Online Appendix

Optimal Regulation of E-cigarettes: Theory and Evidence

Hunt Allcott and Charlie Rafkin

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A Theory Appendix

A.1 Proofs of Propositions 1 and 2

Proof of Proposition 1. After substituting the utility function and consumer budget constraint, social welfare at time 0 is

$$W(\boldsymbol{\tau}) = \sum_{\theta,t} \delta^t s_\theta \left[u_\theta \left(\boldsymbol{q}_{\theta t}; S_t \right) - \boldsymbol{p} \cdot \boldsymbol{q}_{\theta t} + z_{\theta t} + T_t \right]. \tag{23}$$

Substituting in the balanced budget constraint $T_t = \sum_\theta \left(\boldsymbol{\tau} - \boldsymbol{\phi}_\theta \right) \cdot \boldsymbol{q}_{\theta t}$ gives

$$W(\boldsymbol{\tau}) = \sum_{\theta,t} \delta^t s_\theta \left[u_\theta \left(\boldsymbol{q}_t; S_t \right) - \boldsymbol{p} \cdot \boldsymbol{q}_t + z_{\theta t} + \left(\boldsymbol{\tau} - \boldsymbol{\phi}_\theta \right) \cdot \boldsymbol{q}_{\theta t} \right]. \tag{24}$$

The effect of a marginal change in q_t^k on type θ's value function is the effect on current period utility, $\frac{\partial u_\theta(\boldsymbol{q}_{\theta t};S_t)}{\partial q_t^k} - p^k$, plus the discounted effect on the continuation value, $\delta \frac{\partial V_\theta(S_{t+1})}{\partial S_{t+1}} \cdot \frac{\partial S_{t+1}}{\partial q_t^k}$. Thus, recalling that $\boldsymbol{p}$ is the tax-inclusive price, the derivative of social welfare with respect to τ^j is

$$\begin{aligned}
\frac{\partial W_r(\boldsymbol{\tau})}{\partial \tau^j} &= \sum_{\theta,t,k} \delta^t s_\theta \left[\left(\frac{\partial u_\theta \left(\boldsymbol{q}_{\theta t}; S_t \right)}{\partial q_t^k} + \delta \frac{\partial V_\theta \left(S_{t+1} \right)}{\partial S_{t+1}} \cdot \frac{\partial S_{t+1}}{\partial q_t^k} - p^k \right) \frac{d q_t^k}{d \tau^j} - q_{\theta t}^k + \left(\tau^k - \phi_\theta^k \right) \frac{d q_{\theta t}^k}{d \tau^j} + q_{\theta t}^k \right] \\
&= \sum_{\theta,t,k} \delta^t s_\theta \left[-\gamma_\theta^k (\boldsymbol{p}, S_t) \frac{d q_{\theta t}^k}{d \tau^j} + \left(\tau^k - \phi_\theta^k \right) \frac{d q_{\theta t}^k}{d \tau^j} \right] \\
&= \sum_{\theta,t,k} \delta^t s_\theta \left(\tau^k - \varphi_\theta^k (\boldsymbol{p}, S_t) \right) \frac{d q_{\theta t}^k}{d \tau^j},
\end{aligned} \tag{25}$$

where the second line follows from the definition of $\gamma_\theta^j(\boldsymbol{p}, S_t)$ in Equation (5) and the third line follows from the definition of $\varphi_\theta^k(\boldsymbol{p}, S_t)$ in Equation (9). Setting equal to zero and re-arranging gives

$$\tau^j \sum_{\theta,t} \delta^t s_\theta \frac{d q_{\theta t}^j}{d \tau^j} = \sum_{\theta,t} \delta^t s_\theta \varphi_\theta^j (\boldsymbol{p}, S_t) \frac{d q_{\theta t}^j}{d \tau^j} + \sum_{\theta,t} \delta^t s_\theta \left(\varphi_\theta^{-j} (\boldsymbol{p}, S_t) - \tau^{-j} \right) \frac{d q_{\theta t}^{-j}}{d \tau^j}, \tag{26}$$

and dividing by $\sum_{\theta,t} \delta^t s_\theta \frac{d q_{\theta t}^j}{d \tau^j}$ gives Equation (10).

Proof of Proposition 2. The welfare effect of banning e-cigarettes beginning in period 0 is

$$\begin{aligned}
\Delta W &= \int_{\tilde{\tau}^e}^{\infty} \frac{\partial W(\tau)}{\partial \tau^e} d\tau^e \\
&= \int_{\tilde{\tau}^e}^{\infty} \sum_{\theta,t,j} \delta^t s_\theta \left(\tau^j - \varphi_\theta^j(\boldsymbol{p}, S_t)\right) \frac{dq_{\theta t}^j}{d\tau^e} d\tau^e \\
&= \sum_{\theta,t,j} \delta^t s_\theta \left[\int_{\tilde{\tau}^e}^{\infty} \tau^j \frac{dq_{\theta t}^j}{d\tau^e} d\tau^e - \int_{\tilde{\tau}^e}^{\infty} \varphi_\theta^j(\boldsymbol{p}, S_t) \frac{dq_{\theta t}^j}{d\tau^e} d\tau^e\right]. \qquad (27)
\end{aligned}$$

Integrating by parts gives

$$\sum_j \int_{\tilde{\tau}^e}^{\infty} \tau^j \frac{dq_{\theta t}^j}{d\tau^e} d\tau^e = \sum_j \tau^j q_{\theta t}^j \Big|_{\tilde{\tau}^e}^{\infty} - \int_{\tilde{\tau}^e}^{\infty} q_{\theta t}^e d\tau^e = \sum_j \tilde{\tau}^j \Delta q_{\theta t}^j - \int_{\tilde{\tau}^e}^{\infty} q_{\theta t}^e d\tau^e. \qquad (28)$$

Substituting Equations (12) and (28) into Equation (27) gives

$$\Delta W = \sum_{\theta,t} \delta^t s_\theta \left[-\int_{\tilde{\tau}^e}^{\infty} q_{\theta t}^e d\tau^e + \sum_j \tilde{\tau}^j \Delta q_{\theta t}^j - \sum_j \overline{\varphi}_{\theta t}^j \Delta q_{\theta t}^j\right].$$

Re-arranging gives Equation (13).

A.2 Proofs of Corollaries 1 and 2

Proof of Corollary 1. Since $\eta^j = \frac{dq_{\theta t}^j/dp^j}{q_{\theta t}^j/p^j}$, we have $\frac{dq_{\theta t}^j}{dp^j} = \eta^j q_{\theta t}^j/p^j$ and $\frac{dq_{\theta t}^{-j}}{dp^j} = \sigma_{\theta t}^j \eta^j q_\theta^j/p^j$. Under Assumption 1, the optimal tax from Equation (10) becomes

$$\tau^{*j} = \frac{\sum_{\theta,t} \delta^t s_\theta q_{\theta t}^j \varphi_\theta^j(\boldsymbol{p}, S_t)}{\sum_{\theta,t} \delta^t s_\theta q_{\theta t}^j} + \frac{\sum_{\theta,t} \delta^t s_\theta q_{\theta t}^j \sigma_{\theta t}^j \left(\varphi_\theta^{-j}(\boldsymbol{p}, S_t) - \tilde{\tau}_t^{-j}\right)}{\sum_{\theta,t} \delta^t s_\theta q_{\theta t}^j}. \qquad (29)$$

Adding Assumption 2 gives

$$\tau^{*j} = \frac{\sum_\theta s_\theta q_\theta^j \varphi_\theta^j}{\sum_\theta s_\theta q_\theta^j} + \frac{\sum_\theta s_\theta q_\theta^j \sigma_\theta^j \left(\varphi_\theta^{-j} - \tilde{\tau}_t^{-j}\right)}{\sum_\theta s_\theta q_\theta^j}. \qquad (30)$$

Re-arranging yields Equation (14).

Proof of Corollary 2. Under Assumption 3, Equation (13) becomes

$$\Delta W = \sum_{\theta,t} \delta^t s_\theta \left[\Delta q^e_{\theta t} \frac{\tilde{p}^e}{-2\eta} - \sum_j \Delta q^j_{\theta t} \left(\overline{\varphi}^j_\theta(\boldsymbol{p}, S_t) - \tilde{\tau}^j \right) \right]. \tag{31}$$

Adding Assumption 2 gives

$$\Delta W = \frac{1}{1-\delta} \sum_\theta s_\theta \left[\Delta q^e_\theta \frac{\tilde{p}^e}{-2\eta} - \sum_j \Delta q^j_\theta \left(\varphi^j_\theta - \tilde{\tau}^j \right) \right]. \tag{32}$$

Multiplying by $1-\delta$ gives the average per-period welfare effect:

$$\Delta \overline{W} = \sum_\theta s_\theta \left[\Delta q^e_\theta \frac{\tilde{p}^e}{-2\eta} - \sum_j \Delta q^j_\theta \left(\varphi^j_\theta - \tilde{\tau}^j \right) \right]. \tag{33}$$

B Data Appendix

B.1 RMS Data

B.1.1 Data Construction

We construct two datasets: (1) a UPC-cluster-month dataset of *e-cigarette* units sold and prices data, and (2) a UPC-cluster-month dataset of *cigarette* units sold and prices data.

Sample restrictions. We exclude data from stores that are not observed for the full 2013–2017 sample period. Since UPCs with low sales are more likely to enter and exit the sample and create an unbalanced panel, we drop UPCs with less than $100,000 in total sales from the analysis sample.

Weeks that occur in two months are assigned to the later month (i.e., the month in which the week's Saturday falls).

Weights. For simplicity, we refer to our estimates as being weighted by sales, but we do not weight by raw sales because sales are endogenous to the tax rate. We construct e-cigarette weights as follows. We construct the total sales for a given UPC-year that occur in states without e-cigarette taxes. We then divide this number by the total e-cigarette sales that occur in untaxed states in that year. Cigarette sales are nearly always subject to some tax. To construct weights for cigarette analyses, we construct the total sales in a given UPC-year (excluding that observation's own UPC-year-cluster sales), as a fraction of the total sales in that year across UPCs (excluding sales in the given UPC-year-cluster). We exclude the observation's own UPC-cluster-year sales from the numerator and denominator to account for the fact that sales are endogenous to the tax environment.

E-cigarette dataset. We construct unit-weighted prices at the UPC-cluster-month level. The cigarette prices in this dataset are cluster-month unit-weighted cigarette post-tax prices, including the monthly cigarette sales tax per pack. The cigarette tax rate is the state and national cigarette tax in a given state-month, divided by the unit-weighted cigarette post-tax price less the state-month cigarette tax.

Cigarette dataset. We convert Nielsen units and prices per unit to packs. We construct unit-weighted prices at the UPC-cluster-month level. The cigarette tax rate is the state and national cigarette tax as a fraction of the observation's unit-weighted UPC-month cigarette post-tax price less the state cigarette tax, excluding the UPC's own cluster. We drop observations where the official cigarette tax is more than the scanner post-tax price. We construct unit-weighted cluster-month e-cigarette prices, and we obtain the e-cigarette tax by using the algorithm in the following subsection. Since we are working with cluster-month data, we use the sales-weighted e-cigarette size across all clusters and the unit-weighted price across untreated clusters.

State cigarette excise taxes. We assume these are included in the price reported by Nielsen.

Sales taxes. Nielsen excludes state sales taxes. Because these change only infrequently and our regression estimates use state fixed effects and the natural log of price, such ad valorem taxes are unlikely to influence the results.

