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ABSTRACT

To 'Vape' or Smoke? A Discrete Choice Experiment among Adult Smokers*

A growing share of the United States population uses e-cigarettes. In response, policymakers are considering regulating e-cigarettes, or have already done so, due to concerns regarding e-cigarettes' public health impact. However, there is currently little population-based evidence to inform these regulatory choices. More information is needed on how policy-relevant factors will likely drive smokers' decision to use e-cigarettes. To provide this information we conduct an online survey and discrete choice experiment to investigate how adult tobacco cigarette smokers' demand for cigarette type varies by four policy-relevant attributes: 1) whether e-cigarettes are considered healthier than tobacco cigarettes, 2) the effectiveness of e-cigarettes as a cessation device, 3) bans on use in public places such as bars and restaurants, and 4) price. Overall, we find that the demand for e-cigarettes is motivated more by smokers' health concerns than by the desire to avoid smoking bans or higher prices. However, results from latent class models reveal three distinct groups of smokers, those who prefer: tobacco cigarettes, e-cigarettes, and using both products. Each group responds differently to the cigarette attributes suggesting that policies will have different impacts across the groups.

JEL Classification: C35, I12, I18

Keywords: e-cigarettes, smoking, discrete choice experiments, preference heterogeneity, regulation

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I. INTRODUCTION

E-cigarettes are emerging products in United States tobacco markets and are controversial. These products were developed in China in 2003 and entered the U.S. in 2007 (Riker et al. 2012). Since that time, e-cigarette use has proliferated among Americans. For instance, currently 3.6% of adults (Schoenborn and Gindi 2015) and 16% of high school students (Singh 2016) use them. E-cigarettes are battery-operated, often tobacco cigarette-shaped, devices containing a liquid which typically contains nicotine along with other components such as propylene glycol and flavors. A heating element vaporizes the liquid and the resulting vapor is inhaled (referred to as 'vaping'). Because tobacco is not burned, carcinogens are not produced nor inhaled with e-cigarette use.

The controversy over e-cigarettes relates to the extent to which their use improves or harms public health. On the one hand, e-cigarettes are generally considered to be a less harmful alternative to tobacco cigarettes for both smokers and non-smokers (Bahl et al. 2012, Benowitz and Goniewicz 2013, McNeill et al. 2015); although the evidence is not yet conclusive (Allen et al. 2015, Mckee and Capewell 2015, Yu et al. 2016). Moreover, e-cigarettes are currently thought to be effective as a cessation aid, at least for some populations (Hartmann‐Boyce et al. 2016). These attributes suggest that e-cigarette use will improve public health.

On the other hand, there are concerns that e-cigarettes might be used by smokers as a means to circumvent existing public use bans on tobacco cigarettes, thus reducing the motivation to quit. Because e-cigarettes are considered less harmful, smokers could increase their consumption and become even more addicted to nicotine.[1] Addiction to nicotine without the effects of the toxins released in the burning of tobacco cigarettes is not necessary harmful to adults, but may damage the developing adolescent brain (U.S. Department of Health Human

[1] Nicotine is the primary addictive ingredient in tobacco cigarettes and e-cigarettes (although not all e-cigarettes contain nicotine).

Services 2014). Another concern is that e-cigarette use will lead to use of tobacco cigarettes (Fairchild, Bayer, and Colgrove 2014, Friedman 2015, Pesko, Hughes, and Faisal 2016). These attributes suggest that e-cigarette use will harm public health.

Federal, state, and local policymakers are currently determining how best to regulate e-cigarettes and in particular whether or not to favor e-cigarettes over tobacco cigarettes. Policymakers must determine whether their objective is to support or curtail e-cigarette use before implementing regulations. For example, the U.S. Food and Drug Administration (FDA) recently gained the authority to regulate e-cigarettes with the mandate of improving public health. The FDA can directly or indirectly affect the health impact of both e-cigarettes and tobacco cigarettes through, for example, premarket review of ingredients and health claims made by manufacturers. This agency can also regulate information regarding effectiveness of e-cigarettes as cessation devices.[2] In terms of youth access, in 2016 the FDA prohibited the sale of e-cigarettes to minors. Moreover, states and localities have already imposed minimum purchase laws that limit youth access, levied taxes, applied manufacturing restrictions to promote product safety, and banned vaping in public places (Lempert, Grana, and Glantz 2014).

Empirical evidence on the impact of such regulations is critical to informing government decision-making, yet is generally unavailable due to the lack of data. Regulations were implemented by state policymakers beginning only in 2010 (Centers for Disease Control and Prevention 2016) and there is little survey data available to study regulatory effects.[3] Moreover, the market for e-cigarettes is quickly changing and thus survey data may contain information on outdated products when it is available to researchers.

