Understanding the Demand-Side of an Illegal Market: Prohibition of Menthol Cigarettes

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Abstract

The Food and Drug Administration has proposed to prohibit menthol cigarettes, which are smoked by almost 19 million people. Illegal markets for menthol cigarettes could not only blunt the prohibition's intended consequence to reduce smoking but could also lead to unintended consequences. We use data from a discrete choice experiment to estimate a mixed logit model which predicts that the prohibition of menthol cigarettes would substantially increase the fraction of menthol smokers who attempt to quit tobacco product use. However, our model also predicts a substantial potential consumer demand for illegal menthol cigarettes, especially if menthol e-cigarettes are also illegal. JEL Codes: I12, D12.

I. Introduction

After more than a decade of public discussion, in April 2022 the U.S. Food and Drug Administration (FDA) put forth a proposal for "a tobacco product standard that would prohibit menthol as a characterizing flavor in cigarettes" (FDA 2022).[1] Menthol cigarettes are tobacco cigarettes to which natural menthol from mint or synthetic menthol has been added as a flavoring; menthol and non-menthol cigarettes have similar nicotine- and tar-content. Menthol prohibition could be a significant public health policy. According to the FDA, almost 19 million people currently smoke menthol cigarettes, and if they continue to smoke many of them will die from heart disease, lung cancer, or another smoking-related disease. Almost 85 percent of Black smokers use menthol cigarettes as their usual type, compared to 30 percent of white smokers. The FDA describes the prohibition of menthol cigarettes as a targeted step to prevent youth from starting to smoke, help more current smokers quit, and address tobacco-related health disparities.

Illegal markets for menthol cigarettes could not only blunt the prohibition's intended consequence to reduce smoking but could also lead to unintended consequences including implications for racial justice (American Civil Liberties Union 2021). The World Bank (2019) cites a consensus estimate that illegal trade accounts for 10 percent of global cigarette consumption. A National Academy of Sciences study concludes that illicit cigarettes sales accounted for between 8.5 percent and 21 percent of the total cigarette U.S. cigarette market (National Research Council 2015). Illicit cigarette sales in the U.S. mainly reflect two types of tax avoidance behavior. First, smokers in states with high cigarette excise taxes purchase their cigarettes in lower-tax states or from Native American reservations where state taxes are not collected (Lovenheim 2008; DeCicca, Kenkel and Liu 2013, 2015; Bishop 2018). Second,

[1] The finalized version of the proposal has not yet been published. The Fall 2023 Regulatory Agenda lists March 2024 as the anticipated date for publication of the Final Rule.

smokers in some large cities purchase cigarettes in illegal retail or street markets, where again most of the supply originates in lower-tax jurisdictions (Kurti, von Lampe, and Johnson 2014; Prieger 2022). Illegal cigarette markets raise racial justice concerns about unequal enforcement, especially in light of the death of Eric Garner who was killed by police in an attempt to arrest him for selling illegal single cigarettes (American Civil Liberties Union 2021). Because a national prohibition of menthol could not be avoided by cross-state purchases, in its preliminary regulatory impact analysis the FDA (2022, p. 212) concluded that that the impact of menthol prohibition on the illicit cigarette market "would not be significant."

We conducted an online discrete choice experiment (DCE) where adult menthol smokers made hypothetical choices between menthol and non-menthol cigarettes, menthol and non-menthol e-cigarettes, and attempting to quit.[2] Our DCE presented subjects with different choice scenarios where menthol cigarettes are described as either legal, prohibited but available under-the-counter and online from retailers who continue to sell them, or prohibited and strictly enforced and only available from illegal dealers. The DCE allows us to estimate the impact of possible supply-sides of an illegal menthol market on consumers' choices. The menthol prohibition can achieve its intended consequences of improved health and reduced health disparities if menthol smokers switch to less harmful e-cigarettes or quit tobacco product use entirely. But to the extent we find that menthol smokers are willing to switch to non-menthol cigarettes or to illegal menthols, the prohibition's impact on public health and health disparities will be blunted.

[2] We included results from our preliminary analysis of the DCE data in a public comment submitted to the FDA on the proposed rule to prohibit menthol cigarettes. The comment is available online at: https://www.regulations.gov/comment/FDA-2021-N-1349-175778

We contribute new evidence on the likely impacts of the prohibition of menthol cigarettes. We estimate a mixed logit model which predicts that the prohibition of menthol cigarettes would substantially increase the fraction of menthol smokers who attempt to quit tobacco product use. However, our model also predicts a substantial potential consumer demand for illegal menthol cigarettes, especially if menthol e-cigarettes are also illegal. Although menthol e-cigarettes are currently widely available, the FDA has issued marketing denial orders which, if strictly enforced, would result in a *de facto* prohibition of menthol e-cigarettes. Our estimated model predicts that, depending on the impact of illegality on product prices, the potential demand-side of an illegal market for menthol cigarettes could be 59-92 percent the size of the status quo market if menthol e-cigarettes are legal, and 69-100 percent the size of the status quo market if menthol e-cigarettes are also illegal. The results are robust to sub-group analysis for Black versus non-Black subjects.

Discrete choice experiments are commonly used in marketing research and economics to provide predictions of consumer demand in scenarios that are not yet observed in actual markets, as is the case with the proposed national prohibition of menthol cigarettes.[3] Research on external validity reaches a consensus that subjects' stated preferences can provide valuable information and predict actual choices in markets (Carson 2014, McFadden 2017).[4] Instead of using stated preference data, another approach to estimate the impact of the proposed menthol prohibition is to extrapolate results from other countries. Carpenter and Nguyen (2021) point out that public health research on the prohibition of menthol cigarettes in Canada and the European Union does

[3] In economics, for example, Kesternich, Heiss, McFadden, and Winter (2012) report a discrete choice experiment about consumers' decisions to purchase Medicare Part D insurance plans, which was conducted before Part D plans were on the market. Moshary, Drango, and Shapiro (2023) use data from a discrete choice experiment about consumers' choices to purchase firearms to study alternative counter-factual firearm regulations.
[4] The Online Appendix includes a literature review of research on the external validity of predictions from DCEs.

not use quasi-experimental methods required for causal inference. Carpenter and Nguyen (2021) estimate difference-in-difference models of the menthol prohibitions enacted in some Canadian provinces prior to the national prohibition. They estimate that the prohibitions did not decrease overall smoking rates. Carpenter and Nguyen also find evidence that among adult smokers, the prohibitions increased purchases on First Nations reserves, where menthol cigarettes remained legally available for First Nations' peoples but were illegal for non-First Nations customers. In its preliminary regulatory impact analysis, the FDA (2022) relies on public health research and an expert elicitation in which 11 experts were asked to predict the impacts of a prohibition of menthol cigarettes in the U.S. (Levy et al. 2021).

Given the gaps in the existing research base, we believe the stated preference results from our study make a valuable contribution to predict the results of a prohibition of menthol cigarettes. In addition to the lack of quasi-experimental methods, research findings on national prohibitions in Canada and the E.U. might not generalize to the U.S.[5] The E.U. prohibition is more limited than the FDA proposal because it allows for the sale of certain menthol flavored tobacco products like cigars, cigarillos, snus, and pipe tobacco, menthol e-cigarettes and heated tobacco products, as well as the sale of menthol flavored filters, cards and sprays (Brink et al 2022, Hiscock 2020). Moreover, the high market share of menthol cigarettes among U.S. Black smokers raises unique issues for racial disparities and racial justice.

Our study also contributes more broadly to a line of economic research on illegal markets. Economic research has long focused on illegal markets for drugs, including the comparison of prohibition versus legalization combined with excise taxation (Becker, Grossman,

[5] Researchers are beginning to study the menthol prohibitions in Massachusetts in June 2020 and in California in December 2022. State-level menthol prohibitions might not generalize to a national prohibition because of the much different opportunities to avoid the prohibition through cross-border purchases.

Murphy 2006). A recent line of research addresses the continuing opioid epidemic in the U.S. (Alpert, Powell, and Pacula 2018; Cutler and Donahoe 2024). Policy developments also pose new research questions. A number of states have legalized recreational marijuana, which raises research questions about the consequences for public health (Anderson and Rees 2021). Another policy development is to prohibit products with certain attributes, such as proposals to prohibit certain types of firearms (Moshary, Drango, and Shapiro 2023), the proposal to prohibit menthol cigarettes studied in this paper, and a pending proposal to prohibit addictive levels of nicotine in cigarettes. Our use of a discrete choice experiment to collect stated preference data contributes an example of a useful research method to study the economics of both the starts and ends of prohibitions.

This paper proceeds as follows. Section II discusses our discrete choice experiment and the resulting sample. Section III presents the empirical model and results. Section IV reports a cost-benefit analysis of menthol prohibition as a policy to reduce externalities from secondhand smoke. Section V provides a concluding discussion, including possible supply-side responses.

II. Data

The data are from an online discrete choice experiment (DCE) conducted in April 2022 which we designed to evaluate the impact of the prohibition of menthol cigarettes. Subjects were presented with four product choice options – non-menthol and menthol cigarettes and e-cigarettes – and a fifth option "I will quit smoking cigarettes and not use e-cigarettes." Product prices and legality were experimentally varied across three levels: a 3 (non-menthol cigarette price) by 3 (menthol cigarette price) by 3 (non-menthol e-cigarette price) by 3 (menthol e-cigarette price) by 3 (menthol cigarette legality conditions) by 3 (menthol e-cigarette legality conditions) experimental design, for a total of 729 possible combinations. Because 729 choice tasks would be too demanding, each subject was presented with 12 choice tasks. Different subjects were assigned different sets of scenarios; across all subjects the DCE presented 108 of the 729 possibilities. The number of products, attribute levels, and scenarios follow good practice guidelines for DCEs (Johnson et al. 2013). The assignment of scenarios to subjects was designed to maximize statistical efficiency to identify the parameters of interest.

In the DCE, after introductory material that sets the context, subjects are then presented with one of the possible choice sets and were asked to make two choices. First, each subject is asked about their choice today. After the choice for today is made, the scenario reappears, and the subject is asked which choice they would make 6 months from now. This process is repeated 12 times (with different combinations of product attributes), so that we collect 24 choices per subject. Figure 1 shows the introductory material and an example of a DCE scenario.

The survey firm SSRS conducted our online survey.[6] SSRS recruited subjects from their Probability Panel and screened on eligibility for our experiment based on age, current smoker status, and menthol use. We required respondents to be over the age of 18, to have smoked 100 or more cigarettes in their life, to currently smoke either daily or some days, and to usually smoke menthol cigarettes. 673 adult smokers completed our DCE. After dropping subjects with extreme values of the reported price they last paid for 20 cigarettes (less than $1.00 or more than $20.00 per pack), our sample of analysis consists of 639 subjects, each of whom contributes 12

[6] Survey respondents were obtained using the SSRS Probability Panel. SSRS Opinion Panel members are recruited randomly based on nationally representative ABS (Address Based Sample) design (including Hawaii and Alaska). ABS respondents are randomly sampled by MSG through the U.S. Postal Service's Computerized Delivery Sequence (CDS), a regularly updated listing of all known addresses in the U.S. For the SSRS Opinion Panel, known business addresses are excluded from the sample frame. Additionally, the SSRS Opinion Panel recruit hard-to-reach demographic groups via the SSRS Omnibus survey platform. The SSRS Omnibus completes more than 50,000 surveys annually with 80 percent cell allocation.

choice outcomes for a total of 7,668 observations of current and 7,668 observations of 6-months-from-now choices.

We designed our DCE to explore several possible supply-sides of potential illegal markets for menthol cigarettes and e-cigarettes. Smokers in some large cities currently purchase cigarettes in illegal markets to avoid paying high state and city excise taxes (Kurti, von Lampe, and Johnson 2014, Prieger 2022). By one recent estimate, there are about 8,000 illegal smoke shops selling tobacco and cannabis products in New York City (New York City Council 2023). Qualitative ethnographic research on illegal cigarette sales in the South Bronx describes consumer attitudes favoring under-the-counter purchases from retailers like bodegas over purchases from illegal dealers on the street (von Lampe et al., 2016). Our DCE included three levels of the legality condition: legal, prohibited but still available from retailers under-the counter or online, or prohibited and strictly enforced availability only from illegal dealers, e.g. street sellers.

