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

Jiawei Chen and Colin Reinhardt[*]

University of California, Irvine

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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 12.6% and the Black smoking rate by 35%, while demand for e-cigarettes and cessation products increases by 4.9% and 1.7%, respectively. A $1.02-per-pack cigarette sales tax is as effective as the menthol cigarette ban, with a smaller reduction in consumer surplus across most demographic groups, especially Black Americans. Including non-tobacco flavored e-cigarettes in the ban reduces cigarette consumption similarly, while e-cigarette usage decreases by 46%.

JEL: D04, D12, I18, L66. *Keywords:* demand estimation, consumer heterogeneity, tobacco consumption, addiction, public health intervention, policy evaluation.

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

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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, 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 focuses on the menthol cigarette ban proposed by the US Food and Drug Administration (FDA) (FDA, 2021). The ban was initially introduced in 2022, but in April 2024 its implementation was delayed indefinitely due to significant public feedback and political considerations (CNN, 2024), bringing the contentious nature of the ban to the forefront. In our work, we evaluate the expected impact of the removal of menthol cigarettes on the consumption of cigarettes, e-cigarettes, 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 preferences for flavorants in tobacco products are an important issue. For instance, household income has long been found to correlate with price sensitivity and demand for cigarettes, including regular tobacco and menthol (Evans et al., 1999; Wang et al., 2018). Of greater importance to our work, however, is menthol preference among Black Americans. 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 suggest 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 response to these targeted marketing practices and the resulting health inequalities in disadvantaged Black communities, lawmakers and laypersons alike called on the FDA to prohibit the sale of menthol cigarettes. However, the proposed ban saw significant community push-back among activists concerned about its economic burden. Ultimately, due to concerns about the perceived impact on the Black community, the proposed ban was indefinitely delayed in April 2024 in an effort to gather greater community feedback and discussion. This delay underscores the complex interplay between public health objectives and the socioeconomic realities faced by targeted populations, highlighting the importance of our work in better understanding the impact of the ban.

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 cigarette 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.

An alternative to the RCNL approach we utilize in our work is to model within-nest substitution and the distribution of preferences solely through the use of random coefficients on category dummies. McFadden and Train (2000) demonstrate that it is possible to approximate any discrete choice model through the use of only random coefficients. However, our current structure allows for a nuanced model that captures both individual-level preference heterogeneity and the correlation in unobserved factors affecting choice. This dual approach leads to a more flexible and realistic model.

Further, our structure enhances model fit without unduly increasing the computational burden during estimation. This is because a better-specified model can, to some extent, be less sensitive to inaccuracies in the Monte Carlo integration process, as it aligns more closely with the true data-generating process. By capturing the hierarchical decision-making structure and individual preference variations, our model achieves improved accuracy and robustness even with a limited number of Monte Carlo draws.

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 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 regular 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 menthol cigarettes, the weekly cigarette smoking rate would have been 12.6% lower, on average, during the period from April 2015 to April 2019. Black Americans in particular would have experienced a 35% drop in their weekly smoking rate during this period. (2) In comparison to a menthol cigarette ban, a $1.02 national sales tax per pack of 20 cigarettes would be as effective in lowering the weekly smoking

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

rate and would cause a smaller reduction in consumer surplus in most demographic groups, especially among Black Americans who face the greatest economic costs in the event of a menthol cigarette ban. In addition, a back-of-the-envelope calculation finds that this cigarette sales tax would result in an expected weekly tax revenue of $114.6 million, for a total of $24.4 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 the weekly cigarette smoking rate similar to the menthol cigarette ban alone, as well as a drop in 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. (2021)) 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 cigarette 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. (2023) and Issabakhsh et al. (2024) rely on the same expert elicitation of consumer intent post-ban (Levy et al., 2021), 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 menthol 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 cigarette 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) find 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 cigarette 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 smok-

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

ers (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 take action.

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 regulators to act. In January 2020, the FDA placed a temporary enforcement policy that banned the sale of all (fruity, candy, and mint) e-cigarette cartridges. While the ban on flavored e-cigarette cartridges was intended

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[3]See Figure 2.

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 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, Black American communities. However, in April 2024 the ban was delayed indefinitely. According to US Health and Human Services Secretary Xavier Becerra, the decision requires significantly more time due to the extensive public feedback and the need for further discussions with various civil rights and criminal justice groups.

Political considerations have also played a role in the ban's indefinite delay, as President Joe Biden faces potential backlash from both supporters and opponents. While some civil rights leaders worry about the potential criminalization of menthol cigarettes and increased police interactions, organizations like the NAACP and the American Heart Association argue that the delay allows the tobacco industry to continue targeting minority groups, exacerbating health disparities. Thus, as we shift attention to mentholated tobacco, we will continue to focus on addressing preferences in America's Black community, providing research that supports balancing public health priorities with the need for thoughtful policy implementation.

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, 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.

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

(a) Kent Menthol Cigarette Ad (1961)   (b) Winston Menthol Cigarette Ad (1970)

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) finds 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 the Black American smoking rate 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 account for 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, in-

crease 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). However, the future of this ban remains unclear as political pressure has delayed the ban indefinitely, and the current administration seeks further discussions with various civil rights and criminal justice groups to fully understand the potential impact on the Black American community (CNN, 2024).

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 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

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

[5]Yearly, Nielsen tracks the sales of 30,000 to 50,000 stores from roughly 90 retail chains. Estimated coverage as a percentage 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 January 2015 dollar values using the Consumer Price Index for All Urban Consumers (CPI-U).

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.

