Smoking choices, nicotine and addiction: a choice modelling approach applied to smokers in the US

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Highlights:

- We model addiction as a latent variable
- We study the impact of addiction on smokers' tobacco product choices
- We study how preferences and willingness to pay vary with addiction
- We predict the impact of lowering nicotine in cigarettes on smokers' short-term choices

Abstract

Use of choice models is growing rapidly in tobacco research. These models are being used to answer key policy questions. However, certain aspects of smokers' choice behaviour are not well understood. One such feature is addiction. Here, we address this issue by modelling data from a choice experiment on US smokers. We model addiction using a latent variable. We use this latent variable to understand the relationship between choices and addiction, giving attention to nicotine levels. We find that more addicted smokers have stronger preferences for cigarettes and are unwilling to switch to e-cigarettes. Further, addicted smokers value nicotine in tobacco products to a much greater extent than those that are less addicted. Lastly, we forecast short-term responses to lowering nicotine levels in cigarettes. The results suggest that current nicotine-focused policies could be effective at encouraging addicted smokers to less harmful products and lead to substantial public health gains.

Keywords: tobacco; addiction; hybrid choice model; experience-conditioned choice model, willingness to pay and accept, stated choice experiment

JEL codes: C35; I12; I18

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Introduction

In the economics of risky behaviour, and in particular tobacco, the use of discrete choice models has proliferated in recent years (Regmi et al., 2017; Pacula et al., 2019). Standard choice models that are commonly used try to explain differences in sensitivities/behaviour towards products' attributes as a function of individuals' characteristics, i.e. through differences across sociodemographic groups. In so doing, there is the possibility that elements of the cognitive decision-making process are suppressed, and these elements can be important for understanding choice behaviour (Vij and Walker, 2016). Encouragingly, a trend in the risky behaviours literature, which follows the broader choice modelling literature (Hensher, 2015; Balbontin et al., 2019), has been to use more advanced choice models in attempts to understand more complex behaviours of individuals than permitted with standard models. Examples include incorporating measures of risk preferences into models of choice behaviour (Ida and Goto, 2009); the segmentation of individuals into groups or types of individual (Marti et al., 2018); accounting for optimization errors in individuals' choices (Kenkel et al., 2017); accounting for aversive choice behaviours (Buckell and Sindelar, 2019); and embedding real-world behaviours into models based on experimental data (Buckell and Hess, 2019). This information is crucial for policymaking; failure to capture these behaviours can lead to misguided policy recommendations (Buckell and Sindelar, 2019). Given that the complexion of tobacco markets has changed markedly in the past few years with the arrival of e-cigarettes, and that a variety of new policies are being enacted, it is now critical to understand the complex cognitive processes underpinning smokers' choices so as to better inform regulation.

Perhaps surprisingly, one aspect of behaviour that has not been incorporated into choice models is addiction (although there are studies of habitual behaviour such as modal choice in transport, where individuals are captive to a single mode). It is well-known that addiction plays a central role in smokers' behaviours (West, 2009; West and Brown, 2013; Wehbe et al., 2018). Indeed, economists have applied models of addiction to longitudinal smoking data (Chaloupka and Warner, 2000; Cawley and Ruhm, 2011). Yet, the role of addiction in smokers' choice behaviour is not well understood. Moreover, many studies have found heterogeneity in how specific subgroups (defined by observed individual characteristics) react to individual attributes. But it is unclear as to whether these are true preferences, or that the individual characteristics are linked to addiction, and it is the underlying addiction that impacts on choices. This is a key issue because many policies are directed at both addiction (i.e., nicotine policies) and vulnerable subpopulations, and the effectiveness of policies can be improved with a greater understanding of addiction-related choice behaviour.

Attempting to incorporate addiction into choice models is beset by a number of issues. Firstly, addiction is both multifaceted and unobservable. Currently, only indicators of addiction are available, such as the number of cigarettes smoked per day. The number of cigarettes smoked is not a measure of addiction, but a function of addiction (and the underlying direction of causality is unclear). Secondly, there is not a one-to-one correspondence between these indicators and addiction. These are, at best, imperfect measures for the underlying metric of interest. For example, a more addicted smoker with high will power (or lower income) could smoke fewer cigarettes per day than a less addicted smoker with low will power (or higher income). In this case, using cigarettes per day as a direct measure of addiction is incorrect and it should only be used as an indicator of addiction.

There are many other such indicator measures. Thus, it is not always clear which indicators should be used to measure addiction or whether to use the full set of available indicators. Using only a subset of the indicators risks overlooking key information or misattributing effects. On the other hand, using all indicators poses significant problems for modelling, because using many indicators that are also likely to be highly correlated leads to a proliferation of parameters and technical issues such as collinearity. Several indices have been developed that sum these indicators, such as the Fagerstrom Test of Nicotine Dependence (FTND; Heatherton et al., 1991) for cigarettes, or equivalent measures for e-cigarettes (more than 10 now exist, see Bold et al., 2018). This is not an ideal solution because unweighted summation, or equal weighting, may be inappropriate (Fayers and Hand, 2002). In addition, these indices and their constituents are still product-specific and thus only capture addiction towards a specific type of cigarette. Moreover, any indicators that are collected but are not included in the index will be discarded; it is less than ideal to disregard potentially useful behavioural information.

Whether using a single indicator or multiple ones, the issue of causality remains. The indicators are a function of addiction rather than a direct measure thereof. Moreover, there is likely to be correlation between these indicators and other unobserved effects at the individual level that influence choice behaviour. Using these indicators as error-free variables in the model thus potentially leads to endogeneity bias, i.e. breaching the independence assumption of the explanatory variables and the error term.

In this paper, we develop a choice model capable of handling the present issues in measuring and incorporating addiction into the analysis of smokers' choices. This model draws from two areas in the choice modelling literature: hybrid choice models and experience-conditioned choice models. Hybrid choice models allow for a latent, or unobserved, variable to be specified and estimated with the choice model in a system of equations (Abou-Zeid and Ben-Akiva, 2014). As such, it is well-suited to capturing addiction, the nature of which is inherently latent. Figure 1 is a schematic of the modelling framework. Within the system, the latent variable is used to explain observed variables, such as indicators of addiction. Thus, these variables do not enter the choice model directly, avoiding possible endogeneity issues. Moreover, this framework can accommodate any number and form (i.e. the nature of the data) of indicator, using all the available information. The latent variable is then used in the utility function in place of the indicators (which would be a more traditional approach). Because there is only a single addiction variable, having to specify a large number of parameters directly in the utility function is thus also avoided. Of course, additional parameters are required for the measurement model components that are used to explain the values observed for the indicators.