B.1.2 Constructing the E-cigarette Tax Variable

There are two types of e-cigarette taxes: ad-valorem taxes (where the tax is a percentage of the UPC price) and specific taxes (where the tax is a constant per milliliter of e-liquid). In all clusters, taxes collected are included in the UPC price recorded in RMS. Let τ'_{st} represent the ad-valorem tax rate in cluster s. With full pass-through, $\tau_{kst} = \tau'_{st}$ in ad-valorem cluster-months, for all UPCs k. To construct a consistent instrument that appropriately scales the magnitude of the tax across different regimes, we convert specific taxes to ad-valorem taxes. For each UPC-month, we generate the unit-weighted price p'_k, across all months, using only clusters with no e-cigarette taxes. Let size_k denote the mililiters of e-liquid contained in UPC k. The ad-valorem tax for UPC k in a cluster s with a specific tax α_{st} per mililiter of e-liquid in month t is given by $\tau_{kst} = \frac{\alpha_{st} \cdot \text{size}_k}{p'_k}$. In the final analysis, we drop the the observations for which we do not observe any sales in states with no e-cigarette taxes (to construct p'_k). Summarizing,

$$\tau_{kst} = \left\{ \begin{array}{cc} 0, & s \text{ has no e-cigarette tax} \\ \tau'_{st}, & s \text{ has an ad-valorem e-cigarette tax} \\ \frac{\alpha_{st} \cdot \text{size}_k}{p'_k}, & s \text{ has a specific e-cigarette tax} \end{array} \right\}.$$

The RMS data do not consistently record the size, in milliliters of liquid, of vaping products. We begin with the list of UPC sizes generously shared by the authors of Cotti et al. (2021). We augment their list with hand-collected information on the mililiters of liquid for the largest UPCs.

For UPCs where we could accurately record size, we convert the per-ml taxes to taxes that are a fraction of the UPC price. In the final dataset, we observe 79 percent of the observations' sizes. For other UPCs, we convert prices to the average sales-weighted size for UPCs whose size we did record.

The city of Chicago enacted a separate tax several months before Cook County. Because we only observe the county in which sales take place, we assume that: (i) taxes that occur in Chicago apply throughout Cook County, Illinois, and: (ii) the Cook County tax was additive on top of the Chicago tax. Moreover, Chicago enacted a tax of $0.80 per container on top of the $0.55 per ml of e-liquid. Because of the difficulty in converting RMS containers to the units taxed, we exclude the $0.80 tax.

In the event study analysis, we construct a variable τ'_{kstq} that varies by UPC, cluster, calendar month, and event quarter. In months prior to treatment in specific tax states, where τ_{ksq} varies by $k$and q, we construct α_{s0}, the size of the specific tax in cluster s in event-month 0, and generate $\tau_{kstq} = \frac{\alpha_{s0} \cdot \text{size}_k}{p'_k}$.[28]

One caveat is that we do not include a markup in our specifications: we assume that, for the states with taxes on wholesale price, the sales price is equivalent to the wholesale price.

Table A1: **E-cigarette Tax Changes Through 2017**

Area (state, county, or city)	Date	Tax rate
California	4/2017, 7/2017	27.3%, 65.1% of wholesale price
Chicago, IL	1/2016	$0.80 per container / $0.55 per ml
Cook County, IL	5/2016	$0.20 per ml
Kansas	1/2017, 7/2017	$0.20, $0.05 per ml
Louisiana	7/2015	$0.05 per ml
Minnesota	8/2010, 7/2013	35%, 95% of wholesale price
Montgomery County, MD	8/2015	30% of wholesale price
North Carolina	6/2015	$0.05 per ml
Pennsylvania	7/2016	40% of wholesale price
Washington, DC	10/2015, 10/2016, 10/2017	67%, 65%, 60% of wholesale price
West Virginia	7/2016	$0.075 per ml

Notes: Data are from Cotti et al. (2021, Appendix Table 1) and Tax Foundation (2019). The table excludes changes in Alaska, which does not appear in the RMS data. As explained in Appendix B, we exclude the per-container tax for Chicago in our estimates and apply Chicago's taxes to all of Cook County.

B.2 Sample Surveys

This section details our construction of harmonized samples across the BRFSS, MTF, NHIS, NSDUH, and NYTS. Table A2 presents information on each dataset.

[28] For consistency with other sample restrictions, we drop the pre-treatment observations where the implied $\tau_{ksq} > 1$.

Table A2: **Smoking and Vaping Sample Surveys**

Dataset	Population	Observations	Years	Notes
BRFSS	Adults	5,346,115	2004–2018	Sampling change in 2011
MTF	Youth	591,740	2005–2018	Inconsistent race data in 2004
NHIS	Adults	412,888	2004–2018	
NSDUH	Adult sample	590,303	2004–2018	No vaping data
NSDUH	Youth sample	268,676	2004–2018	No vaping data
NYTS	Youth	227,813	2004, 2006, 2009, 2011–2018	

Notes: Datasets are the Behavioral Risk Factor Surveillance System (BRFSS), the National Health Interview Survey (NHIS), the National Survey of Drug Use and Health (NSDUH), Monitoring the Future (MTF), and the National Youth Tobacco Survey (NYTS)

B.2.1 Sample Weights

All surveys excluding MTF come with nationally representative sample weights; MTF provides relative sampling odds, which we transform to sample weights. We use the survey-provided sample weights for adults. For youth, we rescale the sampling weights by the sum of weights within dataset-grade-year grade. Hence, within dataset, each observation retains its sampling weight relative to other observations within the dataset. Once we append the datasets, the sampling weights are appropriately scaled with respect to one another.

B.2.2 Income quintile construction

We construct income quintile within dataset-year, including sampling weights. Income is often recorded in bins, and occasionally the bins cut across quintile cut points. We assign to the lower quintile except in the case of the NHIS's first quintile, because doing so would only four quintiles in some years. To ensure there are five income quintiles in every year, we re-assign incomes that cut across the first and second quintiles to income quintile 1 in the NHIS prior to 2006 and income quintile 2 for 2007–2018. In the 2018 NSDUH, there are only four income groups recorded, which we code as quintiles 1, 2, 4, and 5.

B.2.3 Adult Smoking (NHIS, NSDUH, BRFSS)

NHIS. We use the *smknow*, *cigsda1*, and *cigsda2* variables to identify people who report smoking "every day," "some days," or "not at all." Among people who smoke every day, we use *cigsda1* to construct the average number of cigarettes smoked per day. If someone reports smoking "not at all," we impose that these people smoke 0 cigarettes per day on all days. Among people who report smoking "some days," we use *cigdamo* to generate the average number of days smoked in the past 30 days and the *cigsda2* variable to generate the average number of cigarettes smoked on days when the person smokes; we extract the average number of cigarettes smoked per day as ci*gsda2* $\times$ *cigdamo*/30.

NSDUH. We use the *cig30av* variable to compute the average number of cigarettes smoked per day on days smoked. Because the variable is interval censored, we use the midpoint of the reported ranges. We code the final interval ("35 cigarettes or more, about two packs") as 50 cigarettes (2.5 packs), for consistency with other top-coded datasets. We use the *cig30use* variable to compute the average number of days in the past 30 days when the respondent smoked. Among the small proportion of people who do not remember the precise number of days smoked, we use the midpoint of ranges reported in the *cg30est* variable to compute an estimate of the number of days smoked. We extract the number of cigarettes smoked per day in the past 30 as (number of days smoked in the past 30 / 30) $\times$ (number of cigarettes smoked on days smoked).

BRFSS. We use the *smokeday* and *smokday2* variables to construct a variable encoding whether someone smokes "every day," "some days," or "not at all." We rescale these variables for comparability by using the following algorithm.

For each year in 2004-2018, append the NHIS and NSDUH datasets. Keep only those people with non-missing values of demographic variables used in the main analysis. Extract smoking intensity among "every day" smokers: compute the average number of cigarettes smoked per day among people who report smoking 30 days in the past 30 in the NSDUH, or who smoke "every day" in the NHIS. Extract smoking intensity among "sometimes" smokers: compute the average number of cigarettes smoked per day among people who report smoking between 1 and 29 days in the past 30 in the NSDUH or who smoke "some days" in the NHIS. Construct a "predicted" smoking intensity for that year and smoking status by regressing the number of cigarettes smoked on survey year (i.e, compute a linear fit). Weight regression by sampling weights in each dataset. Divide the number of cigarettes smoked by 20 to obtain number of packs consumed per day.

Among people who report smoking "every day" in BRFSS, we impose that the person smokes the average number of packs in that year among every day smokers. Among people who report smoking "some days" in BRFSS, we impose that the person smokes the average number of packs in that year among "sometimes" smokers.

B.2.4 Adult Vaping (NHIS, BRFSS)

NHIS. We use the *ecig30d2*, *ecigcur2*, and *ecigev2* variables to construct a variable that is 1 if the person vaped "every day" (in *ecigcur2*), 0 if the person vaped "not at all" (in *ecigcur2*) and is *ecig30d2*/30 if the person reports vaping "some days" (in *ecigcur2*).

BRFSS. We use the *ecignow* and *ecigaret* variables to construct a variable that encodes whether the person vapes "every day," "some days," or "not at all." We use a similar algorithm as for vaping to rescale the variable for comparability: Among people who report vaping "not at all" in BRFSS, impose that the person has a vaping equivalent of 0. Among people who report vaping "every day" in BRFSS, impose that the person has a vaping equivalent of 1. For each year in 2016–2018, append the NHIS datasets. Keep only those people with non-missing values of demographic variables used in the main analysis. Extract smoking intensity among "sometimes" vapers: compute the average number of days vaped in the past 30 among people who report vaping "some days" in the NHIS. Among people who report smoking "some days" in BRFSS, impose that the person has a vaping equivalent of the average value extracted among vapers who report vaping "some days." Unlike in the exercise for smoking, do not generate separate values for each year.

B.2.5 Youth Smoking (MTF, NYTS, NSDUH)

MTF. We define packs per day as the number of cigarettes smoked per day on average, divided by 20. We recode the top-coded observations that report smoking 2 or more packs per day as smoking 50 cigarettes per day.

NYTS. We use the midpoint of the interval containing the number of cigarettes per day smoked and the midpoint of the number of days smoked to obtain the number of packs smoked per day. We code "20 or more" cigarettes per day as 30 cigarettes per day.

NSDUH. Same as adults.

B.2.6 Youth Vaping (MTF, NYTS)

Both datasets. We extract the midpoint of the interval containing the number of times the respondent reports vaping electronic cigarettes last month. We define vaping equivalents as the midpoint of this interval, divided by 30.

Additional details about the MTF vaping data. The MTF has several different variables from 2014–2018 that record the number of days the respondent reports vaping. By year, they are as follows (emphasis from MTF codebooks).

2014:

- During the LAST 30 DAYS, on how many occasions (if any) have you used electronic cigarettes (e-cigarettes)?

2015:

- During the LAST 30 DAYS, on how many occasions (if any) have you used electronic cigarettes (e-cigarettes)?
- During the LAST 30 DAYS, on how many days (if any) have you used an electronic vaporizer such as an e-cigarette?

2016:

- During the LAST 30 DAYS, on how many days (if any) have you used electronic cigarettes (e-cigarettes)?
- During the LAST 30 DAYS, on how many days (if any) have you used an electronic vaporizer such as an e-cigarette?