Figure 2: Weekly Sales Quantities for Cigarettes and E-cigarettes
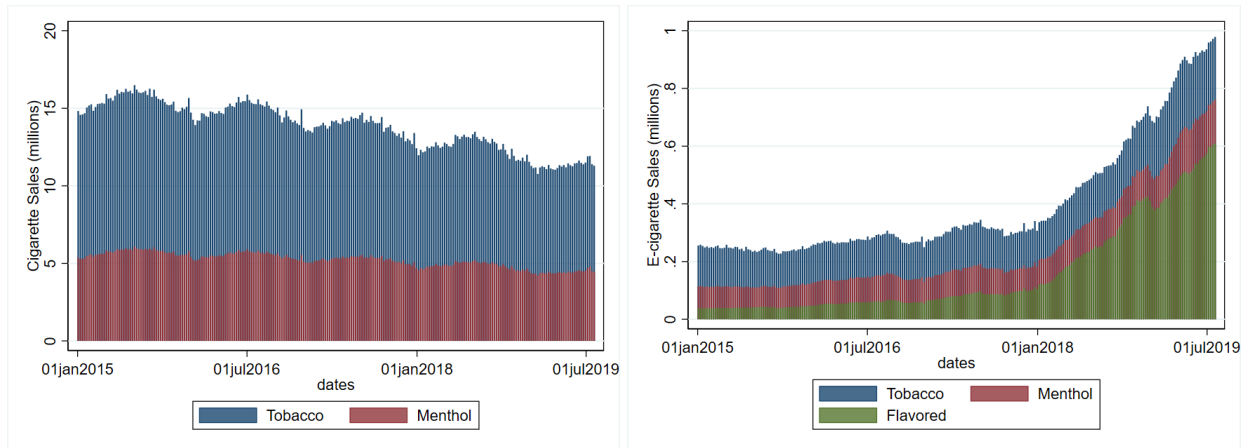
(a) Weekly Cigarette Sales

(b) Weekly E-cigarette Sales

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 (non-Hispanic)"; in our subsequent analysis, this indicator allows us to assess the impact of

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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%.

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. 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

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[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 greater 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)).

cities. (3) DMAs form regions of households with similar characteristics and define local television markets, and therefore demand shocks—particularly those stemming from advertising campaigns run at the DMA level—should be similar across households in the same DMA.

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 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

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[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.

[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.

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.

4.1 Retail Evidence of Preference Heterogeneity

Throughout our analysis, we rely on two primary demographic attributes: income and the prevalence of Black households. 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.

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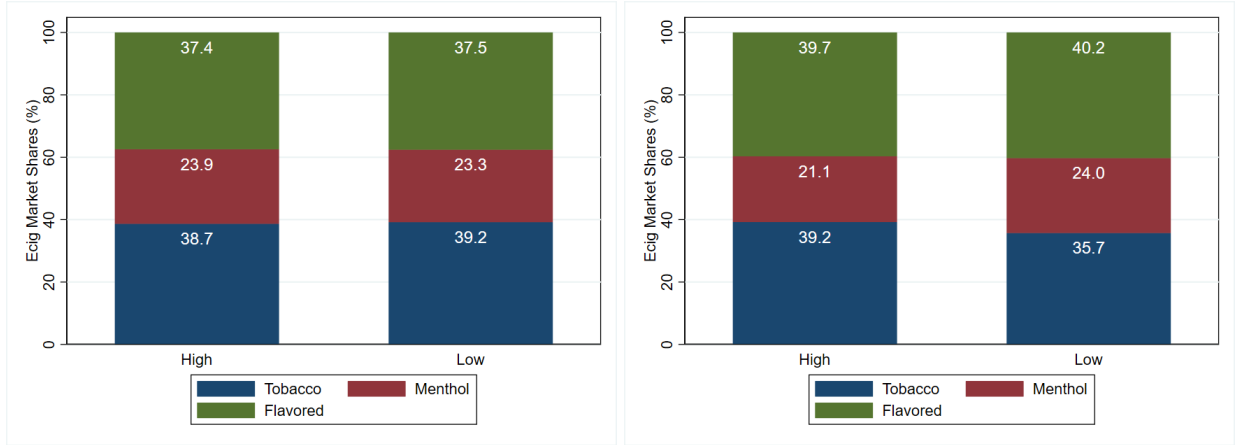
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[13]To avoid confusion, we define the flavor "regular tobacco" to consist of cigarettes/e-cigarettes whose flavor profile is solely tobacco.

Figure 3: Flavorant Choice and DMA Demographics
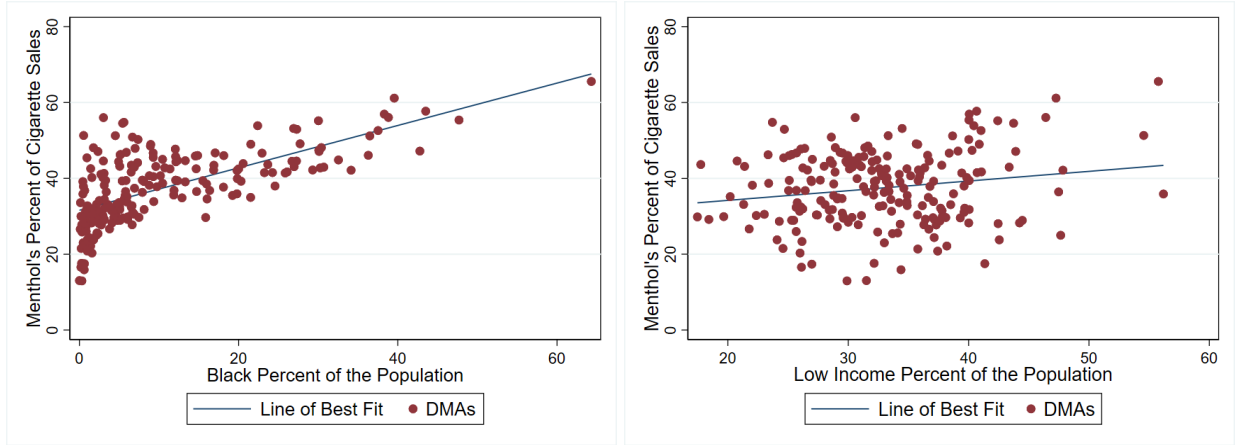
(a) Black and Menthol Cigarette Consumption

(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.

preference for cigarettes. Lastly, markets with a smaller proportion of low-income households display a greater preference for e-cigarettes and cessation products.

