# Behaviour Under Addiction: Dynamic Choice Between Smoking and Vaping *

Ruimin Ao†

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**Abstract**

E-cigarettes are addictive but less harmful than combustible cigarettes. Taxes on e-cigarettes may discourage vaping, but could increase more harmful cigarette demand through substitution. I study this policy trade-off using a dynamic discrete–continuous model of joint demand. Households choose which products to buy and how much to purchase. Two product-specific addiction stocks link past purchases to current choices and evolve with the quantities consumed. The model is estimated using NielsenIQ household panel data from 2019 to 2024 by maximum likelihood. A surrogate neural network approximates continuation values across states and parameter values, making estimation feasible. Addiction plays a central role in determining how households respond to price changes, differently on participation and on quantity choices. Cigarettes and e-cigarettes are substitutes: a permanent 1% increase in the e-cigarette price raises cigarette quantity by 1.3%, and a corresponding increase in the cigarette price raises e-cigarette quantity by 0.6%. Own-price responses weaken with addiction. After two years, an e-cigarette ban sends a third of previous vapers to smoking-only, whereas a cigarette ban sends 91% of previous smokers to abstinence.

**Keywords:** e-cigarettes, sin taxes, dynamic discrete–continuous choice, addiction, deep equilibrium network, surrogate neural network.
**JEL Codes:** D12, H21, I18, I12, L66.

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†Dept. of Economics, University College London. Email: r.ao@ucl.ac.uk.

# 1 Introduction

Smoking is the leading cause of preventable death in the United States, causing more than 480,000 deaths a year (CDC, 2020). In 2018 alone, smoking cost over $240 billion in health-care spending and about $370 billion in lost productivity (CDC, 2024). Policy makers have come up with many tools to discourage smoking and among all these policy tools, taxes are the most widely used and among the most effective (WHO, 2015). Over the past decade, e-cigarettes (or vapes) have gained considerable popularity in the society. They emerged as potential substitutes for combustible cigarettes. They are estimated to be around 95% less harmful (McNeill et al., 2015) than conventional cigarettes, and they can potentially help smokers quit (Hajek et al., 2019). But at the same time they also deliver nicotine, which is highly addictive. They are less harmful but not harm-free, and they can potentially emit toxic substances (NASEM, 2018).

This co-presence of good and bad features has produced a sharp policy tension. A tax that discourages vaping may also increase smoking if the two products are substitutes. Whether e-cigarettes should be taxed heavily or treated differently for their potential harm-reduction role is therefore an open empirical question with significant public-health consequences. The policy trade-off eventually depends on who responds: a smoker who switches products, a dual-user who changes quantities, or a vaper who stops buying either product.

This paper studies how cigarette and e-cigarette taxes affect the participation and consumption quantity, and how the responses vary with addiction. I develop and estimate a dynamic discrete–continuous model with two product-specific addiction stocks. Each month, a forward-looking household chooses cigarettes, e-cigarettes, both, or neither, as well as how much of each product to buy. Each product has its own addiction stock, which grows with the quantity bought and depreciates over time. Households can switch freely among actions.

Addiction plays a key role in determining price responses. Addiction accumulates with past consumption: the more one consumes, the more addicted they become, and the more rewarding consumption is, and potentially they consume more in the future. This creates a positive feedback loop. Because addiction changes the appeal of a product, it is expected that the same price increase can induce different responses from differently addicted people. Heavily addicted users potentially react little to such a price increase,

Disclaimer: Researcher(s)' own analyses calculated (or derived) based in part on data from NielsenIQ Consumer Panel Data provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

because the utility from consumption is much higher than the disutility from increased cost. Non-addicted users react strongly because the increased cost outweighs the benefits.

In the model, addiction affects both participation and quantity. On the participation margin, both smoking and vaping addiction stocks enter the utility function as additive terms. This allows past use of one product to alter the overall appeal of the product itself and the other product. On the quantity margin, each product's own stock shifts the marginal utility of that product and the curvature of its utility. The two margins are linked over time: the quantity bought this month determines how much the stock grows, so a household that buys more today is more addicted tomorrow. A forward-looking household takes this into account when choosing consumption quantity. The quantity margin matters for tax policy since price increases can reduce consumption without changing participation. For example, a heavily smoking-addicted user could cut down smoking quantity rather than quit. Spending on either product lowers utility through a monetary cost term. There is no direct health cost in the model, but the quadratic terms of addiction stocks capture this cost by allowing the utility of participation to rise with the stock at a decreasing rate and to eventually fall.

I estimate the model using the NielsenIQ Consumer Panel (NielsenIQ, 2024a), which records the cigarette and e-cigarette purchases of a sample of representative U.S. households. The estimation sample contains 6,538 single-person households under the age of 50, observed monthly between 2019 and 2024. Over this period, monthly vaping participation more than doubled, from 0.34% to 0.89%, while smoking participation stayed between 5% and 7%. Prices are built at the county-month level using NielsenIQ retail scanner data (NielsenIQ, 2024b). Vaping is a fast growing and changing market. The prices are potentially set based on local demand conditions that the econometrician does not observe. To control for this, I use a dynamic control function built from tax-instrumented price innovations (Petrin and Train, 2010). The control function terms enter the utility of vaping, the marginal utility of e-cigarettes, and the state that households use to forecast continuation values. Section 5.4 describes the prices and Section 4.1 the control function.

One challenge in estimation is that the addiction stocks at the start of the panel are not observed. Two households with the same purchases in the panel can have very different pre-panel stocks, and setting the initial stocks to zero for everyone biases the estimated effect of addiction towards zero. I therefore assign each household to one of four latent *types* indexed by its initial-stock profile $(Q^s_{i0}, Q^v_{i0})$: $\tau_0$ (no prior use), $\tau_s$ (prior smoker), $\tau_v$ (prior vaper), and $\tau_{sv}$ (prior dual-user). The type probabilities depend on demographics and are estimated jointly with the preferences. Types also differ in their action-specific intercepts in utility functions, because permanent preferences are likely correlated with initial addiction. Throughout the paper, I use "prior X" to refer to initial types and the

action names (abstinence, smoking-only, vaping-only, dual-use) for the choice in month $t$. Section 4.2 describes a worked example, the notation (Table 2), and the construction of initial stocks.

Solving the model is computationally difficult. The state has five continuous variables including two prices, two addiction stocks and the e-cigarette control function. Combined with demographic variables, the curse of dimensionality hits very quickly and very strongly. This makes conventional value function iteration on a grid less desirable. In estimation, I adapt the surrogate network approach (Norets, 2012; Kase et al., 2022; Chen et al., 2026) to approximate the value function and policy function. When training the neural network, I treat the parameters as additional inputs and train one network on states and parameters together. There are several benefits to this method. First, it eliminates the need to create the state grid which solves the curse of dimensionality issue. Second, it is computationally friendly and numerically stable. Instead of having to solve the dynamic problem at every trial parameter value, once the neural net is trained, solving the model at a new parameter value takes one single forward pass. The likelihood is then smooth and differentiable, and the parameters can be estimated directly without the Expectation–Maximisation algorithm. Section 4.4 describes the method.

The estimation results highlight the importance of considering choice dynamics when measuring price responses, as the static price responses (where households do not consider future consequences of addiction) are very different from the dynamic ones. The estimates show that addiction works on both the participation choices and quantity choices. For heavily addicted users, most of the pull towards using the products comes from the participation margin. A heavily smoking-addicted user is 40 times more likely to smoke than a non-addicted person, and a heavily vaping-addicted user is 20 times more likely to vape than a non-addicted user. Optimal quantity choices reverse here. The optimal consumption quantities of heavily smoking-addicted and heavily vaping-addicted users are about half of those of non-addicted users. This is because in the dynamic setting, consuming too much tobacco in one period comes with significant costs in the future. These include the potential health costs and higher monetary costs. A forward-looking individual takes this into account when choosing the consumption quantity, and heavily addicted users intentionally reduce the consumption quantities although they are much more likely to keep consuming.

The model reproduces vaping participation and the growth of vaping over time, but it under-predicts smoking participation. The shortfall comes from heavily smoking-addicted users, for whom predicted smoking differs from the data by the most. The model also over-predicts dual-use. The quantity margin fits poorly: predicted quantities barely change with the stock and the model over-predicts the purchases of lightly smoking-addicted

users and under-predicts those of heavily addicted users of both products.

In counterfactual experiments, cigarettes and e-cigarettes are substitutes, and the responses differ sharply by addiction profile. Holding the stocks at their current values, a permanent 1% cigarette tax lowers cigarette quantity by 0.6%, and a 1% e-cigarette tax lowers e-cigarette quantity by 2.6%. The cross-price elasticities are 1.3 for cigarette quantity with respect to the e-cigarette price and 0.6 for e-cigarette quantity with respect to the cigarette price. A higher e-cigarette price raises cigarette quantity, mostly among moderately smoking-addicted users. And a higher cigarette price raises e-cigarette quantity, mostly among smokers with little vaping addiction. Own-price responses weaken as the stocks grow, except among the most heavily addicted users, whose large purchases respond strongly to the price. Two years after e-cigarettes are removed from the market, 67% of previous vape-only users move to abstinence and 33% to smoking-only. 66% of previous dual-users keep smoking, yet cigarette consumption is only 1.5% higher. Two years after cigarettes are banned, 91% of previous smoking-only users move to abstinence and 9% to vaping-only. E-cigarette consumption is 45% higher.

The paper makes four contributions. First, it provides a dynamic structural model of joint cigarette and e-cigarette demand, estimated on household panel data, with two interacting product-specific addiction stocks that act on both participation and quantity. Two stocks let a tax on one product affect demand for the other both temporarily and through the gradual evolution of addiction. Second, it shows how addiction operates on both participation and quantity margins, and how the responses on both margins differ based on the levels of addiction. Third, the results show the importance of considering the addiction profiles when designing tobacco policies, as people's responses can be very different based on their addiction levels. Policies that account for addiction profiles could therefore be targeted at the households whose behaviour a tax actually changes. Fourth, the modelling methods and estimation strategy can be easily ported to study the use of other addictive and potentially correlated substances.

The rest of the paper is organised as follows. Section 2 reviews the related literature. Section 3 presents the model, Section 4 the estimation method and Section 5 the data. Section 6 reports the structural estimates. Section 7 reports the counterfactual tax experiments, and Section 8 concludes.

# 2 Related Literature

**Multiple addictions.** In the rational addiction model of Becker and Murphy (1988), current consumption builds a stock that raises the marginal utility of future consumption.

Forward-looking consumers respond to expected future prices (Chaloupka, 1991; Becker et al., 1994). Gruber and Kőszegi (2001) show that present-biased consumers produce the same dynamics, with different welfare implications. However, most of this work has one good and one stock. Bask and Melkersson (2003) extend the model to two goods, cigarettes and Swedish snus, and estimate negative cross-price elasticities on Swedish aggregate data. Bask and Melkersson (2004) apply the two-good model to alcohol and cigarettes, and Andersson et al. (2006) use it to ask whether smokeless tobacco should be promoted in cessation programmes and whether cigarette taxes should rise. Pierani and Tiezzi (2009) estimate a multi-commodity habit model of alcohol and tobacco using Italian data and find that the two goods are complements, although past consumption of one does not reinforce current consumption of the other. These papers show that cross-stock effects shape how a tax on one good moves demand for the other. Because they use aggregate time series, they cannot tell whether a tax changes how many people use a product or how much each user consumes, nor which users switch. At the household level, Arcidiacono et al. (2007) estimate a dynamic model of discrete drinking and smoking choices, Gordon and Sun (2015) a dynamic model of cigarette addiction with stockpiling on scanner data, and Chen and Rao (2020) a model of cigarettes and e-cigarettes with stockpiling and learning in which both products feed a single nicotine stock. I instead give each product its own stock, let both stocks enter the utility of each action, and treat the four combinations of use as distinct actions. The model can thus capture more complicated switching dynamics across products.

**Participation and quantity.** Taxes move demand on two margins. Since Lewit and Coate (1982), studies of cigarette demand have attributed a large share of the price response to the decision to smoke rather than to the amount smoked (Chaloupka and Warner, 2000). Two-part and double-hurdle models (Cragg, 1971; Jones, 1989) fit the two margins with separate equations, which leaves the link between them unexplained. Discrete–continuous models derive both margins from one utility function (Dubin and McFadden, 1984; Hanemann, 1984), as do models of multiple discreteness (Hendel, 1999; Kim et al., 2002; Dubé, 2004; Bhat, 2008). Modelling participation and quantity simultaneously comes at a price: the same parameters must explain why some households buy and why some buy a lot. Addiction sharpens this tension. The stock that makes a household more likely to buy also raises the quantity it wants, and the quantity bought today sets tomorrow's stock, so an error on one margin feeds into the other over time. Dynamic models of purchase quantities (Erdem et al., 2003; Hendel and Nevo, 2006) focus on inventory and purchase timing rather than on this link. Gordon and Sun (2015) adapt addiction into the inventory-consumption framework to study cigarette price elasticity. In my model the stocks shift the two margins through separate channels: action-specific

stock terms govern participation, and a stock-dependent shifter governs the marginal utility of quantity.

**Neural-network solution and estimation.** Full-solution (Rust, 1987) and conditional choice probability (Hotz and Miller, 1993; Aguirregabiria and Mira, 2002; Arcidiacono and Miller, 2011) estimators work on discrete or low-dimensional state spaces. Here the state has five continuous variables, and households also choose continuous quantities, so a giant grid runs into the curse of dimensionality easily and is not computationally feasible. A growing literature solves high-dimensional dynamic models with neural networks trained on simulated states (Maliar et al., 2021). The deep equilibrium nets of Azinovic et al. (2022) train networks to satisfy the equilibrium conditions along the simulated paths of the economy. In estimation, a network trained at one parameter value must be retrained at every trial value, which makes the likelihood slow to evaluate and noisy in the parameters. One remedy is to treat the parameters as additional state variables, or pseudo-states (Norets, 2012; Kase et al., 2022; Friedl et al., 2023; Chen et al., 2026). Scheidegger (2026) surveys these methods. I bring this surrogate approach to a household-level discrete–continuous choice model with latent types and a dynamic control function. A second network is trained to approximate the optimal quantities that satisfy the first-order condition.

**E-cigarettes and tax policy.** Reduced-form studies mostly find that cigarettes and e-cigarettes are substitutes: higher e-cigarette prices or taxes lower vaping and raise smoking (Huang et al., 2014; Zheng et al., 2017; Pesko et al., 2020; Saffer et al., 2020; Pesko and Warman, 2022), although some papers show dual-usage and gateway effects (Owusu et al., 2019; Soneji et al., 2017). These estimates average over users at different stages of addiction and do not separate the immediate response from the adjustment of the stocks. On the normative side, corrective taxes on addictive goods are justified by internalities as well as externalities (O'Donoghue and Rabin, 2006; Gruber and Kőszegi, 2004; Farhi and Gabaix, 2020). Allcott and Rafkin (2022) show that the optimal e-cigarette tax depends on the cross-price elasticity and on whether e-cigarette users would otherwise smoke or abstain. The model here delivers these responses by addiction profile and on both participation and quantity margins.

# 3 Model

Consumers are assumed to be rational and forward looking. As with the rational addiction literature (Chaloupka, 1991; Becker et al., 1994), the utility of consuming addictive

goods depends on past consumption. Here, addiction stocks for smoking and vaping are measured separately. While nicotine is the main physiologically addictive substance in both products, each product offers a unique experience in terms of the flavour, throat hit, sensation and vibe. Having two different addiction stocks in the utility function enables flexible cross-product addiction-dependent consumption, while also allowing addiction to accumulate from nicotine from both products. For example, conditional on the same nicotine addiction level, a chronic smoker can have a stronger preference for smoking due to factors other than nicotine. This chronic smoker may still find vaping pleasing due to the nicotine addiction captured in the smoking addiction stock, but such appeal could be much weaker compared to if they were to have the same nicotine-equivalent vaping addiction.

The model derives participation and quantities from a single utility function. Section 3.1 sets out the flow utility, Section 3.2 the addiction stocks and Section 3.3 the dynamic problem. Section 3.4 explains why unobserved local demand shocks call for a control function, which Section 4.1 constructs.

## 3.1 Flow Utility

In each month $t$, household $i$, who lives in county $c$, chooses one of four mutually exclusive actions: abstinence, smoking-only, vaping-only or dual-use. Denote the action set $\mathcal{A} \equiv \{0, s, v, sv\}$. There are two products, indexed by $g \in \{s, v\}$: cigarettes ($s$) and e-cigarettes ($v$). Let $\mathcal{G}(a)$ be the set of products consumed under action $a$: $\mathcal{G}(0) = \varnothing$, $\mathcal{G}(s) = \{s\}$, $\mathcal{G}(v) = \{v\}$, and $\mathcal{G}(sv) = \{s, v\}$, as summarised in Table 1.

Table 1: Actions and the products bought.

| Action | Short-hand | Products |
|---|---|---|
| $a = 0$ | 0 | none |
| $a = 1$ | s | cigarettes |
| $a = 2$ | v | e-cigarettes |
| $a = 3$ | sv | cigarettes and e-cigarettes |

In each month $t$, household $i$ observes its pre-action addiction stocks $\boldsymbol{Q}_{it} = (Q^s_{it}, Q^v_{it})$, the county-level prices $\boldsymbol{p}_{ct} = (p^s_{ct}, p^v_{ct})$, and the other demographic variables. The household then selects an action $a \in \mathcal{A}$ and simultaneously chooses a nonnegative quantity $x^g_{it}$ for each $g \in \mathcal{G}(a)$. Quantities are measured in packs per month for cigarettes and millilitres per month for e-cigarettes. The quantities for the product not consumed are set to 0.

Baseline flow utility of household $i$ in month $t$ choosing action $a$ is:

$$u_{it,a}(\boldsymbol{x}) = \underbrace{\boldsymbol{z}_i'\boldsymbol{\gamma}_a + \zeta_{at} + \mu_{a,c} + f_a(\boldsymbol{Q}_{it})}_{\text{participation}} + \underbrace{\sum_{g\in\mathcal{G}(a)} [\Phi^g_{it}\,\phi_g(x^g_{it};\kappa_{git}) - \alpha\, p^g_{ct}\, x^g_{it}]}_{\text{quantity}} + \varepsilon_{iat} \tag{1}$$

where $\boldsymbol{z}_i$ is time-invariant demographics, including income band, $\zeta_{at}$ and $\mu_{a,c}$ are month and county effects for each action, $x^g_{it}$ is the quantity, and $p^g_{ct}$ is the county-month unit price in dollars per pack or per millilitre. The action-specific function $f_a(\boldsymbol{Q})$ contains linear and quadratic terms of the addiction stocks $Q^s_{it}$ and $Q^v_{it}$. The term $\varepsilon_{iat}$ is an i.i.d. Type-I extreme value shock to the payoff of action $a$.

The term $\Phi^g_{it}\phi_g(x)$ is the utility function of the quantity consumed, $x^g_{it}$, scaled by $\Phi^g_{it}$. The scale depends on addiction stocks:

$$\log \Phi^g_{it} = \psi_{0g} + \psi_g Q^g_{it} \tag{2}$$

which allows for own-product addiction to shift the utility of consumption. Cross-product effects work instead through $f_a$. And the utility from quantity consumed has a concave form:

$$\phi_g(x;\kappa) = \frac{(x+\gamma_g)^{1-\kappa} - \gamma_g^{1-\kappa}}{1-\kappa} \qquad \kappa > 0 \tag{3}$$

where $\gamma_g$ is a normalisation term to prevent infinite marginal utility at $x^g = 0$. The curvature depends on the own stock,

$$\kappa_{git} = \kappa_{0g} + \kappa_{1g}\, Q^g_{it} \tag{4}$$

so $\kappa_{git}$ changes as the level of addiction stock changes. The static price elasticity of the desired quantity is about $-1/\kappa_{git}$, which lets the intensive margin become more or less price-sensitive as the household becomes addicted. Abstention is the reference action and its utility is normalised to zero. Since $\phi_g(0) = 0$, a product that is not bought yields no quantity utility.

## 3.2 Addiction Dynamics

The cigarette and e-cigarette stocks evolve separately. For product $g \in \{s, v\}$:

$$Q^g_{i,t+1} = \delta_g Q^g_{it} + \chi_g(x^g_{it}) \tag{5}$$

where $\delta_g \in (0,1)$ is the product-specific monthly retention rate and $\chi_g(\cdot)$ is an increasing function[1] of quantity consumed $x_{it}^g$.

## 3.3 Dynamic Decision Problem

Let $\boldsymbol{S}_{it} = \left(p_{ct}^s,\, p_{ct}^v,\, Q_{it}^s,\, Q_{it}^v\right)$ denote the collection of state variables. The choice-specific value function is:

$$W_a(\boldsymbol{S}_{it}, \boldsymbol{z}_i) = \max_{\boldsymbol{x}_a \geq \boldsymbol{0}} \left\{ \bar{u}_{it,a}(\boldsymbol{x}_a) + \beta \mathbb{E}\left[ V(\boldsymbol{S}_{i,t+1}, \boldsymbol{z}_i) \mid \boldsymbol{S}_{it}, a, \boldsymbol{x}_a \right] \right\} \tag{6}$$

where $\bar{u}_{it,a}$ is Equation (1) without the preference shock $\varepsilon_{iat}$, $\boldsymbol{x}_a$ are quantities consumed under $a$, and $\beta$ is the monthly discount factor. The expectation integrates over next month's price shocks. The addiction stocks evolve deterministically according to Equation (5).

The preference shocks $\varepsilon_{iat}$ are i.i.d. Type-I extreme value distributed. The integrated value function and conditional choice probabilities are therefore:

$$V(\boldsymbol{S}_{it}, \boldsymbol{z}_i) = \log \sum_{a \in \mathcal{A}} \exp\{W_a(\boldsymbol{S}_{it}, \boldsymbol{z}_i)\} + \gamma_E \tag{7}$$

$$P(a \mid \boldsymbol{S}_{it}, \boldsymbol{z}_i) = \frac{\exp\{W_a(\boldsymbol{S}_{it}, \boldsymbol{z}_i)\}}{\sum_{a' \in \mathcal{A}} \exp\{W_{a'}(\boldsymbol{S}_{it}, \boldsymbol{z}_i)\}}. \tag{8}$$

For each product $g \in \mathcal{G}(a)$, an interior optimal quantity satisfies

$$\underbrace{\Phi_{it}^g \phi_g'(x_{iat}^{g*}; \kappa_{git})}_{\text{marginal utility}} = \underbrace{\alpha\, p_{ct}^g - \beta \Lambda^g(\boldsymbol{S}_{it}, a, \boldsymbol{x}_a^*) \chi_g'(x_{iat}^{g*})}_{\text{money cost and future utility costs}} \tag{9}$$

where $\Lambda^g = \frac{\partial\, \mathbb{E}[V(S_{t+1})|\cdot]}{\partial Q_{i,t+1}^g}$ is the derivative of expected continuation value with respect to next month's stock $Q_{i,t+1}^g$. When $\beta = 0$, there is a closed-form solution for quantity:

$$\log(x_{iat}^{g*} + \gamma_g) = \frac{1}{\kappa_{git}} \left[ \log \Phi_{it}^g - \log\left(\alpha\, p_{ct}^g\right) \right]. \tag{10}$$

When $\beta > 0$, the continuation-value term enters and the condition needs to be solved numerically.

[1] In estimation, $\chi_g(\cdot)$ is a smoothly capped transformation of quantity, a smooth version of $\min(x/\bar{x}^g, K)$:

$$\chi_g(x) = K - 0.05K \log\left[1 + \exp\left(\frac{K - x/\bar{x}^g}{0.05K}\right)\right] \quad \text{for } x > 0$$

where $\chi_g(0) = 0$. $\bar{x}^g$ is the median purchase in the estimation sample, so that a median purchase adds one unit to the stock. $K$ is the cap that prevents unusually large recorded purchases from creating implausibly large addiction stocks. A month without a purchase adds nothing to the stock.

### 3.4 Endogeneity Issue

The baseline model omits the local demand shocks that are observed by households and firms but not by the econometrician. In practice, advertising, promotions, product availability, and local attitudes towards smoking or vaping may affect both participation and quantities consumed. Firms can also respond to the same conditions when setting prices. These bring challenges to the estimation. Treating Equations (1)–(8) as if prices were exogenous would create biases. Section 4.1 addresses these concerns explicitly.

## 4 Estimation

The main estimation is carried out using maximum likelihood. I first estimate the price process in the reduced form, which gives me the law of motion on the price innovations. Conditional on the first-stage estimates, I estimate the participation, quantity, and latent-type parameters jointly. The addiction-stock retention rates $\delta_g$ are calibrated as described below.

### 4.1 Price Endogeneity and the Dynamic Control Function

It is common to have local demand shocks that are unobservable in the data, such as local advertising, promotions, and shifts in social norms. These shocks are threats to the estimation as sources of endogeneity. Let $\xi_{ct}^g$ denote the demand shock for product $g \in \{s, v\}$ in county $c$ and month $t$. The shocks are persistent and they are observable to households. Using cigarette consumption as an example (hence dropping the action subscript in utility and product category in shocks), flow utility becomes:

$$u_{it} = \bar{u}_{it} + \xi_{ct} + \varepsilon_{it}, \tag{11}$$

This creates three problems:

**Price endogeneity.** Firms observe local demand shocks when setting prices, which means $\text{Cov}(\boldsymbol{p}_{ct}, \boldsymbol{\xi}_{ct}) \neq \mathbf{0}$. Consequently, the composite residual $\tilde{\varepsilon}_{it} = \xi_{ct} + \varepsilon_{it}$ is correlated with prices, $\mathbb{E}[\tilde{\varepsilon}_{it} \mid \boldsymbol{p}_{ct}] \neq 0$, and the estimators would be biased.

**Distribution of the residual and endogenous stocks.** With unobservable demand shocks, the residual $\tilde{\varepsilon}_{it}$ is no longer i.i.d. EV1. This invalidates the logit form of the choice

probability calculations. In addition, addiction stocks $\boldsymbol{Q}_{it}$ are functions of past choices, which were themselves influenced by past shocks, so persistent shocks induce correlation between $\boldsymbol{Q}_{it}$ and $\tilde{\varepsilon}_{it}$. Omitting them therefore biases not only the price coefficients but also the addiction parameters.

**Misspecified expectations.** The value function depends on the demand shock $V = V(\boldsymbol{p}_{ct}, \boldsymbol{Q}', \boldsymbol{\xi}_{ct})$. Because the shock is persistent, a positive shock today will change tomorrow's value function, and this will then affect choices today via the forward-looking channel. Similarly, this also creates a positive correlation between continuation value and prices.

Let $\xi_{ct}^{ext,g}$ be an unobserved county-month demand shock that shifts the participation preference (extensive margin), and let $\xi_{ct}^{int,g}$ be the shock to the marginal utility of quantity consumed (intensive margin). The utility can be re-written as:

$$u_{iat}^{\text{true}}(\boldsymbol{x}) = \bar{u}_{iat}(\boldsymbol{x}) + \sum_{g \in \mathcal{G}(a)} \xi_{ct}^{ext,g} + \varepsilon_{iat} \tag{12}$$

and the shifter of the utility from quantity consumption can be written as:

$$\log \Phi_{it}^{g} = \psi_{0g} + \psi_{gs} Q_{it}^{s} + \psi_{gv} Q_{it}^{v} + \xi_{ct}^{int,g} \tag{13}$$

The first shock moves participation directly, as it increases the overall utility from action $a$, regardless of the quantity consumed. The intensive-margin shock changes the optimal quantity and therefore also the value of participation. If the shocks are persistent, both will additionally affect the continuation value and its derivative in Equation (9).

Let $\boldsymbol{\tau}_{st}$ be the state taxes on cigarettes and e-cigarettes and $\mathcal{I}_{c,t-1}$ be the information available at the end of month $t-1$.

