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Faculty of Biology and Medicine Publication

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Published in final edited form as:

Title: To "vape" or smoke? Experimental evidence on adult smokers.

Authors: Marti J, Buckell J, Maclean JC, Sindelar J

Journal: Economic inquiry

Year: 2019 Jan

Issue: 57

Volume: 1

Pages: 705-725

DOI: 10.1111/ecin.12693

To 'vape' or smoke? Experimental evidence on adult smokers

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Abstract

A growing share of the United States population uses e-cigarettes but the optimal regulation of these controversial products remains an open question. We conduct a discrete choice experiment to investigate how adult tobacco cigarette smokers' demand for e-cigarettes and tobacco cigarettes varies by four attributes: (i) whether e-cigarettes are considered healthier than tobacco cigarettes, (ii) the effectiveness of e-cigarettes as a cessation device, (iii) bans on use in public places, and (iv) price. We find that adult smokers' demand for e-cigarettes is motivated more by health concerns than by the desire to avoid smoking bans or higher prices.

Keywords: e-cigarettes, smoking, discrete choice experiments, preferences, heterogeneity, regulation, latent class model.

JEL codes: C35; I12; I18.

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Acknowledgements: Research reported in this publication was supported by grant number P50DA036151 from the National Institute on Drug Abuse (NIDA) and FDA Center for Tobacco Products (CTP). The content is solely the responsibility of the author(s) and does not necessarily represent the official views of the National Institutes of Health or the Food and Drug Administration.

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Abstract

A growing share of the United States population uses e-cigarettes but the optimal regulation of these controversial products remains an open question. We conduct a discrete choice experiment to investigate how adult tobacco cigarette smokers' demand for e-cigarettes and tobacco cigarettes varies by four attributes: (i) whether e-cigarettes are considered healthier than tobacco cigarettes, (ii) the effectiveness of e-cigarettes as a cessation device, (iii) bans on use in public places, and (iv) price. We find that adult smokers' demand for e-cigarettes is motivated more by health concerns than by the desire to avoid smoking bans or higher prices.

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I. Introduction

E-cigarettes are relatively new products in United States tobacco markets; they 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. Currently 5.5% of adults (Kasza et al. 2017) and 16% of high school students (Singh 2016) use these products. E-cigarettes are battery-operated devices containing a liquid which typically contains nicotine along with other components such as propylene glycol, glycerin, and flavors. A heating element vaporizes the liquid and the resulting vapor is inhaled by the user ('vaping'). Unlike other nicotine delivery systems (e.g., nicotine gum, nicotine patches), e-cigarettes are specifically designed to simulate the experience of tobacco cigarette smoking. Because tobacco is not burned, far fewer toxins are produced (Shahab et al. 2017), thus e-cigarettes are often considered a healthier alternative to tobacco cigarettes. However, there is controversy over whether e-cigarette use improves or harms public health (Riker et al. 2012, Kenkel 2016, Royal College of Physicians 2016, NHS Health Scotland 2017, Ribisl, Seidenberg, and Orlan 2016).

Evidence of the effect of e-cigarette regulations on e-cigarette use is critical to informing government decision-making, yet is generally unavailable due to the current lack of revealed preference data on e-cigarette use and quasi-experimental variation in e-cigarette attributes. The initial e-cigarette regulations in the U.S. were implemented beginning in 2010 (Lempert, Grana, and Glantz 2016). Most early regulations target youth (e.g., minimum legal purchase ages) and data necessary to study a broader set of regulations that plausibly affect a larger share of the population (e.g., taxes), including adults, is particularly limited. Thus, standard regulation evaluation methods (e.g., differences-in-differences models) are not feasible.[1]

[1] Major U.S. health surveys commonly leveraged by economists to study regulation effects have only recently added e-cigarette questions. For example, the National Health Interview Survey added e-cigarette questions in 2014 and the Centers for Disease Control and Prevention Behavioral Risk Factor Surveillance Survey added e-cigarette questions in 2016. There is often at least a one year delay from survey data collection to survey data release. Thus, these datasets will not offer researchers the opportunity to study the early effects of state regulations through

We conduct a discrete choice experiment (DCE) in a sample of adult tobacco cigarette smokers to help address these information gaps. DCEs, a stated preference technique, are increasingly employed by economists to study tobacco-related products (Pesko et al. 2016, Marti 2012b, Marti 2012a, Czoli, Goniewicz, et al. 2016, Kenkel et al. 2017, Buckell, Marti, and Sindelar 2017, Ida and Goto 2016, Regmi et al. 2017, Shang et al. 2017). These methods are grounded in consumer choice theory established by Lancaster (1966). DCEs are based on the premise that a good or service can be described as a set of attributes and consumers value goods and services as a sum of their attributes and underlying product preferences. In addition, DCEs allow estimation of causal effects of attributes on product choice using experimental variation, and can allow testing of attributes not observed in real-world markets. DCEs are especially attractive, as is the case for e-cigarettes, when suitable revealed preference data are not available.

Choice data from the DCE are used to examine how adult smokers choose between e-cigarettes and tobacco cigarettes, and also how they respond to changes in product attributes and their levels. We focus on three cigarette types: non-refillable, disposable e-cigarettes; refillable, rechargeable e-cigarettes, and tobacco cigarettes. We include four policy-relevant attributes: whether e-cigarettes are healthier than tobacco cigarettes; the effectiveness of e-cigarettes as a cessation device; bans on use in public places such as bars and restaurants; and price. We also estimate willingness-to-pay for non-price cigarette attributes.

Importantly, we estimate heterogeneity in preferences across different groups of smokers by using latent class logit models. In turn, we use the estimated heterogeneity in smoker choice overall and across types of smokers to identify different responses. We use our estimates to

standard regulation evaluation methods for several years. DD regression models used to evaluate regulations are identified off regulation changes and therefore several years of data and regulations changes are required for identification of treatment effects. While findings from future studies employing these data and methods will be important and offer critical insight on how best to regulate e-cigarettes based on historical regulation changes, our argument is that currently, as policymakers are developing new regulations and fine-tuning existing regulations, there is little rigorous analysis using standard data and methods. Thus, it seems prudent to consider alternative methods to elicit this necessary information.

simulate changes in market shares. We first simulate a base case scenario that reflects the state of the world and then we sequentially change the regulation variables and simulate hypothetical market shares overall, and for each of the smoker types we identify.

To the best of our knowledge, only a few extant studies use DCEs in the context of e-cigarettes (Buckell, Marti, and Sindelar 2017, Kenkel et al. 2017, Shang et al. 2017, Pesko et al. 2016, Czoli, Goniewicz, et al. 2016). These studies examine the effects of flavors, warning labels, price, and nicotine content on e-cigarette choice. Overall, these studies suggest that higher prices, reduced flavor availability, and health warnings deter e-cigarette choice while the effect of nicotine is mixed. We add to this small literature in several important ways: (i) We consider tobacco cigarettes alongside both disposable and re-chargeable e-cigarettes, which allows us to better characterize the tobacco product market and allows us to explore differences in pricing schemes across the two e-cigarette types. (ii) We examine the importance of relative health harms between e-cigarettes and tobacco cigarettes, e-cigarette effectiveness as a cessation aid, and the ability to use e-cigarettes to evade tobacco cigarette public use bans. (iii) We use a large, nationally representative sample. (iv) We estimate willingness to pay for non-price attributes. (v) We explore group-wise preference heterogeneity which we argue is essential for development of effective regulation given the vastly different reasons for e-cigarette use. (vi) We provide policy-relevant simulations of the effect of alternative regulations.