2017:

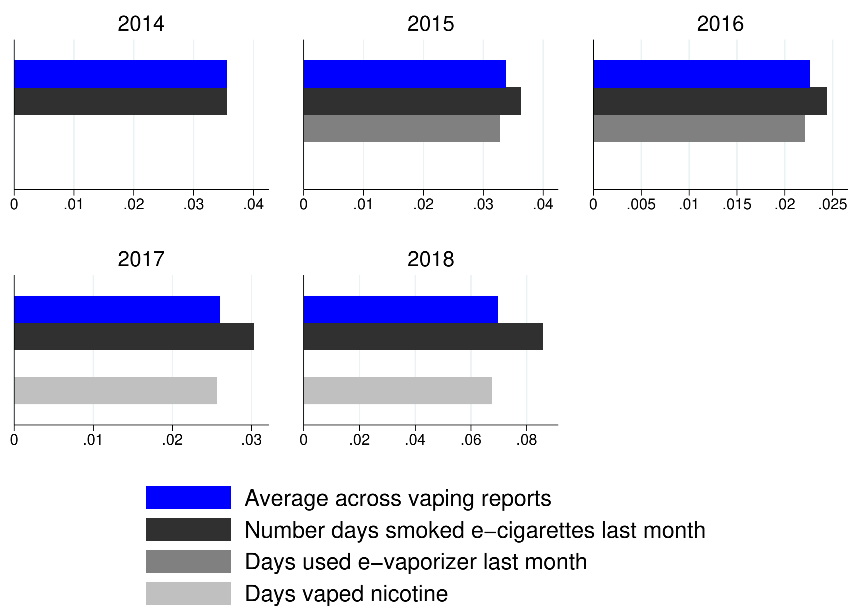
- On how many occasions (if any) have you vaped NICOTINE during the last 30 days?
- During the LAST 30 DAYS, on how many occasions (if any) have you used electronic cigarettes (e-cigarettes)?

2018:

- On how many occasions (if any) have you vaped NICOTINE during the last 30 days?
- During the LAST 30 DAYS, on how many occasions (if any) have you used electronic cigarettes (e-cigarettes)?

We combine these reports as follows. If a respondent is ever recorded asked *multiple* vaping questions, we take the average. If the respondent records vaping more than 30 times in the past month, we recode this as 30 (such that the maximum number of *days* in the last month is 30). Figure A1 illustrates that mean vaping rates align well across these reports.

Figure A1: **MTF Vaping Rates by Question**



Notes: This figure presents vaping rates by year and question from the Monitoring the Future survey.

B.2.7 Additional Issues in Sample Surveys

NSDUH. The NSDUH is the sole youth survey that does not have a clean way of identifying students' current grade to provide comparability with MTF and NYTS. We therefore count people in grades 6–12, or people who are age 18, as youth. Because we include 18–24 year olds in the adult estimations, this means the 18 year-olds in the NSDUH appear in both the youth and adult surveys. The public-use NSDUH data also provide ages in bins that are not comparable to the BRFSS and NHIS for some adults. For demographic controls, we code NSDUH 18–23 year olds as 18–24 year olds and NSDUH 24–29 year olds as 25–29 year olds.

BRFSS. Because of inconsistent data collection, we drop survey respondents from Guam, Puerto Rico, and other territories from the BRFSS sample.

MTF. The MTF samples only the 48 contiguous states. The MTF does not sample dropouts. We are limited to four race/ethnicity groups in the youth dataset because Asian is not a separate category from other race in the public-use MTF.

NYTS. The NYTS does not sample dropouts.

B.2.8 Total Quantities in Sample Surveys versus Sales Data

The total cigarette and e-cigarette sales implied by our sample survey data and unit conversion parameters line up imperfectly with national sales data. Multiplying 2018 average smoking for adults and youths from Figure 2 by the total population sizes gives (0.082 packs/day $\times$ 254 million adults + 0.006 packs/day $\times$ 25 million youth) $\times$ 365 days/year $\approx$ 7.7 billion packs. This is 64 percent of the 12 billion packs sold in 2018 as reported in Figure 1. This 64 percent ratio is consistent with the public health literature on under-reported smoking prevalence in sample surveys: for example, Liber and Warner (2018) find 61 percent ratio in the NHIS and about 70 percent in the NSDUH.

For e-cigarettes, multiplying 2018 average vaping for adults and youths from Figure 2 by total population sizes gives (0.03 $\times$ 254 million adults + 0.06 $\times$ 25 million youth) $\times$ 0.58 ml/day $\times$ \$3.90/ml $\approx$ \$7.54 billion. This is nine percent larger than the \$6.9 billion in vapor products sold in 2018 as reported in Figure 1.

B.3 Other Data

E-cigarette User Survey:

- Weight construction. We construct weights using Entropy Weight Rebalancing (Hainmueller 2012), targeting the distribution of gender, income, and e-cigarette use from adults in the sample of BRFSS and the NHIS who report non-zero vaping.

- E-liquid use per day. Several participants record more than 3 ml per day of e-liquid use. We drop their reports from the data, since these are unrealistically large, and winsorize other reports at 2 ml per day.

- Price per day. We construct the weighted mean among participants who report using 3 ml or less e-liquid per day.

E-cigarette Tax Rates:

- We use January 1, 2018 tax rates from Tax Foundation (2018). We convert specific taxes to ad valorem taxes using the mean e-cigarette size from RMS and price from the E-cigarette User Survey. We exclude Chicago's per container tax due to difficulties in converting the per container tax to per ml units. As in the Nielsen data, we assign Chicago's taxes to all of Cook County.

Cigarette taxes:

- We use information from Federation of Tax Administrators (2020) and Tax Policy Center (2018).

C Cigarette Smoking and Youth Marijuana Use Trends

C.1 Cigarette Smoking

In Section 2.4, we build on the ideas of Levy et al. (2019) in considering the changes in smoking trends that would be expected if vaping and smoking were strong substitutes or complements. To quantify this idea, recall the substitution parameter $\sigma_\theta = \mathbb{E}_t\left[dq^c_{\theta t}/dq^e_{\theta t}|\theta\right]$, in units of cigarette packs per day vaped. The introduction of e-cigarettes increases $q^e_{\theta t}$ from 0 to $q^e_{\theta t}(\tilde{\boldsymbol{p}})$, which in turn changes cigarette consumption by $\sigma_\theta q^e_{\theta t}(\tilde{\boldsymbol{p}})$. In the sample survey data, the average day of smoking by an adult (youth) involves 0.5 (0.15) packs smoked. Thus, $\sigma_\theta \approx -0.5$ ($\sigma_\theta \approx -0.15$) implies that the average smoking day and the average vaping day are perfect substitutes for adults (youth), and $\sigma_\theta \approx 0.5$ ($\sigma_\theta \approx 0.15$) implies that they are perfect complements for adults (youth).

An average vaping day costs 0.58ml $\times$ \$3.90/ml $\approx$ \$2.26 of e-liquid, so if the \$6.9 billion in 2018 e-cigarette sales were all for e-liquid, this would be equivalent to 3.05 billion average vaping days. At 0.5 cigarette packs per average smoking day, 3.05 billion average smoking days would equal about 1.5 billion packs. Thus, if the average vaping and average smoking days were perfect complements (substitutes) over a several-year horizon, cigarette sales would have increased (decreased) by 1.5 billion packs per year by 2018 relative to a counterfactual without e-cigarettes. Since the sales decline on Figure 1 is close to linear over 2004–2018, daily vaping and daily smoking could therefore only be perfect complements or perfect substitutes if the counterfactual sales trend would have been noticeably different from its long-standing historical pattern.

We can do a similar exercise for the sample survey data in Figure 2. In each panel, the left and right y-axes have the same scales. Panel (a) shows that adults vaped on share 0.025 of days in 2018. Thus, if $\sigma_\theta = 0.5$ (or $\sigma_\theta = -0.5$) over several years, adult smoking would have increased (or decreased) by about 0.0125 packs per day relative to counterfactual. Since the adult smoking decline on Panel (a) is close to linear over 2004–2018, σ must be relatively close to zero unless the counterfactual smoking trend would have changed noticeably after 2013. This visual argument is particularly clear for youth, who vape on share 0.05 to 0.08 of days in 2018 but have a steady linear decline in cigarette consumption to less than 0.01 packs per day by 2018.

C.2 Youth Marijuana Use

Our welfare analysis does not account for substitution from e-cigarettes into other drugs like marijuana that may be harmful. In this section, we provide suggestive evidence that any complementarity is limited. Specifically, we show that here was no change in aggregate marijuana consumption as vaping became more popular. While *vaping* marijuana becomes more popular, *total* marijuana use exhibits a small decline.

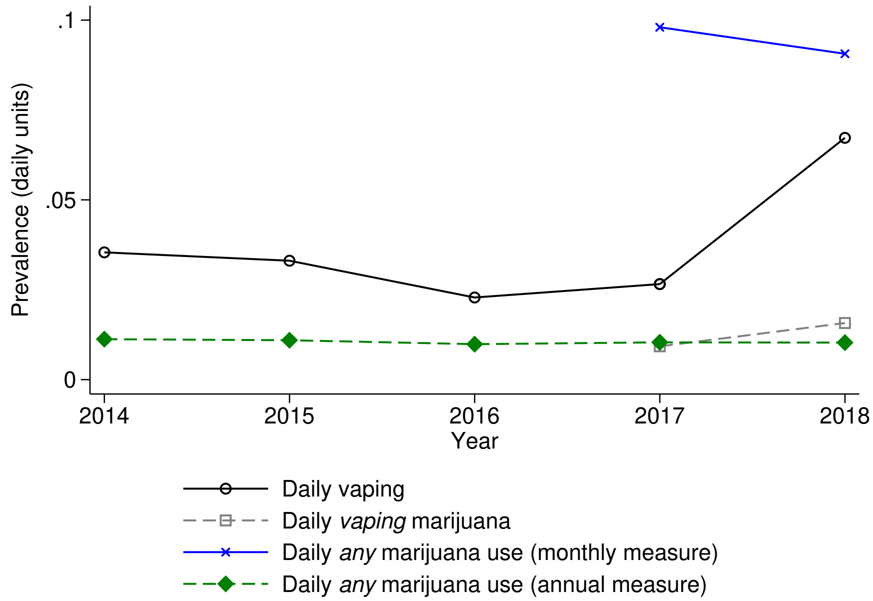
We focus on youth vaping, for whom the concerns about substitution into marijuana products are most salient. The MTF provides several measures of marijuana use. First, beginning in 2014, the MTF asks respondents the number of times they consumed marijuana last year in any form. Second, beginning in 2017, the MTF asks respondents the number of times that they consumed marijuana last month in any form. Third, beginning in 2017, the MTF asks respondents the number of times that they vaped marijuana last month. We standardize these variables to construct the number of times the respondent consumed vaped marijuana each day. Due to interval censoring and top coding, the marijuana consumption measures do not align perfectly. In particular, both the monthly and annual marijuana measures are subject to significant top coding; the participant cannot report consuming marijuana more than 40 times in the past month or year. As a result, the annual measure naturally lies below the monthly estimate. However, we are concerned with trends in marijuana use as e-cigarette use becomes popular and simply discuss changes in marijuana use, comparing each measure over time.

In Appendix Figure A2, Panel (a), we present the time series of e-cigarette use against the time series of our three measures of marijuana use; Panel (b) focuses on grades 11–12, which has higher rates of both e-cigarette use and marijuana consumption. This figure illustates that while *vaping* marijuana does become more popular in 2018 (as e-cigarette use grew), the time series of *aggregate* marijuana use exhibits no change over this period. In fact, the monthly measure of marijuana consumption shows a small decline from 2017–2018 in both the full sample and grades 11–12. While we do not conduct a full substitution analysis, these figures suggest that the aggregate data are inconsistent with the concern that our welfare analysis neglects important distortions induced by e-cigarette use.