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

Figure 4: Category Choice and DMA Demographics
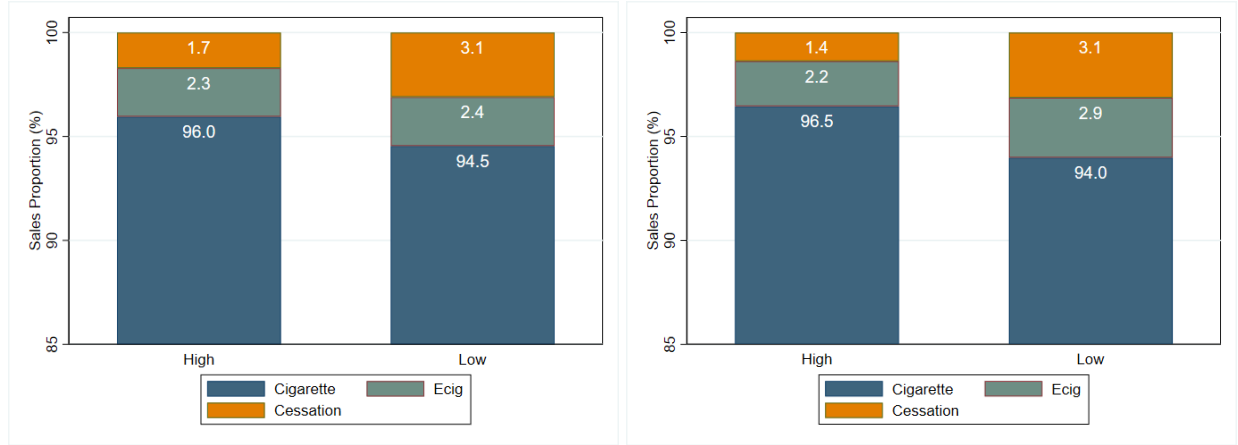
(a) Black and Category Choice

(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.

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.

A key strength of using household-level data is that it allows us to track consumers' product choices over time. 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 correspond to

Table 2: Product Transition Table

| Last Inside Option Purchased | Current Product Choice (%) | | | | | |
| | Cessation | Cigarette | | E-cigarette | | |
		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**

the previously purchased product (93.10% for regular 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 cigarette 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 regular 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, which we discuss next.

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 a nicotine 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.

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.

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 4 presents current categorical choice based upon the prior week's purchase decision. Unlike the product transition table (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.

Flavorant Preference   Finally, regarding within-category choice, we present Figure 5 which illuminates a household's flavorant preference dependent on their observed demographic attributes.

Table 4: Categorical Purchase Probability by Week

Last Week's Category Choice	Current 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**

Figure 5: Product Choice and Household Demographics
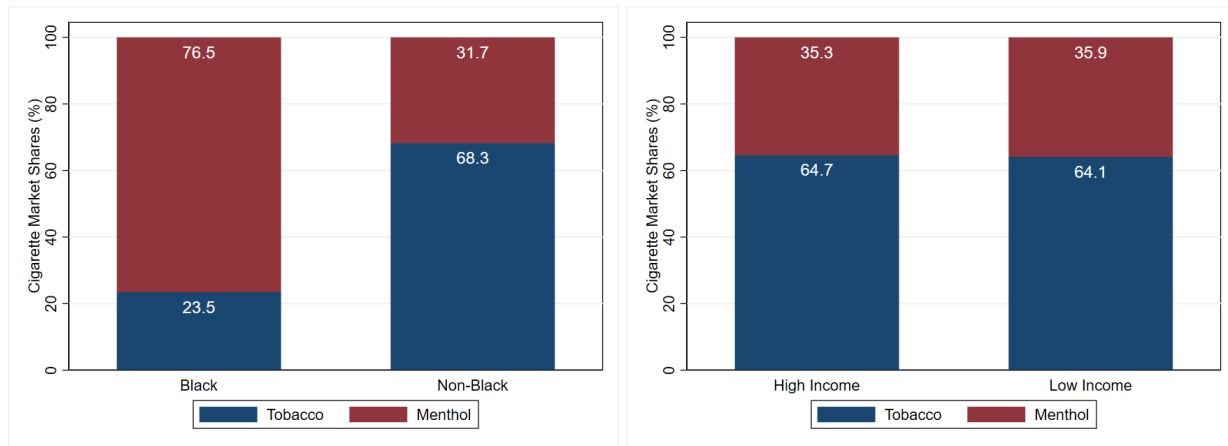
(a) Black and Menthol Cigarette Consumption

(b) Low-Income and Menthol Cigarette Consumption
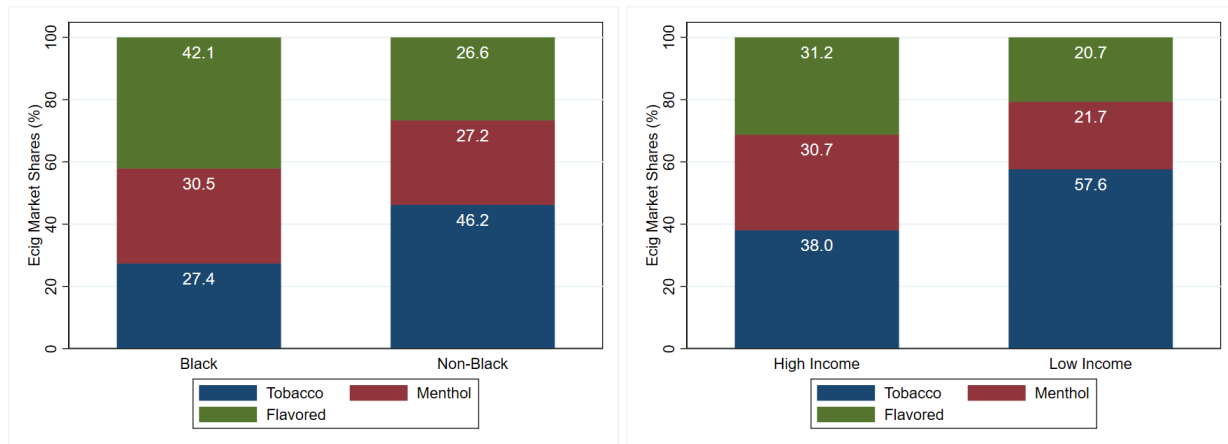
(c) Black and E-cigarette Flavor Choice

(d) Low-Income and E-cigarette Flavor Choice

Similar to the figures in Subsection 4.1, we provide bar charts by demographic 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 households consisting of menthol products.

Additionally, high- and low-income households' 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 households display stronger preferences for flavored and menthol products— shunning regular tobacco e-cigarettes. For low-income households, 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 $G = |\mathcal{G}|$. Further-

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[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.

more, 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 an indirect utility from purchasing product $j \in \mathcal{J}$, where product j is a member of group $g \in \mathcal{G}$, given by

$$u_{ijmt} = x_j' \beta_i + \alpha_i p_{jmt} + \phi \mathbb{I}\left(\sum_{g' \in \mathcal{G}} C_{ig',t-1} > 0\right) + \rho_g C_{ig,t-1} + \xi_{jmt} + \bar{\epsilon}_{ijmt} \tag{1}$$

$$\text{where } i = 1, \ldots, H; \ j = 1, \ldots, J; \ t = 1, \ldots, T; \ \text{and } m = 1, \ldots, M.$$

The $n \times 1$ 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}. $\mathbb{I}(\cdot)$ 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 consumers.

