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ABSTRACT

A small but rapidly growing percentage of the U.S. population uses e-cigarettes. Policymakers, especially the FDA, are concerned about their public health impact and thus are contemplating regulations. We provide empirical evidence to inform such policy choices. Specifically, we examine how the demand for e-cigarettes would vary across policy-relevant attributes: 1) health impact, 2) effectiveness in helping smokers quit, 3) bans in public places, and 4) price. We conduct an online discrete choice experiment of 1,669 adult smokers who select among combustible cigarettes and two types of e-cigarettes as attributes are varied. Using a conditional logit model we estimate smokers’ preferences across attributes. Then, using a latent class model, we identify types of smokers and conduct policy simulations separately by these types and for the full sample. In general, smokers value the attributes in the predicted directions and the demand for e-cigarettes tends to be motivated more by smokers’ health concerns than by price or smoking bans. The latent class model identifies three types of smokers, those who prefer combustible cigarettes (‘smokers’), e-cigarettes (‘vapers’), and using both (‘dual users’). We conclude that varying these policy-relevant attributes will have small, significant impacts on average, but with substantial heterogeneity by smoker type.

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1. Introduction

First developed in China in the early 2000s (Riker, Lee, Darville, & Hahn, 2012), electronic cigarettes (‘e-cigarettes’) entered the United States tobacco market in 2007 (Riker et al., 2012) and are increasingly used in the U.S. and globally. While in 2015 only 12.7% of adults in the U.S. have tried e-cigarettes, use has doubled every year since 2010 (Allen et al., 2015; Ayers, Ribisl, & Brownstein, 2011; Etter, 2010; Regan, Promoff, Dube, & Arrazola, 2013; Schoenborn & Gindi, 2015). Due to the recent growth in use of e-cigarettes, governments at the local, state, and federal levels are considering regulating and taxing them (Lempert, Grana, & Glantz, 2014). The current view is that e-cigarettes are less harmful than smoking combustible cigarettes. However, there is considerable uncertainty around the net health impact of e-cigarettes and the demand for these products. Our study aims to provide policy-relevant evidence in advance of resolution of these uncertainties.

There are several policy options that could directly or indirectly affect e-cigarette use. States and federal agencies may consider governing e-cigarettes with the same policies that they apply to the traditional, combustible cigarettes, e.g. they could ban e-cigarettes in public places and tax them. Importantly, the Food and Drug Administration (FDA) gained the right to regulate the manufacturing, marketing, and sales of tobacco products through the 2009 Family Smoking Prevention and Tobacco Control Act. Recently the FDA claimed, or ‘deemed’, the right to regulate e-cigarettes as well and is waiting for final approval.[1] While the FDA currently has the authority to regulate e-cigarettes sold for therapeutic purposes ("Sottera, Inc. v. FDA," 2010), it is seeking to require the following for commercial e-cigarettes: reporting of product

[1] https://www.gpo.gov/fdsys/pkg/USCOURTS-caDC-10-05032; accessed 12/20/2015).

ingredients, premarket review of new products, review of claims of reduced risk by manufacturers, and inclusion of health warnings among other policies.

These and future FDA regulations could directly and/or indirectly affect both the health impact of e-cigarettes and the effectiveness of e-cigarettes as a smoking cessation strategy. For example, premarket review of e-cigarettes could prevent the more harmful products from reaching the market and improve the effectiveness of e-cigarettes in helping smokers to quit smoking combustible cigarettes.

The FDA is mandated to regulate e-cigarettes and other tobacco products to protect the health of the public, which is contrast to the criteria of safety and effectiveness used by the FDA to regulate pharmaceutical product and devices. Thus the predicted health harm of e-cigarettes relative to that of combustible cigarettes is key in policy deliberations: whether greater use of e-cigarettes will promote or reduce public health is currently debated. The impact on health can be affected by regulation, taxation, pattern of use, and industry decisions. Currently, e-cigarettes are believed to be less harmful to both the user and those around them (Bahl et al., 2012; Goniewicz, Lingas, & Hajek, 2013; Vardavas et al., 2012; Williams, Villarreal, Bozhilov, Lin, & Talbot, 2013) largely because e-cigarettes use a heating filament to vaporize a liquid typically containing nicotine, and thus avoid the burning of tobacco. We note, however, that the current evidence appears far from conclusive (Mckee & Capewell, 2015). Additionally, it is unclear whether current smokers who use e-cigarettes will use them as a harm reduction method, as cessation device, or to evade smoking bans for combustible cigarettes. Also, recent findings highlight the likely toxicity of e-cigarettes (Yu et al., 2016). This uncertainty raises a quandary for regulatory and taxing agencies aiming to protect public health.

In this study, we provide policy-relevant information on adult smokers' preferences and trade-offs between combustible cigarettes and e-cigarettes. Because high quality, revealed preference e-cigarette data are not yet available, we gather original data using a stated-preference approach. More specifically, we conduct a large, online, discrete choice experiment (DCE) to examine the relative importance of key policy-relevant attributes of e-cigarettes. DCEs are widely applied to health and health behaviors (Amaya-Amaya, Gerard, & Ryan, 2008; Clark, Determann, Petrou, Moro, & de Bekker-Grob, 2014; de Bekker‐Grob, Ryan, & Gerard, 2012), and specifically to smoking and e-cigarette use (Czoli, Goniewicz, Islam, Kotnowski, & Hammond, 2015; Heredia-Pi, Servan-Mori, Reynales-Shigematsu, & Bautista-Arredondo, 2012; Marti, 2012; McLaughlin, Gueorguieva, & Sindelar, 2015; Paterson, Boyle, Parmeter, Neumann, & De Civita, 2008; Pesko, Kenkel, Wang, & Hughes, 2015; Salloum et al., 2015). We focus on four key attributes of e-cigarettes that can be affected, directly or indirectly, by policymakers: 1) health impact relative to combustible cigarettes, 2) potential to help smokers quit using combustible cigarettes, 3) bans in public places, and 4) price, which can be affected by taxation. Our DCE allows us to estimate smokers' preferences for these attributes, identify different types of smokers, and make predictions about the impact of different regulatory and tax choices.