**Assumption 1** (Persistent demand shocks)**.** *For each $g$, $\xi_{ct}^{g} = \rho_g \xi_{c,t-1}^{g} + \eta_{ct}^{g}$, where $\mathbb{E}[\eta_{ct}^{g} \mid \boldsymbol{\tau}_{st}, \mathcal{I}_{c,t-1}] = 0$.*

**Assumption 2** (Pricing)**.** *The innovation is $\eta_{ct}^{g} = \eta_{ct}^{g,f} + u_{ct}^{g}$, where firms observe $\eta_{ct}^{g,f}$ when setting prices but not $u_{ct}^{g}$. Prices depend on taxes, policy controls, lagged information, the firm-observed demand innovations, and supply innovations $\boldsymbol{\omega}_{ct}$.*

**Assumption 3** (Distribution)**.** *The firm-observed demand innovations $\boldsymbol{\eta}_{ct}^{f}$ and the supply innovations $\boldsymbol{\omega}_{ct}$ are jointly normal, serially uncorrelated, and independent of $(\boldsymbol{\tau}_{st}, \mathcal{I}_{c,t-1})$.*

One great advantage is that Assumption 1 does not require tax levels to be unrelated to persistent demand shocks. It allows taxes to respond to persistent smoking or vaping prevalence, but only requires that taxes do not respond to the contemporaneous demand innovation.

At the first stage, I estimate[2]

$$\boldsymbol{p}_{ct} = B_0\boldsymbol{\tau}_{st} + B_1\boldsymbol{\tau}_{s,t-1} + \sum_{\ell=1}^{L} B_{2,\ell}\boldsymbol{p}_{c,t-\ell} + \boldsymbol{\mu}_c + \boldsymbol{\zeta}_t + \boldsymbol{v}_{ct} \tag{14}$$

with county and time effects $(\boldsymbol{\mu}_c + \boldsymbol{\zeta}_t)$ absorbing the permanent geographic differences and common price movements. Under the assumptions above, $\boldsymbol{v}_{ct}$ contains the price innovation from the demand shocks.

Rewriting the demand innovation $\eta^g_{ct}$ as a linear function of $\boldsymbol{v}_{ct}$ (as in a least-squares regression) gives $\eta^g_{ct} = \boldsymbol{\lambda}'_g\boldsymbol{v}_{ct} + \widetilde{u}^g_{ct}$. Iterating the demand shock backward yields:

$$\begin{aligned}
\xi^{ext,g}_{ct} =& \rho_g\xi^{ext,g}_{c,t-1} + \eta^g_{ct} && (15)\\
=& \underbrace{\sum_{\ell\geq 0}\rho^\ell_g\boldsymbol{\lambda}'_g\boldsymbol{v}_{c,t-\ell}}_{C^g_{ct}} + \underbrace{\sum_{\ell\geq 0}\rho^\ell_g\widetilde{u}^g_{c,t-\ell}}_{\mathcal{E}^g_{ct}} && (16)
\end{aligned}$$

where

$$C^g_{ct} = \rho_g C^g_{c,t-1} + \boldsymbol{\lambda}'_g\boldsymbol{v}_{ct} \tag{17}$$

The recursively constructed $C^g_{ct}$ is the component of local demand that is correlated with current and past prices. The remainder $\mathcal{E}^g_{ct}$ is orthogonal to the price history under the current assumptions.

To simplify the estimation, I impose the following restriction on the relationship between extensive shocks and intensive shocks:

$$\xi^{int,g}_{ct} = b_g\xi^{ext,g}_{ct} = b_g C^g_{ct} + b_g\mathcal{E}^g_{ct} \tag{18}$$

When $b_g = 0$, the local shocks only affect participation but not optimal quantity. Relaxing Equation (18) would require a separate control and transition process for the quantity margin.

In estimation, the fitted control parts $\widehat{C}^g_{ct}$ enter the utility function where the demand

[2]The lag length $L$ is chosen to remove residual serial correlation.

shocks are:

$$u_{iat}(\boldsymbol{x}) = \bar{u}_{iat}(\boldsymbol{x}) + \sum_{g \in \mathcal{G}(a)} \widehat{C}^g_{ct} \tag{19}$$

$$\log \Phi^g_{it} = \psi_{0g} + \psi_g Q^g_{it} + b_g \widehat{C}^g_{ct} \tag{20}$$

Because the shocks are persistent, the state variable set now expands to include $C^g_{ct}$:

$$\boldsymbol{S}_{it} = (\boldsymbol{p}_{ct}, \boldsymbol{Q}_{it}, C^s_{ct}, C^v_{ct}) \,. \tag{21}$$

The transition of the control function term follows Equation (17). Its innovations $\boldsymbol{v}$ are drawn jointly with the price innovations $\boldsymbol{r}$ (see Equation (25)) when calculating expectations over future realisations. In the estimated specification only the e-cigarette control function is included ($C^s \equiv 0$), because the estimated cigarette loadings were very close to zero. The control function term's persistence is calibrated as $\rho_v = 0.83$ using auxiliary estimates. This is because it is poorly identified when the loadings are small. After conditioning on $\boldsymbol{C}_{ct}$, the omitted component is only $\mathcal{E}^g_{ct}$, and it is orthogonal to prices. The use of the control function, under the current assumptions, removes the source of price endogeneity from the participation margin, the quantity margin, and expected future value.

## 4.2 Initial Addiction Stocks and Latent Types

The calculation of addiction stocks requires knowing the initial values $\boldsymbol{Q}_{i0}$ when a household enters the panel, but pre-panel consumption is unobserved. Setting both initial stocks to zero would classify long-time users in the same way as new users. This would attenuate the estimated contributions from addiction to demand. To alleviate this problem, I represent the missing initial condition with four latent types:

$$\mathcal{T} = \{\tau_0, \tau_s, \tau_v, \tau_{sv}\},$$

corresponding to no prior use, prior smoking, prior vaping, and prior dual-use, respectively. Note that $\tau$ maps households to different initial addiction stock groups, while households in each group can still choose any of the four actions $a \in \mathcal{A}$. The distinction is summarised in Table 2.

To illustrate why initial stocks are important, consider two households that purchase the same cigarette quantity in every observed month, with the addiction accumulation being $\chi_s(x) = 1$. For a given $\delta_s$ (e.g. 0.6), household A enters with $Q^s_{A0} = 0$ and household B with $Q^s_{B0} = 1.5$. Their addiction stock paths in the next three months

Table 2: Latent initial-stock types and current actions.

| Symbol | Description | Cigarette component | E-cigarette component |
|---|---|---|---|
| *Panel A. Latent type $\tau$* | | | |
| $\tau_0$ | no prior use | low | low |
| $\tau_s$ | prior smoker | high | low |
| $\tau_v$ | prior vaper | low | high |
| $\tau_{sv}$ | prior dual-user | high | high |
| *Panel B. Current action $a$* | | | |
| $a = 0$ | abstinence | inactive | inactive |
| $a = s$ | smoking-only | active | inactive |
| $a = v$ | vaping-only | inactive | active |
| $a = sv$ | dual-use | active | active |

are $(1.00, 1.60, 1.96)$ and $(1.90, 2.14, 2.28)$, respectively. While their in-panel choices are identical, their addiction stocks accumulate very differently. Treating every household as having the same initial addiction stock hence introduces considerable measurement error.

Different initial addiction stocks could also indicate heterogeneous preferences towards smoking and vaping. To accommodate this, the intercepts inside each action's utility function are allowed to be type-specific:

$$u_{i\tau at} = c_{\tau,a} + \bar{u}_{iat}(\boldsymbol{x}) + \sum_{g \in \mathcal{G}(a)} \widehat{C}^g_{ct}$$

Type probabilities depend on observed household characteristics. Taking $\tau_0$ as the reference category:

$$\pi_\tau(\boldsymbol{z}_i) = \frac{\exp\{\boldsymbol{z}_i'\boldsymbol{\Gamma}_\tau\}}{1 + \sum_{\tau' \neq \tau_0} \exp\{\boldsymbol{z}_i'\boldsymbol{\Gamma}_{\tau'}\}}, \qquad \tau \in \{\tau_s, \tau_v, \tau_{sv}\} \tag{22}$$

The logit variables $\boldsymbol{z}_i$ contain an intercept, the demographic indicators described in Section 5.5, and interactions of income with education.

For low initial addiction groups I set $Q^g_{L,0} = 0$ for both smoking and vaping. For high initial addiction groups, the initial stock is the steady-state stock implied by heavy observed use. First, I define the household's average monthly stock increment as

$$\bar{\chi}^g_i = \frac{1}{T_i} \sum_{t \in \mathcal{T}_i} \chi_g(x^{g,\text{obs}}_{it})$$

where $\chi_g(x^{g,\text{obs}}_{it})$ is the stock increment of Equation (5) evaluated at the recorded purchase,

so it is zero in months when product $g$ is not purchased. Then

$$Q^g_{H,0} = \frac{\mathrm{P}_{75}(\bar{\chi}^g_i \mid \bar{\chi}^g_i > 0)}{1 - \delta_g} \tag{23}$$

where the 75th percentile is taken over the households with a positive average increment. The seed is the steady-state stock of a household that adds this increment every month. It is about 2.1 for cigarettes and 0.9 for e-cigarettes, below the stock ceilings of Section 3.2.

## 4.3 Joint Likelihood

The likelihood has to account for four unobserved objects: the latent type, the local demand shocks, the future price shocks, and the error in recorded quantities. I describe how each one enters, and then combine them into a single objective.

Conditional on type $\tau$, the stock path $\boldsymbol{Q}^\tau_{it}$ follows from the type's initial stocks, the observed purchases, and Equation (5). The type also shifts utility through the intercepts $c_{\tau,a}$. The type is not observed, so the likelihood is a finite mixture over $\mathcal{T}$ with weights $\pi_\tau(\boldsymbol{z}_i; \Gamma)$ from Equation (22).

The control function is built inside the likelihood. Given the first-stage residuals $\widehat{\boldsymbol{v}}_{ct}$ from Equation (14) and the parameters $(\boldsymbol{\lambda}_g, \rho_g)$, Equation (17) gives $C^g_{ct}(\theta)$ for every county-month, starting from zero in the first month of the county series[3]. The loadings $\boldsymbol{\lambda}_v$ and the coefficient $b_v$ are therefore estimated jointly with the preference parameters. The state of a type-$\tau$ household is then:

$$\boldsymbol{S}^\tau_{it}(\theta) = (\boldsymbol{p}_{ct},\, \boldsymbol{Q}^\tau_{it},\, \boldsymbol{C}_{ct}(\theta)) \tag{24}$$

Households do not know future prices. They forecast them with

$$p^g_{c,t+1} = \mu_g + a_g\, p^g_{ct} + r^g_{c,t+1} \qquad (\boldsymbol{r}_{c,t+1}, \boldsymbol{v}_{c,t+1}) \sim N(\mathbf{0}, \Omega) \tag{25}$$

The price innovations $\boldsymbol{r}$ and the first-stage innovations $\boldsymbol{v}$ are jointly drawn. This is because a demand innovation potentially moves next month's price and next month's control function at the same time. The expectation in Equation (6) integrates over these four innovations (2 for cigarettes and 2 for e-cigarettes). The parameters $(\mu_g, a_g, \Omega)$ are estimated in a first step and held fixed.

The recorded purchase quantity is a noisy measure of the quantity chosen in the model.

[3]In practice, I use the price data of the year prior to sample start (2018–2019) to construct the series of CF terms, with the initial period's $C_0 = 0$.

This is due to factors including the discrepancy between purchase and consumption, data aggregation, rounding, and errors in reporting.

$$\log x_{it}^{g,\text{obs}} = \log x_{i\tau a_{it} t}^{g*} + \nu_{it}^{g}, \qquad \nu_{it}^{g} \sim N(0, \sigma_g^2) \tag{26}$$

The error $\nu_{it}^{g}$ is independent across households and months, and independent of the utility shocks. It is realised after the household has made its choice.

Let $n(\cdot)$ be the standard normal density. Conditional on type $\tau$, household $i$'s likelihood over all observed months is:

$$L_{i\tau}(\theta) = \prod_{t \in \mathcal{T}_i} P_\tau(a_{it} \mid \boldsymbol{S}_{it}^{\tau}(\theta), \boldsymbol{z}_i; \theta) \prod_{g \in \mathcal{G}(a_{it})} \frac{1}{\sigma_g \, x_{it}^{g,\text{obs}}} \, n\!\left( \frac{\log x_{it}^{g,\text{obs}} - \log x_{i\tau a_{it} t}^{g*}(\theta)}{\sigma_g} \right). \tag{27}$$

The first term is the action probability in Equation (8). The second term is the density of the observed quantity around the optimal quantity from Equation (9). The same parameters must therefore explain both which products are chosen and how much is purchased.

Using sampling weights $w_i$, the sample log-likelihood is

$$\mathcal{L}(\theta, \Gamma) = \sum_i w_i \log \left[ \sum_{\tau \in \mathcal{T}} \pi_\tau(\boldsymbol{z}_i; \Gamma) \, L_{i\tau}(\theta) \right] \tag{28}$$

where $\theta$ collects the utility parameters, the type intercepts, the quantity curvatures, the control-function parameters, and the measurement-error variances. The inner sum is over types: exactly one type applies to each household, so the likelihood of its purchase history is the type-probability-weighted sum of the likelihoods conditional on each type. The outer sum adds the logarithms of these household likelihoods, which is the logarithm of their product across households.

## 4.4 Solution and Estimation Algorithm

Evaluating Equation (28) requires the value function at every observed state and every trial value of $\theta$. I first describe the conventional algorithm, then I introduce the surrogate net method.

**EM with a deep equilibrium network.** The Expectation–Maximisation (EM) algorithm is commonly used to estimate models with latent types (Dempster et al., 1977; Arcidiacono and Jones, 2003). It separates the calculation of posterior type probabilities from parameter estimation, which can simplify maximisation of the mixture likelihood.

The E-step computes the posterior probability that household $i$ is of type $\tau$,

$$r_{i\tau} = \frac{\pi_\tau(\boldsymbol{z}_i;\Gamma)L_{i\tau}(\theta)}{\sum_{\tau'\in\mathcal{T}}\pi_{\tau'}(\boldsymbol{z}_i;\Gamma)L_{i\tau'}(\theta)} \tag{29}$$

The M-step updates $\theta$ by maximising $\sum_i w_i \sum_\tau r_{i\tau}\log L_{i\tau}(\theta)$, and updates $\Gamma$ with a multinomial logit of $r_{i\tau}$ on $\boldsymbol{z}_i$. The two steps are repeated until convergence.

Each evaluation of $L_{i\tau}(\theta)$ needs the solution of the dynamic problem. A nested fixed-point estimator (Rust, 1987) would solve Equation (7) on a grid. Here the state has five continuous variables—two prices, two addiction stocks and the control function—besides the two purchase indicators. A grid fine enough to capture the sharp changes in participation and quantity is not feasible. A deep equilibrium network (DEQN) avoids the grid (Azinovic et al., 2022). For a given $\theta$, a neural network $V_\varphi(\boldsymbol{S})$ with network weights $\varphi$ is trained on sampled states to minimise the gap between $V_\varphi$ and the Bellman target

$$\mathcal{T}_\varphi(\boldsymbol{S}) = \log\sum_{a\in\mathcal{A}}\exp\left\{\max_{\boldsymbol{x}_a\geq\mathbf{0}}\left[\bar{u}_a(\boldsymbol{S},\boldsymbol{x}_a)+\beta\,\mathbb{E}[V_\varphi(\boldsymbol{S}')\mid\boldsymbol{S},a,\boldsymbol{x}_a]\right]\right\} \tag{30}$$

The network is precise where the data are, because training states are drawn from the observed and simulated state distribution and are not restricted to grid points.

The network above is trained at one value of $\theta$. For each iteration of new $\theta$ values, the net needs to be retrained completely. Training itself is very computationally costly. This creates two problems.

First, the likelihood is not smooth in $\theta$. Each M-step moves $\theta$, so the network has to be retrained. Training is stochastic, and two networks trained at nearby parameter values differ by training noise. The likelihood then jumps between evaluations, not because $\theta$ itself changed, but because the net has been refit. Numerical Hessians of such a non-smooth objective are unreliable, and so are the standard errors based on them.

Second, the quantity condition (9) depends on the derivative $\Lambda^g$ of the continuation value, but the network is trained to fit the level of the value function. A good fit on the level here does not guarantee a good fit in the slope. And the noise from a non-smooth net passes directly into the predicted quantities. An alternative method to address the slope issue is the endogenous-grid method as in Carroll (2006); Fella (2014); Iskhakov et al. (2017); Druedahl and Jørgensen (2017). This avoids taking derivatives of an interpolated value function between grid points. However, in my model, the addiction stocks enter the marginal utility, so the Euler inversion does not have a closed-form expression. The state space constraint and the need to re-solve the FOC at each trial parameter value make this method less desirable.

**Surrogate network.** I therefore treat the parameters as additional state variables and train a single network on states and parameters together. The idea of approximating the solution as a function of both goes back to Norets (2012). Kase et al. (2022) call the parameters pseudo-state variables and Chen et al. (2026) call the network a deep surrogate.

Let $\boldsymbol{S}_{it}^{+} = (\boldsymbol{p}_{ct}, \boldsymbol{Q}_{i,t+1}, \boldsymbol{C}_{ct})$ be the state after the quantity choice and before the price innovations are drawn. The network approximates the expected continuation value at this point for any parameter value:

$$\bar{V}_{\varphi}(\boldsymbol{S}^{+}, h; \theta) \approx \mathbb{E}\Big[V(\boldsymbol{S}'; \theta) \mid \boldsymbol{S}^{+}\Big], \tag{31}$$

All the parameters entering the value function enter the net: (1) the input $\theta$ contains every parameter that enters the Bellman equation: the stock, quantity and curvature parameters, $\alpha$, and the control-function parameters $(\boldsymbol{\lambda}_v, b_v)$. (2) The type intercepts, the demographic shifters, month effects and the county effects enter through the index $h_{i\tau a} = c_{\tau,a} + \boldsymbol{z}_i'\boldsymbol{\gamma}_a + \mu_{a,c}$.[4] One network therefore serves all types and all households.

Training draws states and parameters jointly. States are drawn from a pool of all possible states. Parameters are drawn from a box $\Theta_B$.[5] At each draw, the target is the average of the integrated value over $N_d$ joint draws of the innovations,

$$\frac{1}{N_d}\sum_{n=1}^{N_d} \log \sum_{a\in\mathcal{A}} \exp\left\{\max_{\boldsymbol{x}_a \geq \boldsymbol{0}} \left[\bar{u}_a(\boldsymbol{S}_n', \boldsymbol{x}_a; \theta) + \beta\, \bar{V}_{\bar{\varphi}}\Big(\boldsymbol{S}_{n,a}^{+\prime}, h; \theta\Big)\right]\right\}, \tag{32}$$

where $\boldsymbol{S}_n'$ is the $n$-th draw of next month's state and $\boldsymbol{S}_{n,a}^{+\prime}$ is the post-choice state that follows from it. A second network approximates the optimal quantities $\boldsymbol{x}_a^*$. It is trained so that its output satisfies the first-order condition (9), with $\Lambda^g$ taken from the value network. Because the target is an unbiased estimate of the expected continuation value and the network is fitted by least squares over many sampled states, a small fixed number of draws per state is enough: the simulation noise averages out across the training sample, as with the all-in-one expectation operator of Maliar et al. (2021). I use $N_d = 4$. After training, the network weights are fixed. Solving the model at a new $\theta$ is a single forward pass.

With the surrogate, $\mathcal{L}(\theta, \Gamma)$ is a deterministic and differentiable function of all parameters. I obtain its exact gradient by differentiating and maximising Equation (28) directly over $(\theta, \Gamma)$ with a quasi-Newton method. The type-logit parameters $\Gamma$ are estimated in the same step as $\theta$, so no E-step and no M-step are needed. Every parameter is estimated in

[4] In estimation, a county with fewer than ten sample households shares one effect with the other such counties of its state, both in $\mu_{a,c}$ and in Equation (14).

[5] The net is trained at a wide-enough parameter range to avoid hitting the box walls.

one step.

The surrogate removes stochastic retraining from likelihood evaluation and allows the approximate likelihood to be differentiated through the fixed network. It also avoids solving the dynamic problem separately at every trial parameter value. The continuation value and its derivative both respond to $\theta$ through the network inputs. Approximation error remains and depends on training accuracy over the states and parameters used in estimation.

## 4.5 Identification and Calibration

The model is identified from both participation and quantity choices. Conditional quantity responses identify the curvature parameters $(\kappa_{0g}, \kappa_{1g})$ and the money coefficient $\alpha$. Participation and quantity jointly identify how each addiction stock shifts action utility and marginal utility. Transitions in both margins identify the dynamic importance of stock accumulation. Dual-use observations and switches between smoking and vaping identify the cross-stock effects and the incremental utility of consuming both products.

After conditioning on the control functions, price sensitivity is identified from price movements generated by the tax instruments and from price innovations that are orthogonal to the projected demand shocks. The exclusion restriction is that, conditional on the policy controls, the county and time effects, taxes affect household utility only through prices and not through contemporaneous demand innovations.

The control function parameters are identified from the first-stage residuals. The loadings $\boldsymbol{\lambda}_v$ are identified by how vaping participation moves with the current residual $\widehat{\boldsymbol{v}}_{ct}$, and $b_v$ by whether the control function shifts conditional e-cigarette quantities in addition to participation. The persistence $\rho_v$ would be identified by how fast the effect of a past residual fades.

Demographic variation identifies $\boldsymbol{\gamma}_a$ and the type-logit coefficients $\Gamma$. The early months of each household are the most informative about the latent initial stocks, because the gap between a high and a low initial stock decays at rate $\delta_g$, which becomes indistinguishable after 6 months. Longer sequences separate this temporary gap from the permanent type intercepts $c_{\tau,a}$.

The discount factor is fixed at $\beta = 0.95$. The monthly retention rates are calibrated to $\delta_s = 0.6$ for cigarettes and $\delta_v = 0.7$ for e-cigarettes. Auxiliary regressions of purchase participation on its own lags guide this calibration.[6] The fitted rates range from 0.46

[6]For each product, I regress the purchase indicator on six consecutive monthly lags, current own

to 0.69 for cigarettes and from 0.62 to 0.76 for e-cigarettes across specifications. The selected values imply habit half-lives of about 1.4 and 1.9 months.

# 5 Data

## 5.1 Data Sources

I estimate the model using the NielsenIQ Consumer Panel (NielsenIQ, 2024a), which records the UPC-level purchases and the demographics of a representative sample of about 60,000 U.S. households per year. Prices are calculated using the NielsenIQ Retail Measurement Services (RMS) scanner data (NielsenIQ, 2024b), which record weekly unit sales and prices by store and UPC for participating retailers. State cigarette excise taxes come from Orzechowski and Walker (2024) and standardised state e-cigarette tax rates from Cotti et al. (2023, 2026). The taxes are used as the instruments in the first stage of the control function (Section 4.1).

## 5.2 Sample Construction

Because purchases are recorded at the household level rather than for individual members, it is unclear who within a household consumes cigarettes and e-cigarettes. To address this, I keep only single-person households, so that purchases can be attributed to one person. Furthermore, households whose head is aged 50 or older are dropped from the sample, because vaping is very rare among older adults. States with 30 or fewer sample households are dropped from the sample entirely.

The final estimation sample contains 6,538 households and 183,147 household-months in 1,214 counties of 38 states (see Appendix Table 11 for a detailed decomposition). The median household is observed for 23 months. The sample starts in 2019 because vaping was rare in the panel before then. All the descriptive statistics reported below are calculated using the NielsenIQ projection weights.

price, demographics, and time effects, dropping the first ten observed months. I estimate pooled and household-demeaned versions. Lagged participation acts only through a geometric stock with a linear effect, $b_k = \lambda\delta_g^{k-1}$. I fit this decay over lags 1–4 in logs and over all six lags allowing an additive constant. This diagnostic draws on the auxiliary-moment approach of Hai and Heckman (2026).

## 5.3 Monthly Observations

Because the data record purchases rather than consumption, they must be aggregated over time so that purchases are informative about consumption. In particular, purchases of cigarettes and e-cigarettes are infrequent. A household that buys two cartons at the start of every month and smokes daily would show three zero-purchase weeks afterwards at weekly frequency. These weeks are inventory consumption, not abstention.[7] On the other hand, aggregating to the quarterly level could further alleviate this problem but discards most of the price variation. It could also blur the timing of quitting and switching that the addiction stocks are meant to capture. In this paper, household consumption is aggregated to the monthly level to balance these two factors.

The monthly action $a_{it} \in \{0, s, v, sv\}$ is calculated as:

- $a = 0$: *abstinence* (no cigarette or e-cigarette purchase).
- $a = s$: *smoking-only* (cigarette purchase only).
- $a = v$: *vaping-only* (e-cigarette purchase only).
- $a = sv$: *dual-use* (positive purchases in both categories).

A household that buys cigarettes early in the month and e-cigarettes later in the same month is classified as $a = sv$. The quantities are the packs of cigarettes and the millilitres of e-liquid bought in a month. Most re-purchases happen within a month. The median re-purchase gap (in weeks) is only one week. Overall, 87% of cigarette and 83% of e-cigarette re-purchases happen within a month (Appendix Figure 23).

## 5.4 Prices

The price of each product is built in two steps. First, for each product I regress the log unit prices on UPC and county-month fixed effects[8]:

$$\log p_{jct} = \alpha_j + \gamma_{ct} + e_{jct}. \tag{33}$$

The UPC effect $\alpha_j$ is the permanent relative price of product $j$, and the average county-month effect $\gamma_{ct}$ is the price level of county $c$ in month $t$, holding the product fixed. The

[7] An alternative is to model purchase timing explicitly. Hendel and Nevo (2006) model inventory and stockpiling of storable goods. The latter mechanism is relevant here, but the thin sample of vaping households limits the information available to identify an additional latent inventory state.

[8] Weighting by units sold.

county-month price index is the cost of a fixed basket at the fitted prices:

$$P_{ct} = e^{\gamma_{ct}} \sum_j \bar{w}_j e^{\alpha_j},$$

where $\bar{w}_j$ is the national unit share of product $j$ in the base year (2019 for the first window of the chained index described below). The design works great for cigarettes, but for e-cigarettes this creates a problem because many new e-cigarette products enter the market during the sample period. To address this issue, the price indices are chained over two consecutive years, so that the composition of products remains constant within each two-year window. This limits changes driven by product composition (Aizcorbe et al., 2003; de Haan and Krsinich, 2014). Appendix B gives the details on the construction of the chained price index.

Second, every household faces the price index of its county. The prices a household itself pays are not used, because they reflect its choice of brands, pack sizes and stores, which is correlated with its tastes, and because they are not observed in months without a purchase. All prices are deflated to 2019 dollars.

Real prices rose over the sample. The average cigarette price increased by 11%, from \$6.90 per pack in 2019 to \$7.65 in 2024, and the average e-cigarette price by 3%, from \$5.14 to \$5.28 per millilitre, after peaking at \$5.61 in 2023. Taxes also changed (Appendix Figure 20). The average state cigarette excise faced by sample households fell from \$1.90 to \$1.75 per pack in real terms (from 26% to 21% of the retail price), because the tax is set in nominal terms. The average e-cigarette tax doubled, from 5.6% to 11.7% of the retail price, as the number of states taxing e-cigarettes rose from 9 states and the District of Columbia in January 2019 to 30 states and D.C. by the end of 2022.

## 5.5 Demographics

Demographic variables enter the flow utility as additive shifters. They are time-invariant and observed at the household level. The vector $\boldsymbol{z}_i$ contains indicators for gender, marital status, age group, education, occupation, race, and income band. Table 3 shows the composition of the sample.