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:

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

where Π is an $(n+1) \times d$ 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

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[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.

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 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 utility u_{ijmt} excluding $\bar{\epsilon}_{ijmt}$ into a common component δ_{jmt} and an idiosyncratic component μ_{ijmt}:

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

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

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 $\mathcal{J}_g$,

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

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

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 a separate entry 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

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

where $\delta_{mt} = (\delta_{1mt}, \dots, \delta_{Jmt})'$, $x = (x_1', \dots, x_J')'$, $p_{mt} = (p_{1mt}, \dots, p_{Jmt})'$, 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

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[16]Multiple distinct products purchased during a single week account for 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.

homogeneity for a moment for ease of explanation, retail market shares are formed as follows:

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

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.

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

6 Identification and Estimation

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

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 fixed effects and product-time fixed effects, market-specific demand shocks at the product-level are independent across DMAs. Under this assumption, the average category-level price across all markets, excluding the market in question, will serve as an instrument for the prices within that category. This average category-level price will be independent of the product-level demand shocks specific to a given market, yet it will be correlated with the observed prices due to shared 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

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

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

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

---

[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.

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).

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 practice, we rewrite each product's mean utility from Eq. (4) as:

$$
\begin{aligned}
\delta_{jmt} &= x_j' \beta + \alpha p_{jmt} + \xi_{jmt} \\
&= \alpha p_{jmt} + \overline{\delta}_m + \overline{\delta}_{jt} + \Delta \xi_{jmt},
\end{aligned}
\tag{16}
$$

---

[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).

where we decompose mean utility into the price response, a market fixed effect, a product-time fixed effect, and deviations therefrom, $\Delta \xi_{jmt}$. The market fixed effect $\bar{\delta}_m$ captures systematic variations in preference for tobacco products across markets, and the product-time fixed effect $\bar{\delta}_{jt}$ captures seasonality and other common changes in product taste over time. These product-time fixed effects reflect the impact of product characteristics, and a further projection of these fixed effects onto x_j provides the average preference for product characteristics, β.

In our evaluation of the relationship in Eq. (16), we proceed with a TSLS regression relying upon the Hausman-style instruments discussed above. Standard errors for $(\widehat{\alpha}, \widehat{\beta})$ 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 $\{(\delta_{111}(\Theta_b), x_1, p_{111}), \ldots, (\delta_{JMT}(\Theta_b), x_J, p_{JMT})\}$ to create a bootstrapped sample of a size equal to the original. Given the bootstrapped sample, we then perform the TSLS regression to estimate (α_b^*, β_b^*). Finally, from the distribution of (α_b^*, β_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 6 category-flavor combinations, 100 markets, and 226 time periods (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) with a total of 2,100,709 household observations post burn-in.

Dummies representing product flavorant are denoted Menthol and Flavored. Flavored products are only available in the form of disposable or cartridge-based e-cigarettes, while 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, while among e-cigarettes flavorant preference is more nuanced. As expected, average product valuation decreases with price.

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[23]After burning the first quarter in our sample, the time frame considered in our demand analysis is April 2015 – July 2019.

Table 5: RCNL Demand Estimates[a]

		Means (α, β)	**Std. Dev.** (Σ)	**Demographic Interactions (Π)**	
				Low-Income	**Black**
Price		-0.290***		-0.017	
		(0.012)		(0.026)	
Cigarette		-1.375***	2.036***	0.351**	-0.700***
		(0.078)	(0.028)	(0.164)	(0.090)
E-cigarette		-7.452***	2.281***	0.365*	-1.929***
		(0.188)	(0.075)	(0.220)	(0.329)
Cessation		-6.581***	2.805***		
		(0.157)	(0.086)		
Menthol		-0.794***	1.188***	0.118***	1.055***
		(0.054)	(0.054)	(0.029)	(0.062)
Menthol $\times$ E-cig.		-0.267***			
		(0.030)			
Flavored		0.072		-0.397*	1.040***
		(0.070)		(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)			
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. To avoid perfect collinearity, we exclude the flavor of tobacco.

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 estimate of Π reveals significant variation in demographic valuation. Low-income households 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)), in that 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 households display a slight preference for menthol, other flavored products are less preferred.

Random Coefficients and State Dependence Turning to the estimates of our random coefficients (Σ), which account for variation in valuation across households, all are statistically significant. In addition, past consumption of an inside option plays a positive and significant role in determining consumption across all product offerings. This result is consistent with the presence of addictive behavior pertaining to nicotine products. However, dynamic state dependence appears to be primarily focused at the category level, with the values of categorical state dependence (ρ_g, $g = q, c, e$) 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 dependence 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 products 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 modeling of heterogeneous product preferences helps reduce potential bias by capturing unobserved factors that influence both current and lagged consumption, thereby mitigating endogenous correlation between the error term and lagged consumption status.

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

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.

Table 6: Price Elasticity of Demand[a]

		Own	**Cross-Elasticity**		
			Same Category	Different Category	All Products
Cigarettes	Tobacco	-1.557	0.651	0.002	0.132
	Menthol	-1.828	0.998	0.002	0.201
	Category-level	**-0.914**	-	**0.167**	**0.167**
E-Cigarettes	Tobacco	-1.577	0.330	0.047	0.160
	Menthol	-1.584	0.318	0.069	0.169
	Flavored	-1.987	0.353	0.046	0.169
	Category-level	**-0.955**	-	**0.002**	**0.002**
	Cessation	-2.118	-	0.033	0.033

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

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 elasticities of demand at both the product and category (nest) levels.[25]

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 products' prices when those products exist within the same category. Similarly, the cross-price elasticity of e-cigarettes is greater when averaged across products within the same category compared to the average across products in alternative categories. Our cross-elasticity calculations provide supportive evidence of within-

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[25]Product-level elasticities are calculated numerically, and category-level elasticities are found via simulation.

category substitution for both cigarettes and e-cigarettes, and suggest sensible substitution patterns across products.

Model estimates indicate that the own-price elasticities of demand for cigarettes and e-cigarettes, at the category-level, are -0.914 and -0.955, respectively. Previous studies have reported own-price elasticities for cigarettes ranging from -0.48 to -1.188, and for e-cigarettes ranging from -0.82 to -2.77 (Zheng et al., 2017); our estimates fall within these ranges. Additionally, compared to cessation products, both cigarettes and e-cigarettes exhibit lower elasticity.