Our study aims to provide behavioral evidence required to better inform policy. To this end, we conduct a discrete choice experiment (DCE) in a sample of adult smokers. DCEs are

[2] The Center for Tobacco Products (CTP) branch of the FDA recenlty gained regulatory control over e-cigarettes. However, e-cigarettes marketed as a product to help people quit smoking (i.e., for therapeutic purposes) have long been under the authority of the FDA through the Center for Drug Evaluation and Research (CDER).
[3] For example, surveys such as the National Health Interview Survey only added e-cigarette questions as of 2014.

increasingly employed by economists to study health and healthcare outcomes (Pesko et al. 2015, Brown et al. 2015, Meenakshi et al. 2012, Marti 2012b, Marti 2012a), and are particularly advantageous when there is little real world data on which to conduct analysis – as is the case in the context of e-cigarettes. DCEs are also advantageous as they allow the researcher to isolate the effects of products and attributes experimentally, and DCEs can allow testing of attributes that are not available in survey data sets and policies that have not yet been implemented by governments.

Although much of the e-cigarette policy debate and empirical analysis to date has focused on youth, we argue that adult smokers are also an important group to study as e-cigarettes potentially offer such individuals substantial health benefits. Many adults are established smokers who have difficulties quitting and may therefore benefit from the ability to substitute to an arguably less harmful product. On the other hand, adult smokers may be the group of smokers that is most likely to use e-cigarettes as a means to circumvent existing use bans on tobacco cigarettes in public places. The impact of e-cigarette regulations on adult smokers will be determined be the relative magnitudes of these off-setting effects. A contribution of our study is to explore regulatory effects in this policy-relevant, yet understudied, population.

Specifically, we examine how adult smokers choose between tobacco cigarettes and e-cigarettes, and also how they respond to their attributes. We focus on three cigarette types: 1) tobacco cigarettes; 2) non-refillable, disposable e-cigarettes; and 3) refillable, rechargeable e-cigarettes; and four policy-relevant attributes: 1) whether e-cigarettes are healthier than tobacco cigarettes, 2) the effectiveness of e-cigarettes as a cessation device, 3) bans on use in public places such as bars and restaurants, and 4) price. We estimate smokers' preferences for the products and the attributes separately.

We empirically identify groups that make systematically different choices in response to variation in product attributes. Information on preference heterogeneity among adult smokers can facilitate the development of more nuanced policies that incorporate differences across smoker groups. Finally, we predict the market shares of each cigarette type under several different plausible policy scenarios.

Overall, findings suggest that adult smokers' demand for e-cigarettes is motivated more by health concerns than by the desire to circumvent tobacco cigarette bans or paying higher prices. However, we identify substantial preference heterogeneity across smoker types. We describe these smoker types by observable characteristics and find three real world groups: 'smokers' (tobacco cigarettes users), 'vapers' (e-cigarettes users (Ayers et al. 2016, Chu et al. 2016)), and 'dual users' (use both cigarette types (Pokhrel et al. 2015)). These findings offer timely evidence to regulators attempting to understand the impact of potential regulations on adult smoker demand for e-cigarettes.

This manuscript is organized as follows: Section II outlines are data and methods. Results are reported in Section III and Section IV presents policy simulations. Section V provides a summary and policy implications.

II. DATA AND METHODS

II.A. Sample and Data Collection

We conducted an online survey and DCE of adults residing in the U.S. following established best practices in DCE development (Johnson et al. 2013). We restricted our sample to adults (18-64) who currently used tobacco cigarettes.[4] [5] We constructed our sample to match a nationally representative survey of adult tobacco cigarette smokers in the 2010-2011 Current Population Survey Tobacco Use Supplement (CPS-TUS). Our sample was matched to the

[4] We define a current tobacco cigarette smoker as an individual who: has smoked 100 tobacco cigarettes in his life time and current smokes tobacco cigarettes (some days or every day).

[5] We required that respondents take the survey on a desktop or laptop computer. We chose to exclude those individuals taking the survey on a cellphone, tablet, etc. as we were concerned that these smaller devices would prevent respondents from viewing the choice sets in their entirety on the device screen. Individuals who attempted to complete the survey on a non-laptop or –desktop device were informed as to why they could not take the survey and were encouraged to take the survey on a laptop or desktop.

national sample based on 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 analytic sample and the national CPS-TUS sample are displayed in Table 1. The samples are broadly similar in terms of demographics. However, there are important differences: smokers in our sample have a higher desire to quit tobacco cigarettes as proxied by a plan to quit in the next 30 days and are more addicted as measured by the time between waking up in the morning and smoking the first tobacco cigarette (Heatherton et al. 1991).