The experience-conditioned choice models (Hensher and Ho, 2016; Hensher et al., 2019; Balbontin et al., 2019) are based on the notion that preferences and choice behaviours are in part a function of a given individual's prior experience with a given product or service. In the context of smoking, this implies a behavioural assumption that tobacco product choices are to some extent determined by the past use of tobacco products. This is highly appealing because the idea is applicable to both the addiction to nicotine and formation of habits that are associated with tobacco product use (Wehbe et al., 2019). For this reason, we test addiction-conditioning in our model[1].

Developing this model allows us to overcome a set of difficult empirical issues and specify a behaviourally appealing model of smoking choices. This model embodies a more sophisticated depiction of smokers' cognitive decision-making processes than in previous work. We use this model to study the relationship between addiction and choice behaviour, examine smokers' willingness to pay for nicotine in tobacco products, and predict the impact of lowering nicotine in cigarettes (which has recently been proposed by the US government). With this, policymakers are better informed in key issues around smoking and addiction. The remainder of the paper is set out as follows. In section 2, we set out the model and its features. In section 3, the results from the model are presented. Section 4 summarizes and discusses.

Methods

Experiment and Data

Data are taken from a labelled smoking choice experiment in which 1,531 adult smokers chose between cigarettes, e-cigarettes and an opt-out option[2] (Buckell et al., 2018; see Fig 2 for a sample choice scenario). Products were described by four attributes: nicotine, flavour, health harms and price. Table 1 shows the experimental design. The design was Bayesian D-optimal, using priors obtained from a pilot study of 87 respondents. Individuals each answered 12 choice sets, which balances concerns of learning and respondent fatigue (Hess et al., 2012). Sampling was based on quotas, defined using the Behavioural Risk Factor Surveillance System (BRFSS) data in 2013/14, based

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[1] In preliminary modelling, we tested a series of specifications based on experience-conditioned choice model versus a conventional hybrid choice model (i.e. with interactions between the latent variable and elements of the utility function). We found that the hybrid choice model led to better fit of the model and we thus used this approach. However, we note both the similarity to, and relevance of, the experience conditioning model for this application. The model in this form allows for addiction to condition utility, but in varied directions (as opposed to conditioning impacting all attributes in a single direction which is the case in the standard experience-conditioned model).

[2] Since there are two alternatives for each label (i.e., each product and the opt-out), there may be difficulty in interpreting preferences for each label separately. To aid interpretation, we use generic constant terms for each label in our models.

on gender, age, education and region, to make the sample representative of US smokers. Table 2 shows the descriptive statistics for individuals in the sample. The sample size was sufficient to ensure statistical power for the main parameters and is larger than most DCEs in health (de Bekker-Grob et al., 2015). Data quality measures, such as minimum time thresholds and practice choice scenarios for respondents, were taken to promote data quality.

A survey was collected alongside the experiment. In this survey, a number of indicators of addiction were collected.

These were:

- daily smoking;
- number of cigarettes smoked per day;
- time before first cigarette of the day is smoked;
- time since last having smoked a cigarette that day;
- time since last having smoked a cigarette in the last few days/weeks;
- the number of quit attempts in the past year;
- e-cigarette use;
- frequency of e-cigarette use;
- current urge to smoke (i.e. craving).

Summary statistics for these measures are shown in table 2.

Choice Models

In a standard random utility model, the utility U_{nit} that individual *n* derives from product *i* in choice *t* comprises a systematic component, V_{nit}, and a remaining error term, ε_{nit} that follows an iid type I extreme value distribution, such that:

$$U_{nit} = V_{nit} + \varepsilon_{nit} \tag{1}$$

The systematic component incorporates two parts, with:

$$V_{nit} = \delta_{ni} + \beta_n x_{nit} \tag{2}$$

where δ_{ni} is a constant capturing product-specific preferences for alternative *i*, while β_n is a vector of estimated sensitivities capturing the impact of changes in explanatory variables x_{nit}, where this includes nicotine, flavour, health harm and price. Both δ_{ni} and β_n are person-specific, where the former is also different across alternatives.

We next allow for deterministic and random heterogeneity across individuals in the values of both δ_{ni} and β_n, both directly, and through the latent addiction variable. In particular, we have:

$$\delta_{ni} = \mu_{\delta_i} + \lambda_{\delta_i} z_n + \sigma_{\delta_i} \xi_{n\delta_i} + \tau_{\delta_i} \alpha_n \tag{3}$$

and for the coefficient associated with attribute x_{ni_kt}:

$$\beta_{nk} = \mu_{\beta_k} + \lambda_{\beta_k} z_n + \sigma_{\beta_k} \xi_{n\beta_k} + \tau_{\beta_k} \alpha_n \tag{4}$$

In this specification, μ_{δ_i} and μ_{β_k} capture mean values in the sample population for δ_{ni} and β_{nk}; λ_{δ_i} and λ_{β_k} capture shifts in their values as a function of socio-demographic characteristics, z_n; σ_{δ_i} and σ_{β_k} capture random heterogeneity, where $\xi_{n\delta_i}$ and $\xi_{n\beta_k}$ follow standard normal distributions across individual respondents; and τ_{δ_i} and τ_{β_k} capture the impact of the latent addiction variable, α_n, a point we return to below.

For the price sensitivity, we relax the oft-assumed constant marginal utility of income imposed in many health choice models (Reed Johnson et al., 2011). Preferences for the cost attribute p, are treated as:

$$\beta_{np} = \left(\mu_{\beta_p} + \lambda_{\beta_p} z_n\right) \cdot \left(\frac{income_n}{\overline{income}}\right)^{\eta} \quad (5)$$

This drops the random heterogeneity and impact of the latent addiction variable, but adds in an income effect where η is an estimated income elasticity, $income_n$ is a given individual's income and $\overline{income}$ is the sample median.