2. Methods and sample

2.1. DCE development

We present respondents with different combinations of our policy-relevant attributes. We ask respondents in our sample to make repeated choices among: 1) combustible cigarettes; 2) single-use, disposable e-cigarettes; and 3) refillable, rechargeable e-cigarettes. Because we focus on a sample of those who currently smoke combustible cigarettes, we consider choice of the combustible cigarette as the relevant 'opt-out' choice. We are most concerned with the trade-offs between combustible cigarettes and e-cigarettes as a group, but we include both the disposable and rechargeable e-cigarettes in our choice sets as these two popular products have different pricing schemes (described later in the manuscript).

Attributes. We describe these cigarette products using four attributes that can be affected directly or indirectly by policymakers: 1) whether e-cigarettes are considered healthier than combustible cigarettes, 2) the effectiveness of e-cigarettes as a cessation device, 3) banning of e-cigarettes use in public places (bars, restaurants, etc.), and 4) price. We confirmed the importance of these attributes to adult smokers in an earlier pilot study (Maclean, Marti, & Sindelar, 2015). We construct indicator variables for the three non-price attributes of e-cigarettes. Attributes and their levels are presented in Table 1. For combustible cigarettes, the above attributes are set to 'no' to reflect the current state of the world. That is, they currently are banned, not healthy, and do not help one quit.

The price of combustible cigarettes and disposable e-cigarettes is well described by their marginal price (i.e., price for a pack of combustible cigarettes or for a single e-cigarette). However, for rechargeable e-cigarettes, consumers must purchase a kit, which includes a battery package and a charger also buy bottles of e-cigarette liquid. Thus we define both a *marginal* price and a *fixed* price to capture the full price of rechargeable e-cigarettes.

We use a single measure of the marginal price for both combustible cigarettes and e-cigarettes. For this, we standardize the marginal price across cigarette types and express it as ‘price per combustible cigarette pack-equivalent’, which we define as the price to smoke the equivalent of 20 combustible cigarettes.

We define a range of prices for the disposable and rechargeable e-cigarette. We set the marginal price for each e-cigarette type to have three levels: $5, $8, and $12 for disposable e-cigarettes; and $3, $5, and $8 for rechargeable e-cigarettes. For the latter we also include a separate price component- the price of the kit which we vary from $20, $40, to $80. We obtained market prices from online sources to use as our midpoint price. Then we provide one lower and one higher price for each. The lower market price for the liquid for rechargeable e-cigarettes reflects both possibility of buying the liquid in more economical quantities and the need to buy only the refill, not a new device each time.

To make the choice task realistic we ask our sample members the current price that they pay for a pack of combustible cigarettes and use this to define their own marginal price for such cigarettes. This price is self-reported by the individual and does not vary across the choice options for a single smoker. Prior to the experiment, we provide respondents with background information on the three cigarette types so that respondents have at least a minimum common knowledge base. In the choice sets, we asked respondents to assume that they could purchase e-cigarettes where they purchased their combustible cigarettes and that all cigarettes contained the same amount of nicotine. We provided a brief description of each type of cigarette and listed several common brands. Of note, we use a labeled experiment rather than an unlabeled experiment because a labeled experiment has several advantages including making the choices realistic to respondents (de Bekker ‐ Grob et al., 2010). We do this knowing that in a labeled experiment respondents may ignore some attributes in their choices, i.e. attribute non-attendance (Hensher, 2014). We also provided respondents with an example of a completed choice set before the experiment commenced to assist respondents in understanding the choice task.

2.2 Experimental design

For each set of four attributes, respondents are asked to choose among the three cigarette types products. Appendix A provides an example choice set. The full factorial design gives rise to 72 (i.e., $2^3 x 3^2$; see Table 1) possible combinations of attributes. We use a fractional factorial design with only 12 choice sets (i.e., each with 2 e-cigarette options and 1 'opt-out' combustible cigarette option) to pilot our survey. Then based on the priors obtained with analyses of the pilot data, we generate a D-efficient design with 12 choice sets using the software Ngene (D-error=0.36) (Carlsson & Martinsson, 2003). Respondents are randomly allocated to one of two mutually exclusive blocks of six choice sets. We confine choices to only six per respondent to prevent respondent fatigue. Although recent evidence suggests that the effects of respondent fatigue are overstated; see for example Hess, Hensher, and Daly (2012).

2.3 Choice modeling

Consistent with the random utility framework, respondents make successive hypothetical choices among three alternatives (j=1, 2, 3) and are assumed to be maximizing utility. Formally, we specify an indirect utility function where the utility for smoker i from product j in choice set c is a linear combination of product attributes and an error term as outlined in Equation (1):

$$V_{ijc} = X_{ijc}'\beta + \varepsilon_{ijc} \tag{1}$$

Where V_{ijc} is the utility derived from the choice, $X_{ijc}'\beta$ is the component of utility that is explained by product attributes (deterministic) and ε_{ijc} stochastic (random) component of utility. The vector X_{ijc} in Equation (1) is specified as a set of product attributes:

$$X'_{ijc}\beta_j = \beta_I Public_j + \beta_H Healthier_j + \beta_Q Quit_j + \beta_P Price_j + \beta_K Price_{kit} + ASC_{dis} + ASC_{rech} \quad (2)$$

Where $Public_j$, $Healthier_j$ and $Quit_j$ are the three policy-relevant product attributes. $Price_{jc}$ and $Price_{kit}$ are the marginal prices of the products and the kit price, respectively. The ASCs are alternative-specific constants that reflect unobserved utility for the e-cigarettes: disposable (ASC_{dis}) and rechargeable (ASC_{rech}). We use combustible cigarettes as the reference alternative. The βs are marginal utilities (taste parameters) to be estimated.