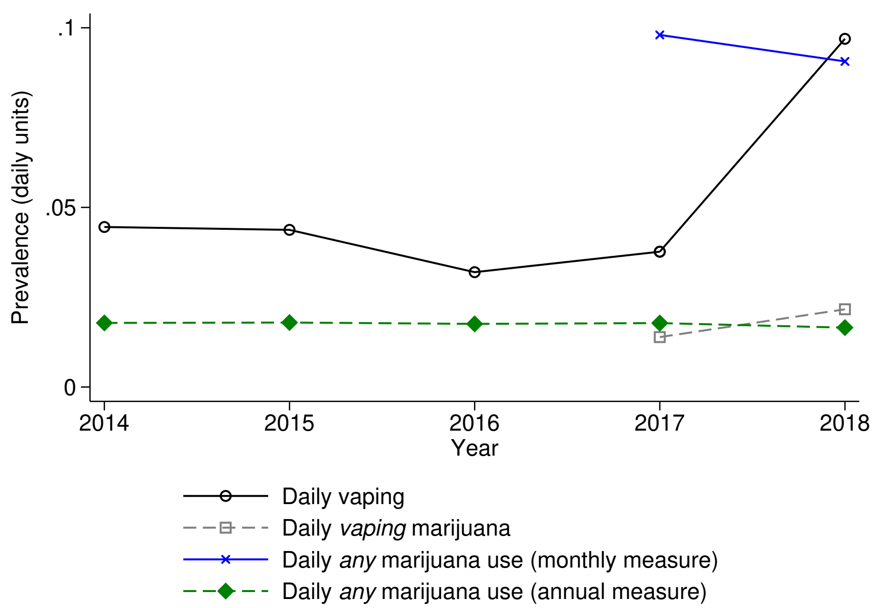
One important caveat is that vaping may be a more harmful way to consume marijuana: the 2,807 lung injuries and 68 deaths from vaping in 2019 and early 2020 were primarily linked to marijuana e-liquids (Centers for Disease Control 2020).

Figure A2: **Trends in Youth Marijuana Use**

(a) **All**



(b) **Grades 11–12**



Notes: This figure presents trends in marijuana and e-cigarette use in the Monitoring the Future (MTF) survey. Panel (a) presents the full sample, while panel (b) focuses on grades 11 and 12. The black lines present our daily vaping measure. The gray lines present the average daily *vaping* marijuana use, constructed from an MTF question that asks about the number of times the respondent vaped in the past month. The blue line presents the average daily marijuana consumption of any form, constructed from an MTF question that asks about the number of times the respondent consumed marijuana in the past *month*. The green line presents the same measure, but from an MTF question that asks about the number of times the respondent consumed marijuana in the past *year*. The green line lies below the blue line due to top-coding.

D Price Elasticity Appendix

Table A3: **Own- and Cross-Price Elasticity of Demand for Cigarettes (UPC-level estimates)**

(a) **First Stage and Reduced Form**

	(1)	(2)	(3)
Dependent variable:	ln(cig price)	ln(e-cig price)	ln(cig units)
ln(cig % tax rate + 1)	1.087	-0.111	-0.828
	(0.021)	(0.123)	(0.194)
ln(e-cig % tax rate + 1)	-0.006	0.555	-0.069
	(0.018)	(0.094)	(0.157)
Observations	1,938,947	1,938,947	1,938,947

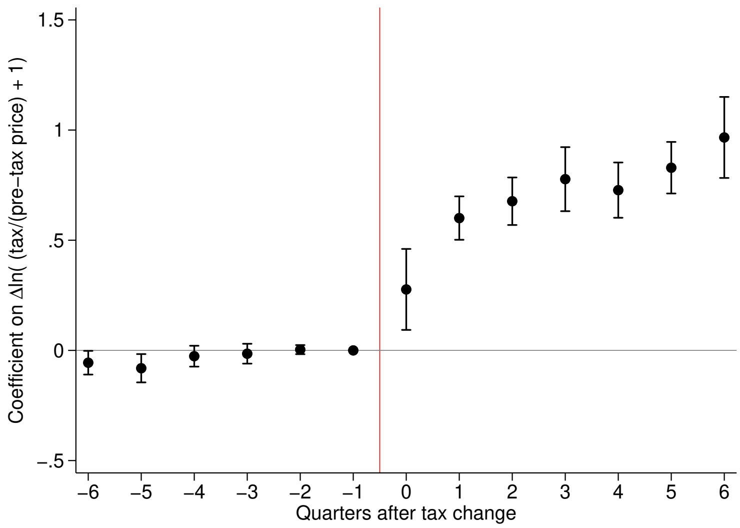
(b) **Instrumental Variables Estimates**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	ln(cig units)	ln(cig units)	ln(cig units)	ln(cig units)	ln(cig units)	ln(cig units)
ln(cig price)	-0.775	-3.839	-0.767	-1.109	-1.098	-0.797
	(0.154)	(1.050)	(0.308)	(0.222)	(0.221)	(0.181)
ln(e-cig price)	-0.134	1.716	0.752	0.827	0.763	-0.256
	(0.270)	(0.653)	(0.379)	(0.338)	(0.266)	(0.301)
UPC-cluster FE	Yes	No	Yes	Yes	Yes	Yes
UPC-month FE	Yes	No	No	Yes	Yes	Yes
Division-month FE	Yes	No	No	No	Yes	Yes
Cluster × month trend	Yes	No	No	No	No	Yes
Time-varying state controls	Yes	Yes	Yes	Yes	Yes	No
Observations	1,938,947	1,940,415	1,938,996	1,938,947	1,938,947	1,938,947

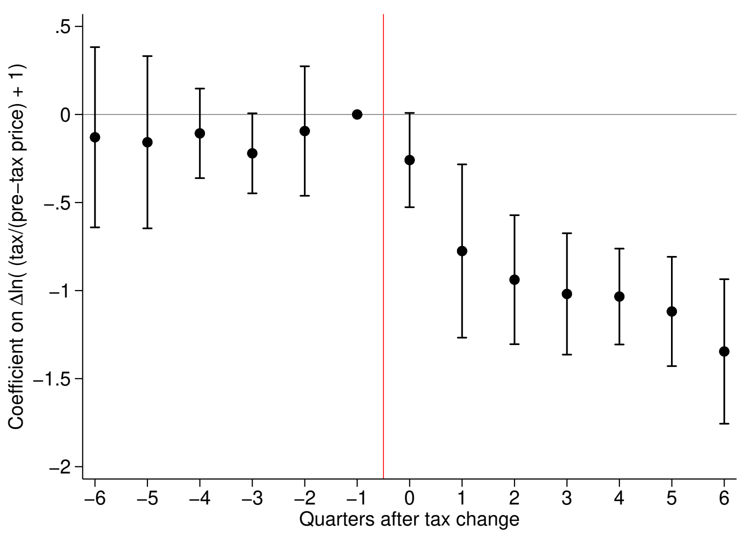
Notes: This table presents estimates of the own- and cross-price elasticity of demand for cigarettes from an analogue to Equation (16), using UPC-cluster-month data. There are 51 geographic clusters: the two counties that have e-cigarette taxes, each of the contiguous 48 states (excluding those two counties), and Washington, D.C. Standard errors are clustered by geographic cluster. Observations are weighted by the UPC's sales in other clusters in that calendar year, divided by total sales in other clusters across all UPCs in that year. Panel (a) presents the first stage and reduced form, using the same set of controls as in our primary estimate in column 1 of Panel (b). Panel (b) presents the instrumental variables estimates. Time-varying state controls are the state unemployment rate and beer tax rate as well as indicators for whether the state has an indoor vaping ban, has a medical marijuana law, passed a prescription drug program, implemented a prescription drug program, and implemented the Medicaid expansion.

Figure A3: **Event Study of E-cigarette Tax Changes without Linear Time Trends**

(a) **First Stage: Effect on ln(Price)**



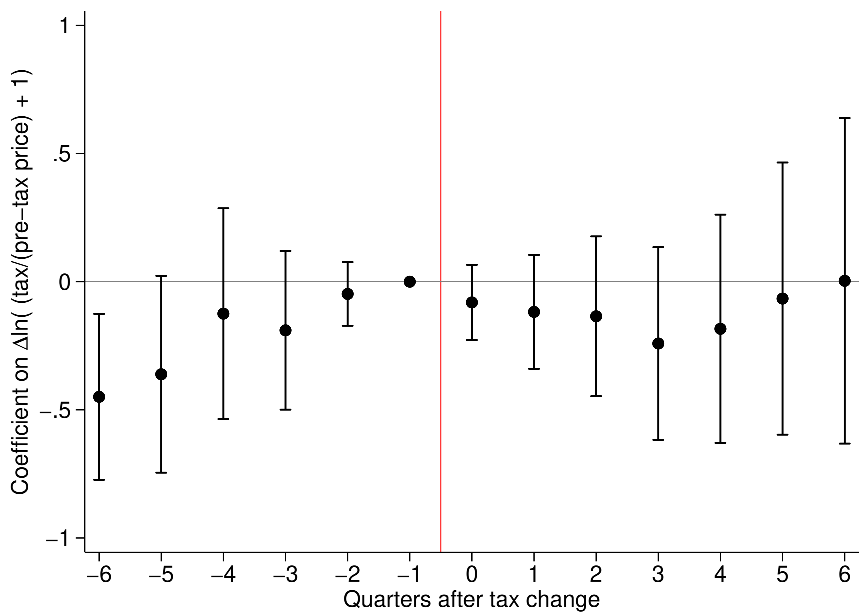
(b) **Reduced Form: Effect on ln(Quantity Sold)**



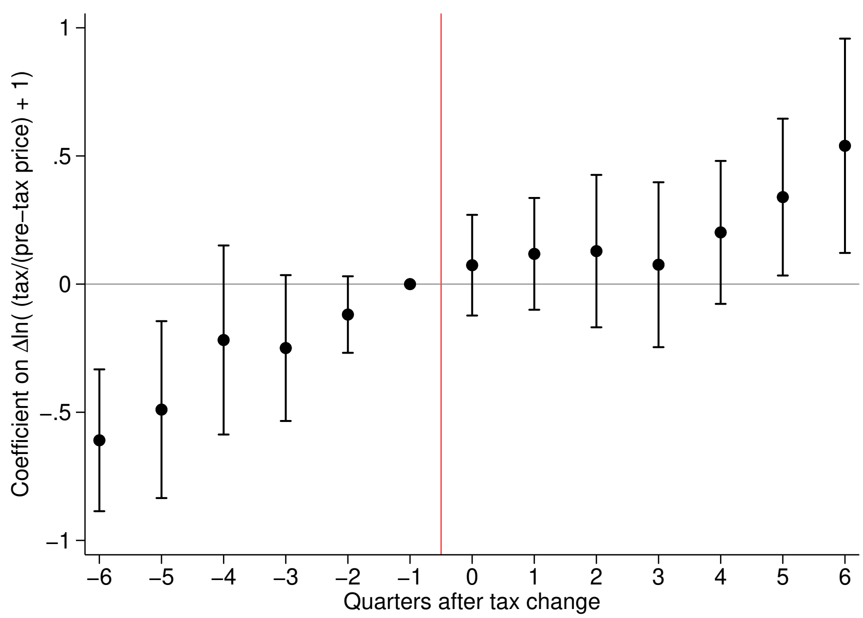
Notes: This figure presents estimates of the η_q parameters from Equation (17), an event study of the effects of e-cigarette tax changes. This parallels Figure 3, except it excludes cluster-specific linear time trends. Panel (a) presents the first stage regression of ln(e-cigarette price) on the change in the log tax variable. Panel (b) presents the reduced form regression of the ln(e-cigarette units sold) on the change in the log tax variable. Confidence intervals represent ± 1.96 standard errors.