As per figure 1, the latent variable for addiction is regressed on individual characteristics in the structural equation:

$$\alpha_n = \gamma z_n + \xi_n \quad (6)$$

where z_n are individual characteristics, γ captures the relationship between addiction and observed individual characteristics, and ξ_n is unobserved individual addiction heterogeneity, which follows a standard normal distribution.

In our specification, we allow for an impact of the latent addiction variable on the constants for the different alternatives as well as the parameters associated with individual attributes. This in essence means that our model is a standard hybrid choice model, albeit one where the latent variable relates to experience/addiction. We did test a model in which the entire utility function was addiction-conditioned, as in the original Hensher and Ho (2016) work, but this led to inferior results, largely as a function of the conditioning exerting itself on all sensitivities in the same direction, whether they relate to desirable or undesirable components.

With the elements of the utility function defined, we move to the specification of the choice model, which, given the assumption on the error term, takes the classic multinomial logit (MNL) form:

$$P_{C_n} = \prod_{t=1}^{T} \frac{e^{V_{ni^*t}}}{\sum_{j=1}^{J} e^{V_{nit}}} \quad (8)$$

where P_{C_n} is the probability of the observed sequence of choices for individual *n*, where i^* refers to the chosen alternative.

Next, we examine the relationship between the latent variable for addiction, α_n , and the indicator measures of addiction. The data for the indicator measures takes three broad forms. For each, its probability is modelled in a series of measurement equations. For the two binary variables (daily smoking, e-cigarette use), such as whether the individual smokes every day or not, a logit model is used:

$$P_{binary_n} = \prod_{k=1}^{2} \frac{\left(e^{(\delta_k + \zeta_k \alpha_n)}\right)^{I_{k_n}==1}}{1 + e^{(\delta_k + \zeta_k \alpha_n)}} \quad (9)$$

where δ_k are constant terms to be estimated, and ζ_k are estimated parameters capturing the relationship between the latent variable for addiction and the indicator at hand, I_{k_n}, where the exponent $I_{k_n} == 1$ ensures that the appropriate numerator is used depending on the observed value for I_{k_n}.

For five ordered variables (frequency of e-cigarette use, time before first cigarette of the day is smoked, time since last having smoked a cigarette that day, time since last having smoked a cigarette in the last few days/weeks, the number of quit attempts in the past year), an ordered logit model is used (Greene and Hensher, 2010):

$$P_{ordered_n} = \prod_{k=1}^{5} \left(\sum_{s=1}^{S} \delta(I_{k_n} == s) \left[\frac{e^{\tau_{k,s} - \zeta_k \alpha_n}}{1 + e^{\tau_{k,s} - \zeta_k \alpha_n}} - \frac{e^{\tau_{k,s-1} - \zeta_k \alpha_n}}{1 + e^{\tau_{k,s-1} - \zeta_k \alpha_n}}\right]\right) \quad (10)$$

where $\tau_{k,s}$ are estimated threshold parameters for threshold *s* of categorical indicator I_{k_n}, and ζ_k are estimated parameters capturing the relationship between the latent variable for addiction and the indicator at hand.

Finally, for two continuous variables (number of cigarettes smoked per day, current urge to smoke), a linear model is used:

$$P_{linear_n} = \prod_{k=1}^{2} \frac{1}{\sqrt{2\pi\sigma_k^2}} e^{-\frac{\left(I_{k_n} - \bar{I}_k - \zeta_k \alpha_n\right)^2}{2\sigma_k^2}} \quad (11)$$

where demeaning the variables, as shown by subtracting $\bar{I}_k$, avoids the need to estimate a constant (Daly et a., 2012b). The variance of the error, σ_k^2, is estimated along with other parameters. ζ_k are estimated parameters capturing the relationship between the latent variable for addiction and the indicator at hand.

Finally, each of the model components are combined into a single likelihood function and jointly estimated:

$$LL = \sum_{n=1}^{N} ln \int_{\beta} \int_{\alpha} P_c P_{binary} P_{ordered} P_{linear} \phi(\zeta) m(\beta|\Omega) d\beta d\alpha \quad (12)$$

We integrate over the parameter mixing distributions and latent variable, where maximum simulated likelihood is used for estimation (Train, 2009), with 500 Halton draws per random component and per individual. All models are estimated using Apollo (Hess and Palma, 2019).

We optimized the specification with several rounds of removing interaction terms that were not statistically significant and updating the starting values. We followed the choice modelling literature in the choice of normalisation for alternative specific constants and categorical variables by deliberately over-specifying the model (attempting to estimate all parameters) and then omitting those with the lowest variance (Walker, 2001). On the basis of this, we normalised to zero the constant for e-cigarettes, the impact of the addiction latent variable on cigarettes, the medium level of nicotine, and the impact of the latent variable on high nicotine.

Finally, because we are using the model for forecasting, it is crucial to calibrate the model constants and the scale of utility. We follow the approach of Buckell and Hess (2019). More specifically, the ASCs are calibrated post-estimation using national data on tobacco product market shares. This aligns the base choice shares in our model to real-world market shares of the products. For calibrating the scale of utility, we use revealed preference (RP) data on respondents collected in the survey and build a RP choice model equivalent of equation (8). We estimate a common price coefficient in model (8) and its RP equivalent, and estimate an additional SP scale parameter, μ_{SP}. This aligns the scale of the SP model to that of the RP model. Terming the choice probability in model (8) $P_{c,SP}$ and its RP equivalent $P_{c,RP}$, the log-likelihood becomes:

$$LL = \sum_{n=1}^{N} ln \int_{\beta} \int_{\alpha} P_{c,SP} P_{c,RP} P_{binary} P_{ordered} P_{linear} \phi(\zeta) m(\beta|\Omega) d\beta d\alpha \quad (13)$$

Limitations

Our methods are subject to a set of limitations. First, we are limited by the set of indicator measures that we collected. However, those that we do use cover important aspects of addiction: we have measures for cigarettes and e-cigarettes; and we have longer and shorter term measures of addiction. Whilst it is common practice to run factor analyses prior to estimating latent variables, we discarded this preliminary exercise in this case. The factor analysis suggested that there were three latent variables. However, the directions of indicator variables across these latent variables were highly implausible. Moreover, attempting to estimate three separate latent variables would have added considerable complexity to the exercise and exposition. And, in fact, the one that we did estimate resulted in plausible directions of coefficients and implied choice behaviours. For these reasons, we kept to a single latent variable. As with all hybrid choice models, the latent variable should not be used in forecasts, due to the fact that it is only a cross-sectional measure (Chorus and Kroesen, 2014). Finally, we were limited by processing power to using 500 Halton draws in estimation. Whilst this is in excess of many other studies in health, we note recent research which suggests this may be too few draws (Czaikowski et al., 2019).