In our DCE we also varied the levels of product prices to explore different possible supply-sides of potential illegal markets for menthol products. Illegality adds costs to the supply chain of illegal products and tends to raise prices (Miron 2003). But because cigarettes are subject to local, state, and federal excise taxes, in some jurisdictions the price of untaxed illegal cigarettes might still be lower than the price of taxed legal cigarettes. For example, in New York City the price of legal cigarettes includes $1.50 local tax, $4.35 state tax, and $1.01 federal tax per pack, which together account for almost 50 percent of the average retail price. In other, lower-tax, jurisdictions, the extra supply-chain costs of illegal cigarettes might more than offset the tax savings. An FDA white paper discusses evidence on the impact of illegality on cigarette prices, including an example from Statistics Canada where prices for illegal cigarettes are thirty percent of legal prices (FDA 2018). The FDA white paper concludes that depending on the context surrounding the illegal market, it is difficult to estimate if the expected price level will be higher or lower than the current market price. Our DCE included three levels of cigarette prices: the price the subject reported paying for their last pack of cigarettes, half that price, or twice that price. E-cigarette price levels could not be set based on the price the subject paid, because many subjects had not previously purchased e-cigarettes. Based on then-current market prices, the experimental e-cigarette price conditions were \$2, \$4, or \$8 for a pack-equivalent e-cigarette.

The DCE was part of a survey that consisted of three sections. The first section included questions focused on their cigarette, e-cigarette, and other tobacco products' consumption habits including frequency of consumption, history of menthol use, location of purchase, previous quit attempts, their intention to quit in the next 6 months and methods they intend to use to quit. Questions were also asked which enabled us to compute the price they last paid for cigarettes. The second section of the survey consisted of presentation of the 12 scenarios/ choice tasks in the DCE. The third section of the survey included follow-up questions that were asked after the DCE to avoid influencing stated preferences. The third section included questions about subjects' knowledge about the proposed prohibition of menthol and their perceptions of its impact. Table A1 in the Online Appendix provides descriptive statistics.

III. Empirical Model and Results

We use our DCE data to estimate a random coefficients mixed logit model of consumer tobacco product choices. Mixed logit is a highly flexible model that allows individual heterogeneity to interact with product characteristics. It relaxes the independence of irrelevant alternatives assumption of McFadden's conditional logit model. Our mixed logit model is based on a random utility model, where individual i's indirect utility from product j at time (choice task) t is linear and additively separable in an alternative specific constant (ASC), the tobacco product's price, and the legal availability of the tobacco product:

$$\boldsymbol{U_{ijt} = ASC_{ijt} + \alpha_i p_{ijt} + \beta_i' Legal\ Availability_{ijt} + \epsilon_{ijt}}$$

The ASCs capture the baseline utility from each tobacco product or the alternative of quitting; the ASC for the alternative of quitting is the omitted category. The ASCs are assumed to have normal distributions. The coefficients α_i and β_i are assumed to have lognormal distributions, which restricts the signs of the effects of these attributes on consumer utility. The variables measuring cigarette and e-cigarette prices are linearized versions of the experimentally assigned price levels. Legal availability takes three levels: legal and available where the subject usually buys cigarettes, prohibited and available under-the-counter and online from some retailers who continue to sell prohibited menthol products, and a strictly enforced prohibition where the products are available from illegal dealers, e.g., street sellers. For convenience we will refer to the legal availability conditions as: legal, illegal retail market, and illegal street market. In the empirical model, legal is the omitted baseline category. The model includes four indicators for two illegality levels for both menthol cigarettes and menthol e-cigarettes.

Table 1 presents the estimated mixed logit model of consumer tobacco product choices. The sizes of the ASCs show that in our sample of menthol smokers, the most preferred option is menthol cigarettes, followed by menthol e-cigarettes, attempting to quit (the omitted alternative), non-menthol cigarettes, and tobacco-flavored e-cigarettes. As expected, the mean of the price coefficient is negative. The legality condition coefficients show consumer disutility from the illegality of tobacco products; more strict illegal street markets impose more disutility; illegal markets for menthol cigarettes and menthol e-cigarettes impose similar levels of disutility.

We use the estimated mixed logit model to predict consumer choices under the status quo market conditions and various policy scenarios. Table 2 presents the predicted market shares, i.e., the fraction of subjects who choose each tobacco product or quitting under the conditions described. For the status quo market condition, we predict choices when menthol cigarettes and menthol e-cigarettes are legal, the prices of menthol cigarettes are the prices the subject reported paying for their last pack, and the price of a cigarette pack-equivalent of menthol e-cigarettes is $4. Policy scenarios 1-3 predict choices with an illegal retail market for menthol cigarettes and a legal market for menthol e-cigarettes; policy scenarios 4-6 predict choices with illegal retail markets for both menthol cigarettes and e-cigarettes; policy scenarios 7-9 predict choices with an illegal street market for menthol cigarettes and a legal market for menthol e-cigarettes; policy scenarios 10-12 predicts choices with illegal street markets for both menthol cigarettes and e-cigarettes. Because the impact of illegality on prices is unknown, to illustrate the range of possibilities, for each market combination we make three sets of predictions where illegal tobacco prices are either the same as in the status quo, 50 percent higher, or 50 percent lower.

Our model predictions under the status quo market conditions roughly match most of the moments from observational data. The model predictions for immediate choices are that 46 percent of subjects will choose menthol cigarettes, 25 percent will choose menthol e-cigarettes, 16 percent will attempt to quit both cigarettes and e-cigarettes, and the remaining 13 percent will be equally split between non-menthol cigarettes and tobacco-flavored e-cigarettes (Table 2). The subjects' stated preferences for tobacco products roughly match the moments from revealed preference data on their choices, as measured in their responses to our background survey (Online Appendix Table A1). In our sample, dual use of cigarettes and e-cigarettes is common; in the past 30 days, 11 percent vaped daily, and another 40 percent vaped on some days.

Although based on the eligibility screening question the entire sample are current smokers who usually smoke menthol cigarettes, 58 percent are daily smokers and 42 percent are non-daily smokers. However, compared to revealed preference data, the predicted 16 percent share of subjects who will attempt to quit in the immediate choice situation appears to be inflated. The immediate choice situation corresponds to the subject's next tobacco product choices, which will often be within a week. In data from the Population Assessment of Tobacco and Health, 7 percent of smokers plan to quit using tobacco products for good within the next seven days.[7]

McFadden (2017) and other research discussed in the Online Appendix stress the importance of calibrating DCE results to revealed preference data on choices in real-world markets. Figure 2 uses a simple approach to calibrate our DCE results and expresses the predicted market shares under the policy scenarios as fractions of the predicted status quo shares.[8] Although our model predicts that menthol prohibition will shift consumers from menthol cigarettes to other tobacco products and to attempts to quit, under many of the policy scenarios the predicted consumer demand for illegal menthol cigarettes will be substantial (Figure 2). We will limit our discussion to the scenarios where illegality does not result in a net change in menthol cigarette prices. In those baseline scenarios, our model predicts that the illegal retail market share of menthol cigarettes would be 73 percent as large as the status quo and an illegal street market share would be 64 percent as large as the status quo. If FDA marketing denial orders result in a *de facto* prohibition of menthol e-cigarettes, our model predicts that the illegal

[7] Authors' calculations.

[8] The Online Appendix provides additional discussion of DCE calibration and reports the results of a calibrated conditional logit model estimated using data from the background survey combined with the DCE responses (Online Appendix Table D1). Table D1 also reports the sensitivity of conditional logit models of tobacco product choices to two alternative approaches to improve the validity of the data from our DCE. In the first approach we drop responses from 8 "speedster" subjects who completed the choice tasks in under 2 minutes. In the second approach, we drop responses from 106 subjects who were inattentive to variation in the attributes of menthol cigarettes, as determined by their responses to survey questions asked after all the DCE choice tasks were completed. The estimated conditional logit models are not sensitive to any of these approaches to improve data validity.

retail and street market shares of menthol cigarettes could be as large as 82 percent and 75 percent as large as the status quo, respectively.

Of course, the potential size of illegal markets for menthol depends on the supply-side response, as well as the FDA enforcement activities. However, the results of our DCE suggest a potentially strong consumer demand for illegal menthol cigarettes, even if strict enforcement means that menthol cigarettes will only be available from street dealers. Our model predicts a much larger consumer demand for illegal menthol cigarettes than some of the estimates from previous research used in the FDA's preliminary regulatory impact analysis (FDA 2022). For example, in the expert elicitation used by the FDA, the mean of the experts' responses was that with a prohibition 6 percent of menthol smokers aged 25-54 will purchase illegal menthol cigarettes (Levy et al. 2021).

Given the high market share of menthol cigarettes among Black smokers and the importance of racial disparities as a rationale for the proposed prohibition, we conduct subgroup analysis for Black versus non-Black subjects (Table 3). As in the full sample models, the results show that in both sub-groups the utility consumers receive from choosing a tobacco product depends on its price and legal availability. The estimated parameters have the same signs and similar but not identical magnitudes across the sub-groups.

The sub-group models yield similar predictions about the impacts of prohibition on the rate of quit attempts in the Black and non-Black sub-groups (Online Appendix Table A4). However, the Black sub-group is predicted to attempt to quit at a higher rate under status quo conditions.[9] As a result, prohibition is predicted to increase the quit attempt rate as a smaller

[9] Under status quo conditions, the predicted rate of quit attempts is 21 percent for the Black sub-group versus 11 percent for the non-Black sub-group. The status quo predictions mirror differences in observational data from the background survey, where 58 percent of the Black sub-group versus 48 percent of the non-Black sub-group report attempting to quit in the past 12 months. Similarly, using observational data from the 2018-2019 Tobacco Use

fraction of status quo quit attempts for the Black sub-group (Online Appendix Figure A1). For example, when prices do not change and menthol e-cigarettes are illegal, the predicted quit attempt rate is 30 percent larger than predicted under status quo conditions for the Black sub-group, compared to 70 percent larger than the status quo for the non-Black sub-group. This difference suggests that the impact of menthol prohibition to reduce racial health disparities might be more limited than expected by the FDA.

The predicted impacts of prohibition on the market share of menthol cigarettes are smaller in the Black sub-group analysis. As a result, the predicted consumer demand for illegal menthol cigarettes is larger in the Black sub-group analysis than in the non-Black sub-group analysis, especially for an illegal street market. For example, when prices do not change and menthol e-cigarettes are illegal, from the Black sub-group model the predicted share of an illegal street market is 88 percent as large as the status quo, while from the non-Black sub-group model the predicted share of an illegal street market is 80 percent as large as the status quo. This difference tends to increase concerns about the racial justice implications of menthol prohibition. The DCE's description of illegal markets informed subjects that the FDA cannot and will not enforce against individual consumers. However, in response to a question asked after the DCE, 36 percent of the Black sub-sample versus 27 percent of the non-Black sub-sample agreed that an illegal menthol purchaser might be subject to arrest.

IV. Cost-Benefit Analysis

In this section we sketch a partial cost-benefit analysis of the prohibition of menthol cigarettes as a policy tool to reduce the externalities created by secondhand smoke. The DCE provide

Supplements to the Current Population Survey, Cheng et al. (2024) find that Black menthol smokers are 6 percentage points more likely to report a past 12 month quit attempt than non-Black menthol smokers.

estimates of the opportunity costs the prohibition imposes on menthol smokers. The mixed logit model reported in Table 1 is estimated in preference space; the estimated coefficients show the impact of the attributes on utility. The price coefficient provides an estimate of the marginal utility of income, so willingness to pay (WTP) for an attribute, for example, Legal Availability, is the ratio of the attribute's coefficient to the price coefficient: $w_i = \beta_i / \alpha_i$. Given that distributional assumptions are imposed on the coefficients, the calculated WTP is a ratio of two distributions, which may not have finite moments. As explained in more detail in the Online Appendix, we re-parameterize the specification to estimate the model in WTP space. The mixed logit model estimated in WTP space implies that the mean WTP to avoid an illegal retail market is \$8.44 per pack, while the mean WTP to avoid an illegal street market is \$10.71 per pack (Online Appendix Table A5). The higher WTP to avoid an illegal street market reflects is consistent with ethnographic research that smokers dislike street markets due to factors such as the extra time and inconvenience costs of obtaining illegal cigarettes and higher perceived risk of arrest and criminal penalties (von Lampe et al. 2016).

