacy groups and regulators to disrupt brand-consumer relationships. In other words, smokers who consume high equity brands might be less responsive to counter-marketing strategies such as excise taxes, counter-advertising, and distribution restrictions.

Our research investigates the role of strong brands on consumers' consumption of "vice" goods in categories that are subject to counter-marketing tactics. Our study is executed using data from the cigarette category. The tobacco industry is an important and useful context for our research for several reasons. First, the tobacco consumption causes significant economic costs and health consequences. Cigarette smoking has been estimated to cause 443,000 premature deaths each year in the U.S. and imposes healthcare costs and productivity losses of about $200 billion each year (CDC 2011). Second, this industry has been the target of a significant amount of counter-marketing activity. Counter marketing efforts in tobacco can be broadly categorized as price interventions, educational advertising campaigns and localized smoking bans. In addition, as counter-marketing tactics are largely determined at the state level, there is a significant amount of variation in policies across states. This variation facilitates identification of the effectiveness of different counter-marketing techniques. Third, advocacy groups and regulators are currently using experience from the tobacco category to guide efforts to reduce obesity (Khan, Misra and Singh 2012). Finally, the existence of significant brand loyalty and differences in brand equity in the cigarette category affords an opportunity to study the interplay between counter-marketing techniques, brand preference and brand equity.

In order to investigate the interplay between brand equity and counter-marketing, we assemble a data set that includes a consumer panel of cigarette purchases over a six-year period from 2004 to 2009, and a comprehensive data set of state level cigarette taxes, anti-smoking advertising ratings points, and smoke-free restrictions. This data is supplemented with information on each brand's nicotine content from Federal Trade Commission reports. We conduct our analysis using a dynamic programming model of consumer behavior that explicitly accounts for the dynamic effects of smokers' monthly nicotine intake levels and expectations about future costs and benefits of continuing to smoke. In this model a smoker's nicotine intake decision depends on his or her anticipated enjoyment of nicotine consumption versus the anticipated economic, convenience (opportunity and time), and perceived health costs associated with smoking. Our model treats these expectations as functions of individual's observed nicotine consumption (addiction), and the three counter-marketing strategies of cigarette excise taxes, smoke-free restrictions, and health-oriented anti-smoking advertising. We incorporate smoker's observed brand preferences as a source of observed heterogeneity and focus on whether smokers of Marlboro and other high equity brands respond differently to counter-marketing tactics than smokers of weak brands. We estimate an infinite horizon dynamic programming model of smoker's consumption and quitting decisions with a computationally efficient Metropolis-

Hasting algorithm proposed by Imai, Jain and Ching (2009). This algorithm reduces the computational burden of conventional nested fixed point algorithms by efficiently using the computational results obtained from past iterations to estimate the value function.

Our results show that the impact of different counter-marketing activities varies based on smoker's nicotine consumption levels. We find that increasing prices have a larger impact on smokers that consume more nicotine. In fact, heavy smokers who consume more than 840 mg of nicotine per month (approximately 2 packs a day) are about 7 times more price sensitive than light smokers who consume less than 210 mg of nicotine per month (less than half a pack a day). Similarly, health education messages are significantly negative for all usage segments but are more effective for the highest nicotine using segments. Heavy smokers are about 4 times more responsive to health oriented anti-smoking advertising than light smokers.

Our results also indicate that counter-marketing efforts need to overcome not only consumers' physical addiction for nicotine but also the psychological relationship between brands and consumers. We find that cigarette taxes and anti-smoking advertising are less effective for consumers that smoke high equity brands such as Marlboro. This is a salient finding, as previous research on smoking cessation has solely focused on the physical addiction of nicotine and neglected the psychological connections between cigarette brands and consumers. However, we do find that smoke free policies are a more effective anti-smoking tactic for reducing consumption by Marlboro and strong brand smokers. Our speculation is that this result occurs because usage restrictions make it more difficult for consumers to use strong brands to project or create an image.

Our work contributes to the existing literature in several ways. In terms of econometrics based marketing studies, our work complements two marketing studies that utilize dynamic models of cigarette purchasing to examine the role of temporary and permanent price promotions in addictive categories (Chen, Sun and Singh 2009; Gordon and Sun 2012). We extend this stream of literature by including counter-marketing activities and through our focus on ending relationships between cigarette brands and consumers. Our study also extends the economics literature on smoking. The economics literature has tended to rely on large-scale surveys and reduced-form models to investigate the role of individual counter-marketing tactics (most often excise taxes) on overall category level consumption (e.g., Chaloupka 1991; Becker, Grossman and Murphy 1994; Coppejans et al. 2007). However, this work has not investigated the role of brands. Finally, our work relates to the broader literature on branding and brand-consumer relationships (Hoeffler and Keller 2003 for a review; Keller and Lehmann 2006). We extend the literature by looking into the ability of high brand equity to make a brand more resilient to counter-marketing tactics. This is likely to be an increasingly important topic as counter-marketing tools are increasingly being used in categories such as soda and fast food.

The rest of the paper is organized as follows. Section 2 discusses relevant literature from economics and marketing. Section 3 describes the multiple data sets used in our analysis and section 4 provides model-free evidence. In sections 5 and 6 we present the model and describe the estimation methodology. Section 7 discusses the estimation results and section 8 concludes the paper with a discussion of the key results and areas for future research.

3.2 Literature Review

Because our paper is relevant to marketing, economic and public policy issues, our work needs to be positioned relative to multiple streams of literature. To frame our research we begin by considering marketing research explicitly focused on consumer behavior in the cigarette category. We then shift to a review of selected literature from economics and public health. These two disciplines have traditions of studying counter-marketing effectiveness. However, these disciplines typically rely on surveys rather than actual customer behavior and marketing issues are neglected. We then return to the marketing literature to review research specifically focused on brand-consumer relationships and brand strength.

3.2.1 Marketing Studies on Cigarettes and Counter-Marketing

The bulk of tobacco related research from marketing academics has focused on issues relating to advertising. For example, Pollay et al. (1996) use aggregate data and find that cigarette brand advertising elasticity is .28. 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 used as the primary dependent variable (Pechmann and Shih 1999; Pechmann et al. 2003; Andrews et al. 2004).

In addition, two marketing studies build dynamic demand models of cigarette purchasing and examine the role of temporary and permanent price promotions using scanner data (Chen, Sun and Singh 2009; Gordon and Sun 2012). Chen, Sun and Singh (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, while Gordon and Sun (2012) investigate the dynamic impact of tobacco companies' temporary versus permanent price adjustments on cigarette consumption. They find that the temporary consumption elasticity is smaller than the permanent consumption elasticity. While these marketing studies illustrate the roles of pricing and promotion on brand tier choice and incidence, these studies do not consider the role of counter-marketing activities.

3.2.2 Economic Literature on Anti-Smoking Interventions

The economics literature has tended to rely on large-scale surveys and reduced-form models to investigate the role of individual counter-marketing tactics on consumption (e.g., Chaloupka 1991; Becker, Grossman and Murphy 1994; Coppejans et al. 2007). Of the various counter-marketing instruments, excise taxes and pricing have received the most attention in the economics literature. Cigarette excise taxes are specified per twenty-cigarette pack and are included in posted retail prices (Chetty, Looney and Kroft 2009). These taxes typically include a federal and state component. Researchers have found that the price elasticity of cigarette demand is about -.4 (see Chaloupka and Warner 2000 for a review).

In conjunction with tax hikes, anti-smoking 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. The majority of anti-smoking advertising campaigns are planned at the state level with the exception of nationwide programs sponsored by the American Legacy Foundation.[10] Anti-smoking advertising has been found to reduce smoking rates. For example, Hu, Sung and Keeler (1995) index California anti-smoking campaigns with advertising pages in *Life* magazine distributed in California. They find anti-smoking advertising elasticity to be significant at -.07. Notably, this estimate is much lower than found by Pollay et al. (1996).

[10] The American Legacy Foundation was created in 2000 as part of the Master Settlement Agreement (MSA) entered into by 46 state attorneys generals who sued the tobacco industry over Medicaid costs related to smoking.

In addition to anti-smoking advertising and excise taxes, anti-smoking advocates have also been increasingly successful in implementing “smoke-free” restrictions such as prohibitions against smoking in bars, restaurants, and public places. The interventions increase convenience and time costs by forcing smokers outdoors to smoke. Smoke-free restrictions affected approximately 50 percent of the population before the year 2000 and have been rapidly 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, Farrelly and Montgomery (1999) find that voluntary workplace smoke-free air rules reduce smoking prevalence by 5 percentage points and daily consumption by 10 percentage points. However, Bitler, Carpenter and Zavodny (2010) and Adda and Cornaglia (2010) find no effect of smoke-free air laws on smoking behavior.

3.2.3 Branding and Brand-Consumer Relationship

The extant literature on smoking cessation has largely ignored the impact of brand equity on efforts to reduce cigarette consumption. This is an important oversight given that marketing researchers have found that brand-consumer relationships have significant effects on consumer decision making (e.g. Howard and Sheth 1969; Jacoby and Kyner 1973; Fournier 1998; Keller and Lehmann 2006). Jacoby and Kyner’s distinction between repeat purchasing behavior and brand loyalty is particularly apt for the cigarette category. Since nicotine is an addictive substance, much of the repeat buying in the cigarette category is driven by physical addiction. However, it also seems likely that some type of attitudinal loyalty exists in the category. Oliver (1999) defines brand loyalty as a “deeply held commitment to rebuy a preferred product/service in the future.” This definition is fairly consistent with Jacoby and Kyner’s notion of attitudinal loyalty. In most contexts this type of loyalty or commitment would be thought of in terms of how it might make a brand less sensitive to the marketing efforts of its competitors. However, in the cigarette category a psychological relationship between a brand and a consumer may be useful for both preventing switching to other brands and as a hindrance to quitting smoking.

Fornier (1998) describes a number of characteristics needed for the existence of a brand-consumer relationship. For instance, Fournier highlights the importance of animating, humanizing or personalizing brands. Cigarette brands such as Camel and Marlboro are prime examples of efforts to create a humanized personality that can be a focal point for the brand-consumer relationship. Fournier also emphasizes the need for a brand-consumer relationship to add meaning to a consumer's life. Image intensive advertising in the cigarette category and the nature of usage whereby the product is continually taken out and consumption is often public leads cigarettes to be known as badge products[11]. Aaker's (1997) research on brand personality is also relevant to the discussion of brand-consumer relationships in the cigarette category. Aaker finds that brands tend to be viewed as having personalities' such as sincerity or excitement and lists Marlboro as a prototypical "rugged" brand.

The outcome or impact of brand-consumer relationships has been a key topic in the brand equity literature. Hoeffler and Keller (2003) provide a review of the advantages of strong brands. One frequently cited advantage is that strong brands can command higher price premiums and are more immune to price increases (Sethuraman 1996; Keller and Lehmann 2006). It has also been shown that strong brands enjoy higher advertising effectiveness (Raj 1982). Although almost all the previous branding literature has focused on the value of strong brands in forming and maintaining brand-consumer relationships, it is reasonable to speculate that strong brands

[11]Cigarette package designer, John Digianni, states: 'a cigarette package is part of a smoker's clothing, and when he saunters into a bar and plunks it down, he makes a statement about himself.'
http://www.tobaccotoday.info/2012/05/23/cigarettes-brand-evolution/

might also make it more difficult for advocacy groups and regulators to disrupt brand-consumer relationships. Specifically, consumers who prefer strong brands might be less responsive to counter-marketing strategies such as excise taxes, health-advertising, and distribution restrictions.

3.2.4 Literature Summary

The preceding discussion highlights several streams of literature that are relevant to the use of counter-marketing techniques in reducing the consumption of vice goods. Two key elements of this review merit emphasis. First, the public health and economics literatures that have studied the effectiveness of counter-marketing instruments have not considered the role of branding and have seldom used panel data samples that afford an opportunity for the analyst to observe individual brand preferences. Second, the marketing literature has found that brand-consumer relationships are of critical importance in understanding consumer behavior. Collectively these two observations suggest a critical need for studies that consider brand loyalty in the context of counter-marketing efforts.

3.3 Data

3.3.1 Purchases

The primary data for our study come from the Nielson Homescan Panel for a six-year period between January 2004 and December 2009. This panel provides each household an optical scanner that is used to scan the barcodes of all consumer packaged goods they purchase, regardless of outlet. The data therefore includes purchases from supermarkets, convenience stores, drug stores, gas stations, and other outlets. This broad coverage is important because, unlike the product categories often studied in the literature (i.e. those primarily sold in supermarkets), smaller retail outlets account for a significant proportion of cigarette sales.

We select smokers by applying the following ordered criteria: (i) keep only households that stayed in the Nielson Panel for all the six years; (ii) keep smokers that had made at least twenty cigarette purchases; (iii) keep smokers that had cigarette purchases in 2004, the beginning of our observation window. The three selection criteria result in a panel of 626 smokers that were potentially in the process of quitting or had quit smoking over the six year horizon. We randomly select 526 smokers for estimation and retain 100 for a hold-out sample. We use year 2004 as an initialization period and years 2005-2009 for estimation.

As is well documented, nicotine is a major addictive agent in cigarettes (Benowitz 2010). As a consequence of this property, smokers may engage in nicotine compensating behavior by switching to higher nicotine content cigarettes (i.e. regular cigarettes) to cope with increasing cigarette taxes (Adda and Cornaglia 2006; Evans and Farrelly 1998). Therefore, we focus on a smoker's monthly nicotine intake quantity to capture the individual's preference for the category. We define monthly nicotine intake as the product of nicotine content per cigarette in milligrams and the number of cigarettes purchased by a smoker in a particular month. Information on UPC level nicotine content was collected from Federal Trade Commission Reports. The FTC annual report provides machine-tested nicotine content in milligrams of sampled SKUs from the major cigarette brands.

Figure 5 shows the distribution of monthly nicotine intake for our estimation sample. We discretize the monthly nicotine intake into five mutually exclusive tiers: zero intake, less than 210 milligrams, less than 420 milligrams, less than 840 milligrams, and more than 840 milligrams. Table 11 shows the frequencies of the five intake levels for the estimation sample. Approximately 23 percent of smokers consume less than 210mg of nicotine per month, 14 percent consume between 210mg and 420mg nicotine per month, and about 25 percent consume more than 420mg nicotine per month. The five monthly nicotine intake levels roughly correspond to zero packs, less than half a pack a day, less than one pack a day, less than two packs a day, and more than two packs per day. This categorization is also used in the National Health Interview Survey (NHIS).

The scanner based nature of our data also allows us to include pricing data in the model. For each smoker, we observe tax-inclusive cigarette purchase prices and quantities. We construct monthly cigarette average prices per pack faced by each smoker. When replacing missing prices in the non-purchasing months we use the average cigarette prices paid by other smokers in the same store and in the same month (Chen, Sun and Singh 2009). If this is not available, we replace it by the average cigarette prices paid by other smokers in the same zip-code and in the same month, or in the same state and in the same month.

3.3.2 Brand Preference Segments

We define a smoker's favorite brand based on share of wallet. A notable feature of the cigarette category is that brand loyalty is very high. Appendix 6 shows a frequency plot of the number of brands purchased by each smoker during the six year time span from 2004 to 2009. Approximately 52 percent of smokers purchased only a single brand during the six-year window, and another 33 percent of smokers purchased only two brands. This setting allows us to segment smokers by their favorite cigarette brand.

We supplement the purchase data with aggregate store-level data on 2001-2005 cigarette sales and prices from the Information Resources, Inc. (IRI) Marketing Data Set (Bronnenberg, Kruger, and Mela 2008). We use this data to rank cigarette brands by their national sales revenues. Appendix 7 lists the top 20 brands by sales revenues. Marlboro is the dominant brand in the cigarette category with a 43 percent market share. We place Marlboro in its own category, the second to tenth ranked brands are categorized as "strong" brands, and the remaining brands are labeled as "weak" brands. Our measure of brand strength (equity) is consistent with the revenue premium measure of brand equity proposed by Ailawadi, Lehmann and Neslin (2003). The key in their revenue premium measure is to identify a benchmark brand that had no equity (i.e. private label), while our assumption is that there is a single benchmark brand for the entire category. Table 12 shows the distribution of smokers' segment memberships. The number of smokers across the three brand segments is fairly evenly distributed. Marlboro smokers account for about 27.4 percent, strong brands account for 36.9 percent, and weak brands account for 35.7 percent of the overall population of smokers.

3.3.3 Counter-Marketing Mix

We supplement the customer purchase information with data on three counter-marketing mix tactics. This information is collected from multiple sources and includes cigarette excise taxes, anti-smoking advertising rating points, and smoke-free restrictions. Cigarette excise taxes are obtained from the Tax Burden on Tobacco report (2011) that provides detailed information on federal, state, and local tax rates and effective dates. To measure anti-smoking advertising intensity, we obtained data on adult-targeted anti-smoking advertising gross rating points from A.C. Nielson. The monthly gross rating points measure all televised anti-smoking advertisements produced by each state's department of health and human services across cable and network television in each Designated Market Area (DMA). To measure smoke-free restrictions, we collect smoke-free air policy information for four common venues defined as restaurants, bars, private workplaces, and government workplaces from the CDC's STATE tracking studies. In each venue smoke-free restrictions are assigned one of three values: 0 for no restriction, .5 for partial restriction, and 1 for a complete restriction. We take the average of the smoke-free restrictions in the four venues to describe a state's smoke-free restriction level.

For each smoker we construct a vector of demographics that includes zip code and household income. Zip codes are used to match the counter-marketing data to each smoker. For simplicity, we assume that a smoker purchases only from stores located in the same state that he or she lives[12] and match the federal, state, and local cigarette excise taxes, respectively. For anti-smoking advertising, we first match each smoker to a specific DMA based on his or her zip code according to Nielson's DMA map. Based on the DMA we then determine each individual's potential exposure to anti-smoking advertising gross rating points. Smoke-free restrictions are matched to each smoker based on the state where he or she lives.

The 526 smokers in our estimation sample cover nine states and 44 DMAs. In Figure 6 we plot the temporal distribution of cigarette excise taxes, anti-smoking advertising, and smoke-free restrictions in the nine states (see summary in Table 13). The figure shows that there is substantial variation in the three counter-marketing mix strategies across states and over time. For example, at the start of our observation window in 2005, the cigarette excise tax per package varied from a low of \$.73 in Florida to a high of \$2.25 in New York. During the data collection period, the federal tax was increased from \$.39 to \$1.01 per pack in April 2009. At the end of the data collection period in 2009, tax per package varied from \$1.85 in Colorado to \$4.12 in New York. The top four states in terms of anti-smoking advertising ratings were New York, Ohio, California, and Colorado. For smoke-free policies five of the nine states had a complete

[12] As smokers purchase not only from supermarkets, but also from convenience stores, drug stores, gas stations, and so on, a large number of stores have missing information on zip codes.

smoking ban in restaurants, bars, private workplaces, and government workplaces by the end of 2009.

3.4 Model-Free Evidence

Prior to presenting our modeling framework, we discuss several descriptive or model-free analyses of the dynamics of smoking behavior and cessation. These analyses are primarily designed to show how consumers' brand preferences differentially influence behavior. To accomplish this objective we examine situations where smokers are exposed to changes in counter-marketing activities.