Figure A4: **Event Study of E-cigarette Tax Changes on Cigarette Demand**

(a) **With Cluster-Specific Linear Time Trends**



(b) **Without Cluster-Specific Linear Time Trends**



Notes: This figure presents estimates of the η_q parameters from Equation (17), an event study of the effects of e-cigarette tax changes. This parallels Figure 3, except with combustible cigarette purchases as the dependent variable. Panel (a) presents estimates with cluster-specific linear time trends. Panel (b) presents estimates without cluster-specific linear time trends. Confidence intervals represent ± 1.96 standard errors.

D.1 Robustness Checks

Appendix Tables A4 and A5 present additional robustness checks.[29] The price elasticity estimates do not change substantially if we limit the identification of η to the 18-month window around the tax change, exclude e-cigarette UPCs with imputed volumes, or include only clusters with ad-valorem taxes, excluding clusters with specific taxes. When we exclude the controls $\boldsymbol{Q}_{kst}$ and thereby also identify off of the effects in the quarter beginning with the tax change, the e-cigarette $\hat{\eta}$ estimate moves slightly toward zero. This is consistent with the small quantity effect in quarter $q = 0$ shown in Panel (b) of Figure 3. Finally, the estimates are similar when we do not weight observations instead of weighting by sales.

Table A4: **Own- and Cross-Price Elasticity of Demand for E-cigarettes, Robustness**

Dependent variable: ln(e-cig units)	(1) 18-month window	(2) Exclude 1(quarter of e-cig tax) controls	(3) Exclude imputed volumes	(4) Exclude specific-tax clusters	(5) Unweighted
ln(e-cig price)	-1.201	-1.189	-1.324	-1.251	-1.133
	(0.383)	(0.445)	(0.421)	(0.465)	(0.416)
ln(cig price)	0.171	0.209	0.220	0.281	0.217
	(0.432)	(0.460)	(0.467)	(0.486)	(0.249)
Observations	287,381	287,381	283,870	258,663	287,381

Notes: This table presents instrumental variables estimates of the own- and cross-price elasticity of demand for e-cigarettes from Equation (16), using UPC-cluster-month data. There are 51 geographic clusters: the two counties that have e-cigarette taxes, each of the contiguous 48 states (excluding those two counties), and Washington, D.C. Standard errors are clustered by geographic cluster. Observations are weighted by the UPC's sales in non-taxed clusters in that calendar year, divided by total sales across all UPCs in that year in non-taxed clusters. All columns include UPC-cluster, UPC-month, and Census division-month fixed effects and cluster-specific linear time trends, as well as time-varying state controls. Column 1 includes additional controls so as to identify the elasticities only using an 18-month window around e-cigarette tax changes. Column 2 excludes controls for the quarter of the e-cigarette tax treatment and interaction with the e-cigarette tax, to identify the elasticities also off of the effects in the first three months after a tax change. Column 3 excludes e-cigarette UPCs with imputed volumes. Column 4 excludes states that ever have a specific (i.e. per-milliliter) e-cigarette tax. Column 5 presents estimates without weights.

[29] In Appendix Tables A3 and A5, our estimates of the cigarette own-price elasticity are higher than most previous estimates, but our primary estimates are within a standard deviation of the mean estimate in the meta-analysis by Gallet and List (2003), and we cannot reject the midpoint of the "consensus" range of -0.4 to -0.7 reported in Chaloupka and Warner (2000). In any event, the cigarette price elasticity is not relevant for any analysis in our paper.

Table A5: **Own- and Cross-Price Elasticity of Demand for Cigarettes, Robustness**

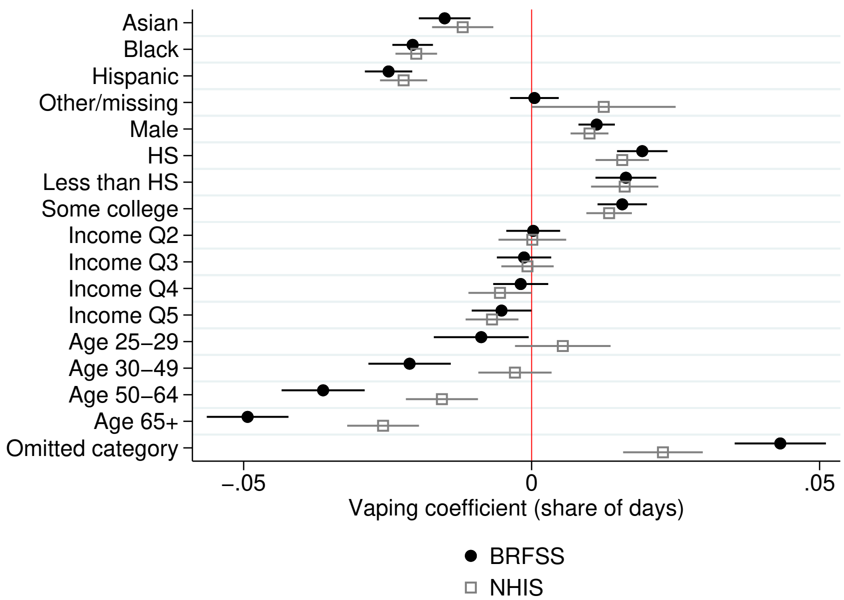
Dep. variable: ln(cig units)	(1) 18-month window	(2) Exclude 1(quarter of e-cig tax) controls	(3) Exclude specific-tax states	(4) Unweighted
ln(cig price)	-0.768	-0.788	-0.836	-0.946
	(0.157)	(0.145)	(0.147)	(0.182)
ln(e-cig price)	-0.166	-0.162	-0.108	-0.145
	(0.257)	(0.286)	(0.173)	(0.282)
Observations	1,938,947	1,938,947	1,754,830	1,938,947

Notes: This table presents instrumental variables estimates of the own- and cross-price elasticity of demand for cigarettes from an analogue to Equation (16), using UPC-cluster-month data. There are 51 geographic clusters: the two counties that have e-cigarette taxes, each of the contiguous 48 states (excluding those two counties), and Washington, D.C. Standard errors are clustered by geographic cluster. Observations are weighted by the UPC's sales in other clusters in that calendar year, divided by total sales in other clusters across all UPCs in that year. All columns include UPC-cluster, UPC-month, and Census division-month fixed effects and cluster-specific linear time trends, as well as time-varying state policy controls. Column 1 includes additional controls so as to identify the elasticities only using an 18-month window around e-cigarette tax changes. Column 2 excludes controls for the quarter of the e-cigarette tax treatment and interaction with the e-cigarette tax, to identify the elasticities also off of the effects in the first three months after a tax change. Column 3 excludes states that ever have a specific (i.e. per-milliliter) e-cigarette tax. Column 4 presents estimates without weights.

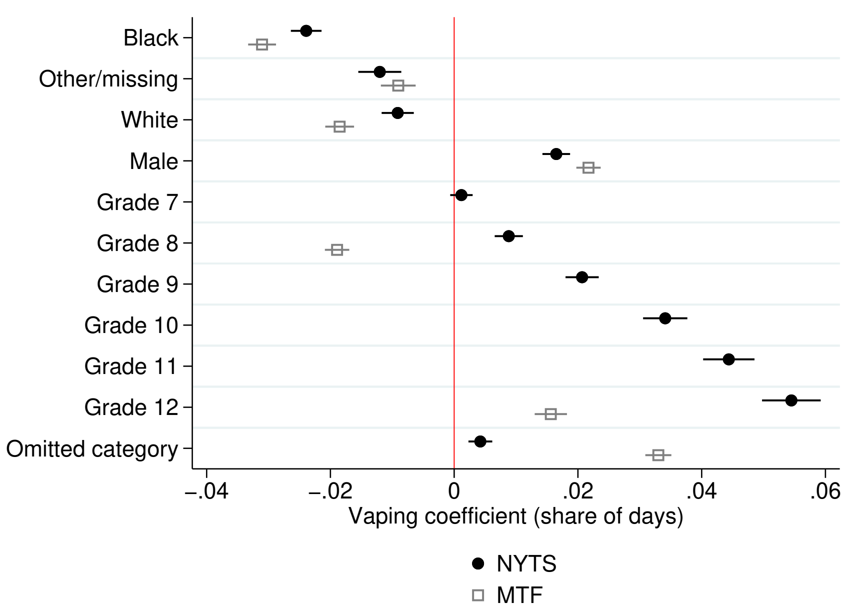
E Substitution Patterns Appendix

Figure A5: **Demographic Predictors of Vaping, by Dataset**

(a) **Adults**

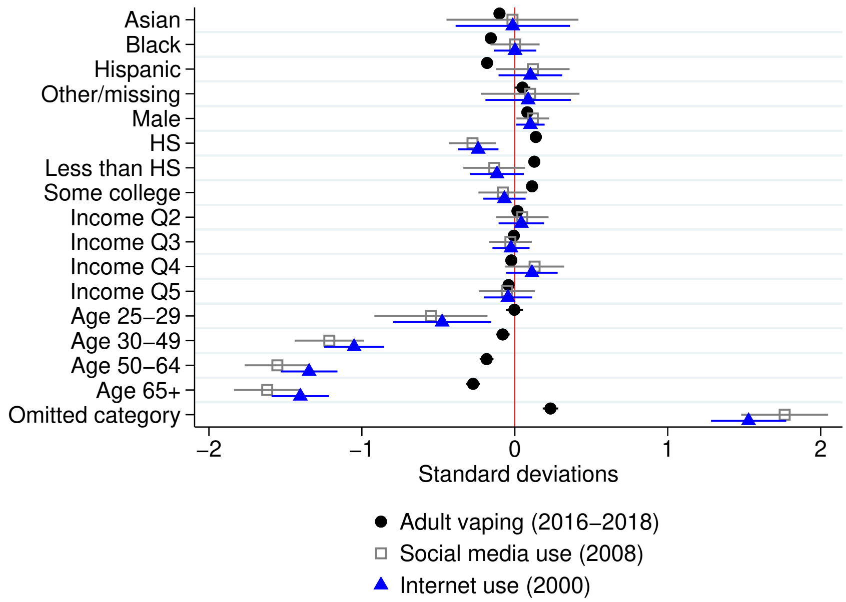


(b) **Youth**



Notes: These figures present coefficients from Equation (18), a regression of vaping on demographic indicators, estimated separately by dataset. For adults, the omitted categories are white, female, college graduate, the lowest income quintile, and age group 18-24. For youth, the omitted categories are white, female, and grade 6. Panel (a) pools 2016–2018 data from BRFSS and NHIS; Panel (b) pools 2014–2018 data from MTF and NYTS. Standard errors are clustered by demographic cell.