Focusing on consumer demographics, we find that markets with a higher proportion of low-income households generally exhibit less elastic demand for cigarettes. This finding aligns with existing literature that highlights the persistence of cigarette consumption among low-income households. Regarding product flavorants, demand for menthol cigarettes is less elastic in markets with larger Black American populations. Interestingly, the market-level average own-price elasticity for e-cigarettes, regardless of flavor, does not show a significant correlation with the proportion of low-income households or Black households. Additionally, demand for cessation products is less elastic in markets with higher percentages of high-income households, suggesting a stronger preference for cessation products among wealthier consumers. Overall, our calculated own-price elasticities demonstrate sensible variation across consumer demographic distributions and are consistent with the consumption differences outlined 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 effects of the proposed menthol cigarette ban as well as other counterfactuals. We evaluate consumer responsiveness to various product bans and provide a taxation rate which results in a consumption level change equivalent to that resulting from the removal of menthol products. We proceed by first describing our supply-side model and the assumptions we impose when performing our analysis. Then, provided estimates of counterfactual prices from our supply-side model, we present expected changes in consumption behavior resulting from our various 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 number of

Table 7: E-Cigarette Brands and Market Shares

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.

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 in 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).[26]

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.[27] If we model firms at the nest level, then we contend that competition exists between products of different nests, and that manufacturers 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 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

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[26]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.

[27]Our choice of modeling cigarettes and e-cigarettes as composite products inhibits our modeling assumptions. We can either consider producers of cigarettes and e-cigarettes as competitors or as a single entity.

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 manufacturers is not surprising. Initially, the e-cigarette 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, i.e. one firm producing both products. Thus, our findings can be perceived as providing bounds for possible firm responses based upon the proportion of the market under traditional producers of tobacco products. In both models of our supply-side analysis, we assume that the producers of cessation products are independent. A detailed description of our counterfactual price calculation 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 menthol cigarettes. Next, we calculate a national cigarette sales tax that would result in a reduction in the average cigarette smoking rate equivalent to that expected under the menthol cigarette ban, weighing the pros and cons of bans vs. taxation. Lastly, we explore the expansion of the menthol cigarette ban to all non-tobacco product flavorants, paying particular attention to the expected reduction in e-cigarette usage. All counterfactual scenarios considered in our analysis rely on supply-side estimates of counterfactual prices discussed above.

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. Weighting our counterfactual shares by the market population, we determine the weekly average rate of consumption across all markets. We burn the first and last quarter of our results and average across all remaining weeks to determine the average product usage over the period from April 2015 through April 2019.

Menthol Cigarette Ban   Table 8 presents the impact of the removal of menthol cigarettes from households' choice set. We display usage rates for cigarettes and e-cigarettes by demographic

profile, while cessation usage rates are presented as the average across all households. Changes in consumption behavior are displayed under both independent producers and merged (cigarette and e-cigarette) producers assumptions. We find that in the absence of menthol cigarettes, the average weekly cigarette smoking rate across all households decreases by 12.6% (from 15.72% to 13.74%) regardless of producer merger status. On average, 68% of menthol cigarette smokers switch to regular tobacco cigarettes upon the removal of menthol cigarettes. Consumer surplus across all households falls by 15.7% to 15.8% (under merged and independent producers, respectively) compared to the status quo.[28]

Among Black households, the reduction in cigarette consumption is significantly higher, with a 35% decrease in their average weekly cigarette smoking rate (from 15.41% to 10.00%). Overall, we find that 53% of all Black menthol cigarette smokers switched to regular tobacco cigarettes when faced with the removal of menthol cigarettes. However, the ban results in the greatest loss of consumer surplus for Black Americans, decreasing by 42.7% to 42.9% (under merged and independent producers, respectively).

These findings offer compelling arguments for both proponents and opponents of the menthol cigarette ban. For proponents, the significant reduction in cigarette consumption among Black households underscores the public health benefits of the ban. A 35% decrease in the smoking rate suggests that the ban effectively reduces tobacco use, which could lead to better health outcomes and lower rates of tobacco-related diseases in the Black community. This aligns with the goal of advancing health equity and reducing disparities caused by targeted marketing of menthol cigarettes to minority groups.

Conversely, the results also provide support for opponents of the ban. The substantial loss in consumer surplus for Black Americans highlights the economic and social costs of the policy. This loss indicates a significant reduction in consumer welfare, suggesting that the ban imposes considerable inconvenience and dissatisfaction among menthol cigarette smokers, who may feel deprived of their preferred products. Additionally, the fact that 53% of Black menthol cigarette smokers switch to regular tobacco cigarettes instead of quitting entirely suggests that the ban might not fully achieve its intended public health benefits, as many smokers continue to consume tobacco products.

Comparing our results to prior works, Levy et al. (2023) evaluated the expected impact of a menthol cigarette ban through the use of an expert elicitation on behavioral changes resulting from the removal of menthol cigarettes. They find an expected decline in the cigarette smoking

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[28]The consumer surplus calculations in our work do not incorporate the potential increase in surplus stemming from longer life expectancy or improved health outcomes. Instead, they provide a method to compare preferences between policies that yield equivalent reductions in the smoking rate.

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%	(-35.10%)	10.00%	(-35.11%)
	Non-Black	15.76%	14.30%	(-9.28%)	14.30%	(-9.30%)
	High-Income	14.91%	13.22%	(-11.35%)	13.22%	(-11.36%)
	Low-Income	17.75%	15.06%	(-15.16%)	15.06%	(-15.19%)
	Average	**15.72%**	**13.74%**	**(-12.57%)**	**13.74%**	**(-12.59%)**
E-Cigarettes	Black	0.23%	0.25%	(+12.27%)	0.28%	(+23.09%)
	Non-Black	0.48%	0.51%	(+4.40%)	0.53%	(+10.08%)
	High-Income	0.43%	0.45%	(+3.78%)	0.47%	(+8.94%)
	Low-Income	0.49%	0.53%	(+7.48%)	0.57%	(+15.45%)
	Average	**0.45%**	**0.47%**	**(+4.93%)**	**0.50%**	**(+10.94%)**
Cessation		0.47%	0.48%	(+1.74%)	0.48%	(+1.74%)

[a]The table above reports expected weekly rates of product usage under the assumption of a menthol cigarette ban, averaged across all weeks from April 2015 to April 2019.

rate of 15%; our results suggest a similar—if slightly smaller—reduction. With regard to changes in the smoking rate among Black Americans, Issabakhsh et al. (2024) 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. Again, our counterfactual study suggests a similar change in cigarette usage among the Black community.