## 5.6 Smoking and Vaping Patterns

**Participation.** At the household-month level, smoking participation is 5.8% while vaping participation is 0.63%. Dual-use participation is only 0.13% (Table 4). Smoking

Table 3: Demographic composition of the estimation sample (%).

| | Share (%) |
|---|---|
| *Age group* | |
| Under 25 | 4.9 |
| 25–29 | 15.3 |
| 30–34 | 32.4 |
| 35–39 | 13.0 |
| 40–44 | 16.4 |
| 45–49 | 18.1 |
| *Annual household income* | |
| Under $25K | 30.0 |
| $25–45K | 22.7 |
| $45–70K | 20.6 |
| $70–100K | 11.9 |
| $100K+ | 14.7 |
| Male | 42.3 |
| Married | 5.2 |
| Employed | 80.2 |
| *Education* | |
| No college degree | 45.9 |
| College degree | 34.1 |
| Postgraduate degree | 20.0 |
| *Race* | |
| White | 66.3 |
| Black | 15.8 |
| Asian | 7.9 |
| Other | 10.0 |
| *Occupation* | |
| Professional | 61.5 |
| Skilled | 17.4 |
| Farmer | 0.3 |
| Retired / unable to work | 3.7 |
| Not working | 17.2 |

*Notes:* One row per household ($N$ = 6,538), demographics at the household's first sample month, weighted by NielsenIQ projection weights.

participation rose from 5.0% in 2019 to 6.6% in 2022 and fell back to 5.5% in 2024. Vaping participation rose steadily from 0.34% to 0.89%. Smoking increases with age but falls steeply with income, from 11.2% for the below $25,000 group to 2.4% for the above $100,000 group. There is little heterogeneity in vaping participation for different income groups. These purchase rates are well below survey prevalence. For example, in the National Health Interview Survey (NHIS), 14.0% of U.S. adults smoked cigarettes in 2019, and 4.5% used e-cigarettes (Cornelius et al., 2020). Part of the reason is under-recording. Households do not record every purchase, and the outlets where much tobacco (gas stations and corner stores) is bought are under-covered. Appendix A compares the two sources, and Appendix C describes a model of under-recording but unfortunately the very thin vaping sample cannot identify it.

Table 4: Participation and monthly purchase quantities.

| | | Participation (%) | | | Packs per smoker-month | | | mL per vaper-month | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | HH-months | Smoking | Vaping | Dual-use | Mean | Median | *N* | Mean | Median | *N* |
| All | 183,147 | 5.80 | 0.63 | 0.13 | 9.5 | 4.0 | 10,144 | 30.4 | 16.0 | 1,218 |
| *A. By year* | | | | | | | | | | |
| 2019 | 30,145 | 4.98 | 0.34 | 0.04 | 7.6 | 3.0 | 1,496 | 24.4 | 7.6 | 124 |
| 2020 | 29,922 | 5.83 | 0.48 | 0.10 | 7.9 | 4.0 | 1,627 | 28.4 | 9.0 | 140 |
| 2021 | 30,551 | 5.93 | 0.57 | 0.15 | 9.2 | 4.0 | 1,687 | 27.9 | 14.0 | 170 |
| 2022 | 31,119 | 6.63 | 0.66 | 0.14 | 9.7 | 4.0 | 1,830 | 24.7 | 14.4 | 207 |
| 2023 | 31,917 | 5.77 | 0.76 | 0.16 | 11.4 | 5.0 | 1,880 | 34.7 | 21.5 | 271 |
| 2024 | 29,493 | 5.54 | 0.89 | 0.17 | 10.6 | 4.0 | 1,624 | 35.1 | 24.0 | 306 |
| *B. By age group* | | | | | | | | | | |
| Under 30 | 13,044 | 3.36 | 0.64 | 0.09 | 7.9 | 3.0 | 405 | 19.5 | 14.4 | 67 |
| 30–39 | 63,858 | 5.21 | 0.48 | 0.15 | 8.7 | 4.0 | 3,159 | 24.3 | 13.0 | 374 |
| 40–49 | 106,245 | 7.28 | 0.77 | 0.13 | 10.5 | 5.0 | 6,580 | 37.5 | 22.0 | 777 |
| *C. By annual household income* | | | | | | | | | | |
| Under $25K | 37,157 | 11.24 | 0.80 | 0.23 | 9.8 | 4.0 | 4,289 | 27.6 | 18.0 | 325 |
| $25–45K | 43,445 | 5.59 | 0.61 | 0.12 | 8.5 | 4.0 | 2,554 | 15.1 | 9.5 | 280 |
| $45–70K | 48,166 | 3.98 | 0.57 | 0.14 | 10.8 | 4.0 | 1,744 | 36.1 | 21.6 | 251 |
| $70–100K | 31,738 | 3.57 | 0.72 | 0.09 | 7.5 | 4.3 | 957 | 16.8 | 14.4 | 275 |
| $100K+ | 22,641 | 2.37 | 0.41 | 0.03 | 10.4 | 4.0 | 600 | 70.2 | 72.0 | 87 |

*Notes:* Participation is the weighted share of household-months with a positive purchase. Dual-use is the share buying both products in the month. Quantities are recorded purchases in months with a positive purchase of the product (packs of 20 cigarettes, millilitres of e-liquid), weighted by NielsenIQ projection weights and not winsorised. *N* counts buyer-months.

**Quantities.** A smoker purchases on average 9.5 packs (median 4) a month, and a vaper 30.4 mL (median 16). Both distributions are right-skewed (Appendix Figure 21). Quantities rise with age: from households under 30 to those aged 40–49, packs per smoker rise from 7.9 to 10.5 and millilitres per vaper from 19.5 to 37.5. They also rise over time: the mean number of packs per smoker increases from 7.6 in 2019 to 10.6 in 2024, and the median millilitres per vaper from 7.6 to 24.

For cigarettes, quantities do not rise within households. The increase comes from changes in which households buy.[9] Appendix Table 12 reports the full decomposition. For e-cigarettes, both channels matter. Within households, e-cigarette quantity jumps in 2020, dips in 2022–2023 and rises again in 2024. The pooled increase is larger, so changes in which households vape add to the rise. Dual-users buy less of each product than single-product users: 8.0 against 9.6 packs, and 26 against 32 mL a month.

Figure 1 plots prices (top row) against participation and quantity per user (bottom rows). Real prices rose modestly: the cigarette price index increases by 13% in 2024 compared to 2019, and the e-cigarette index peaks 10% above it in 2023 before falling back to 3% above. Rising prices did not lower participation or quantities in the raw data. Smoking participation moves between 4.8% and 7.2%, while packs per smoker rise from 6.6 to 11.8. Vaping participation more than doubles, from 0.38% at the beginning of 2019 to 0.83% at the end of 2024. Millilitres per vaper are noisy over time. The annual mean rises from 24 mL in 2019 to 35 mL in 2024 (Table 4). These co-movements are not price responses: they are contaminated with common demand shocks such as the growing popularity of vaping. The estimation therefore relies on tax-driven price variation across states and controls for local demand shocks (Section 4.1).

**Persistence.** Behaviour is highly persistent from month to month (Table 5). Among smokers, 73% are followed by another month of smoking-only. Among vapers, 62% by another month of vaping-only. Direct switching between the two products is rare: 0.3% of smokers move to vaping-only and 1.2% of vapers to smoking-only in the next month. Dual-use is the least stable state. Only 26% of dual-users buy both again the next month, and 41% keep cigarettes and drop e-cigarettes.

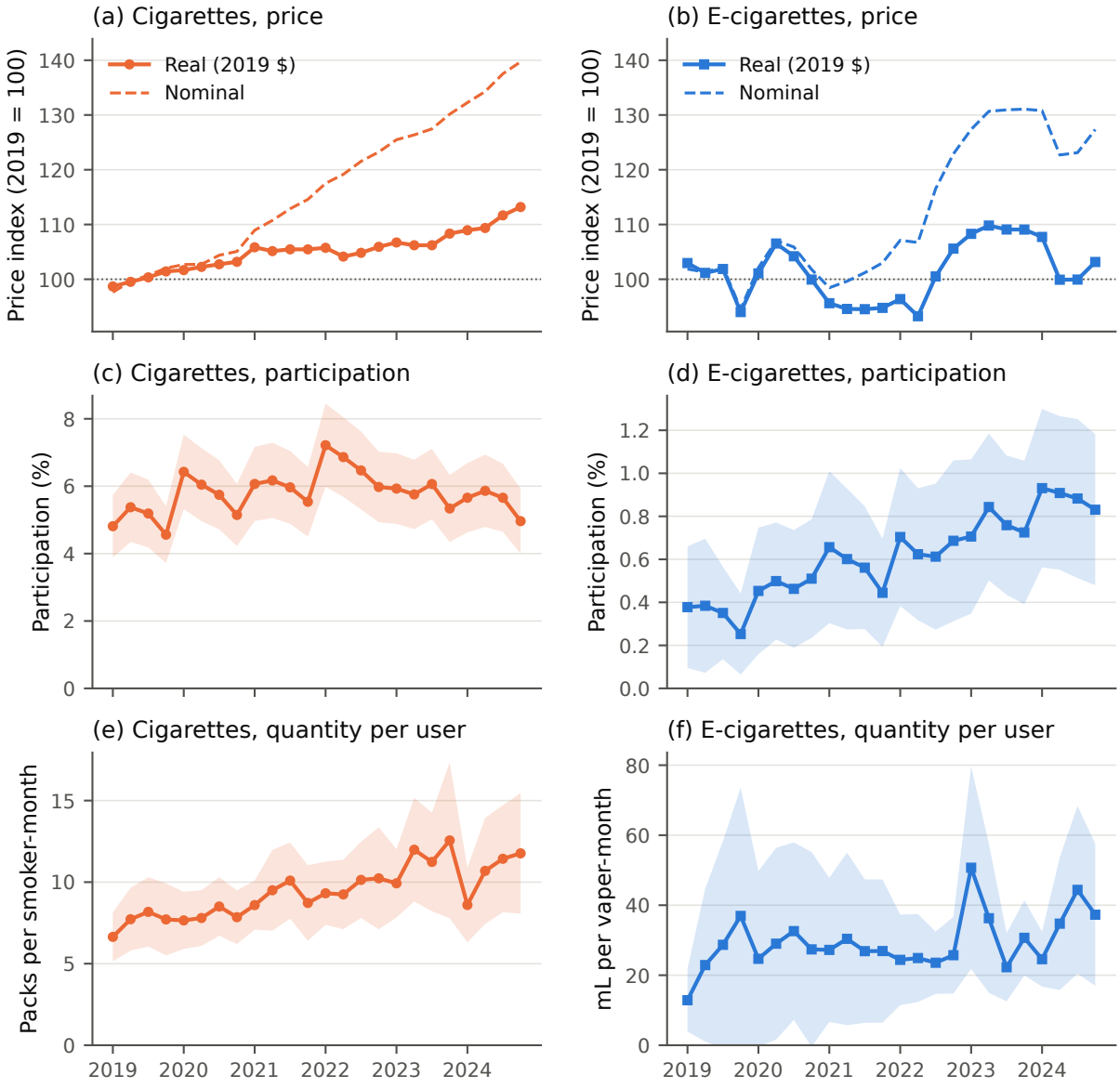
Table 5: One-month action transitions (%).

| | Action in month $t$ | | | | |
|---|---|---|---|---|---|
| Action in month $t-1$ | Abstinence | Smoking-only | Vaping-only | Dual-use | $N$ |
| Abstinence | 98.3 | 1.5 | 0.2 | 0.0 | 163,270 |
| Smoking-only | 26.1 | 72.6 | 0.3 | 0.9 | 9,432 |
| Vaping-only | 34.1 | 1.2 | 61.8 | 2.9 | 934 |
| Dual-use | 20.7 | 41.1 | 12.3 | 26.0 | 234 |

*Notes:* Weighted shares of the action in month $t$ given the action in month $t-1$, over pairs of consecutive calendar months of the same household. Rows sum to 100. $N$ counts origin household-months.

[9] I regress the log monthly purchase on year dummies over buyer-months, $\log x_{it} = \sum_{y=2020}^{2024} \beta_y \mathbf{1}\{y(t) = y\} + \mu_i + u_{it}$, clustering standard errors by household. $\beta_y$ is the change in the average buyer-month relative to 2019. With household effects, it is the change within a household. The difference between the two is the composition effect. For cigarettes, the 2024 estimate is 0.27 without household effects and $-0.15$ with them.

Figure 1: Prices, participation and quantity per user, 2019–2024.




*Notes:* Quarterly values. Panels (a)–(b): weighted mean county price in 2019 dollars (solid) and in nominal dollars (dashed), indexed to the 2019 average ($6.90 per pack, $5.15 per mL). Panels (c)–(d): weighted share of household-months with a purchase. Panels (e)–(f): weighted mean monthly purchase among buyer-months (packs of 20 cigarettes and millilitres of e-liquid). Shaded bands are 95% confidence intervals clustered by household.

# 6 Estimation Results

Table 6 reports the estimated utility coefficients and Table 7 reports the latent type distribution. In the estimated specification, each quantity shifter $\Phi^g_{it}$ depends on the product's own stock $Q^g_{it}$, and the e-cigarette shifter also on the control function $C^v_{ct}$. The cigarette market is mature and not subject to major demand shocks over the sample period, and in estimation the coefficients on cigarette control function terms are very close to 0. Therefore, in the final estimation, only the control function for e-cigarettes is included. In estimation the stocks enter the action utilities and the quantity shifters as z-scores, so the coefficients in Table 6 are per standard deviation of the stock (0.86 for cigarettes and 0.22 for e-cigarettes). Standard errors come from the outer product of the household scores.

**Addiction and participation.** Panel A of Table 6 reports how the two stocks enter the utility of each action. The own-stock terms are positive and precisely estimated for both products (1.09 for smoking and 0.95 for vaping). The own-squared terms are negative. The squared term captures the self-perceived disutility of use: the health cost that a household attaches to its own smoking or vaping grows with its addiction, so the participation utility first rises and then turns down. The dotted lines in Figure 2 trace the implied participation utility over the range of each stock, converted into dollars of monthly spending with the money coefficient (Appendix Figure 26(a) adds the confidence bands). The utility of smoking rises by about \$70 a month as the cigarette stock grows to 1.7 (23% of the ceiling), is back at its zero-stock level at 3.5, and falls to −\$680 at the stock ceiling. The utility of vaping rises by about \$255 a month at $Q^v = 2.0$ (58% of the ceiling) and is still \$120 above its zero-stock level at the ceiling, with wide confidence bands at high vaping stocks.

The cross-stock terms are negative (Appendix Figure 26(b)). Smokers are less inclined to switch to vaping-only. The cigarette stock lowers the utility of vaping-only, and the disutility grows with the stock: it is about \$110 a month for a lightly smoking-addicted user, at a quarter of the stock ceiling, and about \$420 at the ceiling, where it is imprecisely estimated. The vaping stock lowers the utility of smoking-only, by \$44 a month at a quarter of the vaping-stock ceiling and by \$70 at the ceiling, although the levels are not significant. Dual-use is most attractive at moderate cigarette stocks: its squared cigarette-stock term is negative and precisely estimated, while its vaping-stock terms are small and insignificant.

Table 6: Estimated utility parameters.

| *A. Action utility* | Smoking-only | Vaping-only | Dual-use |
|---|---|---|---|
| $\tilde{Q}^s$ | 1.090 | −0.878 | 0.571 |
| | (0.063) | (0.371) | (0.487) |
| $\tilde{Q}^v$ | −0.225 | 0.949 | −0.034 |
| | (0.059) | (0.171) | (0.139) |
| $(\tilde{Q}^s)^2$ | −1.961 | 0.022 | −1.750 |
| | (0.101) | (0.490) | (0.361) |
| $(\tilde{Q}^v)^2$ | 0.136 | −0.744 | 0.034 |
| | (0.142) | (0.145) | (0.130) |
| CF, cigarette price innovation $\lambda_{vs}$ | – | 0.004 | |
| | | (0.040) | |
| CF, e-cigarette price innovation $\lambda_{vv}$ | – | 0.050 | |
| | | (0.045) | |

| *B. Utility of quantity* | Cigarettes | E-cigarettes |
|---|---|---|
| Shifter constant $\psi_{0g}$ | −1.212 | 0.083 |
| | (0.112) | (0.236) |
| Shifter, own stock $\psi_g$ | 0.280 | −0.042 |
| | (0.011) | (0.016) |
| Shifter, CF $b_g$ | – | 0.290 |
| | | (0.261) |
| Curvature at zero stock $\kappa_{0g}$ | 1.180 | 1.129 |
| | (0.059) | (0.125) |
| Curvature, change to the cap $\kappa_{1g}$ | −0.163 | −0.647 |
| | (0.058) | (0.124) |
| Measurement error s.d. $\sigma_g$ | 0.835 | 0.997 |
| | (0.009) | (0.093) |

| *C. Money* | |
|---|---|
| Money coefficient $\alpha$ | 1.971 |
| | (0.157) |

*Notes:* Maximum likelihood estimates, $\beta = 0.95$. Standard errors in parentheses, from the outer product of the household scores. Stocks enter as z-scores $\tilde{Q}$. Squared terms are standardised squared z-scores. The e-cigarette control function (CF) $C^v_{ct} = \rho_v C^v_{c,t-1} + \lambda_{vs} v^s_{ct} + \lambda_{vv} v^v_{ct}$ enters the utility of vaping-only and of dual-use with a unit coefficient and the e-cigarette shifter with coefficient $b_v$. Its persistence is calibrated at $\rho_v = 0.83$. The curvature follows Equation (4), with $\bar{Q}_g$ the cap of the stock grid (7.38 for $Q^s$ and 3.51 for $Q^v$). The money term is monthly spending on the two products divided by its sample standard deviation (\$113). Not reported in the table: type-specific action intercepts (Table 7), demographic shifters, year-month and county effects by action, and the type-probability logit. Sample size: 183,147 household-months with 6,538 households.

**Quantity shifter.** Panel B of Table 6 reports the utility over quantity, $\Phi^g \phi_g(x)$. The cigarette utility shifter rises with the cigarette stock. Because the stock enters $\log \Phi^s$ linearly, each additional unit of stock, which is what a median monthly purchase adds, multiplies $\Phi^s$ by the same factor, 1.39: the marginal utility of every pack is 39% higher. Over the 7.4 units between a new smoker ($Q^s = 0$) and a heavily smoking-addicted user at the stock ceiling ($Q^s = 7.4$, reached by buying about 16 packs every month), these increases compound to $1.39^{7.4} \approx 11$, so $\Phi^s$ is 11 times as large.[10] In money terms, an additional pack is worth \$2.36 to a household with no cigarette stock, \$9.01 at half the ceiling and \$34.45 at the ceiling, against a mean price of \$7.27. At the mean price, a household with no cigarette stock would buy 1.9 packs a month in a static choice, and a household at the stock ceiling 23 packs. At high stocks, the attraction towards smoking therefore comes from the quantity margin, while the participation utility in Panel A has already turned down and, beyond $Q^s = 3.5$, is below its zero-stock level. The e-cigarette shifter falls with the vaping stock, by 17% per unit of stock, so it is half as large at the stock ceiling as for a new vaper ($Q^v = 3.5$, reached by buying about 18 mL every month, close to the median purchase). Desired e-cigarette purchases nevertheless rise with the stock, from 8.8 mL a month for a new vaper to 42 mL at the ceiling at the mean price, because the curvature parameter falls with the stock (Panel B): the marginal utility of e-liquid then declines more slowly with the quantity bought. The additional millilitre is worth \$2.54 at no vaping stock and \$8.13 at the ceiling (against a mean price of \$5.22).

**Utility of use by addiction.** Figure 2 puts the two margins together. For each level of the own stock it shows the participation term, the utility of quantity $\Phi^g \phi_g(x)$ evaluated at the model's predicted purchase of households at that stock, and their sum, all in dollars of monthly spending relative to a household with no stock. For cigarettes, the participation term is \$680 a month below its zero-stock level at the stock ceiling. The utility of quantity rises faster: the predicted purchase grows from 2.2 packs a month at no stock to 23 packs at the ceiling, and the utility from these packs is \$920 a month higher. The total utility of smoking is therefore \$130 above its zero-stock level at a quarter of the ceiling and \$240 at the ceiling, and it never falls below it. Net of the spending on the additional packs at the mean price, the gain is \$90 at the ceiling. The two margins together describe an addicted smoker. The household perceives the health cost of its smoking, and on the participation margin alone a heavily smoking-addicted user would be worse off than a household with no stock. But the large quantity it consumes gives enough utility to keep smoking. For e-cigarettes, the participation term stays positive over the whole range, and the utility

[10] The stock enters $\log \Phi^g$ as a z-score, so the factor per unit of stock is $\exp(\psi_g / \mathrm{sd}(Q^g))$, with $\mathrm{sd}(Q^s) = 0.86$ and $\mathrm{sd}(Q^v) = 0.22$. The factor does not depend on the level of the stock. The money values are the marginal utility of the median purchase (five packs, 16.8 mL) divided by the money coefficient, and the desired quantities are static ($\beta = 0$) solutions at the mean county price.

of quantity adds little until the vaping stock passes three quarters of the ceiling ($200 at the ceiling, where the predicted purchase is 46 mL against 9 mL at no stock). The lack of decreasing participation utility for vaping indicates that households do not perceive e-cigarettes as carrying long-term health consequences. The total utility of vaping rises over the whole range, to $320 a month at the ceiling.

**Curvature.** The curvature parameters fall with the stock: $\kappa_s$ is 1.18 at zero stock and 1.02 at the ceiling, and $\kappa_v$ is 1.13 and 0.48. Both changes are significant, and the e-cigarette one is large. In the static case with no dynamic behaviours ($\beta = 0$), the price elasticity is $-0.89$ for cigarettes at zero stock and $-0.99$ at the ceiling. The price elasticities for e-cigarettes are $-0.91$ and $-2.09$ respectively: addicted vapers adjust their purchases to the price more than new vapers. These elasticities are conditional on use. For cigarettes, the conditional elasticity is larger in magnitude than a historical benchmark discussed by Pesko et al. (2020). For e-cigarettes, the implied elasticity is in line with the estimated total sales elasticity of $-1.5$ in Pesko et al. (2020). That estimate includes both margins and is not directly comparable to the conditional elasticity here. Section 7.2 reports the model's total response and its decomposition. The quantity margin of cigarettes is inelastic in the static case, and the quantity margin of e-cigarettes becomes elastic at high vaping stocks. In the dynamic model a purchase also raises next month's stock (Equation (9)), which adds to the value of buying today through addiction.

**Money and the control function.** The money coefficient is $\alpha = 1.97$. A dollar of monthly spending is worth 0.0174 utility units. This is used to convert utility gains/costs into monetary terms. The two loadings of the e-cigarette control function are small and not jointly significant ($p = 0.46$), and its coefficient in the e-cigarette shifter is also insignificant. Once the stocks and the year-month and county effects are controlled for, local demand shocks correlated with e-cigarette price innovations play little role in this specification.

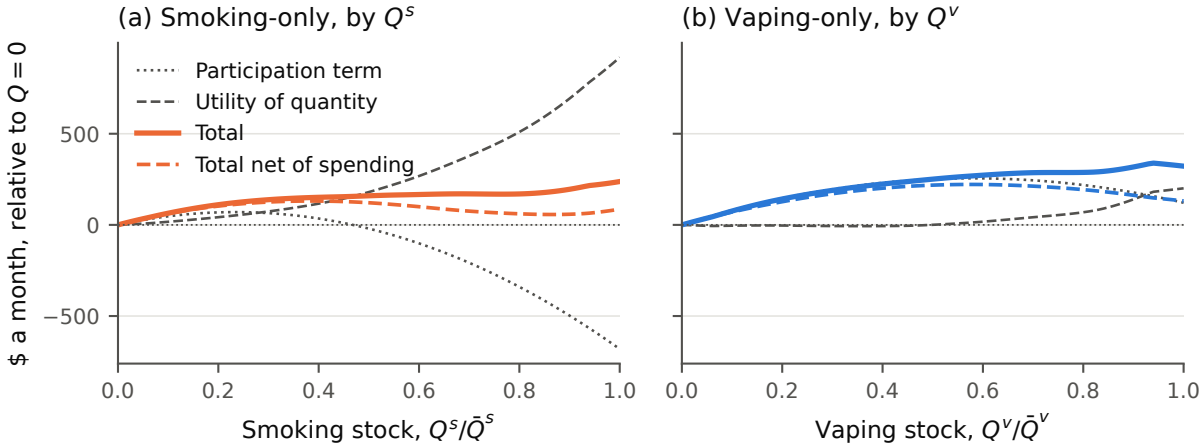
**Latent types.** Table 7 reports the latent type distribution. On average 78% of households have no prior use, 7% are prior smokers, 6% prior vapers and 10% prior dual-users. Low-income households are more likely to have high initial stocks: prior dual-users make up 15% of households below $25,000 and only 4% above $100,000, and prior smokers 11% and 3%. Prior vapers are also most common in the two lowest income groups (8–9%). Different types are allowed to have different intercepts for different actions. This is because permanent preference is likely correlated with initial addiction levels. The type intercepts show that the types are more than initial stocks. Prior smokers have the highest utility of smoking, and also the highest utility of vaping-only.

Table 7: Latent types: prior probabilities and action intercepts.

| | Households | $\tau_0$ No prior use | $\tau_s$ Prior smoker | $\tau_v$ Prior vaper | $\tau_{sv}$ Prior dual-user |
|---|---|---|---|---|---|
| *A. Prior type probabilities (%)* | | | | | |
| All households | 6,538 | 77.5 | 6.7 | 5.9 | 9.9 |
| Under \$25K | 1,608 | 65.5 | 11.3 | 8.1 | 15.1 |
| \$25–45K | 1,664 | 73.8 | 5.8 | 9.3 | 11.0 |
| \$45–70K | 1,642 | 85.2 | 5.2 | 2.4 | 7.2 |
| \$70–100K | 985 | 86.5 | 3.8 | 3.3 | 6.5 |
| \$100K+ | 639 | 89.5 | 3.0 | 3.3 | 4.3 |
| *B. Action intercepts* $c_{\tau,a}$ | | | | | |
| Smoking-only | | −11.53 | −4.14 | −7.75 | −5.88 |
| | | (0.44) | (0.37) | (0.46) | (0.38) |
| Vaping-only | | −19.17 | −9.89 | −10.33 | −13.31 |
| | | (3.26) | (2.24) | (2.49) | (2.37) |
| Dual-use | | −23.02 | −10.96 | −15.44 | −15.26 |
| | | (8.41) | (2.22) | (3.19) | (2.20) |

*Notes:* Panel A: prior probabilities $\pi_\tau(\boldsymbol{z}_i)$ from the estimated type logit, averaged over households with NielsenIQ projection weights. Panel B: standard errors in parentheses. Types with high initial stocks start at the ergodic stock of the 75th-percentile buyer (Section 4.2). The other types start at zero.

Figure 2: Addiction stocks and the utility of smoking and vaping.

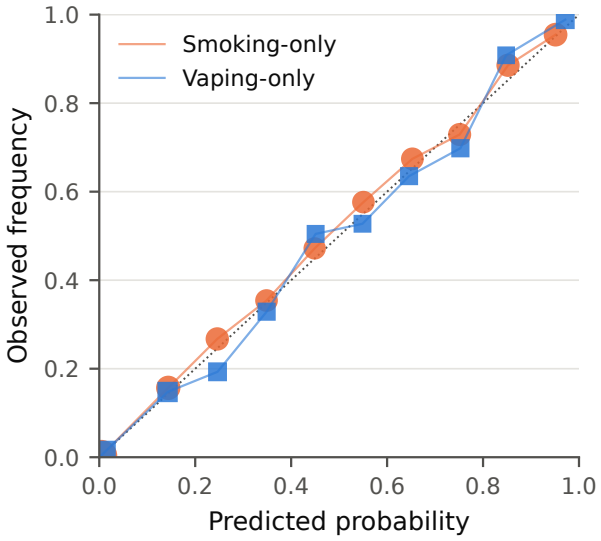



*Notes:* Utility of smoking-only by the cigarette stock (a) and of vaping-only by the vaping stock (b), in dollars of monthly spending relative to $Q = 0$. Dotted: the participation term $f_a(\boldsymbol{Q})$. Dashed grey: the utility of quantity $\Phi^g \phi_g(x)$ at the model's predicted mean purchase of households at that stock. Solid: their sum. Dashed colour: the sum net of spending on the additional quantity at the mean price. The e-cigarette shifter is evaluated at a control function of zero. Stocks are shown as shares of their ceilings, $\bar{Q}_s = 7.4$ and $\bar{Q}_v = 3.5$.

## 6.1 Model Fit

**Participation.** The fit on the participation margin is good. The model predicts abstention in 93.8% of household-months and smoking-only in 5.6%, against 93.7% and 5.7% in the data, and vaping-only and dual-use in 0.50% and 0.12% against 0.50% and 0.13%. Figure 3 shows the predicted choice probabilities against the observed action frequencies in the data. The points lie close to the diagonal. Figure 4 shows the fit by stock. The model matches smoking among households with almost no cigarette stock to mild addiction. It slightly under-predicts smoking at medium to high addiction levels. For vaping the fit is similar. The model reproduces the increase of vaping participation with the vaping stock (34% against 30% at $Q^v \approx 1.1$, and 76% against 87% in the highest bin), and it predicts overall vaping prevalence of 0.62% against 0.63% in the data. Dual-use is matched overall but under-predicted among households with high vaping stocks (Appendix Figure 28). By calendar month (Appendix Figure 27), predicted smoking follows the data within 0.2 percentage points in every year. The predicted participation tracks the data well in general.