Using the β coefficients, we derive the marginal willingness to pay (WTP) as a ratio of the β coefficient of the non-price attribute of interest to the β coefficient of marginal price. For example, the estimated marginal WTP for being able to use the product in public venues is calculated as: $-(\hat{\beta}_I/\hat{\beta}_P)$. This WTP represents the marginal dollar value that each smoker is willing to pay per pack of combustible cigarettes or per volume equivalent for e-cigarettes for the ability to use the product in public places. To generate measures of precision for our marginal WTP estimates, we construct 95% confidence intervals following the method proposed by Krinsky and Robb (1986).

There are several models available for estimating Equation (1). We start by estimating conditional logit models as the baseline specification. This model expresses the probability of individual *i* choosing alternative *j* among the set options *c* as a probabilistic function of products' attributes:

$$P_{ijc} = \frac{\exp\,(X'_{ijc}\beta)}{\sum_j \exp\,(X'_{ijc}\beta)} \quad (3)$$

Where $X_{ijc}^{'}$ is as described in Equation (2). The conditional logit has two important limitations. First, it assumes homogenous preferences across individuals; and second it assumes independence of irrelevant alternatives (IIA) which is concordant with an identical and independent distribution (IID) of the disturbance. We formally investigate this issue using the Hausman and Mcfadden (1984) IIA test.

With respect to relaxing preference homogeneity, our starting point is to examine separately those individuals who only select combustible cigarettes ('non-switchers') and those who vary their selection ('switchers'). Next, we estimate conditional logit models separately among the non-switchers and switchers. Finally, we estimate a latent class logit model.

We chose a latent class logit over a more general mixed multinomial logit (MMNL) or generalized mixed logit (GMXL) approach for several reasons. First, the latent class logit does not require the imposition of assumptions on parameter distributions for estimation, which is the case for the MMNL. Second, mixed logit parameter estimates can be, due to the complexity of the underlying likelihood function, sensitive to features of the estimation (e.g. optimization algorithm, starting values, etc.), which are known to vary between software packages (Chang & Lusk, 2011; Chiou & Walker, 2007). Further, recent studies suggest that the latent class model may outperform the mixed logit (Hess, Ben-Akiva, Gopinath, & Walker, 2011; Shen, 2009), although this result has not been shown conclusively (Greene & Hensher, 2003; Hess, 2014; Keane & Wasi, 2013). While this approach has been used in health contexts (Flynn, Louviere, Peters, & Coast, 2010; Hole, 2008; Lagarde, Pagaiya, Tangcharoensathian, & Blaauw, 2013; Mentzakis & Mestelman, 2013; Sivey, 2012), we are the first to use this model to examine smoking behavior.

The premise of the latent class model is that a set of unobserved 'classes', or types of individuals, can be identified from the data. Separate parameter vectors (and corresponding variances) are estimated for each class, which allows for preference heterogeneity. Importantly, this model relaxes the IIA assumption of the conditional logit model; thus it allows us to capture more realistic substitution patterns for the classes. The latent class logit model gives the probability of respondent *i* choosing alternative *j* in choice set *c* conditional on membership of class *k*. That is,

$$P_{ic}(j|\beta_k) = \sum_{k=1}^{K} \pi_{ik} \; \frac{\exp\,(X'_{ijc}\beta_k)}{\sum_j \exp\,(X'_{ijc}\beta_k)} \qquad (4)$$

This basic conditional logit is extended over k latent classes and k is determined empirically. The probability of respondent *i* belonging to class k is π_{ik}. Therefore, $0 \leq \pi_{ik} \leq 1$ and the sum across all probabilities is 1. While we cannot directly observe a respondent's class membership, we regress the probability of class membership, π_{ik}, on set of individual characteristics to understand the population classes. We adopt a multinomial logit approach to estimate these regressions, as,

$$\pi_{ik} = \frac{\exp\,(Z'_i\delta_k)}{\sum_{k=1}^{K} \exp\,(Z'_i\delta_k)} \qquad (5)$$

where Z_i is a vector of individual characteristics and δ_k is a corresponding vector of parameters to be estimated.

2.4 Policy simulations

We follow Lancsar and Louviere (2008) and perform a series of predicted probability analyses. The analyses use the coefficients estimated in our choice models to calculate predicted probabilities for each alternative product, under different regulatory and 'states of the world' as defined by the attributes.

The policy simulations are designed to estimate choice shares for the three products under various situations. These simulations are conducted for the full population and also for subgroups identified by the latent class model. We define alternative states in which the prevailing attribute (policy) conditions are more and less favorable for e-cigarettes. We analyze the shifts in predicted choice shares across these situations. These choice shares are not directly comparable to real-world market shares because we only observe the choices of cigarette type by smokers, not the volume purchased. Because we cannot benchmark our data to utilization data, we focus on the changes in choices, rather than absolute levels.

2.5 Data collection and sample

Respondents were required to meet the following criteria: age 18 to 64, reside the U.S., consumed at least 100 combustible cigarettes in their lifetime, currently smoke combustible cigarettes, and provide informed consent. We constructed our sample to match a nationally representative survey of adult smokers using 2010-2011 Current Population Survey Tobacco Use Supplement (CPS-TUS). We contracted the survey firm Qualtrics to collect our sample according to our sampling criteria. We also used Qualtrics software to build our survey. We matched the samples in terms of: sex, age (18 to 34, 35 to 49, and 50 to 64 years), education (less than a college degree and a college degree or higher) and region (New England, Mid Atlantic, Midwest, South, Southwest, and West). The demographic characteristics of our sample and the comparisons to the CPS-TUS are displayed in Table 2, column (4). We find that the statistics are broadly similar in terms of demographics but smokers in our sample tend to have a slightly higher desire to quit smoking and seem to be slightly more addicted.

Our sample of 1,669 smokers is well in excess of several rule-of-thumb measures that have been proposed in the literature (McFadden, 1984; Orme, 2010) and is large compared to other choice experiments published in health care economics (de Bekker-Grob, Donkers, Jonker, & Stolk, 2015).