II. Regulatory Issues, Controversy Surrounding E-cigarettes, and Consumer Knowledge and Perceptions of E-cigarettes

II.A Regulatory Issues Related to DCE Product Attributes

We examine four attributes in our DCE: relative health; the effectiveness as a cessation device; bans on use in public places, and price. We select these attributes as they are amenable to policy changes by the U.S. Food and Drug Administration (FDA) and other regulators (e.g., state and local governments). While the relevance of price and public use bans for regulation is obvious and there are numerous historical examples of the application of these regulations in the U.S., i.e. governments increase price through taxation and prohibit product use in a wide range of public places (Centers for Disease Control and Prevention 2016), the relevance for regulation purposes of our remaining product attributes is perhaps less obvious. We discuss the ability of regulators to influence these attributes, and hence, the credibility of including these attributes in our DCE.

At the federal level, the Center for Tobacco Products (CTP) at the FDA has broad authority over the manufacturing, distribution, and marketing of tobacco products, including e-cigarettes as of 2016, through the Family Smoking Act (2009). Thus, the FDA can both directly and indirectly regulate the healthiness of e-cigarettes and the effectiveness of e-cigarettes as a cessation device. Regulation can affect actual product features and consumers' perceptions of these features, both of which are important for consumer choice over e-cigarettes and tobacco cigarettes (Maclean, Webber, and Marti 2014, Kenkel et al. 2017, Viscusi 2016, Czoli, Goniewicz, et al. 2016).

In terms of directly affecting e-cigarette healthiness and effectiveness as a cessation device, the CTP can determine the healthiness of e-cigarettes through regulation of allowable ingredients in these products (e.g., ban harmful toxins such as diacetyl, a butter flavoring used in e-cigarettes which causes lung damage (Barrington-Trimis, Samet, and McConnell 2014), and nicotine which can harm health (Benowitz 1997)) and device features such as limiting the voltage permitted in e-cigarettes to prevent explosions (Kosmider et al. 2014). Relatedly, the FDA, through the Center for Drug Evaluation and Research, has the authority to regulate e-cigarettes that are sold for cessation or therapeutic purposes. This agency can therefore control which e-cigarettes are sold as cessation devices. The FDA can place high standards on e-cigarettes sold as cessation devices, leading to higher quality and more effective cessation products entering the market.

In terms of indirect effects, the FDA can affect perceived e-cigarette healthiness through product labelling (e.g., requiring warning labels to be placed on e-cigarette packages, which lead consumers to perceive e-cigarettes as relatively less healthy (Czoli, Goniewicz, et al. 2016)), regulating flavored e-cigarettes (e.g., consumers may believe that sweet or fruit favored e-cigarettes are healthier than other cigarettes (Brennan et al. 2014)), and public education campaigns (Farrelly et al. 2009, Niederdeppe, Farrelly, and Haviland 2004); for example, the FDA currently has a youth-focused tobacco cigarette campaign ('the Real Cost'[2]) which could be expanded to include e-cigarettes.

State and local governments can implement their own media campaigns (e.g. the 'truth' campaign in Florida (Niederdeppe, Farrelly, and Haviland 2004)), which could focus on e-cigarettes. All states have regulations in place that prohibit manufacturers from making false claims regarding their products; these regulation can be used to correct any erroneous perceptions of e-cigarettes (Tobacco Control Legal Consortium 2018). Finally, some states require warning labels on e-cigarettes (Tobacco Control Legal Consortium 2018), which could change health perceptions.

II.B Controversy and Regulatory Issues Surrounding E-cigarettes

The controversy over e-cigarettes primarily relates to the extent to which their use improves or harms public health (Riker et al. 2012, Kenkel 2016, Ribisl, Seidenberg, and Orlan 2016). This controversy is a barrier to effective regulation development. Key factors preventing consensus include insufficient information on the full health implications of e-cigarettes, and how these implications vary across different groups.

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

[2] See https://www.fda.gov/TobaccoProducts/PublicHealthEducation/PublicEducationCampaigns/TheRealCostCampaign/default.htm (accessed February 17th, 2018).

2013, McNeill et al. 2015, Dinakar and O'Connor 2016, Hajek et al. 2014, Kenkel 2016, NHS Health Scotland 2017, Shahab et al. 2017); although the evidence is not fully conclusive (Allen et al. 2016, McKee and Capewell 2015, Yu et al. 2016). Viscusi (2016), however, estimates that the e-cigarette-attributable mortality risk is approximately 1/100 to 1/1000 the tobacco cigarette-attributable mortality risk. These estimates imply that while both products can harm health, e-cigarettes are substantially less harmful. Clinical evidence suggests that some reports of e-cigarettes toxins have been over-stated (Farsalinos, Voudris, and Poulas 2015, Hajek et al. 2014). Moreover, while the literature is still nascent, e-cigarettes are currently thought to be effective as a smoking cessation aid, at least for some populations (Hartmann‐Boyce et al. 2016, Bullen et al. 2013, Tseng et al. 2016, Adriaens et al. 2014, Caponnetto et al. 2013). The harm reduction and cessation potential of e-cigarettes could improve public health.

On the other hand, there are concerns that e-cigarettes may be used by smokers to circumvent public use bans on tobacco cigarettes, thus reducing the motivation to quit (Patrick et al. 2016, Damle 2015, Shi, Cummins, and Zhu 2016, Filippidis et al. 2017, Brikmanis, Petersen, and Doran 2017, Dawkins et al. 2013, Pepper and Brewer 2014). Smokers could increase their consumption of nicotine (the primary addicitve ingredient in tobacco cigarettes and e-cigarettes[3]) and become even more addicted.[4] Another apprehension is that increased e-cigarette use will lead to use of tobacco cigarettes among individuals, primarily youth, who would not otherwise smoke; i.e., ‘gateway effects’ (Fairchild, Bayer, and Colgrove 2014, Kmietowicz 2014, Grana 2013, Schneider and Diehl 2016, Zhong et al. 2016, Soneji et al. 2017, Primack et al. 2015). The existance of gateway effects, however, has been questioned by some scholars (Etter 2017,

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[3] Not all e-cigarettes contain nicotine.

[4] Of course, smokers can choose the nicotine content of their e-cigarettes, with some e-cigarettes containing no nicotine and other e-cigarettes containing as much as 36 or 42mg/mL per e-cigarette. Thus, the extent to which switching from tobacco cigarettes to e-cigarettes, and therefore the extent to which this switch increases or decreases nicotine addiction, is endogenous to the smoker.

Friedman 2015). Evasion of smoking regulations and gateway effects suggest that expanded e-cigarette use will worsen public health.

