Flavorants and Addiction: An Empirical Analysis of Cigarette Bans and Taxation

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Abstract

We evaluate the proposed FDA menthol cigarette ban using aggregate-level retail data and micro-level household data. The model incorporates addiction and household heterogeneity, with a focus on low-income households and the Black community, who consume menthol cigarettes the most. The ban reduces cigarette usage by 13% and the Black smoking rate by 35%, while demand for e-cigarettes and cessation products increases by 4.9% and 1.7%, respectively. A 10.23% cigarette sales tax is as effective as the menthol cigarette ban, with a smaller reduction in consumer surplus across all demographic groups. Including non-tobacco flavored e-cigarettes in the ban reduces cigarette consumption similarly, while e-cigarette usage reduces by 46%.

1 Introduction

The leading cause of preventable death in the United States is tobacco usage (CDC Smoking and Tobacco Use, 2020). According to the Centers for Disease Control and Prevention, cigarette consumption contributes to one out of every five deaths, and is associated with a variety of ailments including bronchitis, heart disease, and cancer. This amounts to over 480,000 preventable deaths in the US each year. Within the past several decades, public policy experts have relentlessly expanded their efforts to curb tobacco consumption. Minimum age limits, advertising restrictions,

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and heavy taxation are among the tools employed. However, experts concur that more restrictive policies and regulations are necessary, particularly to advance health equity in the face of unethical marketing practices (FDA, 2021).

This paper is focused on a menthol cigarette ban, recently proposed by the Food and Drug Administration (FDA) (FDA, 2021). In particular, we evaluate the expected impact of the removal of mentholated cigarettes on the consumption of cigarette, e-cigarette, and cessation products (nicotine patches, gum, and lozenges) using data from 2015 to 2019. For this purpose, we construct a structural model of consumer demand that takes into account the dynamic effect of nicotine addiction and combines available household- and retail-level data in a way that is internally consistent. We account for unobserved preferences and product substitution through the use of both nesting parameters and random coefficients, and allow household consumption to differ through observed demographic characteristics. The structural model is needed to predict market outcomes for scenarios not observed in the data, including proposed and hypothetical policy measures such as product bans and sales taxes.

Using this model and its estimation, we seek to answer the following key questions: First, what are consumers' preferences and substitution patterns regarding cigarettes and related products? Second, based on such preferences and substitution patterns, what are the effects of the proposed menthol cigarette ban on consumers' cigarette usage and welfare, and how do the effects differ across different demographic groups? Third, how does the performance of the proposed ban compare to that of alternative policies such as a cigarette sales tax and an expanded ban that also covers menthol and flavored e-cigarettes? These are critical questions for understanding consumer behavior and policy effectiveness in the cigarette market, and answers to them offer rich information for policymakers.

Differences in demand arising from demographic preference for flavorants in tobacco products is an important issue. Historically, the Black American community has long been the target of marketing and advertising practices promoting the use of menthol cigarettes (Gardiner, 2004). Current national estimates of the Black American smoking rate suggests that menthol purchases make up 74% to 89% of their total cigarette purchases; their menthol usage is two to three times that of their non-Black peers (Delnevo et al., 2020). In addition, household income has long been correlated with increased price sensitivity and demand for cigarettes, including regular tobacco and menthol (Evans et al. (1999), Wang et al. (2018)). Calls from lawmakers and laypersons seeking to address health inequalities in disadvantaged communities resulting from targeted marketing practices encouraged FDA's recently proposed rule prohibiting the sale of menthol cigarettes.

A major consideration when dealing with banning products for health reasons is the willingness of consumers to substitute to equally harmful products. For example, when presented with a local menthol cigarette ban, many menthol smokers in Ontario, Canada chose to switch to regular tobacco cigarettes (Chaiton et al., 2020). Furthermore, some smokers indicated a willingness to consider electronic smoking devices, which also contain nicotine. E-cigarettes, as they are commonly known, are regarded as a potential avenue to smoking cessation; however they may also offer a new path to further nicotine addiction (Kasza et al. (2021), Kasza et al. (2022)). We include both e-cigarettes and traditional cessation products in our model, recognizing e-cigarettes' role as a substitute for traditional cigarettes as well as their potential to divert nicotine-quitters from more successful cessation products.

In determining the demographic preferences and product substitution patterns, we construct and estimate a model of consumer demand for cigarettes, e-cigarettes, and cessation products in the Random Coefficients Nested Logit (RCNL) framework (Grigolon and Verboven, 2014), using a combination of retail- and household-level data. The use of random coefficients allows for a rich set of unobserved heterogeneity and observed demographic preferences, and our nesting structure is particularly suited for measuring the degree of substitution across flavors within product categories ("nests"). Further, we adapt the RCNL structure to account for nicotine addiction's dynamic state dependence (e.g. Caves (2005), Tuchman (2019)). Micro-level household purchase data covers only a small subset of total product purchases, but allows for the accurate identification of addiction, consumer heterogeneity, and flavorant substitution. Aggregate-level retail data lacks information necessary to track household-level purchases, but provides a far less noisy measure of price responsiveness and product market shares and provides a reliable method to account for endogenous model parameters. We use the availability of household and retail data to our advantage, incorporating them in our modeling procedure in an internally consistent way and combining the strength of both datasets.

Our estimation procedure follows that described in Grieco et al. (2021), adapted for the RCNL structure with dynamic state dependence. This procedure allows us to recover mean utility and unobserved demand shocks while accounting for household heterogeneity, addiction, and categorical substitution.[1]

Several key findings result from our estimation. (1) We find that the willingness to switch

[1]Several other works have adapted similar procedures, including Goolsbee and Petrin (2004), Chintagunta and Dubé (2005), Tuchman (2019), and Murry and Zhou (2020).

among product flavors differs significantly between cigarettes and e-cigarettes, which plays a key role in determining the effectiveness of the various bans considered in our model. Menthol and tobacco cigarettes were found to be closer substitutes for each other when compared to the substitution between e-cigarette flavorants. (2) We identify addiction, in the form of dynamic state dependence, to play a significant role in repeated purchasing behavior. (3) Demographic differences strongly determine product preferences and consumption behavior. We find Black Americans display greater demand for menthol and flavored products, and low-income households exhibit significantly higher rates of cigarette usage.

Conditioned on the results from our structural estimation, we examine several counterfactual scenarios. (1) Our model predicts that with the removal of mentholated cigarettes, weekly cigarette smoking rates would have been 13% lower, on average, during the period from April 2015 to April 2019. Black Americans in particular would have experienced a 35% drop in expected weekly smoking rates during this period. (2) In comparison to a menthol cigarette ban, a 10.23% cigarette sales tax would be as effective in lowering the average weekly smoking rate and would cause a smaller reduction in consumer surplus in every demographic group, demonstrating that the taxation policy (which works through economic incentives) would outperform the menthol cigarette ban (a command and control regulation). In addition, a back-of-the-envelope calculation finds a 10.23% cigarette sales tax would result in an expected weekly tax revenue of $66.1 million, for a total of $1.41 billion over the period from April 2015 to April 2019. (3) Expanding the flavorant ban to include menthol and flavored e-cigarettes over this same period would result in a reduction in weekly cigarette smoking rates similar to the menthol cigarette ban alone, as well as a drop in average weekly e-cigarette usage ranging up to 46% depending on supply side assumptions.

Interest in flavorant bans has grown alongside the popularity of flavored e-cigarette nicotine products, although to date, research addressing the effects of a ban on menthol and other flavorants remains limited. Regarding a menthol cigarette ban, existing empirical research involves either questionnaires of consumer intent (Levy et al. (2021a)) or the study of bans imposed in countries other than the US (Chaiton et al. (2020), East et al. (2022), Fong et al. (2022a)), and so expectations as to the impact of the proposed menthol ban on US smoking rates have had to rely on extrapolations from those works. Using Canadian data, Fong et al. (2022a) estimates an expected decrease of 7.3% in the number of US smokers. In contrast, both Levy et al. (2021b) and Issabakhsh et al. (2022) rely on the same expert elicitation of consumer intent post-ban (Levy et al., 2021a), and these works suggest an expected reduction in US cigarette smoking rates of

15% among all consumers and 35.7% among the Black American community. We complement these existing works by using both retail-level and household-level data to estimate consumer behavior and preference for flavorants, and by conducting counterfactual analyses based on our structural estimation results.

To the best of our knowledge, Olesiński (2020) is the only structural model in the literature examining the impact of a mentholated cigarette ban on consumer demand. While Olesiński's (2020) results and counterfactual analysis pertain to Polish consumers and provide an ex ante evaluation of the 2020 European Union menthol ban, we rely on US aggregate- and individual-level data ranging from 2015 to 2019. Furthermore, our modeling structure differs, in that the inclusion of household-level data allows for a richer set of heterogeneous preferences, and we account for addiction in the form of dynamic state dependence—a crucial factor shaping consumers' purchasing behavior in the cigarette market.

Current literature of addiction commonly considers two modeling formats: "rational addiction" models with forward-looking behavior and myopic models. Myopic models allow past consumption to affect current consumer behavior, but future consequences of addiction play no role in determining one's current actions (Houthakker and Taylor (1970), Mullahy (1985)). Furthermore, under the myopic modeling framework, increases in current and past prices reduce current consumption, while increases in future prices will not affect current consumption (Baltagi and Levin (1986), Jones (1989), Baltagi and Levin (1992)). In comparison, "rational-addiction" models contend that consumers consider future prices and consequences when making current consumption choices (Becker and Murphy (1988), Gordon and Sun (2015)).

Researchers, such as Winston (1980) and Akerlof (1991), have objected to the assumption of perfect foresight present in rational-addiction models. More recently, Hidayat and Thabrany (2011) found rational addiction models inadequate in explaining behavior related to cigarette usage; instead, their findings favor myopic modeling assumptions. In our own work, allowing for forward-looking behavior would inhibit our ability to combine the household- and retail-level data in a way that is internally consistent; therefore, we rely on a myopic framework as detailed in Caves (2005) and Tuchman (2019).

The remainder of this paper proceeds as follows. In Section 2, we introduce background information regarding the history of flavored nicotine products and the reasoning underlying the currently proposed menthol ban. Section 3 describes our data sources and provides details on products, households, and markets. Section 4 provides descriptive evidence of preference heterogeneity, product substitution, and addiction. Section 5 details our discrete choice model of demand which incorporates addiction as well as both retail and household data. In Section 6 we discuss parameter identification and estimation. Estimation results are presented in Section 7. Counterfactual simulations regarding changes in consumption behavior and consumer surplus under product bans and taxation are provided in Section 8. Section 9 concludes.

2 Industry Background

The tobacco industry has long been creative with product development and marketing, much to the detriment of public health. Industry innovations have included cigarette length and width (with ultra long and ultra slim), filters, low-tar tobacco, and a finer control of nicotine content. The introduction of product flavorants began with the countrywide sale of mentholated tobacco in 1927, and in 1999 mass production of flavored (fruity, candy, and mint) cigarettes started (Toll and Ling (2005), Mills et al. (2018)). Fueled by the desire for greater market share, industry research conducted by Big Tobacco led to fine-tuned innovations targeting specific consumer groups.[2] Slim cigarettes (in particular "Virginia Slims") are regarded as the first and most successful female-oriented cigarette brand, menthol cigarette print and billboard advertising has been found to primarily target the Black American community, and archived tobacco industry documents detail the development of sweet, fruity, and candy-like flavors to target young smokers (Cummings (1999), University of California San Francisco (1999), Toll and Ling (2005), Mills et al. (2018)).

In the past two decades, rising health concerns and increasing negative public opinion towards tobacco products have led to the introduction of tobacco control regulations. In particular, the advent of product bans started with the mass introduction of flavored cigarettes in the early 2000s and the subsequent public outcry. From 1999 to 2006, three flavored products were introduced to the US market by well established tobacco companies and quickly rose to public prominence—Camel Exotic Blends, Kool's Smooth Fusions, and Salem's Silver label (Lewis and Wackowski, 2006). Decades of research into youth consumption and preference for flavored products by industry powerhouses, such as Philip Morris, R.J. Reynolds, and Brown & Williamson, encouraged this product development. Flavored cigarettes quickly became popular among young smokers, and while overall cigarette sales fell, market shares of flavored products rose, defying the national downward trend (Cummings (1999), Lewis and Wackowski (2006)). However, public concerns over increasing youth tobacco usage pressured congress to action.

[2]Big Tobacco is a name used to refer to the largest companies in the tobacco industry.

The Family Smoking Prevention and Tobacco Control Act, signed into law on June 22, 2009 by President Barack Obama, provided the FDA the power to regulate the tobacco industry and marked the first ban on flavored (fruity, candy, and mint) cigarettes. The Act also prohibited advertising to children and required tobacco companies to obtain FDA approval for new tobacco products.

A mere decade later saw the next proposed flavorant ban, this time in relation to youth e-cigarettes usage. The introduction of more stylish pod system e-cigarettes, innovative social media marketing campaigns, and the promotion of flavored products, particularly to the youth and young adults, contributed to an increase of over 300% in e-cigarette unit sales from January 2015 to July 2019 (Nardone et al., 2019).[3] Sales of Juul, the most common pod-based e-cigarette, surged over 600% and contributed much to the overall rise in e-cigarette sales during this period, and Juul became the company with the single greatest e-cigarette market share by the end of 2017 (Ali et al., 2020). Juul's small size, sleek USB styled design, variety of flavors, and subtle scent made it particularly appealing to young users (Lee et al. (2020), Vallone et al. (2020)). The term "JUULing" soon became synonymous with the discrete usage of e-cigarettes by teenagers in classrooms, school yards, or restrooms (Ramamurthi et al., 2019).

Concerns over this increased youth e-cigarette smoking pushed the FDA to act. In January 2020, a ban was placed on the sale of all flavored (fruity, candy, and mint) e-cigarette cartridges. While the ban on flavored e-cigarette cartridges was intended to reduce youth consumption, regulators failed to include disposable style e-cigarettes. And, although beyond the scope of this paper, current research suggests consumers—particularly young consumers—simply switched to these disposable products (Hickman and Jaspers, 2022).