Finally, we find the menthol cigarette ban is associated with a rise in the sale of electronic smoking devices, the amount of which differs depending upon the assumption of independent or merged producers. Under the assumption of independent producers, we find the menthol cigarette ban is associated with a 5% rise in the average weekly consumption of e-cigarettes. Unsurprisingly, Black households experience the largest increase in the e-cigarette smoking rate—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 11%. Ultimately, we find the vast majority of smokers who quit cigarettes under a menthol cigarette ban do not substitute their consumption to other nicotine products, i.e., e-cigarettes and cessation products. These results mirror those observed in Ontario, Canada, where, despite a portion of consumers indicating willingness pre-ban to switch to e-cigarettes, research by Chaiton et al. (2020) did not find a significant association between Ontario's menthol cigarette ban (implemented in 2017) and e-cigarette usage. This result bodes well for policymakers concerned about the continuation of addiction through the use of electronic smoking devices post-ban.

However, we must note that for much of our sample, the share of e-cigarette usage remained quite small, but there was a dramatic rise post January 2018. As such, the willingness to substitute to e-cigarettes is very much time-dependent, rising alongside the growth in the popularity of electronic smoking products. Additionally, our counterfactual analysis does not consider that marketing practices by e-cigarette companies may change in an attempt to draw disenfranchised cigarette smokers post-ban.

Cigarette Taxation   For decades, sin taxes—excise taxes placed on items like tobacco, alcohol, and gambling—have funded health, education, and other public programs. For instance, states such as Arizona, New Hampshire, Virginia, and Colorado use revenue from cigarette sales taxes to support initiatives ranging from public education to economic revitalization projects. However, in recent years, tax revenue from tobacco products has declined alongside falling smoking rates, and the FDA's proposed menthol cigarette ban may lead to the steepest reduction yet.

As an alternative to the menthol cigarette ban, we find that an additional $1.02 national sales tax per pack of 20 cigarettes, imposed in addition to current state and federal taxes, could achieve an equivalent reduction in the average weekly cigarette smoking rate (see Table 9). Further, under taxation, the average household faces a reduction in consumer surplus of 14.1% to 14.2% (under merged and independent producers, respectively), whereas the proposed menthol cigarette ban reduces consumer surplus by 15.7% to 15.8%. Of greater disparity is the reduction in consumer surplus experienced by Black households: taxation results in a consumer surplus reduction of 14% regardless of merger status, whereas the proposed menthol cigarette ban lowers consumer surplus by 42.7% to 42.9%. Black households largely prefer menthol products, and a $1.02 national cigarette sales tax reduces consumption among Black households far less than the proposed menthol cigarette ban; therefore it is only logical that Black Americans would prefer a national sales tax as opposed to the removal of menthol cigarettes.

On average, changes in consumer surplus indicate a clear preference for taxation rather than an outright product ban. When focusing on income, we find that among low-income households—those often most impacted by sales taxation policies—a $1.02 national cigarette sales tax results in a smaller reduction in consumer surplus compared to the removal of menthol cigarettes. Low-income households face a reduction in consumer surplus ranging from 14.3% to 14.4% under taxation, versus a loss of 18.7% to 18.9% under the menthol cigarette ban (under merged and independent producers, respectively). Similarly, high-income households also show a preference for taxation over the menthol cigarette ban, although this preference is not as pronounced as that of their low-income counterparts.

Among all demographic groups (Black, non-Black, high-income, and low-income), only one

Table 9: Average Weekly Rate of Product Usage: Cigarette Tax ($1.02)[a]

			Independent Producers		Merged Producers	
		Without Tax	With Tax	% Change	With Tax	% Change
Cigarettes	Black	15.41%	13.51%	(-12.30%)	13.51%	(-12.31%)
	Non-Black	15.76%	13.78%	(-12.58%)	13.78%	(-12.60%)
	High-Income	14.91%	13.04%	(-12.57%)	13.04%	(-12.59%)
	Low-Income	17.75%	15.53%	(-12.49%)	15.53%	(-12.51%)
	Average	**15.72%**	**13.75%**	**(-12.55%)**	**13.74%**	**(-12.56%)**
E-Cigarettes	Black	0.23%	0.23%	(+2.43%)	0.24%	(+5.78%)
	Non-Black	0.48%	0.50%	(+2.60%)	0.51%	(+5.58%)
	High-Income	0.43%	0.44%	(+2.35%)	0.46%	(+5.18%)
	Low-Income	0.49%	0.51%	(+3.19%)	0.52%	(+6.53%)
	Average	**0.45%**	**0.46%**	**(+2.62%)**	**0.48%**	**(+5.62%)**
Cessation		0.47%	0.48%	(+1.78%)	0.48%	(+1.76%)

[a]The table above reports expected weekly rates of product usage under the assumption of a $1.02 national cigarette sales tax, averaged across all weeks from April 2015 to April 2019.

displayed a preference for the menthol cigarette ban over taxation: non-Black households. This preference is likely due to the fact that non-Black smokers smoke menthol cigarettes approximately 33% of the time, compared to Black smokers who smoke menthol cigarettes about 75% of the time. Consequently, the impact of a menthol cigarette ban is less severe for non-Black households. In contrast, Black households, who are more dependent on menthol products, face a significantly greater reduction in consumer surplus under the ban, making taxation a more favorable alternative. This result highlights the importance of considering the disproportionate effects of tobacco control policies on different demographic groups to ensure that public health strategies do not inadvertently exacerbate existing inequities.

Lastly, under taxation, e-cigarette usage does not experience the same increase in demand as under the menthol cigarette ban, as smokers with a high menthol preference are not seeking alternatives among e-cigarettes. As in the prior counterfactual, the assumption of merged producers results in greater e-cigarette usage rates through coordinated pricing strategies between 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 as provided via the household-level data. We find a $1.02 national sales tax per pack of cigarettes generates an average tax revenue of $114.6 million each week across the 100 DMAs making up our sample, for a total tax revenue of $24.4 billion over the period from April 2015

through April 2019.[29] Tax revenue generated has the potential to replace that lost at the state and federal levels as a result of declining smoking rates.