Data were collected by the survey firm Qualtrics which is used by health economists to study health behaviors (e.g., Bradford et al. (2014)). Our analysis is based on a sample of 1,669 adult smokers with complete information to all survey questions utilized in our analysis. This size 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 health economics choice experiments (de Bekker-Grob et al. 2015).

II.B. DCE Development: Products and Attributes

1. Products. In the DCE, we ask respondents to make repeated choices among: 1) tobacco cigarettes; 2) non-refillable, disposable e-cigarettes; and 3) refillable, rechargeable e-cigarettes. Because we focus on a sample of adults that currently smoke tobacco cigarettes, the tobacco cigarettes option is considered as the ‘status quo’ or ‘opt-out’. We are most concerned with the trade-offs between tobacco cigarettes and e-cigarettes, but we include both disposable and rechargeable e-cigarettes in our choice sets as these two products have different pricing schemes (described later in the manuscript).

2. Attributes. We describe the products using four attributes: 1) whether e-cigarettes are considered healthier than tobacco cigarettes (‘Health’); 2) the effectiveness of e-cigarettes as a tobacco cigarette cessation device (‘Quit’); 3) bans on use in public places such as bars and restaurants ('Bans'); and 4) price.[6] We confirmed the importance of these attributes in a pilot study (results available on request) and a review of the e-cigarette literature (Lempert, Grana, and Glantz 2014, Berg et al. 2014, Czoli, Hammond, and White 2014, Dawkins et al. 2013, Goniewicz, Lingas, and Hajek 2013, Etter and Bullen 2011, Richardson et al. 2014, Nonnemaker et al. 2015). Attributes and levels are reported in Table 2.

We use binary variables (yes/no) for our three non-price attributes to avoid an overly complex DCE. While the interpretation is straightforward for smoking bans, the other non-price attributes are less obvious, insofar as respondents' responses will reflect subjective perceptions of what 'healthier' and 'effective' measure. We assume that these indicators accurately capture the current state of the world, that is, e-cigarettes are: healthier than tobacco cigarettes (Bahl et al. 2012, Vardavas et al. 2012, Goniewicz, Lingas, and Hajek 2013, McNeill et al. 2015) and effective in helping at least some smokers quit smoking tobacco cigarettes (Hartmann‐Boyce et al. 2016). Follow up question results in our pilot study suggested that these concepts were clear to respondents (details available on request).

The prices of tobacco cigarettes and disposable e-cigarettes are well described by their marginal prices (i.e., price for a pack of tobacco 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, and 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. To obtain a comparable measure of the marginal price across products, we standardize price and express it as the 'price per tobacco cigarette pack-equivalent' (i.e., the price to smoke the equivalent of 20 tobacco

[6] These attributes can be impacted, either directly or indirectly, through regulation. For example, prices can be manipulated through taxation while public bans can prevent e-cigarette use in specific locations. Moreover, regulation can be utilized to impact e-cigarette health and effectiveness as a cessation device, or the public's perception of these attributes. For example, premarket review of e-cigarettes can prevent the most harmful e-cigarettes from reaching the market. Moreover, regulating reduced risk claims by manufacturers and requiring health warnings on e-cigarettes can impact the public's perception of e-cigarette health impacts. Similarly, regulating the extent to which e-cigarettes may be marketed as a cessation device can impact the public's perception of these devices for cessation purposes.

cigarettes). For both types of e-cigarettes, we obtained market prices from online sources (details available on request) to use as our midpoint price and then provide one lower and one higher price for each (see Table 2). For the latter product we also include the price of the kit. The lower marginal price for rechargeable e-cigarettes reflects both the possibility of buying the liquid in more economical quantities and the need to buy only the refill, not a new device each time. Finally, to make the choice task realistic we asked respondents the price they pay for a pack of tobacco cigarettes and fixed this price for a given respondent.

3. Experimental Design. The full factorial design of our attributes and levels gives rise to 72 (i.e., 2^3x3^2) possible attribute combinations. We first used a fractional factorial design with 12 choice sets (i.e., each with 2 e-cigarette options and 1 tobacco cigarette option) to pilot our survey. Then based on the priors obtained with analyses of the pilot data, we generated a D-efficient design with 12 choice sets using the software Ngene (D-error=0.36) (Carlsson and Martinsson 2003). Respondents were randomly allocated to one of two mutually exclusive blocks of six choice sets. We selected only six sets to prevent respondent fatigue. The order of the choice sets was randomized across respondents. Also, we asked respondents to assume that they could purchase e-cigarettes where they purchased their tobacco cigarettes and that all products contained the same amount of nicotine.