To sketch the partial cost-benefit analysis, we assume that the prohibition of menthol cigarettes results in an illegal market where the price of illegal menthol cigarettes is the same as the current price of legal cigarettes. As discussed above, under these conditions our model predicts that the illegal market will be 73 percent as large as the status quo legal market. The size of the current menthol cigarette market per year is 78 billion sticks or 3.9 billion packs of 20 sticks each (FDA 2022, p. 63). The predicted size of the illegal market is therefore 2.8 billion packs. At the mean estimated WTP of \$8.44 per pack, prohibition creates \$24 billion of opportunity costs per year for consumers who continue to purchase and smoke illegal menthol cigarettes. If there is also a *de facto* prohibition of menthol e-cigarettes our model predicts that the illegal market increases to 3.2 billion packs and the opportunity costs for smokers of illegal menthol cigarettes increase to $27 billion.

In addition to imposing opportunity costs on menthol smokers, prohibition of menthol cigarettes also creates supply-side costs of illegal manufacture, smuggling, distribution, and sales. Maintaining our assumption that prohibition does not increase or decrease cigarette prices implies the corollary assumption that the extra supply-side costs created by prohibition equal the current taxes paid on legal sales, which average $3.63 per pack. Multiplied through by the predicted size of the market, for our cost-benefit analysis we assume that the extra opportunity costs of societal resources used to supply illegal menthol cigarettes are worth $10.3 billion per year.

Our partial cost-benefit analysis quantifies the benefits of the prohibition as the value of the reduction in the externalities created by secondhand smoke from menthol cigarettes. The value of the externalities is driven by the value of the mortality risks menthol smoking imposing on non-smokers, which the FDA estimates at 1,605 lives lost per year. Using the FDA's medium value of $11.8 million per statistical life, the value of the reduction in mortality risks from secondhand smoke are worth $18.9 billion per year.

In our partial cost-benefit analysis, the consumer and supply-side opportunity costs of prohibition exceed the value of the reduction in mortality risks from secondhand smoke by $15.4 billion. On the cost side, our analysis does not include the value of resources used in FDA enforcement of the prohibition, the possible racial justice costs of enforcement of the prohibition, and externalities created by illegal markets. On the benefit side, our analysis does not include the value of the reduction in any internalities that menthol smokers impose on themselves. Internalities would arise if due to present bias or other behavioral biases menthol smokers fail to make smoking decisions that maximize their lifetime utility. One approach to estimate the value of reduced internalities is to estimate the total value of menthol smokers' risk reductions, offset by the foregone consumer surplus from menthol cigarettes (Levy, Norton, and Smith 2018). Note however that consumers who purchase and smoke illegal menthol cigarettes after prohibition do not gain any risk reductions/internality benefits and only experience the opportunity costs of illegal markets, which we estimate at $24 billion for them.

V. Concluding Discussion

We contribute evidence from a discrete choice experiment about how current menthol smokers might respond to the prohibition of menthol cigarettes. Our results suggest that the ban could achieve its intended consequence and lead to menthol smokers attempting to quit at rates 14-28 percent higher than currently. However, results also suggest that the demand-side of an illegal market for menthol cigarettes could be far larger than previously estimated, which could lead to unintended consequences.

Our study does not address the supply-side of an illegal menthol market, but the U.S. has long experience with illegal markets that have supplied user demand for other substances. From the 2022 National Survey on Drug Use and Health, there were an estimated 70 million past-year users of illicit drugs, including 62 million past-year users of marijuana, which is illegal at the federal level but legal for recreational use in some states.[10] Other than marijuana, illegal drug use includes: 5 million users of cocaine; 8.5 million users of hallucinogens; 2.7 million users of methamphetamine; and 9 million users of opioids. Given 18.5 million current menthol smokers,

[10] 2022 National Survey of Drug Use and Health Detailed Tables. https://www.samhsa.gov/data/sites/default/files/reports/rpt42728/NSDUHDetailedTabs2022/NSDUHDetailedTabs2022/NSDUHDetTabsSect1pe2022.htm. Accessed 1/19/2024.

the substantial potential consumer demand that we estimate for illegal menthol cigarettes raises the possibility of active illegal market supply-side responses.

The potential development of illegal markets for menthol cigarettes depends in part upon whether the markets will be thick enough to keep down prices and transactions costs. Using variation in market thickness over time, Jacobson (2004) concludes that the larger youth cohorts due to the baby boom reduced arrest risk and provided informational economies in marijuana markets. In contrast, Cook et al. (2007) provide evidence that even in a high-crime neighborhood in Chicago, the small numbers of buyers and sellers of illegal guns led to thin markets with high transaction costs and high prices. The geographic distribution of menthol smokers suggests that many local markets are likely to be thick, at least in larger metropolitan areas. Using data from the 2018-2019 Tobacco Use Supplements to the Current Population Survey, we calculate that the 20 largest metropolitan statistical areas (MSAs) account for 30 percent of menthol smokers. The potential size of illegal menthol markets in these MSAs is on par with or larger than existing thick markets for illegal drugs and is orders of magnitude larger than the thin market for illegal guns studied by Cook et al. (2007).

Our partial cost-benefit analysis concludes that a menthol prohibition's benefits of reducing the externalities from secondhand smoke would be outweighed by the opportunity costs imposed on consumers who continue to smoke illegal menthol cigarettes. An important direction for future work is to conduct a more complete cost-benefit analysis that includes the benefits of reduced internalities for menthol smokers who quit smoking or switch to e-cigarettes in response to the prohibition. Internalities may also play an important role in youth smoking initiation, which our DCE does not address. However, we note that many tobacco control policies already target youth smoking, including the 2020 federal law that increased the national legal purchase age for tobacco products to 21. In the 2023 National Youth Tobacco Survey, 1.6 percent of middle and high school students report past 30-day use of cigarettes (Birdsey et al. 2023).

Cheng et al. (2024) provide evidence that casts doubt on whether adult menthol smokers are different from non-menthol smokers in ways that provide an internality-based rationale to regulate menthol more strictly than non-menthol cigarettes; they find that among smokers, menthol use is associated with less daily smoking, fewer cigarettes smoked per day, later smoking initiation, and less addiction. However, their evidence does not address whether much stronger regulation – perhaps a prohibition – of all cigarettes, not just menthols, would be socially optimal in an applied welfare economics framework. A more complete cost-benefit analysis of the prohibition of menthol cigarettes could also shed light on optimal regulation of non-menthol cigarettes. The analysis could also follow Becker, Grossman, and Murphy (2006) and compare prohibition of menthol or all cigarettes to the alternative of taxation.

References

Alpert, Abby, David Powell, and Rosali Pacula (2018). "Supply-Side Drug Policy in the Presence of Substitutes: Evidence from the Introduction of Abuse-Deterrent Opioids." *American Economic Journal: Economic Policy* 10 (4): 1–35

American Civil Liberties Union (2021) "Letter of Concern from Over Two Dozed Justice, Law Enforcement, Legal, Drug Policy, and Directly Impacted Organizations." Available at: https://www.aclu.org/letter/coalition-letter-concern-hhs-menthol-cigarette-ban

Anderson, D. Mark and Daniel I. Rees (2021). "The Public Health Effects of Legalizing Marijuana." National Bureau of Economic Research Working Paper No. 28647.

Becker, Gary S., Michael Grossman, and Kevin M. Murphy (2006). "The Market for Illegal Goods: The Case of Drugs." *Journal of Political Economy* 114 (1): 38 – 60.

Birdsey J, Cornelius M, Jamal A, et al. (2023). "Tobacco Product Use Among U.S. Middle and High School Students — National Youth Tobacco Survey, 2023." *MMWR Morb Mortal Wkly Rep* 72:1173–1182. DOI: http://dx.doi.org/10.15585/mmwr.mm7244a1

Bishop, JM. (2018). "Does Cigarette Smuggling Prop Up Smoking Rates?" *American Journal of Health Economics* 4 (1): 80-104.

Brink A, Glahn AS, Kjaer NT (2022). "Tobacco companies' exploitation of loopholes in the EU ban on menthol cigarettes: a case study from Denmark." *Tobacco Control*: doi: 10.1136/tobaccocontrol-2021-057213

Carpenter, C.S., & Nguyen, H.V. (2021). "Intended and Unintended Effects of Banning Menthol Cigarettes". *Journal of Law and Economics* 64 (3) :629-650. Available at: https://doi.org/10.1086/713978.

Carson, Richard. T. (2012). Contingent Valuation: A Practical Alternative When Prices Are Not Available." *Journal of Economic Perspectives* 26: 27–42.

Cheng, Yu-Chung (Elisa), Donald Kenkel, Alan Mathios, and Hua Wang (2024). "Are Menthol Smokers Different? An Economic Perspective." *Southern Economic Journal* 90 (3): 577-611.

Cook, Philip J., Jens Ludwig, Sudhir Venkatesh, and Anthony A. Braga (2007). "Underground Gun Markets." *Economic Journal* 117 (524): F588-F618.

Cutler, David and J. Travis Donahoe (2024). "Thick Market Externalities and the Persistence of the Opioid Epidemic." National Bureau of Economic Research Working Paper 32055.

DeCicca, Philip, Donald Kenkel, and Feng Liu (2013). "Excise Tax Avoidance: The Case of State Cigarette Taxes." *Journal of Health Economics* 32: 1130 - 1141.

DeCicca, Philip, Donald Kenkel, and Feng Liu (2015). "Reservation Prices: An Economic Analysis of Cigarette Purchases on Indian Reservations." *National Tax Journal* 68 (1): 93-118.

Food and Drug Administration (2018). “Illegal Trade in Tobacco Products after Implementation of an FDA Product Standard”. https://www.fda.gov/files/tobacco%20products/published/Illegal-Trade-in-Tobacco-Products-After-Implementation-of-an-FDA-Product-Standard.pdf

Food and Drug Administration (2022). “Tobacco Product Standard For Menthol in Cigarettes: Preliminary Regulatory Impact Analysis, Initial Regulatory Flexibility Analysis, Unfunded Mandates Reform Act Analysis.” U.S. Food and Drug Administration. https://www.fda.gov/about-fda/economic-impact-analyses-fda-regulations/tobacco-product-standard-menthol-cigarettes-proposed-rule-preliminary-regulatory-impact-analysis

Hiscock, Rosemary, Silver, K., Zatoński,M., Gilmore, A.B. (2020). “Tobacco Industry Tactics to Circumvent and Undermine the Menthol Cigarette Ban in the UK.” *Tobacco Control*. doi: https://doi.org/10.1136/tobaccocontrol-2020-055769.

Jacobson, Mireille (2004). "Baby Booms and Drug Busts: Trends in Youth Drug use in the United States, 1975–2000," *Quarterly Journal of Economics*, Oxford University Press, vol. 119(4): 1481-1512.

Johnson, F. Reed, Emily Lancsar, Deborah Marshall, Vikram Kilambi, Axel Muehlbacher, Dean A. Regier, Brian W. Bresnahan, Barbara Kanninen, and John F. P. Bridges (2013). Constructing Experimental Designs for Discrete-Choice Experiments: Report of the ISPOR Conjoint Analysis Experimental Design Good Research Practices Task Force. *Value in Health* 16: 3-13.

Kesternich, I., Heiss, F., McFadden, D., Winter, J., “Suit the action to the word, the word to the action: Hypothetical choices and real decisions in Medicare Part D”, *Journal of Health Economics*, 2012. https://doi.org/10.1016/j.jhealeco.2012.11.006.

Kurti, Marin, Klaus von Lampe, and Jacqueline Johnson (2014). “The Intended and Unintended Consequences of a Legal Measure to Cut the Flow of Illegal Cigarettes Into New York City: The Case of the South Bronx”. *Am. J. Public Health*. Available at: https://doi-org.fda.idm.oclc.org/10.2105/AJPH.2014.302340.

Levy, D.T., Cadham, C.J., Sanchez-Romero, L.M., et al. “An Expert Elicitation on the Effects of a Ban on Menthol Cigarettes and Cigars in the United States.” *Nicotine & Tobacco Research*, 2021. Available at: https://doi.org/10.1093/ntr/ntab121.

Levy, Helen, Edward Norton, and Jeffrey Smith (2018). “Tobacco Regulation and Cost-Benefit Analysis: How Should We Value Foregone Consumer Surplus?” *American Journal of Health Economics* 4 (1): 1-25.

Lovenheim, Michael F 2008). “How Far to the Border? The Extent and Impact of Cross-Border Casual Cigarette Smuggling.” *National Tax Journal* 61 (1): 7–33.

McFadden, Daniel (2017). “Stated Preference Methods and Their Applicability to Environmental Use and Non-use Valuations.” *In Contingent Valuation of Environmental Goods: A Comprehensive Critique.* Daniel McFadden and Kenneth Train, editors. Edward Elgar Publishing. Elgaronline.com.