3.4.1 Consumer Migration

One possible source of temporal variation in a consumer's counter-marketing exposure occurs when a consumer moves across states during the six year observation window. The Nielson Homescan panelists fill in an annual survey on demographic information including address. We define a smoker to be a *migrant* if the self-reported current state is different from that in the prior year, and a *nonmigrant* otherwise. Consumer migration is useful for our purposes as we are able to examine how annual cigarette purchase quantities change when consumers move to states with higher cigarette taxes, more intensive anti-smoking advertising, or stricter smoke-free restrictions. In addition, we can examine whether consumers who consume different brand segments (Marlboro segment, strong brand segment, and weak brand segment) respond differently. The key identifying assumption that underlies this analysis is that a smoker's cross-state moving decision is independent of his or her cigarette purchasing behavior.

As the number of migrant smokers is limited, instead of requiring a six-year panel as in our estimation sample, we select migrant smokers for whom we observe their cigarette purchases for a year before and after the move. Table 14 summarizes changes in purchase patterns for the complete set of migrants. In Figure 7 we plot the annual purchase quantity changes for the three segments, respectively. We find a consistent pattern whereby Marlboro and strong brand smokers are less likely to reduce cigarette purchase quantities when they move to states with more intensified counter-marketing. For example, when moving to a state with higher cigarette excise taxes, Marlboro migrants reduce annual cigarette purchase by 30 packs, while strong brands and weak brands migrants reduce by 45 and 47 packs, respectively. In the case of migration to a state with more anti-smoking advertising, the annual purchase quantity reduction for Marlboro, strong brands, and weak brands migrants are about 28, 32 and 46 packs, respectively. However, these differences are not statistically significant. In addition we had too little variation in smoke free restrictions for a migrant smoker based analysis.[13]

We next investigated non-migrant smokers' reactions to state level changes in counter-marketing tactics. We identified 305 nonmigrant smokers who lived in states that increased cigarette excise taxes by $1.00 during the six-year period and compared their average monthly cigarette purchase quantities before and after tax increases. Table 15 shows that there is a significant reduction in monthly cigarette purchases from about 22 to 12 packs per month after a $1.00 tax hike ($t=-12.02$, $p<.01$). Figure 8 also shows that significant quantity reductions occur for all three brand segments. Table 16 provides regression results that test whether the three segments respond differently to a $1.00 tax hike. The estimation results show that both Marlboro and strong brand customers are significantly less likely to reduce monthly purchase quantities relative to the consumers of weak brands (-8.42 vs. -8.63 vs. -12.35 packs).

[13] We only found ten smokers who move from a state with no smoking restrictions to a state with complete restriction. Due to the limited sample size, we did not present the purchase quantity difference in this scenario.

3.4.2 Quitting Patterns

We can also provide some preliminary results concerning quit rates across the various brand preference defined customer segments. For this analysis we utilize the complete estimation sample. In general counter-marketing efforts are increasing over time. We can use this trend to assess whether increasing counter-marketing differentially affects the probability of quitting by smokers who prefer different tiers of brands. We define a smoker as a quitter if we observe his last cigarette purchase at least a year before the end of our observation window. Table 17 and Figure 9 show the quitting rates in our sample. Approximately 23 percent of smokers quit smoking by one year before the end of our observation period. However, this proportion is lower in the Marlboro (19 percent) and strong brand (22 percent) segments than in the weak brand segment (28 percent).

To exclude an alternative explanation that the differences in quit rates are due to variations in smoking intensity across the three brand segments, we present further evidence on quitting rates in Figure 10. These quit rates are conditional on initial monthly nicotine intake levels in year 2004. We see a similar pattern as Marlboro and strong brand smokers are less likely to quit than those in weak brand segments for all levels of initial smoking intensity in year 2004. Collectively, these descriptive studies suggest that brand strength plays an important role in individual's decisions regarding consumption and quitting decisions.

3.5 Model

In this section we develop a dynamic model of a smoker's nicotine consumption decisions. The model serves two purposes. First, it allows us to quantify the effect of the three counter-marketing tactics in the quitting process. Second, it lets us consider how the effectiveness varies across the three brand segments. We describe the model in two parts. First, we begin by describing the dynamic optimization problem faced by a smoker. Second, we consider the form of smokers' expectations of the future costs and benefits of continuing to smoke.

3.5.1 Setup

We model a smoker's decision of how much nicotine to consume in a particular month as a stochastic dynamic optimization problem. Our assumption of smokers making dynamic optimal decision is consistent with the theoretical framework of rational addiction proposed by Becker and Murphy (1988) which proposes that addictions involve forward-looking behavior. Our model is built on the premise that a smoker's nicotine consumption decision depends on his/her anticipated enjoyment of nicotine intake versus the anticipated economic, convenience and health costs of smoking. Smoker i's objective is to maximize the sum of the discounted future utility given as:

$$\max_{\{d_{ijt}\}_{t=1}^{\infty}} E\left[\sum_{t=1}^{\infty} \beta^{t-1} \sum_{j=1}^{5} d_{ijt} U_{ijt}\left(P_{ijt}, C_{ijt}, H_{ijt}, Adct_{ijt}, \varepsilon_{ijt}\right)\right] \tag{1}$$

where $d_{ijt} = 1$ if smoker i chooses nicotine intake level j in month t and $d_{ijt} = 0$ otherwise. β is the discount factor. The state space for the dynamic decision problem is $\{P, C, H, Adct, \varepsilon\}$, consisting of the set of tax-inclusive cigarette prices P, smoke-free restrictions C, perceived health consequences H, addiction level $Adct$, and unobserved shocks ε.

Smoker i's single period reward, U_{ijt}, of consuming nicotine level j in month t is:

$$U_{ijt} = \alpha_{0ij} - e^{\alpha_{1ij}} \log(P_{it}) + \alpha_{2ij} C_{it} + \alpha_{3ij} H_{it} + \textstyle\sum_k \gamma_{jk} Adct_{ikt-1} + \varepsilon_{ijt} \tag{2}$$

where α_{0ij} captures the intrinsic preference for level j of nicotine intake compared to the outside option of not smoking. The next three terms capture potential costs of continued smoking. These are the economic cost of purchasing cigarettes, the convenience (opportunity) cost of obeying smoke-free restrictions, and the perceived health consequences of smoking.

The three potential costs of smoking are closely related to the three most common counter-marketing tactics. We represent the economic cost of purchasing cigarettes as the sum of cigarette price and excise taxes per pack P_{it} faced by smoker i in a particular state in month t. We transform the price coefficient to $(-e^{\alpha_{1ij}})$ to ensure negativity (Train and Sonnier 2004). The convenience cost C_{it} refers to the average smoke-free restriction level in the four public venues in smoker i's state in month t. Regarding the perceived health consequences of smoking, prior studies have used self-reported annual survey data from the National Health Interview Survey (Arcidiacono, Sieg and Sloan 2007). Similar health report data are not available for our panel. In our model we treat smokers' exposure to the stock anti-smoking advertising, $AntiS_{it}$, as a proxy for the perceived health consequences of smoking, H_{it}. We allow the effect of the three counter-marketing tactics to vary across the four nicotine intake alternatives $j = \{1,2,3,4\}$, such that heavy- or lightly-addicted smokers may respond differently.

We also consider the positive utility of continued smoking by adding a nicotine addiction term, $Adct_{ikt-1}$, which captures the nicotine intake level in the previous month $(t-1)$. We assume that ε enters the single period utility function in an additively separable way. We also assume that ε_{ijt} is unobserved to researchers and extreme-value distributed. The single period mean utility of not smoking is normalized to zero, i.e., $U_{i0t} = \varepsilon_{i0t}$.

3.5.2 Heterogeneity and Brand Segments

Beyond the basic effects of the three counter marketing instruments, we are particularly interested in how Marlboro and strong brand smokers respond differently to the three counter-marketing mix tactics relative to weak brand smokers. We incorporate smoker brand segments as a source of observed heterogeneity by treating the response parameters, α, in the following way:

$$\alpha_{ij} = \delta_{j0} + \delta_{j1} I(BS_i = Marlboro) + \delta_{j2} I(BS_i = Strong) + \delta_{j3}(Lninc_i - \overline{Lninc}) + \xi_{ij} \qquad (3)$$

where α_{ij} is a vector of $\{\alpha_{0ij}, \alpha_{1ij}, \alpha_{2ij}, \alpha_{3ij}\}$ associated with the coefficients of P_{it}, C_{it} and H_{it} in equation (2); $I(\cdot)$ is an indicator function to specify a particular brand segment (BS). Because we explicitly include functions for Marlboro and strong brand segments, coefficients δ_{j0} represent the responsiveness of the weak brand segment to each tactic. δ_{j1} and δ_{j2} are of key interest to our study. Given the log-transform of the price coefficients, $(-e^{\alpha_{1ij}})$, significant negative values for δ_{1j1} and δ_{1j2} would suggest that Marlboro and strong brand smokers are less responsive to cigarette excise taxes. In terms of convenience and health costs of smoking, significant positive values for δ_{2j1}, δ_{2j2}, δ_{3j1} and δ_{3j2} would suggest that Marlboro and strong brand smokers are less responsive to smoke-free restrictions and anti-smoking advertising. This result would also be interpretable as Marlboro and Strong brand smokers being less sensitive to convenience costs and the health consequences of continued smoking. We also include mean centered household income to account for the alternative explanation that it is income that drives the different quitting patterns across the three brand segments.

The ξ_{ij} term captures unobserved heterogeneity. We assume the unobserved heterogeneity follows a multivariate normal distribution $\xi_{ij} \sim N(0, \sum_{\xi})$ with a flexible variance-covariance matrix. The diagonal elements denote the corresponding variance of ξ_{ij}, and the off-diagonal elements denote the covariance between the three counter-marketing mix elements. The flexible variance-covariance matrix captures the co-movement of the three counter-marketing mix tools.[14]

3.5.3 Expectations

We assume that smokers have rational expectations about the four state variables $s_{it} = \{P_{it}, C_{it}, H_{it}, Adct_{ijt}\}$. The stochastic processes governing the evolution of the three future costs of smoking follow a regular Markov transition kernel $\pi(\cdot \mid \cdot)$.

3.5.3.1 Economic Cost Expectations

Following Erdem, Imai and Keane (2003), we assume that smokers can predict the distribution of future prices. We specify the equation of motion for tax-inclusive cigarette prices as the following autoregressive process (in logs):

$$logP_{it} = a_0 + a_1 logP_{it-1} + a_2 \left(logP_{it-1} - log \frac{1}{K-1} \sum P_{k,t-1} \right) + a_3 C_{it-1} + a_4 anti_{it-1} + N_i A_5 + z_{it}, \quad (4)$$

where P_{it-1} is the lagged cigarette price per pack faced by smoker i and N_i refers to state and year dummies. The log difference between cigarette prices faced by smoker i in the last period and the lagged mean cigarette price in other states is included to capture correlations between cigarette prices in a region (e.g. NY) and national price trends. We also add the lagged smoke-free restriction level C_{it-1} and anti-smoking advertising ratings $anti_{it-1}$ to account for co-movement among the three counter-marketing tactics. The variable z_{it} is a random shock in month t and follows a normal distribution $z_{it} \sim N(0, \sigma_z^2)$. This reduced-form representation of

[14] We do not specify heterogeneity in the nicotine addiction coefficients γ_{jk} for identification reasons. Ruud (1996) argues that a mixed logit with all alternative-specific random coefficients is nearly unidentified empirically. Train (2009) suggests holding one or more coefficients fixed.

cigarette price evolution provides an approximation of smokers' expectations of evolving economic costs.

3.5.3.2 Convenience Cost Expectations

We also specify the process of smoke-free restriction level expectations as following an autoregressive process:

$$C_{it} = b_0 + b_1 C_{it-1} + b_2\left(C_{it-1} - \frac{1}{K-1}\sum C_{k,t-1}\right) + b_3 logP_{it-1} + b_4 anti_{it-1} + N_i B_5 + e_{it} \qquad (5)$$

where C_{it-1} is the lagged smoke-free restriction level in the state where smoker i lives. We include the difference between the smoke-free restriction level in the focal state where smoker i lives and the average restriction level in all other states to account for the correlation between state and national trends. Lagged prices and anti-smoking advertising ratings are included to account for co-movement among the three counter-marketing tactics. The e_{it} term is a random shock and is assumed to follow a normal distribution $e_{it}{\sim}N(0, \sigma_e^2)$.

3.5.3.3 Health Cost Expectations

Negative health consequences of smoking are highlighted in adult-targeted anti-smoking advertising. In our empirical application, we proxy smoker i's perceived health consequences of smoking H_{it} by his or her exposure to the stock of health-oriented anti-smoking advertising $AntiS_{it}$. To determine this stock, we begin by defining $anti_{it}$ to be the amount of anti-smoking advertising that smoker i is potentially exposed to in month t. The nature of advertising planning creates a significant amount of interdependence between months. To capture this relationship, anti-smoking advertising is specified as the following autoregressive process:

$$anti_{it} = \omega_0 + \omega_1 anti_{it-1} + \omega_2 \left(anti_{it-1} - \frac{1}{K-1} \sum anti_{k,t-1} \right) + \omega_3 logP_{it-1} + \omega_4 C_{it-1} + N_i w_5 + o_{it} \quad (6)$$

where $anti_{it-1}$ is the lagged anti-smoking ratings experienced by smoker i. We again include the difference between state wide advertising and national advertising to account for nationwide trends in anti-tobacco advertising. Lagged prices and smoke-free restrictions, and state and year dummies are also included in the equation. The o_{it} term is a random shock and is assumed to follow a normal distribution $o_{it} \sim N(0, \sigma_o^2)$. We assume that the anti-smoking advertising stock evolves based on the following equation: $AntiS_{it} = anti_{it} + \rho AntiS_{it-1}$ where ρ is a decay rate. To keep the model tractable, we fix the monthly carryover parameter ρ at .95. This carryover rate has been widely used in prior smoking-related studies (Hamilton 1972). In addition, the anti-smoking advertising stock enters in a logarithm form to account for an expected decreasing marginal effect.

Parameters (a, b, ω) in the expectation equations are estimated from data on prices, smoke-free restrictions, and anti-smoking ratings prior to computing the solution of smokers' dynamic optimization problem. When we solve the smoker's dynamic optimization problem, we treat the three stochastic processes as known and draw the three anticipated costs according to their distributions (i.e. normal distributions).

3.5.3.4 Evolution of Nicotine Addiction

Nicotine addiction plays an important role in our model for two reasons. First, it provides a means for quantifying smoker's enjoyment from smoking. Nicotine therefore provides a positive component in the utility function in equation (2). Second, it creates an intertemporal link between past consumption and current decisions due to the addictive nature of nicotine. We specify the evolution of nicotine addiction $Adct_{it}$ to be deterministic and dependent on smokers' past decisions. Given the current addiction level $Adct_{ijt}$ the next period addiction $Adct_{ijt+1}$ is determined as follows:

$$Adct_{ijt+1} = \begin{cases} 1 & if\ d_{ijt} = 1 \\ 0 & otherwise \end{cases} \qquad (7)$$

The state of nicotine addiction takes on one of the five previously defined levels, $Adct_{it} = \{d_{it}: 0,1,2,3,4\}$, and is represented by four dummy variables in equation (7). Our specification of nicotine addiction is similar to various formulations used to model habit persistence (Heckman 1981; Erdem 1996; Roy, Chintagunta and Haldar 1996; Seetharaman 2004; Gordon and Sun 2012). We allow the states of nicotine addiction to differentially affect the utility of choosing a particular nicotine intake level by including alternative-specific own and cross terms in equation (2). Therefore, it is possible that a smoker would increase or decrease their nicotine intake rather than repeatedly consume the same amount of nicotine.

3.5.4 Dynamic Optimization Problem

The single-period utility function and anticipated costs and benefits of continued smoking provide the core elements of a consumer's dynamic optimization problem. Based on these functions we assume that observed monthly decisions represent each smoker's optimal choice of the level of nicotine intake, d_{jt}^{*} at each point in time. We define s to be the set of state variables $s = \{P_t, C_t, H_t, Adct_t\}$, $s' = \{P_{t+1}, C_{t+1}, H_{t+1}, Adct_{t+1}\}$ is the expected value of the state variables in the next period, and θ represents the parameter vector $\theta = \left(\alpha_{ij}, \gamma_j, a, b, \omega\right)$. We define the value function of the dynamic problem, V, to be the maximum of the discounted sum of expected returns. By Bellman's principle of optimality, the value function V can be expressed in a recursive form as follows:

$$V(s,\varepsilon;\theta) = \max_{d}\{U(s,\varepsilon;\theta) + \beta E_{s',\varepsilon'}[V(s',\varepsilon';\theta)|s,d]\} \tag{8}$$

The alternative-specific value function can be expressed as $V_j(s,\varepsilon;\theta) = v_j(s;\theta) + \varepsilon_j$ where

$$v_j(s;\theta) = u_j(s;\theta) + \beta E_{s',\varepsilon'}[V(s',\varepsilon';\theta)|s,d]. \tag{9}$$

The expected value function $E_{s',\varepsilon'}[V(s',\varepsilon';\theta)]$ is obtained by integrating over the next period's state space s',ε'. We assume that ε are i.i.d. extreme value distributed. The expected value function is then given as follows:

$$E_{s',\varepsilon'}[V(s',\varepsilon';\theta)|s,d] = \int_{s'} ln\left[\sum_{j} exp\left(v_j(s';\theta)\right)\right]\pi(s'|s,d) \tag{10}$$

The probability of smoker i choosing nicotine intake level j given the observed state s_{it} is:

$$Pr\left(d_{ijt} = 1|s_{it},\theta\right) = \frac{exp\{v_j(s_{it};\theta)\}}{\sum_{k=1}^{5} exp\{v_k(s_{it};\theta)\}} \tag{11a}$$

The likelihood of the observed nicotine intake levels across the population of smokers over time is:

$$L(d|\theta,s) = \prod_{i}\prod_{t}\prod_{j}\left[\frac{exp\{v_j(s_{it};\theta)\}}{\sum_{k=1}^{5} exp\{v_k(s_{it};\theta)\}}\right]^{I(d_{ijt}=1)} \tag{11b}$$

3.6 Estimation

We estimate our dynamic model of smoking decisions using a computationally efficient Bayesian MCMC algorithm proposed by Imai, Jain and Ching (IJC 2009). There are two advantages of using the IJC algorithm. First, it makes use of the computational results obtained from the past iterations to solve the value function at the current iteration. Second, the combination of the DP model and Bayesian MCMC algorithm fits our context well, as it produces the posterior distribution of the key set of parameters in our study—the observed heterogeneity parameters for the brand segments in equation (3). The key innovation in the IJC algorithm is the way it solves for the value function. The traditional approach of the Nested Fixed Point Algorithm applies the Bellman operator repeatedly to solve for the value function, which is the unique fixed point of the contraction mapping (Rust 1987). The IJC algorithm relies on the insight that the value function is continuous in the parameter space θ. Therefore, it is possible to approximate the expected value function given any random draws of θ and ε by running a non-parametric regression with a set of value functions obtained from earlier iterations of the MCMC algorithm (see Ching et al. 2012).

Before we outline the algorithm details, we first partition the parameter space θ into 3 elements, (α_i, μ, γ), where γ is a vector of parameters common across smokers, α_i is a vector of smoker-specific parameters, and $\mu = (\delta, \sum)$ is a vector of hyperparameters that governs the distribution of $\alpha_i \sim N(Z_i\delta,\ \sum)$, where $\delta|\sum \sim N(0, \sum \times A^{-1})$ and $\sum \sim IW(v_0, V_0)$. Following Allenby and Rossi (1998) we set $v_0 = k + 3$ and $V_0 = .01I$. Therefore, the posterior distribution of the parameters is:

$$p(\alpha_i \forall i, \delta, \sum, \gamma | d, s) \\ \propto \prod_i L(d_i | \alpha_i, \gamma)\, \Phi(\alpha_i | \delta, \sum)\, \Phi(\delta | A, \sum)\, \Phi(\sum | v_0, V_0)\, \Phi(\gamma) \qquad (12)$$

Note that each smoker's conditional likelihood $L(d_i|\alpha_i, \gamma)$ does not depend on the hyperparameter $(\delta, \sum)$. When approximating the likelihood the "effective" parameter vector only consists of (α_i, γ). We now outline the two loops in our estimation. A diagram is provided in Appendix 8.