4. Data Quality. We used several techniques to promote data quality. Respondents were given detailed narrative and visual information prior to the experiment describing the products, attributes, and levels. An example choice task was provided before the choice tasks were completed (see Appendix A). We first piloted the survey among 50 respondents and collected feedback which we used to improve the survey. Finally, we confirmed that estimated coefficients were in line with theory and prior expectations (e.g., negative price coefficients and increasing disutility with increased health risk).

II.C. Choice Modeling and Sub-group Analysis

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. 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):

(1) $V_{ijc} = X'_{ijc}\beta + \varepsilon_{ijc}$

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:

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

$Health_j$, $Quit_j$, and Ban_j are the three non-price product attributes. $Price_j$ and $Price_{kit}$ are the marginal prices of the products and the kit price. The ASCs are alternative-specific constants that reflect unobserved utility for e-cigarettes: disposable (ASC_{dis}) and rechargeable (ASC_{rech}). We use tobacco cigarettes as the reference alternative. The βs are marginal utilities to be estimated.

To estimate Equation (1) we first use conditional logit models. The conditional logit assumes homogenous preferences across all individuals; however, we wish to investigate the presence of groups. We take two approaches to relaxing this assumption and thus explore preference heterogeneity.

In the first approach, we partition our sample based on respondents' actual choices. We separate our sample into groups of individuals who chose only tobacco cigarettes in the experiment ('non-switchers') and those who vary their selection between tobacco cigarettes and e-cigarettes ('switchers'). We partition the sample in this manner because we are interested in understanding differences between those smokers who are willing to use e-cigarettes, and those smokers who are not.

In the second approach, we use a latent class logit model.[7] [8] The latent class model identifies a set of unobserved 'classes', or groups of individuals based on a number of factors. Separate parameter vectors (and variances) are estimated for each class, which allows for preference heterogeneity across the classes. The latent class logit model gives the probability of respondent *i* choosing alternative *j* in choice set *c* and can be expressed as:

$$(3)\ P_{ic}(j|\beta_k) = \sum_{k=1}^{K} \pi_{ik} \ \frac{\exp(X_{ijc}'\beta_k)}{\sum_j \exp(X_{ijc}'\beta_k)}$$

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

$$(4)\ \pi_{ik} = \frac{\exp(Z_i'\delta_k)}{\sum_{k=1}^{K} \exp(Z_i'\delta_k)}$$

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

II.D Willingness to Pay Calculations

Using the estimated 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 places is calculated as: $-(\hat{\beta}_I/\hat{\beta}_P)$. This WTP represents the marginal dollar value that each

[7] We choose a latent class logit over a more general mixed multinomial logit (MMNL) or generalized mixed logit (GMXL) approach for several reasons. The MMNL does not allow identification of classes of individual. Further, the latent class logit does not require the imposition of assumptions on parameter distributions for estimation, which is the case for the MMNL. Next, 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,), which are known to vary between software packages (Chiou and Walker 2007, Chang and Lusk 2011).

[8] Latent class logit models have been used in various health contexts (Hole 2008, Flynn et al. 2010, Sivey 2012, Mentzakis and Mestelman 2013, Lagarde et al. 2013, Determann et al. 2016).

respondent is willing to pay per pack of tobacco cigarettes, or per volume equivalent for e-cigarettes, for the ability to use the product in public places. To generate estimates of precision for our marginal WTP estimates, we construct 95% confidence intervals following Krinsky and Robb (1986).

II.E Policy Simulations

We perform a series of predicted probability analyses to simulate the market-level response to government policies that would affect the levels of our attributes (Lancsar and Louviere 2008). The analyses use the coefficients estimated in our latent class logit models to calculate predicted probabilities and choice shares for each alternative product, under different states of the world as defined by the attributes that we study. Choice shares are the percentages of the sample that select each cigarette type. These simulations are conducted for the full population and for each of the three classes identified by the latent class model.

III. RESULTS

III.A. Baseline Conditional Logit Model

Results from the baseline conditional logit models are shown in Table 3. Coefficient estimates in these models do not have a direct interpretation in terms of absolute magnitude, but the relative magnitudes of the coefficients are informative. For the full sample (column 1) we find that smokers derive positive utility from the three non-price attributes. The relative size of the coefficients suggests that the most to least important attributes are: effectiveness as a cessation device, relative health impact, and ability to use in public places. As expected, both the marginal price and fixed price of the kit have a negative effect on choice probabilities.