In 2022, the FDA proposed a new ban on menthol cigarettes. Similar to the prior two product bans, regulators sought to advance health equity by reducing tobacco-related health disparities and addiction, particularly among disproportionately affected, menthol-using, minority communities. Thus, as we shift the focus to mentholated tobacco, we will revisit the theme that flavorants attract specific and potentially vulnerable populations.

2.1 Menthol Cigarettes

In 1925, the first menthol cigarette was created by Lloyd "Spud" Hughes who, seeking to alleviate the symptoms of a cold, placed loose tobacco in a tin of medical menthol crystals overnight (Lee and Glantz, 2011). The next day, he found the resulting smoke soothing to his throat,

[3] See Figure 2.

Figure 1: Print Advertising of Menthol Cigarettes Targeting the Black Community

(a) Kent Menthol Cigarette Ad (1961)

(b) Winston Menthol Cigarette Ad (1970)

with the mentholated cigarette providing a more pleasant, "cooler", experience. Hughes later patented his invention and, after selling the patent to the Axton-Fisher Tobacco Company in 1927, "Spud Menthol Cooled Cigarettes" would remain the sole mentholated nicotine product until the introduction of Kool menthol cigarettes in 1933, by Brown & Williamson.

For the next two decades, Kool became the industry leader in menthol cigarettes; nevertheless, during this time, mentholated products represented only 3% of the overall cigarette market (Lee and Glantz, 2011). However, post WWII, Big Tobacco saw new opportunity among the Black American community, as a new, wealthier, urban Black community was growing. By the 1960s, advertising of specialized products—shampoo, skin creams, etc.—targeted towards this burgeoning community began in earnest.

Following the years of post-war growth, Black media had reached record-breaking levels. Over 600 radio stations now catered to Black audiences, where less than two decades prior there were only 20, and readership of Ebony magazine, the leader in Black print media, was at an all-time high (Pollay et al., 1992). The surge in print, radio, and television consumption among Black audiences was a prime opportunity for the advertising of menthol products by Big Tobacco (see Figure 1 for examples). Research by Gardiner (2004) found that, by 1962, Ebony magazine contained twice as many menthol advertisements as the similarly popular—among white communities—Life magazine. Despite some initial advertising to white clientele, Black communities soon became the primary focus of mentholated cigarettes, and Black American smoking rates of menthol products skyrocketed from 14% in 1968 to 44% by 1975 (Gardiner, 2004).

Today, the impact of race-based marketing in the Black community remains clear. Despite a fall in overall smoking rates, Black consumers still display a preference for menthol products at rates 2 to 3 times their non-Black peers (Delnevo et al., 2020). Further, although Black Americans make up approximately 12% of the population, they contribute to about 40% of all menthol-related tobacco deaths (CDC Smoking and Tobacco Use, 2020). In acknowledgement of past wrongs, and to reduce further cigarette consumption, the FDA proposed, on April 22, 2022, new product standards to prohibit menthol as a flavorant in cigarettes. To quote acting FDA commissioner Janet Woodcock, M.D., "With these actions, the FDA will help significantly reduce youth initiation, increase the chances of smoking cessation among current smokers, and address health disparities experienced by communities of color, low-income populations, and LGBTQ+ individuals, all of whom are far more likely to use these tobacco products." (FDA, 2021)

3 Data

In this section, we provide details pertaining to our retail and household data. In addition, we describe our markets of interest, including demographic information and the formation of retail market shares from available data.

3.1 Retail Data

We use the Nielsen retail datasets which cover the period from January 1st, 2015 to July 31st, 2019.[4] Sales information is available for the entirety of 2019, however we do not use the months post July, as some brands began to engage in the voluntary removal of flavored cartridge products in an attempt to appease e-cigarette critics. The data contains store-level information detailing weekly price and quantity sold at the Universal Product Code (UPC) level. Recorded sales include our three primary categories of interest: cigarettes, e-cigarettes, and smoking cessation products (nicotine lozenges, gum, and patches). At the store level, we observe unique

[4]All Nielsen material discussed herein was obtained from the Kilts Center for Marketing at The University of Chicago Booth School of Business.

location identifiers. We choose to focus on 26,916 stores active every year during the entirety of the period studied.[5] In our analysis, based on nicotine content, we consider a pack of cigarettes equivalent to one e-cigarette cartridge, one disposable e-cigarette unit, 15 pieces of 4 mg nicotine gum/lozenges, or a single nicotine patch (additional details on these products in the data are provided in Appendix A1). We adjust product prices for inflation.[6]

Nielsen's retail datasets also provide information pertaining to product flavor in almost all cases—except some e-cigarettes. When product flavor was unavailable, we proceeded with manual identification. There are 10,344 unique cigarette UPCs (5,667 regular tobacco and 4,677 menthol), 1,630 unique e-cigarette UPCs (668 regular tobacco, 493 menthol, and 469 flavored), and 668 unique smoking cessation product UPCs. Among cigarettes and e-cigarettes, all major brands (overall market share $\geq$ 1%) offer tobacco, menthol, and—in the case of e-cigarettes—flavored product varieties. For the remainder of this work, we aggregate UPCs into products, where each product is a category/flavor combination, and the size of each product is standardized to that equivalent to one pack of cigarettes.

Figure 2 plots the trends in cigarette and e-cigarette sales by flavor type from January 2015 through July 2019, based on sales from 26,916 stores. The plots demonstrate seasonality in cigarette sales and an overall negative trend. As for e-cigarettes, sales were steadily though slowly increasing until around January 2018, when a period of rapid growth began, driven primarily by flavored products.

3.2 Household Data

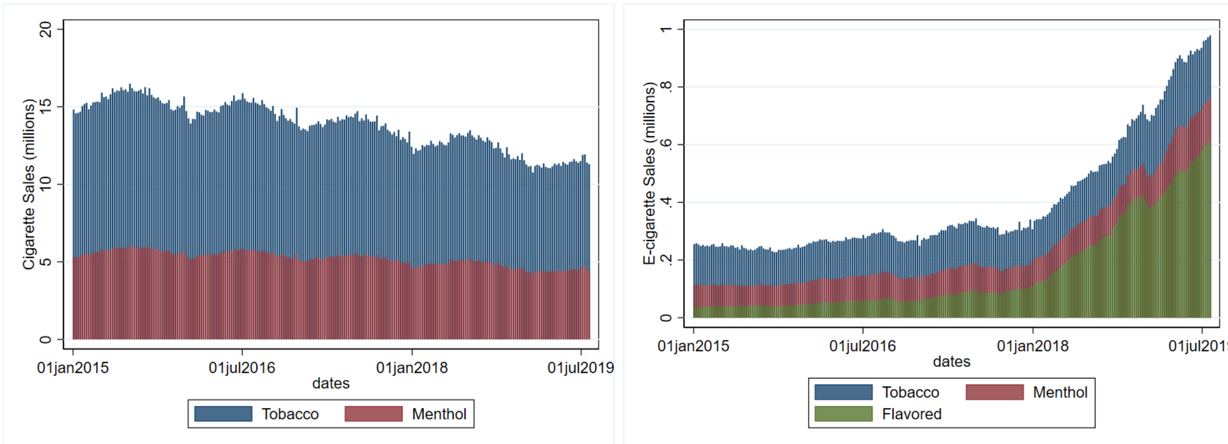
Nielsen provides household purchase data for a sample of US consumers totaling about 50,000 households yearly. Information provided includes cigarette, e-cigarette, and smoking cessation purchases, as well as a household's home county and other demographic data. Pertaining to purchases, we are provided with records that include price, date, quantity and, if available, the unique store identifier where the sale took place.

Between January 2015 and July 2019, we record 17,420 households who engaged in a total of 401,718 purchases of our products of interest. Given the available demographic data, we first generate an indicator for those households recorded as having the racial characteristic "Black

[5] Yearly, Nielsen tracks the sales of 30,000 to 50,000 stores from roughly 90 retail chains. Estimated coverage as a percent of all commodity volume by channel, in 2017, was: Food (26%), Drug (52%), Mass Merchandise (21%), Dollar Stores (23%), Wholesale Clubs (17%) and Convenience Stores (2%).

[6] We adjust prices to their January 2015 dollar values using the Consumer Price Index for All Urban Consumers (CPI-U).

Figure 2: Weekly Sales Quantities for Cigarettes and E-cigarettes



(a) Weekly Cigarette Sales

(b) Weekly E-cigarette Sales

(non-Hispanic)"; in our subsequent analysis, this indicator allows us to assess the impact of proposed policy changes on the Black American community. We focus on Black as a primary racial characteristic of interest because there exists a well-documented difference in preferences between the Black American community and other groups, particularly in regard to menthol cigarettes.

Next, we differentiate between low- and high-income households through the use of an indicator variable denoting low income. We define low-income households to be those whose yearly household income falls within 200% of the 2019 federal poverty guideline, which takes into account household size.[7] Table 1 reports the joint distribution of households by race and income.[8] Finally, the average weekly cigarette smoking rate among all households within our panel is 14.7%.

[7]Nielsen reports household income in ranges rather than as a continuous measure. We define low-income households to be those falling below the range cutoff closest to twice the federal poverty guideline—this difference is never grater than $2,500.

[8]The joint distribution of race and income status for our household data does not exactly match that suggested by the ACS, however by conditioning on these observables the resulting selection bias is removed (see Grieco et al. (2021)).

Table 1: Household Panel Joint Distribution of Race and Income[a]

	High Income	Low Income	Total
Black	**6.02%** (6.89%)	**3.97%** (5.66%)	**9.98%** (12.55%)
Non-Black	**54.63%** (63.92%)	**35.39%** (23.54%)	**90.02%** (87.46%)
Total	**60.64%** (70.81%)	**39.36%** (29.20%)	

[a]U.S. household joint distribution (from American Community Survey (ACS)) included in parentheses for comparison purposes.

3.3 Market Formation

We define our markets based upon the Designated Market Areas (DMAs) provided by Nielsen. As defined, a DMA consists of a group of counties displaying similar regional characteristics and belonging to the same local television market. Often centered around major metropolitan areas, there exist 210 DMAs covering the entire continental US, Hawaii, and parts of Alaska. Defining our markets based upon DMAs provides several advantages: (1) Datasets from Nielsen already contain identifying information as to DMA assignment for both retailers and households. (2) DMAs are generally centered around large urban populations and include surrounding suburban and rural counties, reducing biases that could be present if one only considered, for example, major cities. (3) DMAs form regions of households with similar characteristics and define television markets, and therefore demand shocks should be similar across households—particularly those stemming from advertising campaigns run at the DMA level.

We begin market formation by first determining total sales and quantity-weighted prices at the product/DMA/week level using unique identifiers provided in the store-level data.[9] Next, for population and demographic data, we rely on the 2019 ACS 5-year estimates. Note that DMAs are proprietary to Nielsen; however, from our available retail data, we obtain a list of counties specific to each of the 206 DMAs in which we observe store-level sales. Racial distribution among the total household population is accessible at the county level in the 2019 ACS 5-year estimates. To obtain the joint distribution of income status by race, we rely upon the Public Use Microdata Sample from the 2019 ACS 5-year estimates, available at the Public Use Microdata Area (PUMA) level. We obtain the county-level joint distribution of income status by race as the weighted average of overlapping PUMAs using the PUMA-county crosswalk file

[9]Similar to Tuchman (2019), our analysis is performed at the week level; we find the average time between purchases, among current smokers, to be less than one week, and we do not find significant evidence of stockpiling behavior. For more information, see Appendix A2.

from the Missouri Census Data Center.[10] Finally, from the county-level population estimates and the joint distribution of income status by race, we obtain county-level population classified by race and income status.

From county-specific population distributions by race and income, we aggregate to the DMA level. A final hurdle arises from determining DMA weekly market shares. Our Nielsen retail sample forms a subset of the available stores in each DMA; we do not observe all sales. Therefore, we cannot simply divide observed sales by total population to obtain shares. Instead, we turn to available information pertaining to cigarette smoking rates: countyhealthrankings.org, operated by the University of Wisconsin and Robert Wood Johnson foundation, provides yearly expected county-level smoking rates for all counties for the years 2016, 2017 and 2018. With this data, we form expected DMA-level smoking rates as the population weighted average of the county-level smoking rates. Then, for each DMA we weight the population such that weekly cigarette market shares best fit DMA expected smoking rates.[11,12]

Our final market sample consists of 100 DMAs with the largest populations, each of which displayed positive market shares over all weeks. This provides three major benefits: (1) the remaining DMAs form pricing instruments (Hausman-style instruments as seen in Nevo (2001)), (2) zero market shares would complicate estimation, and (3) model runtime is significantly reduced. The markets forming our sample provide a mix of all regions and range from major urban centers to rural communities. Finally, 85% of our household sample, 86% of our store sample, and 85% of the US population exist within these 100 DMAs.

4 Descriptive Analysis

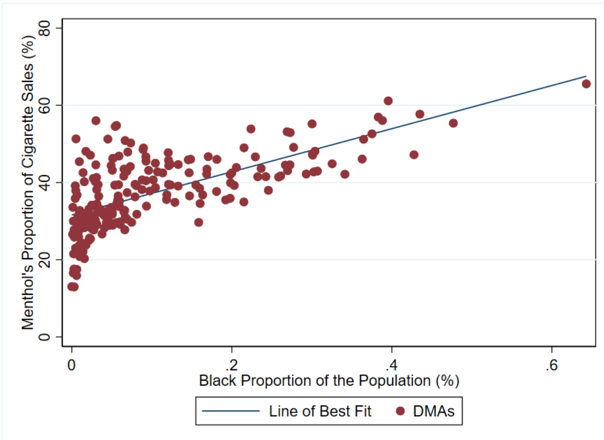
In this section, we provide supportive evidence for our selection of demographic variables through the use of reduced form estimation, figures, and tables. We also explore the impact of addictive behavior on product selection as supportive evidence for the inclusion of this dynamic element in our analysis.