3. Results

3.1 Choice models

Table 3 shows the results of our baseline conditional logit models. Coefficient estimates in these models do not have a direct interpretation in terms of magnitude, but the relative size of the coefficients is informative. For the full sample (column 1) we find that smokers derive positive utility from the three non-price attributes of e-cigarettes. The relative size of the coefficients suggests that the most to least important attributes are: potential as a smoking cessation device, relative health impact, and ability to use in public places. The results suggest that these smokers are negatively responsive to the marginal price, *ceteris paribus*. The price of the kit, which is specific to rechargeable e-cigarettes, also has a significant, negative impact on choice.

In column 1, we observe that adult smokers in our sample have a strong underlying preference for combustible cigarettes relative to e-cigarettes. This is illustrated by the large negative and statistically significant ASC for both types of e-cigarettes. This preference is not surprising given that we sample from current smokers of combustible cigarettes. However, the ASC is larger in absolute value for the disposable as compared to the rechargeable e-cigarette, suggesting a stronger dislike for disposables.

In column 2, we interact the price of the kit with the ASCs for the two types of e-cigarettes. Consistent with cross-price elasticity responses, these results show that a higher kit price increases the probability that the disposable e-cigarette is chosen and it decreases the probability that the rechargeable option is chosen. However, the coefficients on the other variables remain significant and similar in magnitude to column 1.

Column 3 of Table 3 shows results of the same specification estimated in the subgroup of respondents who chose both combustible cigarettes and e-cigarettes across their choice scenarios. We refer to these respondents as 'switchers'. Interestingly, the estimated ASC for disposable e-cigarettes remains negative, but the ASC for the rechargeable e-cigarette becomes positive, indicating an underlying preference for this latter product over combustible cigarettes amongst switchers. The coefficients for switchers and the full sample are very similar with respect to the attributes of: effectiveness as a quitting device, the relative health impact, and the ability to smoke in public places. Switchers also are slightly less sensitive to the marginal price of e-cigarettes but slightly more sensitive to the price of the kit for the rechargeable option.

To put these magnitudes into perspective, the coefficients are expressed as marginal WTP estimates in Table 4. The estimates suggest that a high value is placed on these attributes. We find that for the full sample, smokers on average have a marginal WTP of $3.30 per pack (or equivalent for e-cigarettes) for the ability to smoke in public places, $4.40 per pack for a healthier product, and $5.20 per pack if the product is effective as a cessation aid. For switchers only, the estimated WTP are larger, $5.70, $7.80, and $10.00, for these attributes respectively, reflecting the higher utility derived from these features by this group. These WTP figures are consistently greater than zero and are estimated with some precision as can be seen from the confidence intervals, which generally do not include zero[2].

To characterize switchers, Table 5 displays odd ratios from a logistic regression of the likelihood of being a switcher on a set of individual characteristics.

[2] Note that the WTP measures cannot be summed. Also note that the high WTP estimates are due to a combination of a high value placed on the attributes a relatively low value placed on price.

Switchers appear to be younger, female, more educated, lighter smokers, and less addicted and also have higher income than non-switchers. In addition, switchers are more likely to plan to quit within one month and to live in a state with a high combustible cigarette tax. All the variables are statistically significant.

We now turn in Table 6 to our models that explore preference heterogeneity by interacting individual characteristics with the ASCs. We estimate models with a single ASC for e-cigarettes (column 1) and a separate ASC for each e-cigarette type (columns 2 and 3). Overall, consistent with our earlier findings, we see that those who prefer e-cigarettes overall and rechargeable e-cigarettes in particular are younger, of higher income, lighter smokers, and more likely to be planning to quit combustible cigarettes within the next month. Those who prefer disposable e-cigarettes have all the above preferences but also are more educated and those live in a high combustible cigarette price state. More addicted smokers appear to dislike e-cigarettes, but the coefficient is not significant in the case of disposables.

We then relax the IIA assumption of the conditional logit model[3] and estimate latent class models. We first select the number of classes using a measure of statistical fit (Akaike Information Criteria, 'AIC') over a range of models of two to seven classes. The model with three classes is superior to all models except for the four-class model. The four-class model, however, gives questionable parameter estimates across classes, which we interpret as a signal that the model may be fit with too many classes (Heckman & Singer, 1984). We therefore focus on the three-class model, which gives plausible parameter estimates and determinants of class membership (Table 7).

[3] We tested, and rejected, the IIA assumption of the conditional logit following Hausman and Mcfadden (1984). A chi-squared statistic of 34.49 (6 degrees of freedom) leads us to reject the null at the 99% level.

Class 1 members (27% of the sample) show a strong preference for e-cigarettes and derive significant utility from, in order: e-cigarettes being an effective cessation aid; e-cigarettes being relatively healthier; and the ability to smoke in public places. This group has positive and significant ASCs for both types of e-cigarettes. We refer to this group as 'vapers' as they tend to choose e-cigarettes predominantly. Class 1 members appear to be akin to class 3 members across all observed characteristics, except for living in a high price state.

We consider class 2 members (45% of the sample) to be dedicated smokers of combustible cigarettes, as reflected in their apparent aversion to choosing e-cigarettes that is indicated in their large, significant, and negative ASCs. We refer to this group as 'smokers'. The coefficients suggest that these smokers do not derive utility from the three non-price attributes. In comparing their estimated characteristics to class 3, it can be seen that these 'smokers' appear to be significantly: older, less likely to live in a high combustible cigarette price state, and less likely to quit in the near future. Reassuringly, the proportion in this subgroup is very close to that of the non-switchers identified from the descriptive statistics in Table 2.

Class 3 members (27% of the sample) derive positive utility from all of four of policy attributes. In order of importance they value: e-cigarettes being an effective cessation aid, the ability to smoke in public places, and e-cigarettes being a healthier option. Class 3 members have a negative and significant ASC for disposable e-cigarettes, but their ASC for rechargeable e-cigarettes is not significant. We refer to this group as 'dual users' as their pattern of choices shows that they are often switching between combustible and electronic cigarettes.

'Vapers' appear to place the highest value on quitting. Both vapers and dual users appear similar in terms of their characteristics but vary in their preferences.