Results

Table 3 shows the diagnostic information. The log-likelihood of the joint estimation is shown, both from its starting values and the optimized model. Next, each of the component models' log-likelihoods are given (note all parts sum to the total). Measures of fit, AIC and BIC are presented along with the total number of estimated parameters, 82.

Measurement equations and structural equation

Table 4 shows the results from the measurement equations and the structural equation. This is informative in understanding the nature of addiction captured in the model. By studying the ζ parameters, we note that higher values of the latent variable are associated with:

- lower chance of being a daily smoker;
- smoking fewer cigarettes per day;
- longer time in the morning before smoking their first cigarette;
- longer time since last having smoked a cigarette that day;
- longer time since last having smoked a cigarette in the last few days/weeks;
- more quit attempts in the past year;
- higher probability of being an e-cigarette user;
- no increase in the frequency of e-cigarette use (not statistically significant); and
- reporting a lower level of current craving.

Taken together, these results suggest that a higher value for the latent variable is associated with lower levels of addiction to cigarettes and nicotine (or, equivalently, lower values of the latent variable are associated with higher levels of addiction to cigarettes and nicotine). This is due to, firstly, the lower levels of cigarette use and addiction. But it is of course possible that more addicted smokers could just be switching away from cigarettes to e-cigarettes. In this case, we would expect to see very little change in reported craving and increased frequency of use of e-cigarettes. However, we see the opposite: no increase in the frequency of e-cigarette use and lower reported craving. Moreover, higher values for the latent variable are associated with more past year quit attempts, which again is a sign of lower addiction. For these reasons, we interpret the latent variable as capturing reduced addiction to cigarettes and nicotine, where lower values signify higher levels of addiction. We then move to the structural equation to examine how individual characteristics of vary with addiction.

In the structural equation, individual characteristics are used to explain the latent variable. Higher values of the latent variable (i.e. less addicted) are associated with:

- younger individuals (more likely to be younger and less likely to be older);
- higher education;
- higher income (less likely to be associated with lower income);
- non-white race/ethnicity (positive values for Hispanic, Black and Asian); and
- lower probability that a family member smokes.

This in keeping with what we would expect to see: these demographic patterns are opposite to those of smokers, which would fit with the idea of higher values for the latent variable capturing lower levels of addiction (Wang et al., 2018). (Though note that the definition of smokers varies between this study and that of Wang et al.; and that we are measuring addiction, whereas Wang et al. 2018 study current use.)

Utility function and impact of addiction latent variable

Estimates of the utility function are presented in table 5. All else being equal, the alternative specific constants indicate that cigarettes are preferred to e-cigarettes; and e-cigarettes are preferred to the opt-out. Unobserved preferences for cigarettes (relative to e-cigarettes) vary considerably around the mean, as reflected by the large and significant standard deviation. No preference heterogeneity for cigarettes across sociodemographic characteristics was found. Preferences for the opt-out (relative to e-cigarettes) varied in both unobserved ways (statistically significant estimated standard deviations) and according to age, ethnicity and employment status, as captured by the associated interaction terms of preferences and these characteristics. For nicotine, medium level is preferred to all other levels. Preferences for nicotine levels vary significantly in both observed (i.e. associated interaction terms of nicotine levels and socio-demographic characteristics) and unobserved ways (statistically significant estimated standard deviations). Price sensitivity, as expected, is negative. The income elasticity estimate implies that price sensitivities decline as income increases. In other words, as income increases, individuals are less sensitive to price changes. Tobacco is preferred to all other flavours. And healthier products are preferred to more harmful products. Next, we move to the impact of the latent variable. From the interactions of the latent variable and product constant terms, lower addiction (higher values for the latent variable) is associated with increased preferences for both e-cigarettes and the opt-out increase. Oppositely, this implies that those that are more addicted prefer cigarettes. With reduced addiction, the lower levels of nicotine are preferred to high nicotine; or, oppositely, more addicted smokers prefer higher levels of nicotine in cigarettes – and progressively so with higher levels of addiction, as captured by the interaction of nicotine and the latent variable.

Willingness to pay (WTP) and willingness to accept (WTA)

Table 6 shows the estimated willingness to pay (WTP) (or willingness to accept, WTA, in the case of negative values) for the attributes in the utility function using the standard approach (Hensher et al., 2015). These reflect the dollar value per 20 pack (or e-cigarette equivalent) that individuals are willing to pay (must be compensated for, WTA) for that level of the attribute, relative to the omitted category, so as to remain indifferent (equal utility) between two products with these differing levels. For health harm, smokers, on average, are willing to pay $8.32 extra on a packet of 20 cigarettes to reduce the health risk from losing 10 years of life to losing 2 years of life. For flavours, smokers, on average, must be compensated to move to non-tobacco flavoured tobacco products to attain the same level of utility as for tobacco products. This differs across flavours. For menthol, WTA is $4.29; for fruit, WTA is $1.80; and for sweet, WTA is $2.30.

For nicotine, WTP/WTA is more modest on average than for other attributes (note nicotine valuations are also related to addiction, since the LV is interacted with these attributes in the utility function). Smokers express WTA for all levels of nicotine; that is, smokers must be compensated to achieve the same utility for moving from medium nicotine strength in tobacco products to any other strength of nicotine in tobacco products. More specifically, WTA for no nicotine is $1.33; for low nicotine is $0.68; and for high nicotine is $0.95.