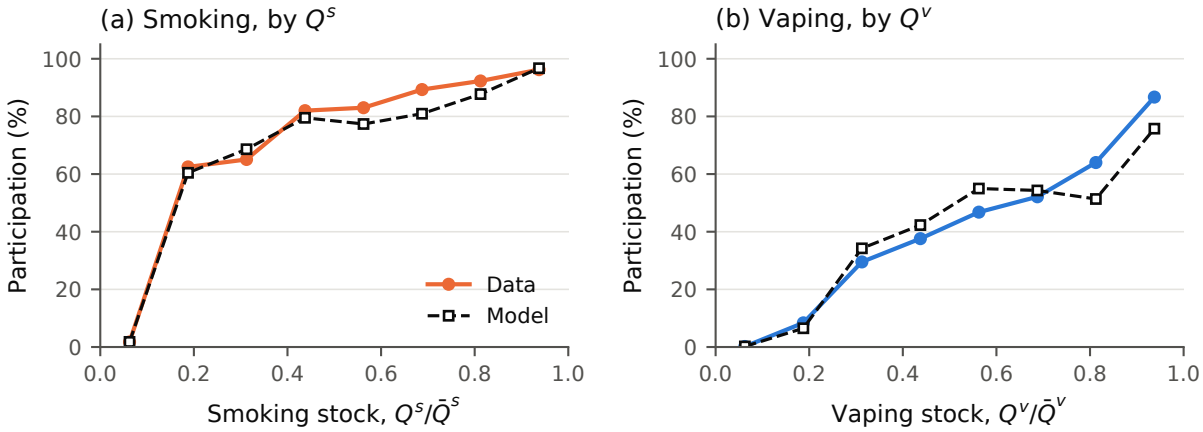
Figure 3: Calibration of predicted action probabilities.




*Notes:* Observed frequency against predicted probability, by bins of the predicted probability. Marker size increases with the number of household-months.

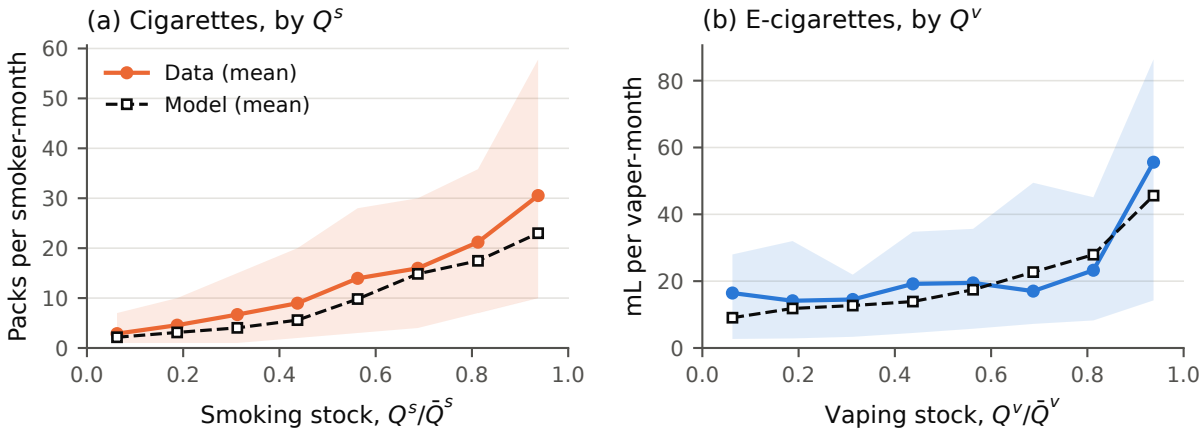
**Quantities.** The fit on the quantity margin is weaker. Among buyers, the model predicts 6.9 packs and 23.5 mL a month on average, against 9.3 packs and 29.2 mL in the data (medians 3.8 against 5.0 packs and 16.3 against 16.8 mL). Figure 5 shows that the shortfall is spread over the stock range. For cigarettes, predicted purchases rise with the stock as in the data but stay slightly below the recorded quantities. For e-cigarettes, the model slightly under-predicts the purchase quantities at low addiction levels but slightly over-predicts at higher stock levels.

Figure 4: Model fit: participation by stock.




*Notes:* Share of household-months with a purchase of the product, by the pre-action stock of the same product.

Figure 5: Model fit: quantity by stock.




*Notes:* Monthly purchase among buyer-months, by the pre-action stock of the product. Lines are means. The shaded bands span the 10th to 90th percentiles of the observed purchases. Model predictions are for the chosen action.

**Dynamic fit.** Figure 29 in Appendix E simulates households forward from a base month along realised prices. It takes the estimation results and each household-month observation as the base period, then simulates the choices and stocks forward. On the participation margin, the simulation tracks the data very well for smoking and vaping. On the quantity margin, the simulation starts too low and stays too low (0.39 against 0.53 packs per household-month in the base month, 0.37 against 0.42 after ten months). Because smaller cigarette purchases add less to the stock, the simulated cigarette stock falls behind the data, by 13% after ten months. The simulated e-cigarette stock tracks the data closely (0.020 against 0.019 after ten months).

# 7 Policy Experiments

I use the estimated model to study three policy choices: a permanent tax of 5% of the price of one product, a ban on one product, and the removal of the current excise tax on one product. I first report price elasticities and their decomposition by addiction stock, then trace the responses over 24 months as the stocks adjust, and finally examine the bans and the tax removals.

## 7.1 Design

The experiments are run on a simulated sample. The sample has 676,000 households on a grid of cells over the two stocks, with 4,000 households per cell. Each addiction cell is filled with simulated households, whose demographic variables are distributed in the same way as observed in the data for that particular addiction level. Each household draws its prices and e-cigarette control function from a random observed month of its county. The grid covers every combination of the two stocks with the same precision, including combinations that are rare in the data, such as heavily smoking-addicted users with a high vaping stock. Cells are weighted by the joint distribution of the stocks in the data.

The first experiment adds a permanent tax of 5% of each household's price, of one product at a time (on average about \$0.36 per pack and \$0.26 per millilitre). The pass-through to the consumer price is assumed to be one. Households expect the tax to persist. The second experiment is a ban: the actions that include the banned product are removed from the choice set, and each household chooses among the remaining actions with its addiction stocks held at their current values. The third removes the average state excise tax, \$1.84 per pack and \$0.31 per millilitre, which lies inside the trained tax range.

Confidence bands come from a bootstrap of 50 draws over the utility parameters from their estimated sampling distribution.

Each experiment is evaluated at month 0, the immediate response at the current stocks, and then simulated forward for 24 months. Households draw their actions from the model's choice probabilities and their purchases from the quantity rule, and their stocks evolve with the quantities bought. The baseline itself drifts slightly over time: starting from the data's stock distribution, simulated smoking participation falls from 5.7% to 5.0% after twelve months while cigarette purchases per household stay near 0.40 packs. Vaping participation rises from 0.61% to 0.76% and e-cigarette purchases per household from 0.13 to 0.20 mL. Policy effects are measured against this moving baseline.

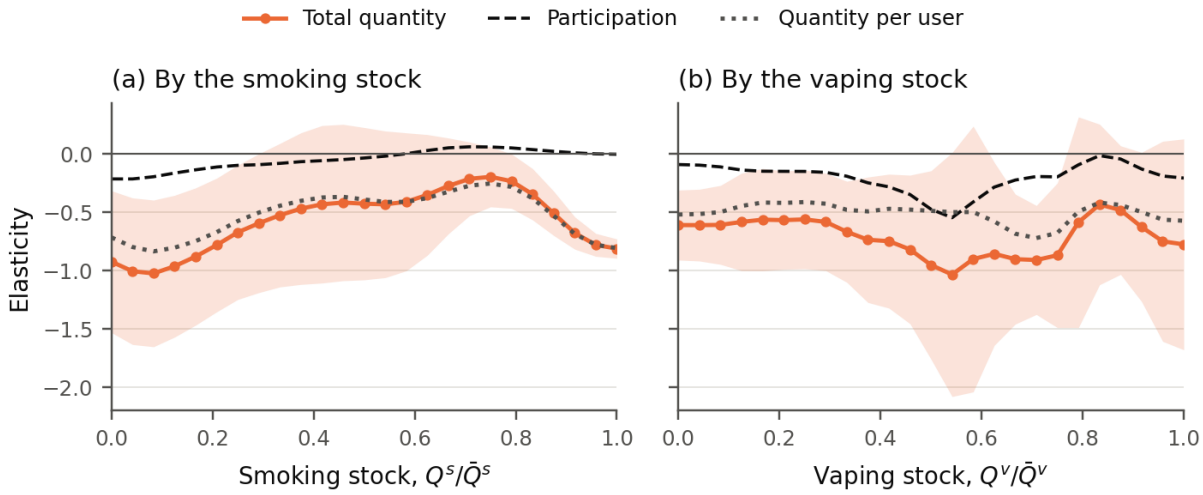
The figures plot each outcome against the cigarette stock $Q^s$ or the vaping stock $Q^v$ at the time of the policy change, as a share of the stock ceiling. Total quantity per household is the product of participation and the quantity conditional on buying. Since households contain one person, this is also quantity per capita. It includes zeros and measures demand across the whole population.

## 7.2 Price Elasticities by Addiction Stock

I first examine the immediate response to the tax. Addiction stocks are held at their current values, while households account for the change in future prices. I go through the four elasticities in turn: first the two own-price elasticities, then the two cross-price elasticities. Each is shown by the smoking stock and by the vaping addiction stock.

**Own-price elasticity of cigarettes.** The aggregate own-price elasticity of cigarette quantity is $-0.61$. Most of the response is on the quantity margin ($-0.51$, against $-0.10$ for participation). The elasticity is slightly larger in magnitude than the historical range of $-0.3$ to $-0.5$ for total adult cigarette demand reviewed by Chaloupka and Warner (2000) and Pesko et al. (2020). Figure 6 shows it by the two stocks. By the smoking stock (panel (a)), it is $-0.9$ among households with no cigarette stock, whose purchases are small and occasional. Its magnitude shrinks on both margins as the stock grows. It is smallest around three quarters of the ceiling, and rises again to $-0.8$ near the ceiling. This increase in magnitude is entirely driven by the quantity margin: the most heavily smoking-addicted users buy large quantities, and their purchases respond to the price. By the vaping stock (panel (b)), it is relatively stable across all vaping stocks, at around $-0.7$.

Figure 6: Own-price elasticity of cigarette quantity, by addiction stock.



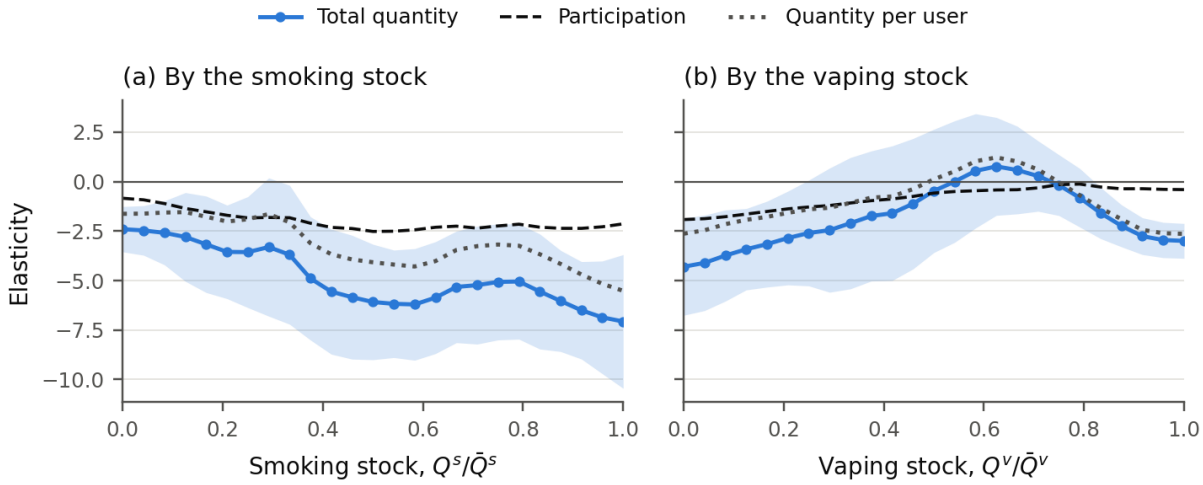

*Notes:* Elasticity of cigarette quantity per capita with respect to a permanent 5% cigarette tax (percent change per 1%), at month 0 in the simulated population, by the smoking stock (panel a) and the vaping stock (panel b), with its participation and quantity-per-user components. Shaded bands: estimate ±1.96 bootstrap standard errors.

**Own-price elasticity of e-cigarettes.** The aggregate own-price elasticity of e-cigarette quantity is −2.63. Both margins matter, quantity per user slightly more (−1.65, against −1.06 for participation). By the vaping stock (Figure 7, panel (b)), it is −4.3 among households with no vaping stock. It shrinks to about zero at middle addiction levels and is −3.0 near the ceiling, where quantity per user dominates. By the smoking stock (panel (a)), it is −2.4 among households with no cigarette stock and grows in magnitude with the stock, to −7.1 near the ceiling. The e-cigarette purchases of households with high smoking addiction, who vape mostly as dual-users, are very sensitive to the e-cigarette price on both margins.

The cross-price elasticities are positive, indicating that the two products are substitutes. However, they are less precisely estimated than the own-price elasticities.

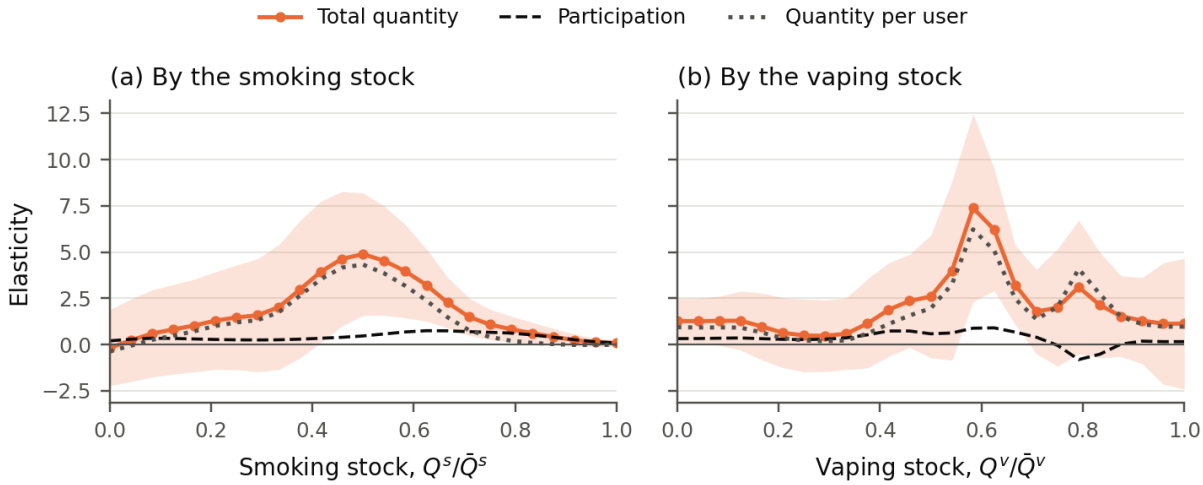
**Cigarette quantity and the e-cigarette price.** Overall, a 1% higher e-cigarette price raises cigarette quantity by 1.26%, through participation (0.32) and quantity per user (0.92). By the smoking stock (Figure 8, panel (a)), the elasticity is close to zero among households with no cigarette stock and near the ceiling. It is largest around half the ceiling, mostly through quantity per user: moderately smoking-addicted users smoke more when e-cigarettes become more expensive, while households with no cigarette stock and the heavily smoking-addicted users barely respond. The pattern is similar when looking by the vaping stock (panel (b)): it is around 1.2 among households with no vaping stock and near the ceiling. It peaks a little above half the ceiling. Most of the peak is driven by the quantity margin response.

Figure 7: Own-price elasticity of e-cigarette quantity, by addiction stock.




*Notes:* Elasticity of e-cigarette quantity per capita with respect to a permanent 5% e-cigarette tax (percent change per 1%), at month 0 in the simulated population, by the smoking stock (panel a) and the vaping stock (panel b), with its participation and quantity-per-user components. Shaded bands: estimate ±1.96 bootstrap standard errors.

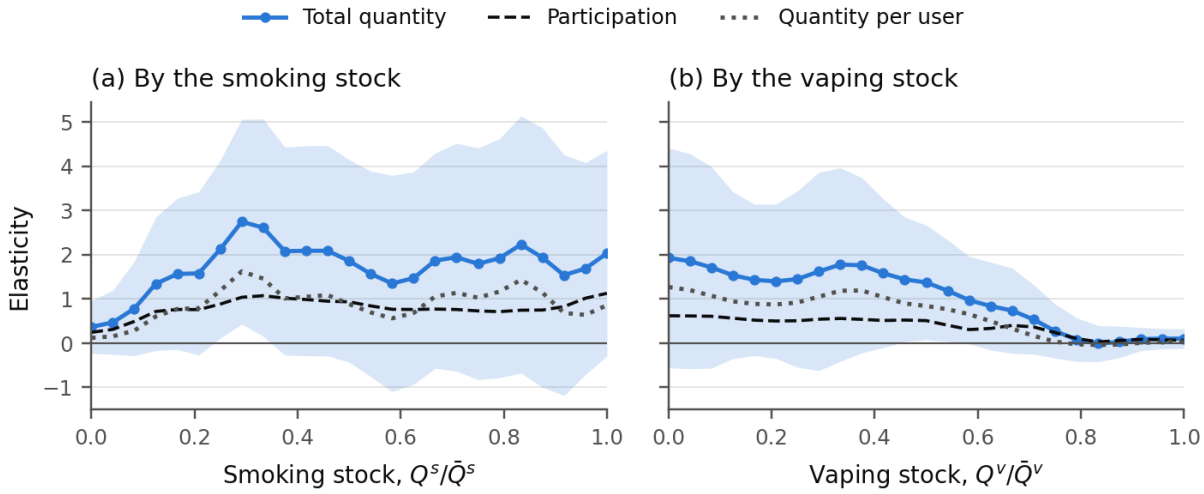
Figure 8: Elasticity of cigarette quantity with respect to the e-cigarette price, by addiction stock.




*Notes:* Elasticity of cigarette quantity per capita with respect to a permanent 5% e-cigarette tax (percent change per 1%), at month 0 in the simulated population, by the smoking stock (panel a) and the vaping stock (panel b), with its participation and quantity-per-user components. Shaded bands: estimate ±1.96 bootstrap standard errors.

**E-cigarette quantity and the cigarette price.** In general, a 1% higher cigarette price raises e-cigarette quantity by 0.60%, more through participation (0.39) than through quantity per user (0.21). By the smoking stock (Figure 9, panel (a)), the elasticity is 0.4 among households with no cigarette stock. The elasticity stays around 2.0 from lightly to heavily smoking-addicted users. It shows that smoking-addicted users are the ones that respond to a cigarette price increase by vaping more. By the vaping stock (panel (b)), it is 1.9 among households with no vaping stock and fades to 0.1 near the ceiling. Heavily vaping-addicted users do not vape more when cigarettes become more expensive, whereas households with little vaping addiction do.

Figure 9: Elasticity of e-cigarette quantity with respect to the cigarette price, by addiction stock.




*Notes:* Elasticity of e-cigarette quantity per capita with respect to a permanent 5% cigarette tax (percent change per 1%), at month 0 in the simulated population, by the smoking stock (panel a) and the vaping stock (panel b), with its participation and quantity-per-user components. Shaded bands: estimate ±1.96 bootstrap standard errors.

To summarise, own-price responses are largest among households with little addiction to the product and shrink as its stock grows, except among the most heavily addicted users, whose large purchases respond on the quantity margin. Cross-price responses are concentrated at moderate stocks: substitution into cigarettes comes mostly from moderately smoking-addicted users and is largest at moderate vaping stocks. Substitution into e-cigarettes comes from smokers with little vaping addiction.

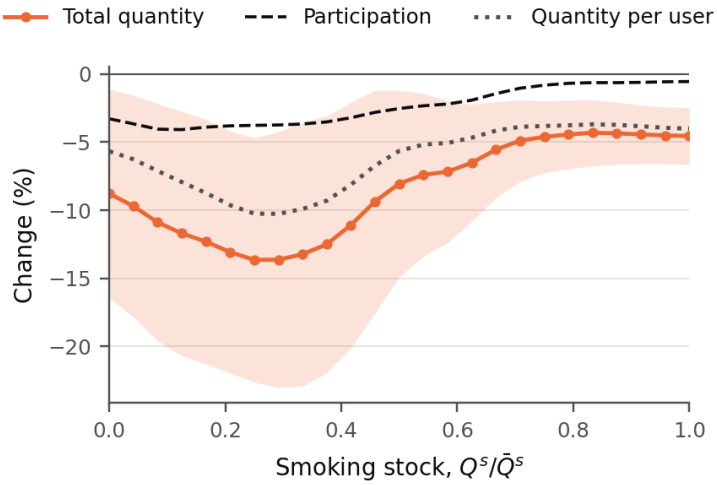
## 7.3 Long-term Quantity Responses by Addiction Stock

The above elasticities describe the immediate response to a permanent price increase, before addiction stocks adjust. I next allow stocks to evolve and examine how the responses change over time.

As in Section 7.2, I take the own-price responses first and then the cross-price responses. Each figure shows the change in total quantity per capita after 24 months by the responding product's own stock at the time of the tax, with its participation and quantity-per-user components. Appendix F shows the same responses by the other product's stock.

**Own-price response of cigarettes.** A 5% cigarette tax lowers cigarette quantity per household by 3.0% in the first month, by 6.5% after a year and by 7.1% after two years. The response grows because the stocks adjust: smaller purchases lower the cigarette stock, which lowers later purchases and participation. The fall in cigarette participation grows from 0.5% in the first month to 2.9% after two years, and the fall in quantity per user from 2.6% to 4.3%. Two years after the tax change, by the smoking stock (Figure 10), cigarette quantity falls by 8.8% among households with no cigarette stock and by 4.6% near the ceiling. The fall is largest among lightly smoking-addicted users and mostly driven by quantity responses. The participation part shrinks as the stock grows, so that near the ceiling almost all of the fall is on quantity per user.

Figure 10: Response of cigarette quantity to a 5% cigarette tax after 24 months, by smoking stock.

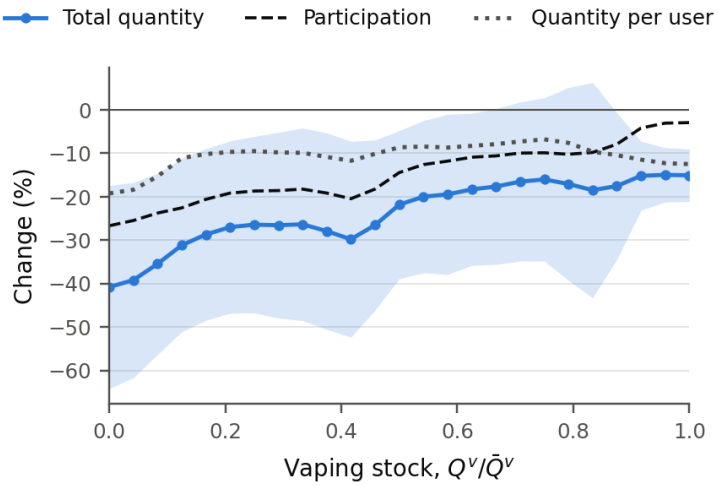



*Notes:* Percent change in cigarette quantity per capita 24 months after a permanent 5% cigarette tax, by the smoking stock at the time of the tax, with its participation and quantity-per-user components. Shaded band: estimate ±1.96 bootstrap standard errors.

**Own-price response of e-cigarettes.** A 5% e-cigarette tax lowers e-cigarette quantity by 13.1% in the first month and by 29% after two years, with vaping participation down 19%. By the vaping stock (Figure 11), e-cigarette quantity falls by 41% among households with no vaping stock and by 15% near the ceiling. Participation accounts for most of the fall, except near the ceiling, where quantity per user does.

The cross-price responses are positive at every stock, and they grow over time as the

Figure 11: Response of e-cigarette quantity to a 5% e-cigarette tax after 24 months, by vaping stock.



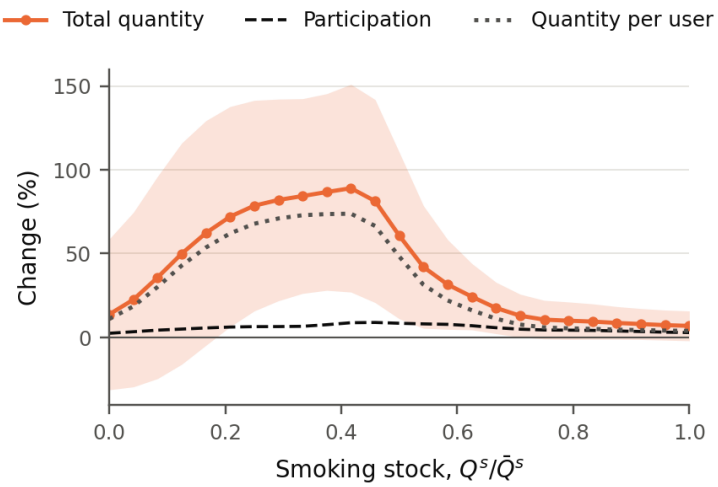

*Notes:* Percent change in e-cigarette quantity per capita 24 months after a permanent 5% e-cigarette tax, by the vaping stock at the time of the tax, with its participation and quantity-per-user components. Shaded band: estimate ±1.96 bootstrap standard errors.

stocks adjust.

**Cigarette quantity and the e-cigarette tax.** The effect of the e-cigarette tax on cigarettes grows over time: cigarette quantity rises by 6.3% in the first month and by 29% after two years, mostly through quantity per user. Cigarette participation rises by 1.6% and 5.0% over the same period. The size of the long-run cross effect reflects the addiction dynamics of the model: the households that smoke more build a larger cigarette stock, which raises the marginal utility of every further pack (Section 6). By the smoking stock (Figure 12), cigarette quantity rises by 14% among households with no cigarette stock and by 7% near the ceiling. The households that smoke more in response to higher e-cigarette prices are moderately smoking-addicted users, whose purchases and stocks have room to grow.

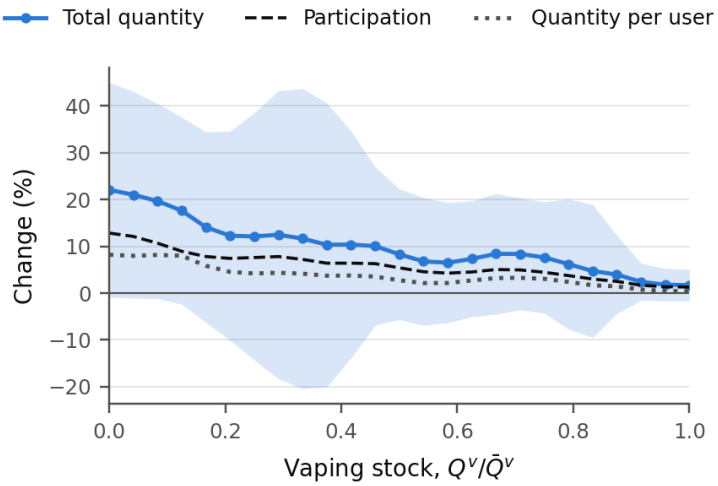
**E-cigarette quantity and the cigarette tax.** A 5% cigarette tax raises e-cigarette quantity by 3.0% in the first month and by about 13% after a year. By the vaping stock (Figure 13), e-cigarette quantity rises by 22% among households with no vaping stock and by 1.7% near the ceiling, mostly through participation. As in the first month, the substitution into e-cigarettes comes from households with little vaping addiction, while heavily vaping-addicted users barely respond.