[10] The Public Use Microdata Sample could be used to obtain the joint distribution of race and income. However, to avoid introducing greater error via the PUMA-to-county conversion, we only calculate the proportion of low-income households by race. Data pertaining to the population distribution, in addition to the total population, comes from the county-level 2019 ACS 5-year estimates.

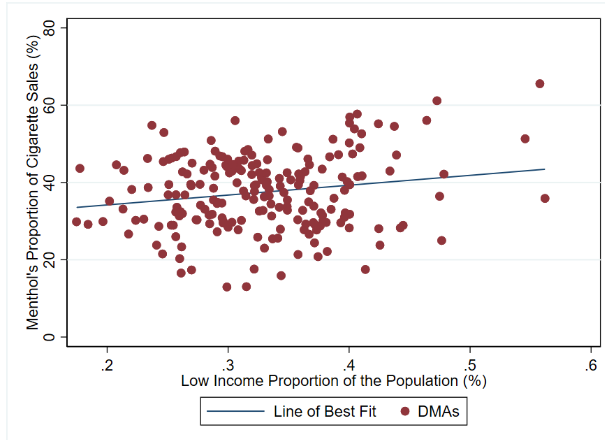
[11] The DMA specific population weight applies to all weeks and years; we do not adjust the weight weekly or yearly.

[12] Our formation of DMA-level weekly product usage rates abstracts from illicit sales; we discuss the impact of this limitation in Appendix A6.

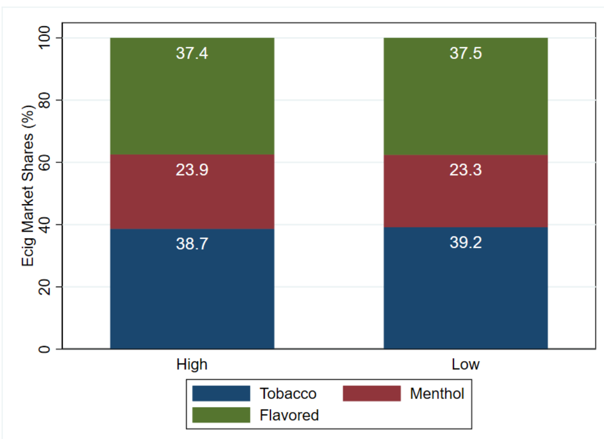
Figure 3: Flavorant Choice and DMA Demographics



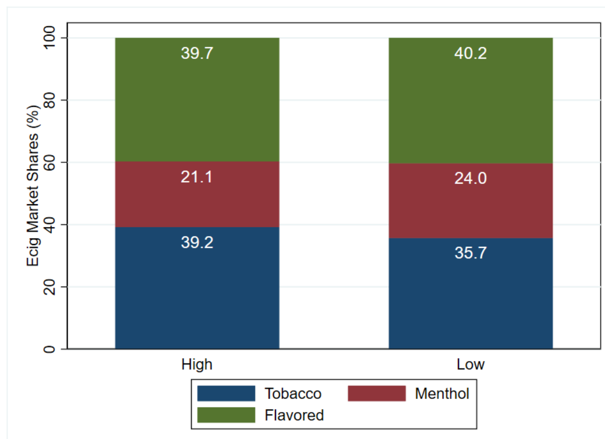
(a) Black and Menthol Cigarette Consumption



(b) Low Income and Menthol Cigarette Consumption



(c) Black and E-cigarette Flavor Choice



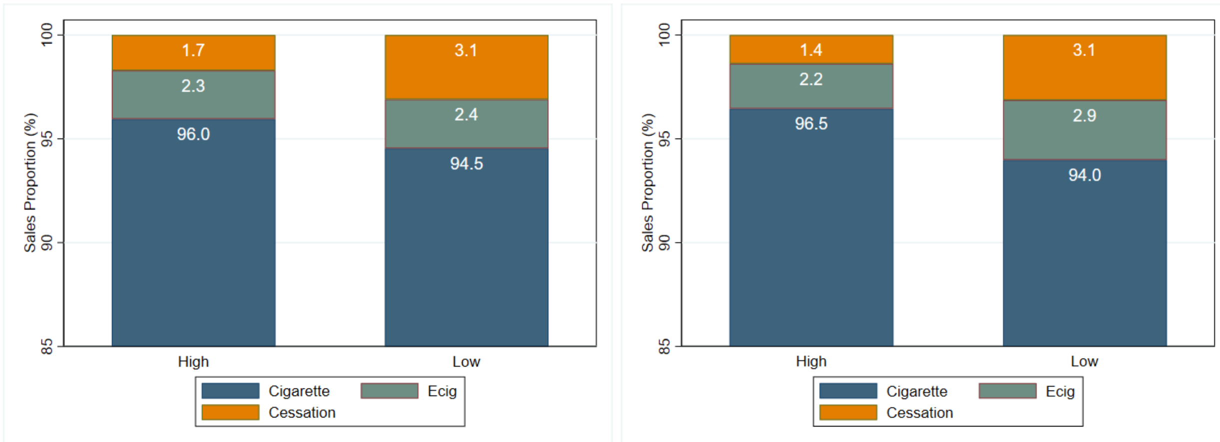
(d) Low Income and E-cigarette Flavor Choice

Notes: The top two panels pertain to cigarettes and plot each DMA's menthol proportion of cigarette sales against its demographics. The bottom two panels pertain to e-cigarettes, where we compare DMAs in the top ("High") and bottom ("Low") quartiles of a demographic trait: in Panel c, "High" denotes those DMAs with the greatest proportion of Black households, and in Panel d, "High" denotes those DMAs with the greatest proportion of low-income households. These four panels are generated from the 206 DMAs in which we observe store-level sales.

4.1 Retail Evidence of Preference Heterogeneity

Throughout our analysis, we rely on two primary demographic attributes: income and the prevalence of Black consumers. Prior empirical work provides support for the selection of these demographic variables, especially when considering rates of smoking behavior and the removal of menthol products. We begin by documenting potential systematic differences—or the lack thereof—in consumer preferences along these demographic dimensions.

Figure 4: Category Choice and DMA Demographics



(a) Black and Category Choice

(b) Low Income and Category Choice

Notes: In this figure, we compare DMAs in the top ("High") and bottom ("Low") quartiles of a demographic trait: in Panel a, "High" denotes those DMAs with the greatest proportion of Black households, and in Panel b, "High" denotes those DMAs with the greatest proportion of low-income households. As cigarettes have by far the largest market share, for display purposes both panels start at a y-intercept of 85%. These panels are generated from the 206 DMAs in which we observe store-level sales.

We examine the relationship between flavorant choice and market demographics in Figure 3. Regarding cigarettes, consistent with prior research, we find that markets with a greater proportion of Black households have a significantly higher proportion of menthol cigarette sales (Panel a). However, when considering e-cigarettes, there aren't marked differences in flavorant preference between markets of high and low Black populations (Panel c). In markets with a greater proportion of low-income consumers, there is a slightly higher proportion of menthol cigarette sales (Panel b); in comparison, these markets display a noticeably greater demand for regular tobacco e-cigarettes (Panel d).[13]

Next, we display differences in category preference by observed DMA demographic characteristics in Figure 4. The figure shows that markets with a larger proportion of Black households have higher sales of cigarettes, whereas markets with a smaller proportion of Black households display greater preference for cessation products. Markets with a larger proportion of low-income households, similar to those with a larger proportion of Black households, have a greater preference for cigarettes. Lastly, as a market's income increases, so does the proportion of sales involving e-cigarettes and cessation products.

[13] To avoid confusion, we define the flavor "regular tobacco" to consist of cigarettes/e-cigarettes whose flavor profile is solely tobacco.

4.2 Household Evidence of Substitution, Addiction, and Flavorant Heterogeneity

In this subsection, we first present household-level evidence of product substitution through the use of a matrix describing the transitional probability of product purchase. Next, we document consumer addiction through the use of a linear probability model, controlling for time and individual fixed effects. Lastly, we provide figures demonstrating heterogeneous responsiveness in product choice, similar to the figures shown above. As before, our demographic covariates of interest are Black and low income.

Product Substitution Table 2 provides the probability of observing product choice conditional on the last observed inside option purchased. We focus on the last observed inside option purchased, rather than the prior week's purchase, to highlight household product substitution and heterogeneous preference; we discuss weekly continuation of product usage and addiction later in this subsection. The last observed inside option purchased makes up the first column; each subsequent column provides the conditional probability of transitioning from the last observed purchase to the current product choice, provided the consumer decides to purchase an inside option. If a consumer decides not to purchase an inside option, then their last observed purchase remains unchanged.

Table 2: Product Transition Table

	Current Product Choice					
Last Inside		Cigarette		E-cigarette		
Option Purchased	Cessation	Tobacco	Menthol	Tobacco	Menthol	Flavored
Cessation	**75.48**	15.12	8.36	0.61	0.18	0.24
Cig. Tobacco	0.26	**93.10**	6.03	0.37	0.07	0.16
Cig. Menthol	0.24	10.81	**88.36**	0.10	0.31	0.17
E-cig. Tobacco	0.61	22.12	2.91	**66.78**	1.96	5.61
E-cig. Menthol	0.30	7.82	16.20	3.99	**64.68**	7.01
E-cig. Flavored	0.26	14.62	7.21	8.52	7.84	**61.55**

A key strength of using household-level data is that it allows us to track consumers' product choices overtime. Table 2 shows that across all product categories, a consumer's most likely product choice is their previously purchased product. This persistence in consumption is strongest among cigarette users, where subsequent purchases almost always consist of the previously purchased product (93.10% for tobacco cigarettes and 88.36% for menthol cigarettes). The willingness of consumers to switch products within the cigarette category is an important consideration regarding the proposed menthol ban. Here, household-level data suggests that when cigarette smokers switch products, it is primarily to an alternative flavor within the same product category (6.03% from tobacco cigarettes to menthol cigarettes, and 10.81% in the other direction), supporting the notion of within-nest substitution among cigarette users.

E-cigarette users also demonstrate persistence in product preference, although not to the degree observed among cigarette smokers. Furthermore, the second most popular choice for past e-cigarette smokers is cigarettes, rather than a different product within the e-cigarette category. Specifically, conditional on switching products, users of regular tobacco and flavored e-cigarettes prefer to switch to regular tobacco cigarettes, while smokers of menthol e-cigarettes generally choose menthol cigarettes—indicating persistent preference for menthol products. These findings suggest degrees of within-category substitution differ between cigarettes and e-cigarettes.

Unfortunate for individuals dedicated to smoking cessation, we find that nearly 24% of all purchases of cessation products are followed by a choice of cigarettes. Furthermore, although not large, there appears to be a willingness for users of cessation products to switch to e-cigarettes; the probability of choosing e-cigarettes grows in the latter half of the sample as e-cigarettes rise in popularity, and consumers looking to quit smoking may consider e-cigarettes a viable substitute for cessation products. Regardless of the methods by which one may attempt to quit smoking, the presence of addiction is clear.

Addiction and Dynamic State Dependence Table 3 provides an illustration of the addictive nature of nicotine products. To examine the presence of dynamic state dependence, for which addiction is the primary factor in our context, we analyze the weekly consumption habits of the 17,420 households in our household dataset. Specifically, we consider how the purchase of a nicotine product in the past week influences the probability of purchasing such a product in the current week through the use of a linear probability model. To control for individual preferences, time trends, and seasonality, we include household and time fixed effects and cluster the errors at the household level.

We find that consumption in the prior week plays a positive and significant role in determining the probability of purchasing in the current period. This result is unsurprising, as on average 53% of all purchases immediately follow a purchase in the prior week. The regression result provides supportive evidence that state dependence plays a significant role in determining the choice to purchase. However, the impact of prior purchase on the probability of purchasing appears to differ by product category.

Table 3: Linear Regression on the Probability of Purchasing

	Coefficient
Purchase in Prior Week	0.104***
	(0.003)
HH FEs	Y
Week FEs	Y
Mean DV	.112
Num HH	17,420
Num Obs	2,622,559

***p<.01, **p<.05, *p<.1

Standard errors, clustered at the household level, are included in parentheses.

Table 4 presents current categorical choice based upon the prior week's purchase decision. Unlike the transition table presenting product substitution (Table 2), Table 4 displays current categorical choice as a function of a household's purchase decision during the preceding week, and includes the outside option to highlight how state dependence may differ between categories. We find cessation product purchases are followed by a choice of the outside option 78% of the time, whereas cigarette purchases and e-cigarette purchases are followed by the outside option only 47% and 50% of the time, respectively. These results, coupled with those displayed in Table 3, suggest that dynamic state dependence differs by category choice in the prior week, affecting the probability of purchasing an inside option as well as the probability of purchasing the previous choice of product.

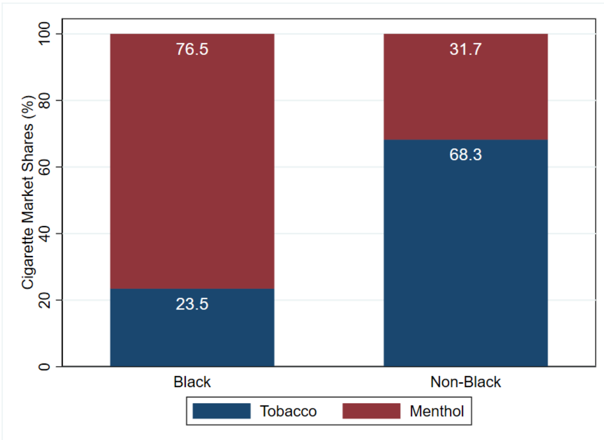
Table 4: Categorical Purchase Probability by Week

Last Week's	**Current Category Choice**			
Category Choice	Outside Op.	Cessation	Cigarettes	E-cigarettes
Outside Op.	**91.47**	0.14	8.20	0.19
Cessation	78.27	**15.88**	5.58	0.26
Cigarettes	46.52	0.08	**53.09**	0.31
E-Cigarettes	49.57	0.16	12.40	**37.86**

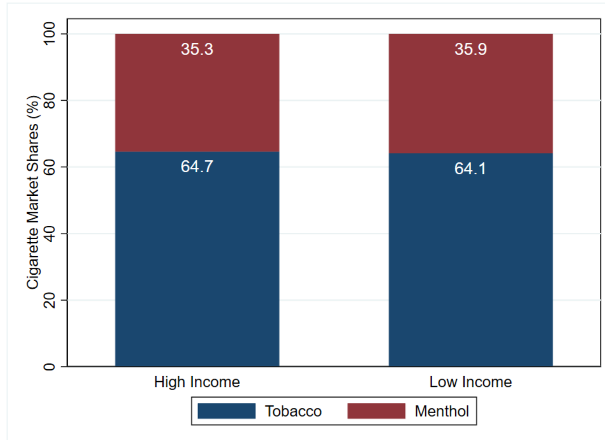
Notes: In the above table, we present the probability of current category choice conditioned upon the category choice made during the prior week ("Last Week's Category Choice").