In column 1 we observe that adult smokers in our sample have a strong underlying preference for tobacco cigarettes relative to e-cigarettes, as indicated by the large negative and statistically significant ASC for both types of e-cigarettes. In column 2 we interact the price of the kit with the ASCs for the two types of e-cigarettes. A higher kit price increases the probability that the disposable e-cigarette is chosen and decreases the probability that the rechargeable option is chosen. The coefficients on the other variables remain significant and similar in sign and magnitude to column 1.

III.B. Choice Models: Heterogeneous Groups Based on Respondent Choices

We investigate group-wise heterogeneity in Tables 3, 4, and 5.[9] Column 3 in Table 3 reports coefficient estimates from the baseline conditional logit in the switcher sample (i.e., respondents who choose both tobacco cigarettes and e-cigarettes in the DCE). 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 tobacco cigarettes among switchers.

Table 4 reports WTP estimates for non-price attributes for the full sample and for switchers. We find that, for the full sample, smokers have a marginal WTP per tobacco cigarette pack (or equivalent for e-cigarettes) of \$3.30 for use in public places, \$4.40 for a healthier product, and \$5.20 for an effective cessation device. The high WTP estimates occur because smokers derive substantial utility from the availability of these attributes and, at the same time, derive modest disutility from high prices. For switchers, the estimated WTP estimates are larger, \$5.70, \$7.80, and \$10.00 respectively, reflecting the higher utility derived from these attributes.

Table 5 displays odd ratios from a logistic regression of the likelihood of being a switcher on a set of individual characteristics. Switchers appear to be younger, female, more educated, lighter tobacco cigarette smokers, and less addicted to tobacco cigarettes and also have higher income than non-switchers. In addition, switchers are more likely than non-switchers to plan to quit smoking within one month and to live in a state with a high tobacco cigarette tax.

[9] 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) led us to reject the null at the 99% level.

III.C. Choice Models: Latent Class Logit Model

We next investigate group-wise heterogeneity using the latent class logit model. We first select the number of classes using a measure of statistical fit (i.e., Akaike Information Criteria) over a range of models of two to seven classes. We find that the models with three and four classes provide the best fit. As the four-class model generated implausible parameter estimates we focus on the three-class model (Heckman and Singer 1984).[10]

Table 6 displays the results for the three classes. The three classes are determined by multiple factors and thus cannot described by a single characteristic. But to make the class types more intuitive and easier to refer to, we name them as: 'vapers' (27% of the sample), 'smokers' (46% of the sample), and 'dual users' (27% of the sample).

Vapers are most likely to choose either type of e-cigarette. They show a strong preference for e-cigarettes (positive, significant ASCs) and derive significant utility from, in the following order of importance, e-cigarettes: as an effective cessation device, being relatively healthy, and the ability to use the product in public places.

Smokers are most likely to choose a tobacco cigarette. They appear to be averse to choosing e-cigarettes (similar to the preference of the non-switchers identified in the descriptive statistics in Table 2); this preference is indicated in their large, significant, and negative ASCs. The coefficient estimates suggest that these smokers do not derive utility from the three non-price attributes. Interestingly, in comparing their estimated characteristics to dual users it can be seen that smokers are: older, less likely to live in a high tobacco cigarette price state, and less likely to plan to quit tobacco cigarettes in the near future.

Among dual users, when policies favor rechargeable e-cigarettes, they will likely choose e-cigarettes; otherwise they will likely choose tobacco cigarettes. This choice pattern occurs

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[10] Results for the four-class model are available on request. Heckman and Singer (1984) suggest that imprecise or volatile parameter estimates may indicate a latent class model fit with too many classes. Based on this guide, we prefer the three-class model.

because dual users have a negative and significant ASC for disposable e-cigarettes, but their ASC for rechargeable e-cigarettes is not statistically different from zero. Dual users also derive positive utility from all non-price attributes. In order of importance members of this class value e-cigarettes: as an effective cessation device, for the ability to use the product in public places, and being a healthier option.