In the *outer* loop, we apply a MCMC algorithm to draw the parameter vector from the posterior distribution in three blocks. Suppose that we are in iteration r with parameter estimates being $(\mu^r, \alpha_i^r, \gamma^r)$. We proceed with the following three steps.

Step 1: We update the hyperparameter $\mu^r = (\delta^r, \Sigma^r)$ in a way similar to the multivariate regression setting. Given α_i^{r-1} and priors on $\delta, \sum$, there is simple procedure to draw δ^r, Σ^r from the posterior distributions (see details in Appendix 9).

Step 2: The specification implies that $N(Z_i\delta^r,\ \Sigma^r)$ is effectively the prior $(\cdot)$ for α_i^r. For each smoker i, we draw a candidate parameter from the random walk metropolis chain $\alpha_i^{*r} = \alpha_i^{r-1} + \tau_\alpha$, where $\tau_\alpha \sim N(0, \tau^2\Sigma^r)$. We accept α_i^{*r} with probability $\lambda_\alpha = min\left\{\frac{\Phi(\alpha_i^{*r}|\delta^r,\Sigma^r)\mathrm{L_i}\left(d_i|s_i,\alpha_i^{*r},\gamma^{r-1}\right)}{\Phi(\alpha_i^{r-1}|\delta^r,\Sigma^r)\mathrm{L_i}\left(d_i|s_i,\alpha_i^{r-1},\gamma^{r-1}\right)}, 1\right\}$. The computation of L_i requires us to compute the expected value functions for smoker i, which is the output from an inner loop discussed below.

Step 3: We next draw a candidate parameter from the random walk metropolis chain for the common parameter vector $\gamma^{*r} = \gamma^{r-1} + \tau_\gamma$, where $\tau_\gamma \sim N(0, \tau^2 I)$. We accept γ^{*r} with probability λ_γ, where $\lambda_\gamma = min\left\{\frac{\mathrm{L}\left(d|s,\alpha_i^r,\gamma^{*r}\right)}{\mathrm{L}\left(d|s,\alpha_i^r,\gamma^{r-1}\right)}, 1\right\}$. Different from step2, the computation of L requires us to compute the expected value functions for all smokers. Below we discuss how to approximate the expected value function in the inner loop from steps 4-6.

Step 4: We store the outputs of the N past iterations into $\{\alpha_i^{*l}, \gamma^{*l}, v^l(\alpha_i^{*l}, \gamma^{*l})\}_{l=r-N}^{r-1}$, where $v^l(\alpha_i^{*l}, \gamma^{*l})$ is a vector of alternative-specific value functions. Note that $v^l(\alpha_i^{*l}, \gamma^{*l})$ is also individual-smoker specific due to the individual-specific coefficients, α_i^{*l}.

Step 5: To approximate the expected value function in equation (10) at iteration r, we run a non-parametric regression with a set of value functions obtained from earlier iterations of the MCMC :

$$E_{s',\varepsilon'}[V(s',\varepsilon';\theta^{*r})] = \int_{s'} \sum_{l=r-N}^{r-1} \left[ln\left(\sum_j exp\left(v_j(s';\theta^{*l})\right)\right) \cdot \omega(\theta^{*l},\theta^{*r}) \right] \pi(s'|s,d) \qquad (13)$$

Here $\omega(\cdot)$ is a weight that takes high (low) value for α_i^{*l} and γ^{*l} that are close to (far away from) the current $\alpha_i^{*r}, \gamma^{*r}$. We use a Gaussian kernel density.

Step 6: We then update the value function in iteration r and store $\{\alpha_i^{*r}, \gamma^{*r}, v^r(\alpha_i^{*r}, \gamma^{*r})\}$. The non-parametric approximation of the value function relies on a “moving window” of the output of past iterations. In addition, we store the parameters evaluated at proposed candidate draws $\alpha_i^{*r}, \gamma^{*r}$ instead of accepted draws α_i^r, γ^r to avoid repetition due to low acceptance rates and to ensure that the algorithm spans the parameter space.

3.7 Results

This section presents an evaluation of the model's fit, discusses the parameter estimates, and provides results from several policy simulations.

3.7.1 Model Fit and Comparison

We ran a total of 50,000 MCMC iterations and report the posterior distributions of the parameters based on iterations 25,000 to 50,000. To evaluate the model, we report the marginal likelihood as approximated by the harmonic mean, and hit rate from three different specifications in Table 18. The columns in Table 18 correspond to the following: (1) a homogenous myopic model with $\beta = 0$, (2) a homogenous dynamic model with $\beta = .98$, and (3) a dynamic model with $\beta = .98$ that includes heterogeneity as described in the last section. Table 18 shows that the dynamic model with heterogeneity has a marginal likelihood of (-23,304) and outperforms the homogenous myopic model (-33,504) and the homogenous dynamic model (-32,838). The dynamic model also has a higher hit rate (67.70%) than the other two models (39.2% and 39.3%). The following discussion of the estimation results is based on the dynamic model with heterogeneity (model 3).

3.7.2 Parameter Estimates in Expectations

Table 19 reports the parameter estimates for the stochastic process of the anticipated economic costs of continued smoking. The positive and significant coefficients on the lagged price indicate that if prices are higher in the previous period, they are also likely to be higher in the current period. The coefficient of the difference in tax-inclusive cigarette prices between the focal state and the rest of states is significantly negative, indicating that there is a national price co-movement trend. If cigarette prices in the focal state are lower than the average of the remaining states in the previous period, they are likely to be higher this period. There is also a significant negative co-movement between lagged smoke-free restrictions and lagged anti-smoking ad rating points, and cigarette prices in the current period. If a state has strict smoke-free restrictions and airs a high level of anti-smoking advertising then prices likely decrease in the next period.

The parameters for the evolution of smoke-free restrictions are reported in the second column in Table 19. The significance of the lagged smoke-free restriction level indicates a strong persistence of smoke-free air policies. Interestingly, we find the coefficient for the difference in smoke-free restrictions between the focal state and the rest of states in U.S. to be significantly positive. If smoke-free restrictions in the focal state are higher than the average of the other states in the previous period, it is likely to be even stricter in the next period. There is also a significant negative co-movement between lagged cigarette prices (or lagged anti-smoking ads ratings) and smoke-free restrictions in the next period.

The third column in Table 19 reports the parameter estimates for the perceived health costs. The significance of the lagged anti-smoking advertising gross rating points in the last period indicates persistence in smokers' exposure to anti-smoking advertising campaign. The difference in anti-smoking ads rating points between the focal state and the remaining states indicates a national co-movement trend. If the anti-smoking advertising gross rating points in the focal state are lower than the average of other states in the previous period, the focal state is likely to air more anti-smoking advertising in the next period. Lagged prices and smoke-free restrictions appear to have a significant negative impact on the anti-smoking advertising level in the next period.

3.7.3 Reward Function Estimates

We now discuss the parameter estimates in the single-period reward function in equations (2) and (3). Estimation results are reported in Table 20. We discuss the estimation results in three stages. We begin with a discussion of the coefficient estimates for the baseline case of “weak” brand smokers. Next, we discuss segment level heterogeneity for Marlboro and Strong brand smokers. We then consider unobserved and income based differences in response parameters.

3.7.3.1 Mean Estimates

The first set of parameters of interest is the mean coefficients of the economic, convenience, and health costs of smoking. These coefficients correspond to the response parameters of weak brand smokers. We estimate the price coefficients ($-e^{\delta_{1j0}}$) to be significantly negative for the four monthly nicotine intake decisions. The magnitudes of the mean estimates of δ_{1j0} are in order from -.329 for the lowest level of nicotine intake to 1.614 for the highest level of nicotine intake. After the transformation, the price sensitivities range from -.72 for the lightest smokers to -5.02 for the heavy smokers. The estimates suggest that heavy smokers who consume more than 840mg of nicotine (approximately 2 packs a day) are about 7 times more price sensitive than light smokers who consume less than 210mg of nicotine (less than half a pack a day).

The estimate of the convenience cost δ_{2j0} is non-significantly different from zero across all levels of nicotine intake. That is, smoke-free restrictions are ineffective for light, moderate, or heavy smokers of weak brands. As such smoking prohibitions in environments such as restaurants may not influence consumptions rates for the segment of weak brand smokers. This result is consistent with Bitler, Carpenter and Zavodny (2010) and Adda and Cornaglia (2010) who find no effect of smoke-free air laws on smoking behavior.

The estimates of the health cost δ_{3j0} are significantly negative for all nicotine intake decisions. The coefficients ranged from -.559 for the lowest level of intake to -2.024 for the highest level of nicotine intake. The estimates suggest that heavy smokers (approximately 2 packs a day) are about 3.6 times more responsive to health-oriented anti-smoking advertising than light smokers (less than half a pack a day). This is an interesting finding from a public health perspective. The lower sensitivity of light smokers suggests that this segment may feel that their lower levels of smoking mitigate the health risks of tobacco consumption.

Our results consistently imply that, all things being equal, counter-marketing tactics are most effective in reducing the nicotine intake of heavy smokers and relatively less effective in deterring light smokers. Our results are consistent with a CDC report[15] states "fewer heavy smokers while light smokers are on the rise." The CDC report, which covers data from 2005 to 2010, shows that the percent of U.S. adult daily smokers who smoke nine or fewer cigarettes per day rose to 21.8 percent in 2010, up from 16.4 percent in 2005. The percent who smoke 30 or more cigarettes per day fell from 12.7 percent to 8.3 percent during the same period.

The table also includes indicator variables, Adct, that represent each smoker's previous level of nicotine consumption. The nicotine consumption parameters γ_{jk} are all positive and significant except for one. This indicates that nicotine consumption provides positive utility. More importantly, the magnitude of the own- and cross-terms of the four nicotine addiction levels produces a pattern consistent with the "addictive" nature of smoking. We find that for any level of nicotine intake in the last month, smokers exhibit a tendency to increase their nicotine consumption. For example, in the absence of marketing and counter-marketing activity a smoker who consumes less than 210 mg nicotine in the last month, would progress to an intake level

[15] http://www.cdc.gov/media/releases/2011/p0906_smoking_less.html

between 210 and 420mg this month (estimate=1.482), followed by nicotine intake between 420 and 840mg (estimate=1.116) in the following month. Our results are consistent with the theoretical formulation of addiction by Becker and Murphy (1988) and empirical results reported by Gordon and Sun (2012). The pattern of results is also interesting in terms of a comparison of the counter-marketing and the nicotine consumption terms. The addictive nature of the product continually exerts an upward pressure towards constant or higher levels of smoking while the public health interventions tend to exert a downward force.

3.7.3.2 Heterogeneity of Brand Segments

The bottom portion of Table 20 reports terms that speak to the roles of heterogeneity based on brand tier preference and socio-economic status. In terms of brand tier preference, the key set of parameters of interest is δ_{j1} and δ_{j2}, which represent the differential responses of Marlboro and (other) strong brand smokers to the three counter-marketing tactics relative to the baseline of weak brand smokers. The estimates of differential responses to cigarette prices, δ_{1j1} and δ_{1j2}, are all significantly negative for both Marlboro and (other) strong brand smokers across all nicotine consumption levels. Given the log-transform of the price coefficients ($-e^{\alpha_{1ij}}$), the significantly negative values of δ_{1j1} and δ_{1j2} suggest that both Marlboro and strong brand smokers are less responsive to cigarette excise taxes and therefore less likely to quit smoking as a result of increasing economic costs of continued smoking. The magnitude of the estimates further implies that light smokers of Marlboro are the least price sensitive segment. In comparison to light "weak" brand smokers, light Marlboro smokers are about half as responsive to price changes. The next least price sensitive segment is light smokers of (other) strong brands, who are 41 percent less price sensitive than the same level weak brand smokers. In contrast, heavy smokers of weak brands are the most price sensitive.

The four estimates of differential responses to health-oriented anti-smoking advertising between Marlboro and weak brand smokers, δ_{3j1}, are all positive, with three being significant. The magnitude of the estimates suggests that moderate smokers of Marlboro with monthly nicotine intake between 420 and 840mg (approximately one to two packs a day) are 24 percent less responsive to health-oriented anti-smoking advertising than moderate smokers of weak brands. The largest variation in response is between Marlboro and weak brand light smokers with Marlboro light smokers being 52 percent less responsive. We find similar patterns in the variability in responses to health-oriented anti-smoking advertising between strong (non-Marlboro) and weak brand smokers, δ_{3j2}. They are all positive with three being significant. For example, we find that light smokers of (other) strong brands are 38 percent significantly less responsive to health-oriented anti-smoking advertising than weak brand light smokers.

Contrary to our speculation, the eight estimates δ_{2j1} and δ_{2j2} of differential responses to smoke-free restrictions for Marlboro and (other) strong brands are all negative, with three being significant. Specifically, if a Marlboro smoker is exposed to a complete smoking ban in all the four public venues, he or she will face a reduction in the utility of monthly nicotine intake of greater than 840mg (between 420 and 840mg) by an additional 3.324 (1.969) units than a weak brand smoker. The magnitude of our estimates implies that Marlboro smokers are most responsive to smoke-free restrictions, followed by (other) strong brand smokers, and then weak brand smokers.

While our initial conjecture was that Marlboro and strong brand smokers would be more resilient to all counter-marketing activities, there is a theoretical explanation for our finding that stronger brands are more susceptible to usage restrictions. The literature on intrinsic versus image-related motivations provides an explanation. *Intrinsic motivations* are derived from internally focused concerns such as economic costs or health fears (Ryan and Deci 2000). *Image-related motivations*, on the other hand, are based on smokers being motivated to reduce smoking based on how they are perceived by others (Fehr and Falk 2002; Toubia and Stephen 2013). Among the three counter-marketing tactics, economic costs and health consequences of smoking are related to intrinsic motivations, while smoke-free restrictions reduce image motivation. Thus, the stronger brand-consumer relationship between Marlboro and (other) strong brands makes them less responsive to intrinsic-motivated counter-marketing tactics of cigarette prices and anti-smoking advertising. In contrast, public smoking bans are more effective means for reducing consumption of Marlboro and other strong brands (Keller 1993).[16]

3.7.3.3 Heterogeneity of Income and Unobserved Heterogeneity

The estimates of the price coefficients of the mean centered household income terms are all significantly negative, which is consistent with prior research (Becker and Murphy 1988) and confirms that lower income smokers are more sensitive to increasing cigarette prices. However, we find no significant difference between low income smokers and high income smokers in their responses to smoke-free restrictions or anti-smoking advertising. The estimates of the unobserved heterogeneity terms are all significant. The standard deviations of the unobserved heterogeneity terms are also found to be comparable to the mean estimates. For example, the mean estimate of the price coefficient for monthly nicotine intake between 210 and 420mg is .895, while the standard deviation of the unobserved heterogeneity is 1.322.

3.7.3.4 Counter-Marketing Effectiveness across Segments

[16] We also estimated the model using an alternative brand segmentation scheme. Specifically, we divided brands into Marlboro, "strong" brands and "weak" brands using based on averages prices. This price premium based segmentation scheme yielded similar results (see Appendix 7).

Combining brand segment, income and unobserved heterogeneity, we plot the distribution of smokers' responses to the three counter-marketing techniques (α_{ij}) across Marlboro, Strong and Weak brands segments in Figure 11-14. We see that cigarette excise taxes and anti-smoking advertising are less effective for consumers that smoke stronger brands such as Marlboro. This is consistent with our descriptive analysis and confirms that the magnitude of the differential responses is in the same order as our revenue premium based measure of brand power.

3.7.4 Policy Experiments

Given the dynamic nature of consumer decision making in the cigarette category and the multi-dimensional nature of the marketing environment it is useful to evaluate the model implications using multiple period simulations. Table 21 reports simulation results for scenarios that increase each counter marketing instrument by ten percent. The simulations are executed for 5 years of monthly nicotine consumption decisions. The simulated sample includes 526 consumers that have identical initial states as the estimation sample.

The first line of the table reports the overall effect of each counter-marketing instrument on nicotine consumption. The simulation results predict that a ten percent increase in cigarette taxes will reduce nicotine consumption by about 15%. Greater smoke free restrictions are predicted to decrease consumption by about 11% and a ten percent increase in anti-smoking ads reduces consumption by only 3%. These results are consistent with the previously reported effects and illustrate the feedback effects embedded in the model specification.

The bottom three rows of the table report the long-term effects for each of the brand defined segments. In the case of the tax increase, the reduction in nicotine consumption is mainly driven by reduced smoking within the "weak" brand segment. In contrast, for the Smoke

Free Air restrictions (SFA) the reduction in nicotine consumption is driven by members of the Marlboro and strong brand segments. The anti-smoking ads also mainly impact members of the weak brand segment. More dramatically, anti-smoking advertising has a minimal impact of nicotine consumption of the Marlboro segment. This is an important result as it suggests that educational campaigns may be relatively ineffective against brands that lead their categories.

Simulation experiments are also of particular use in evaluating the impact of simultaneous changes in the marketing and counter-marketing environments. To illustrate the dynamic implications of simultaneous changes in the marketing environment Table 22 reports the results of increased smoke free restrictions and anti-smoking advertising combined with permanent price decreases. The results show that the stronger brands are better able to counter health oriented ads through price decreases. In contrast, when smoke free restrictions are increased, price cuts by strong brands are relatively ineffective.

Collectively these findings highlight the importance of considering brand asymmetries when designing a counter-marketing strategy. Market leaders are best targeted via techniques that make public consumption more difficult. Removing the ability to consume the product in public may reduce the value of the stronger brands because consumers can no longer benefit from using these products to create a public image. Furthermore, while the smoking category is extremely controversial, the results may also have implications for brand managers faced with counter-marketing programs. One lesson seems to be that stronger brands are more resistant to most counter-marketing techniques. A potential implication is that brand development is of critical importance in these types of categories. It may be that the value oriented and non-differentiated brands will be the most vulnerable. Our findings related to usage restrictions are also managerially important. Our findings suggest that the stronger brands should aggressively fight efforts to impose usage restrictions that curtail public consumption.

We also conducted two “extreme” policy simulations. Specifically, we evaluated the impact of a nationwide shift to the strict counter-marketing used in New York City and to the relatively lax policies of South Carolina. Our model predicts that the aggressive New York Policy that involves taxes of almost $4 per package and highly restrictive smoke free policies would reduce nicotine consumption by about 60%. In contrast, if the minimal interventions used in South Carolina were employed nationwide, our model predicts that nicotine consumption would increase by 78%. Details about the specific policies used in the two states and a segment level breakdown of smokers’ behavioral changes are given in Table 23.

3.8 Discussion

Efforts to reduce smoking have an extensive history dating back to the early 1950s. In general, these efforts have been successful as smoking rates have dropped from 44% in the 1950s to about 20% currently. The anti-smoking movement has been primarily supported by researchers from public health and economics (Chaloupka 1991; Coppejans et al. 2007). Marketing academics have considered issues related to smoking such as what type of advertising is most effective for preventing youth smoking (Pechmann et al. 2003) or assessing the differences in demand elasticity from permanent versus temporary price cuts (Sun et al. 2009). However, a gap in this literature is the lack of research that focuses on how brand strength may mitigate the efficacy of counter-marketing efforts.