Federal, state, and local policymakers in the U.S., faced with these uncertain and potentially divergent health effects across groups of smokers, are currently determining how best to regulate the e-cigarette market and, in particular, whether or not to favor e-cigarettes over tobacco cigarettes. Our study aims to provide evidence required to better inform such regulation. In particular, we focus on adult tobacco cigarette smokers as this group may use e-cigarettes for separate reasons: to quit smoking tobacco cigarettes, to reduce harm, or to circumvent tobacco cigarette regulations (e.g., public use bans) and thus increase the ability to consume nicotine.

II.C Consumer Perceptions of E-cigarettes

Consumers' perceptions of e-cigarettes are important because they can affect choices of cigarette types. Also, regulations can affect consumers' preferences, which again can affect demand. We summarize consumer awareness of e-cigarettes and perceptions of the attributes we study in our DCE: relative healthiness, effectiveness of e-cigarettes as a cessation device, usefulness in evading tobacco cigarette public use bans, and price.

Huerta et al (2017) analyze data on e-cigarette awareness among U.S. adults over the period 2012 to 2014. The authors show that awareness of e-cigarettes rose from 77.1% in 2012 to 94.3% in 2014, and that smokers (current and former) are more likely to report awareness of e-cigarettes than non-smokers. Similar levels and trends in product awareness are reported in a recent large-scale review of the e-cigarette literature (Glasser et al. 2017).

Two recent systematic reviews of the literature examine perceived relative risk between e-cigarettes and tobacco cigarettes (Glasser et al. 2017, Czoli, Fong, et al. 2016). Czoli, Fong, et al. (2016) identify 23 studies that cover 50 samples that consider these perceptions. Across studies, 70% of consumers and 81% of tobacco cigarette smokers perceive e-cigarettes to be less harmful to health than tobacco cigarettes. Glasser et al.

(2017) reach a similar conclusion in their review. Viscusi (2016), using data on 1,041 adults, documents that, while consumers tend to over-estimate the mortality risks of both e-cigarettes and tobacco cigarettes, e-cigarettes are perceived to present lower mortality risk than tobacco cigarettes. For example, consumers perceive the total mortality risk to be 33.3% for e-cigarettes and 50.3% for tobacco cigarettes; with similar patterns for smokers and non-smokers. Kenkel et al. (2017) document similar perceptions within a sample of current smokers.

Consumers also perceive e-cigarettes as being effective as a cessation device (Glasser et al. 2017). For example, 66.4% of e-cigarette users report that they believe e-cigarettes can help at least some smokers quit smoking tobacco cigarettes (Berg 2016). Within a sample of U.S. adults one third perceive e-cigarettes as helpful in cessation attempts (Tan, Lee, and Bigman 2016). Current e-cigarette users perceive e-cigarettes as less risky and more efficacious in reducing tobacco cigarette cravings than nicotine replacement therapies (Harrell et al. 2015), and 67% to 79% of tobacco cigarette smokers report using e-cigarettes to address cravings (Hummel et al. 2015).

Many consumers, particularly e-cigarettes users, view e-cigarettes as less expensive than tobacco cigarettes and effective in allowing smokers to evade tobacco cigarette public use bans (Glasser et al. 2017, Baggett et al. 2016). For example, in a sample of U.S. adult tobacco cigarette smokers, 24.5% perceived e-cigarettes as less expensive than tobacco cigarettes and 53.2% perceive e-cigarettes as an effective means to circumvent tobacco cigarette smoking bans (Rutten et al. 2015).

Overall, the available literature suggests that many consumers: are aware of e-cigarettes, and perceive e-cigarettes as healthier than tobacco cigarettes, an effective cessation device, an effective method to consume nicotine in places in which tobacco cigarettes are banned, and less expensive than tobacco cigarettes.

III. Data and Methods

Our study uses stated preferences data. Such data are generally viewed as less credible than revealed preferences data and the use of such data is not without controversy among economists (Hausman 2012). However, stated preference data and methods can be particularly useful, and indeed potentially the only available option, when there is little to no suitable revealed preference data. We argue that e-cigarettes present precisely the setting in which stated preference data is preferred, or perhaps even necessary, to provide economic insight required for ongoing and future regulatory decisions. Economists have little revealed preferences data on e-cigarette use and there is scant quasi-experimental variation in e-cigarette product attributes (e.g., e-cigarette taxes and public use bans) that can be used to identify treatment effects utilizing standard revealed preference methods (e.g., differences-in-differences).

Additionally, leading economists are increasingly showing support for the use of stated preference data and/or methods broadly, and DCE methods in particular, through the use of these methods and/or data (Carson 2012, Viscusi 2016, Kenkel et al. 2017, McFadden 2017). Indeed, Kenkel et al. (2017) note that DCEs may be particularly valuable in the context of e-cigarettes given that a substantial amount of future e-cigarette regulation is likely to occur at the federal level through the FDA. This regulation will limit researchers' ability to use standard policy analysis methods (e.g., differences-in-differences) which leverage within-state/county variation. Further, the ability to experimentally vary product attributes allows estimation of causal effects that are not contaminated by omitted variables or reverse causality. The main concern with stated preferences data is the risk of hypothetical bias (Harrison 2014). However, studies have documented a high comparability between stated and revealed choices in health behaviors such as smoking (Harrison and Rutstrom 2006, Wilson et al. 2016, Few et al. 2012), and DCE data are most reliable for those who are familiar with the products, as is the case for adult smokers

(McFadden 2017). In sum, the use of DCEs to study factors that influence consumer e-cigarette choices appears well-founded.

III.A. Sample and Data Collection

We conducted an online survey and DCE of adult smokers residing in the U.S. following established best practices in DCE development (Johnson et al. 2013). Data were collected by the survey firm Qualtrics between June and July 2015. We restricted our sample to adults 18 to 64 years old who used tobacco cigarettes at the time of the survey.[5] [6] We constructed our sample to match a nationally representative survey of current adult tobacco cigarette smokers in the 2010-2011 Current Population Survey Tobacco Use Supplement (TUS). The TUS is sponsored by the National Cancer Institute to allow for monitoring of tobacco use within the U.S. population. These data are commonly utilized by health economists to study tobacco cigarette smoking (DeCicca, Kenkel, and Liu 2013, Callison and Kaestner 2014, Maclean, Webber, and Marti 2014). Our sample was matched to the national TUS sample based on sex (male and female), 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). Our analysis is based on a sample of 1,669 adult smokers. This size is well in excess of several rule-of-thumb measures that have been proposed in the literature (McFadden 1984, Orme 2010, Lancsar and Louviere 2008) and requirements based on a statistical calculation of minimum sample size (de Bekker-Grob et al. 2015). Finally, the sample size is large compared to other health economics DCEs (de Bekker-Grob et al. 2015).

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[5] We define a tobacco cigarette smoker as an individual who: has smoked 100 tobacco cigarettes in his life time and currently smokes tobacco cigarettes (some days or every day). This definition is commonly used in health surveys such as the TUS (https://www.census.gov/prod/techdoc/cps/cpsjan11.pdf; accessed March 10th, 2017) and the Center for Disease Control and Prevention's Behavioral Risk Factor Surveillance Survey (https://www.cdc.gov/brfss/annual_data/2015/pdf/codebook15_llcp.pdf; accessed March 10th, 2017).

[6] We require that respondents take the survey on a desktop or laptop computer. We choose 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 non-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.