Figure 12: Response of cigarette quantity to a 5% e-cigarette tax after 24 months, by smoking stock.




*Notes:* Percent change in cigarette quantity per capita 24 months after a permanent 5% e-cigarette tax, by the smoking stock at the time of the tax, with its participation and quantity-per-user components. Shaded band: estimate ±1.96 bootstrap standard errors.

Figure 13: Response of e-cigarette quantity to a 5% cigarette tax after 24 months, by vaping stock.




*Notes:* Percent change in e-cigarette quantity per capita 24 months after a permanent 5% cigarette tax, by the vaping stock at the time of the tax, with its participation and quantity-per-user components. Shaded band: estimate ±1.96 bootstrap standard errors.

## 7.4 Product Bans and Tax Removal

I consider two larger interventions: a ban on one product, and the removal of its average excise tax. The ban removes the actions that include the product from the choice set. Households choose among the remaining actions with their addiction stocks held at their current values, so the first month of the ban shows how existing users redistribute given their addiction, and the 24-month simulation shows how the stocks and choices adjust afterwards. The tax removal subtracts the average state excise tax, \$1.84 per pack or \$0.31 per millilitre, from the price. The tables and figures below compare month 24 of each intervention with month 24 of the baseline. Appendix G reports the immediate responses without addiction stock adjustments (the month-0 responses).

**Aggregate changes.** Table 8 reports the share of households in each action in the simulated population 24 months after each intervention, and in the baseline at month 24. An e-cigarette ban moves households that would vape at month 24 into other actions. 67% of them move to abstinence and 33% to smoking-only. 66% of would-be dual-users keep smoking while 34% move to abstinence (Table 10). Smoking participation is 4.3% above the baseline and cigarette quantity increases by 1.5%. The previous vapers who switch to smoking would buy fewer packs than existing smokers (Table 9).

A cigarette ban shifts the households that would smoke at month 24 into other actions. Of the would-be smoking-only households, 91% go to abstinence and 9% to vaping-only. 63% of would-be dual-users switch to abstinence while 37% keep vaping. Vaping participation is 42% above the baseline and e-cigarette quantity 45% above it, although vaping participation and quantity consumed are small without the ban. The effects of a ban are much stronger after two years than in its first month. Right after the bans' introduction, 13% of previous vapers switch to smoking and 1% of previous smokers switch to vaping (Appendix G).

Removing the \$1.84 cigarette excise raises the smoking-only share at month 24 from 4.50% to 5.72%, cigarette participation by 26% and cigarette quantity by 113%, mostly through more packs per smoker (+69%). The vaping-only share falls from 0.72% to 0.46%, and e-cigarette quantity by 44%. Removing the \$0.31 e-cigarette excise raises the vaping-only share from 0.72% to 0.84%, vaping participation by 16% and e-cigarette quantity by 34%. It also raises cigarette participation by 3.3% and cigarette quantity by 5.1%: cheaper e-cigarettes do not lower smoking.

**Quantities by action.** Table 9 reports the purchase size of the households in each action at month 24, with and without each intervention. The action is the one chosen at

Table 8: Action shares 24 months after the bans and the tax removals.

| | | After 24 months | | | |
|---|---|---|---|---|---|
| Action | Baseline | E-cig. ban | Cig. ban | No cig. tax | No e-cig. tax |
| Abstinence | 94.65 | 95.17 | 98.79 | 93.73 | 94.38 |
| Smoking-only | 4.50 | 4.83 | – | 5.72 | 4.64 |
| Vaping-only | 0.72 | – | 1.21 | 0.46 | 0.84 |
| Dual-use | 0.13 | – | – | 0.09 | 0.15 |

*Notes:* Percent of households in each action in the simulated population at month 24, with the intervention in place from month 0 and without it (baseline), weighted by the data's stock distribution. A ban removes the product's actions from the choice set (dash), and the removals subtract the sample-average state excise tax ($1.84 per pack, $0.31 per millilitre). Bootstrap standard errors: 1.05 (abstinence), 0.54 (smoking-only), 0.64 (vaping-only) and 0.12 (dual-use) percentage points in the baseline, and at most 1.11 percentage points after an intervention. Month 0: Table 14.

month 24, so differences in the means reflect both changes in purchase size and changes in which households choose the action. Under the e-cigarette ban, packs per smoking-only month fall from 8.11 to 7.81: the former vapers who smoke buy fewer packs than existing smokers. Under the cigarette ban, millilitres per vaping-only month barely change. Removing the cigarette excise raises packs per smoking-only month by 69% (8.11 to 13.67) and per dual-use month by 86% (5.31 to 9.86). It also lowers millilitres per vaping-only month (30.8 to 28.1) and per dual-use month (22.5 to 13.7). Removing the e-cigarette excise raises millilitres per vaping-only month by 15% (30.8 to 35.4) and per dual-use month by 23% (22.5 to 27.8). Packs per smoking-only month increase by 1.6% (8.11 to 8.24).

Table 9: Purchase size by action 24 months after the bans and the tax removals.

| | | | After 24 months | | | |
|---|---|---|---|---|---|---|
| Product | Action | Baseline | E-cig. ban | Cig. ban | No cig. tax | No e-cig. tax |
| Cigarettes (packs) | Smoking-only | 8.11 | 7.81 | – | 13.67 | 8.24 |
| | Dual-use | 5.31 | – | – | 9.86 | 5.96 |
| E-cigarettes (mL) | Vaping-only | 30.8 | – | 30.1 | 28.1 | 35.4 |
| | Dual-use | 22.5 | – | – | 13.7 | 27.8 |

*Notes:* Mean purchase per month among the households choosing the action at month 24 in the simulated population (packs of cigarettes, millilitres of e-liquid). A dash marks an action removed from the choice set. Scenarios are as in Table 8. Bootstrap standard errors: at most 2.9 packs for smoking-only, 6.9 packs for dual-use, 9 mL for vaping-only and 14 mL for dual-use. Month 0: Table 15.

**Action transitions.** Table 10 shows, for each baseline action that a ban removes, how its households are distributed over the remaining actions at month 24. Under the e-cigarette ban, 67% of the vaping-only households stop and 33% switch to smoking-only. 34% of the previous dual-users go to abstinence and 66% of them switch to smoking-only. Under the cigarette ban, 91% of the smoking-only households stop and 9% switch to

vaping-only. 63% of dual-users quit using and 37% keep vaping. Smokers remain less likely to switch to the other product than vapers, but the gap is smaller than in the first month (9% against 33% of the exclusive users after two years, 1% against 13% at month 0). The cigarette stock lowers the utility of vaping alone (Section 6), and without cigarettes it decays, so vaping alone becomes attractive to former smokers. The former vapers who smoke build up their smoking stocks, which keep them smoking.

Table 10: Action transitions 24 months after the bans.

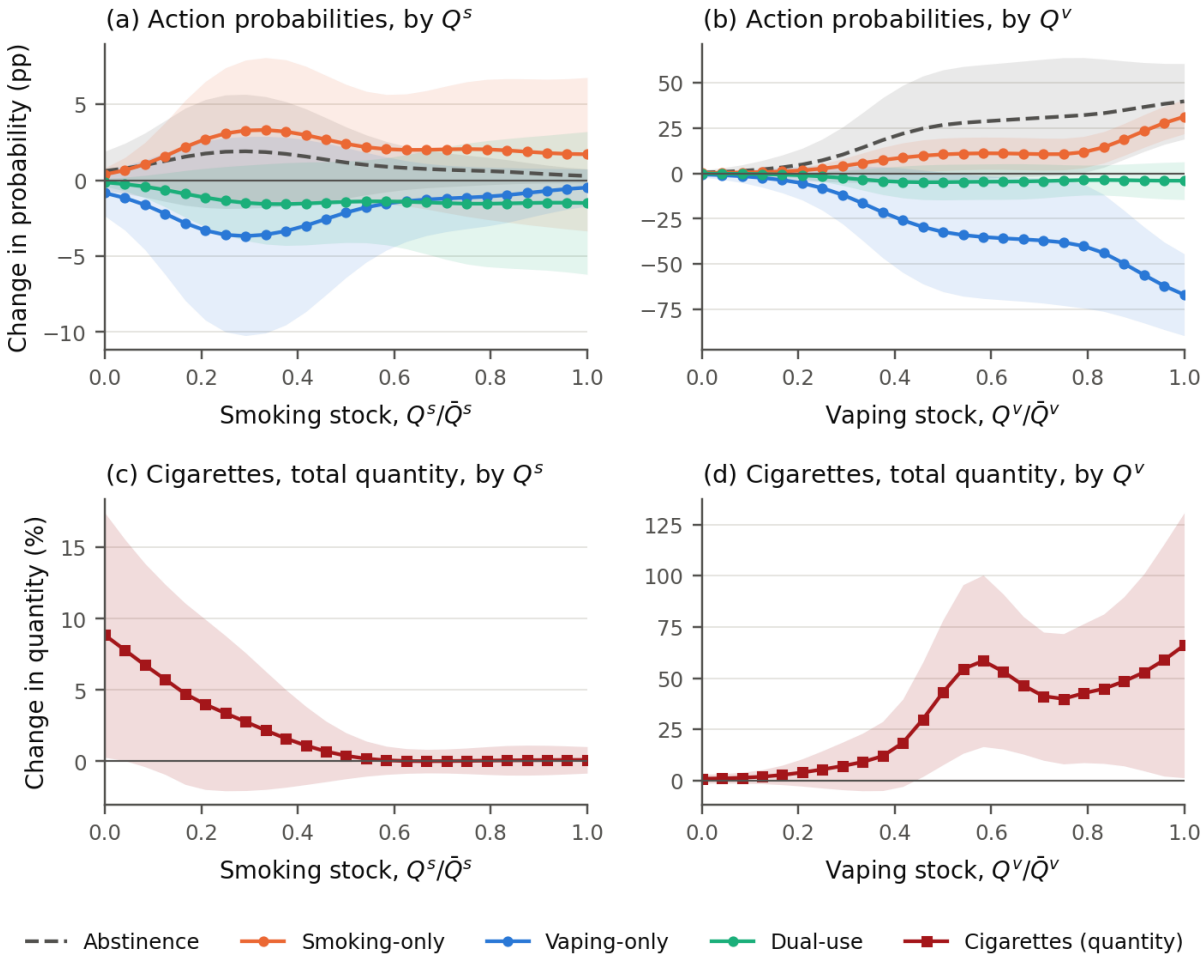
| | | | Action at month 24 (% of the row) | | |
|---|---|---|---|---|---|
| Ban | Baseline action | Share (%) | Abstinence | Smoking-only | Vaping-only |
| E-cigarettes | Vaping-only | 0.72 | 67.2 | 32.8 | – |
| | Dual-use | 0.13 | 33.9 | 66.1 | – |
| Cigarettes | Smoking-only | 4.50 | 90.7 | – | 9.3 |
| | Dual-use | 0.13 | 62.8 | – | 37.2 |

*Notes:* Each row distributes the households in a baseline action at month 24 over the actions that remain available after 24 months of the ban, in percent of the row, in the simulated population. Share = the baseline share of the action at month 24. Built from the minimal-movement coupling of each household's month-24 action probabilities with and without the ban, averaged over the simulated paths. The actions that remain available keep almost all their households: 0.3% of the smoking-only households under the e-cigarette ban and 0.8% of the vaping-only households under the cigarette ban move to abstinence. Bootstrap standard errors: the same for both entries of a row: 7.6 (vaping-only) and 7.3 (dual-use) under the e-cigarette ban, 5.0 (smoking-only) and 17.4 (dual-use) under the cigarette ban, in percentage points. Month 0: Table 16.

**Responses by stock.** The remainder of this section looks at each intervention by addiction stock, 24 months after it starts, by the stocks at the time it starts, against the baseline at month 24. Each figure has four panels. The top row shows the change in the action probabilities, in percentage points, by the cigarette stock (panel a) and by the vaping stock (panel b). The bottom row shows the percent change in total quantity per capita of each product on the same two axes (panels c and d). In the two ban scenarios the banned product's quantity falls by 100% at every stock, so only the other product's quantity is drawn.

**E-cigarette ban, by stock.** Figure 14 shows the change after a vaping ban by stock. The response grows with the vaping stock (panel (b)): the more addicted the vapers, the more households leave vaping. Of the 70% of people who vape near the e-cigarette stock ceiling, about 40 p.p. go to abstinence and 30 p.p. to smoking-only. Cigarette quantity rises with the vaping stock as well, by about 65% near the ceiling (panel (d)). By the cigarette stock the changes are small (panels (a) and (c)).

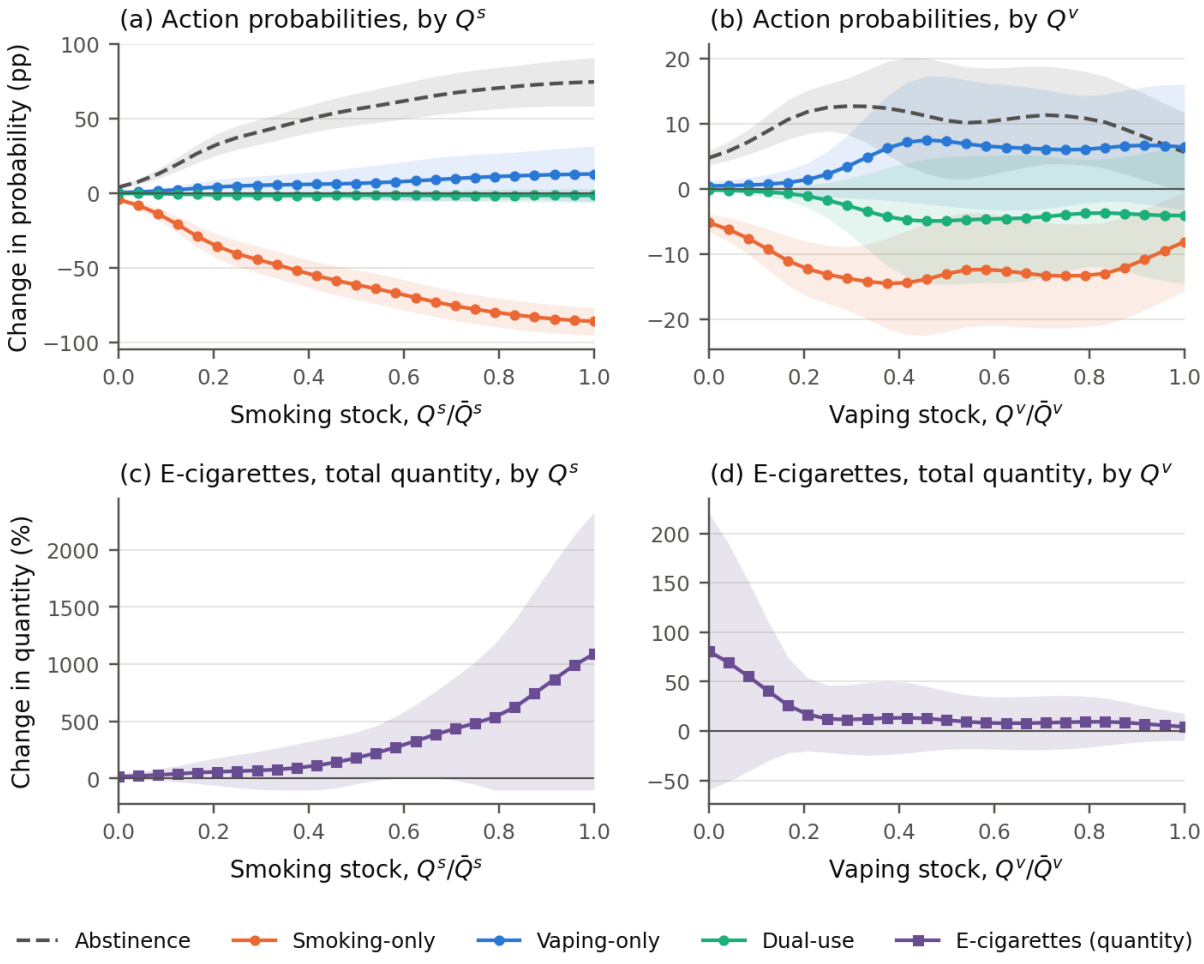
Figure 14: E-cigarette ban.




*Notes:* The vaping-only and dual-use actions are removed from the choice set. Changes 24 months after the ban, by the stocks at the time of the ban, in the simulated population. Top row: change in action probabilities (percentage points), by the cigarette stock (panel a) and the vaping stock (panel b). Bottom row: percent change in cigarette quantity per capita on the same axes (panels c, d). E-cigarette quantity falls by 100% at every stock and is not drawn. Band: estimate ±1.96 bootstrap standard errors. Curves smoothed over neighbouring stock levels (seven-point weighted moving average). Month 0: Figure 31.

**Cigarette ban, by stock.** Figure 15 shows the changes by stock. The response grows with the cigarette stock (panel (a)): smoking-only falls by up to 86 p.p. near the smoking stock ceiling, most of them going to abstinence. Vaping-only rises steadily with the cigarette stock, to about 13 p.p. near the ceiling. E-cigarette quantity therefore rises most among the most heavily smoking-addicted users, to about 12 times its baseline level (panel (c)). By the vaping stock the changes are smaller, and e-cigarette quantity rises most, by about 80%, among households with no vaping stock (panel (d)).

Figure 15: Cigarette ban.

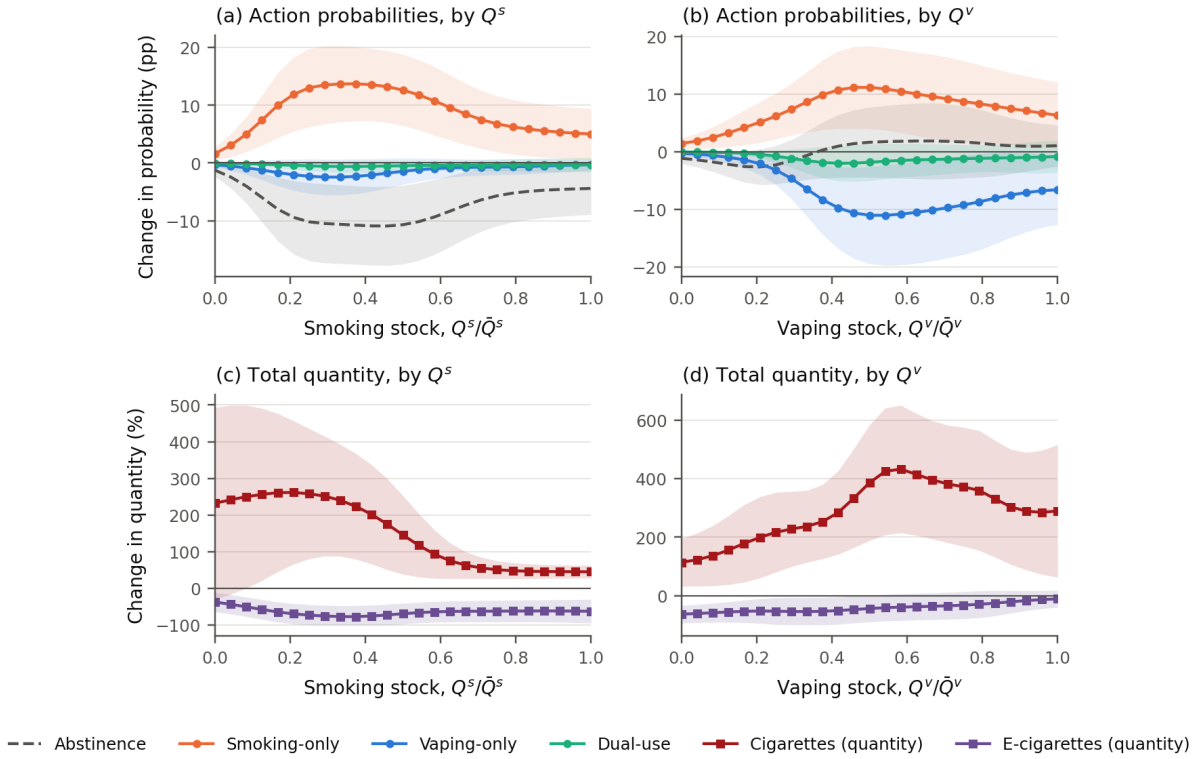



*Notes:* The smoking-only and dual-use actions are removed from the choice set. Changes 24 months after the ban, by the stocks at the time of the ban, in the simulated population. Top row: change in action probabilities (percentage points), by the cigarette stock (panel a) and the vaping stock (panel b). Bottom row: percent change in e-cigarette quantity per capita on the same axes (panels c, d). Cigarette quantity falls by 100% at every stock and is not drawn. Band: estimate ±1.96 bootstrap standard errors. Curves smoothed over neighbouring stock levels (seven-point weighted moving average). Month 0: Figure 32.

**Removing the cigarette excise tax, by stock.** Figure 16 shows the changes after the removal of the cigarette excise by stock. The response is largest among lightly and moderately smoking-addicted users (panel (a)): smoking-only rises by up to 14 p.p. between a quarter and half of the cigarette-stock ceiling, drawn from abstinence. Cigarette

quantity rises by about 250% among households below a third of the ceiling, against about 45% among the most heavily smoking-addicted users (panel (c)). By the vaping stock, vaping-only falls by about 11 p.p. at around half the vaping stock ceiling. Addicted vapers who leave vaping switch to smoking-only (panel (b)). E-cigarette quantity falls at every stock (panels (c) and (d)).

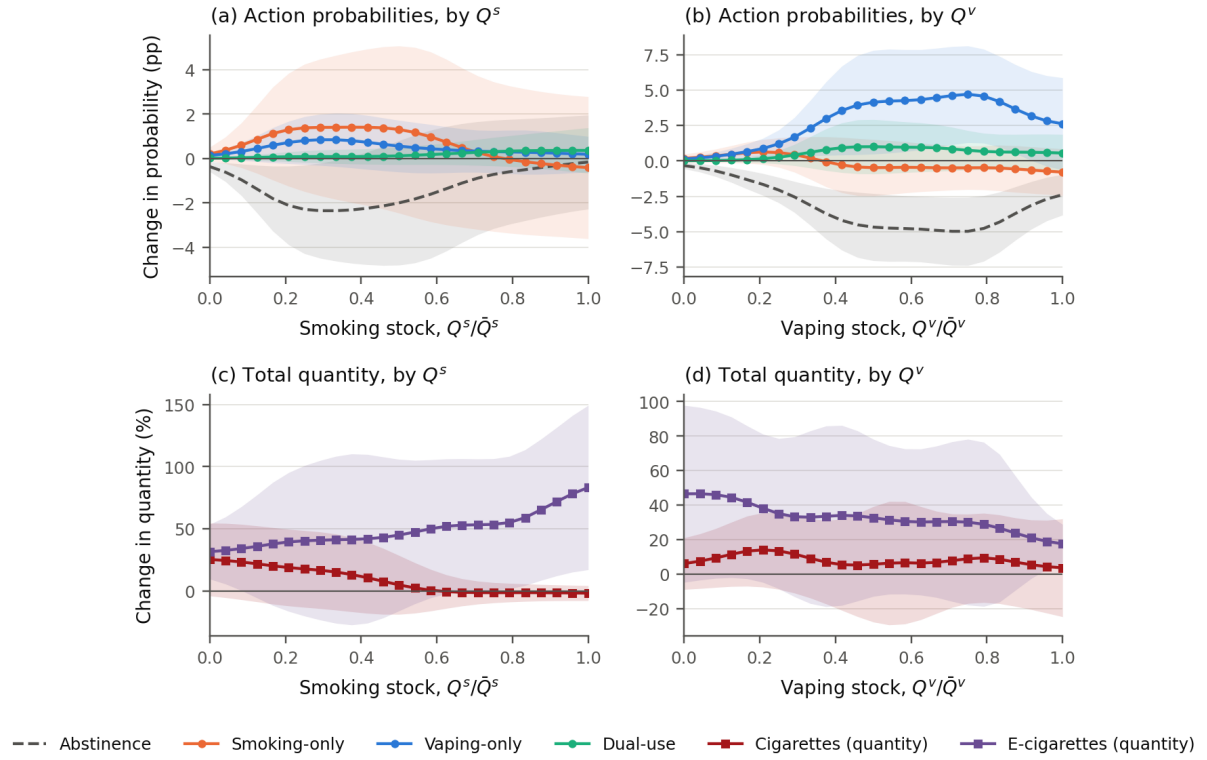
Figure 16: Removal of the cigarette excise tax.




*Notes:* Removal of the state cigarette excise tax ($1.84 per pack, sample mean). Changes 24 months after the removal, by the stocks at the time of the removal, in the simulated population. Top row: change in action probabilities (percentage points), by the cigarette stock (panel a) and the vaping stock (panel b). Bottom row: percent change in total quantity per capita of cigarettes and of e-cigarettes on the same axes (panels c, d). Band: estimate ±1.96 bootstrap standard errors. Curves smoothed over neighbouring stock levels (seven-point weighted moving average). Month 0: Figure 33.

**Removing the e-cigarette excise tax, by stock.** Figure 17 shows the changes by stock. The response is largest among moderately vaping-addicted users: vaping-only rises by up to about 5 p.p. around three quarters of the vaping-stock ceiling, drawn from abstinence (panel (b)). E-cigarette quantity rises with the cigarette stock, from about 30% among households with no cigarette addiction to about 80% near the stock ceiling (panel (c)). Heavily smoking-addicted users who vape respond strongly to cheaper e-liquid. Cigarette quantity rises by up to 25% among lightly smoking-addicted users and fades to zero above about 60% of the cigarette-stock ceiling (panel (c)). Cheaper e-cigarettes do not reduce smoking.

Figure 17: Removal of the e-cigarette excise tax.




*Notes:* Removal of the state e-cigarette excise tax ($0.31 per millilitre, sample mean). Changes 24 months after the removal, by the stocks at the time of the removal, in the simulated population. Top row: change in action probabilities (percentage points), by the cigarette stock (panel a) and the vaping stock (panel b). Bottom row: percent change in total quantity per capita of cigarettes and of e-cigarettes on the same axes (panels c, d). Band: estimate ±1.96 bootstrap standard errors. Curves smoothed over neighbouring stock levels (seven-point weighted moving average). Month 0: Figure 34.

**Summary.** Cigarettes and e-cigarettes are substitutes in the estimated model, with cross-price elasticities of 1.3 (cigarette quantity with respect to the e-cigarette price) and 0.6 (e-cigarette quantity with respect to the cigarette price). Own-price responses are largest among lightly addicted households and shrink with the own stock, and the responses grow over two years as the stocks adjust. The bans show the asymmetry between the two products: after two years of an e-cigarette ban, 33% of previous vapers move to smoking-only and 66% of previous dual-users keep smoking. After two years of a cigarette ban, 9% of previous smokers move to vaping-only and 37% of previous dual-users keep vaping. E-cigarette consumption is then about 45% above the baseline under the cigarette ban, and cigarette consumption about 1.5% above it under the e-cigarette ban.

# 8 Discussion and Conclusion

This paper develops and estimates a dynamic discrete–continuous model of cigarette and e-cigarette demand in which two product-specific addiction stocks shift both the utility of each action and the marginal utility of quantity. Unobserved pre-panel addiction is represented by latent types, estimated jointly with the preferences by maximum likelihood, using a surrogate neural network that takes the parameters as inputs.

Addiction raises the utility of smoking and of vaping up to moderate stocks, and for cigarettes it acts mainly on the quantity margin at high stocks: the quantity shifter of a smoker at the stock ceiling is 11 times that of a new smoker. Each product's stock lowers the utility of using the other product alone. The model fits participation closely for both products and slightly under-predicts purchase sizes.

In the counterfactual experiments, cigarettes and e-cigarettes are substitutes, with cross-price elasticities of 1.3 and 0.6 that are imprecisely estimated. The responses depend on addiction: own-price responses weaken as the stocks grow, substitution into vaping comes from smokers with little vaping addiction, and substitution into cigarettes comes from moderately smoking-addicted users and from moderately vaping-addicted users. After two years of an e-cigarette ban, 67% of previous vaping-only users would move to abstinence and 33% to smoking-only, and 66% of dual-users would keep smoking, raising cigarette consumption by about 1.5%. After two years of a cigarette ban, 91% of previous smoking-only users would move to abstinence and 9% to vaping-only, and e-cigarette consumption would be about 45% higher. Higher e-cigarette taxes nonetheless carry a cost in cigarette consumption (a 5% e-cigarette tax raises cigarette quantity by 6% at once and by 29% after two years), which grows over time as the cigarette stocks of the households that switch build up.