This is a significant gap given the nature and importance of brand-consumer relationships. Our findings highlight the importance of brand-consumer relationships in efforts to reduce the consumption of vice goods. Since brands may serve a variety of purposes for consumers such as providing status or filling psychological needs, it is critical that counter-marketing strategies in the tobacco and other categories consider branding issues. We find that smokers who prefer “strong” brands tend to be less price sensitive than consumers that smoke “weak” brands. However, we also find evidence that strong brands are more susceptible to smoke free air policies. Our work suggests that the Australian Government’s plan to replace brand elements with health warning on packages may be particularly effective for reducing consumption of high equity brands.[17]

Given the success of the anti-smoking efforts, it is not surprising that counter-marketing activities are now being used or proposed for use in other categories. The most notable efforts are now occurring in categories that are blamed for growing rates of obesity. However, while lessons learned from tobacco control efforts are likely to be useful for designing counter-marketing tactics in categories such as fast food or soda, it should be noted that these categories are viewed differently than tobacco by most consumers. While a large majority of consumers view tobacco as dangerous, opinions about fast food and soda are more diverse. In particular, many consumers believe that these categories are only harmful when they are excessively consumed.

Additional research is therefore needed to understand how counter-marketing and brand strength will affect these categories. For example, if consumers merely reduce consumption then based on our findings from the cigarette category we might speculate that they will tend to

[17] http://www.health.gov.au/internet/main/publishing.nsf/Content/tobacco-plain

maintain consumption levels with their favorite brands and most reduction will occur with less preferred brands. However, this is speculation and additional research is needed.

It may also be useful to pursue more psychologically oriented research. Our segmentation scheme relies on observations of past brand choices. Our assumption is that Marlboro and other "strong" brands are likely to have different relationships with consumers. This is, however, a challengeable assumption since the observed or behavioral loyalty patterns between brands in different categories (weak or strong) may be identical. Our conjecture is that the different responses to counter-marketing across these brand tiers are due to some underlying difference in the nature of the brand-consumer relationships. Given evidence from more general categories that high equity brands have more positive associations and greater loyalty rates (Aaker 1997), this is a logical assumption. However, it would be useful to pursue survey research that could more explicitly measure individual level brand-consumer relationship characteristics.

The preceding argument also highlights the business problem faced by brands in categories that are targeted by advocacy groups and regulators. The categories now targeted by anti-obesity groups include exceptionally powerful brands such as McDonald's and Coca-Cola. For instance, Coca-Cola has launched anti-obesity ads and argued that it is unfair to put the blame on any single brand (Bittman 2013; Sauer 2013; France 2012). However, the response from advocates has been negative and the campaign has been attacked as a public relations effort. Our results suggest that Coca-Cola might be better off with advertising that stresses the relationship between Coke and consumers.

Our research also reveals that different tactics are appropriate for different types of brands when faced by various counter-marketing techniques. Relationships between consumers and relatively weak brands may be disrupted using taxes while for strong brands the appropriate tactic seems to be usage restrictions that limit public consumption. Educational campaigns also tend to be less effective when consumers are in relationships with strong brands. In sum, it seems that when a category contains powerful brands that public health campaigns need to both lessen the attractiveness of the physical product and also attack the psychological elements of the consumer-brand relationship.

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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
	(.834)	(.847)	(.851)	(.887)	(.867)	(.903)	(.822)
Promotion Frequency	.362	.357	.274	.530	.513	.336	.337
	(.481)	(.479)	(.446)	(.499)	(.500)	(.472)	(.473)
Nicotine (mg/piece)	1.090	.808	.505	1.221	.808	.403	.840
	(.021)	(.009)	(.021)	(.541)	(.115)	(.094)	(.143)
Monthly Brand Ads Spend	31.987	33.582	31.987	210.367	239.540	167.639	179.784
($1,000)	(78.131)	(80.184)	(78.131)	(237.897)	(280.992)	(204.382)	(207.070)

Note: a) standard deviations are reported in the parentheses; b) the summary statistics are calculated using 54,180 observations for the seven brands across 645 stores across 592 zip codes, 196 counties, 52 designated media areas and 38 states over 84 months from year 2001 to year 2007; c) the monthly brand advertising spending is at DMA level.

Table 2: Summary Statistics of Counter-Marketing Strategies

state	Cigarette Excise Taxes/Pack ($)		Smoke-Free Restriction to Adults		Smoke-Free Restriction to Children		Monthly Anti-Smoking Advertising GRPs (100)
	Min	Max	Min	Max	Min	Max	Mean (std)
AL	.505	.815	-.624	.235	-1.311	-.546	129 (275)
AZ	.940	2.390	-1.821	2.023	1.798	2.833	542 (437)
CA	1.210	1.260	2.090	2.090	-.354	-.354	699 (555)
CT	.840	2.390	-.066	2.124	-1.027	.239	63 (169)
DC	.990	1.390	-.160	2.717	-.394	1.300	269 (251)
DE	.580	1.540	.820	2.763	-.298	.163	287 (434)
GA	.460	.760	-.579	1.688	-.627	-.315	296 (458)
IA	.700	1.750	.215	.215	-.746	-.746	323 (283)
ID	.620	.960	-.180	1.466	-1.049	.940	872 (647)
IL	1.016	3.150	-.754	-.754	1.380	1.380	49 (141)
IN	.495	1.385	-.610	-.610	-.715	-.715	293 (483)
KS	.580	1.180	-.309	-.309	.563	.563	95 (227)
LA	.580	.750	-1.190	1.109	1.613	2.583	155 (588)
MA	1.100	1.900	-.037	2.763	-.243	.163	577 (873)
MD	1.000	1.390	1.624	1.624	1.044	1.044	189 (303)
MI	1.090	2.390	-.772	-.772	.933	.933	70 (177)
MN	.820	1.620	-.351	-.351	.777	.777	755 (623)
MO	.510	.560	.127	.127	.443	.443	78 (187)
MS	.520	.570	-1.579	-1.377	.936	1.073	155 (588)
NC	.390	.740	-.624	-.624	-1.311	-1.311	164 (283)
NE	.680	1.030	.236	.283	-.241	-.079	380 (352)
NH	.860	1.470	.571	1.020	-.826	-.639	143 (446)
NJ	1.140	2.965	-.989	1.977	1.771	1.960	526 (743)
NM	.550	1.300	-.523	3.240	-1.242	-.980	406 (454)
NY	1.461	2.533	-.627	1.475	1.520	1.863	925 (967)
OH	.588	1.734	-.588	2.702	-.134	.256	793 (556)
OK	.570	1.420	-1.174	1.292	.724	1.316	182 (341)
OR	.720	1.670	-.315	1.243	-.612	-.026	455 (410)
PA	.650	1.740	-.273	-.273	-.099	-.099	221 (404)
RI	1.340	2.850	-.969	2.763	.163	1.741	586 (838)
SC	.410	.460	-.382	-.382	-.053	-.053	88 (205)
TN	.470	1.010	-1.535	-.546	1.245	1.449	.013 (.083)
TX	.750	1.800	-.437	-.437	-.908	-.908	149 (342)
UT	.855	1.085	.435	.763	1.332	2.854	2,598 (1,288)
VA	.365	.690	-.709	-.709	.435	.435	298 (307)
VT	.780	2.180	1.197	1.806	-.153	.371	542 (892)
WA	1.165	2.415	.225	2.717	-.995	.326	777 (577)
WI	.930	1.160	-.276	-.168	.166	.201	414 (570)
Average	1.174 (.595)		.217 (1.212)		.302 (.988)		419 (666)

Note: a) minimum and maximum tax/pack are reported in the parentheses; b) the two-dimensional smoke-free restriction are based on the factor-analyses of the state-level smoke-free restriction on twelve areas; c) the mean and standard deviations of GRPs of the anti-smoking ads campaigns across the DMA markets within a certain state are reported over the 84 months from year 2001 to year 2007.

Table 3: Summary Statistics of Store Demographics

State	# of Stores	Median Household Income		College Percentage (%)	
		Min	Max	Min	Max
AL	6	20,838	47,106	0.06	0.38
AZ	16	35,576	73,758	0.12	0.46
CA	118	20,593	139,997	0.06	0.68
CT	17	37,333	78,114	0.11	0.64
DC	6	57,87	80,651	0.49	0.84
DE	6	36,493	75,608	0.14	0.53
GA	19	36,349	95,468	0.13	0.66
IA	5	40,316	76,309	0.10	0.50
ID	1	32,951	32,951	0.20	0.20
IL	17	34,293	127,809	0.10	0.78
IN	7	36,028	77,730	0.06	0.60
KS	7	37,464	106,984	0.16	0.68
LA	1	47,447	47,447	0.34	0.34
MA	35	26,049	94,049	0.08	0.79
MD	20	44,928	95,511	0.11	0.79
MI	24	31,159	64,009	0.11	0.48
MN	12	34,216	67,776	0.19	0.52
MO	15	39,176	112,017	0.17	0.68
MS	1	28,186	28,186	0.13	0.13
NC	30	34,345	71,066	0.08	0.64
NE	3	48,431	58,173	0.20	0.40
NH	4	41,481	84,392	0.17	0.49
NJ	29	36,163	185,466	0.10	0.79
NM	5	34,207	49,897	0.14	0.34
NY	41	22,107	90,630	0.08	0.52
OH	14	34,688	77,600	0.13	0.50
OK	2	21,705	29,986	0.21	0.33
OR	13	27,718	59,280	0.16	0.53
PA	29	31,588	94,085	0.10	0.69
RI	8	22,452	54,656	0.10	0.41
SC	4	33,110	38,112	0.12	0.26
TN	9	23,807	43,150	0.14	0.54
TX	45	21,950	96,118	0.03	0.60
UT	13	22,219	73,938	0.10	0.49
VA	33	26,390	100,390	0.12	0.71
VT	2	34,418	35,060	0.20	0.34
WA	19	33,158	81,929	0.13	0.61
WI	9	32,980	80,346	0.18	0.53
Total	645	52,936 (18,883)		.315 (.163)	

Table 4: Model Comparisons

	Log-likelihood	# of parameters	# of observations	AIC	BIC
Model 1	-257,037	44	433,430	514,161	514,321
Model 2	-255,560	47	433,430	511,213	511,384
Model 3	-255,408	53	433,430	510,921	511,114
Model 4	-254,960	55	433,430	510,029	510,229

Table 5: Model Estimation Results

Market Share			Category Sales		
Estimates in the observation equation (1)			Estimates in the observation equation (2)		
Price P_{jst}^*	-.404	(.003)***	Price $\log P_{st}$	-.843	(.059)***
Endogeneity correction $\hat{\mu}_t$	.012	(.002)***	Endogeneity correction $\hat{\mu}_t$	.465	(.058)***
Promotion Pr_{jst}^*	.011	(.001)***	Monthly dummies	Yes	
Estimates in the transition equation (4)			Estimates in the transition equation (5)		
$Tax_{st} \times Nico_{jst}^*$	.003	(.0004)***	$\log Tax_{st}$	-.004	(.001)***
$Tax_{st} \times Nico_{jst}^* \times I_{s,income\_q1}$	.004	(.001)***	$\log Tax_{st} \times I_{s,income\_q1}$	-.004	(.001)***
$SF_{st} \times Nico_{jst}^*$	.002	(.0003)***	SF_{st}	.0001	(.0002)
$SF_{st} \times Nico_{jst}^* \times I_{s,income\_q1}$	-.002	(.0006)***	$log\ Anti_{st}$	-.003	(.001)***
$\log Anti_{st} \times Nico_{jst}^*$	.0001	(.0001)	$\log Ads_{st}$	.009	(.0002)***
$\log Anti_{st} \times Nico_{jst}^* \times I_{s,income\_q1}$	-.0003	(.0003)	$log\ Anti_{st} \times \log Ads_{st}$	-.006	(.0002)***
$\log Ads_{jst}^*$	.0006	(.0001)***	Initial $Q_{s0}{}'$		
$\log Anti_{st} \times \log Ads_{jst}^*$	-.0003	(.0001)***	- Category sales	9.275	(.058)***
Decay δ	.994	(.0001)***			
Initial $H_{s0}^{*\prime}$					
- Marlboro regular	.099	(.021)***			
- Marlboro lights	.544	(.019)***			
- Marlboro ultra lights	-.969	(.028)***			
- Other regular	.770	(.022)***			
- Other lights	.652	(.019)***			
- Other mild	-1.289	(.032)***			
- Other ultra lights	.217	(.030)***			

Note: a) the decay parameter is re-parameterized as $\exp(\delta')/(1+\exp(\delta'))$, and delta method is used to recover the standard error; b) *** indicates p value <.01;

Table 6: Long-Term Elasticity of the Three Anti-Smoking Policies

	Cigarette Excise Taxes	Smoke-Free Restriction	Anti-Smoking Ads
Category Sales	-.667 [-.993, -.340]	.017 [-.049,.082]	-.610 [-.936, -.283]
Market Shares of			
- Regular cigarettes	.141 [.104, .177]	.034 [.024, .044]	.015 [-.014, .044]
- Light cigarettes	-.0005 [-.0006, -.0004]	-.0002 [-.0003, -.0001]	-.0002 [-.001, .019]
- Ultra light cigarettes	-.192 [-.242, -.142]	-.049 [-.064, -.035]	-.020 [-.058, .019]

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

Table 7: Counterfactual Effects on Nicotine Intake Levels over the Seven-Year Data Period

	100% Tax Hike	One Deviation of Smoke-Free Restriction Increase	100% Anti-Smoking GRP Increase
Net Nicotine Intake Chg %	-8.49	1.06	-14.03
Due to Market Share Shifts	2.91	.79	0
Due to Category Sales Reduction	-11.40	.27	-14.03

Table 8: Counterfactual Effects on Nicotine Intake Levels among Bottom Income Quartile over the Seven-Year Data Period

	100% Tax Hike	One Deviation of Smoke-Free Restriction Increase	100% Anti-Smoking GRP Increase
Net Nicotine Intake Chg %	-12.70	0	-11.93
Due to Market Share Shifts	5.26	-.22	0
Due to Category Sales Reduction	-17.96	.22	-11.93

Table 9: Counterfactual Effects on Tar Intake Levels over the Seven-Year Data Period

	100% Tax Hike	One Deviation of Smoke-Free Restriction Increase	100% Anti-Smoking GRP Increase
Net Tar Intake Chg %	-8.76	1.05	-13.95
Due to Market Share Shifts	2.87	.78	0
Due to Category Sales Reduction	-11.3	.27	-13.95

Table 10: Counterfactual Effects on Tar Intake Levels among Bottom Income Quartile over the Seven-Year Data Period

	100% Tax Hike	One Deviation of Smoke-Free Restriction Increase	100% Anti-Smoking GRP Increase
Net Tar Intake Chg %	-13.14	0	-11.79
Due to Market Share Shifts	5.13	-.22	0
Due to Category Sales Reduction	-18.27	.22	-11.79

Table 11: Frequency of the Five Monthly Nicotine Intake Levels

Monthly nicotine intake level	Frequency	Percent (%)
Zero mg	12,115	38.39
Less than 210 mg	7,237	22.93
Less than 420 mg	4,415	13.99
Less than 840 mg	4,571	14.48
More than 840 mg	3,222	10.21
Total	31,560	100

Note: the five nicotine intake levels are mutually exclusive. Assume the average nicotine content of a light cigarette at .7 milligrams. The five monthly nicotine intake levels correspond to approximate zero pack, less than half a pack a day, less than one pack a day, less than two packs a day, and more than two packs a day.

Table 12: Distributions of Smokes' Brand Segments

Smoker' Brand Segment	Frequency	Percent (%)
Marlboro	144	27.38
Strong Brands	194	36.88
Weak Brands	188	35.74
Total	526	100

Note: we rank cigarette brands by their national sales revenues. We refer to Marlboro as an extra-strong brand, to the 2nd to 10th ranked brand as strong brands, and to the rest as relatively weak brands, respectively.

Table 13: Summary of Counter-Marketing Mix

State	Cigarette Tax per Package ($)	Anti-Smoking GRP (100)	Smoke-Free Restriction Level
AZ	2.166 (.520)	207.26 (234.76)	.606 (.439)
CA	1.353 (.223)	346.34 (320.01)	.500 (-)
CO	1.323 (.223)	270.74 (428.63)	.775 (.347)
FL	.922 (.499)	161.02 (379.01)	.750 (-)
MD	1.883 (.639)	33.08 (88.80)	.625 (.309)
NY	2.730 (.742)	820.68 (728.09)	1.000 (-)
OH	1.746 (.226)	404.97 (427.01)	.738 (.361)
PA	1.841 (.247)	148.68 (209.40)	.450 (.116)
TX	1.493 (.608)	24.11 (41.66)	0 (-)
All	1.718 (.689)	268.54 (435.57)	.501 (.442)

Note: standard deviations in parentheses;

Table 14: Migrant Smokers' Annual Cigarette Purchase Quantity Changes

Move to States	# of Migrant Smokers	State Difference in the Counter-Mkt Mix	Difference in Annual Purchase Quantity	t-statistic (d.f.)	p-value
Higher Taxes	122	$.724 (.573)	-41.75 (125.2)	-3.68 (121)	<.01
More Anti-Ads	123	8,508 (9,949)	-37.03 (119.9)	-3.42 (122)	<.01
Stricter Restriction	44	1 (-)	-43.59 (115.5)	-2.50 (43)	<.05

Note: standard deviations in parentheses;

Table 15: Purchase Changes for Nonmigrant Smokers Whose States Raise Cigarette Taxes by $1.00

Segment	# of Smokers	Average Monthly Purchase in Packs			t-value (d.f.)
		Before the tax raise	After the tax raise	Difference	
Overall	305	21.66 (20.43)	11.78 (15.21)	-9.97 (14.49)	-12.02 (304) ***
Marlboro	67	17.34 (20.52)	9.12 (13.80)	-8.42 (13.24)	-5.17 (65) ***
Strong brands	127	21.06 (20.19)	12.50 (15.05)	-8.63 (14.41)	-6.69 (124) ***
Weak brands	114	24.87 (20.30)	12.52 (16.12)	-12.35 (15.07)	-8.75 (113) ***

Note: a) standard deviations in parentheses; b) *** indicates two-side p-value <.01;

Table 16: Regression of Monthly Purchase Quantity Difference Before and After the Tax Raise on Segments

	Estimate	S.E.	T-value
Intercept	-12.350	(1.351)	-9.14 ***
Marlboro segment	3.929	(2.231)	1.76 *
Strong brand segment	3.725	(1.868)	1.99 **
N=305			

Note: *** indicates two-side p-value <.01; **<.05 and *<.1;

Table 17: Quitting Patterns among the Three Brand Segments

Segment	# of smokers	% Quit in Year				% Quit by Year
		2005	2006	2007	2008	2009
Overall	526	2.09	3.42	7.60	10.27	23.38
Marlboro	144	.69	2.78	6.25	9.03	18.75
Strong brands	194	2.8	2.58	6.70	10.31	22.16
Weak brands	188	2.66	4.79	9.57	11.17	28.19

Table 18: Model Comparisons

	Model1: Homogenous Myopic	Model 2: Homogenous Dynamic	Model 3: Heterogeneous Dynamic
# of observations	31,560	31,560	31,560
# of parameters	32	32	96
Marginal log-likelihood	-33,504	-32,838	-23,304
In-sample Hit Rate	39.2%	39.3%	67.70%

Note: model 1 refers to a homogenous myopic model with $\beta = 0$; model 2 refers to a homogenous dynamic model with $\beta = .98$; model 3 refers to a dynamic model with heterogeneity described in the last section.