We focus on adults who currently use tobacco cigarettes in our study and this has implications for the generalizability of our findings. We select this group as we seek to understand how current tobacco cigarette smokers might switch to e-cigarettes, use e-cigarettes to quit, increase e-cigarette use, or remain smoking tobacco cigarettes in response to changes attributes of both cigarette types. We suspect that this group likely considers different factors when choosing between cigarette types as compared to other groups (e.g., youth) and we wish to examine these factors. Adult tobacco users are at greatest risk for health problems associated with smoking and thus where regulators can have a substantial effect on public health by reducing smoking within this population (Levy et al. 2017). Moreover, adult smokers represent the largest subgroup of adult tobacco product users: there are substantially more tobacco cigarette smokers than e-cigarette users – in 2016 that 16% of adults currently use tobacco cigarettes and 5.5% of adults currently use e-cigarettes (we note that 2% of adults use both products; 'dual use'); see also Kasza et al. (2017).[7] Finally, McFadden (2017) notes that DCEs are more reliable when respondents are familiar with the products, we suspect that established adult tobacco cigarette smokers are familiar with tobacco cigarettes and are likely more familiar with e-cigarettes than the general population.[8]

Of course, a natural limitation of focusing on adults is that we cannot provide insight into other groups, including non-smokers, youth, or adult smokers who have fully transitioned from tobacco cigarettes to e-cigarettes. While we view our ability to focus on an understudied group, we do not wish to extrapolate our findings to other groups.

The demographic characteristics of our analysis sample and the national TUS sample are displayed in Table 1. The samples are broadly similar in terms of demographics. For example, the share of men and women in our sample is equal to the national sample in the TUS. The age

[7] Authors' calculations of the 2016 Behavioral Risk Factor Surveillance Survey. Details available on request.
[8] Within our sample, 84% and 11% report purchasing tobacco cigarettes and e-cigarettes within the week prior to the survey. Moreover, as documented in the clinical literature (Huerta et al. 2017), smokers are more aware of e-cigarettes than non-smokers. Thus, we suspect that respondents in are familiar with these products.

distributions, while not identical, are comparable across the two samples. For instance, the share of the sample that is 18 to 34 is 21% in our analysis sample and 23% in the TUS, while the shares of these samples that fall into the oldest age category (50 to 64 years) are 23% and 18% respectively. There are important differences between the samples; which is a study limitation. For example, smokers in our sample have a higher desire to quit tobacco cigarettes (proxied by a plan to quit in the next 30 days) and are more addicted (proxied by the time between waking up and smoking the first tobacco cigarette (Heatherton et al. 1991)) than smokers in the TUS. [9]

III.B. DCE Development

1. Products. In the DCE, we ask respondents to make repeated choices among three labelled cigarette types: non-refillable, disposable e-cigarettes; refillable, rechargeable e-cigarettes; and tobacco cigarettes. We use a labelled, versus unlabeled, DCE as the products we consider are visually recognizable to respondents (see Appendix A) and use of an unlabeled experiment would reduce choice set realism. We are most concerned with the trade-offs between e-cigarettes and tobacco cigarettes, but we include both disposable and rechargeable e-cigarettes in our choice sets as these two products have different pricing schemes (described later).

A concern within the DCE literature is whether or not to include an opt-out in the choice sets or to force respondents to select one of the included products (Louviere, Hensher, and Swait 2000, Carson et al. 1994).[10] As our sample includes current adult tobacco cigarette smokers only, the tobacco cigarette option can be considered as the 'status quo' or opt-out option.

[9] The inability to fully match online samples to the population of interest is a concern within the literature that uses experimental methods generally (Bradford et al. 2014). While developing methods to generate more representative samples in such studies would clearly benefit the fields of economics and experimental analyses, how best to select such a sample is beyond the scope of our study. Thus, we simply encourage more research on this important topic and suggest that readers to interpret our results in the context of our sample, which reflects the preferences of adult smokers who complete an online survey.

[10] Whether or not it is reasonable to include or exclude an opt-out options is context-specific, preventing a universal recommendation to researchers (Carson et al. 1994). The benefits of including an opt-out option are twofold: (i) an opt-out may increase task realism as consumers can simply decline to purchase any product in real-world markets and (ii) the opt-out allows the researcher to estimate market penetration; that is whether or not consumers are willing to purchase any products included in choice sets. Overall, including the opt-out allows respondents to indicate the circumstances under which they are not, and are not, willing to purchase alternatives in the choice sets. On the other

2. Attributes and levels. We describe the products using four attributes: whether e-cigarettes are considered healthier than tobacco cigarettes ('Health'); the effectiveness of e-cigarettes as a tobacco cigarette cessation device ('Quit'); bans on use in public places such as bars and restaurants ('Bans'); and price. Attributes and levels are reported in Table 2.

While it is not feasible to include all relevant attributes in a single DCE, we contend that the attributes we include are important to adult smokers. First, and following best practices for DCEs (Johnson et al. 2013), we confirmed the importance of these attributes to current smokers in a pilot study prior to development of our DCE.[11] Second, we conducted a review of the e-cigarette literature to determine important e-cigarettes attributes among adult smokers.[12] Third, as outlined earlier in the manuscript, these attributes can be influenced by regulators.

We use binary variables (yes/no) for our three non-price attributes to avoid an overly complex DCE and due to lack of consensus on the levels that should be used based on the underlying science (see Section II). While the interpretation is straightforward for the smoking bans in public places variable, 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 smokers in our sample form their subjective perceptions based on the information available at the time of survey completion: e-cigarettes are healthier than tobacco cigarettes and e-cigarettes are an effective cessation aid for some smokers.

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hand, there are costs to including an opt-out option. Of particular concern is that respondents, rather than carefully considering their valuations between the choice set alternatives, may instead simply select the opt-out. These respondents have a preference between the products, but they chose to not make a choice rather than expend the energy to carefully review the products and make a choice that reflects their true preference ranking. Such a behavior muddles the interpretation of the opt-out choice and may limit variation in the data.

[11] We conducted a vignette survey of 2,030 current smokers ages 18 to 64 years between November 2014 and January 2015 via Qualtrics. We asked the smokers to rank 11 different reasons for using e-cigarettes. The attributes that we selected for our survey here mapped to the top ranked attributes in our vignette survey of, arguably, very similar smokers. Vignette survey specifics and results are available on request from the authors. Moreover, within our sample, 73%, 64%, 48%, 81%, and 76% reported less harmful, effectiveness as a cessation device, effective means to evade smoking bans in public places, kit price, and marginal price as somewhat or extremely important in their e-cigarette purchasing decisions.

[12] Details available on request from the authors.

The prices of disposable e-cigarettes and tobacco cigarettes are well described by their marginal prices (i.e., price for a single e-cigarette or for a pack of tobacco cigarettes). 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. 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 cigarettes). The purpose of this standardization is to ensure that a perception among respondent of being able to 'smoke more' with rechargeable e-cigarettes, relative to other cigarettes, is not driving respondent choices. Put differently, the relevant price should be the 'price per puff' and not smokers' perception that one device will allow for more puffs for the same price. See Appendix B for the wording in the DCE.