The results come with limitations. The retention rates are calibrated at $\delta_s = 0.6$ and $\delta_v = 0.7$, which imply habit half-lives of about 1.4 and 1.9 months, and results reported by stock are on a scale that depends on this calibration. A complete estimation will also pick the value of $\delta$ based on likelihood. The fit at high cigarette stocks is weak, indicating the model misbehaves at higher smoking stocks.

**Next steps.** The most immediate extension is to compute welfare measures and the implied optimal cigarette and e-cigarette taxes, which would turn the substitution patterns documented above into a normative prescription. The agenda also includes counterfactuals at addiction-specific tax levels (the optimal tax design). A structural profile-likelihood sweep over the retention rates $(\delta_s, \delta_v)$ is needed to replace the auxiliary-regression calibration used here.

# References


Aguirregabiria, V. and Mira, P. (2002). Swapping the nested fixed point algorithm: A class of estimators for discrete Markov decision models. *Econometrica*, 70(4):1519–1543.

Aizcorbe, A., Corrado, C., and Doms, M. (2003). When do matched-model and hedonic techniques yield similar measures? Working Paper 2003-14, Federal Reserve Bank of San Francisco.

Allcott, H. and Rafkin, C. (2022). Optimal regulation of e-cigarettes: Theory and evidence. *American Economic Journal: Economic Policy*, 14(4):1–50.

Andersson, L., Bask, M., and Melkersson, M. (2006). Economic man and the consumption of addictive goods: The case of two goods. *Substance Use and Misuse*, 41:453–466.

Arcidiacono, P. and Jones, J. B. (2003). Finite mixture distributions, sequential likelihood and the EM algorithm. *Econometrica*, 71(3):933–946.

Arcidiacono, P. and Miller, R. A. (2011). Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity. *Econometrica*, 79(6):1823–1867.

Arcidiacono, P., Sieg, H., and Sloan, F. (2007). Living rationally under the volcano? An empirical analysis of heavy drinking and smoking. *International Economic Review*, 48(1):37–65.

Arrazola, R. A., Husten, C. G., Cornelius, M. E., and Armour, B. S. (2025). Notes from the field: Tobacco product use among adults — United States, 2017–2023. *MMWR Morbidity and Mortality Weekly Report*, 74(7):118–121.

Azinovic, M., Gaegauf, L., and Scheidegger, S. (2022). Deep equilibrium nets. *International Economic Review*, 63(4):1471–1525.

Bask, M. and Melkersson, M. (2003). Should one use smokeless tobacco in smoking cessation programs? A rational addiction approach. *European Journal of Health Economics*, 4(4):263–270.

Bask, M. and Melkersson, M. (2004). Rationally addicted to drinking and smoking? *Applied Economics*, 36:373–381.

Becker, G. S., Grossman, M., and Murphy, K. M. (1994). An empirical analysis of cigarette addiction. *American Economic Review*, 84(3):396–418.

Becker, G. S. and Murphy, K. M. (1988). A theory of rational addiction. *Journal of Political Economy*, 96(4):675–700.

Bhat, C. R. (2008). The multiple discrete-continuous extreme value (MDCEV) model: Role of utility function parameters, identification considerations, and model extensions. *Transportation Research Part B: Methodological*, 42(3):274–303.

Carroll, C. D. (2006). The method of endogenous gridpoints for solving dynamic stochastic optimization problems. *Economics Letters*, 91(3):312–320.

CDC (2020). Smoking and tobacco use: Fast facts. `https://www.cdc.gov/tobacco/data_statistics/fact_sheets/fast_facts/`. Accessed 2025.

CDC (2024). Health and economic benefits of tobacco use interventions. `https://www.cdc.gov/nccdphp/priorities/tobacco-use.html`. Published July 12, 2024.

Chaloupka, F. J. (1991). Rational addictive behavior and cigarette smoking. *Journal of Political Economy*, 99(4):722–742.

Chaloupka, F. J. and Warner, K. E. (2000). The economics of smoking. In Culyer, A. J. and Newhouse, J. P., editors, *Handbook of Health Economics*, volume 1, pages 1539–1627. Elsevier.

Chen, H., Didisheim, A., and Scheidegger, S. (2026). Deep surrogates for finance: With an application to option pricing. *Journal of Financial Economics*, 177:104222.

Chen, J. and Rao, V. R. (2020). A dynamic model of rational addiction with stockpiling and learning: An empirical examination of e-cigarettes. *Management Science*, 66(12):5886–5905.

Cornelius, M. E., Wang, T. W., Jamal, A., Loretan, C. G., and Neff, L. J. (2020). Tobacco product use among adults — United States, 2019. *MMWR Morbidity and Mortality Weekly Report*, 69(46):1736–1742.

Cotti, C. D., Nesson, E. T., Pesko, M. F., and Phillips, S. (2026). Standardising the measurement of e-cigarette tax rates in the USA (2nd edition), 2010–2023. *Tobacco Control*, 35(2):173–178.

Cotti, C. D., Nesson, E. T., Pesko, M. F., Phillips, S., and Tefft, N. W. (2023). Standardising the measurement of e-cigarette taxes in the USA, 2010–2020. *Tobacco Control*, 32(e2):e251–e254.

Cragg, J. G. (1971). Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica*, 39(5):829–844.

de Haan, J. and Krsinich, F. (2014). Scanner data and the treatment of quality change in nonrevisable price indexes. *Journal of Business & Economic Statistics*, 32(3):341–358.

Dempster, A. P., Laird, N. M., and Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society: Series B*, 39(1):1–22.

Druedahl, J. and Jørgensen, T. H. (2017). A general endogenous grid method for multi-dimensional models with non-convexities and constraints. *Journal of Economic Dynamics and Control*, 74:87–107.

Dubé, J.-P. (2004). Multiple discreteness and product differentiation: Demand for carbonated soft drinks. *Marketing Science*, 23(1):66–81.

Dubin, J. A. and McFadden, D. L. (1984). An econometric analysis of residential electric appliance holdings and consumption. *Econometrica*, 52(2):345–362.

Erdem, T., Imai, S., and Keane, M. P. (2003). Brand and quantity choice dynamics under price uncertainty. *Quantitative Marketing and Economics*, 1(1):5–64.

Farhi, E. and Gabaix, X. (2020). Optimal taxation with behavioral agents. *American Economic Review*, 110(1):298–336.

Fella, G. (2014). A generalized endogenous grid method for non-smooth and non-concave problems. *Review of Economic Dynamics*, 17(2):329–344.

Friedl, A., Kübler, F., Scheidegger, S., and Usui, T. (2023). Deep uncertainty quantification: With an application to integrated assessment models. Working paper.

Gordon, B. R. and Sun, B. (2015). A dynamic model of rational addiction: Evaluating cigarette taxes. *Marketing Science*, 34(3):452–470.

Gruber, J. and Kőszegi, B. (2001). Is addiction "rational"? Theory and evidence. *Quarterly Journal of Economics*, 116(4):1261–1303.

Gruber, J. and Kőszegi, B. (2004). Tax incidence when individuals are time-inconsistent: The case of cigarette excise taxes. *Journal of Public Economics*, 88(9–10):1959–1987.

Hai, R. and Heckman, J. J. (2026). The causal effects of youth cigarette addiction and education. *Journal of Political Economy*, 134(5):1347–1400.

Hajek, P., Phillips-Waller, A., Przulj, D., Pesola, F., Myers Smith, K., Bisal, N., Li, J., Parrott, S., Sasieni, P., Dawkins, L., Ross, L., Goniewicz, M., Wu, Q., and McRobbie, H. J. (2019). A randomized trial of e-cigarettes versus nicotine-replacement therapy. *New England Journal of Medicine*, 380(7):629–637.

Hanemann, W. M. (1984). Discrete/continuous models of consumer demand. *Econometrica*, 52(3):541–561.

Hendel, I. (1999). Estimating multiple-discrete choice models: An application to computerization returns. *Review of Economic Studies*, 66(2):423–446.

Hendel, I. and Nevo, A. (2006). Measuring the implications of sales and consumer inventory behavior. *Econometrica*, 74(6):1637–1673.

Hotz, V. J. and Miller, R. A. (1993). Conditional choice probabilities and the estimation of dynamic models. *Review of Economic Studies*, 60(3):497–529.

Huang, J., Tauras, J., and Chaloupka, F. J. (2014). The impact of price and tobacco control policies on the demand for electronic nicotine delivery systems. *Tobacco Control*, 23(suppl 3):iii41–iii47.

Iskhakov, F., Jørgensen, T. H., Rust, J., and Schjerning, B. (2017). The endogenous grid method for discrete-continuous dynamic choice models with (or without) taste shocks. *Quantitative Economics*, 8(2):317–365.

Ivancic, L., Diewert, W. E., and Fox, K. J. (2011). Scanner data, time aggregation and the construction of price indexes. *Journal of Econometrics*, 161(1):24–35.

Jones, A. M. (1989). A double-hurdle model of cigarette consumption. *Journal of Applied Econometrics*, 4(1):23–39.

Kase, H., Melosi, L., and Rottner, M. (2022). Estimating nonlinear heterogeneous agents models with neural networks. CEPR Discussion Paper 17391, Centre for Economic Policy Research.

Kim, J., Allenby, G. M., and Rossi, P. E. (2002). Modeling consumer demand for variety. *Marketing Science*, 21(3):229–250.

Lewit, E. M. and Coate, D. (1982). The potential for using excise taxes to reduce smoking. *Journal of Health Economics*, 1(2):121–145.

Maliar, L., Maliar, S., and Winant, P. (2021). Deep learning for solving dynamic economic models. *Journal of Monetary Economics*, 122:76–101.

McNeill, A., Brose, L. S., Calder, R., Hitchman, S. C., Hajek, P., and McRobbie, H. (2015). E-cigarettes: An evidence update. Technical report, Public Health England, London, UK. "the current best estimate is that using e-cigarettes is around 95% less harmful than smoking".

National Academies of Sciences, Engineering, and Medicine (2018). *Public Health Consequences of E-Cigarettes*. The National Academies Press, Washington, DC.

National Center for Health Statistics (2025). National health interview survey, 2024. Public-use data file and documentation. `https://www.cdc.gov/nchs/nhis/documentation/index.html`.

NielsenIQ (2024a). Consumer panel data, 2019–2024. Kilts Center for Marketing Data Center, The University of Chicago Booth School of Business.

NielsenIQ (2024b). Retail scanner data, 2019–2024. Kilts Center for Marketing Data Center, The University of Chicago Booth School of Business.

Norets, A. (2012). Estimation of dynamic discrete choice models using artificial neural network approximations. *Econometric Reviews*, 31(1):84–106.

O'Donoghue, T. and Rabin, M. (2006). Optimal sin taxes. *Journal of Public Economics*, 90(10–11):1825–1849.

Orzechowski and Walker (2024). The tax burden on tobacco: Historical compilation. Redistributed by the Centers for Disease Control and Prevention (CDC) STATE System.

Owusu, D., Huang, J., Weaver, S. R., Pechacek, T. F., Ashley, D. L., Nayak, P., and Eriksen, M. P. (2019). Patterns and trends of dual use of e-cigarettes and cigarettes among US adults, 2015–2018. *Preventive medicine reports*, 16:101009.

Pesko, M. F., Courtemanche, C. J., and Maclean, J. C. (2020). The effects of traditional cigarette and e-cigarette tax rates on adult tobacco product use. *Journal of Risk and Uncertainty*, 60(3):229–258.

Pesko, M. F. and Warman, C. (2022). Re-exploring the early relationship between teenage cigarette and e-cigarette use using price and tax changes. *Health Economics*, 31(1):137–153.

Petrin, A. and Train, K. (2010). A control function approach to endogeneity in consumer choice models. *Journal of Marketing Research*, 47(1):3–13.

Pierani, P. and Tiezzi, S. (2009). Addiction and interaction between alcohol and tobacco consumption. *Empirical Economics*, 37(1):1–23.

Rust, J. (1987). Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica*, 55(5):999–1033.

Saffer, H., Dench, D. L., Grossman, M., and Dave, D. M. (2020). E-cigarettes and adult smoking: Evidence from Minnesota. *Journal of Risk and Uncertainty*, 60(3):207–228.

Scheidegger, S. (2026). Deep learning for solving and estimating dynamic models in economics and finance. arXiv:2605.14493.

Soneji, S., Barrington-Trimis, J. L., Wills, T. A., Leventhal, A. M., Unger, J. B., Gibson, L. A., Yang, J., Primack, B. A., Andrews, J. A., Miech, R. A., et al. (2017). Association between initial use of e-cigarettes and subsequent cigarette smoking among adolescents and young adults: a systematic review and meta-analysis. *JAMA pediatrics*, 171(8):788–797.

Vahratian, A., Briones, E. M., Jamal, A., and Marynak, K. L. (2025). Electronic cigarette use among adults in the united states, 2019–2023. NCHS Data Brief 524, National Center for Health Statistics, Hyattsville, MD.

World Health Organization (2015). *WHO Report on the Global Tobacco Epidemic, 2015: Raising Taxes on Tobacco*. World Health Organization, Geneva.

Zheng, Y., Zhen, C., Dench, D., and Nonnemaker, J. M. (2017). U.S. demand for tobacco products in a system framework. *Health Economics*, 26(8):1067–1086.

# A Data Description

This appendix documents the sample, the construction of the variables, and descriptive patterns that complement Section 5. Unless stated otherwise, statistics are monthly, weighted by the NielsenIQ projection weights, and computed on the estimation sample. Confidence intervals are 95% and clustered by household.

## Sample

Table 11 traces the sample from all single-person households observed in 2019–2024 to the estimation sample. The age restriction removes three quarters of the households. The remaining filters (a missing price, incomplete demographics, or residence in one of the 11 states with 30 or fewer sample households) remove a further 241 households.

Table 11: Construction of the estimation sample.

| | Households | Household-months |
|---|---|---|
| Single-person households, 2019–2024 | 27,780 | 1,100,736 |
| Head of household under 50 | 6,779 | 189,845 |
| Price observed, complete demographics, states with $> 30$ sample households | 6,538 | 183,147 |

## Variable construction

**Action indicators.** For each household-month, I construct the discrete action $a_{it} \in \{0, s, v, sv\}$ defined in Section 5.3. Smoking and vaping participation dummies are

$$d_{it}^{s} = \mathbf{1}\{\text{total cigarette expenditure}_{it} > 0\}, \qquad d_{it}^{v} = \mathbf{1}\{\text{total vape expenditure}_{it} > 0\},$$

and $a_{it}$ is the combination of $(d_{it}^{s}, d_{it}^{v})$. Quantities and expenditures are summed within the month before the binary measures are formed. Demographics are essentially time-invariant within the window.

**Quantities.** Cigarette quantities are measured in *packs* of 20 cigarettes bought in the month. E-cigarette quantities are measured in *millilitres of e-liquid*: the number of packages bought times the total millilitres per package, taken from UPC-level size information. Using millilitres rather than device counts matters because vaping products vary widely in capacity (closed-system pods, disposables, and bottles of refill liquid). Millilitres are not nicotine-equivalent across formats, however, because nicotine strength differs across products.

**Prices and expenditures.** The price state is the county-month price of Section 5.4. The unit value a household pays, expenditure divided by quantity, is never used as the price, because it depends on the household's own choice of product and store.

**Addiction stocks.** The observed stocks $Q^s_{it}$ and $Q^v_{it}$ follow the law of motion of the model, Equation (5), with retention rates $\delta_s = 0.6$ and $\delta_v = 0.7$:

$$Q^g_{it'} = \delta_g^{\Delta}\, Q^g_{it} + \delta_g^{\Delta-1}\chi_g(x^{g,\text{obs}}_{it}), \qquad g \in \{s, v\},$$

where $Q^g_{it}$ is the pre-action stock of month $t$, as in the model, $t'$ is the household's next observed month and $\Delta = t' - t$. With $\Delta = 1$ this is Equation (5). Here $x^{g,\text{obs}}$ is the recorded monthly purchase, $\chi_g(0) = 0$, and the median quantity $\bar{x}^g$ in $\chi_g$ is computed over buyer-months in the estimation sample (unweighted: 5 packs and 16.8 mL, while the weighted medians in Table 4 are 4 packs and 16 mL). A purchase of the median quantity therefore adds one unit to the stock, and a purchase of three times the median or more adds the cap $K = 3$. The stocks are bounded by $\bar{Q}_s = 7.4$ and $\bar{Q}_v = 3.5$. Households are observed with occasional gaps in the panel, so $\Delta$ can exceed one: retention is compounded over the gap, with no imputed purchases during missing months.

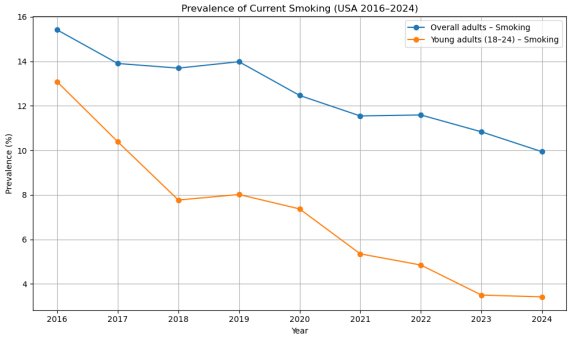
## Comparison with national prevalence

Figure 18 shows the recent trend of cigarette and e-cigarette use among U.S. adults, computed by the author from the National Health Interview Survey (NHIS) Sample Adult public-use files (2016–2024) using the sample-adult final weights (National Center for Health Statistics, 2025). Panels (a) and (b) plot the overall and young-adult (ages 18–24) prevalence of current cigarette smoking and current e-cigarette use, and panels (c) and (d) plot the same series split by sex. Cigarette smoking continues its steady decline, while e-cigarette use has risen rapidly, especially among young adults. Earlier years contain too few vapers for estimation, while the 2019–2024 window combines substantial vaping prevalence with several state-level tax changes.

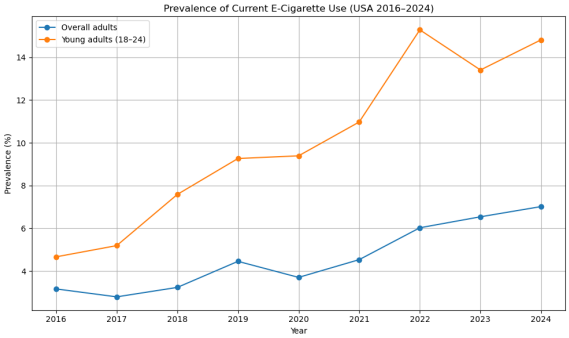
The panel's monthly purchase rates are well below these prevalence figures. Smoking participation is 5.0–6.6% of household-months and vaping participation 0.34–0.89% (Table 4). For adult cigarette smoking, NHIS estimates fell from 14.0% in 2019 (Cornelius et al., 2020) to 11.6% in 2022 and 11.0% in 2023 (Arrazola et al., 2025). For adult e-cigarette use, NHIS estimates were 4.5% in 2019, 3.7% in 2020, 4.5% in 2021, 6.0% in 2022, and 6.5% in 2023 (Vahratian et al., 2025).

Three features of the data account for most of the gap. First, the two measures differ: a monthly purchase rate counts months with a recorded purchase, while prevalence counts people who use the product on some days. Occasional users who buy rarely, or who use products bought by others, lower the purchase rate. The share of households that ever buy over the panel, 17% for cigarettes and 3.4% for e-cigarettes, is closer to the prevalence concept. Second, panellists record purchases mainly at grocery, mass-merchandise, drug,

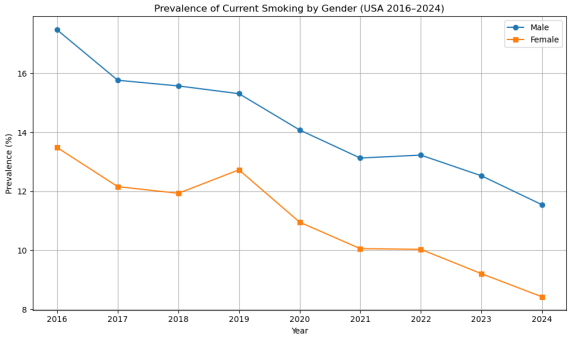
Figure 18: Smoking and e-cigarette use among U.S. adults, 2016–2024.



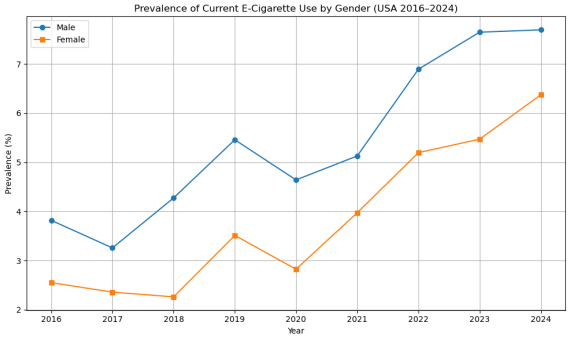

(a) Cigarette smoking: overall vs. young adults (18–24).




(b) E-cigarette use: overall vs. young adults (18–24).




(c) Cigarette smoking: men vs. women.




(d) E-cigarette use: men vs. women.

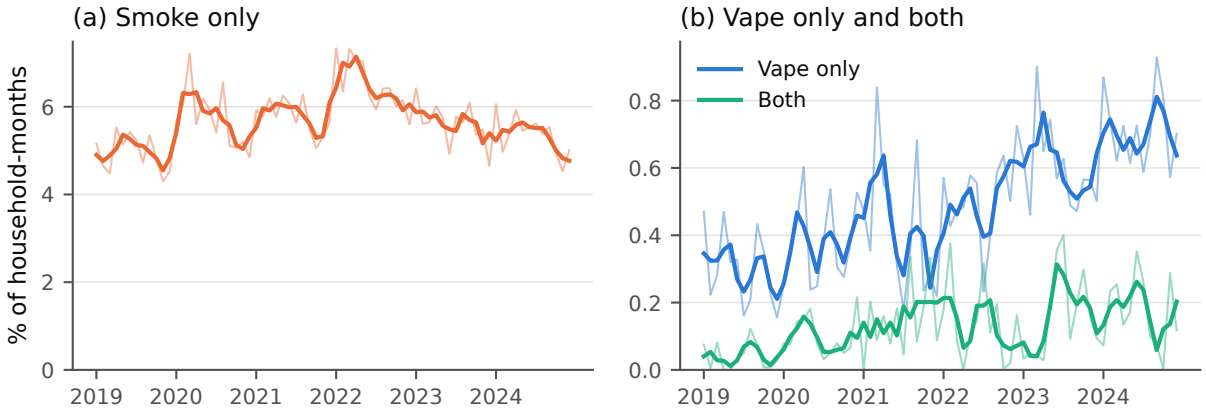
*Notes:* Prevalence of current cigarette smoking and e-cigarette use, computed by the author from the National Health Interview Survey (National Center for Health Statistics, 2025). "Current" use follows the standard NHIS definition (now uses every day or some days). Panels (a) and (b) split by age (all adults vs. ages 18–24), and panels (c) and (d) split by sex. See Arrazola et al. (2025) and Vahratian et al. (2025) for related NHIS-based prevalence estimates.

club, and dollar stores. Convenience stores, gas stations, tobacco specialty stores, and online vape retailers are under-covered, and they account for a disproportionate share of cigarette and especially e-cigarette sales. Third, single-person households are a non-random subset of the adult population. Appendix C describes a model of the recording margin. The aim of the paper is not to recover population prevalence but to identify within-household responses to price variation, for which detailed, time-stamped purchase records linked to local prices are well suited.

## Action shares over time

Figure 19 shows the monthly shares of the three nicotine actions. Smoking-only participation jumps in early 2020 and again in early 2022 and drifts down from mid-2022. Vaping-only participation more than doubles over the panel, and dual-use rises from almost zero to about 0.2%. Monthly shares of the two small actions are noisy, because a month contains only 7–32 vaper-months.

Figure 19: Monthly action shares, 2019–2024.

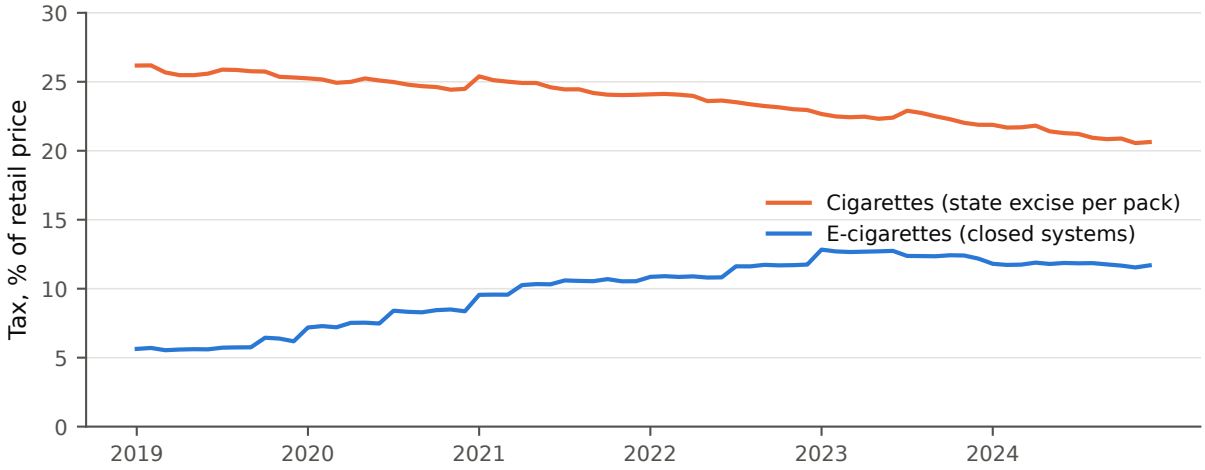



*Notes:* Weighted share of household-months in each action. Thin lines are monthly values, and thick lines are centred three-month moving averages.

## Prices and taxes

Figure 20 shows state excise taxes as a percentage of the current retail price. The average state cigarette excise falls from $1.90 to $1.75 per pack in 2019 dollars, with discrete steps when states raise their rates, and its share of the price falls from 26% to 21%: a tax set in nominal dollars per pack erodes with inflation. E-cigarette taxes rise in steps from 5.6% of the price in January 2019 to 12.8% in January 2023, as states adopt new taxes, and stand at 11.7% at the end of 2024. Over the same period the weighted share of households living in a state that taxes e-cigarettes rises from 26% to 68%.

Figure 20: State excise taxes, 2019–2024.

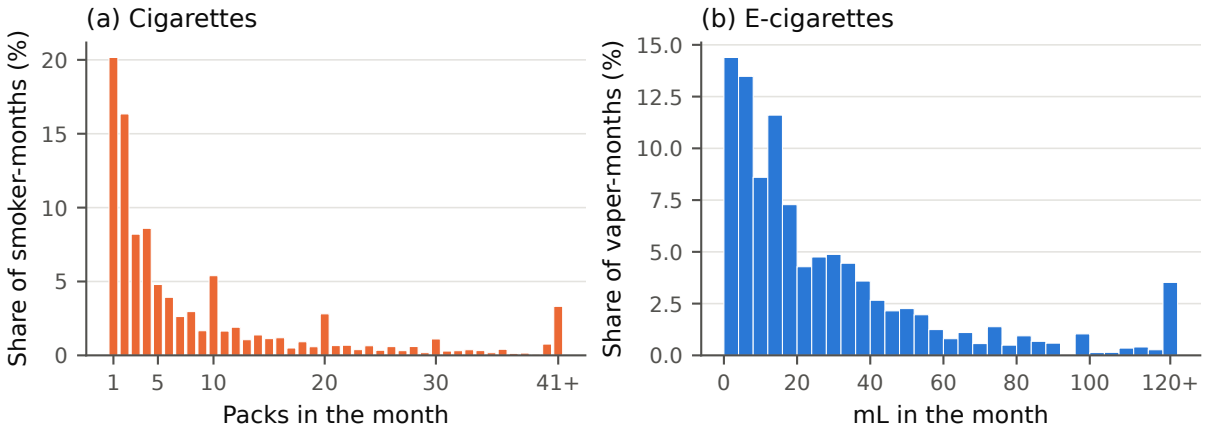



*Notes:* Taxes as a percentage of the current retail price, weighted mean over sample households. Cigarettes: state excise per pack over the state's average retail price per pack. E-cigarettes (closed systems: pods and disposables): specific taxes per millilitre over the state's average retail price per millilitre. Ad valorem taxes are the statutory rate on the wholesale price times a wholesale-to-retail ratio of 0.55. Households in states without the tax count as zero.