Miron, Jeffrey (2003). "The Effect of Drug Prohibition of Drug Prices: Evidence from the Markets for Cocaine and Heroin." *Review of Economics and Statistics* 85 (3): 522-530.

Moshary, S., Shapiro, B., & Drango, S. (2023). Preferences for firearms and their implications for regulation (No. w30934). National Bureau of Economic Research.

National Research Council (2015). *Understanding the U.S. Illicit Tobacco Market: Characteristics, Policy Context, and Lessons from International Experiences*. Washington, DC: The National Academies Press. https://doi.org/10.17226/19016.

New York City Council (2023). "In Response to Explosion of Unlicensed Smoke Shops in NYC, Council Members, Real Estate Officials Announce New Law Taking Effect to Curb Illegal Stores." (August 14, 2023). https://council.nyc.gov/press/2023/08/14/2454/

Prieger, J.E. Tax evasion and illegal cigarettes in California: prevalence and demand-side correlates. *Crime Law Soc Change* (2022). https://doi.org/10.1007/s10611-022-10030-5

von Lampe K, Kurti M, Johnson J, Rengifo AF (2016). "I Wouldn't Take My Chances on the Street": Navigating Illegal Cigarette Purchases in the South Bronx. *Journal of Research in Crime and Delinquency* 53 (5):654-680. doi:10.1177/0022427816637888

World Bank Group (2019). Confronting Illicit Tobacco Trade: A Global Review of Country Experiences. WBG Tobacco Control Program. Washington DC.

Tables and Figures

Table 1: Mixed Logit Models of Consumer Tobacco Product Choices

	Immediate Choice Today		**Choice of 6 Months from Now**	
	Mean	SD	Mean	SD
ASC (Non-menthol cigarettes)	-0.176	3.117***	-0.202	3.012***
	(0.222)	(0.223)	(0.215)	(0.214)
ASC (Menthol cigarettes)	4.472***	3.098***	4.507***	3.036***
	(0.165)	(0.205)	(0.186)	(0.181)
ASC (Tobacco-flavored e-cigarettes)	-2.053***	3.908***	-1.262***	3.380***
	(0.322)	(0.276)	(0.256)	(0.247)
ASC (Menthol-flavored e-cigarettes)	1.737***	3.292***	1.654***	3.341***
	(0.150)	(0.182)	(0.166)	(0.182)
Price ($)	-0.384***	0.654***	-0.778***	2.452
	(0.034)	(0.180)	(0.103)	(1.865)
Illegal Retail Market for Menthol Cigarettes	-1.544***	1.192***	-2.391***	5.066
	(0.226)	(0.403)	(0.675)	(5.353)
Illegal Street Market for Menthol Cigarettes	-2.157***	1.688**	-3.076***	4.074***
	(0.338)	(0.715)	(0.395)	(1.302)
Illegal Retail Market for Menthol E-cigarettes	-1.534***	0.484***	-1.667***	0.211
	(0.136)	(0.187)	(0.126)	(0.179)
Illegal Street Market for Menthol E-cigarettes	-2.547***	2.623**	-2.316***	1.073***
	(0.378)	(1.022)	(0.195)	(0.303)
Log-likelihood	-6736.713		-6255.026	
Observations	7668		7668	

Notes: ASC = alternative specific constant. ASCs are assumed to follow normal distributions, price and legality variables are assumed to follow lognormal distributions. All random coefficients are assumed to be correlated. 500 Halton draws are used for simulation. Standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.
Source: Cornell online Discrete Choice Experiments 4/26-5/9, 2022.

Table 2. Predicted Market Shares of Tobacco Products and Quitting, Immediate Choices

Policy Scenario	Non-menthol Cigs	Menthol Cigs	Tabacco-flavored E-cigs	Menthol-flavored E-cigs	Quitting
Status quo	0.065	0.455	0.066	0.253	0.162
Illegal Retail Market for Menthol Cigs					
1. 50% lower price for illegal products	0.077	0.420	0.072	0.274	0.156
2. No price change	0.085	0.330	0.082	0.306	0.197
3. 50% higher price for illegal products	0.093	0.270	0.088	0.328	0.221
Illegal Retail Market for Menthol Cigs & E-cigs					
4. 50% lower price for illegal products	0.088	0.455	0.080	0.211	0.166
5. No price change	0.100	0.374	0.094	0.194	0.237
6. 50% higher price for illegal products	0.113	0.316	0.106	0.176	0.290
Illegal Street Market for Menthol Cigs					
7. 50% lower price for illegal products	0.084	0.372	0.078	0.294	0.172
8. No price change	0.092	0.290	0.087	0.322	0.210
9. 50% higher price for illegal products	0.099	0.236	0.093	0.342	0.231
Illegal Street Market for Menthol Cigs & E-cigs					
10. 50% lower price for illegal products	0.101	0.418	0.091	0.191	0.199
11. No price change	0.114	0.340	0.104	0.174	0.268
12. 50% higher price for illegal products	0.125	0.286	0.115	0.157	0.317

Notes: Predictions are derived from estimation results of a mixed logit model.

Table 3: Mixed Logit Models Subgroup Analysis of Consumer Tobacco Product Choices by Race

Immediate Choice Today	**Black**		**Non-black**	
	Mean	SD	Mean	SD
ASC (Non-menthol cigarettes)	-0.846**	2.058***	0.181	3.705***
	(0.423)	(0.287)	(0.255)	(0.344)
ASC (Menthol cigarettes)	3.825***	3.467***	5.021***	3.742***
	(0.308)	(0.445)	(0.215)	(0.191)
ASC (Tobacco-flavored e-cigarettes)	-2.176***	3.517***	-1.456***	3.413***
	(0.531)	(0.475)	(0.265)	(0.217)
ASC (Menthol-flavored e-cigarettes)	1.136***	2.805***	2.097***	3.764***
	(0.365)	(0.289)	(0.167)	(0.220)
Price ($)	-0.431***	1.341	-0.305***	0.328***
	(0.110)	(1.838)	(0.022)	(0.046)
Illegal Retail Market for Menthol Cigarettes	-1.129***	0.621	-1.879***	1.267***
	(0.328)	(0.569)	(0.216)	(0.337)
Illegal Street Market for Menthol Cigarettes	-2.212	5.670	-2.654***	1.552***
	(1.456)	(17.383)	(0.236)	(0.371)
Illegal Retail Market for Menthol E-cigarettes	-1.170***	0.329	-2.007***	2.285
	(0.253)	(0.356)	(0.593)	(1.859)
Illegal Street Market for Menthol E-cigarettes	-1.523***	1.122	-2.849***	2.820***
	(0.484)	(0.887)	(0.408)	(0.992)
Log-likelihood	-1917.161		-4786.768	
Observations	2112		5556	

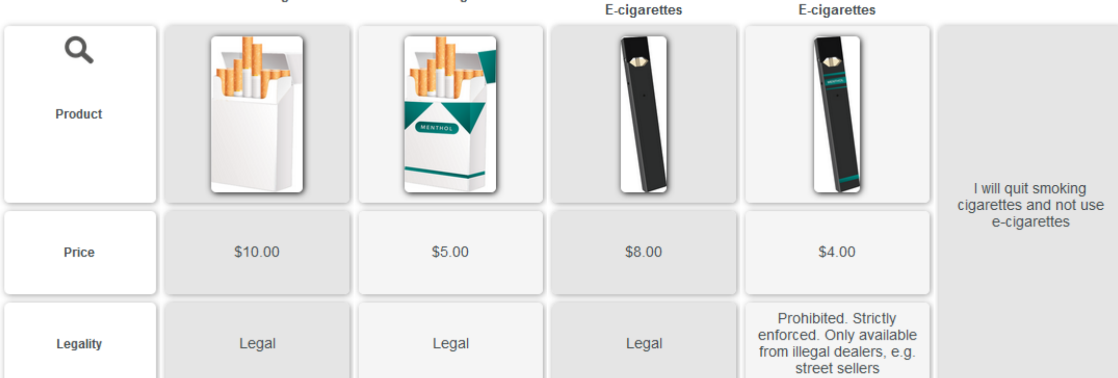
Notes: ASC = alternative specific constant. ASCs are assumed to follow normal distributions, price and legality variables are assumed to follow lognormal distributions. All random coefficients are assumed to be correlated. 500 Halton draws are used for simulation. Standard errors are in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
Source: Cornell online Discrete Choice Experiments 4/26-5/9, 2022.

Figure 1: Introduction to Choice Scenarios and Sample Scenario

We are interested in smokers' choices between menthol and non-menthol cigarettes, e-cigarettes which contain nicotine, or quitting. We want you to imagine that you can buy non-menthol cigarettes and e-cigarettes where you usually buy your cigarettes or e-cigarettes. In some questions, we will ask you to imagine that menthol cigarettes and e-cigarettes are legal and available where you usually buy your cigarettes. In other questions, we will ask you to imagine that menthol cigarettes and menthol little cigars/cigarillos and/or menthol flavored e-cigarettes are prohibited so that you will no longer be able to purchase them at many locations, but some locations might still sell the prohibited products. When a menthol-flavored product is described as prohibited, you should assume that the U.S. Food and Drug Administration has prohibited the product in all 50 states and DC. The FDA's enforcement of any prohibition on menthol-flavored products would only address manufacturers, distributors, wholesalers, importers and retailers. The FDA cannot and will not enforce against individual consumer possession or use of menthol cigarettes or any other tobacco product.

In what follows you will see different scenarios each with different combinations of the price of your cigarette brand, the price of an e-cigarette, along with descriptions of the legal status of menthol cigarettes and e-cigarettes and flavored little cigars/cigarillos and how this might affect their availability for purchase.

When considering e-cigarettes, we will be asking you about e-cigarette packages that are equivalent to one pack of your brand of cigarettes. For the purposes of your choices, please do not consider the price of buying the startup kit for reusable e-cigarettes.



Here is another set of products that could be available to you.

Think about your immediate choice **today**. Here are the set of cigarettes and e-cigarettes available when you are shopping.

Please select one option **for your immediate choice today** from the choices below.

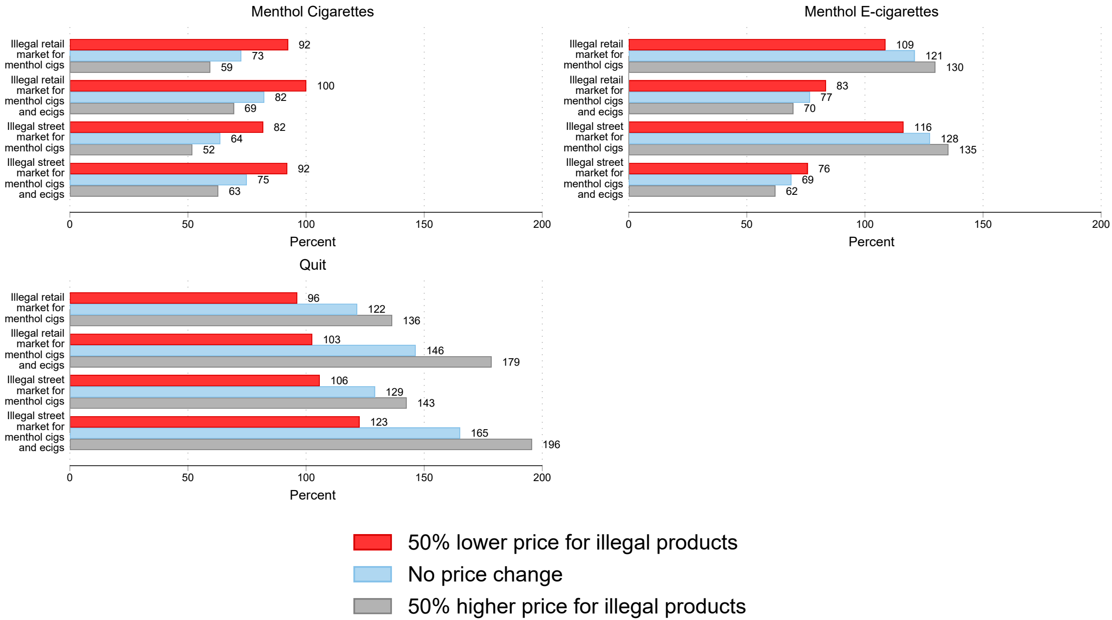
(If you want to see a larger version of the images, please click the magnifying glass below.)