Dual users place greater importance on the ability to smoke in public than the relative healthiness of e-cigarettes. However, even for dual users, preferences are strongest for e-cigarettes being useful as a cessation aid, indicating that dual users may also want to quit smoking. Further, that vapers and dual users are, relative to smokers, living in higher price states may indicate that vapers and dual users are seeking to avoid high taxes on combustible cigarettes.

3.2 Policy simulations

We conduct our simulations for the full sample and for the three classes of smokers identified by our latent class model. Results from these simulations are reported in Table 8 and are displayed graphically in Figure 1. Whilst we have modeled disposable and rechargeable e-cigarettes separately due to differences in pricing structures, here we combine the two e-cigarette types to focus on the policy-relevant issue of the selection of combustible cigarettes vs. e-cigarettes. Thus we provide predicted choice shares for combustible and e-cigarettes. Rows A and B show shares for sets of attributes that are least and most favorable of the use of e-cigarettes, respectively. The four cigarette policy attributes are altered in differing combinations in Rows C to J. While the current state of the world cannot be described using our set of attributes, we consider scenarios in which e-cigarettes are healthier than combustible cigarettes to be closest to reality (i.e. scenarios E, G, I and J).

To predict policy responses, we focus on the changes in choice shares, rather than levels. We focus on changes because our choice shares reflect predictions to counterfactual sets of attribute levels that cannot be measured in real world data on e-cigarettes. Also these are hypothetical choices and are not bound by the respondents' personal realities. For example, some smokers do not have instant access to e-cigarettes. Specifically, respondents may not have easy access to dedicated e-cigarettes stores, or ‘vape shops’, to buy e-cigarette kits. In addition, respondents make choices of type of cigarette, but not intensity of use, i.e. number of cigarettes smoked, making comparisons to real world data difficult.

We find that for the sample as a whole, e-cigarette selection grows around 13 percentage points from least to most favorable (comparing row A to B). This might be considered a relatively large change as measured as percentage from the bases of 33.7% for e-cigarettes and 66.3% for combustible cigarettes. But changes are even larger for specific classes of smokers. Class 3 smokers (‘dual users’) are most responsive to attribute variations, with a difference in e-cigarette share choice of around 30 percentage points between the least and most favorable scenarios from. For class 1 (‘vapers’) and class 2 (’smokers’), the comparable shifts are around 7 percentage points and 10 percentage points, respectively.

With regard to the impact of prices, we first compare the scenario in which only the price for e-cigarettes increases. Comparing rows A (the least favorable for e-cigarettes) to C in which the only difference is the 50% higher price of e-cigarettes, we find only a decrease of 2 percentage points in use of e-cigarettes. The remaining rows show the effects of varying each non-price attribute individually (rows D-F) and in a pairwise fashion (G to I). Each of the policy attributes separately appears to increase the predicted choice share for e-cigarettes when activated by 2 to 3 percentage points. The combined effect of applying all the attributes (comparing row C to row J) is that the predicted choice share for e-cigarettes increases by around 10 percentage points in the full sample. Interestingly, the changes in predicted choice share are again particularly strong in Class 3 individuals and especially for the ‘ability to smoke in public places’ (4 percentage points increase) and ‘cessation aid’ (8 percentage point increase).

4. Discussion

In this paper, we estimate how adult smokers' preferences for newer e-cigarettes versus traditional, combustible cigarettes vary in response to the four key, policy-relevant attributes. We use DCEs as there are few other methods to obtain information on the counterfactual policy scenarios. Our study provides policy-relevant findings in advance of decisions that the FDA and governments of different levels will make with regard to e-cigarette regulation and taxation.

We find that on average, smokers in our sample place significant value on the non-price attributes we study. In order of importance they value e-cigarettes being effective as a cessation aid, as a healthier option compared to combustible cigarettes, and ability to use in public places. Thus we conclude that the desire to improve health is a key motivator of the demand for e-cigarettes for the average adult smoker. Price has a significant, negative impact as expected.

We find substantial heterogeneity in preferences by smoker type. Our preferred specification includes three latent classes of smokers: 'smokers', 'vapers' and 'dual-users'. Vapers and smokers seldom divert from their preferred cigarette type while dual users' choices vary depending on the attribute scenarios. We find that preferences for these non-price policy attributes vary across groups. Specifically, these attributes are valued highly by 'vapers' and to a lesser extent by 'dual users'. The ranking of preferences for these attributes suggest that 'vapers' value e-cigarettes mostly for their relative health benefits, whereas 'dual users' value both the health benefits and the evasion of smoking bans. 'Smokers' place very little value on these attributes and are therefore unlikely to respond greatly to potential changes, but they are more price-sensitive, older and less interested in quitting as compared to the other two groups.

Our study has several limitations that should be noted. Clearly DCEs rely on hypothetical choice, i.e. we observe stated choices and not real-world behaviors. Although there is a risk of hypothetical bias (Harrison, 2014), several studies have documented a high comparability between stated and revealed choices in health behaviors (Few, Acker, Murphy, & MacKillop, 2012; Harrison & Rutstrom, 2006; Wilson, Franck, Koffarnus, & Bickel, 2015). A second limitation is that while the demographics of our sample are nationally representative, smokers in our sample smoke slightly more heavily and are more addicted than the average U.S. smoker. Third, our results are pertinent only to adult smokers. Youth smoking decisions should be examined separately but is beyond the scope of this study. Lastly, we do not observe if smokers alter their quantity of consumption depending on product selected. For example, by changing to e-cigarettes, smokers may decide to smoke either more or less heavily.

The results from this study have implications for policies relating to e-cigarettes. While we show that each of our policy-related attribute affects the demand for e-cigarettes and combustible cigarettes among current smokers, we find important heterogeneity in response to attributes in the three smoker types we identified. As discussed above, those who have strong preferences for combustible cigarettes are the least likely to be influenced by changes in e-cigarette policies. However, these smokers are particularly price-responsive, thus higher taxes on combustibles may encourage them to cutback, quit or switch. Conversely, ‘dual-users’ are the most likely to be persuaded to switch to e-cigarettes following policy changes. ‘Vapers’ are also affected by the policies relating to e-cigarettes but to a lesser degree as they already have strong underlying preference for this product.