From a policy perspective, it is of interest to examine how WTP/WTA for nicotine varies as a function of addiction[3]. The results indicate that key heterogeneity in WTP/WTA for nicotine by addiction is masked by analysis at the sample level. In Figure 3, how WTP/WTA for the levels of nicotine varies as a function of addiction is shown. For no nicotine (Fig 3 (i), reference: medium nicotine) and low nicotine (Fig. 3 (ii), reference: medium nicotine), those that are less addicted are willing to pay for lower levels of nicotine in cigarettes. Conversely, those that are more addicted must be compensated for the loss of utility for lower levels of nicotine in cigarettes. In some cases the value of WTP/WTA is in excess of average the price of a packet of 20 cigarettes (around $8), underlining the importance of nicotine to smokers. For high nicotine (Fig. 3 (iii), reference: medium nicotine), there appears to be very little association between WTP/WTA and addiction.

Forecasting of lowering levels of nicotine in cigarettes

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[3] For this, a slightly more involved computation for WTP is used. Taking low nicotine as an example, WTP/WTA at the mean is computed as, $WTP_{lownicotine} = \frac{\mu_{\beta_{lownicotine}} + \lambda_{\beta_{lownicotine,unmarried}} unmarried_n + \tau_{\beta_{lownicotine}} \alpha_n}{\hat{\mu}_{\beta_{price}} \cdot \left(\frac{income_n}{\overline{income}}\right)^{\eta}}$. In figure 3, this value is plotted for each draw from the mixing distributions.

A key policy issue is the extent to which smokers would switch away from cigarettes if nicotine levels were reduced in cigarettes. Table 7 shows two models' forecasts of lowering nicotine in cigarettes[4]. Our preferred specification is the calibrated model. Here, we see that the model predicts that lowering nicotine levels in cigarettes would result in around a 3% decline in the choice share of cigarettes; and 7% and 6% increases, respectively, in choice shares for e-cigarettes and the opt-out option. The table also indicates that smokers are slightly less responsive to the reduction in nicotine levels than dual users, because the reduction in cigarette choice share for smokers is less than that for dual users. However, this difference is fairly modest and smokers appear at least somewhat responsive to the lowering of nicotine. Of course, these should be considered as short-term responses in demand; longer term forecasts are not possible with these data.

Discussion and conclusions

In this paper, we developed a model to evaluate the role of addiction in smokers' choice behaviour. The hybrid choice model seeks to better understand smokers' decision-making by allowing addiction to flexibly impact on smokers' choices. This framework allows us to overcome a set of empirical issues that present in trying to measure addiction and to incorporate addiction in choice models in a traditional manner. We used the model to estimate preferences, willingness to pay for nicotine in cigarettes, and to predict the impact of lowering nicotine levels in cigarettes in the US.

We find that the latent variable captures addiction, with higher values explaining lower levels of addiction and lower values capturing higher levels of addiction. Higher levels of addiction are associated with increased use of cigarettes (including more cigarettes smoked per day), lower use for e-cigarettes, fewer quit attempts, and higher levels of reported craving. This addiction was associated with sociodemographic characteristics in a way that corresponds to known, observed patterns of cigarette use nationwide.

In terms of the impact of addiction on stated choices, we find that addiction drives preferences for cigarettes, and away from either e-cigarettes or the opt-out. Those that are more addicted prefer higher levels of nicotine in tobacco products.

Analysis of WTP indicates that, on average, smokers prefer medium levels of nicotine, and must be compensated by around \$0.68-1.33 per 20 pack to be equally satisfied with no nicotine, low nicotine or high nicotine (reference: medium nicotine) in tobacco products. However, these valuations vary considerably across respondents when the range of addiction is taken into account. More addicted smokers exhibit utility for higher levels of nicotine in tobacco products where WTA is, in some cases, in excess of the price of a packet of 20 cigarettes; less addicted smokers value lower levels of nicotine in tobacco products where WTP is, in some cases, in excess of the price of a packet of 20 cigarettes.

Our results suggest that the short-run response to the FDA's proposed lowering of nicotine in cigarettes would result in a slight shift away from cigarettes; roughly 3% of its choice share. Shifts in choice shares would be towards both e-cigarettes (7% increase in its choice share); and a 6% increase in the choice share of the opt-out - either cessation behaviour or alternative tobacco products (depending on one's interpretation of the opt-out in the experiment - we have previously interpreted as the former; see Buckell et al., 2019).

These results are likely to have significant meaning for policy. In the US, the FDA has set out its regulatory agenda, the centrepiece of which is reducing the level of nicotine in cigarettes (FDA, 2019). Therefore, these findings are likely to be of direct relevance to current policymaking. The results suggest that this policy is likely to be effective at shifting smokers' choices away from cigarettes; though with limited impact in the short run (NB – we can make no determination on the medium- to long-term impacts of this policy). Whilst there seems to be more of a response to

[4] NB – we used "low" rather than "no" nicotine to make these predictions. This is because the FDA's stated position is to lower nicotine to "non-addicting levels" and, as such, cigarettes would still contain some (albeit very little) nicotine. Therefore, we think that low nicotine makes for more realistic forecasts.

this policy from the dual users, smokers, too, showed some switching away from cigarettes. Since the smokers are most at harm, this encouraging for the public health implications of this policy.

These results are important because, from a behavioural and policy perspective, we have greater insight into smokers' decision-making processes with respect to nicotine preferences and product choices. Our basic utility function parameter estimates are in keeping with previous results elsewhere in the literature (Pesko et al., 2016; Marti et al., 2018; Buckell et al., 2018; Shang et al., 2018; Shang et al., 2018). Here, where measured, the preference estimates for nicotine are typically lower than other attributes. However, these studies do not explicitly study the impact of addiction. And now that we do, the results appear to be markedly different. Thus, the key point is that, even when nicotine is used in choice experiments, the behaviour of smokers towards products and nicotine is likely to be underestimated if addiction is not explicitly modelled.

References

Abou-Zeid, M. , Ben-Akiva, M. , 2014. Hybrid choice models. In: Hess, S., Daly, A. (Eds.), Handbook of Choice Modelling. Edward Elgar, Cheltenham .

Balbontin, C., Hensher, D. A., & Collins, A. T. (2019). How to better represent preferences in choice models: The contributions to preference heterogeneity attributable to the presence of process heterogeneity. Transportation Research Part B: Methodological, 122, 218-248.