Table 19: Process Estimates of Economic, Convenience and Health Cost

	Cigarette Price per pack $LogP_{it}$	Smoke Free Restriction Level C_{it}	Anti-smoking ads rating $anti_{it}$
$LogP_{it-1}$	.929 (.020) ***	-.013 (.002) ***	-119.551 (7.047) ***
$LogP_{it-1} - Log\bar{P}_{t-1}$	-.533 (.024) ***	/	/
C_{it-1}	-.075 (.005) ***	.452 (.009) ***	-204.987 (8.676) ***
$(C_{it-1} - \bar{C}_{t-1})$	/	.473 (.009) ***	/
$anti_{it-1}$	-2.25e-5 (.29e-5) ***	-8.71e-6 (1.19e-6) ***	.416 (.018) ***
$(anti_{it-1} - \overline{anti}_{t-1})$	/	/	-.133 (.018) ***
State dummy	Y	Y	Y
Year dummy	Y	Y	Y
Observations	31,560	31,560	31,560
R-squared	58.21%	96.53%	33.50%

Note: a) $\bar{P}_{t-1}$ refers to the average prices in other states; b) $\bar{C}_{t-1}$ refers to the average smoking restriction level in other states; c) a) $\overline{anti}_{t-1}$ refers to the average anti-smoking ads GRPs in other states; d) *** for two-sided significance level <.01

Table 20: Model Estimates Based on Model 3

	Monthly nicotine intake <210mg ($j = 1$)	Monthly nicotine intake <420mg ($j = 2$)	Monthly nicotine intake <840mg ($j = 3$)	Monthly nicotine intake >=840mg ($j = 4$)
Mean Coefficients δ_{j0}				
Intercept	**-1.748**	**-2.653**	**-3.633**	**-3.513**
	(-3.337, -.009)	*(-4.922, -.577)*	*(-5.569, -1.868)*	*(-5.049, -1.833)*
Log(price)	**-.329**	**.895**	**1.575**	**1.614**
	(-.593, -.062)	*(.634, 1.127)*	*(1.335, 1.747)*	*(1.270,1.811)*
Convenience cost	-.079	-.381	.528	-.630
	(-.764, .633)	*(-1.120, .353)*	*(-.252, 1.240)*	*(-1.571, .245)*
Health cost	**-.559**	**-.990**	**-1.531**	**-2.024**
	(-.756, -.361)	*(-1.218,-.714)*	*(-1.762,-1.249)*	*(-2.270,-1.768)*
$Adct_{i,j=1,t-1}$	**1.101**	**1.482**	**1.116**	.349
	(.992, 1.179)	*(1.331, 1.566)*	*(.904, 2.248)*	*(-.167, .455)*
$Adct_{i,j=2,t-1}$	**1.294**	**1.989**	**2.086**	**1.943**
	(1.111, 1.457)	*(1.860, 2.135)*	*(1.876, 2.258)*	*(1.655, 2.259)*
$Adct_{i,j=3,t-1}$	**1.009**	**2.175**	**2.479**	**2.678**
	(.795, 1.232)	*(1.975, 2.392)*	*(2.283, 2.717)*	*(2.393, 2.988)*
$Adct_{i,j=4,t-1}$	**.332**	**1.650**	**2.200**	**2.531**
	(-.016, .792)	*(1.358, 1.979)*	*(1.898, 2.517)*	*(2.242, 2.829)*
Observed Heterogeneity: $I(BS_i = Marlboro)$				
Intercept	1.033	.378	.629	1.423
	(-.234, 2.218)	*(-1.087, 1.651)*	*(-.723, 1.659)*	*(-.316, 2.734)*
Log(price)	**-.697**	**-.358**	**-.333**	**-.419**
	(-1.108, -.279)	*(-.684, -.053)*	*(-.566, -.095)*	*(-.666, -.128)*
Convenience cost	-.875	-.661	**-1.969**	**-3.324**
	(-1.924, .002)	*(-1.753, .375)*	*(-3.005, -.801)*	*(-5.072, -1.097)*
Health cost	**.288**	**.330**	**.362**	.298
	(.091, .483)	*(.056, .606)*	*(.077, .652)*	*(-.172, .721)*
Observed Heterogeneity: $I(BS_i = Strong\ Brands)$				
Intercept	-.273	-.725	-.366	.262
	(-1.421, .872)	*(-2.439, .519)*	*(-1.945, .820)*	*(-1.189, 1.555)*
Log(price)	**-.529**	**-.416**	**-.414**	**-.310**
	(-.914, -.154)	*(-.674, -.171)*	*(-.605, -.232)*	*(-.531, -.106)*
Convenience cost	-.489	-.837	**-1.235**	.467
	(-1.412, .491)	*(-1.791, .113)*	*(-2.200, -.280)*	*(-.942, 1.805)*
Health cost	**.211**	**.441**	**.542**	.242
	(.099, .514)	*(.190, .711)*	*(.255, .833)*	*(-.135, .627)*
Observed Heterogeneity: $(Lninc_i - \overline{Lninc})$				
Intercept	-.712	-.623	.553	-.156
	(-1.764, .088)	*(-1.611, .130)*	*(-2.805, 1.868)*	*(-.943, .528)*
Log(price)	**-.496**	**-.207**	**-.241**	**-.221**
	(-.747, -.244)	*(-.406, -.011)*	*(-.387, -.098)*	*(-.382, -.061)*
Convenience cost	-.222	.013	.234	-.395
	(-.602, .161)	*(-.449, .509)*	*(-.286, .736)*	*(-1.320, .272)*
Health cost	.106	.069	-.028	.095

	(-.050, .278)	(-.108, .281)	(-.227, .158)	(-.146, .362)
Unobserved Heterogeneity: sqrt($\sum_{\xi jj}$)				
Intercept	**4.289**	**4.484**	**3.649**	**4.739**
	(2.356, 6.388)	*(2.331, 7.218)*	*(2.348, 5.555)*	*(2.870, 6.249)*
Log(price)	**1.942**	**1.322**	**.975**	**1.000**
	(1.825, 2.065)	*(1.187, 1.487)*	*(.857, 1.126)*	*(.876, 1.172)*
Convenience cost	**2.867**	**2.905**	**3.065**	**2.545**
	(2.387, 3.237)	*(2.251, 3.357)*	*(2.261, 3.662)*	*(2.011, 3.056)*
Health cost	**.958**	**1.208**	**1.341**	**1.476**
	(.828, 1.105)	*(1.035, 1.408)*	*(1.188, 1.517)*	*(1.267, 1.663)*

Note: a) the estimation is based on 25,000-50,000 iteration results; b) 95% HPD reported in parentheses; c) bold indicates 95% HPD not including zeros.

Table 21: Elasticity of the Three Counter-Marketing Tactics

	Tax up 10%	Anti-ads up 10%	Sfa up 10%
Overall	-14.9%	-3.0%	-10.8%
Marlboro segment	-11.3%	-0.5%	-14.2%
Strong segment	-13.6%	-2.8%	-14.6%
Weak segment	-21.7%	-9.0%	-9.7%

Notes: 1) % nicotine intake changes over five year period in each cell; 2) smoke-free restriction is capped at one; therefore the 10% increase smoke-free restriction is actually equal to 9.2% increase; 3) simulation involves monthly decisions for 526 smokers.

Table 22: Brands' Marketing Mix and Counter-Marketing Tactics

	Anti-ads up 10%		Sfa up 10%	
Marlboro price cut 10%	Marlboro segment	**12.5%**	Marlboro segment	**2.1%**
	Strong segment	-2.8%	Strong segment	-14.6%
	Weak segment	-9.0%	Weak segment	-9.7%
Strong brand price cut 10%	Marlboro segment	-0.5%	Marlboro segment	-14.2%
	Strong segment	**9.3%**	Strong segment	**-0.2%**
	Weak segment	-9.0%	Weak segment	-9.7%
Weak brand price cut 10%	Marlboro segment	-0.5%	Marlboro segment	-14.2%
	Strong segment	-2.8%	Strong segment	-14.6%
	Weak segment	**8.3%**	Weak segment	**6.6%**

Note: 1) % nicotine intake changes over five year period in each cell; 2) smoke-free restriction is capped at one; therefore the 10% increase smoke-free restriction is actually equal to 9.2% increase; 3) simulation involves monthly decisions for 526 smokers.

Table 23: What If We Adopt a State X's Counter-Marketing Mix

	Counter-Marketing Profile	
	New York City	State of South Carolina
Avg cigarette excise taxes	$3.875 (.742)	$.562 (.231)
Monthly anti-smoking ads GRPs	821 (728)	24 (49)
Avg smoke-free restrictions	1 (-)	.13 (-)
	Nicotine Intake	
Overall	-60.27%	78.3%
Marlboro smokers	-54.2%	81.1%
“Strong” brand smokers	-56.7%	70.8%
“Weak” brand smokers	-67.4%	81.8%

Note: nicotine intake changes are reported in the bottom portion of the table, under the scenarios of adopting a state X’s counter-marketing mix.

Figure 1: Geographical and Temporal Distribution of the Three Anti-Smoking Policies

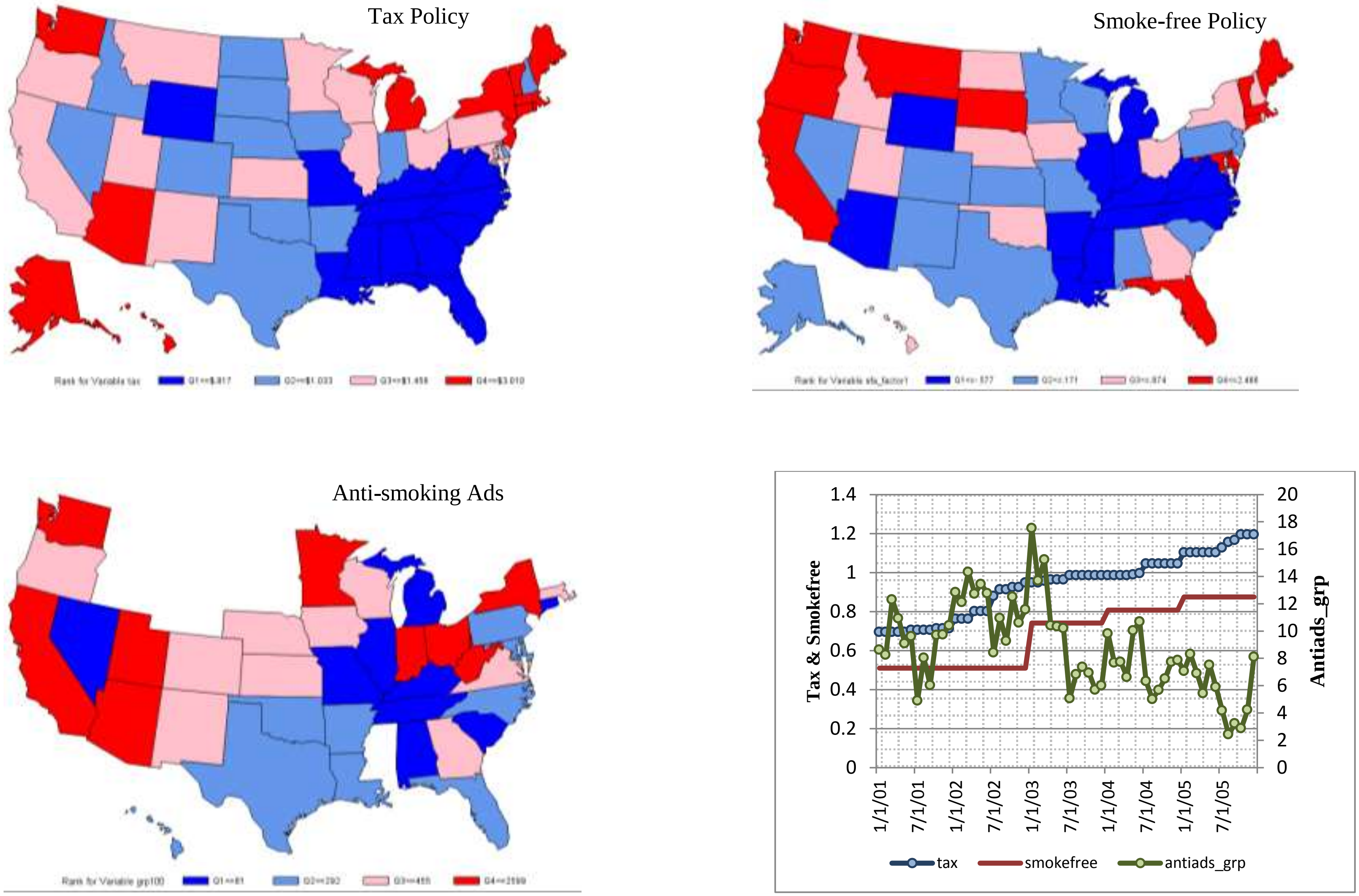
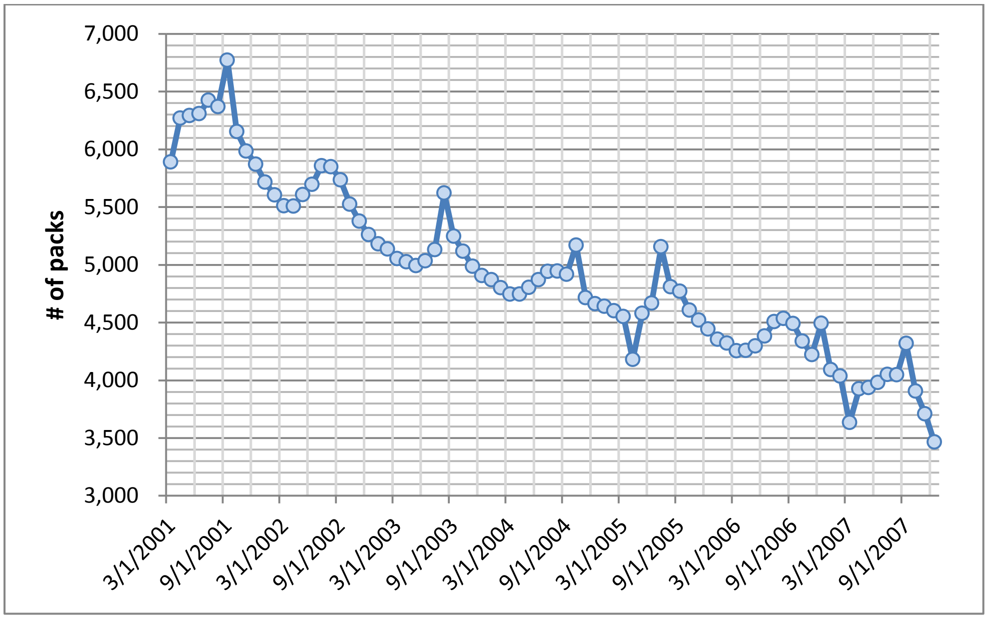


Figure 2: Moving Average of the Overall Cigarette Volume (Packs)



Note: the moving average is a three-month period average.

Figure 3: Market Shares of Regular, Light, Ultra Light by Tax, Smoke Free, Anti-Smoking Ad, and Median Income

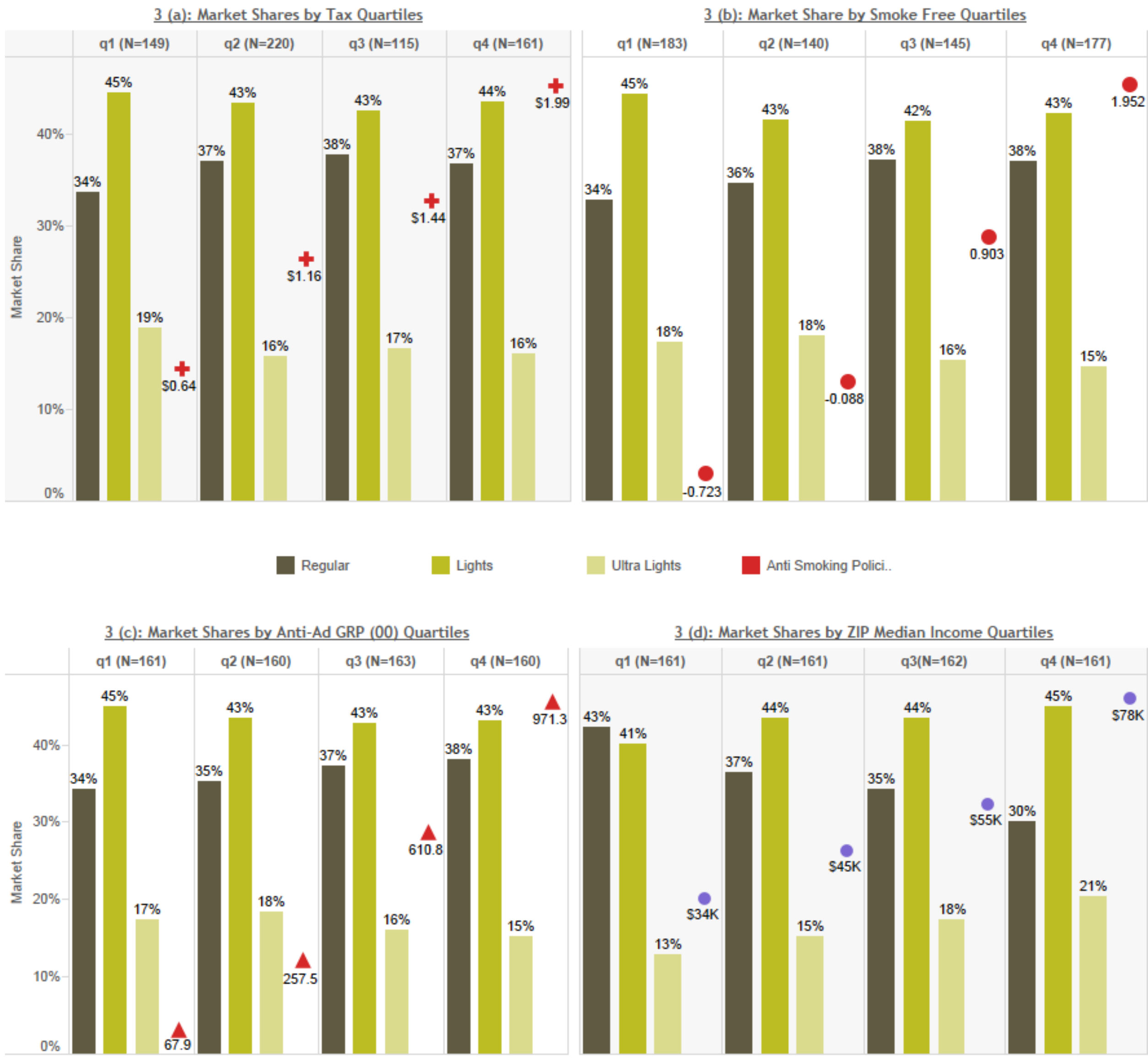


Figure 3: Market Shares of Regular, Light, and Ultra Light by Tax (3a), Smoke Free (3b), Anti-smoking Ad (3c) and Median Income (3d).
Note the correlation between Regular cigerette and Median Income is -0.49 (p-value <.05)