	Non-Menthol Cigarettes	Menthol Cigarettes	Tobacco Flavored E-cigarettes	Menthol Flavored E-cigarettes	None
Product					I will quit smoking cigarettes and not use e-cigarettes
Price	$10.00	$5.00	$8.00	$4.00	
Legality	Legal	Legal	Legal	Prohibited. Strictly enforced. Only available from illegal dealers, e.g. street sellers	

>>

Finish Later

Figure 2: Predicted Market Shares of Menthol Products Relative to the Status Quo



Source: 2022 online Cornell survey

Online Appendix: Understanding the Demand-Side of an Illegal Market: Prohibition of Menthol Cigarettes

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Sen Zeng

In this Appendix we first present some additional results, then discuss several lines of evidence that shed light on the validity of the stated preference (SP) data we collected through our discrete choice experiment (DCE), and the implications for the empirical results reported in the text of the paper. In section A we report additional results including descriptive statistics, analysis of consumer tobacco product choices by race (black vs. non-black), and results estimated from a mixed logit model of tobacco product choices in willingness-to-pay (WTP) space, which is an alternative specification of the model in preference space implemented in the paper. In section B we review previous research that compares SP and revealed preference (RP) data in a range of applications. In section C we review previous research that conducts DCEs of tobacco product choices. In section D we provide additional empirical evidence on the validity of our SP data. Based on previous research and the empirical evidence in section D, we conclude that because tobacco products are familiar market goods, econometric models estimated using the SP data from our DCE are likely to provide reliable forecasts of consumer demand.

A. Additional Results

In table A1, we present some descriptive statistics of the sample characteristics, in table A2, we show the Average tobacco product choices across all 12 Scenarios in the experiment.

A.1. Descriptive Statistics

Table A1. Descriptive Statistics of the Sample

	Mean	Sd	Min	Max
Age	44.0	12.7	18	82
Male	0.33	0.47	0	1
Female	0.66	0.47	0	1
Non-Binary, Agender, Gender Nonconforming, etc.	0.0063	0.079	0	1
Non-Hispanic White	0.50	0.50	0	1
Non-Hispanic Black	0.24	0.43	0	1
Non-Hispanic Asian	0.025	0.16	0	1
Non-Hispanic other	0.049	0.22	0	1
Hispanic	0.18	0.39	0	1
Grade school/ some high school	0.064	0.25	0	1
Completed high school (With diploma or GED Certificate)	0.26	0.44	0	1
Technical/ trade school or community college	0.42	0.49	0	1
Completed university degree (Four-year bachelor degree)	0.26	0.44	0	1
Full-time employed	0.51	0.50	0	1
Self-employed	0.080	0.27	0	1
Part-time employed	0.12	0.32	0	1
Not employed	0.15	0.36	0	1
Student	0.020	0.14	0	1
Retired	0.12	0.32	0	1
Household income <$25,000	0.28	0.45	0	1
Household income $25,000-$49,999	0.30	0.46	0	1
Household income $50,000-$74,999	0.18	0.38	0	1
Household income $75,000+	0.25	0.43	0	1
Price ($) paid for the last pack of cigarettes	8.46	2.99	1.20	19.5
Smoking status: Every day	0.58	0.49	0	1
Smoking status: Some days	0.42	0.49	0	1
Vaping status: Every day	0.11	0.31	0	1
Vaping status: Some days	0.40	0.49	0	1
Vaping status: Not at all	0.24	0.43	0	1
Vaping status: Never	0.25	0.43	0	1
Use of other tobacco products: Every day	0.16	0.37	0	1
Use of other tobacco products: Some days	0.23	0.42	0	1
Use of other tobacco products: Never	0.61	0.49	0	1
Current vaper uses menthol flavored e-cigarettes	0.31	0.46	0	1
Tried quitting smoking in past 12 months	0.51	0.50	0	1
Considering quitting smoking in the next 6 months	0.65	0.48	0	1
Observations	639			

Source: Cornell online survey (4/26-5/9, 2022) of menthol smokers.

Table A2. Average DCE Responses across all 12 Scenarios

	Today	In 6 months
Non-menthol Cigarettes	0.089	0.082
Menthol Cigarettes	0.43	0.34
Tobacco-flavored E-cigarettes	0.080	0.077
Menthol-flavored E-cigarettes	0.18	0.17
I will quit smoking cigarettes and not use e-cigarettes	0.22	0.33
Observations	7,668	7,668

Source: Cornell online survey (4/26-5/9, 2022) of menthol smokers.

A.2. Subgroup Analysis by Race

We estimate the mixed logit models of consumer tobacco product choices by black group and non-black group separately, estimates are in table A3. We also use the estimated results to predict the market shares of tobacco products and quitting under different policy scenarios, results are shown in table A4 and figure A1.

Table A3: Mixed Logit Models Subgroup Analysis of Consumer Tobacco Product Choices by Race

Immediate Choice Today	Black		Non-black	
	Mean	SD	Mean	SD
ASC (Non-menthol cigarettes)	-0.846**	2.058***	0.181	3.705***
	(0.423)	(0.287)	(0.255)	(0.344)
ASC (Menthol cigarettes)	3.825***	3.467***	5.021***	3.742***
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	(0.531)	(0.475)	(0.265)	(0.217)
ASC (Menthol-flavored e-cigarettes)	1.136***	2.805***	2.097***	3.764***
	(0.365)	(0.289)	(0.167)	(0.220)
Price ($)	-0.431***	1.341	-0.305***	0.328***
	(0.110)	(1.838)	(0.022)	(0.046)
Illegal Retail Market for Menthol Cigarettes	-1.129***	0.621	-1.879***	1.267***
	(0.328)	(0.569)	(0.216)	(0.337)
Illegal Street Market for Menthol Cigarettes	-2.212	5.670	-2.654***	1.552***
	(1.456)	(17.383)	(0.236)	(0.371)
Illegal Retail Market for Menthol E-cigarettes	-1.170***	0.329	-2.007***	2.285
	(0.253)	(0.356)	(0.593)	(1.859)
Illegal Street Market for Menthol E-cigarettes	-1.523***	1.122	-2.849***	2.820***
	(0.484)	(0.887)	(0.408)	(0.992)
Log-likelihood	-1917.161		-4786.768	
Observations	2112		5556	

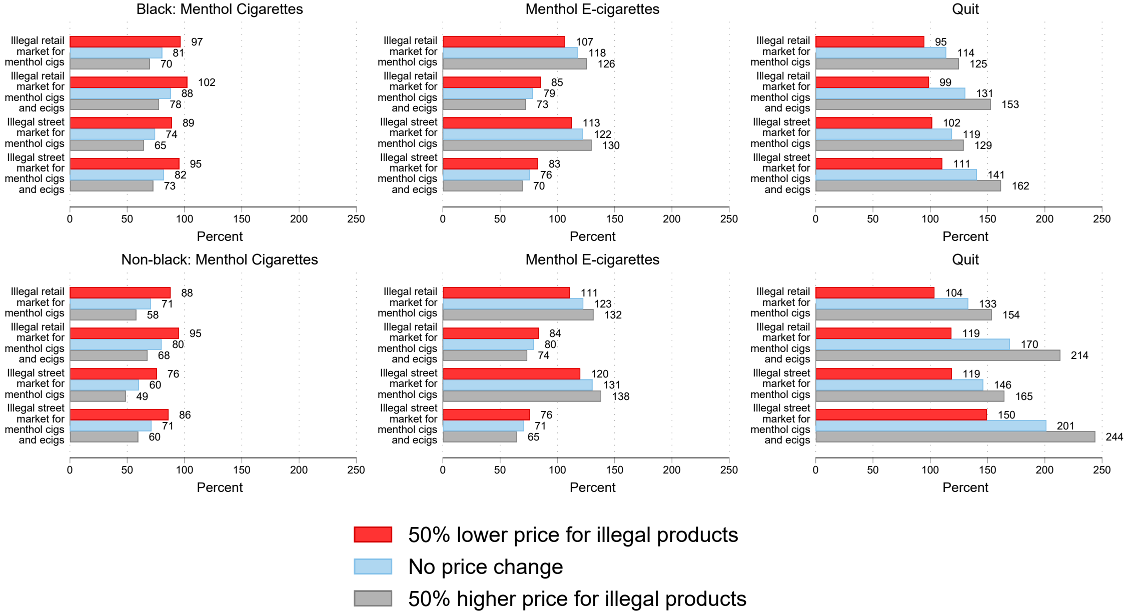
Notes: ASC = alternative specific constant. ASCs are assumed to follow normal distributions, price and legality variables are assumed to follow lognormal distributions. All random coefficients are assumed to be correlated. 500 Halton draws are used for simulation. Standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.
Source: Cornell online Discrete Choice Experiments 4/26-5/9, 2022.

Table A4. Predicted Market Shares of Tobacco Products and Quitting, Immediate Choices

(A) Black Smokers	Non-menthol Cigs	Menthol Cigs	Tabacco-flavored E-cigs	Menthol-flavored E-cigs	Quitting
Status quo	0.034	0.467	0.065	0.225	0.209
Illegal Retail Market for Menthol Cigs					
1. 50% lower price for illegal products	0.041	0.451	0.070	0.240	0.198
2. No price change	0.044	0.376	0.077	0.265	0.238
3. 50% higher price for illegal products	0.048	0.326	0.083	0.283	0.261
Illegal Retail Market for Menthol Cigs & E-cigs					
4. 50% lower price for illegal products	0.047	0.478	0.076	0.192	0.206
5. No price change	0.053	0.411	0.087	0.177	0.272
6. 50% higher price for illegal products	0.058	0.363	0.096	0.164	0.319
Illegal Street Market for Menthol Cigs					
7. 50% lower price for illegal products	0.045	0.415	0.074	0.254	0.212
8. No price change	0.048	0.347	0.081	0.276	0.248
9. 50% higher price for illegal products	0.051	0.302	0.086	0.292	0.269
Illegal Street Market for Menthol Cigs & E-cigs					
10. 50% lower price for illegal products	0.054	0.445	0.083	0.187	0.231
11. No price change	0.059	0.383	0.093	0.171	0.293
12. 50% higher price for illegal products	0.064	0.339	0.102	0.157	0.337
(B) Non-black smokers	Non-menthol Cigs	Menthol Cigs	Tabacco-flavored E-cigs	Menthol-flavored E-cigs	Quitting
Status quo	0.086	0.481	0.056	0.270	0.106
Illegal Retail Market for Menthol Cigs					
1. 50% lower price for illegal products	0.102	0.423	0.065	0.300	0.110
2. No price change	0.112	0.341	0.074	0.332	0.141
3. 50% higher price for illegal products	0.121	0.279	0.081	0.355	0.163
Illegal Retail Market for Menthol Cigs & E-cigs					
4. 50% lower price for illegal products	0.115	0.459	0.074	0.227	0.126
5. No price change	0.131	0.385	0.088	0.215	0.180
6. 50% higher price for illegal products	0.147	0.326	0.101	0.199	0.227
Illegal Street Market for Menthol Cigs					
7. 50% lower price for illegal products	0.112	0.365	0.072	0.324	0.126
8. No price change	0.122	0.289	0.080	0.353	0.155
9. 50% higher price for illegal products	0.130	0.235	0.087	0.374	0.175
Illegal Street Market for Menthol Cigs & E-cigs					
10. 50% lower price for illegal products	0.134	0.414	0.087	0.206	0.159
11. No price change	0.150	0.343	0.101	0.192	0.214
12. 50% higher price for illegal products	0.165	0.287	0.114	0.175	0.259

Notes: Predictions are derived from estimation results of mixed logit models.

Figure A1: Predicted Market Shares Relative to the Status Quo (Black smoker vs. Non-black smoker)



Notes: Upper panel features predicted shares for black smokers, lower panel features predicted shares for non-black smokers.
Source: 2022 online Cornell survey

A.3. Mixed Logit Models in Willingness-to-Pay (WTP) Space

Recall that in the paper, we estimated the model in preference space as follows:

$$U_{ijt} = ASC_{ijt} + \alpha_i p_{ijt} + \beta_i' Legal\ Availability_{ijt} + \epsilon_{ijt}$$

The coefficients are marginal utilities of associated attributes. WTP for an attribute, for example, $Legal\ Availability$, is the ratio of the attribute's coefficient to the price coefficient: $w_i = \beta_i/\alpha_i$. Given that distributional assumptions are imposed on the coefficients, the calculated WTP is a ratio of two distributions, which may not have finite moments. We can re-parameterize the specification as follows:

$$U_{ijt} = ASC^{\star}{}_{ijt} + \alpha_i p_{ijt} + (\alpha_i w_i)' Legal\ Availability_{ijt} + \epsilon_{ijt}$$

Here $ASC^{\star}$ are WTP for the alternative-specific constants, α_i is the price coefficient, and w_i is the WTP associated with legal availability variables. In WTP space models, distributional assumptions are imposed directly on WTPs. To avoid non-convergence issues, we estimate the model using hierarchical bayes, results are reported in table A5.