However, to paraphrase FDA commissioner Janet Woodcock, the primary objective of the proposed menthol cigarette ban is to address health disparities resulting from unscrupulous marketing practices, particularly in communities of color; concerns of tax revenue are secondary to this overarching goal (FDA, 2021). For this purpose, an outright menthol cigarette ban has the greatest effect. Despite this, the burden of the ban disproportionately falls on Black households. A $1.02 national sales tax per pack of cigarettes, on the other hand, could generate significant tax revenue while imposing a smaller reduction in consumer surplus. Therefore, while the menthol cigarette ban addresses critical health disparities, many Black Americans might prefer a tax-based approach that balances public health goals with economic considerations, reducing smoking rates without the severe economic impact of an outright ban.

Flavorant Ban   Pending 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, with flavored cartridges being banned since 2020 in an attempt to reduce youth consumption. Further, lawmakers in California, New York, Massachusetts, and New Jersey have passed some forms of flavored product restriction, while many other states have opted to ban the purchasing of flavored products through online marketplaces—avenues of illegal sales to youth and young adults. Therefore, it would be remiss of us not 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 cigarette ban. In addition, the fall in the Black smoking rate mirrors that seen under the menthol cigarette 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% (depending on supply-side assumptions). However, the reduction in weekly e-cigarette usage as a result of a flavorant ban is very much time-dependent.

The e-cigarette market in the last third of our sample was 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 usage should be considered on a week-by-week basis. Figure 6 graphs the weekly expected percent reduction in e-cigarette usage upon the removal of product

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[29]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 efforts.

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%	(-35.07%)	10.02%	(-34.96%)
	Non-Black	15.76%	14.32%	(-9.17%)	14.34%	(-9.04%)
	High-Income	14.91%	13.24%	(-11.24%)	13.25%	(-11.11%)
	Low-Income	17.75%	15.08%	(-15.07%)	15.10%	(-14.94%)
	Average	**15.72%**	**13.76%**	**(-12.47%)**	**13.78%**	**(-12.34%)**
E-Cigarettes	Black	0.23%	0.06	(-72.41%)	0.07%	(-71.21%)
	Non-Black	0.48%	0.27%	(-44.65%)	0.28%	(-42.89%)
	High-Income	0.43%	0.23%	(-46.83%)	0.24%	(-45.10%)
	Low-Income	0.49%	0.27%	(-45.63%)	0.28%	(-43.88%)
	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 ban, averaged across all weeks from April 2015 to April 2019.

flavorants, as compared to the status quo.

As the popularity of flavored e-cigarettes grows, so does the impact of a flavorant ban. We find the 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.

9 Conclusion

In this paper, we employ a model of consumer demand that incorporates retail- and household-level data to study consumer demand for cigarette and e-cigarette flavorants and evaluate the impact of the proposed menthol cigarette ban and other counterfactual scenarios. Our work is among the first to analyze the effects of flavorant bans on the demand for cigarettes, e-cigarettes and cessation products, and is the only work that incorporates addiction, categorical substitution, as well as both retail- and household-level data in the study of these effects.

We show that the menthol cigarette ban reduces consumption significantly, resulting in a 12.6% decrease in the average weekly smoking rate across all households. By considering a rich set of heterogeneous parameters, we find that demographic differences play an important role in consumers' responsiveness to the ban. In particular, Black households reduce their cigarette consumption by 35% when faced with the removal of menthol cigarettes, a much larger reduction than that experienced by other demographic groups.

Figure 6: Percent Change in Weekly E-cigarette Usage Relative to the Status Quo
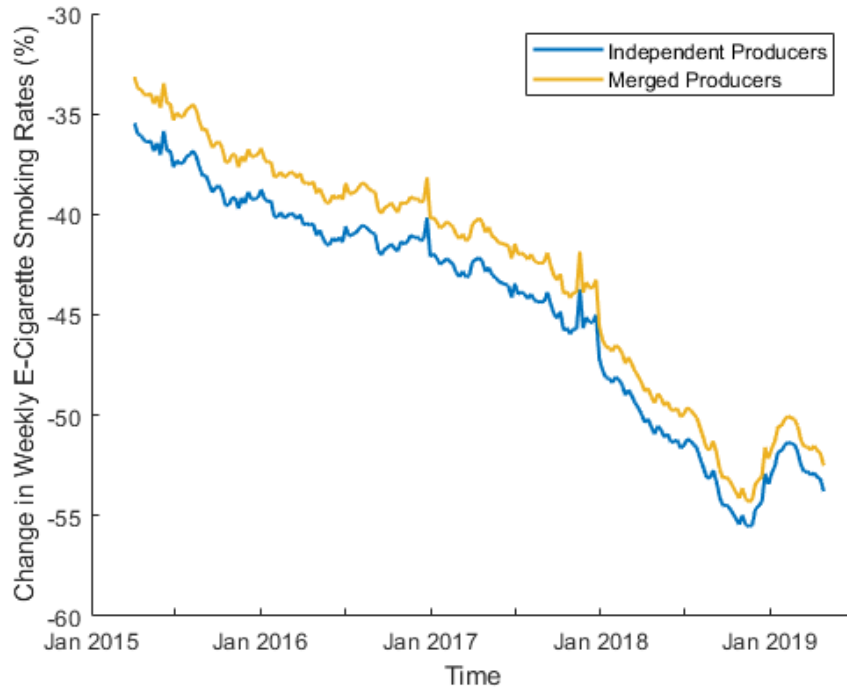
To more comprehensively evaluate the menthol cigarette ban, we compare it with an alternative policy. A $1.02 national sales tax per pack of 20 cigarettes is as effective in reducing the weekly cigarette smoking rate among all households, but results in a smaller reduction in consumer surplus—significantly smaller when considering Black households alone. On the other hand, the cigarette sales tax induces a much smaller reduction in cigarette smoking among Black households, and therefore may not fulfill the intent of the menthol cigarette ban, whose primary objective is to address health disparities resulting from unscrupulous marketing practices that promoted menthol cigarettes to the Black community.

Furthermore, our analysis reveals that while an outright menthol cigarette ban effectively reduces the Black smoking rate, it also imposes a substantial economic burden on Black households, who predominantly prefer menthol products. Under the menthol cigarette ban, Black households experience a 43% reduction in consumer surplus, tripling the 14% reduction under a $1.02 national sales tax.

Additionally, we consider a counterfactual scenario in which all menthol and flavored products for both cigarettes and e-cigarettes are banned. We find that the reduction in e-cigarette usage under such a ban is time-dependent, increasing from around 40% in the period before 2018 to more than 50% in the period since 2018, as the market share of flavored e-cigarettes grew

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rapidly in the latter period.