Bold, K. W., Sussman, S., O'Malley, S. S., Grana, R., Foulds, J., Fishbein, H., & Krishnan-Sarin, S. (2018). Measuring E-cigarette dependence: Initial guidance. Addictive Behaviors, *79*, 213-218.

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

Buckell, J., Marti, J., & Sindelar, J. L. (2019). Should flavours be banned in cigarettes and e-cigarettes? Evidence on adult smokers and recent quitters from a discrete choice experiment. Tobacco Control, *28*(2), 168.

Buckell, J. and J. L. Sindelar (2019). "The impact of flavors, health risks, secondhand smoke and prices on young adults' cigarette and e-cigarette choices: a discrete choice experiment." Addiction **0**(0).

Cawley, J. and C. J. Ruhm (2011). Chapter Three - The Economics of Risky Health Behaviors. Handbook of Health Economics. M. V. Pauly, T. G. McGuire and P. P. Barros, Elsevier. **2:** 95-199.

Chaloupka, F. J. and K. E. Warner (2000). Chapter 29 The economics of smoking. Handbook of Health Economics, Elsevier. **1:** 1539-1627.

Chorus, C. G. and M. Kroesen (2014). "On the (im-)possibility of deriving transport policy implications from hybrid choice models." Transport Policy **36**: 217-222.

Czajkowski, M. and W. Budziński (2019). "Simulation error in maximum likelihood estimation of discrete choice models." Journal of Choice Modelling **31**: 73-85.

Daly, A., Dekker, T., & Hess, S. (2016). Dummy coding vs effects coding for categorical variables: Clarifications and extensions. Journal of Choice Modelling, *21*, 36-41.

Daly, A., Hess, S., & de Jong, G. (2012a). Calculating errors for measures derived from choice modelling estimates. Transportation Research Part B: Methodological, *46*(2), 333-341.

Daly, A., Hess, S., Patruni, B., Potoglou, D., & Rohr, C. (2012b). Using ordered attitudinal indicators in a latent variable choice model: a study of the impact of security on rail travel behaviour. Transportation, *39*(2), 267-297.

de Bekker-Grob, E. W., Donkers, B., Jonker, M. F., & Stolk, E. A. (2015). Sample Size Requirements for Discrete-Choice Experiments in Healthcare: a Practical Guide. The Patient - Patient-Centered Outcomes Research, *8*(5), 373-384. Fayers,

P. M. and D. J. Hand (2002). "Causal variables, indicator variables and measurement scales: an example from quality of life." Journal of the Royal Statistical Society: Series A (Statistics in Society) **165**(2): 233-253.

Greene, W.H. and Hensher, D.A. (2010) Modeling Ordered Choices: A Primer and Recent Developments, Cambridge University Press, Cambridge.

Heatherton TF, Kozlowski LT, Frecker RC, Fagerstrom KO (1991). The Fagerstrom Test for Nicotine Dependence: a revision of the Fagerstrom Tolerance Questionnaire. Br J Addict 86:1119-27.

Hensher, D. A. (2015). "Data Challenges: More Behavioural and (Relatively) Less Statistical – A Think Piece." Transportation Research Procedia **11**: 19-31.

Hensher, D. A. and C. Q. Ho (2016). "Experience conditioning in commuter modal choice modelling – Does it make a difference?" Transportation Research Part E: Logistics and Transportation Review **95**: 164-176.

Hensher, D., Balbontin, C., Greene, W. 2019. Experience as a conditioning effect on choice – Does it matter whether it is exogenous or endogenous? Working paper, University of Sydney

Hess, S., Hensher, D. A., & Daly, A. (2012). Not bored yet – Revisiting respondent fatigue in stated choice experiments. Transportation Research Part A: Policy and Practice, *46*(3), 626-644.

Hess, S., Spitz, G., Bradley, M., & Coogan, M. (2018). Analysis of mode choice for intercity travel: Application of a hybrid choice model to two distinct US corridors. Transportation Research Part A: Policy and Practice, *116*, 547-567.

Hess, S. and D. Palma (2019). "Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application." Journal of Choice Modelling **32**: 100170.

Ida, T. and R. Goto (2009). "Simultaneous measurement of time and risk preferences: stated preference discrete choice modeling analysis depending on smoking behavior*." International Economic Review **50**(4): 1169-1182.

Kenkel, D., Peng, S., Pesko, M., Wang, H., 2017. Mostly Harmless Regulation? Electronic Cigarettes, Public Policy And Consumer Welfare. National Bureau of Economic Research Working Paper Series, No 23710

Louviere, J.J., Hensher, D.A., Swait, J.D., 2000. Stated Choice Methods: Analysis and Applications. Cambridge, UK.

Marti, J., Buckell, J., Maclean, J. C., & Sindelar, J. (2019). TO "VAPE" OR SMOKE? EXPERIMENTAL EVIDENCE ON ADULT SMOKERS. Economic Inquiry, *57*(1), 705-725.

Pesko, M. F., Kenkel, D. S., Wang, H., & Hughes, J. M. (2016). The effect of potential electronic nicotine delivery system regulations on nicotine product selection. Addiction, *111*(4), 734-744.

Reed Johnson, F., Mohamed, A. F., Özdemir, S., Marshall, D. A., & Phillips, K. A. (2011). How does cost matter in health-care discrete-choice experiments? Health Economics, *20*(3), 323-330.

Regmi, K., Kaphle, D., Timilsina, S., & Tuha, N. A. A. (2018). Application of Discrete-Choice Experiment Methods in Tobacco Control: A Systematic Review. PharmacoEconomics - Open, *2*(1), 5-17.

Shang, C., Huang, J., Chaloupka, F. J., & Emery, S. L. (2018). The impact of flavour, device type and warning messages on youth preferences for electronic nicotine delivery systems: evidence from an online discrete choice experiment. Tobacco Control, *27*(e2), e152.

Shi, Y., Cao, Y., Shang, C., & Pacula, R. L. (2019). The impacts of potency, warning messages, and price on preferences for Cannabis flower products. International Journal of Drug Policy, *74*, 1-10.

Train, K., 2009. Discrete Choice Methods with Simulation. Cambridge University Press, Cambridge.