Flavorant Preference Finally, in the consideration of within-category choice, we present Figure 5 which illuminates a household's flavorant preference dependent on their observed demographic attributes. Similar to the figures in Subsection 4.1, we provide bar charts by demographic

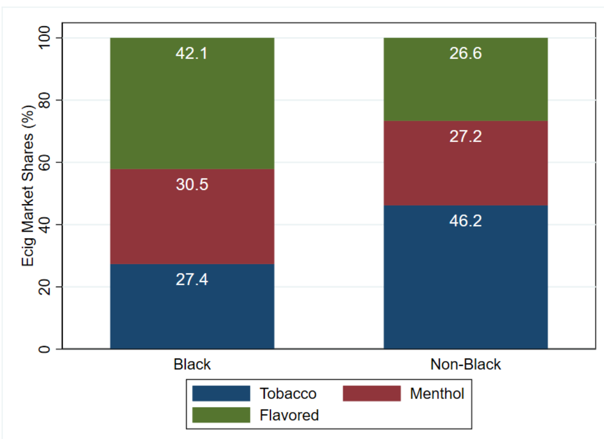
Figure 5: Product Choice and Household Demographics



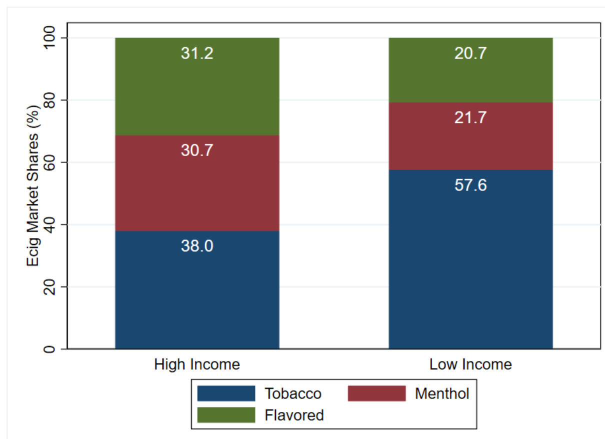
(a) Black and Menthol Cigarette Consumption



(b) Low Income and Menthol Cigarette Consumption



(c) Black and E-cigarette Flavor Choice



(d) Low Income and E-cigarette Flavor Choice

status showing the sales proportions by flavorant for cigarettes and e-cigarettes.

As observed in the DMA-level data, Black households display a strong preference for menthol cigarettes, with 77% of cigarette purchases by Black consumers consisting of menthol products. Additionally, high- and low-income household preferences for menthol products appear nearly identical—similar to the results found in the DMA sales data. Regarding e-cigarettes, both Black and high-income consumers display stronger preferences for flavored and menthol products—shunning regular tobacco e-cigarettes. For low-income consumers, this result is similar to that suggested above (Figure 3); however, Black households display a clear flavorant preference—for menthol and flavored products—that was not apparent in the retail-level data. This finding stresses the importance of household-level information, and its ability to present a markedly less noisy reference as to demographic product preference.

5 Choice Model

We follow the literature on demand estimation employing retail-level data (e.g. Berry et al. (1995), Nevo (2000), etc.) in modeling the demand for cigarettes, e-cigarettes, and smoking cessation products as a function of product characteristics, heterogeneous consumers, demographic information, and addiction. We adjust traditional methods to exploit the availability of household data (similar to Chintagunta and Dubé (2005), Goolsbee and Petrin (2004), Murry and Zhou (2020), etc.). Our work extends the model of addiction proposed in Tuchman (2019) through the use of a nested framework, inclusion of product flavorants, and modeling of demographic responses. Lastly, our estimation procedure differs in methodology from that performed in Tuchman (2019); rather, we adapt the work of Grieco et al. (2021) in designing our estimation procedure.[14]

The use of retail data coupled with household data allows us to leverage the benefits of both. Specifically, retail data measures demand responsiveness with less noise—particularly for sparsely purchased products. In addition, the retail modeling structure provides a reliable method by which one can account for parameter endogeneity. On the other hand, household data allows a more accurate estimation of heterogeneity, substitution, and addiction. The model we propose utilizes both datasets to their full potential in a way that is internally consistent.

5.1 Demand Specification

Let $\mathcal{J}$ represent the set of available products denoted $j = 1, \ldots, J$, where $J = |\mathcal{J}|$, and let $\mathcal{G}$ represent the set of product categories ("nests") denoted $g = 1, \ldots, G$, where $G = |\mathcal{G}|$. Furthermore, consider the outside option to be choice $j = 0$ and a member of group $g = 0$. Then, at the individual level, in week t, a consumer i living in market m obtains indirect utility from purchasing product $j \in \mathcal{J}$, where product j is a member of group $g \in \mathcal{G}$, given by

$$\begin{gathered} u_{ijmt} = x_j'\beta_i + \alpha_i p_{jmt} + h_{gmt}'\gamma + \phi \mathbb{I}\Big(\sum_{g' \in \mathcal{G}} C_{ig',t-1} > 0\Big) + \rho_g C_{ig,t-1} + \xi_{jmt} + \bar{\epsilon}_{ijmt} \\ \text{where } i = 1, \ldots, H;\ j = 1, \ldots, J;\ t = 1, \ldots, T;\ m = 1, \ldots, M. \end{gathered} \tag{1}$$

[14] Tuchman (2019) follows a process described in Chintagunta and Dubé (2005), which involves a four-step estimation procedure, iterating between a maximum likelihood step and the inversion described in Berry et al. (1995). We find in testing that, through the inclusion of numerical gradients, the estimation procedure developed in Grieco et al. (2021) provides a faster and more reliable estimation of the parameters of interest.

The $n_1 \times 1$ vector of product characteristics x_j includes elements such as category and flavor. Retail price for product j in market m at time t is p_{jmt}. The $n_2 \times 1$ vector h_{jmt} contains market-category and time-category fixed effects. $\mathbb{I}(\cdot)$ is an indicator function and $C_{ig,t-1}$ signifies the choice of group g by consumer i in the prior week.[15] Therefore, ϕ captures the change in demand common across all inside options provided consumption of any nicotine product during the prior week, and ρ_g captures state dependence at the category level. Finally, $\bar{\epsilon}_{ijmt}$ denotes unobserved individual preferences for product j in market m at time t, and we allow for common variation in consumer utility through the use of demand shocks (ξ_{jmt}) unobserved by the researcher—but known to the consumer.

We characterize consumer i through the use of a $d \times 1$ vector of observed demographic attributes, D_i, including race and income. We model unobserved individual preference heterogeneity for product characteristics, v_i, through the use of a multivariate normal distribution. Preferences for product characteristics and prices are as follows:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma v_i, \quad v_i \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_{n_1+1}), \tag{2}$$

where Π is an $(n_1 + 1) \times d$ matrix that measures the impact of observable demographic attributes on the preference for product characteristics, while Σ captures the covariance of unobserved individual preferences for product characteristics. In practice, we restrict $\Sigma_{jk} = 0 \ \forall j \neq k$, and estimate only the variance of unobserved preference for characteristics.

Furthermore, we follow the work of Grigolon and Verboven (2014) in assuming that unobserved individual preferences for products are correlated across products of the same category. In our analysis, we observe $G = 3$ product categories: cigarettes, e-cigarettes, and cessation products. Within each category, flavor defines the set of available products. In the case of cigarettes, the available flavors are regular tobacco and menthol. E-cigarettes are available in regular tobacco, menthol and flavored products (e.g., fruit, candy, and mint). The choice of cessation products, having no within category options, represents a degenerate nest. Finally, our outside option is defined to be group zero. Thus, the unobserved individual preference $\bar{\epsilon}_{ijmt}$ for product j, where j falls in category g, follows the distributional assumption of a two-level nested logit

[15] In principle, it is possible to consider addiction as lasting multiple weeks. However, doing so significantly increases modeling complexity and runtime—particularly regarding the gradient estimation. In the retail data step, when evaluating the gradient, state dependence requires we model the propagation of changes in demand over time due to changes in parameter values, and this calculation is computationally intensive. Our current procedure strikes a balance between modeling complexity and runtime. We discuss cases of multiple observed product purchases in Subsection 5.2.

model and can be decomposed into

$$\bar{\epsilon}_{ijmt} = \zeta_{igmt} + (1-\lambda_g)\epsilon_{ijmt}, \tag{3}$$

where ϵ_{ijmt} is iid type-I extreme value, the nesting parameter $\lambda_g \in [0,1]$, and ζ_{igmt} has a (unique) distribution such that $\bar{\epsilon}_{ijmt}$ is distributed Type-I extreme value.

The random coefficient nested logit (RCNL) model, described in equations (2) and (3), can encompass a variety of demand specifications, allowing for correlation in both observed and unobserved preferences. Within nest, perfect substitution is obtained if the category-level nesting parameter equals one. As the category-level nesting parameter tends toward zero, the model reduces to the standard random coefficient specification. Lastly, in modeling different values of λ_g for each category, we allow for products within different nests to display varying degrees of within-nest substitution.

When accounting for consumer heterogeneity, it is useful to decompose the indirect consumer utility excluding $\bar{\epsilon}_{ijmt}$ into a common component δ_{jmt} and an idiosyncratic component μ_{ijmt}:

$$\begin{aligned} &\delta_{jmt} = x_j'\beta + \alpha p_{jmt} + h_{gmt}'\gamma + \xi_{jmt}, \\ &\mu_{ijmt}(\mathbf{C}_{i,t-1}) = \left[x_j', p_{jmt}\right](\Pi D_i + \Sigma v_i) + \phi \mathbb{I}\Big(\sum_{g' \in \mathcal{G}} C_{ig',t-1} > 0\Big) + \rho_g C_{ig,t-1}, \end{aligned} \tag{4}$$

where $\mathbf{C}_{i,t-1} = (C_{i0,t-1}, C_{i1,t-1}, \ldots C_{ig,t-1}, \ldots C_{iG,t-1})'$.

The probability of a consumer i living in market m purchasing product j during time period t is then

$$\pi_{ijmt}(\mathbf{C}_{i,t-1}) = \frac{\exp\left(\frac{\delta_{jmt}+\mu_{ijmt}(\mathbf{C}_{i,t-1})}{1-\lambda_g}\right)}{\exp\left(\frac{I_{igmt}(\mathbf{C}_{i,t-1})}{1-\lambda_g}\right)} \times \frac{\exp\left(I_{igmt}(\mathbf{C}_{i,t-1})\right)}{\exp\left(I_{imt}(\mathbf{C}_{i,t-1})\right)}, \tag{5}$$

where, after denoting the set of products in group g as $\mathcal{J}_g$,

$$I_{igmt}(\mathbf{C}_{i,t-1}) = (1-\lambda_g)\log \sum_{j \in \mathcal{J}_g} \exp\Big(\frac{\delta_{jmt} + \mu_{ijmt}(\mathbf{C}_{i,t-1})}{1-\lambda_g}\Big), \text{ and} \tag{6}$$

$$I_{imt}(\mathbf{C}_{i,t-1}) = \log\Big(1 + \sum_{g \in \mathcal{G}} \exp\Big(I_{igmt}(\mathbf{C}_{i,t-1})\Big)\Big). \tag{7}$$

The final equation includes the group composed of the outside option; as the utility from the decision not to purchase is normalized to 0, it is the source of the "1" in the equation.

5.2 Consumer Choice Probabilities

In the household dataset, we consider a consumer i choosing to purchase product j at the weekly level, matching the weekly data format available at the retail level. When focusing on household purchases, we do not consider quantity and instead consider purchase incidence—whether at least one unit was purchased. To do otherwise would require strong assumptions to make the model tractable, as retail data does not provide information pertaining to individual consumers' purchase quantities. Furthermore, we derive our retail market shares from observed smoking rates, and as such, our model is one of changes in smoking behavior rather than purchase quantities. In the case of multiple distinct products purchased during a single week, we generate duplicate entries for each.[16] To do otherwise (e.g., model the purchase of multiple products as bundling into a composite good) is beyond the scope of this paper, and moreover our assumption is one innately made by a researcher working solely with retail data (Berry et al. (1995), Nevo (2000), etc.).

Turning now to individual choice probabilities, for ease of notation, we let Θ denote $(\Pi, \Sigma, \phi, \rho_q, \rho_c, \rho_e, \lambda_c, \lambda_e)$. The parameters ρ_q, ρ_c, and ρ_e provide the impact of category-level state dependence for cessation products, cigarettes, and e-cigarettes, respectively. λ_c and λ_e denote the nesting parameters for cigarettes and e-cigarettes, respectively.[17] After integrating out the distribution of unobserved individual attributes, denoted $F_v(v_i)$, the density of a consumer's observed sequence of choices is given by

$$L_i(Y_i|x, p_m, h_m, D_i; \delta_m, \Theta) = \int \prod_{t=1}^{T_i} \prod_{j=0}^{J} [\pi_{ijmt}(x, p_{mt}, h_{mt}, D_i, \mathbf{C}_{i,t-1}, \delta_{mt}, \Theta, v_i)]^{y_{ijt}} \, dF_v(v_i), \tag{8}$$

where $\delta_{mt} = (\delta_{1mt}, \ldots, \delta_{Jmt})'$, $x = (x_1', \ldots, x_J')'$, $p_{mt} = (p_{1mt}, \ldots, p_{Jmt})'$, $h_{mt} = (h_{1mt}', \ldots, h_{Jmt}')'$, and Y_i denotes the observed sequence of a consumer's choices where $y_{ijt} = 1$ if consumer i, who lives in market m, chooses product j during time period t.