Table A5. Mixed Logit Models in WTP Space of Consumer Tobacco Product Choices

In WTP Space	**Immediate Choice Today**	
	Mean	SD
Price ($) [scale parameter]	-0.660***	1.054***
	(0.068)	(0.298)
ASC (Non-menthol cigarettes)	0.622	20.652***
	(1.240)	(1.620)
ASC (Menthol cigarettes)	21.852***	16.293***
	(0.731)	(0.799)
ASC (Tobacco-flavored e-cigarettes)	-7.802***	23.682***
	(1.004)	(1.936)
ASC (Menthol-flavored e-cigarettes)	7.225***	20.645***
	(0.736)	(1.304)
Illegal Retail Market for Menthol Cigarettes	-8.444***	14.855***
	(0.536)	(1.037)
Illegal Street Market for Menthol Cigarettes	-10.712***	14.715**
	(0.658)	(0.963)
Illegal Retail Market for Menthol E-cigarettes	-12.830***	21.079***
	(0.744)	(1.239)
Illegal Street Market for Menthol E-cigarettes	-15.189***	23.269**
	(1.078)	(1.700)
Simulated Log-likelihood	-6250.9	
Observations	7668	

Notes: ASCs follow normal distributions, price coefficient follows a lognormal distribution, legal availability coefficients follow truncated normal distributions, standard errors are in parentheses.

A. Literature Review of Studies that Compare SP and RP Data[1]

DCEs and the related contingent valuation method are used to collect SP data in a range of applications. DCEs are commonly used in marketing research and economics to provide predictions of consumer demand in scenarios that are not yet observed in actual markets. In addition to the tobacco product DCEs discussed below in section C, examples of the use of DCEs to study hypothetical market situations include studies of electricity markets (Blass, Lach, and Manski, 2010), health insurance markets (Kesternich, Hiess, McFadden, and Winter, 2013), labor markets (Mas, Alexandre and Pallais, 2017; Maestas et al. 2023), and firearms markets (Moshary, Shapiro, and Drango 2023). DCEs are also widely used in health economics to evaluate existing or prospective pharmaceutical products and health care treatment interventions (Ryan et al. 2007). Another large body of research uses DCEs and the related contingent valuation method to estimate willingness to pay for non-market goods like environmental quality.

Research that compares SP and RP data concludes that the external validity of SP data is much stronger in applications similar to familiar market goods. In a narrative review of DCE research, McFadden (2017) concludes that there is a “sharp reliability gradient”:

> Forecasts that are comparable in accuracy to RP forecasts can be obtained from well-designed SP studies for familiar, relatively simple goods that are similar to market goods purchased by consumers, particularly when calibration to market benchmarks can be used to correct experimental distortions. However, studies of unfamiliar, complex goods give erratic, unreliable forecasts.

McFadden is therefore skeptical about SP data on complex and unfamiliar environmental public goods. Although he does not discuss health care applications, by the same reasoning DCEs might not provide reliable data on unfamiliar pharmaceutical and health care treatment interventions.

Penn and Hu (2018) report a meta-analysis that provides quantitative evidence consistent with McFadden’s (2017) conclusion that SP data are more reliable for familiar market goods. The meta-analysis used estimates from 132 studies that provided 908 observations of comparisons of SP and RP data. For studies including choice experiments that did not provide estimates of willingness to pay but did provide proportions of responses, Penn and Hu inferred lower-bound estimates of willingness to pay. Each observation is an estimate of the “calibration factor” (CF) which shows the ratio of willingness to pay estimated from SP data to the willingness to pay estimated from RP data. When SP and RP estimates are similar, the CF will be close to one. In the meta-analysis, about one quarter of the CFs are between 0.81 and 1.2. The distribution of CFs is skewed right showing a tendency for SP willingness-to-pay estimates to be larger than RP estimates, sometimes to a large extent. The median CF is 1.94, implying that for almost half of the observations the SP estimate is over twice as large as the RP estimate. Penn and Hu estimate regression models of the effects of study characteristics on CFs. The results imply that compared to studies of public goods, studies of private goods find lower CFs. The results also imply that compared to other hypothetical elicitation methods, CFs are lower for studies that used choice experiments. The meta-analysis empirical results are consistent with McFadden’s conclusion that although SP data from DCEs are reliable for private goods, there is a sharp reliability gradient for SP data on willingness to pay for public goods.

In the remainder of this section, we discuss examples of studies that compare SP and RP data on health-related choices. Quaife et al (2018) review a number of studies of health-related choices that focused on

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[11] Sections B and C of the Online Appendix are mainly the same as sections of an Online Appendix of another paper by the same authors which is currently under review.

the external validity of DCEs (by comparing SP and RP estimates) and conclude that DCEs provide moderate levels of external validity in terms of matching actual choices. de Bekker-Grob et al (2020) find that when measured at the individual level, stated preferences in a DCE about vaccinations predict 91 percent of actual choices. Telser and Zweifel (2007) examine the external validity of a DCE focused on decisions about a harm reduction product (hip protectors for accidental falls). They compare the willingness to pay for risk reduction that was derived from the DCE to other measures of willingness to pay for the same risk reduction derived from established alternatives that used revealed preference data. The comparison supports a high level of convergent validity. Linley and Hughes (2013) examine hypothetical decisions about new medicine approvals and find that the predicted probabilities of recommending new medicines derived from the DCE match well with the cumulative probability of actual positive recommendations (though the ability of the DCE to discriminate between individual new medicines was limited). Mahammad et al (2017) use a DCE and estimate a mixed logit based on the hypothetical choices with respect to type of tuberculosis treatment (or none) in response to each treatment having six treatment attributes. They compare these choices with actual choices and find strong external validity and the degree of accuracy depends on the distributional assumptions used in the mixed logit models with some models. Kesternich et al (2013) implement a DCE to analyze Medicare part D choices and compare these results to those that emerge from analysis of actual choices. They conclude that hypothetical choice experiments are useful in studying insurance choices as hypothetical behavior is related to actual behavior. They find that the coefficients that emerge in the DCE experiment are of the same sign as the coefficients that are estimated from market behavior. They note that the magnitudes of the coefficients are quite similar and do not find significant differences between hypothetical and real choices between different attributes of the insurance scenarios. They do find a higher willingness to pay for insurance in the hypothetical market and thus higher insurance take-up rates but attribute this to the nature of the default option in the DCE.

B. DCE Studies of Tobacco Product Choices

A growing body of research conducts DCEs to study the determinants of consumer choices about tobacco products. Table C1 lists recent DCE studies of tobacco product choices published in economics journals. Table C1 includes two studies that report results from exercises that use a combination of RP and SP data to develop a calibrated model that is grounded in real-world behavior. Kenkel, Peng, Pesko, and Wang (2020) report in an Online Appendix the results of a conditional logit model estimated using a combination of SP data from a DCE and RP data from the DCE subjects' responses about their prior use of e-cigarettes, combustible cigarettes, and nicotine replacement products. The estimated scale parameter is close to 1, suggesting that the scales in the RP and SP data are similar. The estimated coefficients on the tobacco product attributes show the same patterns as in the model based on SP data only.

Buckell and Hess (2019) report the results of a more in-depth investigation of combining SP and RP data on tobacco product choices. In a model estimated using combined SP and RP data they estimate a scale parameter greater than 1, consistent with the argument that in SP data subjects overstate the impact of interventions which leads to elasticities that are biased upwards. In terms of forecasts from the models, they find that compared to calibrated models the uncalibrated forecasts under-predict cigarette choices and over-predict e-cigarette choices. They conclude that appropriately calibrated choice models "provide better quality empirical evidence for policymakers." (Buckell and Hess 2019, p. 100)

The remaining tobacco product DCEs listed in Table C1 do not provide in-depth discussions of external validity, but the results of the studies are consistent with predictions from health economic models of consumer behavior. For example, Marti, Buckell, Maclean, and Sindelar (2019) conduct a DCE to study how smokers' product choices are affected by variations in the perceived healthiness and cessation effectiveness of e-cigarettes, as well as by bans on smoking in public places and prices. Buckell, Hensher, and Hess (2021) use SP data from a DCE combined with a latent variable approach to model addiction. They find that more addicted smokers are unwilling to switch to e-cigarettes. More broadly, the studies in Table C1 find that smokers' product choices respond to cigarette and e-cigarette prices; the estimated price-responsiveness is generally consistent with the large body of econometric estimates from observational (RP) data (DeCicca, Kenkel, and Lovenheim 2022).

DCE studies of tobacco product choices are also published in inter-disciplinary public health journals, including journals focusing on tobacco such as *Tobacco Control* and the *Journal of Nicotine and Tobacco Research*.[2] These articles are not included in our Table C1 review because they have a different focus for a different audience. For example, Shang, Huang, Chaloupka, and Emery (2018) focus on the roles flavors, e-cigarette device type, and e-cigarette warning labels play in youth stated preferences to try e-cigarettes. Subjects were presented with e-cigarette products with varying attributes but were not given the alternative of choosing combustible cigarettes.

In addition, we note that outside economics journals the term "discrete choice experiment" is used in both a broad and narrow sense. In the broad sense, DCE has been used to describe various surveys that asks subjects to make choices with random assignment of the descriptions of the alternatives. In contrast, Louviere, Flynn, and Carson (2010) define DCEs as being necessarily grounded in random utility theory. Some of the studies published in public health journals do not fit this narrow definition of DCEs, even though the studies use the term to describe their research method. For example, Reynolds, Popova, Ashley et al. (2022) report a DCE about very low nicotine cigarettes (VLNCs) that asked respondents which message would most motivate them and least motivate them to quit smoking; the message attributes varied in terms of content about VLNCs and the source of the message. Subjects did not make choices between products. This is a study of consumer perceptions of message effectiveness which cannot be grounded in random utility theory. A related concern is that in some DCEs where subjects make choices between tobacco products, the product attributes are described in terms of consumer perceptions rather than observable characteristics of the products and/or the product marketplace. For example, Shang, Weaver, White, et al. (2020) report a DCE about e-cigarettes that included "less harmful to health than cigarettes" and "effective for helping people quit" as product attributes. The Marti et al. (2019) study included in Table C1 also uses this approach. Although the results of these studies provide information about the relative importance of these perceptions on tobacco product choices, the results are less useful for policy analysis because perceptions are not directly policy manipulable. For this reason, in our DCE we describe the policy-manipulable attribute of warning labels.

Table C1. Recent DCE Studies of Tobacco Product Choices, Published in Economics Journals

Authors	Year	Journal
Buckell, Hensher, and Hess	2021	Health Economics
Buckell and Hess	2019	Journal of Health Economics
Kenkel, Peng, Pesko, and Wang	2020	Health Economics
Marti, Buckell, Maclean, and Sindelar	2019	Economic Inquiry

[2] Regmi, Kaphle, Timilsina, and Tuha (2018) report a systematic review of peer-reviewed studies published from 2000 – 2016 that used DCE methods in tobacco control. Of the 12 studies included in their review, 4 were published in health economics journals. Because these 4 studies focused on pharmaceutical smoking cessation products and did not include e-cigarettes, they are not included in Table C1.

D. Empirical Evidence on the Internal and External Validity of SP Data Collected through the Cornell DCE

D.1. Validity Checks of the Quality of the Stated Preference Data

In sub-sections D.1 and D.2 we present empirical evidence on the internal and external validity of the SP data we collected through our DCE. Like other experimental research designs, the randomly assigned variation in product attributes in DCEs provides an internally valid research design to estimate the causal treatment effects of product attributes on subjects' stated preferences for tobacco products and quit attempts. However, because SP data are the subjects' responses about hypothetical choices, subjects might not provide thoughtful and meaningful responses that provide useful information about the actual choices they would make in real-world markets. In this section D.1, we report the results of validity checks on the quality of our SP data and the implications for the empirical results reported in the text of the paper.