Figure 4: Observed vs. Predicted Market Shares and Category Sales

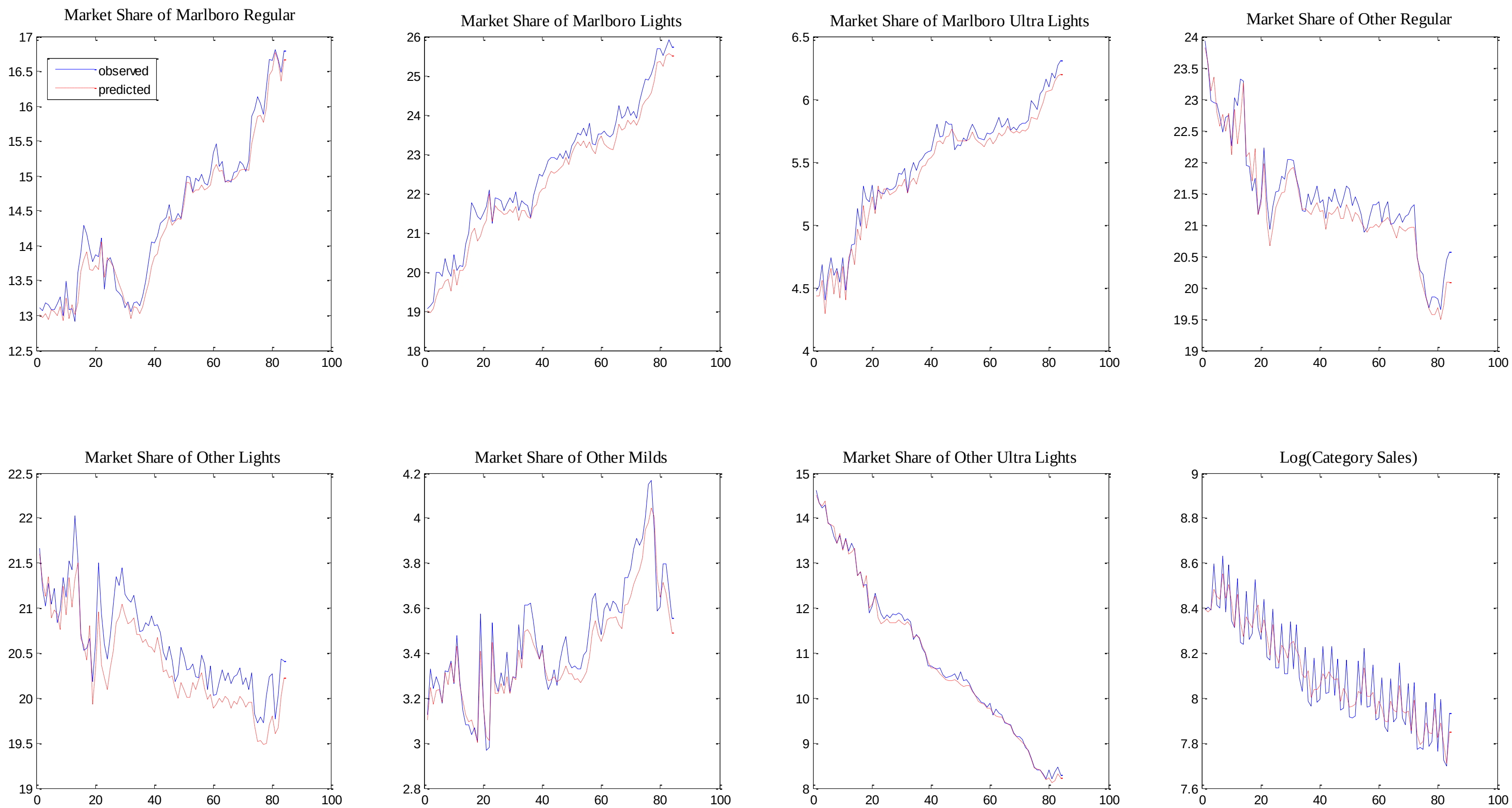


Figure 5: Observed Monthly Nicotine Intake Levels

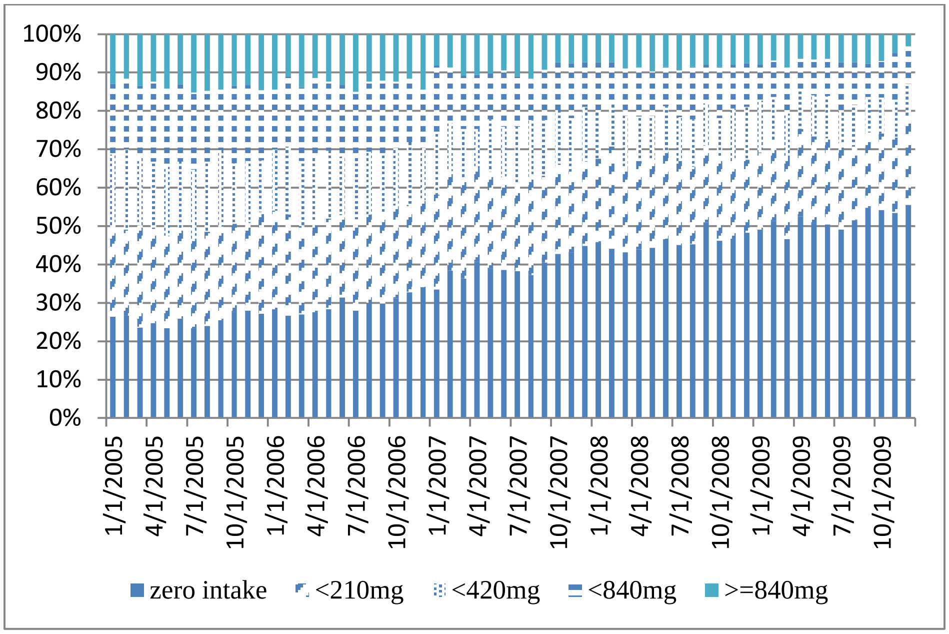
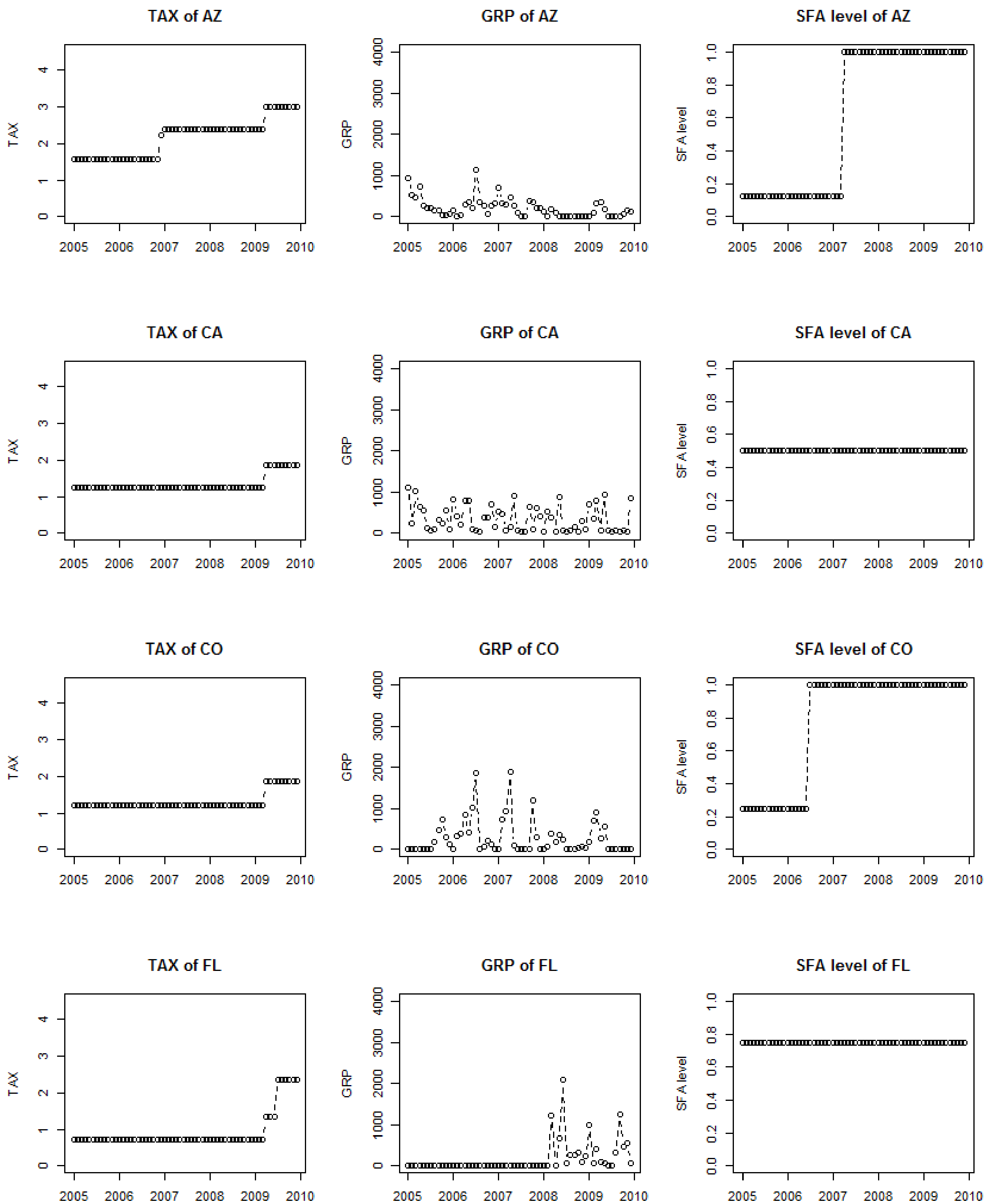


Figure 6: Geographical and Temporal Distribution of the Three Counter-Marketing Mix



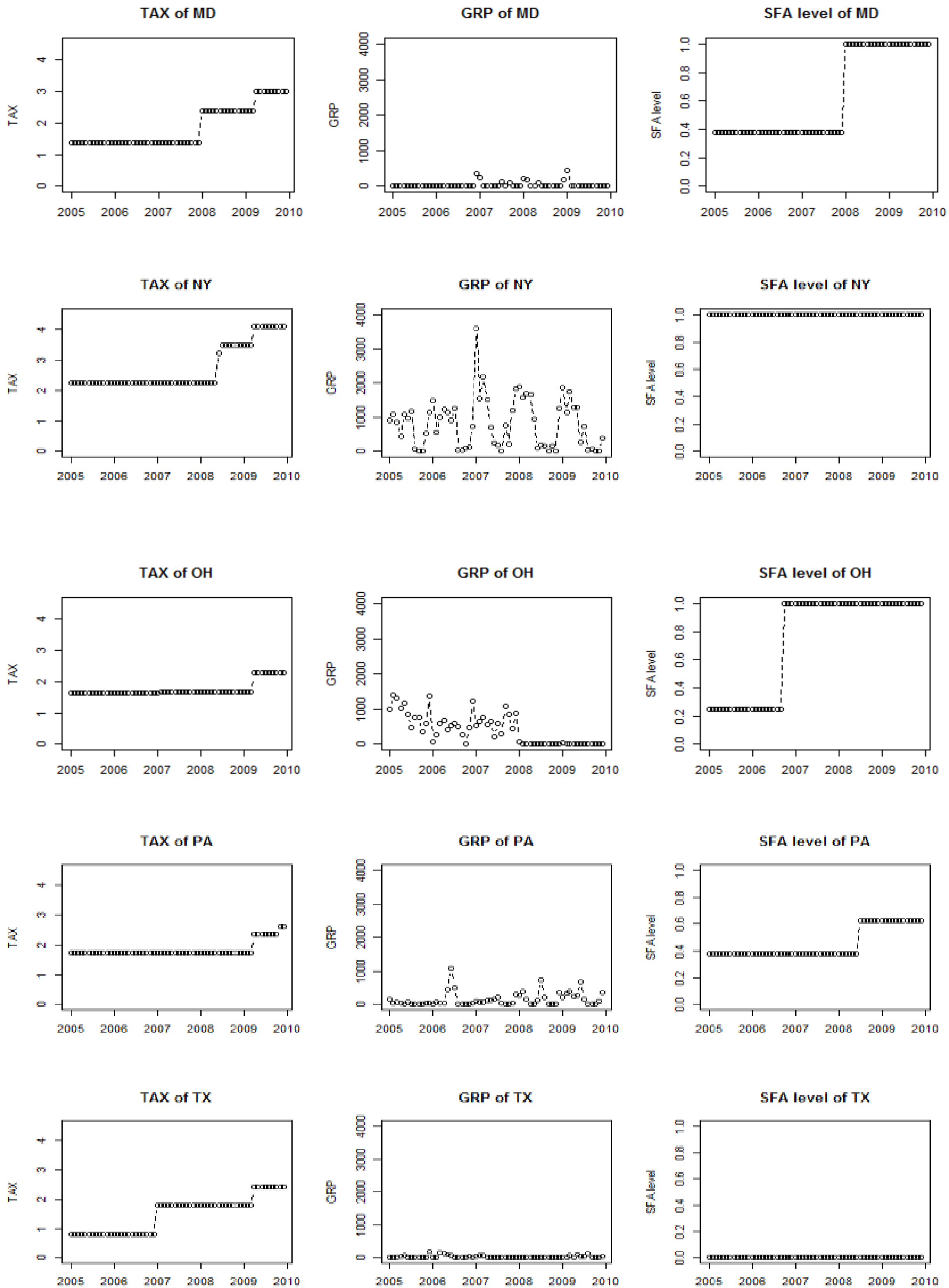

TAX of MD
GRP of MD
SFA level of MD
TAX of NY
GRP of NY
SFA level of NY
TAX of OH
GRP of OH
SFA level of OH
TAX of PA
GRP of PA
SFA level of PA
TAX of TX
GRP of TX
SFA level of TX
TAX
GRP
SFA level
2005
2006
2007
2008
2009
2010

Figure 7: Annual Cigarette Purchase Quantity Changes

a) Moving to a State with Higher Taxes b) Moving to a State with More Anti-Ads

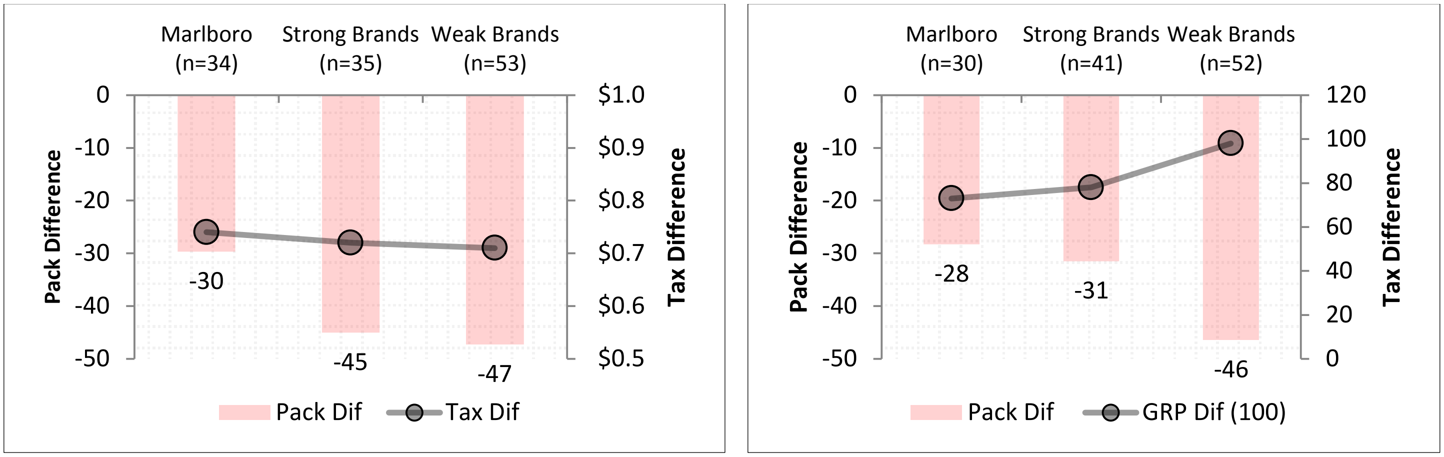
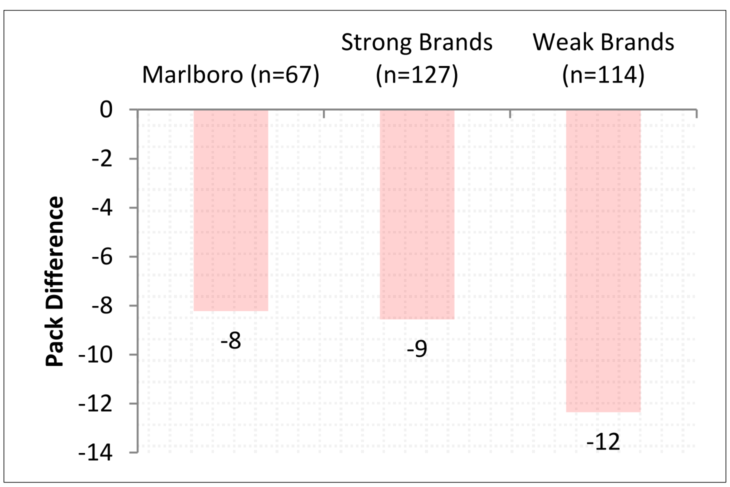
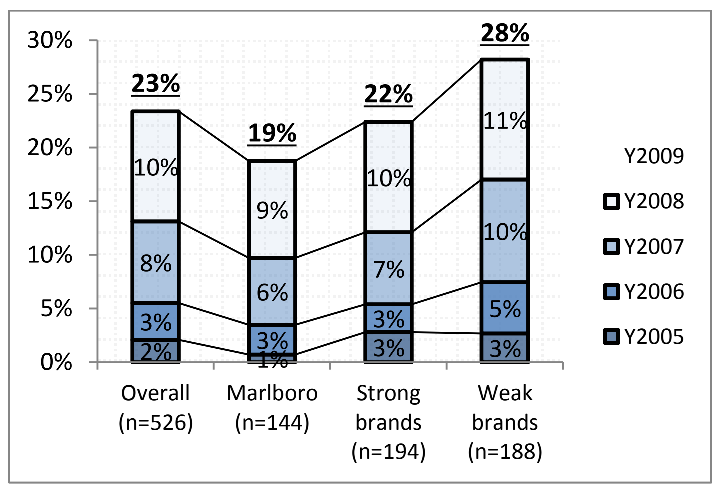


Figure 8: Average Monthly Purchase Quantity Changes for Nonimmigrant Smokers Where States Raise $1.00 Taxes



Note: differences across the three brand segments are statistically signiticant at a two-sided significnace level <.01

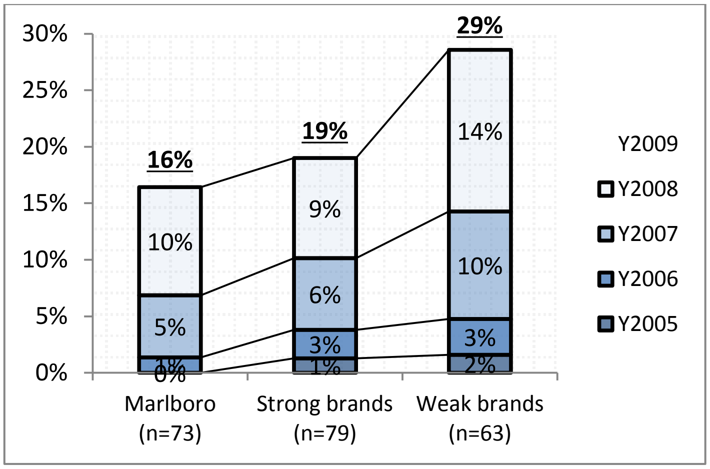
Figure 9: Quitting Patterns among the Three Brand Segments