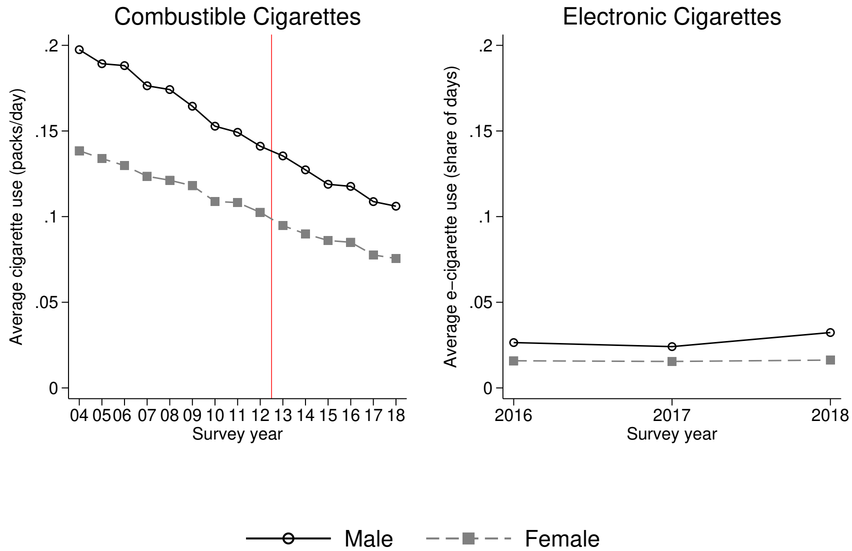
Figure A6: **Demographic Predictors of E-cigarette, Social Media, and Internet Use**



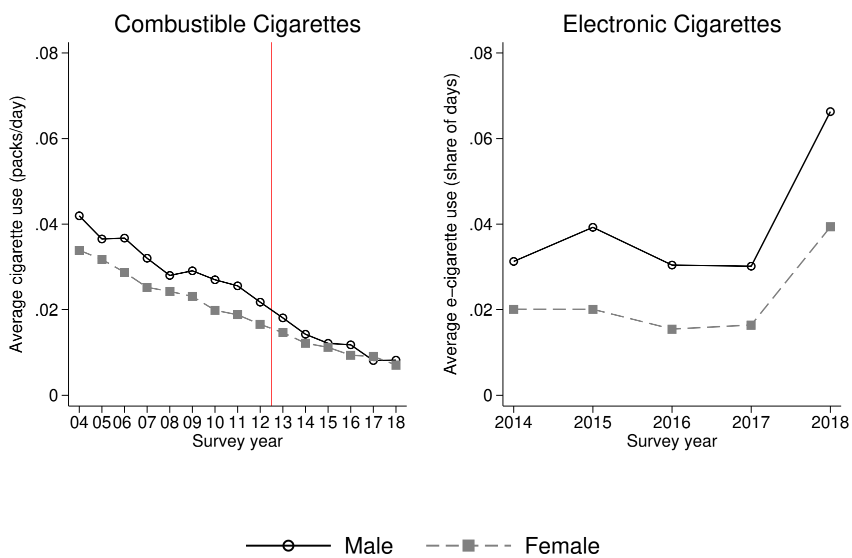
Notes: These figures present coefficients from regressions of vaping, social media use, or internet use on demographic indicators. Each dependent variable is normalized into standard deviation units for comparability. For adults, the omitted categories are white, female, college graduate, the lowest income quintile, and age group 18-24. For youth, the omitted categories are white, female, and grade 6. Standard errors are clustered by demographic cell.

Figure A7: **Smoking and Vaping Trends by Sex**

(a) **Adults**



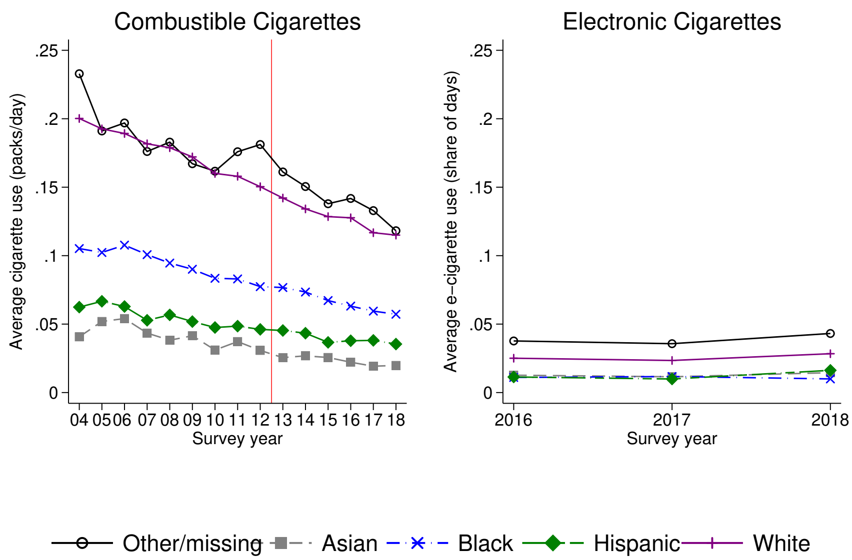
(b) **Youth**



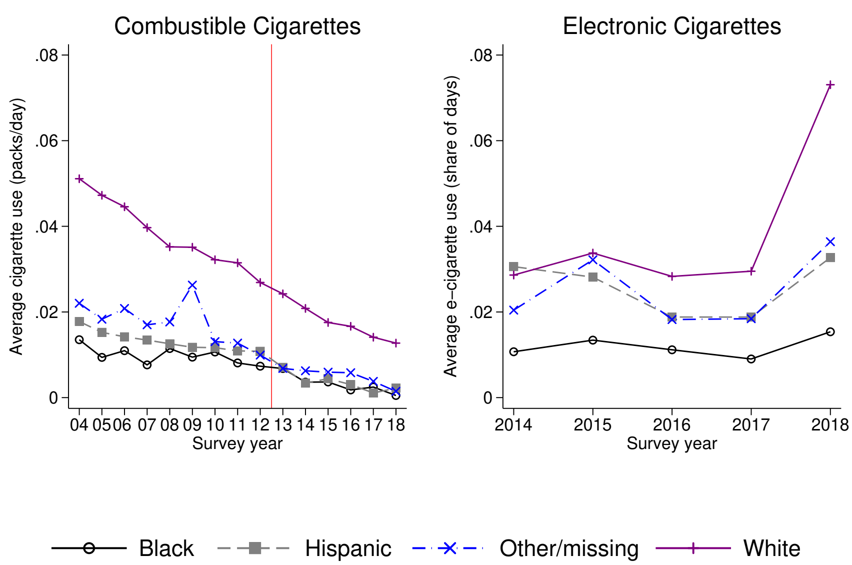
Notes: These figures present combustible cigarette and e-cigarette use by demographic group. Average cigarette use for each group is residual of dataset controls, which address the 2011 BRFSS sampling frame change and rescale cigarette use to levels in the NSDUH.

Figure A8: **Smoking and Vaping Trends by Race/Ethnicity**

(a) **Adults**



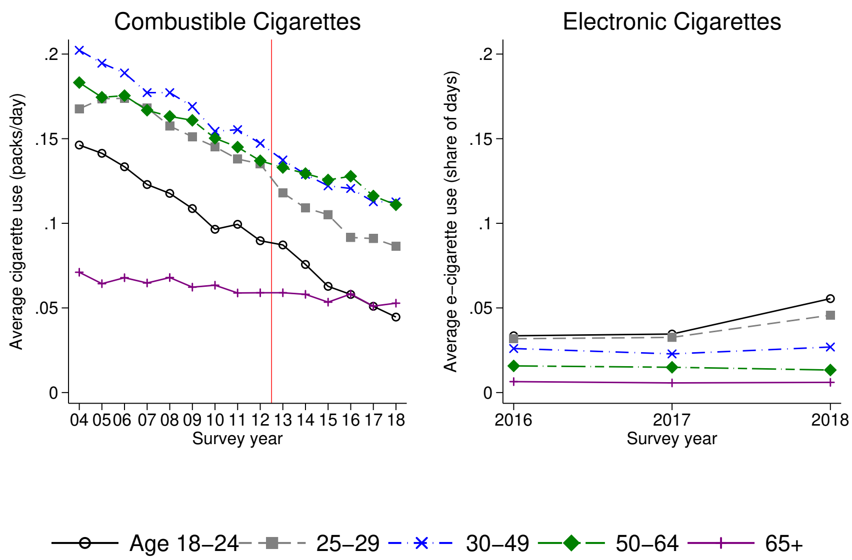
(b) **Youth**



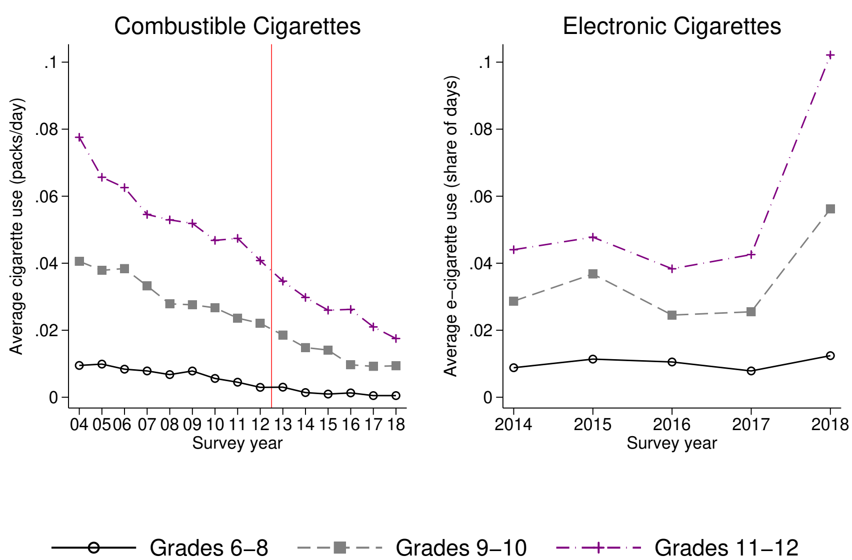
Notes: These figures present combustible cigarette and e-cigarette use by demographic group. Average cigarette use for each group is residual of dataset controls, which address the 2011 BRFSS sampling frame change and rescale cigarette use to levels in the NSDUH.