As an overview of the sensitivity of the empirical results to the validity checks, Table D1 reports the sensitivity of conditional logit models of tobacco product choices to alternative approaches to improve SP data validity. Column (0) reports a baseline conditional logit model estimated over the same sample used in estimation of the main text models. Columns (1) – (2) report conditional logit models estimated using sample restrictions to improve the quality of the SP data. Column (3) reports a conditional logit model estimated using a combination of SP and revealed preference (RP) data. In columns (1) – (2) the point estimates of the alternative specific constants (ASCs) and the product attribute parameters tend to be very similar to the baseline model parameter estimates in column (0). The combined SP + RP model reported in column (3) yields estimated ASCs that are slightly different than the estimated ASCs in the baseline column (0) model. We will discuss the SP + RP data model results in more detail in the next sub-section D.2 of this Appendix.

In this sub-section we focus on sample restrictions that might improve the quality of our SP data. First, we examine data on the length of time subjects spent answering the DCE choice tasks, to identify possible "speedsters" who provided lower-quality responses. Figure D1 shows the distribution of time spent on the choice tasks. The median and mode times spent on the choice tasks are 5.7 and 4.7 minutes (there are multiple modes, the minimum mode is 4.2 and the maximum mode is 5.2), respectively. Each subject completed 12 immediate choice tasks and 12 six-months-from-now choice tasks; the six-months-from-now choice tasks might be easier to complete quickly because they presented the subject with the same choices as in the preceding immediate choice task. For the model reported in column (1) of Table D1, we drop responses from 8 speedster subjects who completed the choice tasks in under 2 minutes.

Second, we examine data on the extent to which subjects paid attention to attribute variation across choice tasks. After subjects completed the choice tasks, we asked subjects which attributes varied across the tasks. Figure D2 shows the fraction of subjects who correctly indicated that the attribute in question varied. Although substantial fractions of the responses about attribute variation were incorrect, the results suggest that subjects paid the most attention to the price attribute of menthol cigarettes, which was the most common tobacco product choice. The patterns of attentiveness across attributes and products are consistent with rational decisions to pay the most attention to the attributes and products that matter to their preferences. We also note that there is an ambiguity in our measure of attentiveness. As noted above, the six-months-from-now choice task was always identical to the preceding immediate choice task, i.e., in those pairs of tasks the attributes did not vary. For the model reported in column (2) of Table D1, we drop responses from 106 subjects who were inattentive to variation in the attributes of menthol cigarettes.

D.2. Improving Data Quality by Combining SP and RP Data

In this sub-section we discuss the approach reported in column (3) of Table D1, where we estimate a conditional logit model of tobacco product choices using a combination of SP and RP data. In his monograph on econometric analysis of discrete choice data, Train (2002, pp. 174-175) discusses the advantages and disadvantages of SP and RP data:

> Revealed preference data have the advantage that they reflect actual choices…. However, RP data are limited to the choice situations and attributes of alternatives that currently exist or have existed historically. Often a researcher will want to examine people's responses in situations that do not currently exist, such as the demand for a new product. RP data are simply not available for these new situations.
>
> Stated-preference data complement revealed-preference data…. The limitations of SP data are obvious: what people say they will do is often not the same as what they actually do. People might not know what they would do if a hypothetical situation were real. Or they might not be willing to say what they would do.

Train suggests that by combining RP and SP data, "the advantages of each can be obtained while mitigating the limitations. The SP data provide the needed variation in attributes, while the RP data ground the predicted shares in reality." He outlines the approach we take, where we use our DCE's subjects' responses about their tobacco product use and quit attempts over the past year as SP data to calibrate our model.

To construct RP choices, we propose a probabilistic classification rule that uses information from the background survey of respondents' smoking behaviors. The process and classification rule are described in table D3. The construction takes three steps, first, we classify respondents as either choosing cigarettes or e-cigarettes. Second, we classify respondents as either choosing menthol flavor or non-menthol flavor. Thrid, we classify respondents as either choosing quit or not quit. To classify the choices of cigarettes and e-cigarettes, we use information of subjects' vaping history, vaping status, and smoking status. Among all the subjects, those who have never vaped are classified as choosing cigarettes, among those who have ever vaped, if they currently do not vape at all, they are classified as choosing cigarettes, for those who vape ever day and someday, we classify their choices according to their smoking status. Specifically, among those who vape ever day, if they also smoke every day, then their probabilities of choosing cigarettes versus e-cigarettes are 50% versus 50%, if they smoke someday (say m days out of 30 days), then their probabilities of choosing cigarettes versus e-cigarettes are $m/(30+m)$ versus $30/(30+m)$. For those who vape someday, the probability rules are similar, and the choice of quitting is constructed following a similar rule, details are reported in table D2.

After obtaining RP choices, we jointly estimate the model with SP and RP data. We assume that the random error term for the RP data follows an i.i.d. type I extreme value distribution with scale parameter normalized to 1, and the scale parameter for the SP data is given by λ. The choice probabilities for individual i chooses alternative j in the RP and SP data can then be written as:

$$P_{ij}^{RP} = \frac{e^{(\alpha_j + X_{ij}^{RP}\beta)}}{\sum_k e^{(\alpha_k + X_{ik}^{RP}\beta)}}$$

$$P_{ij}^{SP} = \frac{e^{[\lambda(\alpha_j + X_{ij}^{SP}\beta)]}}{\sum_k e^{[\lambda(\alpha_k + X_{ik}^{SP}\beta)]}}$$

In the joint estimation we maximize the joint likelihood function:

$$L(\alpha, \beta, \lambda) = \sum_{i=1}^{N} \sum_{j=1}^{J} y_{ij}^{RP} \log P_{ij}^{RP} + \sum_{i=1}^{N} \sum_{j=1}^{J} y_{ij}^{SP} \log P_{ij}^{SP}$$

The results are presented in column (4) of table D1. The estimated scale parameter λ is 0.8, suggesting that the scales in the RP and SP data are similar. The estimated coefficients on the product attributes show similar patterns as in the column (0) model based on SP data only. We further use the model to predict the choice shares under a status quo scenario and various counterfactual policy scenarios considered in the paper. We report the predicted product shares and the size of the market relative to status quo in table D3. We see that the calibrated model predicts larger shares of menthol cigarettes and smaller shares of quitting, while the represented size of market relative to status quo is fairly similar to those predicted by the model using only SP data. Overall, we interpret the results from the calibrated model as supporting the usefulness of our SP data.

Table D1. Estimation Results from Conditional Logit Models

Variables	(0)	(1)	(2)	(3)
ASC (Non-menthol cigarettes)	-0.200*	-0.184	-0.054	-0.166
	(0.115)	(0.116)	(0.125)	(0.277)
ASC (Menthol cigarettes)	1.904***	1.914***	2.100***	2.429***
	(0.095)	(0.095)	(0.101)	(0.315)
ASC (Tobacco-flavored e-cigarettes)	-0.667***	-0.668***	-0.607***	-0.749***
	(0.116)	(0.116)	(0.126)	(0.217)
ASC (Menthol-flavored e-cigarettes)	0.626***	0.637***	0.762***	0.813**
	(0.098)	(0.099)	(0.106)	(0.395)
Price ($)	-0.079***	-0.080***	-0.091***	-0.102***
	(0.006)	(0.006)	(0.006)	(0.008)
Illegal Retail Market for Menthol Cigarettes	-0.616***	-0.628***	-0.708***	-0.781
	(0.060)	(0.061)	(0.069)	(0.549)
Illegal Street Market for Menthol Cigarettes	-0.866***	-0.880***	-0.992***	-1.087***
	(0.066)	(0.067)	(0.075)	(0.081)
Illegal Retail Market for Menthol E-cigarettes	-0.740***	-0.745***	-0.847***	-0.911***
	(0.077)	(0.078)	(0.086)	(0.263)
Illegal Street Market for Menthol E-cigarettes	-0.945***	-0.958***	-1.140***	-1.170***
	(0.093)	(0.094)	(0.106)	(0.300)
Scale Parameter of SP Data				0.808***
				(0.224)
Log-likelihood at convergence	-10349	-10224	-8512	-10959
Respondents	639	631	533	639
Observations	38340	37860	31980	38340

Notes: Standard errors are clustered at the individual level (except for column (4)). *** p<0.01, ** p<0.05, * p<0.1.

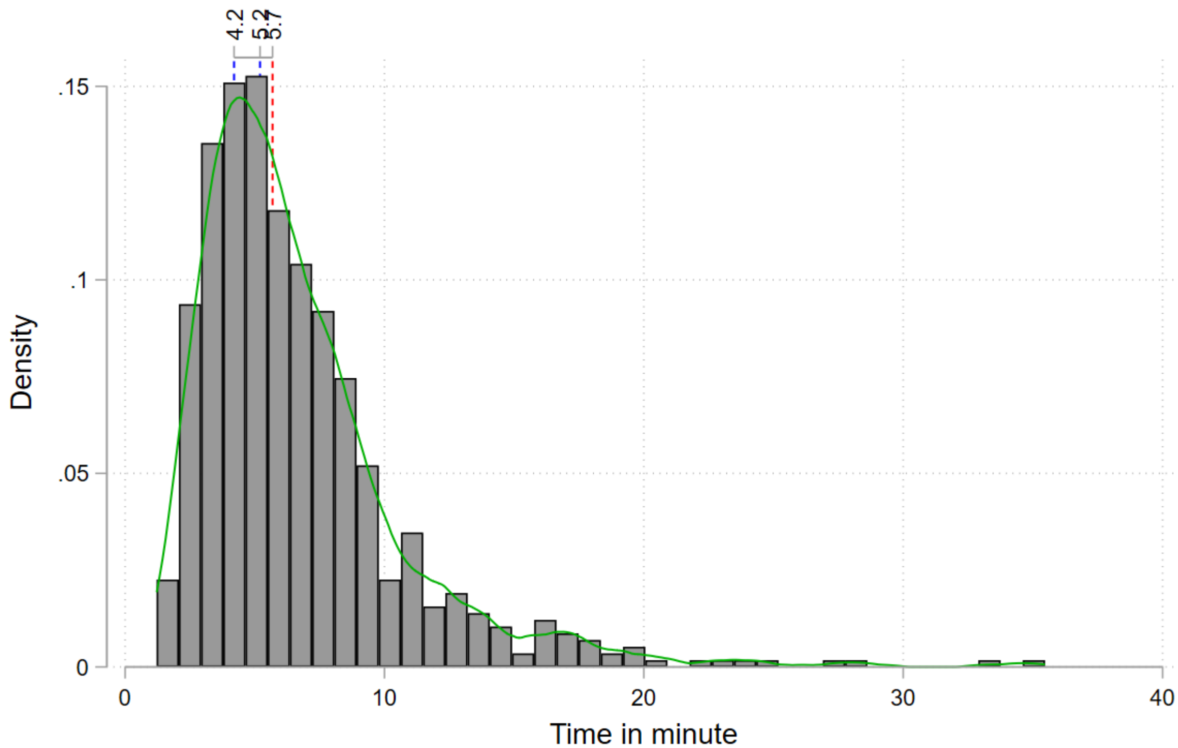

Figure D1. Distribution of Subject's Time Spent on the Choice Tasks

Notes: The blue and red dash lines indicate the modes and median of time spent on the DCE section respectively. There are multiple modes in the distribution, we show the minimum mode (4.2) and maximum mode (5.2).

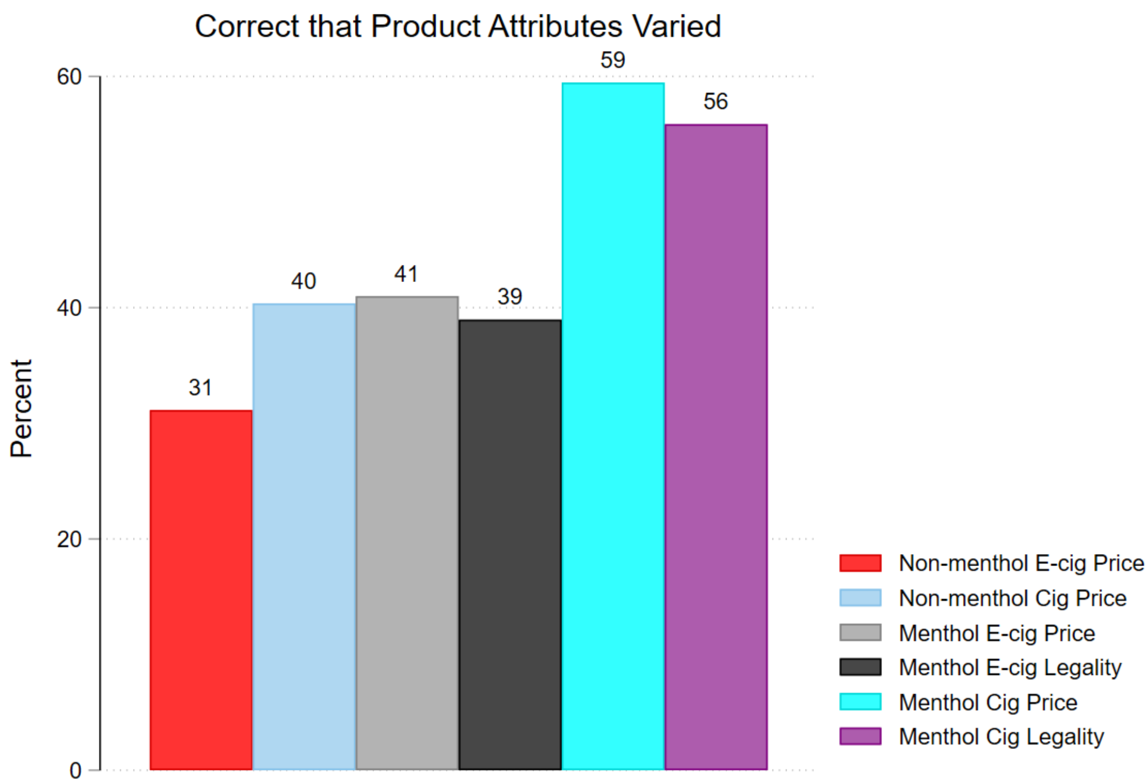

Figure D2. Fraction of Subjects that Were Correct that the Attribute in Question Varied.