5.3 Retail Market Shares

Unlike individual consumer choice probabilities, deriving market shares from aggregate retail sales data introduces a difficulty, namely, we do not observe a consumer's prior choice of product. Instead, we are provided with weekly sales data transformed into product-level market shares, which are a function of individual-level smoking behavior. As such, assuming consumer homogeneity for a moment for ease of explanation, retail market shares are formed as follows:

$$s_{jmt} = \sum_{g=0}^{G} \pi_{jmt}(C_{g,t-1} = 1) P(C_{g,t-1} = 1), \tag{9}$$

[16] Duplicate entries make up less than .02% of weekly observed household-level choices.

[17] As the choice of cessation products is a degenerate nest, it requires no nesting parameter.

where s_{jmt} denotes the market share of product j in market m and time period t, $\pi_{jmt}(C_{g,t-1}=1)$ denotes a consumer's probability of choosing product j conditional on having chosen a product in group g in the prior period, and $P(C_{g,t-1}=1)$ denotes the probability that group g was chosen in the prior period. $P(\cdot)$ evolves each period according to a recursive equation, where the probability of choosing a product in group g this period is equal to the sum of observed choice shares within group g across all possible category choices in the prior period:

$$P(C_{g,t}=1)=\sum_{j\in\mathcal{J}_g}\sum_{g'=0}^{G}\pi_{jmt}(C_{g',t-1}=1)P(C_{g',t-1}=1). \tag{10}$$

In application, we incorporate consumer heterogeneity in our model, so the simulated retail shares take the form

$$s_{jmt}=\int_{v_m}\int_{D_m}\sum_{g=0}^{G}\pi_{ijmt}(C_{ig,t-1}=1)P(C_{ig,t-1}=1)dF_D(D_i)dF_v(v_i). \tag{11}$$

We now integrate over the distribution of observable and unobservable consumer attributes, denoted $F_D(D_i)$ and $F_v(v_i)$, respectively. In practice, we evaluate the above integrals by Monte Carlo simulation through the use of Halton draws from the empirical distributions of v and D.[18] For each market m, we draw R simulated consumers and evaluate their choices over time such that

$$s_{jmt}=\frac{1}{R}\sum_{r=1}^{R}\sum_{g=0}^{G}\pi_{rjmt}(C_{rg,t-1}=1)P(C_{rg,t-1}=1). \tag{12}$$

From Eq. (10), it follows that for each simulated consumer r, the probability of choosing a product in group g during the current week is

$$P(C_{rg,t}=1)=\sum_{j\in\mathcal{J}_g}\sum_{g'=0}^{G}\pi_{rjmt}(C_{rg',t-1}=1)P(C_{rg',t-1}=1). \tag{13}$$

Eq. (13) provides an evolving joint distribution of consumer heterogeneity and consumption status that is easily derived. This recursive equation demonstrates that the consumption behavior of a simulated consumer r relies on each prior time period. Therefore, when performing our demand estimation, we require an initial distribution of consumption status, which we cover in Subsection 6.1.

6 Identification and Estimation

Our objective is to estimate the parameter vectors α, β, γ and Θ corresponding to the mean responses, demographic interactions, unobserved taste heterogeneity, addiction, and nesting pa-

[18] A Halton sequence is a low-discrepancy quasi-random number sequence. See Train (1999).

rameters. While we are not necessarily interested in the values of δ, they provide the means by which we can recover our mean taste parameters. Our estimation proceeds through a two-step process: first, we maximize the individual likelihood function through the use of our household and retail data, and then we perform a two stage least squares (TSLS) regression to estimate our mean utility parameters, α, β and γ.

We rely on a Hausman-style instrument, as used in Nevo (2001), to control for price endogeneity. Our identifying assumption is that, by conditioning on market/category and time/category fixed effects, market-specific demand shocks are independent across DMAs. Given this assumption, the average product price across the markets not included in our estimation will be independent of our market's demand shocks, but this average will be correlated with our observed prices due to common marginal costs.[19]

6.1 Maximum Likelihood Estimation

Given Eq. (8), for any candidate values of δ and Θ the log likelihood of the household data is

$$\mathcal{L}(Y;\delta,\Theta) = \sum_{i=1}^{H} \log[L_i(Y_i|x, p_m, h_m, D_i;\delta,\Theta)]. \tag{14}$$

In theory, one can estimate δ directly via maximum likelihood, requiring only household data; in practice, this is computationally infeasible.[20] Instead, we rely upon the work of Berry (1994), who shows that for any given value of Θ, there exists a unique vector δ such that predicted shares from Eq. (12) exactly match those observed in the retail dataset. Thereby, we treat δ as a known function of Θ provided retail market shares—as is common practice in discrete choice demand estimation with retail data (Berry et al. (1995), Nevo (2000), Nevo (2001)).

Thus, the log likelihood of the household data, Eq. (14), can be rewritten as

$$\mathcal{L}(Y;\Theta) = \sum_{i=1}^{H} \log[L_i(Y_i|x, p_m, h_m, D_i;\delta(\Theta),\Theta)], \tag{15}$$

where $\delta(\Theta)$ is provided by the contraction mapping specified in Grigolon and Verboven (2014). When evaluating simulated retail market shares during the contraction mapping step (Eq. (12)), we make $R = 200$ Halton draws per market from the empirical distributions of v and D. In each time period, the joint distribution of consumer heterogeneity and consumption status for our simulated consumers evolves according to Eq. (13).

[19] In Appendix A4 we compare our model predicted mean utility coefficients with and without the use of our pricing instrument.

[20] In the household dataset there are many product/market/time combinations lacking observed product purchases, rendering product/market/time-level identification of δ impossible when relying solely on household-level data.

To perform the contraction mapping, we require an initial distribution of consumption status for simulated consumers. Two possibilities are: (1) we specify the initial distribution as a parameter of interest to be estimated, or (2) we provide an arbitrary initial distribution and forward simulate during a burn-in period (Erdem et al. (2003), Hendel and Nevo (2006), Tuchman (2019)). We use the second approach, treating the first quarter of 2015 as our burn-in period, and provide the initial joint distribution as $P(C_{rg1} = 1) = 1/(G+1)$, $\forall g \in \{0, \ldots, G\}$, $\forall r \in \{1, \ldots, R\}$. Tests using other arbitrary initial distributions demonstrate convergence to the same steady state well within our allotted burn-in period. Finally, Appendix A3 provides more detail regarding how a unique vector of $\delta(\Theta)$ is derived from our retail data.

After obtaining $\delta(\Theta)$ for a given value of Θ, we evaluate the integral governing the density of a household's observed sequence of choices (Eq. (8)) via Monte Carlo simulation. In practice, we use 100 Halton draws from the empirical distribution of v.[21] Our estimation procedure then searches over the values of Θ to find the one that maximizes Eq. (15).[22] Upon obtaining the optimal value $\widehat{\Theta}$, we calculate robust standard errors for $\widehat{\Theta}$ as described in (Train, 2009, p. 201), sandwiching the covariance of the household-level gradient between the inverted Hessian at the optimum of the likelihood function.

6.2 Mean Utility Coefficients

Given $\widehat{\Theta}$ from the maximum likelihood step, the resulting unique vector $\widehat{\delta}$ provides the relationship between a product's mean utility and our covariates of interest—see Eq. (4). In our evaluation of this relationship, we proceed with a TSLS regression relying upon the Hausman-style instruments discussed above. Standard errors for $(\widehat{\alpha}, \widehat{\beta}, \widehat{\gamma})$ are calculated using a two-step bootstrap procedure where estimation error from the maximum likelihood step is captured by the first stage of the procedure, and the second step accounts for typical sampling error. We begin by taking $B = 1000$ draws from the asymptotic distribution of Θ found in subsection 6.1. Next, for each of the 1000 draws, Θ_b, we find the corresponding vector $\delta(\Theta_b)$ and sample with replacement from the set $\{(\delta_{111}(\Theta_b), x_1, p_{111}, h_{111}), \ldots, (\delta_{JMT}(\Theta_b), x_J, p_{JMT}, h_{JMT})\}$ to create a bootstrapped sample of a size equal to the original. Given the bootstrapped sample, we then

[21] Results from Train (1999) show simulation variance with 100 Halton draws to be lower than 1000 random draws in a mixed logit application with a similar number of random coefficients.

[22] Our tolerance during the contraction mapping step is set to $1e^{-13}$. For the likelihood maximization algorithm, we set a tolerance of $2e^{-10}$ and provide computed numerical gradients. We consider several randomized starting values when proceeding with the maximization algorithm to rule out local minima. Finally, the RCNL contraction mapping requires a dampening procedure discussed in Grigolon and Verboven (2014).

perform the TSLS regression to estimate $(\alpha_b^*, \beta_b^*, \gamma_b^*)$. Finally, from the distribution of $(\alpha_b^*, \beta_b^*, \gamma_b^*)$, we find the standard errors of our mean utility parameters.

7 Estimation Results

Table 5 presents the demand estimates of our model's preferred specification using the two-stage process described above. In total, we have 100 markets with 226 time periods each (after removing the burn-in weeks per Subsection 6.1) for a total of 135,600 market-level observations.[23] At the individual level, we have 14,712 households (residing in the 100 markets) for a total of 2,100,709 household observations post burn-in. To control for common time- and market-specific demand shocks, our estimation includes fixed effects at the category/time and category/market levels. We exclude the regular tobacco flavor, the final time period, and the last market, making them the reference categories.

Dummies representing product flavorant are denoted Menthol and Flavored. Flavored products are only available in the form of disposable or cartridge-based e-cigarettes; however, menthol products are available for both e-cigarettes and traditional cigarettes. To account for heterogeneous flavorant preferences across product categories, we include an interaction of menthol and e-cigarettes. On average, consumer valuations of tobacco products exceed that of menthol, but, in terms of e-cigarettes, flavored products are the most preferred. As expected, average product valuation decreases with price.

Demographic Interactions In addition to average consumer valuation, we allow for a rich set of heterogeneous parameters to account for variations in preferences across demographic groups. The estimates of Π reveals significant variation in demographic valuation. Low-income consumers display a greater preference for cigarettes and e-cigarettes and, interestingly, we do not find a statistically significant difference in average price responsiveness for low-income households. Racial disparities in demand for cigarettes mirror those found in other works (Sakuma et al. (2016), Sakuma et al. (2020)); Black households' demand for cigarettes and e-cigarettes is less than that of other consumer types. Preference for flavorants also varies across demographic groups: black households strongly favor menthol and flavored products; in contrast, while low-income consumers display a slight preference for menthol, other flavored products are less preferred.

[23] After burning the first quarter of our sample, the time frame considered in our demand analysis ranges from April 2015 through July 2019.

Table 5: RCNL Demand Estimates[a]

		Means	**Std. Dev.**	**Demographic Interactions (Π)**	
		(α, β)	(Σ)	**Low Income**	**Black**
Price		-0.759***		-0.017	
		(0.094)		(0.026)	
Cigarette		1.303**	2.036***	0.351**	-0.700***
		(0.606)	(0.028)	(0.164)	(0.090)
E-cigarette		-4.771***	2.281***	0.365*	-1.929***
		(0.352)	(0.075)	(0.220)	(0.329)
Cessation		-1.749**	2.805***		
		(0.889)	(0.086)		
Menthol		-0.718***	1.188***	0.118***	1.055***
		(0.051)	(0.054)	(0.029)	(0.062)
Menthol × E-cig.		-0.348***			
		(0.042)			
Flavored		0.451***		-0.397*	1.040***
		(0.078)		(0.213)	(0.319)
Past Consumption	(ϕ)	0.247***			
		(0.096)			
Cess State Dependence	(ρ_q)	0.958***			
		(0.204)			
Cig State Dependence	(ρ_c)	0.405***			
		(0.099)			
E-cig State Dependence	(ρ_e)	2.672***			
		(0.166)			
Cigarette Nest	(λ_c)	0.768***			
		(0.013)			
E-cigarette Nest	(λ_e)	0.357***			
		(0.086)			
Cat. × Time FEs		Y			
Cat. × Market FEs		Y			
Num HH		14,712			
Num HH Obs		2,100,709			
Num Markets		100			
Num Time Periods		226			
Num Market-Level Obs		135,600			

***p<.01, **p<.05, *p<.1

[a]Standard errors are included in parentheses. Our estimation includes fixed effects at the category/time and category/market levels. We exclude the regular tobacco flavor, the final time period, and the last market, making them the reference categories. We additionally explored the inclusion of demographic interactions with cessation, as well as a three-level nested logit model with the choice between inside options and the outside option at the highest level and the choices of product category (cigarettes, e-cigarettes, cessation) and then flavor at subsequent nodes, however such changes did not improve model fit.

Random Coefficients and State Dependence Turning to the estimates of our random coefficients (Σ), all are statistically significant, and account for variation in valuation across households. In addition, past consumption of an inside option plays a positive and significant role in determining consumption status across all product offerings. This result is consistent with the presence of addictive behavior in nicotine products. However, dynamic state dependence appears to be primarily focused at the category level, with the values of categorical state dependence (ρ_g) nearly 2 to 10 times larger than the effect of past consumption on the demand for all inside options (ϕ).