To make full use of our findings, policymakers will have to determine their stance on the potential health impacts of e-cigarettes. Specifically, do they want to encourage smokers of combustible cigarettes to change to e-cigarettes to reduce the harms to their health? E-cigarettes are currently considered to be healthier than combustible cigarettes by most experts. Thus if current smokers substitute e-cigarettes for the more harmful, combustible cigarettes, or use e-cigarettes as a method to quit smoking combustible cigarettes the health of the public would be improved. In contrast, there is concern that e-cigarette use might increase smoking of combustible cigarettes by normalizing smoking in general and/or by reducing the motivation to quit smoking combustible cigarettes. However, there is little evidence in either direction with regard to the former argument. The latter could occur because currently smokers could meet their demand for nicotine by using e-cigarettes where combustible cigarettes are banned.

Our evidence suggests that the demand for e-cigarettes by adult smokers is driven most strongly by the desire for better health. Consequently, we suggest that the use of e-cigarettes may, on average, help current smokers protect their health relative to the use of combustible cigarettes. In this context, regulations that tax or ban e-cigarette use could reduce public health, whereas regulations that directly or indirectly reduce the health harm of e-cigarettes and increase their effectiveness in helping smokers quit smoking combustible cigarettes would likely improve the health of adult smokers. However, this set of conclusions should be balanced against the net impact of e-cigarettes on youths, which is beyond the scope of this paper. Thus for our sample of adult smokers, the net effect of e-cigarettes might well be to improve public health, and governments could design policies to promote smokers to either quit smoking or switch to e-cigarettes.

Table 1. Product attributes and levels

Product attribute:	Disposable e-cigarette levels	Rechargeable e-cigarette levels	Combustible cigarette levels
Use of product is permitted in public places	Yes, no	Yes, no	No
Product considered to be healthier than combustible cigarettes	Yes, no	Yes, no	No
Product can be used as a cessation aid	Yes, no	Yes, no	No
Marginal price	\$5, \$8, \$12	\$3, \$5, \$8	Respondent reported
Kit price	-	\$20, \$40, \$80	-

Table 2. Sample characteristics

Sample:	Full sample	Switcher sample	Non-switcher sample	CPS-TUS sample
Variable				
Male (proportion)	0.52	0.52	0.51	0.52
Female (proportion)	0.48	0.48	0.49	0.48
18-29 years (proportion)	0.21	0.28	0.11	0.23
30-44 years (proportion)	0.30	0.34	0.24	0.32
45-54 years (proportion)	0.26	0.21	0.33	0.27
55-64 years (proportion)	0.23	0.17	0.32	0.18
Less than high school (proportion)	0.06	0.05	0.07	0.16
High school (proportion)	0.47	0.45	0.51	0.40
Some college (proportion)	0.27	0.26	0.29	0.33
College (proportion)	0.20	0.24	0.13	0.12
Household income <$30,000 (proportion)	0.38	0.34	0.44	0.43
Household income $30,000-$60,000 (proportion)	0.38	0.40	0.34	0.32
Household income >$60,000 (proportion)	0.24	0.26	0.21	0.25
Daily combustible cigarette consumption (mean, SD)	14.2 (9.7)	12.9 (9.1)	16.3 (10.1)	13.8 (8.6)
Plan to quit within 1 month (proportion)	0.32	0.41	0.17	0.16
Addicted smoker† (proportion)	0.28	0.26	0.31	0.17
Live in high price combustible cigarette state†† (proportion)	0.09	0.13	0.04	0.02
N	**1,669**	**993**	**676**	**19,364**

Notes: A switcher is defined as a respondent who picks an e-cigarette option at least at one choice occasion. A non-switcher is defined as a respondent who does not pick an e-cigarette in any choice occasion. CPS-TUS sample includes respondents' ages 18 to 64 years of age who currently smoke combustible cigarettes in the 2010-2011 Current Population Survey Tobacco Use Supplements.
†Addicted smoker=Smoke first cigarette within 5 minutes of waking up.
††High price combustible cigarette state=pay $10 or more for a pack of combustible cigarettes.

Table 3. Determinants of cigarette choices: Conditional logit model

Sample:	Full sample	Full sample	Switcher sample
ASC: disposable e-cigarette	-1.75***	-1.95***	-0.70***
	(-38.84)	(-30.52)	(-14.32)
ASC: rechargeable e-cigarette	-1.13***	-1.21***	0.15*
	(-19.33)	(-24.34)	(2.26)
Use of product is permitted in public places	0.22***	0.21***	0.21***
	(6.72)	(6.39)	(6.31)
Product considered to be healthier than combustible cigarettes	0.29***	0.29***	0.29***
	(8.92)	(8.65)	(8.63)
Product can be used as a cessation aid	0.35***	0.36***	0.37***
	(10.69)	(10.85)	(10.99)
Marginal price	-0.07***	-0.07***	-0.04***
	(-14.68)	(-14.74)	(-7.11)
Kit price	-0.01***	--	-0.01***
	(-7.27)		(-9.13)
ASC disposable e-cigarette*low kit price†	--	0.20**	--
		(2.59)	
ASC disposable e-cigarette*high kit price††	--	0.36***	--
		(4.96)	
ASC rechargeable e-cigarette* low kit price††	--	-0.36***	--
		(-6.15)	
ASC rechargeable e-cigarette* high kit price††	--	-0.39***	--
		(-6.51)	
N	**1,669**	**1,669**	**993**

Notes: Dependent variable is an alternative choice. All models estimated with a conditional logit model and control for personal characteristics listed in Table 2. *t* statistics in parentheses. A switcher is defined as a respondent who picks an e-cigarette option at least at one choice occasion.
ASC=Alternative-specific constant.
†Low kit price is defined as $40.
††High kit price is defined as $80.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Willingness-to-pay (WTP) estimates for policy product attributes

Product attribute:	**Full sample**	**Switcher sample**
Use of product is permitted in public places	$3.3 [$2.2-$4.3]	$5.7 [$3.3-$8.1]
Product considered to be healthier than combustible cigarette	$4.4 [$3.2-$5.5]	$7.8 [$5.0-$10.6]
Product can be used as a cessation aid	$5.2 [$4.1-$6.4]	$10.0 [$6.7-$13.3]

Notes: WTP for the full sample and switcher sample calculated using estimates from models (2) and (3) in Table 3 respectively. Krinsky-Robb (1986) 95% confidence intervals in square brackets. A switcher is defined as a respondent who picks an e-cigarette option at least at one choice occasion.