Notes: Subjects are allowed to give correct but inconsistent answers, for example, they could select both price varied across scenarios and price was always the same. We use a strict criterion that the subject was correct that one attribute in question varied if she only selects the attribute varied and does not select the attribute was always the same.

Table D2. A Probabilistic Classification Rule to Construct Revealed Preference Choices

<table>
<tr><td colspan="6">Step 1: classification of choices between cigarettes and e-cigarettes</td></tr>
<tr><td>Subject</td><td>Vaping history</td><td>Vaping status</td><td>Smoking status</td><td>Probability of choosing cigarettes</td><td>Probability of choosing e-cigarettes</td></tr>
<tr><td rowspan="6">N=639</td><td rowspan="5">Vape ever (Yes)
N=478</td><td rowspan="2">Vape every day
(N=71)</td><td>Smoke every day
(N=35)</td><td>50%</td><td>50%</td></tr>
<tr><td>Smoke someday
(m out of 30 days) (N=36)</td><td>$m/(30+m)$</td><td>$30/(30+m)$</td></tr>
<tr><td rowspan="2">Vape someday
(n out of 30 days) (N=255)</td><td>Smoke every day
(N=115)</td><td>$30/(30+n)$</td><td>$n/(30+n)$</td></tr>
<tr><td>Smoke someday
(m out of 30 days) (N=140)</td><td>$m/(m+n)$</td><td>$n/(m+n)$</td></tr>
<tr><td>Not at all
(N=152)</td><td>Smoke every day (N=111)
Smoke someday (N=41)</td><td rowspan="2">100%</td><td rowspan="2">0</td></tr>
<tr><td>Vape every (No)
N=161</td><td></td><td>Smoke every day (N=109)
Smoke someday (N=52)</td></tr>
<tr><td colspan="6">Step 2: classification of choices between menthol flavor and non-menthol flavor</td></tr>
<tr><td colspan="6">Among those classified as choosing cigarettes</td></tr>
<tr><td colspan="3" rowspan="2">During last 12 months, did you ever switch to non-menthol cigarettes to try to quit?</td><td>Yes</td><td colspan="2">Choose non-menthol cigarettes</td></tr>
<tr><td>No</td><td colspan="2">Choose menthol cigarettes</td></tr>
<tr><td colspan="6">Among those classified as choosing e-cigarettes</td></tr>
<tr><td colspan="3" rowspan="2">Usually vape menthol flavored e-cigarettes</td><td>Yes</td><td colspan="2">Choose menthol e-cigarettes</td></tr>
<tr><td>No</td><td colspan="2">Choose non-menthol e-cigarettes</td></tr>
<tr><td colspan="6">Step 3: classification of choices of quitting</td></tr>
<tr><td>Subject</td><td>Quitting intention</td><td>Quitting history</td><td colspan="3">Probability of choosing quitting</td></tr>
<tr><td rowspan="2">N=639</td><td>Plan to quit (Yes)
N=416</td><td>Tried quitting (N=289)
Didn't try to quit (N=127)</td><td colspan="3">1/26</td></tr>
<tr><td>Plan to quit (No)
N=223</td><td>Tried quitting (N=38)
Didn't try to quit (N=185)</td><td colspan="3">1/52
0</td></tr>
</table>

Table D3. Predicted Choice Shares under Status Quo and Counterfactual Scenarios

Policy Scenario	Non-menthol Cigs	Menthol Cigs	Tabacco-flavored E-cigs	Menthol-flavored E-cigs	Quitting
Status quo	0.045	0.599	0.040	0.190	0.126
Illegal Retail Market for Menthol Cigs					
1. 50% lower price for illegal products	0.056	0.514	0.048	0.229	0.153
2. No price change	0.067	0.410	0.059	0.279	0.186
3. 50% higher price for illegal products	0.077	0.316	0.068	0.323	0.215
Illegal Retail Market for Menthol Cigs & E-cigs					
4. 50% lower price for illegal products	0.063	0.582	0.054	0.128	0.173
5. No price change	0.080	0.490	0.071	0.135	0.224
6. 50% higher price for illegal products	0.098	0.400	0.087	0.137	0.278
Illegal Street Market for Menthol Cigs					
7. 50% lower price for illegal products	0.064	0.439	0.056	0.265	0.176
8. No price change	0.075	0.339	0.065	0.312	0.208
9. 50% higher price for illegal products	0.084	0.256	0.074	0.352	0.234
Illegal Street Market for Menthol Cigs & E-cigs					
10. 50% lower price for illegal products	0.077	0.524	0.067	0.121	0.212
11. No price change	0.095	0.430	0.084	0.124	0.266
12. 50% higher price for illegal products	0.114	0.343	0.101	0.122	0.320

Policy Scenario	Size of market relative to status quo		
	Menthol Cigs	Menthol-flavored E-cigs	Quitting
Illegal Retail Market for Menthol Cigs			
1. 50% lower price for illegal products	0.858	1.208	1.208
2. No price change	0.684	1.471	1.471

3. 50% higher price for illegal products	0.528	1.704	1.704
Illegal Retail Market for Menthol Cigs & E-cigs			
4. 50% lower price for illegal products	0.971	0.675	1.368
5. No price change	0.817	0.713	1.774
6. 50% higher price for illegal products	0.668	0.721	2.196
Illegal Street Market for Menthol Cigs			
7. 50% lower price for illegal products	0.732	1.396	1.396
8. No price change	0.566	1.644	1.644
9. 50% higher price for illegal products	0.427	1.853	1.853
Illegal Street Market for Menthol Cigs & E-cigs			
10. 50% lower price for illegal products	0.875	0.636	1.673
11. No price change	0.718	0.654	2.106
12. 50% higher price for illegal products	0.573	0.642	2.534

References

Blass, A. A., Lach, S., & Manski, C. F. (2010). Using elicited choice probabilities to estimate random utility models: Preferences for electricity reliability. *International Economic Review*, *51*(2), 421-440.

Buckell, J., & Hess, S. (2019). Stubbing out hypothetical bias: improving tobacco market predictions by combining stated and revealed preference data. *Journal of Health Economics*, *65*, 93-102.

Buckell, J., Hensher, D. A., & Hess, S. (2021). Kicking the habit is hard: A hybrid choice model investigation into the role of addiction in smoking behavior. *Health Economics*, *30*(1), 3-19.

de Bekker-Grob, E. W., Donkers, B., Bliemer, M. C., Veldwijk, J., & Swait, J. D. (2020). Can healthcare choice be predicted using stated preference data? *Social Science & Medicine*, *246*, 112736.

DeCicca, P., Kenkel, D., & Lovenheim, M. F. (2022). The economics of tobacco regulation: a comprehensive review. *Journal of Economic Literature*, *60*(3), 883-970.

Lancsar, E., & Louviere, J. (2006). Deleting 'irrational' responses from discrete choice experiments: a case of investigating or imposing preferences? *Health Economics*, *15*(8), 797-811.

Linley, W. G., & Hughes, D. A. (2013). Decision-makers' preferences for approving new medicines in wales: a discrete-choice experiment with assessment of external validity. *Pharmacoeconomics*, *31*, 345-355.

Louviere, J. J., Flynn, T. N., & Carson, R. T. (2010). Discrete choice experiments are not conjoint analysis. *Journal of Choice Modelling*, *3*(3), 57-72.

Kenkel, D. S., Peng, S., Pesko, M. F., & Wang, H. (2020). Mostly harmless regulation? Electronic cigarettes, public policy, and consumer welfare. *Health Economics*, *29*(11), 1364-1377.

Kesternich, I., Heiss, F., McFadden, D., & Winter, J. (2013). Suit the action to the word, the word to the action: Hypothetical choices and real decisions in Medicare Part D. *Journal of Health Economics*, *32*(6), 1313-1324.

Maestas, N., Mullen, K. J., & Powell, D. (2023). The Effect of Population Aging on Economic Growth, the Labor Force, and Productivity. *American Economic Journal: Macroeconomics*, *15*(2), 306-332.

Marti, J., Buckell, J., Maclean, J. C., & Sindelar, J. (2019). To "vape" or smoke? Experimental evidence on adult smokers. *Economic Inquiry*, *57*(1), 705-725.

Mas, A., & Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review*, *107*(12), 3722-3759.

McFadden, Daniel (2017). "Stated Preference Methods and Their Applicability to Environmental Use and Non-use Valuations." *In Contingent Valuation of Environmental Goods: A Comprehensive Critique.* Daniel McFadden and Kenneth Train, editors. Edward Elgar Publishing. Elgaronline.com.

Mohammadi, T., Bansback, N., Marra, F., Khakban, A., Campbell, J.R., FitzGerald, J.M., Lynd, L.D., & Marra,C.A. (2017) Testing the External Validity of a Discrete Choice Experiment Method: An Application to Latent Tuberculosis Infection Treatment, Value in Health, 20 (7), 969-975.

Moshary, S., Shapiro, B., & Drango, S. (2023). *Preferences for firearms and their implications for regulation* (No. w30934). National Bureau of Economic Research.

Penn, J. M., & Hu, W. (2018). Understanding hypothetical bias: An enhanced meta-analysis. *American Journal of Agricultural Economics*, *100*(4), 1186-1206.

Quaife, M., Terris-Prestholt, F., Di Tanna, G. L., & Vickerman, P. (2018). How well do discrete choice experiments predict health choices? A systematic review and meta-analysis of external validity. *The European Journal of Health Economics*, *19*, 1053-1066.

Regmi, K., Kaphle, D., Timilsina, S., Tuha, N. A. A. (2018). Application of discrete-choice experiment methods in tobacco control: A systematic review. *PharmacoEconomics Open*, 2, 5-17.

Reynolds, R. M., Popova, L., Ashley, D. L., Henderson, K. C., Ntansah, C. A., Yang, B., ... & Thrasher, J. (2022). Messaging about very low nicotine cigarettes (VLNCs) to influence policy attitudes, harm perceptions and smoking motivations: a discrete choice experiment. *Tobacco Control*.

Rousu, M.C., Marette, S., Thrasher, J. F., Lusk, J. L. (2014). The economic value to smokers of graphic warning labels on cigarettes: Evidence from combining market and experimental auction data. J*ournal of Economic Behavior and Organization,* 108, 123-134.

Ryan, M., Gerard, K., & Amaya-Amaya, M. (Eds.). (2007). *Using discrete choice experiments to value health and health care* (Vol. 11). Springer Science & Business Media.

Shang, C., Huang, J., Chaloupka, F. J., and Emery, S. L. (2018). The impact of flavor, device type, and warning messages on youth preferences for electronic nicotine delivery systems: evidence from an online discrete choice experiment. *Tobacco Control* 27: e152-e159.

Shang, C., Weaver, S. R., White, J. S., Huang, J., Nonnemaker, J., Cheng, K. W., & Chaloupka, F. J. (2020). E-Cigarette product preferences among adult smokers: a discrete choice experiment. *Tobacco Regulatory Science*, *6*(1), 66.

Telser, H., & Zweifel, P. (2007). Validity of discrete-choice experiments evidence for health risk reduction. *Applied Economics*, *39*(1), 69-78.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge University Press.