Figure A9: **Smoking and Vaping Trends by Age/Grade**

(a) **Adults**



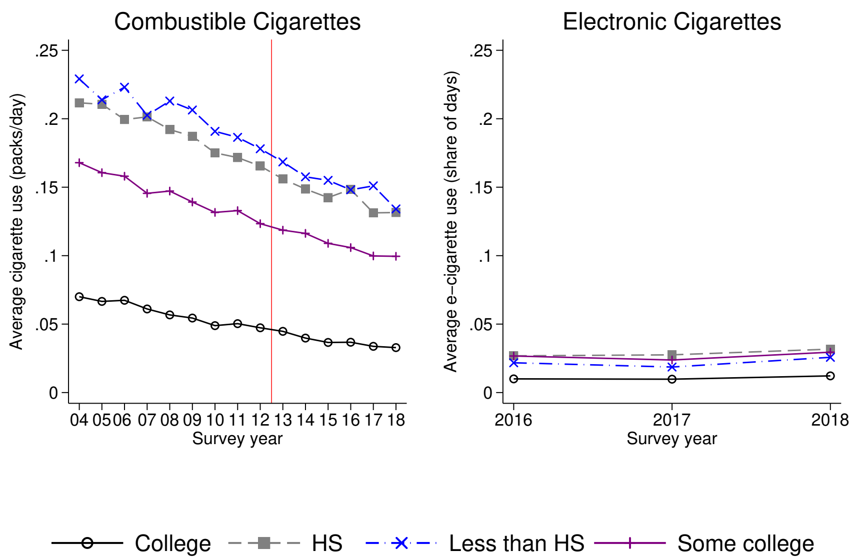
(b) **Youth**



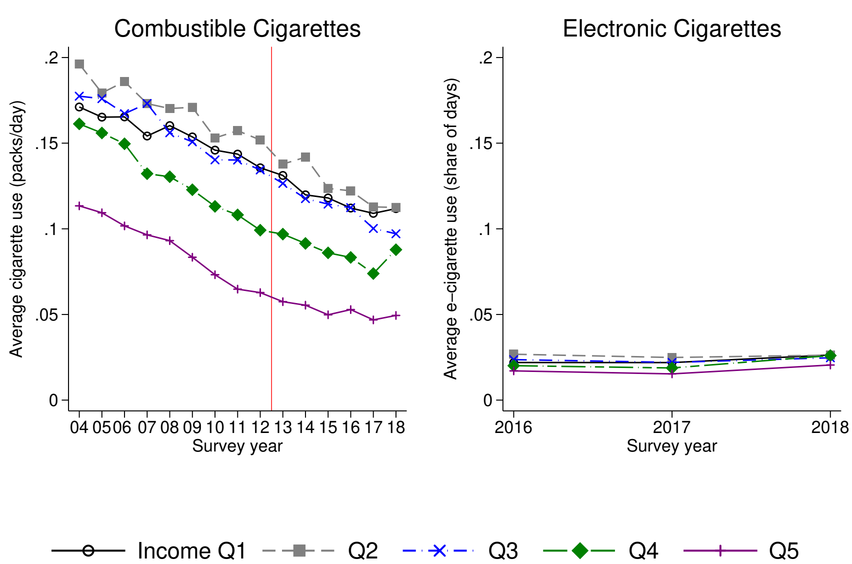
Notes: These figures present combustible cigarette and e-cigarette use by demographic group. Average cigarette use for each group is residual of dataset controls, which address the 2011 BRFSS sampling frame change and rescale cigarette use to levels in the NSDUH.

Figure A10: **Smoking and Vaping Trends by Education and Income, for Adults**

(a) **Education**



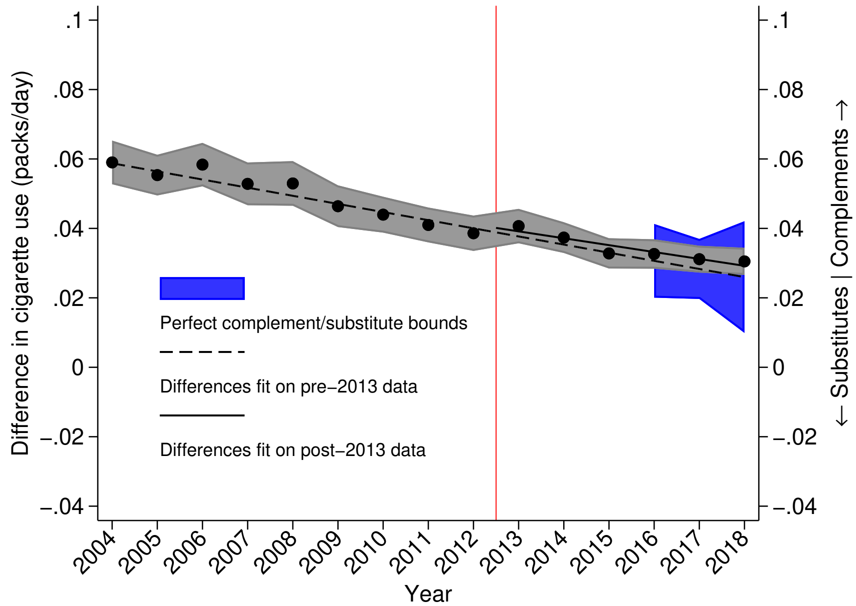
(b) **Income**



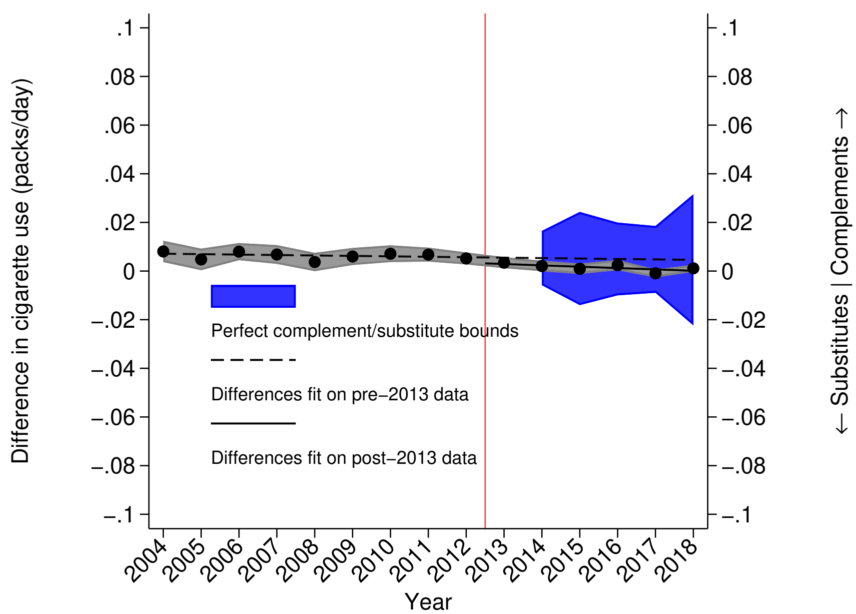
Notes: These figures present combustible cigarette and e-cigarette use by demographic group. Average cigarette use for each group is residual of dataset controls, which address the 2011 BRFSS sampling frame change and rescale cigarette use to levels in the NSDUH.

Figure A11: **Difference in Smoking Trends by Sex**

(a) **Adults**



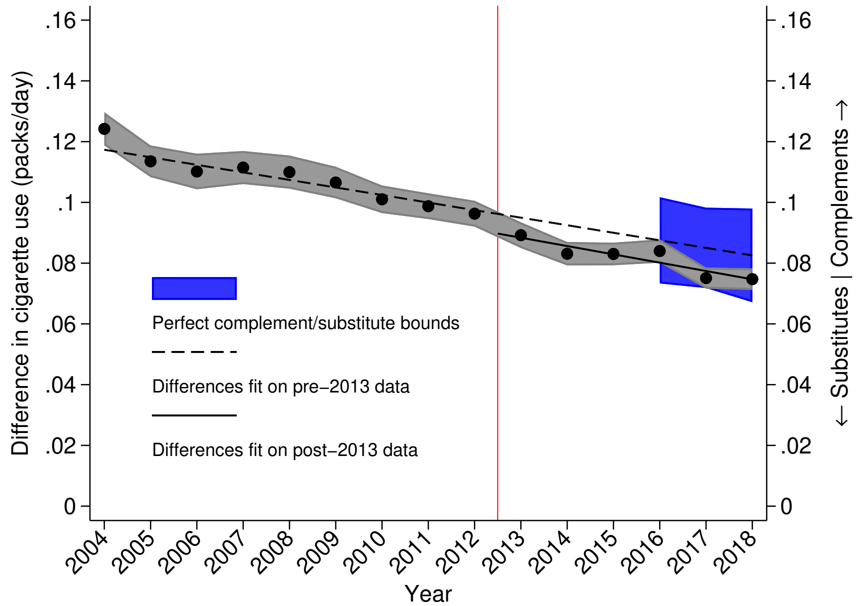
(b) **Youth**



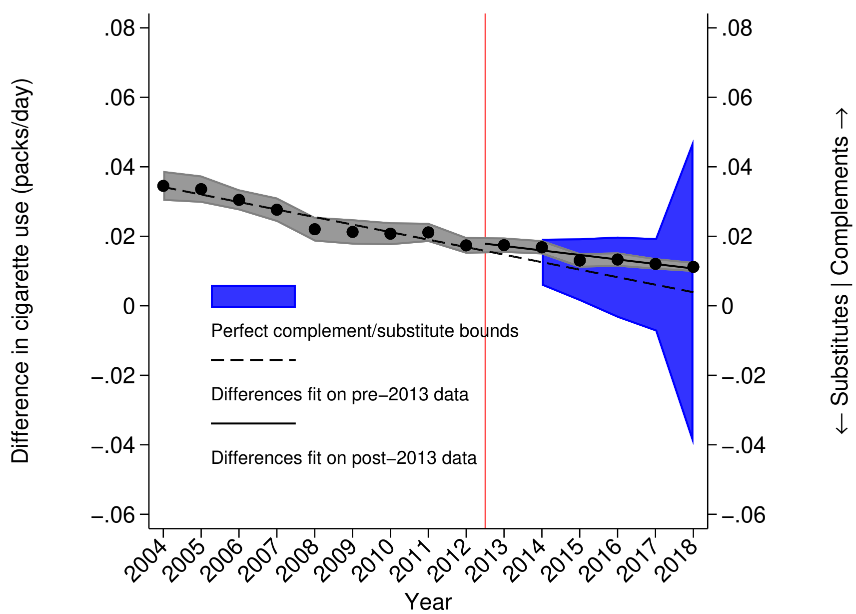
Notes: These figures present the difference in cigarette use for men versus women. Average cigarette use for each group is residual of dataset controls, which address the 2011 BRFSS sampling frame change and rescale cigarette use to levels in the NSDUH. The perfect complement (substitute) bounds show the difference in cigarette use that would be expected if daily vaping were a perfect complement (substitute) for smoking one pack of cigarettes per day. To construct perfect complement (substitute) bounds, we predict the difference in cigarette use using the pre-2013 time trend, then add (subtract) the difference in share of days vaped.