Notably, cessation products and e-cigarettes demonstrate the greatest degree of state dependence. For cessation products, we find ρ_q to be twice that of the state dependent parameter for cigarettes, ρ_c, and, in the case of e-cigarettes, ρ_e is roughly 6 times larger than ρ_c. We hypothesize that the differences in state dependence between product categories may arise from consumer learning behavior, particularly for goods with small market shares or, in the case of e-cigarettes, products newly introduced.[24] It is important to note that while indicators of prior consumption status may capture forms of structural state dependence beyond that of addiction, the presence of heterogeneous product preferences helps reduce potential bias by capturing unobserved factors that influence both current and lagged consumption - mitigating endogenous correlation between the error term and lagged consumption status.

Nesting Parameters We also obtain significant estimates of our nesting parameters for cigarettes and e-cigarettes (λ_c and λ_e), indicating that products of the same category are considered closer substitutes. Interestingly, we find the nesting parameter for cigarettes is greater than twice that of e-cigarettes. This suggests degrees of within-nest substitution differ between product categories. Households consider tobacco and menthol cigarettes to be close substitutes, whereas e-cigarette flavorants are not held in the same regard. To corroborate this point, we calculate short-run own-price and cross-price elasticities of demand; capturing consumer responsiveness to a one-time price increase during the same week.

Price Elasticity Table 6 provides the price elasticity of demand. The cross-price elasticity between the focal product and other products is averaged across three groups: the focal product and those that share its same category, the focal product and those in different categories, and the focal product and all other products. Finally, we present own-price and cross-price elastic-

[24]In exploring for presence of consumer learning behavior, we examined, and did not find, a statistical difference in e-cigarette state dependence pre- and post-2018.

Table 6: Price Elasticity of Demand.[a]

Average Level		Own	Cross-Elasticity		
			Same Category	Different Category	All Products
Cigarettes	Tobacco	-4.028	1.682	0.006	0.341
	Menthol	-4.724	2.581	0.006	0.521
	Average	**-4.376**	**2.132**	**0.006**	**0.431**
E-Cigarettes	Tobacco	-4.077	0.854	0.121	0.414
	Menthol	-4.085	0.820	0.178	0.435
	Flavored	-5.153	0.914	0.118	0.436
	Average	**-4.438**	**0.863**	**0.139**	**0.429**
	Cessation	-5.487	-	0.086	0.086

[a] The table above reports own and cross-elasticities at the product and category average level. Cross-elasticities are averaged across products from the same category, different categories, and across all products.

ities of demand at the product and category average level. Consider, the cross-price elasticities of demand averaged across products within the same category compared to the average across products from a different category; tobacco and menthol cigarettes are far more responsive to changes in other product prices when those products exist within the same nest. Similarly, the cross-price elasticity of e-cigarettes is greater when averaged across products within the same nest when compared to the average across products in alternative categories. Our cross-elasticity calculations provide supportive evidence of within nest substitution for both cigarettes and e-cigarettes, and suggests sensible substitution patterns across products.

Model estimates imply category average own-price elasticities of demand for cigarettes and e-cigarettes to be -4.376 and -4.438, respectively. In comparison to cessation products, cigarettes and e-cigarettes are generally less elastic. We find that markets with a greater proportion of low-income households have, on average, less elastic demand for cigarettes. This finding is generally in line with literature demonstrating persistence in cigarette consumption among low-income consumers. In terms of product flavorant, we find demand for menthol cigarettes the least elastic in markets with the greatest Black American populations. Interestingly, market-level average own-price elasticity for e-cigarettes—regardless of flavor—does not appear to be significantly correlated with the proportion of low-income households nor Black consumers. Lastly, demand for cessation products is the least elastic in those markets with the greatest percentage of high-income households—suggesting a persistence in preference for cessation products among wealthier consumers. Overall, our calculated own-price elasticities provide sensible variation along consumer demographic distributions and are consistent with consumption differences displayed in Subsection 4.1.

8 Counterfactual Product Bans and Taxation

We now use our estimates of cigarette, e-cigarette and cessation product demand to measure the effect of the proposed menthol ban—in addition to other counterfactuals. Thus, we can evaluate consumer responsiveness to various product bans, and to provide a taxation rate which results in consumption-level changes equivalent to that resulting from the removal of menthol products. We proceed by first describing our supply-side model, and the assumptions we impose while performing our analysis. Then, provided estimates of counterfactual prices from our supply-side model, we present expected changes in consumption behavior resulting from our varied counterfactual scenarios.

8.1 Supply-Side Model

We begin our model of supply-side behavior by considering multi-product firms interested in maximizing their profits. Generating a full supply-side model with true forward-thinking firm behavior would be exceedingly complex given the presence of dynamic state dependence. We simplify by considering firms to be interested in maximizing profits over the finite sum time-periods included in our sample, and we rely upon the fact that changes in consumption behavior resulting from price changes made weeks prior tend towards zero as time progresses. Thus, when considering optimal prices for a given week, we find firms place almost no weight on the resulting changes for profits occurring a quarter or more in the future. As such, in our analysis, only counterfactual prices calculated towards the final weeks of our sample would inherit bias resulting from our specifying a finite time problem (as opposed to considering profit maximization over an infinite number of periods). In practice, we drop the final quarter of our counterfactual analysis, analogous to how we rely upon a burn-in period when forward simulating in our maximum likelihood estimation (see Subsection 6.1).[25]

Next, of note, is our decision to either consider firms as operating at the nest level, or consider a single firm as the producer of both cigarettes and e-cigarettes.[26] If we model firms at the

[25] After burning the first quarter and last quarter of our sample, the time frame considered under our counterfactual analysis ranges from April 2015 through April 2019.

[26] Our choice of modeling cigarettes and e-cigarettes as a composite product inhibits our modeling assumptions. We can either consider producers of cigarettes and e-cigarettes as competitive firms or a single entity.

Table 7: E-Cigarette Brands by Market Share

Brand	**Market Share**	**Owner**
Blu	24.02%	Imperial Brands*
Juul	23.40%	Juul, Altria* (35% Post Dec. 2018)
NJOY	18.22%	NJOY
Logic	11.08%	Logic, JTI* (Post April 2015)
Vuse	7.23%	R. J. Reynolds*
21st Century Smoke	5.46%	21st Century Smoke
FIN	4.23%	FIN
Mark Ten	2.51%	Altria*
Mistic	2.26%	Ballantyne
Other	1.59%	Other

* Tobacco company.

nest level, then we contend that competition exists between products of differing nests, and that manufactures of cigarettes, for instance, do not likewise produce e-cigarettes. Otherwise, we could consider cigarettes and e-cigarettes to be owned and produced by a singular entity interested in maximizing the collective sum of their profits. Consider Table 7, which presents brand-level market shares for e-cigarettes sold between January 2015 and July 2019.

We observe that prior to 2019, 55.16% of e-cigarettes sold were by companies not directly owned or operated by Big Tobacco. With the purchase of a 35% stake in Juul by Altria (formerly known as Philip Morris) in late December 2018, the proportion of independent producers fell to 31.76%. The trend towards e-cigarette acquisition by large multinational tobacco manufactures is not surprising. Initially, the industry was composed of small independent companies interested, primarily, in producing products to assist in smoking cessation behavior, but Big Tobacco's entry into the market during the early 2010s changed producer incentives, and led to growing market concentration among the largest players (University of Bath, 2012).

To compensate for both the independence of firms and the growth in market concentration, we consider two versions of our supply-side model. The first defines firms at the nest level (cigarette and e-cigarette producers considered as competitors), and the second models the total acquisition of e-cigarette producers by Big Tobacco, e.g. one firm producing both products. Thus, our findings can be perceived as providing bounds for possible firm responses based upon the proportion of market concentration under traditional producers of tobacco products. Throughout both models of our supply-side analysis, we assume the producers of cessation products are now, and continue to be, independent. Finally, a detailed description of our counterfactual price estimation is provided in Appendix A5.

8.2 Counterfactual Simulations

This subsection begins with the proposed menthol cigarette ban; we report expected changes in cigarette and e-cigarette consumption by demographic profile, as well as the average change in cessation product usage upon removal of all non-tobacco cigarettes. Next, we calculate an average national sales tax that results in a similar reduction in smoking rates as those expected under the menthol ban—weighing the pros and cons of bans vs taxation. Lastly, we explore the expansion of the menthol ban to all, non-tobacco, product flavorants—paying particular attention to the expected reduction in e-cigarette usage. All counterfactual scenarios considered in our model rely on supply-side estimates of counterfactual price discussed above, in Subsection 8.1.

To obtain average weekly usage rates, we impose our counterfactual scenarios beginning in 2015, and simulate weekly demand over the following four and a half years, for each simulated consumer r. Weighting our counterfactual shares by the market population, and averaging over each week, we determine the weekly average rate of consumption for all products—across all markets. We burn the first and last quarter of our results, and average across all weeks to determine the average change in product usage over the period from April 2015 through April 2019.

Menthol Cigarette Ban Table 8 presents the impact of the removal of mentholated cigarettes from a household's choice set. We display smoking rates for cigarettes and e-cigarettes by demographic profile; cessation usage rates are presented as the average across all households. Changes in consumption behavior are displayed under the assumption of both independent and merged (cigarette and e-cigarette) producers. We find that in the absence of menthol cigarettes, weekly cigarette smoking rates reduce, across all households, by 13% (from 15.72 to 13.74 percent) regardless of producer merger status. On average, 67.5% of menthol smokers switch to tobacco cigarettes upon removal of mentholated product offerings; expected consumer surplus, across all households, falls by 15.7 to 15.9% (dependent on merger status) compared to the status quo.

Among Black households, the average reduction in cigarette consumption is far higher; a 35% drop in their average weekly cigarette smoking rate (from 15.41 to 10.00 percent). This

Table 8: Average Weekly Rate of Product Usage: Menthol Cigarette Ban.[a]

			Independent Producers		**Merged Producers**	
		Without Ban	With Ban	% Change	With Ban	% Change
Cigarettes	Black	15.41%	10.00%	(-35.12%)	9.99%	(-35.13%)
	Non-Black	15.76%	14.30%	(-9.29%)	14.30%	(-9.31%)
	High Income	14.91%	13.22%	(-11.32%)	13.22%	(-11.33%)
	Low Income	17.75%	15.04%	(-15.24%)	15.04%	(-15.27%)
	Average	**15.72%**	**13.74%**	**(-12.58%)**	**13.74%**	**(-12.59%)**
E-Cigarettes	Black	0.23%	0.25%	(+12.23%)	0.28%	(+22.74%)
	Non-Black	0.48%	0.51%	(+4.38%)	0.53%	(+10.06%)
	High Income	0.43%	0.45%	(+3.75%)	0.47%	(+8.96%)
	Low Income	0.49%	0.53%	(+7.48%)	0.0.57%	(+15.21%)
	Average	**0.45%**	**0.47%**	**(+4.91%)**	**0.50%**	**(+10.90%)**
	Cessation	0.47%	0.48%	(+1.74%)	0.48%	(+1.71%)

[a] The table above reports expected weekly rates of product usage under the assumption of a menthol cigarette ban, averaged across April 2015 through April 2019 and adjusted for market population. We display usage rates for cigarettes and e-cigarettes by demographic profile; cessation rates are presented as the average across all consumers.

result bodes well for the proponents of the proposed menthol ban; it addresses disparities in smoking behavior thought to be influenced by race-based advertising practices. Overall, we find that 52.8% of all Black menthol smokers switched to tobacco cigarettes when faced with the removal of mentholated products, and expected consumer surplus among Black households falls by 42.7 to 42.9% (dependent on merger status) when compared to the status quo.

Researchers Levy et al. (2021b) evaluated the expected impact of a menthol cigarette ban through the use of a recent expert elicitation on behavioral changes resulting from the removal of mentholated cigarettes. They find an expected decline in cigarette smoking rates of 15%; our results suggest a similar—if slightly smaller—reduction. With regard to changes in smoking rates among Black Americans, researchers Issabakhsh et al. (2022) rely upon the same expert elicitation of behavioral changes as in the aforementioned study. Their results suggest an expected 35.7% reduction in the Black smoking rate when compared to the status quo scenario. Again, our counterfactual study suggests similar changes in cigarette usage among the Black community.

Finally, we find the menthol ban is associated with a rise in the sale of electronic smoking devices, the amount of which differs dependent upon the assumption of independent or merged (cigarette and e-cigarette) producers. Under the assumption of independent producers, we find the menthol ban is associated with at 4.91% rise in the average weekly consumption of e-cigarettes. Unsurprisingly, Black households experience the largest growth in e-cigarette smoking rates—these consumers being most affected by the removal of menthol cigarettes.

Provided the total acquisition of e-cigarette producers by Big Tobacco (one firm producing both products), the rise in average weekly e-cigarette usage more than doubles to 10.90%. Ultimately, we find the vast majority of smokers who quit cigarettes, provided a menthol ban, do not substitute their consumption to other nicotine products, i.e. e-cigarettes and cessation products. Our results mirror those observed in Ontario, Canada, where, despite a fraction of consumers indicating willingness pre-ban (Ontario having banned menthol cigarettes in 2017) to switch to e-cigarettes, research by Chaiton et al. (2020) did not find a significant association between the Ontario's menthol ban and e-cigarette usage. This result bodes well for policymakers concerned with the continuation of addiction through the use of electronic smoking devices post ban.

However, we must note that for much of our sample, the relative share of e-cigarette usage remained quite small; shares post January 2018 seeing a dramatic rise in the proportion of e-cigarettes. As such, the willingness to substitute to e-cigarettes remains very much time-dependent; rising alongside the growth in popularity of electronic smoking products. Nor does our counterfactual model consider that marketing practices by e-cigarette companies, may change in an attempt to draw disfranchised cigarette smokers post-ban.

Cigarette Taxation For decades, sin taxes—excise taxes placed on things like tobacco, alcohol and gambling—have been used for health, education, and other public programs; for example, states such as Arizona, New Hampshire, Virginia, and Colorado, use revenue generated from cigarette sales to fund programs from public education to economic revitalization projects. In recent years, tax revenue from tobacco products has fallen with the decline in smoking rates, and the FDA's proposed menthol ban may lead to the steepest reduction yet seen.