III.D. Comparison of Results across Econometric Approaches

While we cannot directly compare the approaches we apply in terms of model fit, there are reasons to prefer the latent class approach over the baseline conditional logit using either the full sample or the partitioned sample. First, the latent class approach makes use of all the data so the groups are determined by all the data; not just by use of the choice data as in the first approach. Further, the latent class approach allows us to test a range of possible group numbers which not possible with other methods. We note that the size of the smoker group here is similar to that of the non-switchers in our grouping based on respondent choices. Indeed, the descriptive statistics of these groups are similar. We then further dissect the switchers group into vapers and dual users using the latent class model. This further grouping is behaviorally plausible: it is clear that in real tobacco product markets there are individuals that identify as vapers (Chu et al. 2016, Ayers et al. 2016) and dual users (Pokhrel et al. 2015). While these groups appear similar in terms of observable characteristics, their product preferences diverge considerably.

IV. POLICY SIMULATIONS

We next conduct simulations of predicted choice shares for each cigarette type for the full sample and separately for the three classes of smokers identified by our latent class model. For the full sample results, we combine the two e-cigarette types to focus on the arguably more policy-relevant issue of the selection of tobacco cigarettes versus e-cigarettes. Also, we focus on the latent class groupings only for the reasons explained in Section III.D.

Our starting point is that which we believe to be closest to the real world: use of e-cigarettes is allowed in public places, e-cigarettes are considered to be healthier than tobacco cigarettes, and e-cigarettes are considered useful as cessation aids. See scenario A in Table 7. In our simulations, the four attributes are changed individually (rows B-D) and in combinations (rows E-H) and we assess the impact of these changes on choice shares of e-cigarettes and tobacco cigarettes.

First we examine the effect of changing each of three non-price attributes alone and calculate the impact on the market shares for the sample as a whole. As expected, when each of these attributes is changed to the less desirable state for e-cigarettes, we find that the market share of e-cigarettes declines. The largest decline is in response to e-cigarettes not being effective in helping smokers quit, with a 4.3 percentage points (pp) decline in market share of e-cigarettes (row A vs. D). Declines are of similar magnitude with the two other non-price attributes; 3.6 pp and 3.7 pp decline when use is not permitted in public places and e-cigarettes not being healthier, respectively. When all of the favorable attributes are taken away (row H), the market share of e-cigarettes declines by 8.7 pp.

We next turn to similar analyses using the latent class models. Changes in market shares are concentrated in certain classes due to preference heterogeneity. For instance, dual users are most responsive to attribute variations, with a reduction in e-cigarette market share of almost 16 pp between the most (row A) and least favorable scenario (row H) for non-price attributes. For vapers and smokers, consistent with their strong preferences of their preferred cigarette type, the comparable reductions are smaller: 5.7 pp and 6.8 pp, respectively.

Lastly, we define the most and least favorable scenarios for e-cigarettes to be rows I and J respectively. In these rows we also manipulate the relative prices of e-cigarettes and tobacco cigarettes (see Figure 1). We find that, for the sample as a whole, the share of e-cigarette selection declines by 13 pp from the most (row I) to the least favorable (row J) scenario for e-cigarettes. Again there is substantial heterogeneity by class. We next examine the pure impact of price by comparing row I (most favorable for e-cigarettes) to A (current state of the world) with the only difference being the 50% higher price of tobacco cigarettes. In this case, we find that the market share of e-cigarettes increases by 2.8 pp for the full sample. If the price of e-cigarettes is increased by 50% when the price of cigarettes remains stable, the market share of e-cigarettes declines by 1.7 pp (comparing row J to H) for the full sample. Dual users are most sensitive to prices. Thus our results suggest a relatively low price-sensitivity by smokers as measured by market shares with larger responses for changes in the non-price attributes.

V. DISCUSSION

We estimate how adult smokers' preferences for e-cigarettes versus tobacco cigarettes vary in response to four policy-relevant attributes across different groups of smokers. Our study therefore provides policy-relevant findings of use to policymakers in determining how best to regulate the e-cigarette market. We use data from a discrete choice experiment (DCE) as there are few other methods to obtain information on the counterfactual policy scenarios. In addition, our choice of latent class model allows us to identify vapers, smokers, and dual users, characterize them, and analyze their unique smoking-related choices.

One of the key strengths of this study is that it provides policy-relevant information and predictions prior to adoption of policy decisions. For example, the FDA has recently (2016) gained the authority to regulate e-cigarettes, but has enacted only a few regulations for these products. This agency requires solid evidence on how policies will affect smokers' choices between combustible and e-cigarettes in order to anticipate the net impact of policies on the health of the population. Moreover, different levels of government are considering taxing e-cigarettes and banning their use in public places, among other policies, and thus need to know how smokers will alter their use of both tobacco cigarettes and e-cigarettes. Also we focus on adults, which is an important addition given the much larger literature on youths (Pesko, Hughes, and Faisal 2016, Pesko, Seirup, and Currie 2016, Friedman 2015). Another important strength of our study is that we allow for, and document, heterogeneity in preferences and choice behavior across smoker groups. This feature of our study moves the literature forward substantially as other studies have not yet included latent groups in studies of cigarette types.