For both types of e-cigarettes we obtained market prices from online sources[13] to use as a midpoint price and then provide a lower and higher price for each (see Table 2). For rechargeable e-cigarettes we also include the kit price. The lower marginal price for rechargeable e-cigarettes versus disposable e-cigarettes reflects both the possibility of buying the e-cigarette liquid in more economical quantities and the need to buy only the refill rather than an

[13] Broadly, to develop our e-cigarette price variables, marginal and fixed, in advance of our DCE we reviewed online websites in Spring 2015 (e.g., Amazon, specific e-cigarette manufacturers such as NJoy, consumer review websites) to determine a range of prices in the marketplace. We then generated unweighted means from the data we collected. We note that a limitation of this approach is that there is controversy in terms of how best to assign e-cigarette prices. Developing such methods is critically important for improving the analyses of e-cigarette price elasticity of demand, but it is beyond the scope of our study. Further complicating price development for our study, U.S. states that have opted to tax e-cigarettes have applied different methods (Centers for Disease Control and Prevention 2016). As a primary objective of our study is to offer economic insight on how best to set e-cigarette regulations, including taxes, the lack of standardized methods applied by regulating states prevents us from using established methods within our target audience. More details on our price method development are available on request from the corresponding author. In sum, we note that our method for developing e-cigarette price values is a potential limitation of our study and we encourage methodological research on how best to price e-cigarettes, both disposable and re-chargeable.

entirely new device.[14] 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.

An issue related to our relative healthiness and effectiveness as a cessation device attributes is that they are defined subjectively. Historically, within the DCE literature attributes are defined objectively and concretely. We have opted to depart from this historical tradition for several reasons. First, there are no concrete and objective measures of these values as e-cigarettes are relatively new products. Moreover, the available evidence is continuously shifting, suggesting that consumer perceptions are at times incorrect and change quickly. Thus, we are concerned that presenting exact numbers that many respondents likely knew are not based on evidence would lead to lower quality responses (Johnson et al. 2013). Additionally, the use of subjective attributes is more common within health economics than in other fields that employ DCEs. For example, Marti (2012a), in a DCE that studies factors that predict smoker choices of cessation devices, operationalizes cessation medication-associated weight gain as a simple binary indicator: no weight gain vs. no weight gain. Brown et al. (2015), in a study of hospital choice, defines procedure scheduling convenience as 'not convenient – scheduled at the best time for the hospital' and 'convenient – scheduled at the best time for you' and the level of noise in the hospital ward as 'quiet– low level of activity' and 'noisy – high level of activity.'

Binary classification (i.e. 'healthier' or 'not healthier') is a common heuristic employed to process health risk information because health risk is difficult to understand (Ryan, Watson, and Entwistle 2009). E-cigarettes, given their controversy and newness, likely pose such difficulty. Finally, when attributes are defined in numerical terms, some

[14] Our review of e-cigarette prices revealed that this price pattern was observable in real world markets at the time of data collection (more details available from the authors).

individuals have difficulty interpreting them (Lancsar and Burge 2014, Ryan and Gerard 2003). Thus, the simpler specification promotes comprehensibility for respondents.[15]

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 two e-cigarette options and one 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 (Johnson et al. 2013). 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 techniques to promote data quality following established best practices (Johnson et al. 2013). (i) Respondents were given detailed narrative and visual information prior to the experiment describing the products, attributes, and levels. (ii) An example choice task was provided to all respondents before the choice tasks were completed (see Appendix B). (iii) We piloted the survey among 50 respondents and collected feedback which we used to improve the survey. (iv) We confirmed that estimated coefficients were in line with economic theory and prior expectations (e.g., negative price coefficients).

III.C. Choice Modeling and Sub-group Analysis

In line with the random utility framework (McFadden 1974), 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

[15] Given that our sample consists entirely of current adult tobacco cigarette smokers who regularly purchase cigarettes, we are not concerned that they will have substantial difficultly understanding cigarette prices.

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. βs are marginal utilities.

To estimate Equation (1) we first use conditional logit models. A critical assumption of the conditional logit model is that the data satisfy the Independence of Irrelevant Alternatives (IIA) assumption (Hausman and Mcfadden 1984). The IIA implies that adding an additional product to a choice set will not alter the ranking of incumbent products. We test this assumption in our data. The conditional logit also assumes homogenous preferences across all individuals. However, a central contribution of our study is to investigate heterogeneity across different groups of smokers which we argue is necessary for development of effective e-cigarette regulation. We take two approaches to relaxing this assumption and thus explore preference heterogeneity among smokers.

First, we partition our sample based on respondents' choices in the DCE and estimate the above-noted conditional logit. We separate our sample into groups of smokers who chose only tobacco cigarettes ('non-switchers') and those who vary their selection between e-cigarette sand tobacco 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.

Second, and in our preferred approach to study heterogeneity, we use a latent class logit model which is commonly applied to study health outcomes (Hole 2008, Flynn et al. 2010, Sivey 2012, Mentzakis and Mestelman 2013, Lagarde et al. 2013, Determann et al. 2016).[16] In the latent class model, a set of unobserved classes, or groups of individuals, are estimated on the data. 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 the *k* 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. We view the latent class model as our preferred estimation approach as it allows the data to formally determine groups of smokers who plausibly have similar

[16] We choose a latent class logit over a more general mixed multinomial logit (MMNL) or generalized mixed logit (GMXL) approach for several reasons. (i) The MMNL does not allow identification of classes of individuals. (ii) The latent class logit does not require the imposition of assumptions on parameter distributions for estimation, which is the case for the MMNL. (iii) 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). For these reasons, we chose to estimate the latent class logit.

preferences rather than relying on arguably *ad hoc* stratifications of the data, as is the case in our first approach to studying heterogeneity.

III.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 average marginal dollar value that respondents are 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 the WTP estimates we construct 95% confidence intervals following Krinsky and Robb (1986). We use the marginal price for our WTP estimates (rather than the fixed price for the e-cigarette kit) as the marginal price is defined for all cigarette types we examine.

III.E Simulations

We perform a series of predicted probability analyses to simulate the market-level response to government regulations 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. We refer to choice shares as 'market shares.'

IV. Results

IV.A. Baseline Conditional Logit Model

Results from the baseline conditional logit models are shown in Table 3. As noted, this model assumes IIA and homogeneity in preferences, we relax these assumptions later in the manuscript. Coefficient estimates in these models do not have an intuitive interpretation in terms of absolute magnitude, but their relative magnitudes are informative. 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 e-cigarette is chosen, suggesting that the two e-cigarette types are substitutes in our sample. The coefficients on the other variables remain statistically significant and similar in sign and magnitude to estimates in column 1.

IV.B. Willingness to Pay Estimates

Table 4 reports WTP estimates for non-price attributes. We find that smokers have a marginal WTP per tobacco cigarette pack (or equivalent for e-cigarettes) of $5.20 for an effective cessation device, $4.40 for a healthier product, and $3.30 for the ability to use in public places. The high WTP estimates arise because smokers derive substantial utility from the availability of these attributes and, at the same time, derive modest disutility from high prices. The combination of these preferences leads to the large WTP estimates.