As an alternative to the menthol ban, we find that a 10.23% sales tax, imposed in addition to current state and federal-level taxes, leads to a comparable reduction in the average weekly cigarette smoking rate (see Table 9). Further, under taxation, the average household faces a reduction in consumer surplus of 13.9% to 14% dependent on merger status, whereas the proposed menthol ban reduced average surplus by 15.7% to 15.9%. Of greater disparity is the reduction of surplus experienced, on average, by Black households: taxation resulting in an average consumer surplus reduction of 12.9% to 13%, whereas the proposed menthol ban lowers consumers surplus by 42.7% to 42.9%. Black households largely prefer menthol products, and a 10.23% sales tax reduces household consumption far less than the proposed menthol ban among Black consumers; therefore it's only logical that Black Americans would prefer a 10.23% tax to the removal of mentholated cigarettes.

Table 9: Average Weekly Rate of Product Usage: Cigarette Tax (10.23%).[a]

			Independent Producers		**Merged Producers**	
		Without Tax	With Tax	% Change	With Tax	% Change
Cigarettes	Black	15.41%	13.63%	(-11.52%)	13.64%	(-11.50%)
	Non-Black	15.76%	13.76%	(-12.72%)	13.76%	(-12.71%)
	High Income	14.91%	12.98%	(-12.94%)	12.98%	(-12.93%)
	Low Income	17.75%	15.66%	(-11.78%)	15.66%	(-11.77%)
	Average	**15.72%**	**13.74%**	**(-12.57%)**	**13.74%**	**(-12.56%)**
E-Cigarettes	Black	0.23%	0.23%	(+2.38%)	0.24%	(+6.14%)
	Non-Black	0.48%	0.50%	(+2.79%)	0.52%	(+6.40%)
	High Income	0.43%	0.45%	(+2.60%)	0.46%	(+6.15%)
	Low Income	0.49%	0.51%	(+3.15%)	0.53%	(+6.93%)
	Average	**0.45%**	**0.46%**	**(+2.77%)**	**0.48%**	**(+6.39%)**
	Cessation	0.47%	0.48%	(+1.93%)	0.48%	(+1.93%)

[a] The table above reports expected weekly rates of product usage under the assumption of a 10.23% cigarette tax, averaged across April 2015 through April 2019. We display usage rates for cigarettes and e-cigarettes by demographic profile; cessation rates are presented as the average across all households.

Regardless of demographic group, changes in consumer surplus demonstrate a clear preference for taxation rather than an outright product ban. For instance, we find that among low-income households—those often most impacted by sales taxation policies—a 10.23% cigarette sales tax results in a smaller reduction in consumer surplus when compared to the removal of menthol cigarettes. Low-income households face a reduction in consumer surplus ranging from 13.3% to 13.4% under taxation vs. a loss of 18.8% to 19% under the menthol cigarette ban. Lastly, under taxation, e-cigarette consumption does not experience the same increase in demand—smokers with a high menthol preference no longer seeking an alternative among e-cigarettes. Again, the assumption of merged producers results in greater e-cigarette usage rates through coordinated pricing strategies among taxed and untaxed products.

As a back-of-the-envelope calculation, we multiply DMA-level weekly smoking rates by market population, weighted by the average number of packs purchased each week among cigarette smokers—provided via the household-level data. We find a 10.23% sales tax generates an average tax revenue of $66.1 million each week, across the 100 DMAs making up our sample, for a total revenue of \$1.41 billion over the period from April 2015 through April 2019.[27]

Revenue generated has the potential to replace that lost, at the state and federal level, as a result of reduced smoking rates. However, to paraphrase FDA commissioner Janet Woodcock, the primary objective of the proposed menthol ban is to address health disparities as a result of unscrupulous marketing practices—particularly in communities of color; for this purpose, an outright ban has the greatest effect (FDA, 2021).

Flavorant Ban Pursuant to the successful implementation of the menthol cigarette ban, flavored and menthol e-cigarettes will likely be the FDA's next target. Already, flavored e-cigarettes are only available in disposable form; flavored cartridges were banned in 2020 in an attempt to reduce youth consumption. Further, lawmakers in California, New York, Massachusetts, and New Jersey have passed some form of flavored product restriction, and many other states opting to ban purchasing of flavored products through online marketplaces—avenues of illegal sales to youth and young adults. Therefore, it would be remiss of us to fail to consider the implications of a ban on all—cigarette and e-cigarette—menthol and flavored (fruity, candy, mint) products. Table 10 presents our findings.

Banning flavorants across all products leads to a similar reduction in average cigarette usage as that seen under the menthol ban. In addition, the fall in Black smoking rates mirrors those seen with the earlier menthol ban. Of greater interest is the expected change in weekly e-cigarette usage. On average, a flavorant ban reduces weekly e-cigarette usage by 44.7% to 46.5% (dependent on supply side assumptions). Of course, the average reduction in weekly e-cigarette usage, as a result of a flavorant ban, is very much time dependent.

E-cigarette market shares in the latter half of our sample are dominated by flavored products, whereas pre-2018, regular tobacco was the primary choice. It then follows, that a flavorant ban's effect on weekly e-cigarette consumption should be considered on a week-by-week basis. Figure 6 graphs the weekly expected reduction in e-cigarette sales upon the removal of product flavorants when compared to the status quo scenario.

As the popularity of flavored e-cigarettes grows, so does the impact of a flavorant ban. We find an average reduction in weekly e-cigarette usage, pre-2018, to be 41.1% assuming independent producers and 39.1% assuming merged producers. Post-2018, the average weekly reduction becomes 51.9% and 50.5% when assuming independent and merged producers, respectively.

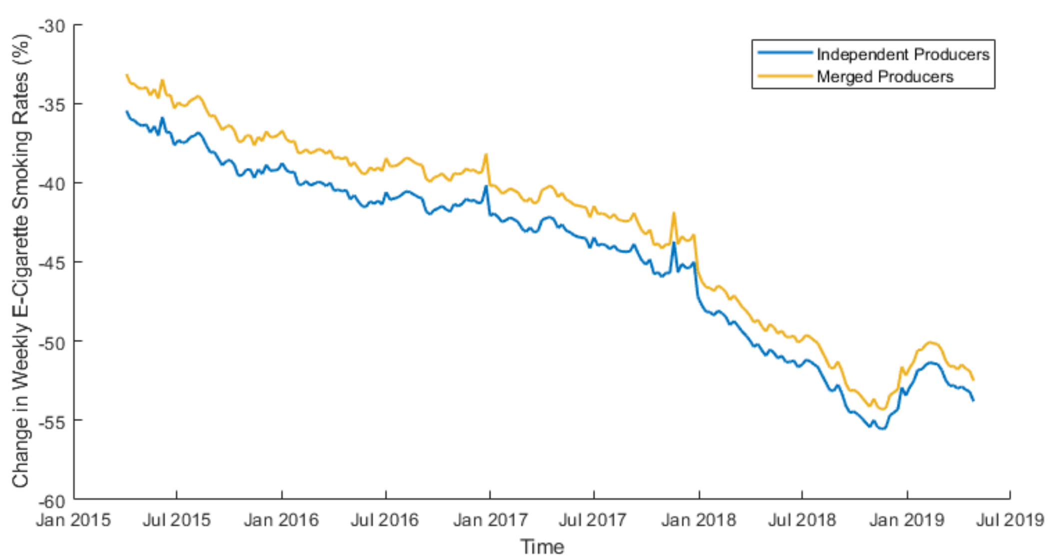
[27] This expected tax revenue should be treated as an upper bound as our model does not consider possible reductions in the number of packs smoked each week; rather, our model is one of smoking incidence. Nor do we address how tax revenue, itself, may be used to fund anti-smoking campaigns and other cessation inducing behavior.

Table 10: Average Weekly Rate of Product Usage: Flavorant Ban.[a]

			Independent Producers		**Merged Producers**	
		Without Ban	With Ban	% Change	With Ban	% Change
Cigarettes	Black	15.41%	10.00%	(-35.09%)	10.02%	(-34.98%)
	Non-Black	15.76%	14.32%	(-9.18%)	14.34%	(-9.05%)
	High Income	14.91%	13.24%	(-11.21%)	13.26%	(-11.08%)
	Low Income	17.75%	15.06%	(-15.15%)	15.08%	(-15.03%)
	Average	**15.72%**	**13.76%**	**(-12.48%)**	**13.78%**	**(-12.35%)**
E-Cigarettes	Black	0.23%	0.06	(-72.41%)	0.07%	(-71.26%)
	Non-Black	0.48%	0.27%	(-44.65%)	0.28%	(-42.89%)
	High Income	0.43%	0.23%	(-46.81%)	0.24%	(-45.06%)
	Low Income	0.49%	0.27%	(-45.67%)	0.28%	(-43.98%)
	Average	**0.45%**	**0.24%**	**(-46.46%)**	**0.25%**	**(-44.73%)**
	Cessation	0.47%	0.48%	(+1.88%)	0.48%	(+1.86%)

[a] The table above reports expected weekly rates of product usage under the assumption of a flavorant (non-tobacco) ban, averaged across April 2015 through April 2019. We display usage rates for cigarettes and e-cigarettes by demographic profile; cessation rates are presented as the average across all consumers.

Figure 6: Percent Change in Weekly E-cigarette Consumption Relative to the Status Quo



9 Conclusion

In this paper, we employ a model of consumer demand that incorporates retail- and household-level data, in a way that is internally consistent, to study consumer demand for cigarette and e-cigarette flavorants, and evaluate the impact of the proposed menthol cigarette ban among other counterfactual scenarios.

Our work is among the first that analyzes the effect of flavorant bans on demand for cigarettes, e-cigarettes and cessation products, and is the only work that incorporates addiction, categorical substitution, as well as both household- and retail-level data in the study of these effects. We demonstrate that product bans significantly reduce cigarette and e-cigarette consumption, and we find a taxation level which reduces average weekly consumption, among all consumers, by the same rate as the proposed menthol ban. To account for the purchase of e-cigarette companies by cigarette manufactures, we consider our counterfactual results under the assumption of independent and merged producers of cigarettes and e-cigarettes. Our results suggest that, across all households, the removal of mentholated cigarettes results in a 13% decrease in the average weekly smoking rate.

Further, by considering a rich set of heterogeneous parameters, we find demographic differences play a key role in responsiveness to product bans; Black households reduce their cigarette consumption by 35% when faced with the removal of menthol cigarettes. In contrast, we find a 10.23% cigarette sales tax as effective, on average, in reducing weekly cigarette smoking rates among all households, and results in a reduction in consumer surplus less than that experienced under the proposed menthol ban (and significantly less when considering Black households).[28] Our results suggest, when it comes to e-cigarettes, only a fraction of e-cigarette smokers switch among products. In addition, increases in e-cigarette usage under the proposed menthol cigarette ban are heavily dependent on the assumption of independent or merged (cigarette and e-cigarette) producers; coordination in product pricing playing a key role.

As a final counterfactual scenario, we consider the removal of all menthol and flavored products for both cigarettes and e-cigarettes. We find, on average, the reduction in e-cigarette usage is time-dependent, as market shares of flavored e-cigarettes grew rapidly near the end of our sample. As it stands, we find an average reduction in weekly e-cigarette usage, pre-2018, to be 41.1% assuming independent producers and 39.1% assuming merged producers. Post-2018, the average weekly reduction becomes 51.9% and 50.5%, respectively.

[28]The imposition of a 10.23% tax does not cause nearly as great a reduction in cigarette smoking among Black consumers, and therefore may not fulfill the intent of the menthol ban.

Although not considered in this paper, future work has the potential to address youth consumption of product flavorants; our analysis is limited by the unavailability of youth and young adults in the Nielsen household dataset. Further, we do not address the long-term health benefits as the result of the reduction in product usage. Nor do we consider inter brand substitution; rather, our model is one of product usage at the flavor level. Also, beyond the scope of our work is the recent self-regulation by producers designed to avoid government intervention—the effectiveness of which may be a topic of interest. Finally, we form market shares by considering average smoking rates and weekly purchase incidence; we do not consider purchase quantities. Future work has the potential to bridge this gap, forming a model linking both incidence and quantity choice.

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Appendix

A1 Additional Details on Cigarettes, e-Cigarettes, and Smoking Cessation Products in the Data

In the data, products within the e-cigarette category contained a mixture of battery units, starter kits, refill cartridges, disposable e-cigarettes, and flavored e-juice. In our analysis, we remove from consideration those UPCs pertaining to battery units, starter kits, and flavored e-juice. Battery units and starter kits were removed because they primarily consist of the rechargeable smoking device to be used with refill cartridges. These purchases are generally not repeat, and are significantly more costly. E-juice, on the other hand, contains greater variation in terms of price as well as inconsistent sizing and nicotine content. In contrast, cartridge packs and disposable e-cigarettes have standardized quantities and similar prices, and account for 89% of unit sales.

Sold in 3 to 5 cartridge packs, each refill cartridge contains a nicotine content generally equivalent to 1-1.5 cigarette packs and is priced around \$3 to \$5 per cartridge. We find disposable e-cigarettes are generally sold individually or in packs of 10; each unit contains a nicotine content equivalent to 1-1.5 cigarette packs and are generally priced around \$5 to \$10 per unit. Traditional cigarettes are sold in packs of 20 cigarettes or 10 pack cartons, and prices range from \$3.50 to \$15 a pack, depending upon marketing strategies, and federal, state, and local tax. Finally, smoking cessation products such as nicotine lozenges and gum are sold in sizes ranging from 20 to 100 pieces, with a nicotine content of either 2 mg or 4 mg per piece. We weight the sizes of lozenges and gum to a standardized 4 mg per piece, with 15 pieces costing about \$8.50 and providing the about same nicotine as one cigarette pack. Nicotine patches are most commonly sold in packs of 7 or 14; one patch provides a nicotine content equivalent to 1 pack of cigarettes and costs around \$4. In our analysis, based on nicotine content, we consider a pack of cigarettes equivalent to one e-cigarette cartridge, one disposable e-cigarette unit, 15 pieces of 4 mg nicotine gum/lozenges, or a single nicotine patch.