## Quantities

Figure 21 shows the distribution of monthly purchase quantities. One in five smoker-months contains a single pack and one in six two packs. Purchases heap at ten and twenty packs (one and two cartons), and 3% of smoker-months exceed 40 packs. E-cigarette purchases span two orders of magnitude, from 3.5 mL at the 10th percentile to 58 mL at the 90th and 168 mL at the 99th. The heavy right tail of e-cigarette purchases, from households buying refill bottles, is why the mean is well above the median in Table 4.

Figure 21: Monthly purchase quantities among buyers.

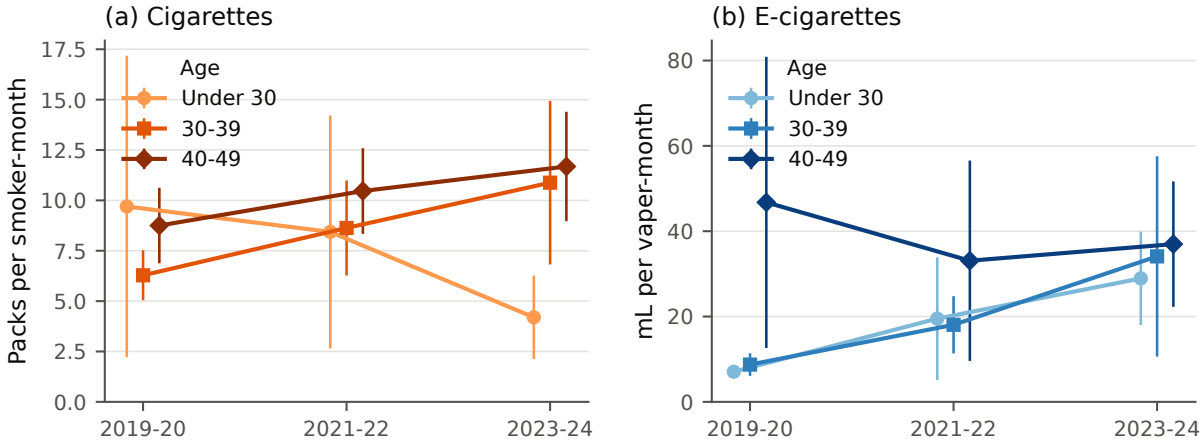



*Notes:* Weighted distribution over buyer-months. Panel (a): packs of cigarettes, top-coded at 41. Panel (b): millilitres of e-liquid, 4-mL bins, top-coded at 120 mL.

Figure 22 crosses the two dimensions of Table 4: quantity per user by age group and two-year period. Smokers aged 30–49 buy more over time, while smokers under 30 buy

less. Millilitres per vaper-month rise in the two younger groups, from about 8 mL in 2019–20 to around 30 mL in 2023–24, and stay high among vapers aged 40–49. The cells are small: the under-30 cells rest on 20–35 smoking and 4–13 vaping households, and the other vaping cells on 26–66, so these intervals are wide and the under-30 vaping estimates are only indicative.

Figure 22: Purchase quantity by age group and period.




*Notes:* Monthly purchase quantity per buyer-month by age group and two-year period. Weighted means, with 95% confidence intervals clustered by household.

Table 12 reports two further facts. Panel A shows that dual-users buy less of each product than single-product users. Panel B separates the change in quantities over time into within-household change and changes in who buys. The pooled cross-section of cigarette buyer-months shows log quantity rising by 0.27 between 2019 and 2024, but with household fixed effects the change is −0.15. The rise in packs per smoker therefore comes from the composition of smoker-months shifting towards heavier smokers, not from smokers buying more. For e-cigarettes, quantity rises within households too.

## Purchase gaps

Figure 23 shows the number of weeks between consecutive purchase weeks of the same household, computed from the weekly panel from which the monthly data are built. A gap counts only if the household is in the sample in every month it spans, so exits from the panel do not create long gaps. For both products most gaps are short: the median gap is one week, and 87% of cigarette gaps and 83% of e-cigarette gaps are four weeks or shorter. A monthly period therefore contains most purchase cycles. Long gaps are more common for e-cigarettes: 8.3% of e-cigarette gaps exceed eight weeks, against 5.6% for cigarettes, consistent with pods and bottles lasting longer than a pack. A month without an e-cigarette purchase is therefore somewhat weaker evidence of non-use than a month

Table 12: Purchase quantities by action, and composition versus within-household change.

| *A. Quantity per buyer-month, by current action* | Packs (cigarettes) | | mL (e-cigarettes) | |
|---|---|---|---|---|
| | Mean (median) | *N* | Mean (median) | *N* |
| Single product | 9.6 (4.0) | 9,897 | 31.5 (18.0) | 971 |
| Dual-use | 8.0 (4.0) | 247 | 26.0 (14.4) | 247 |
| *B. Change in log quantity per buyer-month relative to 2019* | Cigarettes | | E-cigarettes | |
| | Pooled | Within HH | Pooled | Within HH |
| 2020 | 0.09 (0.10) | 0.06 (0.07) | 0.04 (0.22) | 0.52 (0.10) |
| 2021 | 0.20 (0.11) | 0.10 (0.10) | 0.13 (0.27) | 0.37 (0.13) |
| 2022 | 0.16 (0.11) | -0.05 (0.09) | 0.39 (0.33) | 0.12 (0.13) |
| 2023 | 0.31 (0.12) | 0.00 (0.09) | 0.60 (0.37) | 0.20 (0.13) |
| 2024 | 0.27 (0.12) | -0.15 (0.10) | 0.71 (0.38) | 0.48 (0.19) |

*Notes:* Panel A: weighted mean (median) monthly purchase among buyer-months. "Single product" is smoke-only months for packs and vape-only months for mL. Panel B: weighted regressions of log monthly purchase on year dummies over buyer-months. "Within HH" adds household fixed effects. Standard errors clustered by household in parentheses.

without a cigarette purchase, consistent with the slower calibrated depreciation of the vaping stock (Section 4.5).

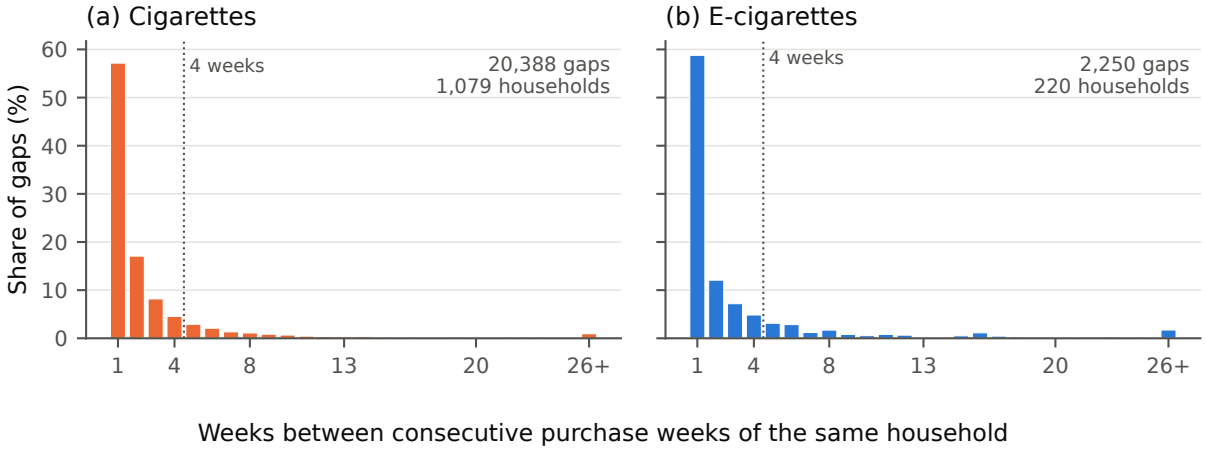
## Participation by other demographic groups

Figure 24 extends the age and income gradients of Table 4. Smoking participation falls steeply with education, from 9.8% of household-months without a college degree to 2.1% with a postgraduate degree, and is highest among households not working (13.6%). It is very low among Asian households (0.6%) and similar for men and women. Vaping participation is about a tenth as high, with broadly similar gradients.

## Transitions by age group

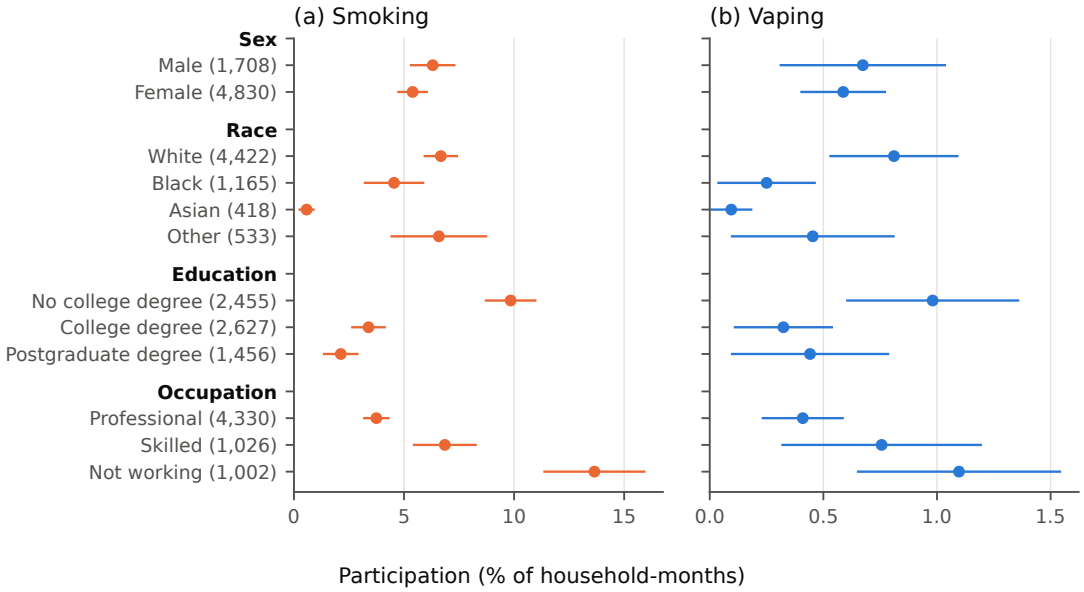
Figure 25 disaggregates the transition matrix of Table 5 by age group. Persistence rises with age in every participation state. Smokers keep smoking in 61% of next months under 30, against 75% at ages 40–49, and vapers keep vaping in 39% against 74%. Younger users mostly exit to non-use: 56% of vaper-months under 30 are followed by a month without any purchase, against 23% at 40–49. Rows with few origin months are imprecise. The under-30 dual-use row rests on 10 household-months.

Figure 23: Weeks between purchases.



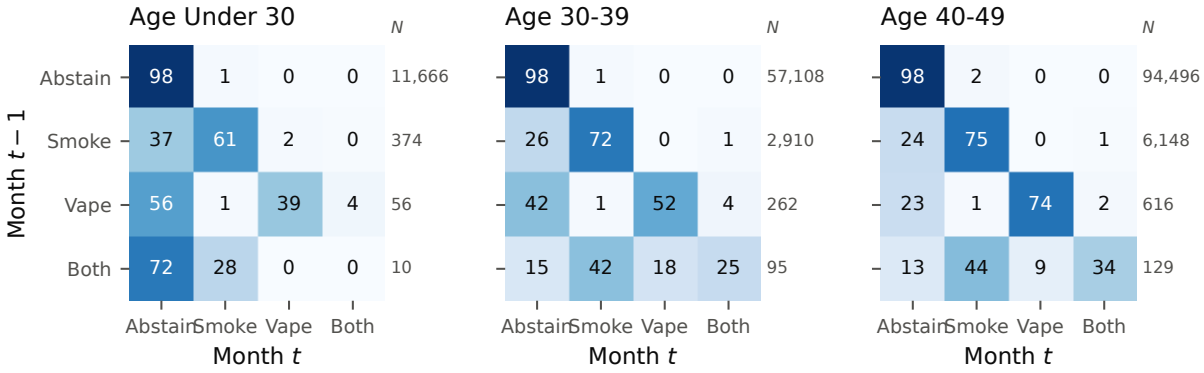

*Notes:* Weeks between consecutive purchase weeks of the same household, weighted by NielsenIQ projection weights. Gaps of 26 weeks or more are top-coded, and the dotted line marks four weeks.

Figure 24: Participation by demographic group.




*Notes:* Weighted share of household-months with a purchase, with 95% confidence intervals clustered by household. Numbers of households in parentheses. Occupation groups with fewer than 200 households (farmers, and those retired or unable to work) are omitted.

Figure 25: One-month action transitions by age group.




*Notes:* Percent. Each panel shows the weighted distribution of the action in month $t$ given the action in month $t-1$, over consecutive calendar months. Rows sum to 100. $N$ is the number of origin household-months.

These patterns establish three facts that the structural model must reconcile. First, participation is low, with smoking flat and vaping rising over the panel. Second, prices vary substantially over time and across counties, and taxes contribute much of this variation. Third, both participation and quantity are strongly persistent and build up with past use, while direct switching between the products is rare. Sections 6 and 7 return to these implications.

# B Price Index Construction

**Retail prices.** The RMS data report weekly unit sales and revenue for each UPC in each participating store. For every store-week-UPC cell I take the unit-weighted median shelf price and divide it by the package size, which gives a price per pack of 20 cigarettes or per millilitre of e-liquid. The cells are then collapsed to county-month-UPC sufficient statistics.

**Composition-adjusted index.** A county's average shelf price mixes the price level with the products its stores carry: a county whose stores stock more cartons and discount brands looks cheap even if every product is priced as elsewhere. Equation (33) separates the two. It is estimated by weighted least squares, with units sold as weights, by alternating projections on the UPC and county-month effects. The dollar index is the cost of a fixed basket at the fitted prices,

$$P_{ct} = e^{\hat{\gamma}_{ct}} \sum_{j} \bar{w}_j e^{\hat{\alpha}_j},$$

where $\bar{w}_j$ is the national unit share of UPC $j$ in 2019. The index is the arithmetic cost of the basket. The exponential of the mean UPC effect would be a geometric index, which understates the basket cost when relative prices are dispersed. The index does not depend on how the UPC and county-month effects are normalised.

**Chaining.** One set of UPC effects for the whole panel is restrictive for e-cigarettes: relative prices drift and the 2019 basket covers about half of 2024 sales. The regression is therefore estimated on overlapping two-year windows $\{y, y+1\}$, each with its own UPC effects and its own basket (2019 shares in the first window, the window's first-year shares otherwise). The first year takes its values from the first window. Each later year takes the values of the window in which it is the second year, shifted by one constant so that this window agrees, on average over the counties and months of the overlap year and weighted by units, with the values already assigned to that year. Every year-to-year change is thus measured within one window on that window's common products, as in the rolling-window indices of Ivancic et al. (2011). Both products use the chained index. For cigarettes it is almost identical to the fixed-basket index (the standard deviation of the log difference is 0.007). For e-cigarettes the standard deviation is 0.045.

**Thin cells.** County-months whose index rests on fewer than five UPCs take the state index, built in the same way at the state level. This applies to 3% of sample household-months for cigarettes and 15% for e-cigarettes.

**Price faced by households.** Every household faces the index of its county, $p^g_{ct} = P^g_{ct}$, deflated by the CPI-U (2019 = 1). Two properties follow. The price does not respond to a household's own purchase in a given month, and it does not depend on the household's choice of brands, pack sizes and stores. These choices are correlated with tastes (heavier smokers tend to buy cheaper brands), so a price built from a household's own unit values would mix its price response with its tastes. Local demand shocks that move prices and purchases together are handled by the control function of Section 4.1.

# C Under-Recording of Tobacco Purchases

Recorded purchases in the Homescan panel fall well short of survey use in the same population. Table 13 compares single-person Homescan households with NHIS adults living alone in 2019–2024 (all ages). Recorded annual cigarette purchasing is 59% of NHIS current smoking, recorded monthly purchasing 30% of monthly smoking, and recorded

packs 34% of reported consumption. For e-cigarettes the annual ratio is 17%. Differences in demographic composition explain only 6–14% of the cigarette gap and 24–44% of the e-cigarette gap. The rest lies within demographic cells.

Table 13: Homescan recorded purchases and NHIS current use, single-person households and adults living alone, 2019–2024.

| | Homescan | NHIS | Ratio |
|---|---|---|---|
| Any cigarette purchase in the year / current smoker | 8.8% | 14.9% | 0.59 |
| Any e-cigarette purchase in the year / current e-cigarette user | 1.0% | 5.9% | 0.17 |
| Months with a cigarette purchase / smoked in the month | 4.4% | 14.7% | 0.30 |
| Packs per year, purchasers / current smokers | 68 | 203 | 0.34 |

**A recording model.** Let $a_{it}$ be the true action and $o_{it}$ the recorded one. Suppose recording is one-sided: a recorded purchase is a true purchase, but a true purchase of product $g$ is recorded only with probability $r_k^g$, which varies across demographic cells $k$. With the purchase month recorded either completely or not at all, the probability of recording $o$ given the true action $a$ is

$$M(o \mid a; r) = \begin{array}{c|cccc} a \backslash o & 0 & s & v & sv \\ \hline 0 & 1 & 0 & 0 & 0 \\ s & 1 - r^s & r^s & 0 & 0 \\ v & 1 - r^v & 0 & r^v & 0 \\ sv & (1 - r^s)(1 - r^v) & 0 & 0 & 1 - (1 - r^s)(1 - r^v) \end{array}$$

and the likelihood of a recorded month replaces the choice probability with $\sum_a M(o_{it} \mid a; r)\, P_\tau(a \mid \boldsymbol{S}_{it}, \boldsymbol{z}_i; \theta)$. Only recorded zeros mix: a month without a recorded purchase is a true abstention or an unrecorded purchase, with weights that depend on the state, so a household with a high addiction stock that records nothing has most likely bought. The rate can be calibrated as the ratio of the Homescan monthly purchase rate to the NHIS monthly use rate in the cell, the latter from the NHIS question on use in the past 30 days. If unrecorded purchases also raise the addiction stock, the stock becomes a hidden state. The likelihood is then a sum over true purchase paths, which can be computed by a forward recursion over a small set of candidate stock values for each household.

**Why the main estimates do not use it.** I estimated both versions in exploratory runs with earlier versions of the model. The cigarette margin is estimable: the implied true monthly smoking rate rises from the recorded 5.3% in that exploratory sample to about 9%, recovering roughly half of the gap to NHIS. The e-cigarette margin is not. The calibrated e-cigarette rate is about 0.045, and it does not separate recording from

purchase frequency: pods and bottles last weeks, so a current vaper need not buy every month, and 39% of households that record vaping do so in only one month of a year. At such a rate a recorded zero says almost nothing about vaping, so the vaping probability of the 97% of households that never record a vaping purchase is unrestricted by the data. With 220 vaping households and 0.6% of household-months with a vaping purchase, the estimates degenerated: the addiction-stock effects on vaping turned convex and the implied true vaping rate approached one. Because substitution between the two products is the object of the paper, and the vaping side is the thin part of the data, the main estimates treat recorded purchases as true purchases. The estimated preferences therefore describe recorded purchasing. To the extent that e-cigarette purchases are under-recorded, the vaping intercepts absorb it, and the level of vaping implied by the model should be read with this in mind.

# D Participation Utility by the Addiction Stocks

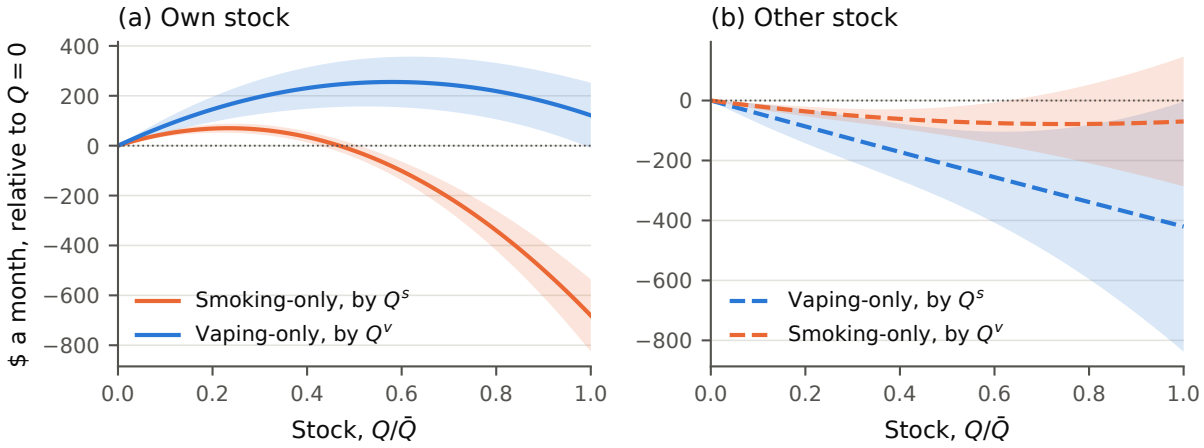
Figure 26 shows the participation term $f_a(\boldsymbol{Q})$ of the utility of smoking-only and of vaping-only, with 95% confidence bands, by the product's own stock (panel (a), the dotted lines of Figure 2) and by the other product's stock (panel (b)). The own-stock curves are inverted U-shapes: the positive linear term dominates at low stocks and the negative squared term, the self-perceived health cost of use, at high stocks. The smoking curve crosses zero at $Q^s = 3.5$ and is precisely estimated over the whole range. The vaping curve stays positive but its band widens beyond half the ceiling, where few households are observed. By the other product's stock, the cigarette stock lowers the utility of vaping-only throughout, with a band that widens with the stock, while the vaping stock lowers the utility of smoking-only by a small amount, with a band that includes zero beyond half the ceiling.

# E Additional Model-Fit Diagnostics

Figure 27 compares observed and predicted participation by calendar month. The model follows the time pattern of smoking, including the step up in 2022, within 0.2 percentage points of the data in every year. Predicted vaping rises over the panel as in the data, from 0.31% of household-months in 2019 to 0.87% in 2024, against 0.34% and 0.89% observed. Predicted series are smoother than observed shares, especially for vaping, whose monthly shares rest on few households.

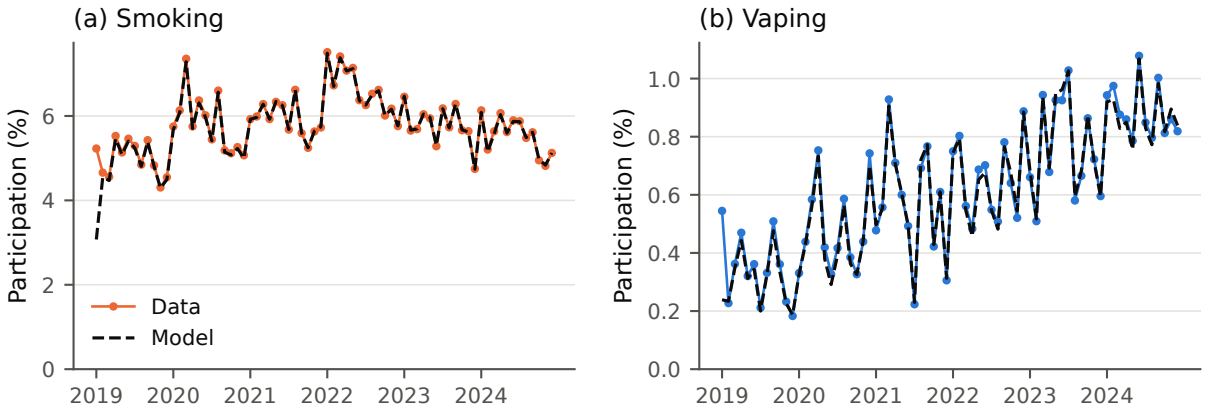
Figure 28 shows the fit for dual-use. The model matches dual-use overall: 0.12% of

Figure 26: Participation utility by the addiction stocks.




*Notes:* Participation utility of smoking-only and of vaping-only, relative to $Q = 0$, in dollars of monthly spending: (a) by the product's own stock and (b) by the other product's stock. Stocks are shown as shares of their ceilings, $\bar{Q}_s = 7.4$ and $\bar{Q}_v = 3.5$. Shaded bands are 95% confidence intervals.

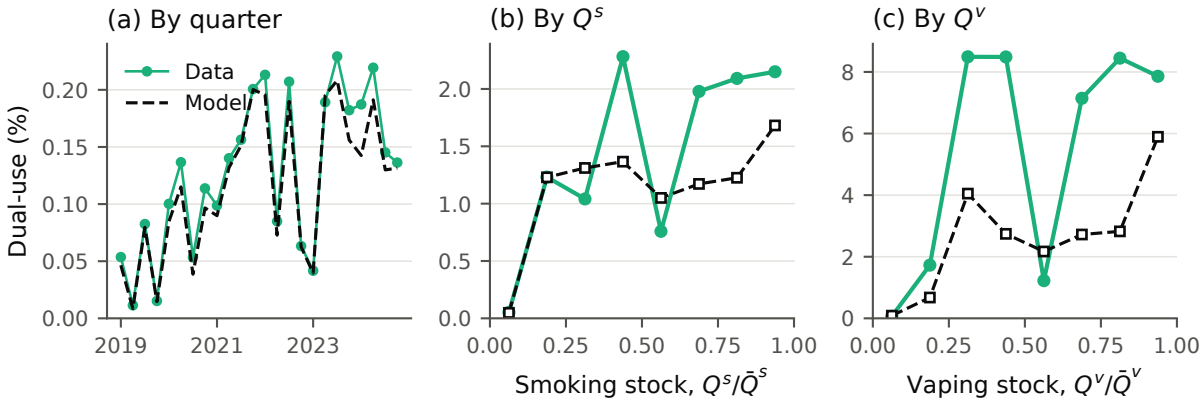
Figure 27: Model fit by calendar month.




*Notes:* Share of household-months with a purchase of the product, observed and predicted.

household-months against 0.13% in the data, and in every year (0.04–0.15% against 0.04–0.17%). By cigarette stock the predictions stay within one percentage point of the data (1.1–1.7% against 0.8–2.3% at $Q^s$ above 1). Among households with high vaping stocks the model under-predicts it: above $Q^v \approx 1$, 7–8.5% of household-months are dual-use in the data (1.2% at $Q^v \approx 2.0$) and 2–6% in the model. The high-stock cells rest on few household-months (70 to 520 above $Q^v \approx 1$).

Figure 28: Model fit: dual-use.