IV.C. Heterogeneous Groups Based on Respondent Choices

We first investigate preference heterogeneity across cigarette types in Table 5 by stratifying the sample based on respondents' choices in the DCE (i.e., those who choose both e-cigarettes and tobacco cigarettes; we cannot report estimates for those smokers who choose the same type of e-cigarette each time or only tobacco cigarettes as there is no variation in the outcome variable). Among switchers, the estimated ASC for disposable e-cigarettes remains negative, but the ASC for the rechargeable e-cigarette becomes positive. This set of estimates indicates an underlying preference for both disposable and rechargeable e-cigarettes over tobacco cigarettes among switchers.

Given that switchers display different preferences towards the cigarette types in our DCE relative to the full sample of smokers, we explore factors that predict the probability of being a switcher. Table 6 displays odd ratios from a logistic regression of the likelihood of being a switcher on a set of individual characteristics. Switchers are more likely to be younger, female, higher education, lighter tobacco cigarette smokers, less addicted to tobacco cigarettes, and 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. Our findings regarding the factors that predict switching are comparable to a recent e-cigarette study that explores e-cigarettes versus tobacco cigarettes in nationally representative U.K. sample (Carrieri and Jones 2016), which may support the generalizability of our findings.

IV.D. Independence of Irrelevant Alternatives Assumption Testing

We test the independence of irrelevant alternative IIA assumptions following Hausman and Mcfadden (1984). More specifically, we estimate our conditional logit models twice: (i) using the full set of alternatives (i.e., all three cigarettes types) and (ii) on a sub-set of alternatives (i.e., we remove one cigarette type from the choice set). We then compare the regression coefficient estimates generated in (i) and (ii), and assess whether they are statistically different from one another. A χ^2statistic of 34.49 (6 degrees of freedom) leads us to reject the null hypothesis that the estimates are the same at the 99% level. Thus, we conclude from this testing that our data do not satisfy the IIA.

One possibility for the failure of the IIA is that smokers first choose between e-cigarettes and tobacco cigarettes, and second, among those that choose to use an e-cigarette, smokers choose between disposable and rechargeable e-cigarettes. We therefore first use a nested logit model to relax the IIA assumption. Results are reported in Appendix C and are comparable to results generated in our conditional logit model. We next estimate a latent class logit. Testing indicates that the latent class logit is preferred to the nested logit. We test IIA in the latent class logit by introducing mixing distributions within classes (Train 2009). Here, we do not find variance around the parameter means, and conclude that the model exhibits IIA in this form and retain the simpler specification. Results are available upon request.

IV.E. Latent Class Logit Model

We next investigate preference heterogeneity more formally using the latent class logit model. Here, the researcher must determine the appropriate number of classes. In unreported analyses, we estimate models that included two to seven classes (our data will not support models with more than seven classes). We find that the model with three classes provides the best fit and report results generated in these model in Table 7.[17] The three classes are determined by multiple factors and cannot be described by a single characteristic. However, to make the three class types more intuitive, we label them as 'vapers' (27% of the sample), 'smokers' (46% of the sample), and 'dual users' (27% of the sample).

Vapers are more likely to choose either type of e-cigarette than smokers and dual users. Vapers show a strong preference for e-cigarettes (as indicated by 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; this preference is indicated in their large, significant, and negative ASCs for each e-cigarette type. The coefficient estimates suggest that these smokers do not derive

[17] We first consider statistical fit for all estimated models (i.e., Akaike information criterion [AIC]). Second, following Heckman and Singer (1984), we examine the coefficient estimates generated in the models that offered the best statistical fit. Models fit with three and four classes provide the best statistical fist based on the AIC. However, the models fit with four classes generate coefficient estimates that departed substantially from standard economic theory (e.g., positive price coefficients) and implausibly large effect sizes. Such findings are interpreted by Heckman and Singer (1984) as evidence that a model is fit with too many classes, regardless of the statistical fit. Based on this evidence, we select the model fit with three classes. Details are available on request.

utility from the non-price attributes. Interestingly, in comparing their estimated characteristics to dual users, smokers are: older, less likely to live in a high tobacco cigarette price state, and less likely to plan to quit tobacco cigarettes soon.

Among dual users, when regulations favor rechargeable e-cigarettes, they will likely choose e-cigarettes; otherwise they will likely choose tobacco cigarettes. This choice pattern occurs 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.[18]

V. Simulations

We 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 logit model, to study how changes in e-cigarette and tobacco cigarette attributes affects market shares. We combine the two e-cigarette types into one type to focus on the more regulation-relevant issue of the selection of e-cigarettes versus tobacco cigarettes, rather than the decision to use disposable or rechargeable e-cigarettes.[19]

Our starting point for the simulation analysis is a scenario which we believe to approximate the state of the world at the time our DCE was conducted (2015). We define the state of the world as follows: e-cigarettes are considered to be healthier than tobacco cigarettes

[18] In unreported analyses we explore synergistic effects between health-related attributes (i.e., health vis-à-vis tobacco cigarettes and e-cigarette effectiveness as a cessation device). Specifically, we interact the 'health' and 'quit' attributes. We view results generated in this analysis as descriptive as our experiment is not designed to estimate such interactive effects. Nonetheless, our findings suggest interesting patterns. In particular, some of the utility vapers derive from these health-related attributes is determined by a common underlying (presumably health-related) dimension; smokers derive negative utility from effectiveness as a cessation aid but do gain some positive utility when the two health-related attributes are present in a product; and dual users derive more utility from effectiveness as a cessation device rather than health benefits. Results are available on request.

[19] To the best of our knowledge, at the time of writing, regulations decisions within the U.S. relate to e-cigarettes and tobacco cigarettes, and do not differentiate between different types of e-cigarettes.

by 70% of adults (Czoli, Fong, et al. 2016), e-cigarettes are considered to be an effective cessation device by 33% of adults (Tan, Lee, and Bigman 2016), use of e-cigarettes in public places is allowed in most states, and there is no e-cigarettes tax.[20] To implement assumptions regarding health and effectiveness as cessation device, 70% and 33% of respondents in our sample were randomly assigned a value of one for the corresponding attribute.[21] This state of the world is reflected in the baseline scenario in Table 8.

We simulate 11 scenarios in total. Scenarios 1 to 3 (i.e., rows A to C) reflect plausible regulation changes public use bans and prices, i.e. extending e-cigarettes vaping bans to all states, a 50% increase in e-cigarettes price, and 50% increase in tobacco cigarette price. Second, we simulate a range of scenarios regarding the level of public perceptions on the healthiness of e-cigarettes as well as their effectiveness as a cessation device (i.e., rows D to I). Third, we simulate two extreme regulatory scenarios: specifically, the least (scenario J) and most (scenario K) favorable scenarios to e-cigarettes vis-à-vis tobacco cigarettes. The least favorable scenario (J) is defined as: e-cigarettes are not viewed as healthier than tobacco cigarettes by any adults, e-cigarettes are not perceived as effective as a cessation device by any adults, e-cigarettes cannot be used in any public places, and there is a 50% increase in e-cigarette price. In the most favorable scenario (K), e-cigarettes are viewed as healthier than tobacco cigarettes by all adults, e-cigarettes are perceived as effective as a cessation device by all adults, e-cigarettes use in public places is allowed in all states, and there is a 50% increase in tobacco cigarette price. While these two scenarios depart most substantially from the state of the world, they are

[20] Based on CDC regulation data, states with a ban (i.e. restaurant, bar, private workplace, government workplace) in place in 2015 are considered as having an active e-cigarettes ban: Minnesota, New Jersey, North Dakota, Oregon, and Utah (Centers for Disease Control and Prevention 2016).
[21] In unreported analyses we explore the robustness of our results to alternative approaches to imposing this assumption: (i) we assign 0.70/0.33 to all respondents, (ii) we use an alternative random allocation of the 70%/30%, and (iii) we use simulated predictions with different random allocations over the simulations. Results, which are available on request, are not substantially different from those reported in the manuscript.

informative as they simulate possible options available to regulators seeking to curtail/enhance e-cigarette use substantially.