Table 5. Characteristics associated with being a switcher: Logit model

Variable:	**Odds ratio (Standard error)**
Male	0.94**
	(0.02)
30-44 years	0.52***
	(0.02)
45-54 years	0.29***
	(0.01)
55-64 years	0.26***
	(0.01)
Some college	1.30***
	(0.03)
Household income <$30,000	0.85***
	(0.02)
Heavy smoker†	0.89***
	(0.03)
Addicted smoker††	0.91***
	(0.03)
Plan to quit within 1 month	2.72***
	(0.08)
Lives in high price combustible cigarette state†††	2.41***
	(0.14)
N	**1,669**

Notes: Dependent variable is an indicator for being a switcher. A switcher is defined as a respondent who picks an e-cigarette option at least at one choice occasion. Omitted categories are female, 18-29 years, less than a college education, and household income ≥ $30,000. Standard errors are clustered around the respondent and reported in parentheses.

†Heavy smoker=Smoke more than 20 combustible cigarettes per day.

††Addicted smoker= Smoke first cigarette within 5 minutes of waking up.

†††High price combustible cigarette state=pay $10 or more for a pack of combustible cigarettes.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6. Determinants of cigarette choices: Multinomial logit model with interactions between alternative-specific constants and individual characteristics

Specification:	**Joint ASC for e-cigarettes**	**ASC for disposable e-cigarette**	**ASC for rechargeable e-cigarette**
Product ASC	-1.78*** (0.07)	-2.30*** (0.09)	-1.52*** (0.07)
Interactions between ASC and individual characteristics			
Male	-0.04 (0.04)	-0.05 (0.06)	-0.03 (0.05)
18-29 years	0.63*** (0.05)	0.51*** (0.07)	0.72*** (0.06)
Some college	0.14 (0.04)	0.24*** (0.06)	0.08 (0.05)
Household income <30,000	-0.26*** (0.05)	-0.32*** (0.07)	-0.24*** (0.05)
Heavy smoker†	-0.30*** (0.07)	-0.48*** (0.10)	-0.22*** (0.08)
Addicted smoker††	-0.12** (0.05)	-0.07 (0.07)	-0.16*** (0.06)
Plan to quit within 1 month	0.92*** (0.05)	0.84*** (0.06)	0.97*** (0.05)
Live in high price combustible cigarette state†††	-0.05 (0.09)	0.33*** (0.11)	0.08 (0.10)
N	**1,669**	**1,669**	**1,669**

Notes: Dependent variable is an alternative choice. The reported coefficients and their standard errors are obtained by estimating a conditional logit model with the same specification as model (2) in Table 3 where the alternative-specific constants are interacted with a set of individual characteristics. The joint ASC model uses a unique ASC that indicates e-cigarettes, irrespective of the type (disposable or rechargeable). Omitted categories are female, 30 to 64 years, less than college, and household income ≥ $30,000. ASC=Alternative-specific constant.

†Heavy smoker=Smoke more than 20 combustible cigarettes per day.

††Addicted smoker=Smoke first cigarette within 5 minutes of waking up.

†††High price combustible cigarette state=pay $10 or more for a pack of combustible cigarettes.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7. Determinants of cigarette choices: Latent class model with 3 classes

Sample:	**Class 1: Vapers**	**Class 2 : Smokers**	**Class 3: Dual users**
Utility function (taste) parameters			
ASC: disposable e-cigarette	1.24***	-6.22**	-1.31***
	(0.19)	(2.35)	(0.20)
ASC: rechargeable e-cigarette	2.13***	-5.51***	-0.38
	(0.21)	(0.62)	(0.27)
Use of product is permitted in public places	0.19***	1.17	0.18*
	(0.05)	(1.15)	(0.07)
Product considered to be healthier than combustible cigarette	0.34***	1.25	0.14*
	(0.05)	(1.26)	(0.07)
Product can be used as a cessation aid	0.37***	0.66	0.36***
	(0.05)	(0.43)	(0.07)
Marginal price	-0.02*	-0.11***	-0.07***
	(0.01)	(0.03)	(0.01)
Kit price	-0.01***	-0.03	-0.02***
	(0.002)	(0.05)	(0.003)
Class membership parameter estimates			
Male	-0.02	0.02	-
	(0.16)	(0.14)	
18-30 years	0.10	-0.99***	-
	(0.18)	(0.20)	
Some college	-0.04	-0.28	-
	(0.17)	(0.15)	
Household income <$30,000	-0.33	0.10	-
	(0.18)	(0.17)	
Heavy smoker†	-0.51	0.05	-
	(0.27)	(0.20)	
Addicted smoker††	0.06	0.22	-
	(0.20)	(0.19)	
Plan to quit within 1 month	0.57**	-0.86***	-
	(0.17)	(0.17)	
Live in high price combustible cigarette state†††	-0.18	-0.66*	-
	(0.28)	(0.27)	
Constant	-0.06	0.99***	-
	(0.20)	(0.17)	
Class shares	**0.274**	**0.454**	**0.271**
N (total)		**1,669**	