Our study underscores the importance of considering the unique preferences of the Black community when devising tobacco control policies. The proposed menthol cigarette ban, which has been under heavy debate and has now been delayed indefinitely, highlights the complexity of implementing such measures. Policymakers must weigh the public health benefits of a menthol cigarette ban against its economic drawbacks, recognizing that a taxation scheme may offer a more balanced solution. Our findings equip decision-makers with useful data for crafting policies that not only reduce smoking rates but also promote social and economic equity.

Finally, 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 resulting from the reduction in the usage of tobacco products. 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 (such as voluntary advertising restrictions and health warning labels) 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, and 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 contain 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 are removed because they primarily consist of rechargeable smoking devices 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. Disposable e-cigarettes are generally sold individually or in packs of 10, with each unit containing a nicotine content equivalent to 1-1.5 cigarette packs and 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 taxes. 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 convert the sizes of lozenges and gum to a standardized 4 mg per piece, with 15 pieces costing about $8.50 and providing about the same nicotine as one cigarette pack. Nicotine patches are most commonly sold in packs of 7 or 14, with one patch providing a nicotine content equivalent to 1 pack of cigarettes and costing around $4. In our analysis, based on nicotine content, we consider one pack of cigarettes equivalent to one e-cigarette cartridge, one disposable e-cigarette unit, 15 pieces of 4 mg nicotine lozenges/gum, 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 be-

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[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% below the modal price in each DMA. Weekly cigarette DMA-level price is taken

havior 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). To control for outliers in our sample—particularly on-again, off-again smokers—we narrow down our sample to those store trips where the difference between the current and next purchase dates 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 trip on cigarette sale 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 the time between cigarette purchase occasions.

Table A1: Days Until Next Store Trip Regressed on Cigarette Sale Occasions

	Coefficient
Sale Occasions	-.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.

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

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

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

to be the quantity weighted average price of all observed sales at the DMA/week level.

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 draws 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 probabilities conditioned upon prior consumption status $C_{rg,t-1}$ as well as x, p_{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

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

until the relative difference between δ_{mt}^{k+1} and δ_{mt}^{k} is less than our tolerance of $1e^{-13}$. Note, λ 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). 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 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 category-level price across all markets, excluding the market in question, as an instrument for the market prices within that category.

[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.

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

	Mean Utility	
	OLS	With Price IV
Price	-0.301***	-0.290***
	(0.013)	(0.012)
Cigarette	-1.313***	-1.375***
	(0.084)	(0.078)
E-cigarette	-7.403***	-7.452***
	(0.174)	(0.188)
Cessation	-6.488***	-6.581***
	(0.174)	(0.157)
Menthol	-0.793***	-0.794***
	(0.054)	(0.054)
Menthol × E-cig.	-0.268***	-0.267***
	(0.031)	(0.030)
Flavored	0.081	0.072
	(0.068)	(0.070)
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. To avoid perfect collinearity, we exclude the flavor of tobacco.

Using this instrument decreases the price response in our model. Typically, one would expect an instrument for price to increase the price response, as companies often raise prices when demand rises. However, our data includes e-cigarettes, a relatively new product. As the popularity of e-cigarettes rose over our model's time period, we observed an increase in product entry, an increase in competition, and a decrease in product prices. This price reduction can possibly be attributed to heightened competition and reduced production costs correlated with the rising demand for e-cigarettes. These factors could then contribute to endogenous behavior that mitigates the price response.

Specifically, the interaction between rising demand and decreasing prices creates two competing effects. On one hand, increased demand would normally drive prices up through endogenous firm behavior. On the other hand, the increased competition and economies of scale in production endogenously drive prices down as demand increases. In our model, these dynamics result in the instrumented price response falling (in absolute value) from -.30 to -.29. The

instrument's role in capturing this nuanced relationship explains why the expected increase in price response does not occur; instead, the price response is slightly dampened, reflecting the unique market conditions of the e-cigarette industry during its growth phase.

A5   Supply-Side Model

In this appendix, we detail how we calculate counterfactual prices based on the demand estimates found in Section 7. First, under the assumption that prices are set optimally, marginal costs are inferred from observed prices and 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. The first-order condition with respect to the price of product j in the set of products $\mathcal{J}_f$ sold by firm f in time t (we drop the market m subscript; prices are set at the market level) is

$$0 = \frac{\partial \pi_f}{\partial p_{jt}} = \frac{\partial}{\partial p_{jt}} \sum_{k=1}^{T} \sum_{n \in \mathcal{J}_f} S_{nk}(p_{nk} - mc_{nk}) = S_{jt} + \sum_{k=1}^{T} \sum_{n \in \mathcal{J}_f} \frac{\partial S_{nk}}{\partial p_{jt}}(p_{nk} - mc_{nk}),$$

which can be rewritten in vector form as

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

where $S = (S_{11}, \ldots, S_{J1}, \ldots, S_{JT})'$, $p = (p_{11}, \ldots, p_{J1}, \ldots, p_{JT})'$, $mc = (mc_{11}, \ldots, mc_{J1}, \ldots, mc_{JT})'$, and 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

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

with the (n, j) element of $\Delta_{k,t}$ equal to $\frac{\partial S_{nk}}{\partial p_{jt}}$ if 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 imposition of cigarette taxes. We assume that these changes do not impact our demand parameters or marginal costs. Provided a gradient vector comprising the first-order conditions for profit maximization, we find the vector of firm prices

such that $\hat{p}_f$ maximizes firm profits. In application, we iterate over the firms, maximizing each firm's profits given the other firms' 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 worldwide 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) finds the total proportion of illegal cigarette sales rose slightly over the latter half of their sample period, from 7.1% in 2003 to 8.5% by 2011.

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

[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%. The lower end, 8.5%, is the committee's own estimate and is found by comparing total tax-paid sales with self-reported consumption.

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 cigarette ban. In consideration of Massachusetts' 2020 menthol cigarette ban, Ali et al. (2022) find no significant impact on cross-border sales in neighboring states, where menthol products remain accessible to consumers and smugglers. Similarly, an analysis of the 2015 Nova Scotia menthol cigarette ban finds no significant increase in the seizure of illicit cigarettes post-ban, suggesting that the sale of illicit cigarettes is unlikely to be increasing in response to the removal of mentholated products (Stoklosa, 2019). Finally, Fong et al. (2022b) compare the purchases by Canadian smokers pre- and post-ban and find no increase in the self-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 prices, and Paraje et al. (2022) hypothesize that, on a global scale, common reductions in cigarette affordability have largely stymied growth of illicit trade and led to similar reductions in 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.