Results suggest that extending e-cigarettes public use bans to all states would lead to a 1 percentage point (pp) decline in e-cigarettes market share overall. The largest change in market share is observed among class 3 (switchers) smokers, with a 3.6 pp decline. When, in addition to extending the public use bans, we simulate a 50% increase in e-cigarette price, the e-cigarette market share for switchers declines an additional 5.5 pp (scenario B). As one would expect, a parallel 50% increase in tobacco cigarette price would offset the e-cigarette price increase (scenario C). We then turn to scenarios aimed at assessing the effect of changes in public perceptions of e-cigarettes (D to I). Scenario F suggests that if 100% of smokers considered e-cigarettes to be (i) healthier than cigarettes and (ii) effective as a cessation aid, the overall market share for e-cigarettes would increase by 3.9 pp, driven by a 6.7 pp increase among switchers.

Lastly, in rows J and K, we simulate and compare market shares for the least and most favorable regulatory scenarios within our empirical model for e-cigarettes vis-à-vis tobacco cigarettes. Overall, the difference in market shares between these two extreme cases is of 13.2 pp. Again, this shift in market shares is mostly driven by the effect by switchers for which e-cigarette market share would increase by 26.5 pp from the least to the most favorable scenario. Interestingly, the least favorable scenario predicts almost no e-cigarette users in class 2 (smokers), while the market share for e-cigarette in this group would be 10.2% in the most favorable scenario. Thus, our results suggest that the largest responses of smokers are for changes in the non-price attributes.[22]

[22] In our simulation analyses thus far, we have made assumptions regarding how best to characterize the state of the real world at the time our DCE was conducted. Given uncertainties regarding e-cigarettes, these assumptions could be incorrect. Thus, to explore the sensitivity of our simulations to other assumptions regarding the true state of the world, we conduct a supplementary simulation in which we propose a different state of the world. More specifically, use of e-cigarettes is permitted in all public places, e-cigarettes are considered to be healthier than tobacco cigarettes by all respondents, and e-cigarettes are considered to be an effective cessation aid. We report this simulation and provide an interpretation in Appendix D. Overall, our simulation results do not appear to be sensitive to our selection of the state of the world.

VI. Discussion

In this study, we estimate adult smokers' preferences for e-cigarettes and tobacco cigarettes and how these preferences vary in response to four policy-relevant attributes: whether e-cigarettes are considered healthier than tobacco cigarettes, the effectiveness of e-cigarettes as a cessation device, bans on use in public places, and price.

Our use of an experiment, in which we randomize product attributes across smokers, allows us to recover causal estimates which can be used to guide future regulations. Further, our use of a latent class logit model allows us to identify groups of smokers that display heterogeneity in their preferences toward e-cigarettes vis-à-vis tobacco cigarettes, characterize them, and analyze their cigarette choices.

One of the key contributions of this study is that it provides timely and policy-relevant information and predictions prior to adoption of e-cigarette regulations. This contribution is arguably important given regulatory interest in e-cigarettes. For example, in the U.S. the FDA recently (2016) gained the authority to regulate e-cigarettes with a mandate of promoting public health, but has enacted only a few regulations which predominately focus on youth access (e.g., a prohibition on the sale of e-cigarettes to youth in August 2016). This agency requires and is actively seeking solid evidence on how regulations will affect smokers' choices between e-cigarettes and tobacco cigarettes in order to anticipate the net impact of regulation on public health.[23] Moreover, different state and local governments are considering taxing e-cigarettes and banning their use in public places, among other regulations, and thus need to understand how smokers will alter their use of both e-cigarettes and tobacco cigarettes following regulation. Also we focus on adult smokers, which is an important addition given the much larger economic literature on e-cigarette use among youth (Pesko, Hughes, and Faisal 2016, Pesko, Seirup, and Currie 2016, Friedman 2015). Studying adult smokers is important for regulation designed to

[23] See: https://www.fda.gov/TobaccoProducts/NewsEvents/ucm568425.htm. (accessed November 24th, 2017).

improve overall population health because adults are the largest group of smokers and are most likely to use e-cigarettes as a cessation device or for harm reduction.

Another contribution is that, in contrast to most of the literature, this study empirically explores heterogeneity in preferences toward e-cigarettes and tobacco cigarettes across different groups of adult smokers. The groups we identify, based on their choices in our experiment and latent class models, closely match three groups observed in real-world tobacco markets: those who prefer e-cigarettes (‘vapers’), those who prefer tobacco cigarettes (‘smokers’), and those prefer using both cigarette types (‘dual users’). To the best of our knowledge this heterogeneity has not been explored previously in the context of cigarettes.

Our study has however several limitations: (i) DCEs rely on stated preferences even though revealed preference data are generally viewed as more credible in economic analyses (Hausman 2012). However, stated preference methods can be particularly useful, and indeed potentially the only available option, when there are little to no suitable revealed preference data. (ii) We do not observe if smokers alter their quantity of consumption depending on the product selected. For example, smokers who choose an e-cigarette may either smoke tobacco cigarettes less heavily or leave their smoking unchanged, and/or increase/decrease nicotine consumption through the combined use of these cigarette types; (iii) As is the case in all choice experiments of which we are aware, we are unable to include all relevant products and attributes in our experiment. (v) Although we view the benefits of our subjective attributes (health and effectiveness as a cessation device) as greater than their costs, our approach contrasts with the extant DCE literature and is a potential limitation. Further, these attributes do not directly relate to a particular regulation such as, for example, prices relates to taxation. (vii) Our study focuses exclusively on adult tobacco cigarette smokers. However, e-cigarettes may impose harms on youth health. For example, nicotine (regardless of the whether consumed via tobacco cigarettes or e-cigarettes) is believed by health experts to harm the development the adolescent brain and the risks that use of e-cigarettes will lead youth to take up tobacco cigarette smoking which, in turn, could increase nicotine addiction in the next generation (U.S. Department of Health and Human Services 2016). While it is beyond the scope of our study to explore youth preferences for e-cigarettes and tobacco cigarettes, we encourage future studies on this topic.