A2 Purchase Frequency and Stockpiling among Cigarette Purchases

In analyzing the frequency of cigarette purchases and potential stockpiling behavior, we calculate both the number of days between cigarette store trips and the occurrence of short-lived price reductions, "sales".[A1] As suggested in Hendel and Nevo (2006), if significant storage behavior is observed, cigarette sale occasions should be positively correlated with the number of days between store trips (as households increase their stock of stored products when prices are reduced). Controlling for outliers in our sample—particularly on-again, off-again smokers—we subset our sample to those store trips where the difference between the current and next purchase date is less than or equal to 4 weeks. We find the average number of days between each trip to be 6.77, and 68% of all cigarette store trips fall within 7 days of a prior purchase.

To address cigarette storability, we consider a regression of the number of days until the next store trips on cigarette sales occasions. To control for individual preferences, time trends, and seasonality, we include household and week fixed effects, and cluster the errors at the household level. Table A1 presents our results. We find the regression coefficient for sale occasions to be negative and statistically insignificant—suggesting temporary price reductions are uncorrelated with cigarette purchase frequency. Therefore, we conclude storability does not appear to play a significant role in determining time between cigarette purchase occasions.

Table A1: Days Until Next Store Trip Regressed on Cigarette Sales occasions

	Coefficient
Sale Occasion	-.093
	(0.083)
Week FEs	Y
HH FEs	Y
Mean DV	3.994
Num HH	10,344
Num Obs	487,307

***p<.01, **p<.05, *p<.1

Standard errors clustered at the household level are included in parentheses.

[A1] We define cigarette sale occasions similar to how they are defined in Hendel and Nevo (2006)—any time in which weekly cigarette price falls at least 5 percent below the modal price in each DMA. Weekly cigarette DMA-level price is taken to be the quantity weighted average price of all observed sales at the DMA/week level.

A3 Retail Data Step Estimation Procedure

Provided a candidate draw of Θ, for each market m and week t, we need to solve for $\delta_{mt} = (\delta_{1mt}, \ldots, \delta_{Jmt})'$ such that

$$\begin{aligned} s_{jmt}(\delta_{mt}; \Theta) &= S_{jmt}, \\ \text{for } j = 1, \ldots, J &\text{ and } m = 1, \ldots, M, \end{aligned} \tag{A1}$$

where $s_{jmt}(\cdot)$ are the predicted retail market shares from Eq. (11) and S_{jmt} are the observed retail market shares. In solving this system of equations, we require two steps to be performed iteratively each period, starting from $t = 1$, as state dependence causes the current period purchase probabilities to rely on prior consumption status.

Thus, for a given period, we start by calculating the left-hand side of (A1). In practice, we rely upon Monte Carlo integration where Eq. (11) is approximated by

$$s_{jmt}(\delta_{mt}; \Theta) = \frac{1}{R} \sum_{r=1}^{R} \sum_{g=0}^{G} \pi_{rjmt}(C_{rg,t-1} = 1) P(C_{rg,t-1} = 1). \tag{A2}$$

Each simulated household $r = 1, \ldots, R$ is represented by Halton draw from the empirical distributions of v and D, respectively. We draw $R = 200$ simulated households per market to compute Eq. (A2). Finally, $\pi_{rjmt}(\cdot)$ denotes the household-level purchase probability conditioned upon prior consumption status $C_{rg,t-1}$ as well as x, p_{mt}, h_{mt}, δ_{mt}, Θ, D_r, and v_r.[A2]

Next, we invert the system of equations (A1) to obtain δ_{mt}. This system of equations is non-linear, and we solve it numerically. Grigolon and Verboven (2014) provides the contraction mapping algorithm, based on that described in Berry et al. (1995), for the random coefficients logit model with the inclusion of nesting parameters. In the case of a two-level nested model, the algorithm iteratively solves

$$\begin{aligned} &\delta_{mt}^{k+1} \equiv \delta_{mt}^{k} + (1 - \boldsymbol{\lambda})[\ln(S_{mt}) - \ln(s_{mt}(\delta_{mt}^{k}; \Theta))], \; k = 1, 2, \ldots, \\ &\text{where } S_{mt} = (S_{1mt}, \ldots, S_{Jmt})' \text{ and } s_{mt} = (s_{1mt}, \ldots, s_{Jmt})', \end{aligned} \tag{A3}$$

until the relative difference between δ_{mt}^{k+1} and δ_{mt}^{k} is less than our tolerance of 1e^{-13}. Note, $\boldsymbol{\lambda}$ represents a $1 \times J$ vector of nesting parameters where each element, $j = 1, \ldots, J$, is given by λ_g such that $j \in \mathcal{J}_g$.

After obtaining a unique δ_{mt}, in market m for a given period t, the evolving joint distribution of consumer heterogeneity and consumption status for the period $t+1$ is defined by Eq. (13).

[A2] At $t = 1$, prior consumption status is assumed to be $P(C_{rg1} = 1) = 1/(G+1)$, $\forall g \in \{0, \ldots, G\}$, $\forall r \in \{1, \ldots, R\}$, and it evolves according to Eq. (13) in subsequent weeks. We treat the first quarter of our sample as a burn-in period and derive our results only from data in the post-burn period.

Once the inversion has been completed iteratively for each $t = 1, \ldots, T$, across all markets, a unique $\delta(\Theta)$ has been obtained, and we proceed to the evaluation of our household-level log-likelihood.

A4 Comparison of Results With and Without Pricing Instrument

Table A2: Mean Utility Estimates With and Without Pricing Instrument.[a]

	Mean Utility	
	Price IV	**OLS**
Price	-0.759***	-0.321***
	(0.094)	(0.028)
Cigarette	1.303**	-1.511***
	(0.606)	(0.188)
E-cigarette	-4.771***	-6.701***
	(0.352)	(0.159)
Cessation	-1.749**	-5.687***
	(0.889)	(0.329)
Menthol	-0.718***	-0.789***
	(0.051)	(0.053)
Menthol $\times$ E-cig.	-0.348***	-0.272***
	(0.042)	(0.033)
Flavored	0.451***	0.098
	(0.078)	(0.064)
Category $\times$ Time FEs	Y	Y
Category $\times$ Market FEs	Y	Y
Num HH	15,223	15,223
Num HH Obs	2,317,585	2,317,585
Num Markets	100	100
Num Time Periods	226	226
Num Market Level Obs	135,600	135,600

***p<.01, **p<.05, *p<.1

[a] Standard errors are included in parentheses. Our estimation includes fixed effects at the category/time and category/market level; for presentation purposes, and to avoid perfect collinearity, we exclude the flavor tobacco, the final time period, and the last market.

Table A2 presents a comparison of our results with, and without, our pricing instrument. As discussed in Section 6, to account for the possible correlation between the price variable and unobserved demand shocks, we use an instrumental variable technique. Specifically, we take the average product price over all DMAs not included in our estimation to be our pricing instrument.

The use of this instrument generates substantial changes in our estimation. Category dummies for cigarettes and cessation products now enter utility positively, and the parameter value for e-cigarettes rises by a sizable amount. Moreover, the mean price response, in terms of absolutes, increases significantly (more than doubles). These differences are those we would expect if (1) there exists simultaneity between price and demand, and (2) our instrument successfully corrects for this existence. Finally, with the inclusion of our instrument, all parameters remain statistically significant at the 95% level or greater.

A5 Supply-Side Model

In this appendix, we detail how we calculate counterfactual prices provided in our demand estimates found in Section 7. To begin, under the assumption that prices are set optimally, marginal cost is inferred from observed prices, market shares, and expected price sensitivity. Specifically, we assume that prices are set at the firm level, where each firm sets their product prices to maximize the total profits over the weeks in our finite sample. In this case, the FOCs are given by the vector $\frac{\partial \pi^f}{\partial p_{ft}}$ with the element corresponding to product j in the set F_j of products sold by firm f in time t (we drop the m subscript, assuming prices are set at the market level) being

$$0 = \frac{\partial \pi^f}{\partial p_{jt}} = \frac{\partial}{\partial p_{jt}} \sum_{k=1}^{T} \sum_{n \in F_j} S_{nk}(p_{nk} - mc_{nk}) = S_{jt} + \sum_{k=1}^{T} \sum_{n \in F_j} \frac{\partial S_{nk}}{\partial p_{jt}} (p_{nk} - mc_{nk})$$

which can be rewritten in vector form as

$$0 = S + \Delta'(p - mc), \tag{A4}$$

for $S = (S_{11}, \ldots, S_{J1}, \ldots, S_{JT})'$, $p = (p_{11}, \ldots, p_{J1}, \ldots, p_{JT})'$, and $mc = (mc_{11}, \ldots, mc_{J1}, \ldots, mc_{JT})'$. Finally, Δ is a $(J \times T) \times (J \times T)$ matrix made up of $J \times J$ blocks, $\Delta_{k,t}$ for $k, t = 1, \ldots, T$, such that

$$\Delta = \begin{bmatrix} \Delta_{1,1} & 0 & 0 & 0 & 0 \\ \vdots & \ddots & 0 & 0 & 0 \\ \Delta_{k,1} & \ddots & \ddots & 0 & 0 \\ \vdots & \ddots & \ddots & \ddots & 0 \\ \Delta_{T,1} & \ldots & \Delta_{T,t} & \ldots & \Delta_{T,T} \end{bmatrix} \tag{A5}$$

with the (n, j) elements of $\Delta_{k,t}$ equal to $\frac{\partial S_{nk}}{\partial p_{jt}}$ if both n and j are owned by the same firm, and zero otherwise. Thus, the vector of marginal costs for all products, across all weeks, is

$$mc = (\Delta')^{-1} S + p. \tag{A6}$$

Once the vector of marginal costs has been obtained, we can predict the impact of changes such as the removal of flavorants or the impact of cigarette taxes. We assume that these changes do not impact our demand parameters or marginal costs. Thus, provided a gradient vector comprising the first order conditions of our firm's profit maximization equation, we find the vector of firm prices such that $\hat{p}_f$ maximizes firm prices. In application, we iterate between the firms, maximizing each firm's profits with respect to the other firm's choice of prices. We continue iterating until $\hat{p}_f$ converges for each firm.[A3]

A6 Illicit Cigarette Sales

A possible source of bias in our weighting procedure, when forming DMA-level weekly product usage rates, is the presence of illicit cigarette sales. Research by the Committee on the Illicit Tobacco Market, appointed by the National Research Council and tasked by the FDA, suggests that the sale of illegal cigarettes makes up 8.5% of the total cigarette market (National Research Council, 2015).[A4] At the DMA-level, if the sale of illegal cigarettes remains a constant proportion of total cigarette sales over the course of our sample period, then the population weight will account for the sale of illicit products when forming our market/time-level product usage rates. In this case, our observed retail sales can act as a proxy for illicit consumption. Supporting this notion, Paraje et al. (2022) suggests that the world-wide market for illicit cigarettes, as a percentage of total consumption, has largely stabilized over the past decade; with the consumption of illicit products trending similarly to that of legal sales. However, research by the National Research Council (2015) found the total proportion of illegal cigarette sales rose slightly over the latter half of their sample period—from 7.1 percent in 2003 to 8.5% by 2011.

Further, of greatest concern to the formation of our market shares is the impact of DMA-level price on the market for illicit cigarettes, as rising product price is considered a primary motivation for the trade in illegal cigarettes (National Research Council, 2015). In this case, legal

[A3]Our tolerance for convergence is set to 1e-7.

[A4]Estimates of the size of the illicit cigarette market ranges from 8.5 to 21 percent. The low end, 8.5 percent, is the committee's own estimate and is found by comparing total tax paid sales with self reported consumption.

and illegal sales may no longer trend similarly, and our observed sales can no longer serve as a proxy for illicit consumption.

In this regard, we find that brand-specific pricing strategies remain largely consistent across all markets. Therefore, general increases in price may not encourage substitution to the illicit cigarette market, as the presence of profit maximizing smugglers implies that illicit cigarette prices increase alongside that of their legal counterpart. However, localized price changes (predominantly in the form of taxation) have a possibility of encouraging cross-border shopping and smuggling operations. If localized taxation increases the proportion of illicit cigarette sales in a market, then our market shares formation procedure may underweight responsiveness to changes in price—stressing the importance of accounting for price endogeneity.

Further, the sale of illicit products may also bias our counterfactual results—bans and taxation considered are common motives for illicit trade. However, to date, empirical research has not found an increase in illegal sales after the implementation of a menthol ban. In consideration of Massachusetts' 2020 menthol ban, Ali et al. (2022) found no significant impact on cross-border sales of neighboring states, where menthol products remain accessible to consumers and smugglers interested in menthol cigarettes. Similarly, an analysis of the 2015 Nova Scotia menthol ban found no significant increase in the seizure of illicit cigarettes pre- and post-ban; suggesting that the sales of illegal cigarettes is unlikely to be increasing in response to the removal of mentholated products (Stoklosa, 2019). Finally, Fong et al. (2022b) compared the purchases of Canadian smokers pre- and post-ban, in their respective provinces, and found no increase in the reported purchasing of illicit products.

Although sales of illicit products may not respond significantly to the removal of mentholated tobacco, what remains less clear is consumer responsiveness to our counterfactual taxation scheme. The National Research Council (2015) suggests much of the growth in the illicit tobacco market is a function of taxation—smugglers purchasing products in low tax states/territories and selling in high tax locations. However, our counterfactual taxation scheme is proposed at the federal level, subjecting all markets to an increase in price, and Paraje et al. (2022) hypothesizes that, on a global scale, common reductions in cigarette affordability have largely stymied growth of illicit trade and led to similar reductions both legal and illegal sales. Overall, due to the nature of illegal sales, the degree to which changes in observed cigarette sales can act as a proxy for illicit transactions remains largely unknown, and our results reflect an expectation formed by the assumption that our counterfactual scenarios do not significantly change illicit consumption behavior.