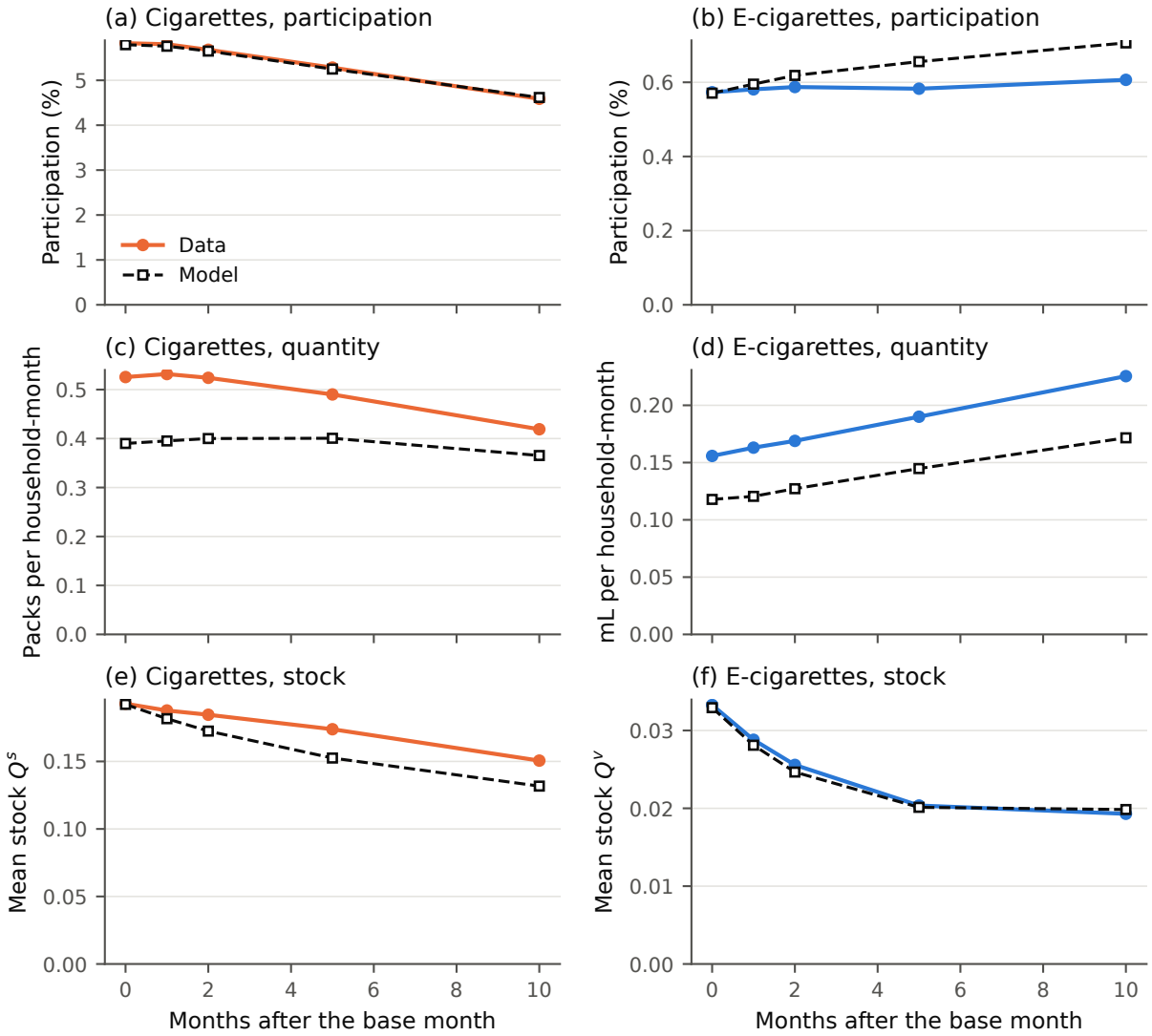



*Notes:* Share of household-months with purchases of both products, observed and predicted, (a) by quarter, (b) by the pre-action cigarette stock and (c) by the pre-action vaping stock.

Figure 29 assesses the dynamic fit. Starting from each of 62 base months (January 2019 to February 2024), the model is simulated forward for ten months along realised prices, and the simulated shares, quantities and stocks are compared with the same households in the data. At each horizon the comparison is restricted to households observed in every month from the base month on. Results are averaged over base months with equal weights.

On the participation margin the simulation tracks smoking and drifts up for vaping (panels (a) and (b)). Smoking falls from 5.8% to 4.6% over ten months in this panel of continuously observed households, and so does the simulation. Simulated vaping rises from 0.57% to 0.71%, while observed vaping rises from 0.57% to 0.61%. On the quantity margin the simulation is too low (panels (c)–(f)). Simulated purchases per household start at 0.39 packs and 0.12 mL a month, against 0.53 and 0.16 in the data. After ten months the mean cigarette stock is 0.132 against 0.151, and the mean e-cigarette stock 0.020 against 0.019. The simulated cigarette stock falls behind the data because simulated purchases are too small. The simulated e-cigarette stock stays with the data.

Figure 29: Dynamic fit.

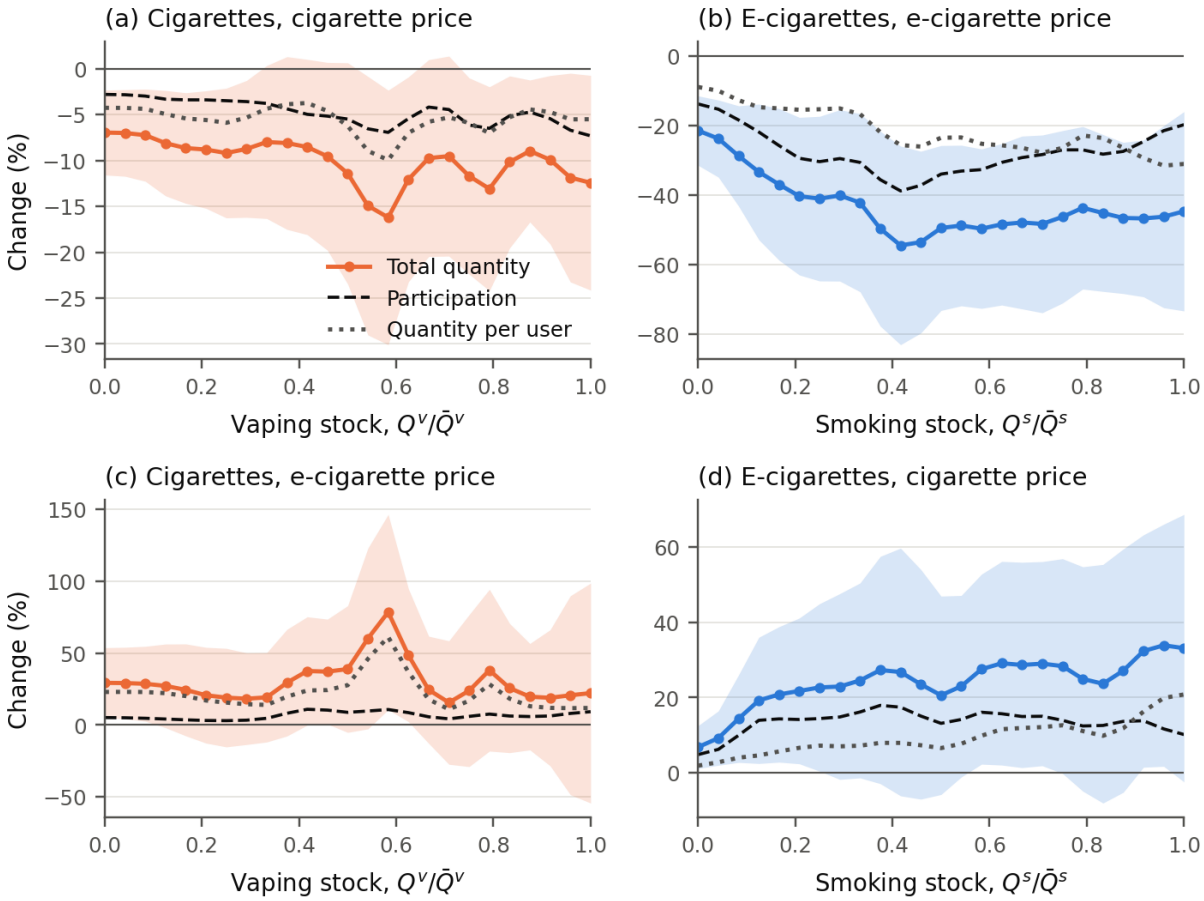



*Notes:* By months after the base month, averaged over 62 base months. Panels (a)–(b): participation. Panels (c)–(d): monthly purchase per household, including zeros. Panels (e)–(f): mean pre-action stock, simulated by the model and implied by the observed purchases.

# F Tax Responses by the Other Product's Stock

Figure 30 shows the four 24-month responses of Section 7.3 by the other product's stock at the time of the tax. A 5% cigarette tax lowers cigarette quantity by 7% among households with no vaping stock and by 12% near the vaping-stock ceiling (panel (a)). A 5% e-cigarette tax lowers e-cigarette quantity by 21% among households with no smoking stock and by 45% near the smoking-stock ceiling (panel (b)): as in the first month, the e-cigarette purchases of heavily smoking-addicted users are the most sensitive to the e-cigarette price. The e-cigarette tax raises cigarette quantity by 29% among households with no vaping stock and by 22% near the ceiling, mostly through quantity per user (panel (c)). The cigarette tax raises e-cigarette quantity by 7% among households with no smoking stock and by 33% near the ceiling (panel (d)): smokers, not households without a cigarette stock, are the ones that move to e-cigarettes.

Figure 30: Response to a 5% tax after 24 months, by the other product's stock.




*Notes:* Percent change in total quantity per capita 24 months after a permanent 5% tax, by the other product's stock at the time of the tax, with its participation and quantity-per-user components: (a) cigarette quantity under a cigarette tax by the vaping stock, (b) e-cigarette quantity under an e-cigarette tax by the smoking stock, (c) cigarette quantity under an e-cigarette tax by the vaping stock and (d) e-cigarette quantity under a cigarette tax by the smoking stock. Each panel has its own vertical scale. Shaded bands: estimate ±1.96 bootstrap standard errors.

# G Bans and Tax Removals in the First Month

This appendix reports the interventions of Section 7.4 at month 0, the first month, when the stocks have not yet adjusted: the action shares (Table 14), the purchase size by action (Table 15), the action transitions under the bans (Table 16) and the changes by stock (Figures 31 to 34). Each comparison is with the baseline at month 0, 93.8% abstinence, 5.6% smoking-only, 0.48% vaping-only and 0.12% dual-use.

An e-cigarette ban sends 87% of the vaping-only households to abstinence and 13% to smoking-only, and 61% of dual-users keep smoking. Cigarette quantity does not change (−0.1%): the households that move into smoking-only buy fewer packs than existing smokers (5.0 against 6.9), and they replace the cigarettes the dual-users bought before. The households that leave vaping are mostly heavily vaping-addicted users, and most of them go to abstinence (Figure 31). A cigarette ban sends 99% of the smoking-only households to abstinence and 1% to vaping-only, and 85% of dual-users stop. Vaping participation falls by 8% and e-cigarette quantity by 3.7%, because the dual-users who stop vaping outnumber the smokers who switch. At high cigarette stocks almost every vaping household is a dual-user, and these households stop vaping rather than vape alone, because a high cigarette stock makes vaping alone unattractive (Figure 32).

Removing the $1.84 cigarette excise raises cigarette quantity by 33% at once, through new smokers from abstinence and 25% more packs per smoker, and lowers e-cigarette quantity by 6%. The cigarette quantity response is largest among households with no cigarette stock, about 57% (Figure 33). Removing the $0.31 e-cigarette excise raises e-cigarette quantity by 17%. Smoking participation does not move (−0.2%), but existing smokers buy 2.6% more packs. E-cigarette quantity rises with the cigarette stock, from about 15% to about 50% (Figure 34).

Table 14: Action shares in the first month of the bans and the tax removals.

| | | After | | | |
|---|---|---|---|---|---|
| Action | Baseline | E-cig. ban | Cig. ban | No cig. tax | No e-cig. tax |
| Abstinence | 93.79 | 94.26 | 99.44 | 93.50 | 93.77 |
| Smoking-only | 5.60 | 5.74 | – | 5.94 | 5.58 |
| Vaping-only | 0.48 | – | 0.56 | 0.45 | 0.52 |
| Dual-use | 0.12 | – | – | 0.11 | 0.14 |

*Notes:* Percent of households in each action in the simulated population at month 0, weighted by the data's stock distribution. A ban removes the product's actions from the choice set (dash), and the removals subtract the sample-average state excise tax ($1.84 per pack, $0.31 per millilitre). Bootstrap standard errors over 50 parametric draws: 0.52 (abstinence), 0.28 (smoking-only), 0.22 (vaping-only) and 0.13 (dual-use) percentage points in the baseline, and at most 0.56 percentage points after an intervention.

Table 15: Purchase size by action in the first month of the bans and the tax removals.

| | | | After | | | |
|---|---|---|---|---|---|---|
| Product | Action | Baseline | E-cig. ban | Cig. ban | No cig. tax | No e-cig. tax |
| Cigarettes (packs) | Smoking-only | 6.90 | 6.86 | – | 8.66 | 7.08 |
| | Dual-use | 5.86 | – | – | 7.24 | 6.23 |
| E-cigarettes (mL) | Vaping-only | 24.3 | – | 23.2 | 24.9 | 26.3 |
| | Dual-use | 13.7 | – | – | 12.4 | 15.8 |

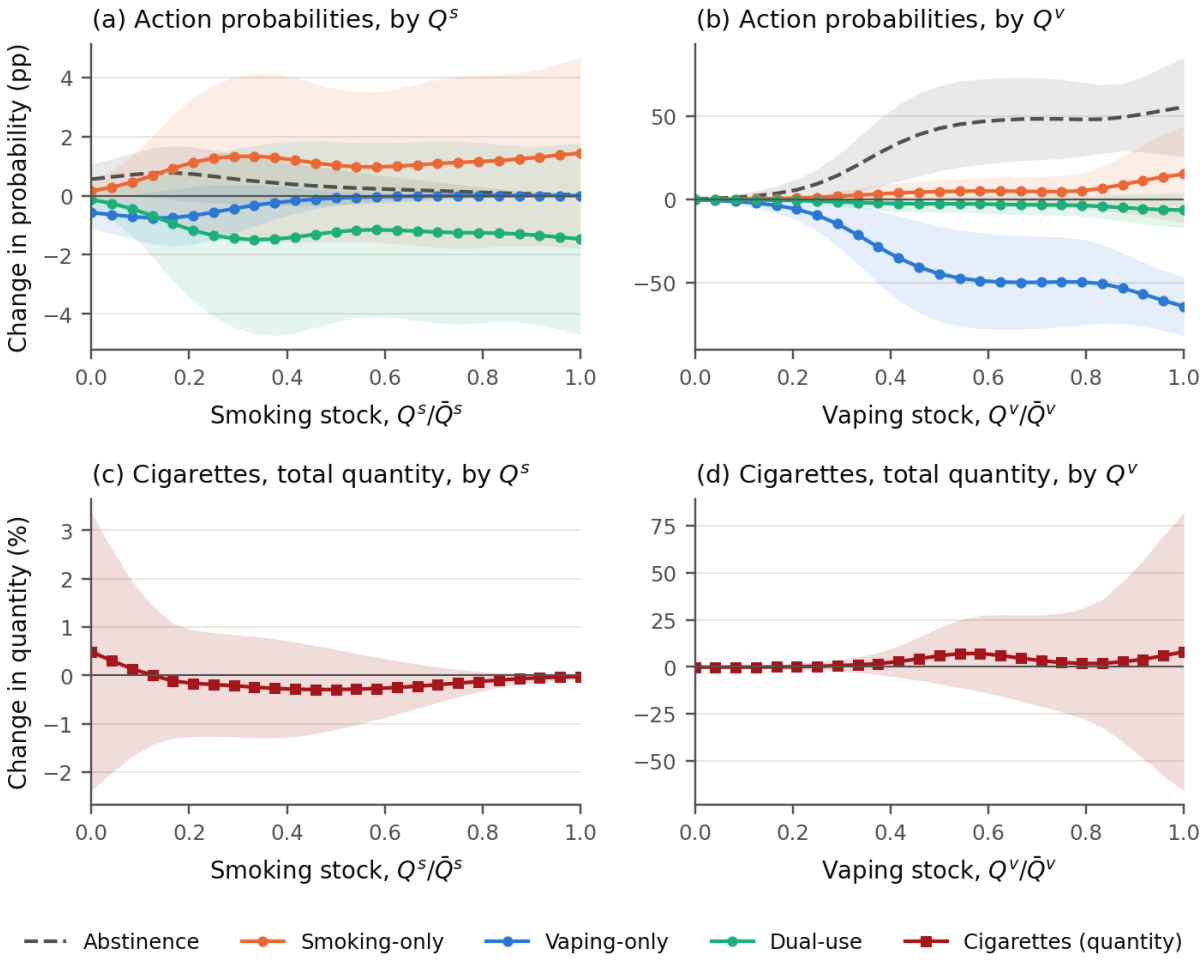
*Notes:* Mean purchase per month among the households choosing the action at month 0 in the simulated population (packs of cigarettes, millilitres of e-liquid). A dash marks an action removed from the choice set. Scenarios are as in Table 14. Bootstrap standard errors over 50 parametric draws: at most 0.5 packs for smoking-only, 2.5 packs for dual-use, 6 mL for vaping-only and 6 mL for dual-use.

Table 16: Action transitions in the first month of the bans.

| | | | Action after the ban (% of the row) | | |
|---|---|---|---|---|---|
| Ban | Baseline action | Share (%) | Abstinence | Smoking-only | Vaping-only |
| E-cigarettes | Vaping-only | 0.48 | 87.1 | 12.9 | – |
| | Dual-use | 0.12 | 39.2 | 60.8 | – |
| Cigarettes | Smoking-only | 5.60 | 99.0 | – | 1.0 |
| | Dual-use | 0.12 | 85.4 | – | 14.6 |

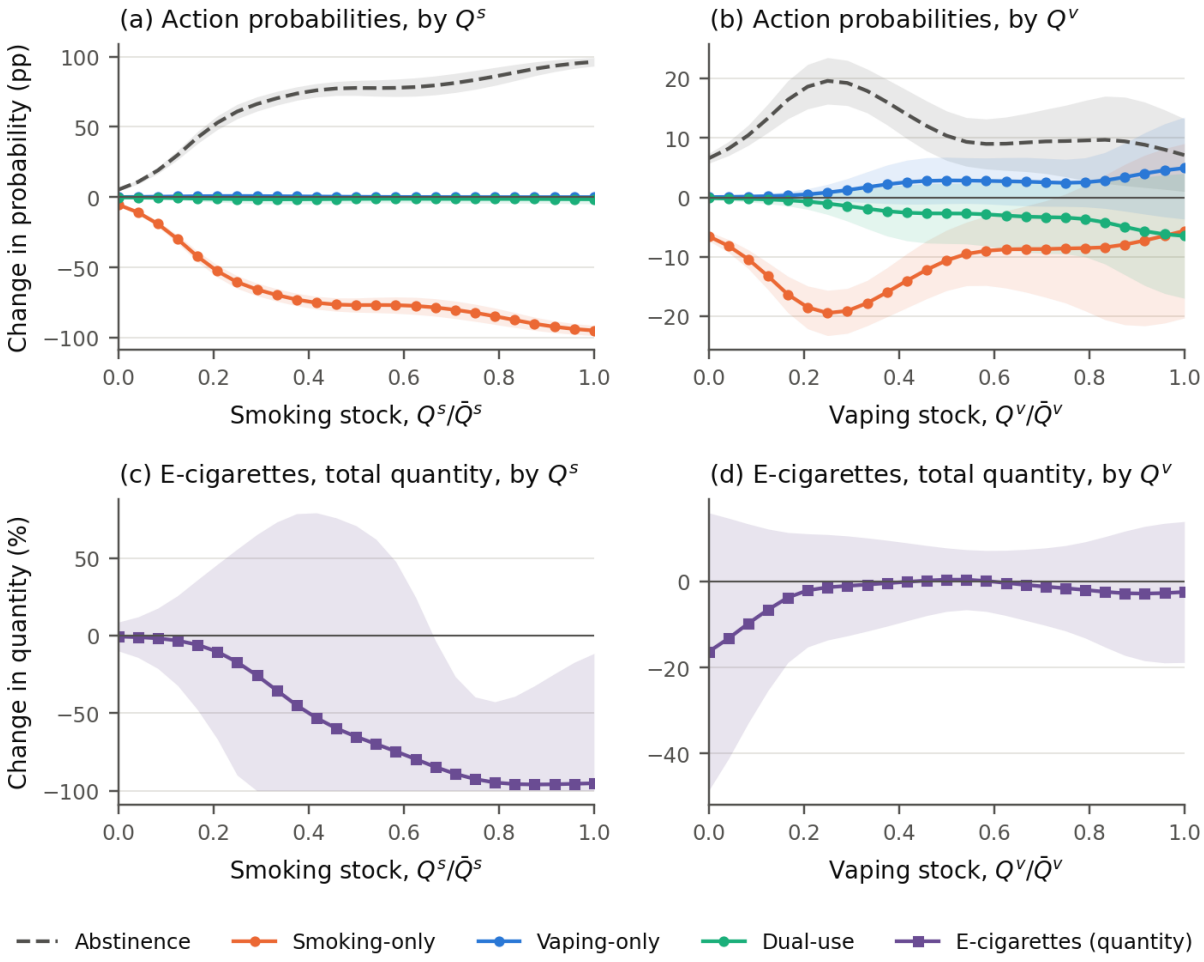
*Notes:* Each row distributes the households in a baseline action over the actions that remain available after the ban, in percent of the row, at month 0 in the simulated population. Share = the baseline share of the action. Built from the minimal-movement coupling of each household's action probabilities before and after the ban. The actions that remain available keep their households. Bootstrap standard errors over 50 parametric draws, the same for both entries of a row: 7.9 (vaping-only) and 8.6 (dual-use) under the e-cigarette ban, 0.8 (smoking-only) and 7.8 (dual-use) under the cigarette ban, in percentage points.

Figure 31: E-cigarette ban, first month.



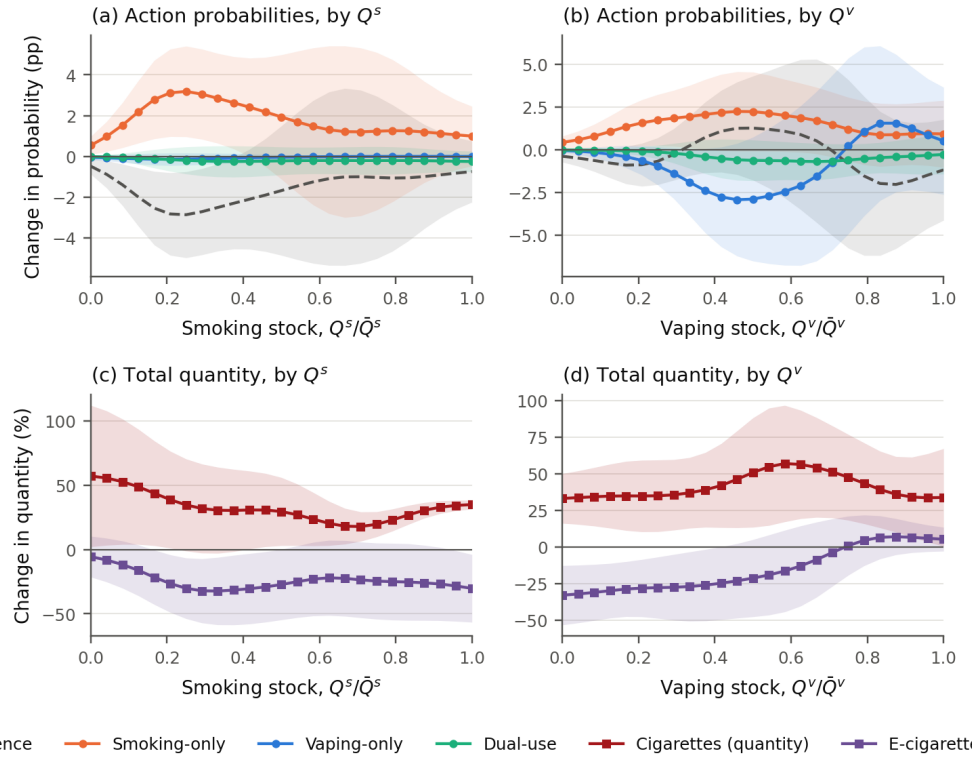

*Notes:* The vaping-only and dual-use actions are removed from the choice set. Changes at month 0 in the simulated population. Top row: change in action probabilities (percentage points), by the cigarette stock (panel a) and the vaping stock (panel b). Bottom row: percent change in cigarette quantity per capita on the same axes (panels c, d). E-cigarette quantity falls by 100% at every stock and is not drawn. Band: estimate ±1.96 bootstrap standard errors. Curves smoothed over neighbouring stock levels (seven-point weighted moving average).

Figure 32: Cigarette ban, first month.



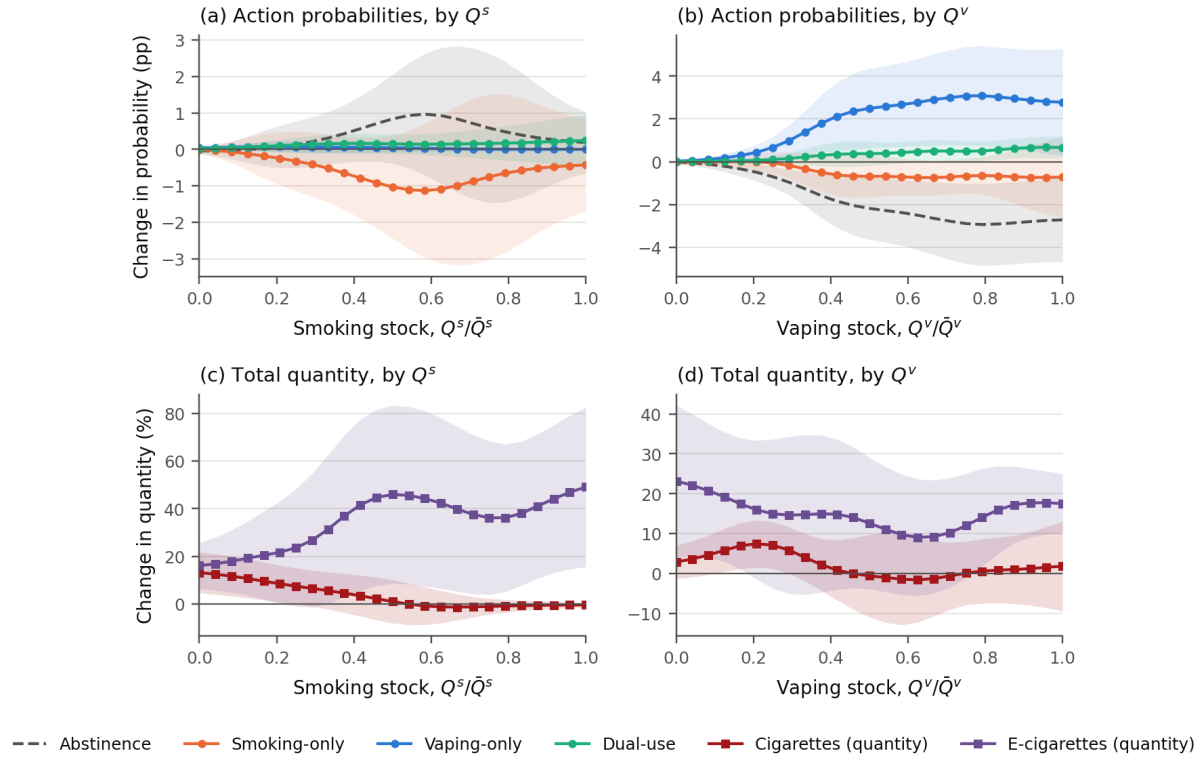

*Notes:* The smoking-only and dual-use actions are removed from the choice set. Changes at month 0 in the simulated population. Top row: change in action probabilities (percentage points), by the cigarette stock (panel a) and the vaping stock (panel b). Bottom row: percent change in e-cigarette quantity per capita on the same axes (panels c, d). Cigarette quantity falls by 100% at every stock and is not drawn. Band: estimate ±1.96 bootstrap standard errors. Curves smoothed over neighbouring stock levels (seven-point weighted moving average).

Figure 33: Removal of the cigarette excise tax, first month.




*Notes:* Removal of the state cigarette excise tax ($1.84 per pack, sample mean). Changes at month 0 in the simulated population. Top row: change in action probabilities (percentage points), by the cigarette stock (panel a) and the vaping stock (panel b). Bottom row: percent change in total quantity per capita of cigarettes and of e-cigarettes on the same axes (panels c, d). Band: estimate ±1.96 bootstrap standard errors. Curves smoothed over neighbouring stock levels (seven-point weighted moving average).

Figure 34: Removal of the e-cigarette excise tax, first month.




*Notes:* Removal of the state e-cigarette excise tax ($0.31 per millilitre, sample mean). Changes at month 0 in the simulated population. Top row: change in action probabilities (percentage points), by the cigarette stock (panel a) and the vaping stock (panel b). Bottom row: percent change in total quantity per capita of cigarettes and of e-cigarettes on the same axes (panels c, d). Band: estimate ±1.96 bootstrap standard errors. Curves smoothed over neighbouring stock levels (seven-point weighted moving average).