Vij, A. and J. L. Walker (2016). "How, when and why integrated choice and latent variable models are latently useful." Transportation Research Part B: Methodological **90**: 192-217.

Walker, J. 2001. Extended Discrete Choice Models: Integrated Framework, Flexible Error Structures, and Latent Variables. PhD Thesis, Massachusetts Institute of Technology.

Wang TW, Asman K, Gentzke AS, Cullen, K., Holder-Hayes, E., Reyes-Guzman, C., Jamal, A., Neff, L. & King, B. Tobacco Product Use Among Adults — United States, 2017. MMWR Morb Mortal Wkly Rep 2018;67:1225–1232. DOI: http://dx.doi.org/10.15585/mmwr.mm6744a2

Wehbe, L., Ubhi, H. K., & West, R. (2018). Want, need and habit as drivers of smoking behaviour: A preliminary analysis. Addictive Behaviors, *76*, 135-138.

West, R. (2009). "The Multiple Facets of Cigarette Addiction and What They Mean for Encouraging and Helping Smokers to Stop." COPD: Journal of Chronic Obstructive Pulmonary Disease **6**(4): 277-283.

West, R. and J. Brown (2013). Theory of addiction. Chichester, John Wiley & Sons.

	E-cigarette	Cigarette
Flavour	Plain tobacco Menthol Fruit Sweet	Plain tobacco Menthol
Life years lost by average user	10 5 2 Unknown	10
Level of nicotine	High Medium Low None	High Medium Low
Price	\$4.99 \$7.99 \$10.99 \$13.99	\$4.99 \$7.99 \$10.99 \$13.99

Table 1: Experimental Design

	Mean	Standard deviation	Min	Max
Age	41.09	12.55	18	64
Female	0.55	0.50	0	1
Higher education	0.41	0.49	0	1
Income	52974.67	34199.27	15000	150000
Hispanic	0.08	0.26	0	1
White	0.86	0.35	0	1
Black	0.10	0.30	0	1
Asian	0.03	0.16	0	1
Employed	0.60	0.49	0	1
Married	0.36	0.48	0	1
Family member smokes	0.44	0.50	0	1
daily smoker	0.95	0.22	0	1
number of cigarettes smoked per day	14.61	9.34	1	61
time before first cigarette of the day is smoked: less than 5 minutes	0.32	0.47	0	1
time before first cigarette of the day is smoked: 5 to 30 minutes	0.46	0.50	0	1
time before first cigarette of the day is smoked: 31 to 60 minutes	0.12	0.33	0	1
time before first cigarette of the day is smoked: longer than 60 minutes	0.10	0.31	0	1
time since last having smoked a cigarette that day: less than 15 minutes	0.31	0.46	0	1
time since last having smoked a cigarette that day: 15 to 30 minutes	0.27	0.44	0	1
time since last having smoked a cigarette that day: 30 to 60 minutes	0.19	0.39	0	1
time since last having smoked a cigarette that day: 1 to 3 hours	0.11	0.31	0	1
time since last having smoked a cigarette that day: 3 to 6 hours	0.02	0.15	0	1
time since last having smoked a cigarette that day: more than 6 hours	0.02	0.15	0	1
time since last having smoked a cigarette in the last few days/weeks: today	0.90	0.30	0	1
time since last having smoked a cigarette in the last few days/weeks: yesterday	0.07	0.26	0	1
time since last having smoked a cigarette in the last few days/weeks: in the last week	0.02	0.14	0	1
time since last having smoked a cigarette in the last few days/weeks: in the last month	0.00	0.06	0	1
time since last having smoked a cigarette in the last few days/weeks: longer than a month	0.00	0.05	0	1
quit attempts in the past year: none	0.53	0.50	0	1
quit attempts in the past year: 1	0.32	0.47	0	1
quit attempts in the past year: 2 to 3	0.11	0.31	0	1
quit attempts in the past year: more than 4	0.03	0.18	0	1
e-cigarette use	0.36	0.48	0	1
frequency of e-cigarette use: daily	0.12	0.32	0	1
frequency of e-cigarette use: several times per week	0.14	0.35	0	1
frequency of e-cigarette use: once per week	0.04	0.20	0	1
frequency of e-cigarette use: less than once per week	0.05	0.23	0	1
current urge to smoke (i.e. craving)	5.19	2.49	1	10

Table 2: Descriptive Statistics

LL(start)	-40410.8
LL(final, whole model)	-40106.2
LL(choice model: SP)	-22414.1
LL(choice model: RP)	-951.056
LL(Cigarette every day)	-300.326
LL(E-cigarette use)	-957.885
LL(Time in the morning until first cigarette)	-1778.47
LL(Quit attempts past year)	-1567.48
LL(Craving)	-3343.4
LL(Last smoked a cigarette today)	-571.822
LL(How long ago had a cigarette in the past days/weeks)	-2058.84
LL(E-cigarette use frequency)	-1163.04
LL(Cigarettes per day)	-5355.97
AIC	80376.34
BIC	81023.87
Estimated parameters	82

Table 3: Model diagnostic information

	Estimate	t-ratio
Measurement equations		
Gamma * young	0.5959	4.25
Gamma * older	-0.2166	-2.76
Gamma * higher education	0.2977	4.89
Gamma * low income	-0.2949	-4.03
Gamma * Hispanic	0.5696	5.5
Gamma * Black	0.5842	7.28
Gamma * Asian	0.6277	3.87
Gamma * family member smokes	-0.2968	-5.45
Structural equation		
Zeta * Daily smoker	-2.1105	-5.35
Zeta * Cigarettes per day	-6.6202	-20.89
Zeta * Time to first cigarette	1.4307	11.66
Zeta * Last cigarette	1.9861	6.67
Zeta * Long ago last cigarette	0.376	5.11
Zeta * Quit attempts	0.2809	4.28
Zeta * E-cigarette user	0.2965	2.78
Zeta * Frequency of e-cigarette use	0.187	1.69
Zeta * Current craving	-0.3129	-5.02

Table 4: estimates from the measurement equations and the structural equation of the latent variable. NB – zeta parameters are each taken from separate measurement equations; whereas the gamma parameters all comprise the structural equation.