Despite these strengths, this study has several limitations. DCEs rely on hypothetical choices and there is a risk of hypothetical bias (Harrison 2014). However, several studies have documented a high comparability between stated and revealed choices in health behaviors (Harrison and Rutstrom 2006, Wilson et al. 2015, Few et al. 2012). Also, our results are pertinent only to adult smokers; youth smoking should be examined separately, but to do so beyond the scope of this study. Finally, 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.

Adult smokers in our sample, on average, place substantial value on the non-price attributes that we study. In order of importance they value e-cigarettes as an effective cessation aid, as a healthier option compared to tobacco cigarettes, and for the ability to use the product 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 negative impact as expected and it is significant, but the magnitude of the price effects we identify are small. The relatively high value placed on the non-price attributes compared to the relatively small price response, yields high willingness to pay for the health relative attributes.

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' cigarette choices vary depending on the attribute scenarios. We find that preferences for the 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 ability to evade smoking bans. Smokers place very little value on these attributes and are therefore unlikely to respond greatly to potential policy changes targeting these attributes. However, smokers are more price-sensitive, older and less interested in quitting as compared to the other two groups.

These results suggest that policies will likely have differential effects across adult smoker types. For example, policies targeting the relative healthiness of e-cigarettes are predicted to increase the demand for e-cigarettes the most for dual uses. Vapers too would increase their demand, but smokers who prefer tobacco cigarettes are unlikely to respond to such a policy in terms of their use of e-cigarettes. This latter group of smokers, who are older and less interested in quitting, are more price responsive than vapers and dual users. Thus policies will have different welfare impacts across smoker types and governments should consider this heterogeneity in policy decisions. When possible, policymakers should incorporate the heterogeneous nature of the combustible and e-cigarette using population.

Table 1. Sample characteristics by type of smoker

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 tobacco 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 tobacco 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 have smoked at least 100 tobacco cigarettes in their lives and currently smoke tobacco cigarettes in the 2010-2011 Current Population Survey Tobacco Use Supplements. SD=standard deviation.

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

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

Table 2. 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 tobacco cigarettes	Yes, no	Yes, no	No
Product is effective for smoking cessation	Yes, no	Yes, no	No
Marginal price	\$5, \$8, \$12	\$3, \$5, \$8	Respondent reported
Kit price	-	\$20, \$40, \$80	-

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***
	(0.05)	(0.06)	(0.05)
ASC: rechargeable e-cigarette	-1.13***	-1.21***	0.15*
	(0.06)	(0.05)	(0.07)
Use of product is permitted in public places	0.22***	0.21***	0.21***
	(0.03)	(0.03)	(0.03)
Product considered to be healthier than tobacco cigarettes	0.29***	0.29***	0.29***
	(0.03)	(0.03)	(0.03)
Product is effective for smoking cessation	0.35***	0.36***	0.37***
	(0.03)	(0.03)	(0.03)
Marginal price	-0.07***	-0.07***	-0.04***
	(0.00)	(0.00)	(0.01)
Kit price	-0.01***	--	-0.01***
	(0.00)		(0.00)
ASC disposable e-cigarette*low kit price†	--	0.20**	--
		(0.08)	
ASC disposable e-cigarette*high kit price††	--	0.36***	--
		(0.07)	
ASC rechargeable e-cigarette* low kit price††	--	-0.36***	--
		(0.06)	
ASC rechargeable e-cigarette* high kit price††	--	-0.39***	--
		(0.06)	
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 1. Standard errors are clustered around the respondent and reported 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 tobacco cigarette	$4.4 [$3.2-$5.5]	$7.8 [$5.0-$10.6]
Product is effective for smoking cessation	$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 1 respectively. Krinsky-Robb (1986) 95% confidence intervals reported 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 tobacco cigarette smoker†	0.89***
	(0.03)
Addicted tobacco cigarette smoker††	0.91***
	(0.03)
Plan to quit within 1 month	2.72***
	(0.08)
Lives in high price tobacco 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 tobacco cigarettes per day.