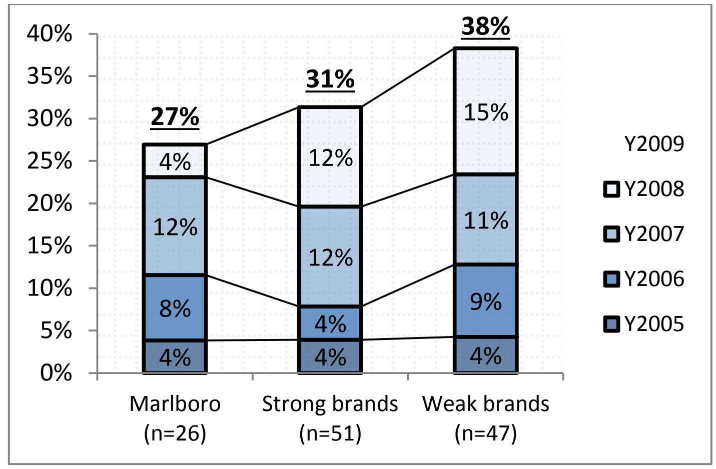
Note: % in Year 05-08 refers to those who quit in that year; % in year 09 refers to the cumulative quit %

Figure 10: Quitting Patterns among the Three Brand Segments

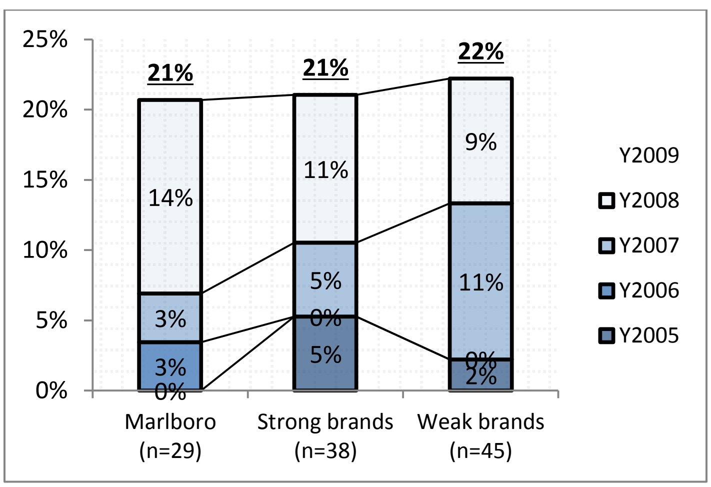
a): Conditional on Initial Monthly Nicotine Intake level (<210 mg)



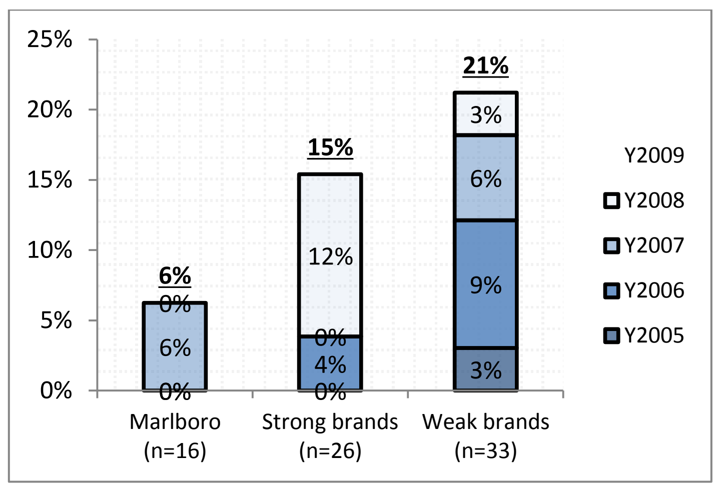
b) Conditional on Initial Monthly Nicotine Intake level (>=210 mg but < 420mg)



c) Conditional on Initial Monthly Nicotine Intake level (>=420 mg but <840mg)



d) Conditional on Initial Monthly Nicotine Intake level (>=840 mg)



Note: % in Year 05-08 refers to those who quit in that year; % in year 09 refers to the cumulative quit %.

Figure 11: Heterogeneity Price, Convenience, Health Estimates across All Sample

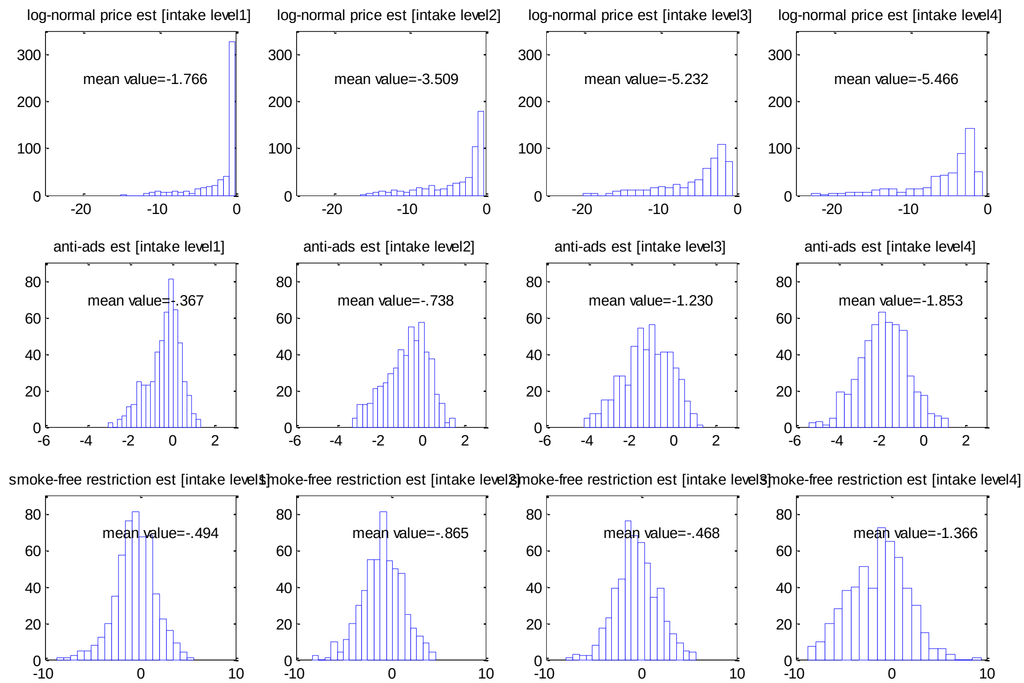


Figure 12: Price Estimates across the Three Brand Segments

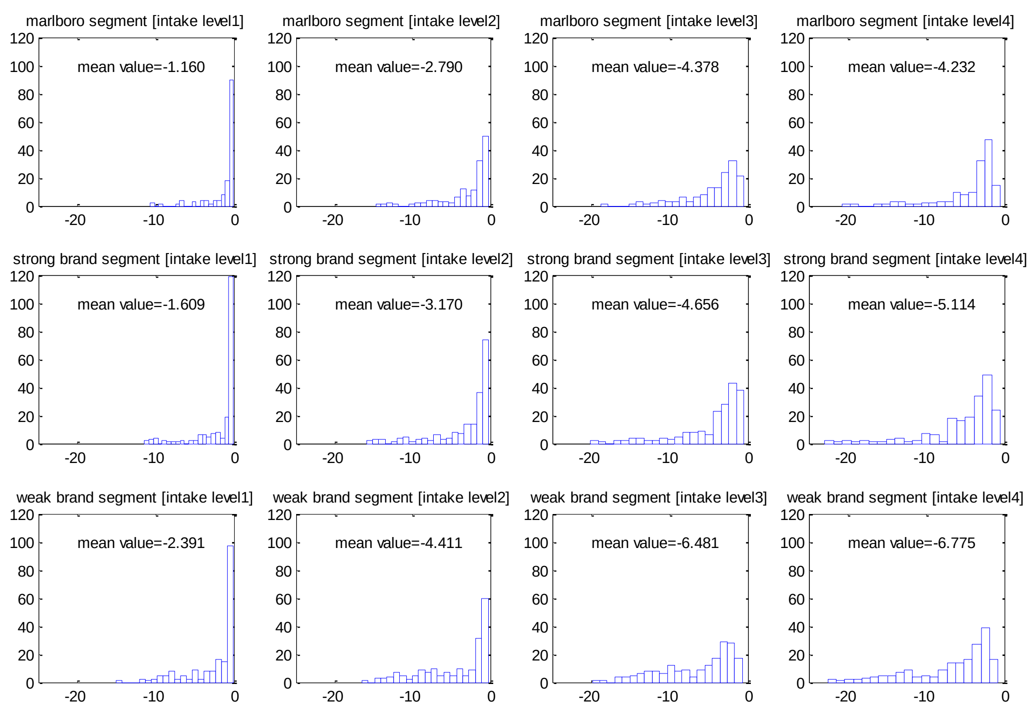


Figure 13: Anti-Smoking Estimates across the Three Brand Segments

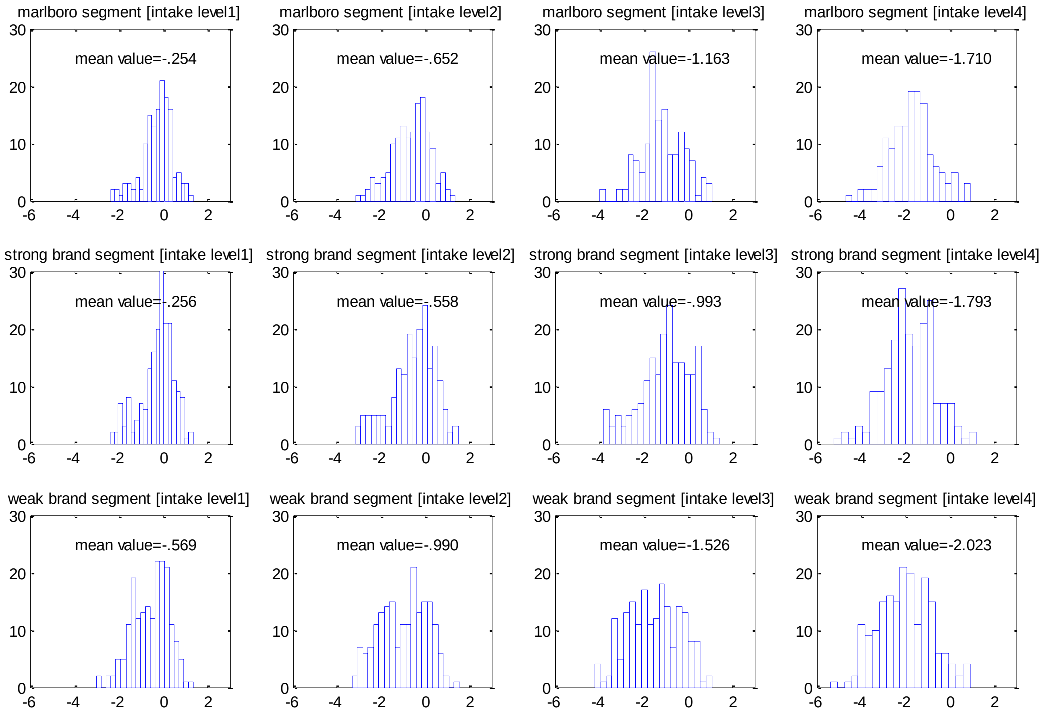
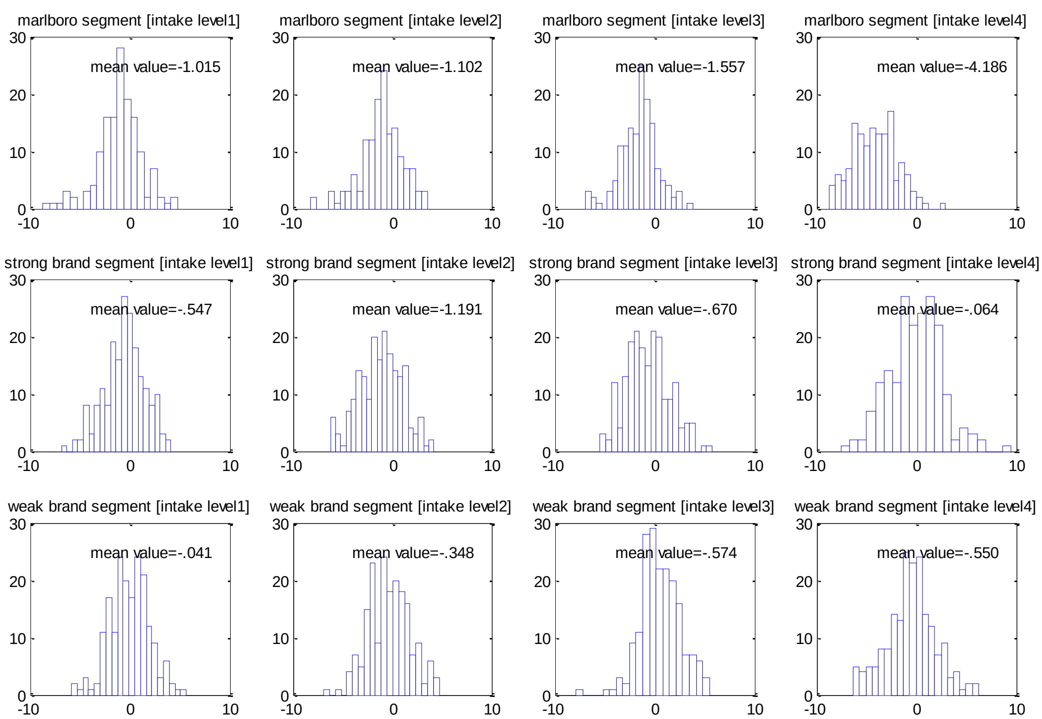


Figure 14: Smoke-Free Restriction Estimates across the Three Brand Segments

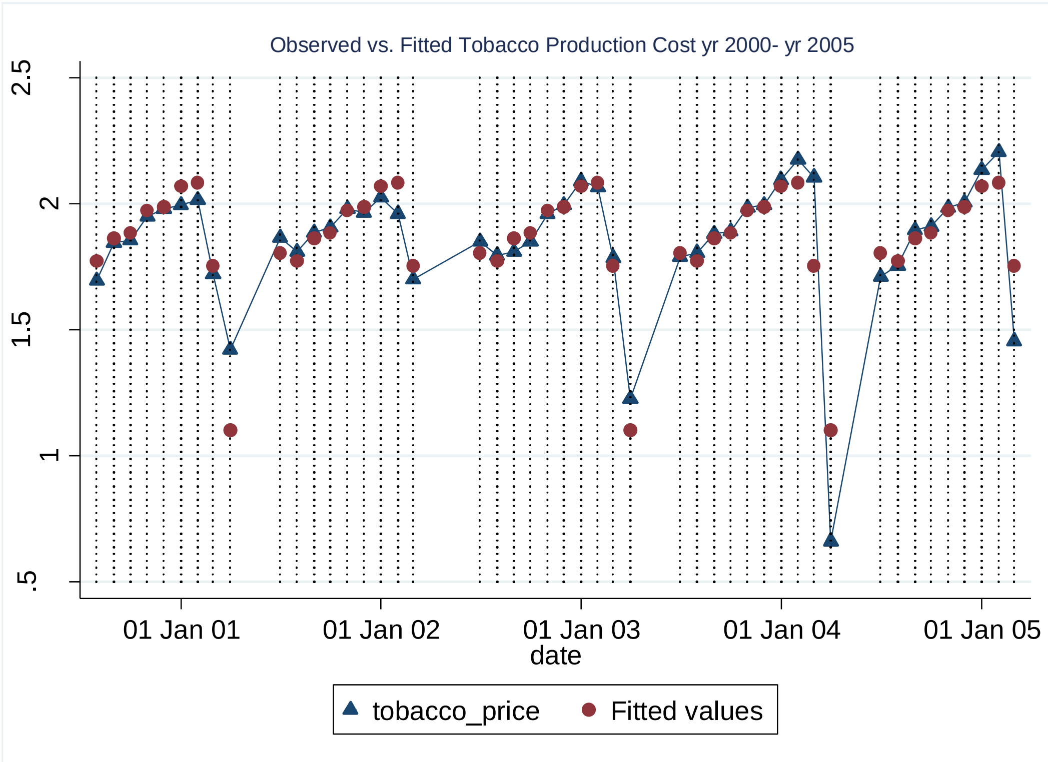


Appendix 1: Standardized Scoring Coefficients of the Factor Analysis of the Smoke-Free Restrictions on Twelve Areas

	Component 1	Component 2
Shopping malls	.261	-.182
Bars	.242	-.208
Restaurants	.198	-.083
Recreational facilities	.184	-.059
Healthcare facilities	.175	-.072
Private worksites	.147	-.002
Cultural facilities	.123	.021
Government worksites	.095	.064
Public transportation	.095	.015
Public schools	-.319	.659
Private schools	-.206	.494
Child care centers	-.083	.288

Note: the raw data is CDC-reported smoke-free restriction level from 0 to 5 on twelve areas including government worksites, private worksites, restaurants, healthcare facilities, public transportation, shopping malls, bars, recreational facilities, cultural facilities, private schools, child care centers and public schools.

Appendix 2: Imputed Monthly Tobacco Production Cost



Note: we obtained monthly tobacco production cost from the US Department of Agriculture. The US Department of Agriculture only provides monthly production cost till Year 2005, while only annual tobacco production cost is available for year 2006 and 2007. The five-year monthly data showed a strong seasonality. Therefore, we imputed the monthly tobacco production cost for year 2006 and 2007 based on a linear regression model of tobacco production cost on monthly dummies using the available five-year data $Tobacco\_Cost_m = 2.068 + .016 \times Feb_m - .315 \times Mar_m - .966 \times Apr_m - .264 \times Jul_m - .296 \times Aug_m - .205 \times Sep_m - .186 \times Oct_m - .096 \times Nov_m - .08 \times Dec_m$

Estimates of Regressing Brand Prices on Instruments

	Estimate	S.E.	p-value
Tobacco production cost	.033	.002	***
Crude oil price (10^{-3})	.4	.03	***
Agriculture raw material price	.002	.0001	***
# of observations	379,260		
Adjusted R-square	33.95%		

Note: a) the dependent variable is the tax-exclusive cigarette price per pack at store-month level; b) brand and store dummies are included in the regression; c) all the other variables in equation (1) and (4) are also included in the regression; d) To check the over-identification issue, we ran GMM regression of market share on all the variables in equation (1) and (4) using the three cost variables as instruments. We cannot reject the null hypotheses with Sargan statistic at $x^2(2) = 3.958$, p=.1382.

Appendix 3: Steps in Kalman Filter Estimation

a. We estimate the parameters $\theta = \{\boldsymbol{a}, \boldsymbol{g}, \delta, \tau, \mathrm{V}, \mathrm{F}\}$ through a Kalman filtering process. The observation and transition equation in (3) and (6) can be rewritten in a vector form as : ecall the observation and transition equation in (3) and (6) as:

(A1) $Y_t = H_t + X_t\boldsymbol{a} + \tau\hat{\mu}_t + \tilde{\varepsilon}_t$ $\quad$ $where\ \tilde{\varepsilon}_t \sim N(0, \tilde{V})$
(A2) $H_t = \delta H_{t-1} + W_t\boldsymbol{g} + v_t$ $\quad$ where $v_t \sim \mathrm{N}(0, \mathrm{F})$

b. We assume that the prior of state variable H_t at time 0 is $H_o' \sim \mathrm{N}(H_0, \mathrm{F}_0)$. 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 the information up to time t-1. Therefore, our knowledge of $\hat{H}_{t|t-1}$ and $\hat{B}_{t|t-1}$ is:

(A3) $\hat{H}_{t|t-1} = \delta\hat{H}_{t-1|t-1} + W_t\hat{\boldsymbol{g}}$
(A4) $\hat{B}_{t|t-1} = \delta\hat{B}_{t-1|t-1}\delta + F$

d. We then obtain the prediction error and the variance of this prediction error as:

(A5) $\tilde{Y}_{t|t-1} = Y_t - \hat{H}_{t|t-1} - X_t\hat{\boldsymbol{\alpha}} - \hat{\tau}\hat{\mu}_t$
(A6) $S_{t|t-1} = cov(\tilde{Y}_{t|t-1}) = \hat{B}_{t|t-1} + \tilde{V}$

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

(A7) $\hat{H}_{t|t} = \hat{H}_{t|t-1} + K_t\tilde{Y}_{t|t-1}$
(A8) $\hat{B}_{t|t} = \hat{B}_{t|t-1} - \mathrm{K}_t\hat{B}_{t|t-1}$, where $K_t = \hat{B}_{t|t-1}S_{t|t-1}^{-1}$

f. Iterate step b to step d and obtain for each t=1, …, T.