To summarize our findings, 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 such as restaurants and bars. Thus the desire to improve health seems to be a key motivator of the demand for e-cigarettes for the average adult smoker. Higher prices, as predicted by basic demand theory, have a negative, significant effect on choice probability and it is significant, but the magnitude of the price effects we identify are relatively 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: vapers, smokers, and dual-users. Vapers and smokers seldom divert from their preferred cigarette type while dual users' cigarette choices vary depending on the attribute scenarios, and therefore this final group likely offers the most scope for regulation-induced change in product choice. Importantly, this final group reflects 27% of our sample, which suggests that there is an important role for regulation. We find that preferences for the non-price attributes vary across groups. Specifically, these attributes are valued highly by vapers and to a lesser extent by dual users. These results thus 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 regulation 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 regulations will likely have differential effects across adult smoker types. For example, regulations 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 regulation in terms of their purchases 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, regulations will have different welfare impacts across smoker types and governments should consider this heterogeneity in regulation decisions.

In sum, this study provides needed predictions on the effect of potential regulations of e-cigarettes and tobacco cigarettes on the health of the public. Given the interest in regulation of e-cigarettes at different levels of the government, this information may be useful in guiding selection of the optimal set of regulations.

Table 1. Sample characteristics by type of smoker

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

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. 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	Tobacco 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

Model:	**Model (1)**	**Model (2)**
ASC: disposable e-cigarette	-1.75***	-1.95***
	(0.05)	(0.06)
ASC: rechargeable e-cigarette	-1.13***	-1.21***
	(0.06)	(0.05)
Use of product is permitted in public places	0.22***	0.21***
	(0.03)	(0.03)
Product considered to be healthier than tobacco cigarettes	0.29***	0.29***
	(0.03)	(0.03)
Product is effective for smoking cessation	0.35***	0.36***
	(0.03)	(0.03)
Marginal price	-0.07***	-0.07***
	(0.00)	(0.00)
Kit price	-0.01***	--
	(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**

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 non-price product attributes

Product attribute:	**WTP estimate [95% CI]**
Use of product is permitted in public places	$3.3 [$2.2-$4.3]
Product considered to be healthier than tobacco cigarette	$4.4 [$3.2-$5.5]
Product is effective for smoking cessation	$5.2 [$4.1-$6.4]

Notes: WTP for the full sample and switcher sample calculated using estimates from Model (2) in Table 3 respectively. We use the marginal price in our WTP estimates. Krinsky-Robb (1986) 95% confidence intervals reported in square brackets.

Table 5. Determinants of cigarette choices: Conditional logit model

Variable:	**Switcher sample**
ASC: disposable e-cigarette	-0.70***
	(0.05)
ASC: rechargeable e-cigarette	0.15*
	(0.07)
Use of product is permitted in public places	0.21***
	(0.03)
Product considered to be healthier than tobacco cigarettes	0.29***
	(0.03)
Product is effective for smoking cessation	0.37***
	(0.03)
Marginal price	-0.04***
	(0.01)
Kit price	-0.01***
	(0.00)
N	**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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6. 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: 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 7. 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)
Probability of 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. 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.

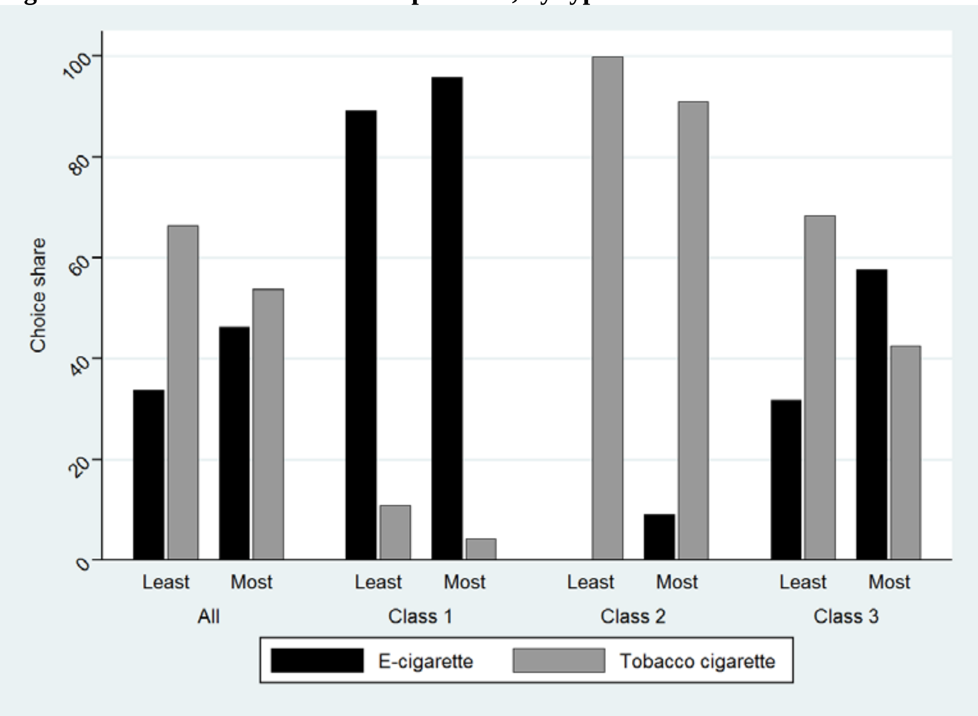
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8. Policy simulations

	Use permitted in public places	E-cig considered to be healthier than t-cig (%)	E-cig perceived as effective for smoking cessation (%)	50% higher e-cig mariginal price	50% higher t-cig marginal price	Full Sample		Class 1 (vapers, 27%)		Class 2 (smokers, 46%)		Class 3 (dual users, 27%)	
						E-cig	T-cig	E-cig	T-cig	E-cig	T-cig	E-cig	T-cig
Base	States with a ban in 2015	0.7	0.33	0	0	39.6	60.4	93.7	6.3	2.3	97.7	45.4	54.6
A	All states	0.7	0.33	0	0	37.7	62.3	92.7	7.3	0.6	99.4	41.8	58.2
B	All states	0.7	0.33	1	0	35.9	64.1	92.2	7.8	0.4	99.6	36.3	63.7
C	All states	0.7	0.33	1	1	37.7	62.3	92.7	7.3	0.7	99.3	41.8	58.2
D	States with a ban in 2015	1	0.33	0	0	40.6	59.4	94.3	5.7	3.7	96.3	46.4	53.6
E	States with a ban in 2015	0.7	1	0	0	42.2	57.8	95	5.0	3.8	96.2	51.1	48.9
F	States with a ban in 2015	1	1	0	0	43.5	56.5	95.5	4.5	6.1	93.9	52.1	47.9
G	States with a ban in 2015	0	0.33	0	0	37.9	62.1	92.2	7.8	0.7	99.3	43.1	56.9
H	States with a ban in 2015	0.7	0	0	0	38.4	61.6	92.9	7.1	1.8	98.2	42.6	57.4
I	States with a ban in 2015	0	0	0	0	36.8	63.2	91.2	8.8	0.6	99.4	40.3	59.7
J	All states	0	0	1	0	33.7	66.3	89.2	10.8	0.1	99.9	31.7	68.3
K	No states	1	1	0	1	46.9	53.1	95.9	4.1	10.2	89.8	58.2	41.8

Notes: Predictions are based on coefficient estimates presented in Table 7.

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



Notes: Least=least favorable conditions to tobacco cigarettes (row J in Table 8); and Most=most favorable conditions to tobacco cigarettes (row K in Table 8). Predictions are based on coefficient estimates presented in Table 7.

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