	Estimate	t-ratio (0)
Utility function		
Cigarette	1.874	5.75
Cigarette s.d.	2.386	6
Opt-out	-2.9983	-5.34
Opt-out s.d.	-3.092	-5.77
Opt-out * young	-1.2379	-1.82
Opt-out * older	1.5572	4.67
Opt-out * Black	-0.9109	-2.08
Opt-out * unemployed	0.5806	1.96
No nicotine	-0.1779	-2.18
No nicotine s.d.	0.6591	4.93
No nicotine * female	-0.1663	-1.89
No nicotine * older	0.2506	2.5
Low nicotine	-0.0922	-2.03
Low nicotine s.d.	0.7759	5.81
Low nicotine * unmarried	-0.1569	-2.2
High nicotine	-0.1271	-2.36
High nicotine s.d.	-0.4447	-4.95
High nicotine * female	0.142	2.46
High nicotine * older	-0.1813	-2.66
High nicotine * unemployed	0.1338	2.17
Price	-0.129	-6.23
Lambda income	-0.2801	-4.99
Menthol	-0.554	-5.39
Fruit	-0.231	-3.65
Sweet	-0.2971	-4.18
Unknown health harm	0.8338	5.4
2 years of life lost	1.0732	5.5
5 years of life lost	0.4442	4.27
mu_SP	0.9917	6.07
Addiction-utility function interactions		
Tau * E-cigarette	0.4242	2.64
Tau * Opt-out	0.4258	2.33
Tau * No nicotine	0.293	3.75
Tau * Low nicotine	0.2791	4.5
Tau * Medium nicotine	0.133	3.55

Table 5: Utility function and addiction interactions in the hybrid choice model

variable	wtp	t-ratio	rob s.e.	LCB, 95%	UCB, 95%
No nicotine	-1.330	-2.287	0.582	-2.470	-0.190
Low nicotine	-0.679	-2.035	0.334	-1.333	-0.025
High nicotine	-0.953	-2.440	0.391	-1.718	-0.187
Menthol	-4.291	-10.275	0.418	-5.109	-3.472
Fruit	-1.795	-4.499	0.399	-2.577	-1.013
Sweet	-2.299	-5.654	0.407	-3.096	-1.502
year2	8.322	12.445	0.669	7.012	9.633
year5	3.471	6.172	0.562	2.369	4.573
Unknown	6.471	11.075	0.584	5.326	7.616

Table 6: Estimates of willingness to pay (WTP), $ per 20-pack of cigarettes, for the hybrid choice model. Standard errors are computed using the delta method (see Daly et al., 2012a).

	Cigarette Choice share	E-cigarette Choice share	Optout Choice share
Base choice shares, uncalibrated	0.5612	0.2966	0.1422
Low nicotine in cigarettes, uncalibrated	0.5382	0.3137	0.1481
% change in choice shares	-3.98%	5.97%	5.97%
Base choice shares, calibrated	0.6486	0.2092	0.1422
Low nicotine in cigarettes, calibrated	0.6273	0.2236	0.1491
% change in choice shares	-3.18%	7.12%	5.95%
% change in choice shares, if smokes only	-2.85%	6.39%	5.45%
% change in choice shares, if dual user	-3.77%	8.45%	6.85%

Table 7: predicted choice shares and changes in choice shares from lowering nicotine in cigarettes

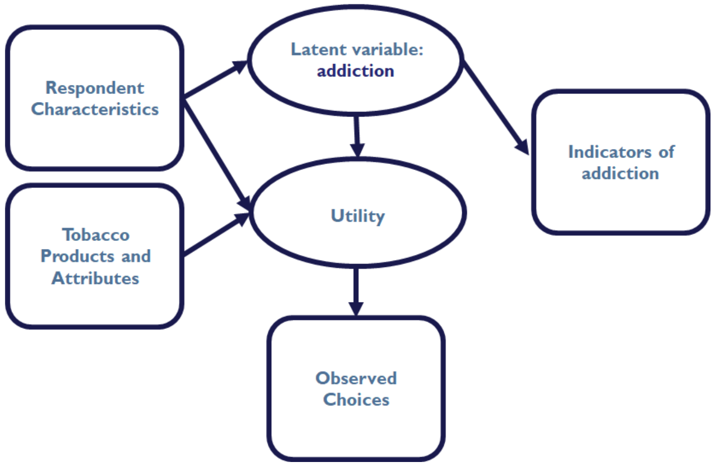

Fig 1. Schematic of hybrid choice model for addiction. Square boxes are observed variables; ellipses are unobserved variables.

Fig. 2: Sample choice scenario

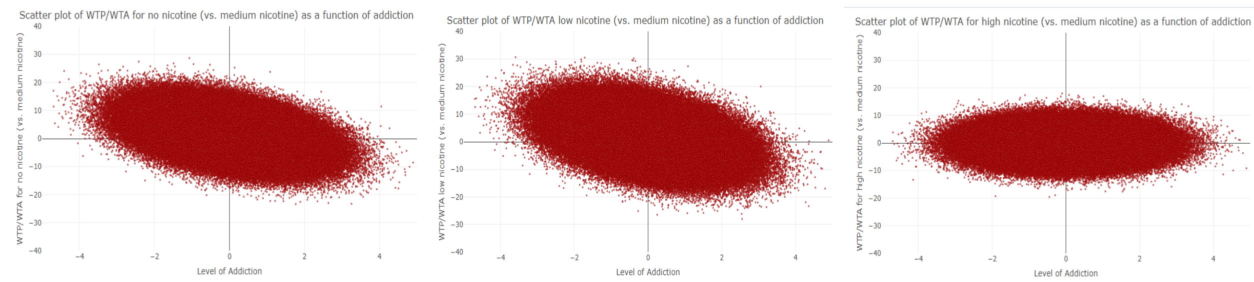

Fig. 3: Willingness to pay/willingness to accept (WTP/WTA) for nicotine as a function of addiction. (i) WTP/WTA for no nicotine (reference: medium nicotine) as a function of addiction; (ii) WTP/WTA for low nicotine (reference: medium nicotine) as a function of addiction; (iii) WTP/WTA for high nicotine (reference: medium nicotine) as a function of addiction. Addiction is defined as the latent variable (for ease of interpretation we have reversed the scale so that higher score on the latent variable denotes higher addiction).