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

$$(A9)\ \ LL = \sum_{t=1}^{T}\sum_{js=1}^{JS} -\frac{1}{2}\log(2\pi) - \frac{1}{2}\log\left|S_{jst|t-1}\right| - \frac{1}{2}\tilde{Y}_{jst|t-1}{}'S_{jst|t-1}^{-1}\tilde{Y}_{jst|t-1}$$

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

Appendix 4: Variance-Covariance Estimates in the Observed Equation (3)

	Variance		Correlation with category sales	
	Estimate	S.E.	Estimate	S.E.
- Marlboro regular	.014	(.0001)***	.004	(.006)
- Marlboro lights	.010	(.0001)***	.023	(.005)***
- Marlboro ultra lights	.030	(.0003)***	-.027	(.003)***
- Other regular	.011	(.0001)***	-.076	(.005)***
- Other lights	.011	(.0001)***	-.082	(.004)***
- Other mild	.051	(.0004)***	-.058	(.003)***
- Other ultra lights	.022	(.0002)***	-.083	(.006)***
- Category sales	.022	(.0002)***	/	

Note: a) the variance parameter is re-parameterized as $\exp(\cdot)$; the correlation parameter is re-parameterized as $\text{atan}(\cdot)$; delta method is used to recover the standard error; b) *** indicates p value <.01;

Appendix 5: Variance-Covariance Estimates in the Transition Equation (6)

	Variance		Correlation with category sales	
	Estimate	S.E.	Estimate	S.E.
- Marlboro regular	.003	(.0001)***	-.069	(.013)***
- Marlboro lights	.003	(.0001)***	-.101	(.013)***
- Marlboro ultra lights	.006	(.0001)***	-.115	(.013)***
- Other regular	.004	(.0001)***	-.051	(.012)***
- Other lights	.003	(.0001)***	.002	(.016)
- Other mild	.007	(.0002)***	-.137	(.015)***
- Other ultra lights	.006	(.0001)***	-.051	(.011)***
- Category sales	.004	(.0001)***	/	

Note: a) the variance parameter is re-parameterized as $\exp(\cdot)$; the correlation parameter is re-parameterized as $\text{atan}(\cdot)$; delta method is used to recover the standard error; b) *** indicates p value <.01;

Appendix 6: The Number of Cigarette Brands an Average Smoker Have Over Six-Year Horizon

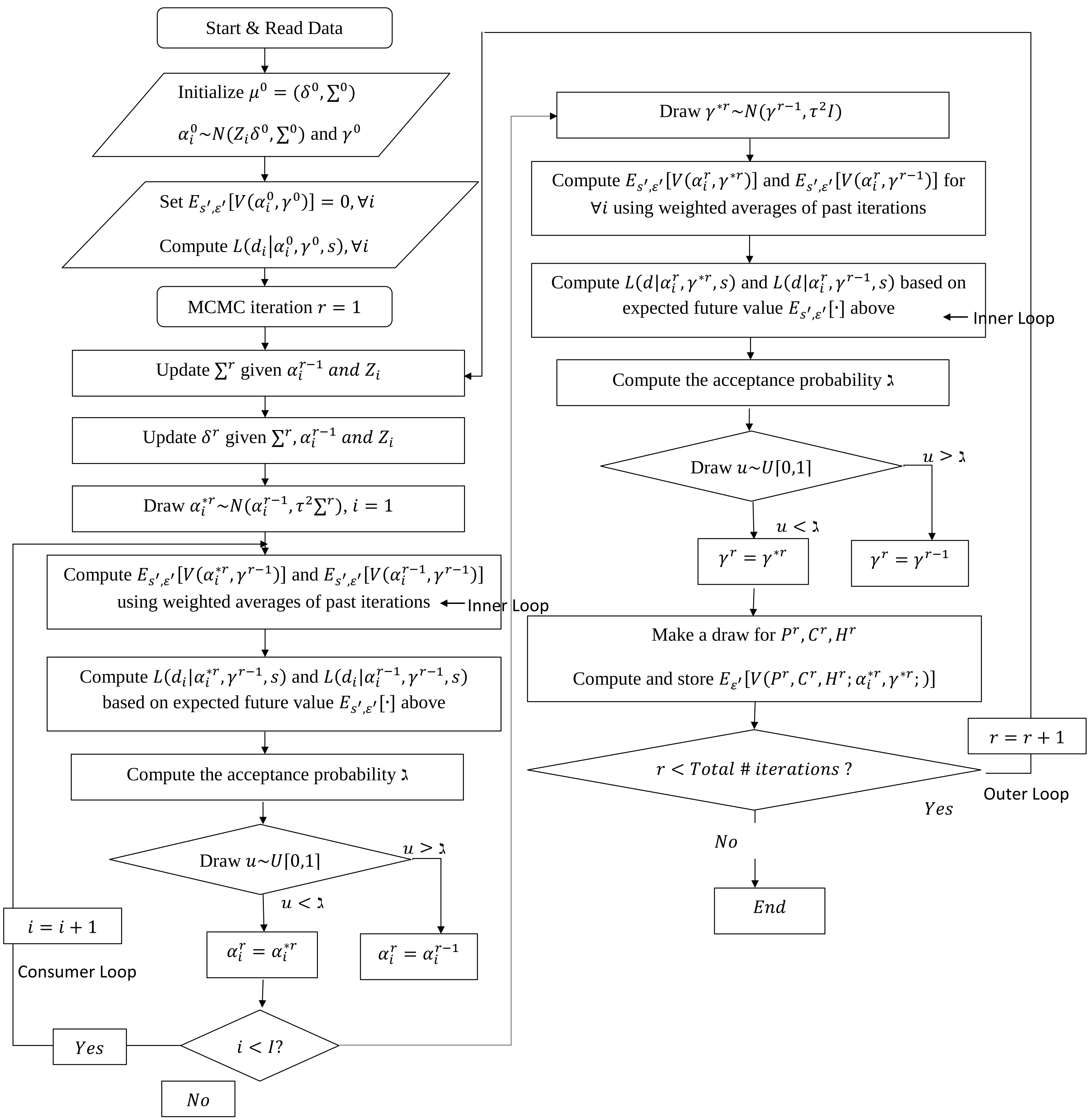
# of Cigarette Brands	Frequency	Percent (%)
1	273	51.90
2	173	32.89
3	60	11.41
4	16	3.04
5	4	.76
Total	526	100

Appendix 7: List of Top 20 Brands by the National Sales Revenues

Rank	Cigarette Brand	Sales Revenues ($1,000,000)	Market Shares (%)	Tax Exclusive Average Retail Price per Pack ($)
1	Marlboro	657.0	42.56	2.32
2	Newport	95.8	5.04	2.86
3	Basic	88.6	6.23	2.14
4	Virginia Slims	87.9	5.22	2.54
5	Winston	84.4	4.67	2.72
6	Camel	71.3	3.87	2.77
7	Salem	59.5	3.14	2.85
8	Doral	54.4	3.64	2.25
9	Merit	45.1	2.16	3.15
10	Benson & Hedges	40.9	1.94	3.17
11	Kool	38.9	2.42	2.41
12	Parliament	32.4	2.06	2.37
13	Carlton	27.7	1.32	3.15
14	Pall Mall	26.1	1.73	1.95
15	Capri	21.9	1.05	1.99
16	Misty	20.9	1.61	1.57
17	GPC Approved	17.6	1.34	2.02
18	Kent	14.8	.70	3.20
19	Vantage	14.1	.79	3.06
20	USA Gold	10.9	1.03	1.62

Note: the sales revenue rank is based on aggregate store-level data on 2001-2005 cigarette sales and prices from the IRI (Bronnenberg, Kruger, and Mela 2008).

Appendix 8: Diagrams of Estimation Steps



Appendix 9: Details of Estimation Procedures

Suppose that we are in iteration r with parameter estimates being $(\mu^r, \alpha_i^r, \gamma^r)$.

Step 1: we update hyperparameter $\mu^r = (\delta^r, \Sigma^r)$ in a way similar to the multivariate regression setting. Given α_i^{r-1} and priors on $\delta, \sum$, there is simple procedure to draw δ^r, Σ^r from the posterior distributions:

$$\sum|\alpha_i, Z_i \sim IW(v_0 + n, V_0 + S) \qquad (b1)$$

$$\delta|\alpha_i, Z_i, \Sigma \sim N\left(\tilde{\delta}, \Sigma \times (Z'Z + A)^{-1}\right) \qquad (b2)$$

$$\tilde{\delta} = vec\left(\widetilde{D}\right), \qquad \widetilde{D} = (Z'Z + A)^{-1}\left(Z'Z\hat{\delta}\right), \qquad \hat{\delta} = (Z'Z)^{-1}Z'\alpha \qquad (b3)$$

$$S = \left(\alpha - Z\widetilde{D}\right)'\left(\alpha - Z\widetilde{D}\right) + \widetilde{D}'A\widetilde{D} \qquad (b4)$$

Step 2: The model specification implies that $N(Z_i\delta^r,\ \Sigma^r)$ is effectively the prior $(\cdot)$ for α_i^r. For each smoker i, we draw a candidate parameter from the random walk metropolis chains

$$\alpha_i^{*r} = \alpha_i^{r-1} + \tau_\alpha, \quad \tau_\alpha \sim N(0, \tau^2\Sigma^r) \qquad (b5)$$

We accept α_i^{*r} with probability λ_α, where

$$\lambda_\alpha = min\left\{\frac{\Phi(\alpha_i^{*r}|\delta^r, \Sigma^r)\mathrm{L_i}(d_i|s_i, \alpha_i^{*r}, \gamma^{r-1})}{\Phi(\alpha_i^{r-1}|\delta^r, \Sigma^r)\mathrm{L_i}\left(d_i\middle|s_i, \alpha_i^{r-1}, \gamma^{r-1}\right)}, 1\right\} \qquad (b6)$$

Note that the computation of L_i requires us to compute the expected value functions for smoker i, which is the output from an inner loop discussed in Step 4-6.

Step 3: We next draw a candidate parameter from the random walk metropolis chain for the common parameter vector γ:

$$\gamma^{*r} = \gamma^{r-1} + \tau_\gamma, \quad \tau_\gamma \sim N(0, \tau^2 I) \qquad (b7)$$

We accept γ^{*r} with probability λ_γ, where

$$\lambda_\gamma = min\left\{\frac{\mathrm{L}(d|s, \alpha_i^r, \gamma^{*r})}{\mathrm{L}\left(d\middle|s, \alpha_i^r, \gamma^{r-1}\right)}, 1\right\} \qquad (b8)$$

Different from step2, the computation of L requires us to compute the expected value functions for all smokers. Below we discuss how to approximate the expected value function.

Step 4: We store the outputs of the N past iterations into $Q^r = \left\{\alpha_i^{*l}, \gamma^{*l}, v^l\left(\alpha_i^{*l}, \gamma^{*l}\right)\right\}_{l=r-N}^{r-1}$, where $v^l\left(\alpha_i^{*l}, \gamma^{*l}\right)$ is a vector of alternative-specific value function. Note that $v^l\left(\alpha_i^{*l}, \gamma^{*l}\right)$ is also individual-smoker specific due to the individual-specific coefficients α_i^{*l}.

Step 5: To approximate the expected value function in equation (10) at iteration r, we run a non-parametric regression with a set of value functions obtained from earlier iterations of the MCMC algorithm Q^r as:

$$E_{s',\varepsilon'}[V(s',\varepsilon';\theta^{*r})] = \int_{s'} \sum_{l=r-N}^{r-1} \left[ln\left(\sum_j exp\left(v_j\left(s';\theta^{*l}\right)\right)\right) \cdot \omega(\theta^{*l},\theta^{*r}) \right] \pi(s'|s,d) \qquad (b9)$$

Here $\omega(\cdot)$ is the weight that takes high(low) value for $\alpha_i^{*l}, \gamma^{*l}$ that is close to (far away from) the current $\alpha_i^{*r}, \gamma^{*r}$. In particular, a Gaussian kernel density with bandwidth h is used:

$$\omega\left(\alpha_i^{*l}, \gamma^{*l}, \alpha_i^{*r}, \gamma^{*r}\right) = \frac{K_h(\alpha_i^{*l}, \gamma^{*l}, \alpha_i^{*r}, \gamma^{*r})}{\sum_{k=r-N}^{r-1} K_k(\alpha_i^{*l}, \gamma^{*l}, \alpha_i^{*r}, \gamma^{*r})} \qquad (b10)$$

Step 6: We then update the value function in iteration r according to equation (8) and (9), and store $\{\alpha_i^{*r}, \gamma^{*r}, v^r(\alpha_i^{*r}, \gamma^{*r})\}$ to Q^{r+1}. In another way, the non-parametric approximation of the value function relies on a "moving window" of the output of past iterations. In addition, we store the parameters evaluated at proposal candidate draws $\alpha_i^{*r}, \gamma^{*r}$ instead of accepted draws α_i^r, γ^r to avoid repetition due to low acceptance rate and to span the parameter space as well. Note that we approximate the expected value function in equation (13) for all smokers i across all the five addiction levels $Adct_t$ in each time period t, as each smoker i has different expectations for the economic, convenience and health costs of smoking.

Appendix 10: Model Estimates of Model 3 using Price Premium to Form Brand Segments

	Monthly nicotine intake <210mg ($j = 1$)	Monthly nicotine intake <420mg ($j = 2$)	Monthly nicotine intake <840mg ($j = 3$)	Monthly nicotine intake >=840mg ($j = 4$)
Mean Coefficients $\boldsymbol{\delta_{j0}}$				
Intercept	-2.615	**-3.763**	**-6.342**	**-4.990**
	(-5.173, .096)	*(-6.515, -1.043)*	*(-8.789, -3.918)*	*(-6.565, -3.780)*
Log(price)	.060	**1.207**	**1.887**	**1.853**
	(-.306, .433)	*(.949, 1.474)*	*(1.719, 2.056)*	*(1.663,2.034)*
Convenience cost	.040	**-.779**	**-1.276**	**-2.793**
	(-.495, .605)	*(-1.312, -.234)*	*(-1.958, -.470)*	*(-3.596, -2.040)*
Health cost	**-.503**	**-1.123**	**-1.419**	**-2.056**
	(-.816, -.184)	*(-1.522,-.733)*	*(-1.806,-1.032)*	*(-2.444,-1.694)*
$Adct_{i,j=1,t-1}$	**1.035**	**1.408**	**1.172**	**.643**
	(.947, 1.123)	*(1.228, 1.581)*	*(.974, 1.468)*	*(.380, .928)*
$Adct_{i,j=2,t-1}$	**1.165**	**1.823**	**2.051**	**2.001**
	(1.025, 1.314)	*(1.688, 1.983)*	*(1.875, 2.322)*	*(1.713, 2.182)*
$Adct_{i,j=3,t-1}$	**.889**	**2.065**	**2.454**	**2.726**
	(.719, 1.079)	*(1.868, 2.333)*	*(2.293, 2.667)*	*(2.487, 2.937)*
$Adct_{i,j=4,t-1}$	.265	**1.642**	**2.187**	**2.587**
	(-.062, .550)	*(1.275, 1.950)*	*(1.905, 2.481)*	*(2.297, 2.885)*
Observed Heterogeneity: $\boldsymbol{I(BS_i = Strong\ Brands)}$				
Intercept	-2.492	-2.857	-1.573	1.048
	(-6.010, 1.004)	*(-6.687, .858)*	*(-4.897, 1.866)*	*(-.355, 2.868)*
Log(price)	**-.641**	**-.528**	**-.445**	**-.326**
	(-1.046, -.230)	*(-.833, -.225)*	*(-.634, -.258)*	*(-.526, -.126)*
Convenience cost	-.104	.590	**-1.158**	**-2.322**
	(-.803, .628)	*(-.041, 1.211)*	*(-1.985,-.347)*	*(-3.236,-1.534)*
Health cost	**.509**	**.775**	**.691**	.165
	(.100, .920)	*(.300, 1.272)*	*(.215, 1.164)*	*(-.231, .580)*
Observed Heterogeneity: $\boldsymbol{I(BS_i = Marlboro)}$				
Intercept	-1.554	-2.557	-3.234	.188
	(-5.668, 2.088)	*(-6.447,1.155)*	*(-7.156, .444)*	*(-1.254, 1.561)*
Log(price)	**-1.135**	**-.553**	**-.531**	**-.366**
	(-1.590, -.677)	*(-.923, -.194)*	*(-.756, -.306)*	*(-.600, -.126)*
Convenience cost	.366	**-1.011**	-.072	-.122
	(-.408, 1.129)	*(-1.850, -.248)*	*(-.823, .979)*	*(-.845, 1.108)*
Health cost	**.632**	**.866**	**1.079**	.360
	(.204, .919)	*(.370, 1.272)*	*(.490, 1.164)*	*(-.095, .580)*
Observed Heterogeneity: $\boldsymbol{(Lninc_i - \overline{Lninc})}$				
Intercept	-1.595	-1.093	.861	-.177
	(-3.167, .013)	*(-2.873, .609)*	*(-.743, 2.416)*	*(-.892, .625)*
Log(price)	**-.419**	**-.180**	**-.158**	**-.161**
	(-.653, -.193)	*(-.369, -.001)*	*(-.283, -.035)*	*(-.277, -.126)*
Convenience cost	-.161	-.089	-.117	-.107
	(-.602, .147)	*(-.449, .311)*	*(-.286, .284)*	*(-1.320, .231)*
Health cost	.221	.132	-.058	.109

	(-.469, .415)	(-.475, .375)	(-.485, .175)	(-.448, .328)
Unobserved Heterogeneity: sqrt($\sum_{\xi jj}$)				
Intercept	**11.380**	**13.110**	**11.178**	**5.227**
	(9.663, 12.746)	*(10.770, 14.784)*	*(9.260, 12.618)*	*(4.340, 6.468)*
Log(price)	**1.876**	**1.300**	**.852**	**.851**
	(1.771, 1.987)	*(1.226, 1.375)*	*(.792, .910)*	*(.780, .922)*
Convenience cost	**2.089**	**2.464**	**2.495**	**2.467**
	(1.936, 2.248)	*(2.285, 2.660)*	*(2.299, 2.680)*	*(2.251, 2.705)*
Health cost	**1.457**	**1.819**	**1.748**	**1.680**
	(1.269, 1.613)	*(1.579, 2.032)*	*(1.502, 2.007)*	*(1.499, 1.884)*

Note: a) we segment brands with average prices above $2.00 (excluding Marlboro) as strong brands, place Marlboro in its own category, and categorize the remaining brands as weak brands; b) the estimation is based on 25,000-50,000 iteration results with marginal log-likelihood at -23,367; c) 95% HPD reported in parentheses; d) bold indicates 95% HPD not including zeros.