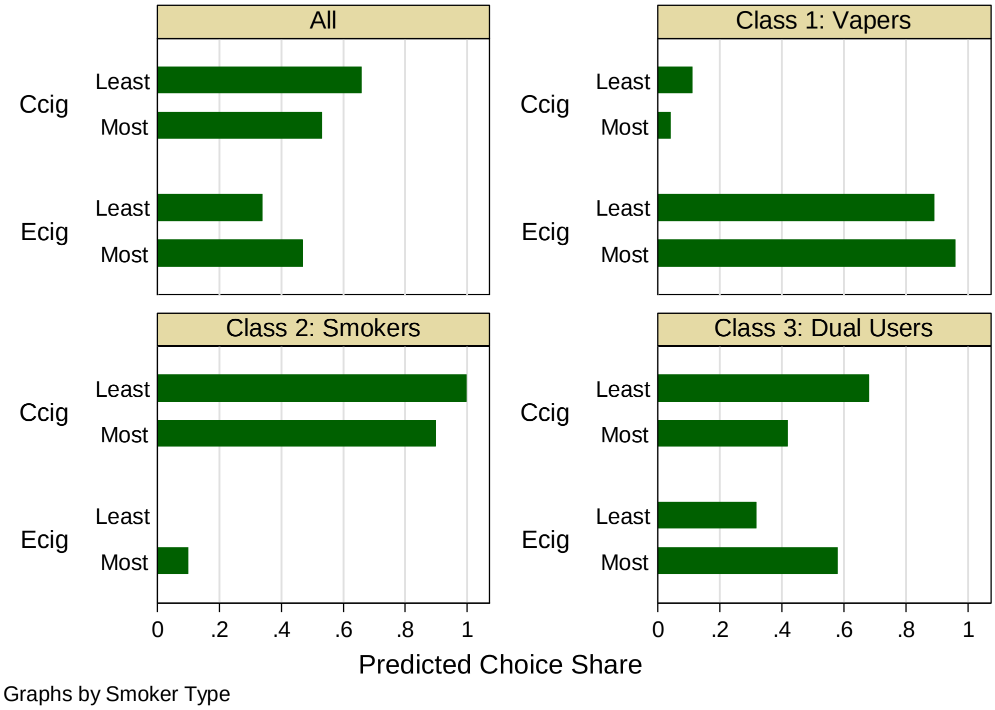
Notes: Dependent variable is an alternative choice. Omitted categories are female, 31 to 64 years, less than college, and household income ≥ $30,000. Standard errors in parentheses. ASC=Alternative-specific constant.
†Heavy smoker=Smoke more than 20 combustible cigarettes per day.
††Addicted smoker=Smoke first cigarette within 5 minutes of waking up.
†††High price combustible cigarette state=pay $10 or more for a pack of combustible cigarettes.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Policy simulations

	Use in public places is permitted	Product considered to be healthier than tobacco	Product can be used as a cessation aid	50% higher ecig price	50% higher ccig price	Full Sample: All Smokers		Class 1: Vapers (27%)		Class 2: Smokers (46%)		Class 3: Dual users (27%)	
						Ecig	Ccig	Ecig	Ccig	Ecig	Ccig	Ecig	Ccig
	Two "extreme scenarios"												
A	**0**	**0**	**0**	**1**	**0**	**33.7%**	**66.3%**	**89.2%**	**10.8%**	**0.1%**	**99.9%**	**31.7%**	**68.3%**
B	**1**	**1**	**1**	**0**	**1**	**46.9%**	**53.1%**	**95.9%**	**4.1%**	**10.2%**	**89.8%**	**58.2%**	**41.8%**
	Policy attributes activated/deactivated												
C	0	0	0	0	0	35.4%	64.6%	89.9%	10.1%	0.1%	99.9%	36.9%	63.1%
D	1	0	0	0	0	37.1%	62.9%	91.5%	8.5%	0.7%	99.3%	41.0%	59.0%
E	0	1	0	0	0	37.2%	62.8%	92.6%	7.4%	0.8%	99.2%	40.0%	60.0%
F	0	0	1	0	0	38.5%	61.5%	92.8%	7.2%	0.3%	99.7%	45.1%	54.9%
G	1	1	0	0	0	39.8%	60.2%	93.8%	6.2%	3.3%	96.7%	44.3%	55.7%
H	1	0	1	0	0	40.4%	59.6%	94.0%	6.0%	1.4%	98.6%	49.4%	50.6%
I	0	1	1	0	0	40.5%	59.5%	94.7%	5.3%	1.6%	98.4%	48.5%	51.5%
J	1	1	1	0	0	44.1%	55.9%	95.6%	4.4%	6.9%	93.1%	52.8%	47.2%

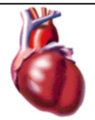
Notes: Simulations were performed using the latent class model with 3 classes shown in Table 7. For each product type, the table shows the unconditional choice probabilities (class-specific class-probabilities weighted by the corresponding class shares) and the choice probabilities conditional on belonging to a particular class. The baseline scenario uses a price of $5.33 for rechargeable cigarettes with a kit price of $45, a price of $8.33 for disposable e-cigarettes and the self-reported price for tobacco cigarettes. All policy and public health attributes were set to zero. Key: ecig – e-cigarette, ccig – combustible cigarette.

Figure 1. Predicted choice shares of products (conditional on being a smoker), by type of smoker



Notes: Ecig=e-cigarette; Ccig=combustible cigarette; Least=least favorable conditions for e-cigarettes (row A in Table 8); and Most=most favorable conditions for e-cigarettes (row B in Table 8). Predictions are based on coefficient estimates presented in Table 7.

Appendix A: Example of choice set

	Characteristics	Disposable e-cigarette	Rechargeable e-cigarette	Tobacco cigarette
				
$	**Price for the equivalent of 20 tobacco cigarettes (400 puffs)**	**$5** per e-cigarette	**$8** per refill	**[respondent self-reported price]** per pack
	Price of the starter kit	**$0** (no kit needed)	**$20**	**$0** (no kit needed)
	**Are you allowed to smoke the cigarette in public places (restaurants, bars, workplaces, and shopping malls)?**	No	Yes	No
	**Is this cigarette healthier than tobacco cigarettes?**	Yes	No	No
	**Does this cigarette help you quit smoking tobacco cigarettes?**	No	Yes	No
YOU CHOOSE	**Please mark which cigarette type you would buy (CHOOSE ONLY ONE):**	☐	☐	☐

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