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

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

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

Table 6. Latent class model with 3 classes: Vapers, smokers, and dual users

Sample:	**Class 1**	**Class 2**	**Class 3**
Utility function (taste) parameters	**(Vapers)**	**(Smokers)**	**(Dual users)**
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 tobacco cigarette	0.34***	1.25	0.14*
	(0.05)	(1.26)	(0.07)
Product is effective for smoking cessation	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 tobacco cigarette smoker†	-0.51	0.05	-
	(0.27)	(0.20)	
Addicted tobacco cigarette 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 tobacco cigarette state†††	-0.18	-0.66*	-
	(0.28)	(0.27)	
Constant	-0.06	0.99***	-
	(0.20)	(0.17)	
Class shares	**0.27**	**0.46**	**0.27**
N		**1,669**	

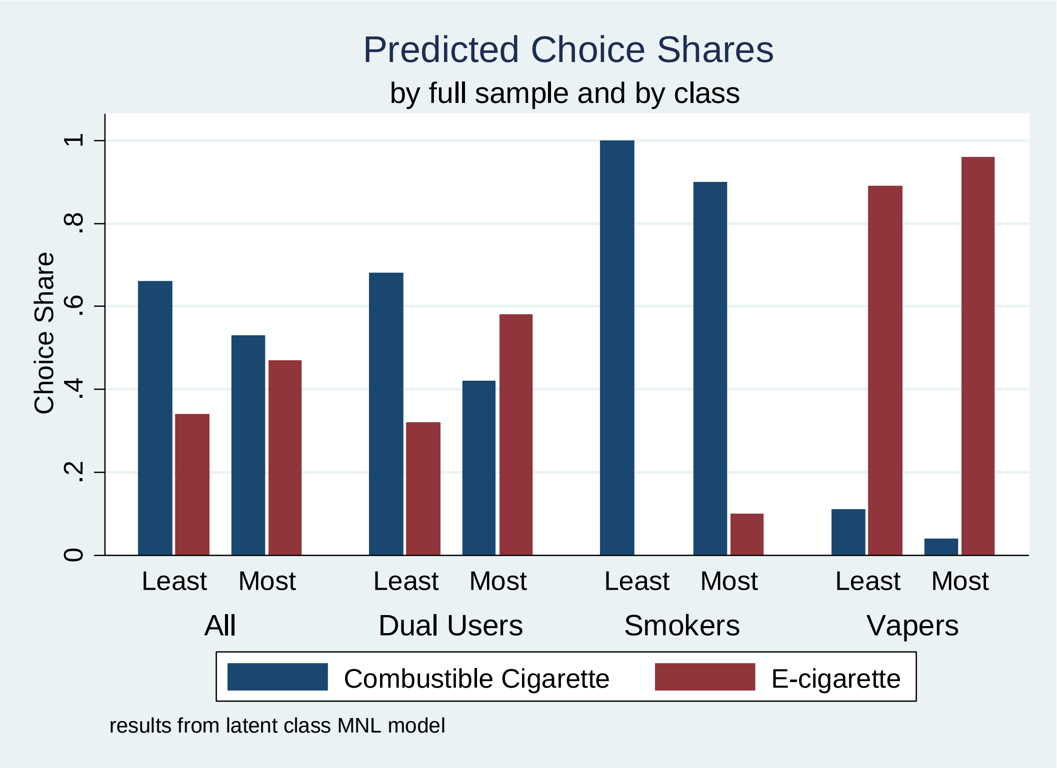
Notes: Dependent variable is an alternative choice. Omitted categories are female, 31 to 64 years, less than college, and household income ≥ $30,000. Standard errors clustered around the respondent and reported in parentheses. ASC=Alternative-specific constant.
†Heavy tobacco cigarette smoker=Smoke more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

Table 7: Policy simulations

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

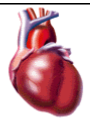
*Notes***:** Simulations were performed using the latent class model with 3 classes shown in Table 6. For each product type, the table shows the unconditional choice probabilities (class-specific class-probabilities weighted by the corresponding class shares) and the choice probabilities conditional on belonging to a particular class. The baseline scenario uses a price of \$5.33 for rechargeable e-cigarettes with a kit price of \$45, a price of \$8.33 for disposable e-cigarettes and the self-reported price for tobacco cigarettes. Key: Ecig – e-cigarette, Ccig – tobacco cigarettes.

Figure 1. Predicted choice shares of products, by type of smoker



Notes: Least=least favorable conditions to tobacco cigarettes (row I in Table 7); and Most=most favorable conditions to tobacco cigarettes (row J in Table 7). 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):**	☐	☐	☐

Notes: In the choice sets presented to respondents in our DCE we used the term 'tobacco cigarette' as we believe that this terminology is more familiar to smokers than 'tobacco cigarette'.

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