Figure A12: **Difference in Smoking Trends by Race**

(a) **Adults**



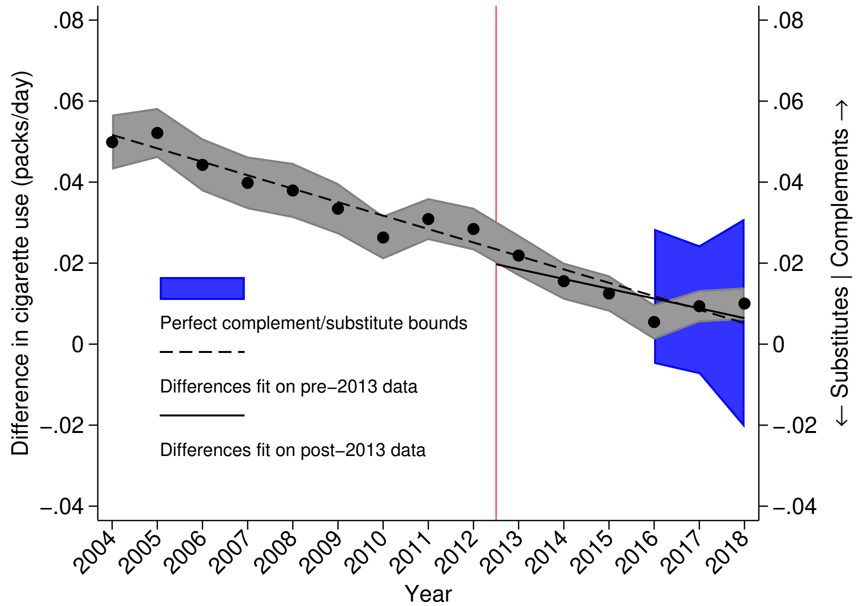
(b) **Youth**



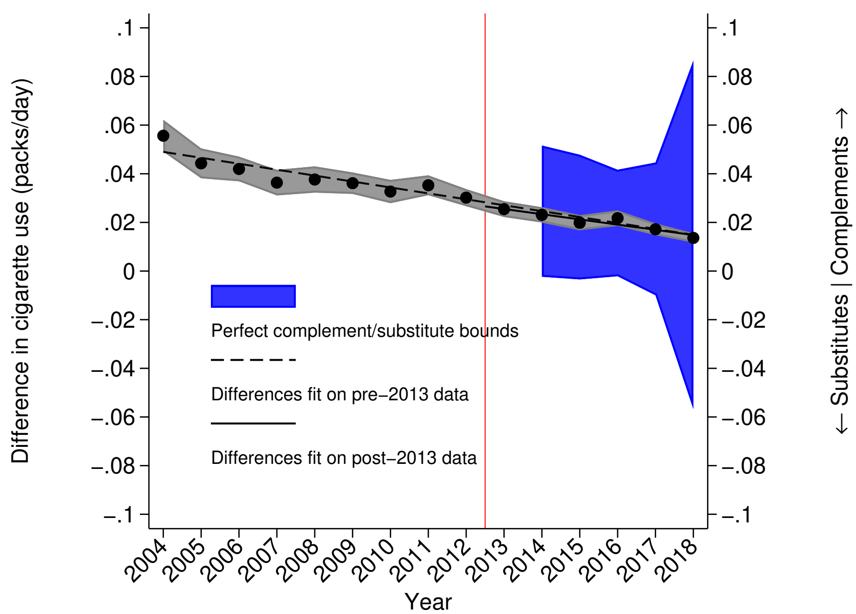
Notes: These figures present the difference in cigarette use for whites and other races versus non-whites (for adults) and whites versus non-whites (for youth). Average cigarette use for each group is residual of dataset controls, which address the 2011 BRFSS sampling frame change and rescale cigarette use to levels in the NSDUH. The perfect complement (substitute) bounds show the difference in cigarette use that would be expected if daily vaping were a perfect complement (substitute) for smoking one pack of cigarettes per day. To construct perfect complement (substitute) bounds, we predict the difference in cigarette use using the pre-2013 time trend, then add (subtract) the difference in share of days vaped.

Figure A13: **Difference in Smoking Trends by Age/Grade**

(a) **Adults**



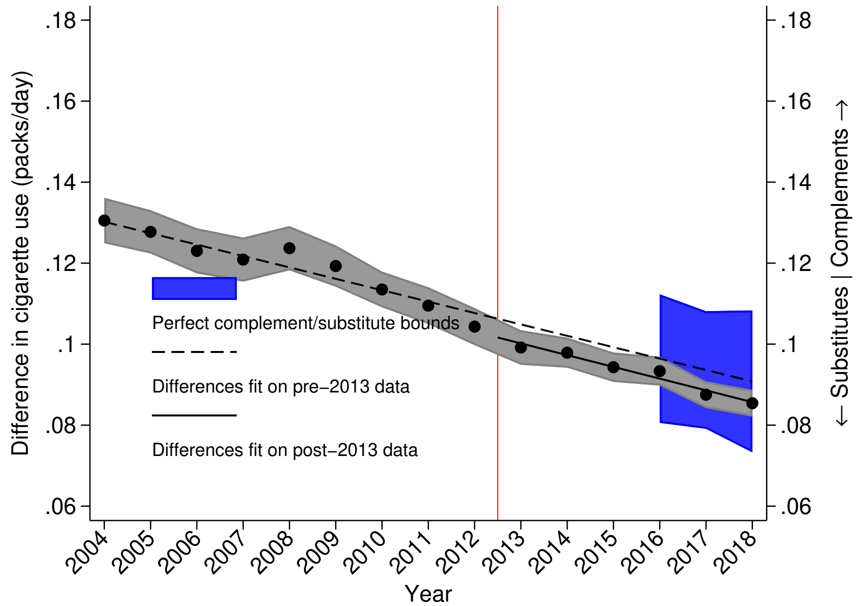
(b) **Youth**



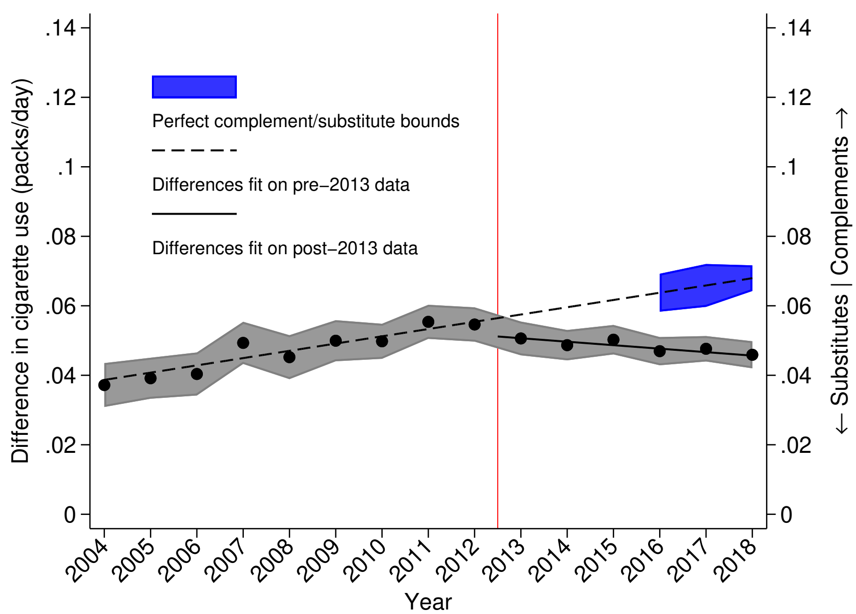
Notes: These figures present the difference in cigarette use by year for age ≤ 49 versus age ≥ 50 (for adults) and for grades ≥ 11 versus grades ≤ 10 (for youth). Average cigarette use for each group is residual of dataset controls, which address the 2011 BRFSS sampling frame change and rescale cigarette use to levels in the NSDUH. The perfect complement (substitute) bounds show the difference in cigarette use that would be expected if daily vaping were a perfect complement (substitute) for smoking one pack of cigarettes per day. To construct perfect complement (substitute) bounds, we predict the difference in cigarette use using the pre-2013 time trend, then add (subtract) the difference in share of days vaped.

Figure A14: **Difference in Smoking Trends by Education and Income, for Adults**

(a) **Education**



(b) **Income**



Notes: These figures present the difference in cigarette use by year for adults without versus with college degrees (Panel (a)) and adults in the bottom three versus top two income quintiles (Panel (b)). Average cigarette use for each group is residual of dataset controls, which address the 2011 BRFSS sampling frame change and rescale cigarette use to levels in the NSDUH. The perfect complement (substitute) bounds show the difference in cigarette use that would be expected if daily vaping were a perfect complement (substitute) for smoking one pack of cigarettes per day. To construct perfect complement (substitute) bounds, we predict the difference in cigarette use using the pre-2013 time trend, then add (subtract) the difference in share of days vaped.

E.1 Robustness Checks

Figure A15 presents separate estimates of Equation (19) for adults and youth. The first row of each panel presents our primary estimates. The subsequent rows in each panel present robustness checks. *Control for 2003 smoking* allows the smoking trends to differ for demographics with higher versus lower initial smoking rates, by including an additional control for the 2003 smoking rate in person i's demographic cell and the interaction of that variable with a linear time trend. *Vaping begins in 2012* modifies the construction of $\tilde{q}^e_{it}$ in Equation (21) to use 2012 instead of 2013 as the year when e-cigarettes first saw non-negligible use. The standard errors widen slightly as the linear demographic time trends $\boldsymbol{\omega}$ must be estimated off fewer years, but the point estimates do not change much. *No imputed vaping data* uses only observed vaping q^e_{it} instead of imputing missing q^e_{it} beginning in 2013. We find evidence of modest complementarity among youth if we do not impute vaping.

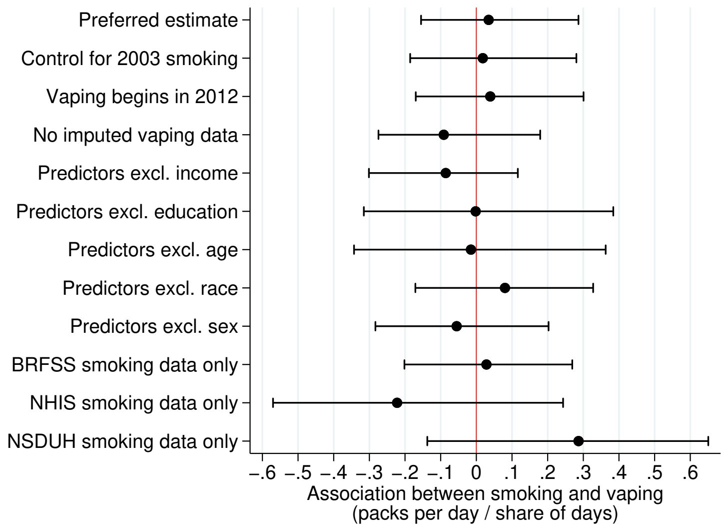
In the youth estimates, *Demog. cell predictors* uses demographic cells, i.e. the interactions of our usual demographic groups, to construct $\boldsymbol{G}_i$. *Drop race other/missing* is motivated by Appendix Figure A5, which shows that the predicted vaping among people whose race is other/missing differs in MTF versus NYTS.

The next set of robustness checks, *Predictors excl. age (or race, etc.)* omit age (or race, or other demographic categories) from the vaping predictors $\boldsymbol{G}_i$. These are informal overidentification tests, allowing us to see whether the results are driven by any one demographic category. Consistent with the earlier informal overidentification tests in Appendix Figures A11–A14, the point estimates move little when we exclude any given demographic category. The standard errors illustrate that most of the identifying variation is from age (for adults) and grade (for youth), consistent with fact that these are the most predictive demographic categories illustrated in Figure 4.

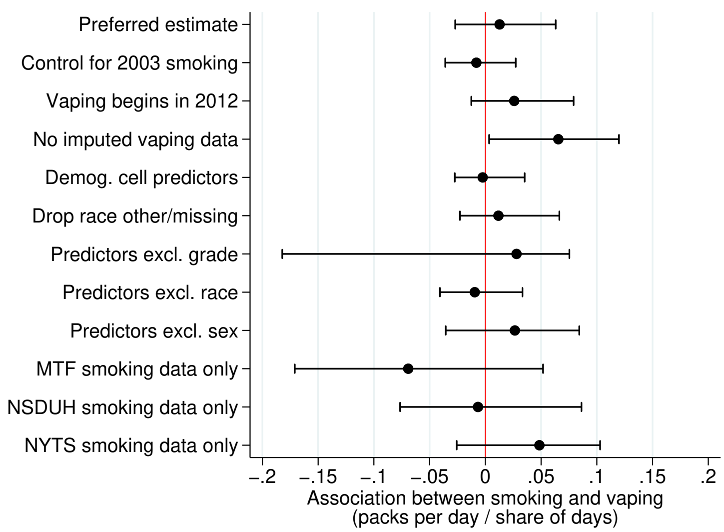
The final set of robustness checks presents estimates using each dataset individually in the second stage regression. Our primary results from combining three datasets are about the average of the estimates from each individual dataset. The point estimates differ somewhat across datasets, which highlights the importance of our efforts to use all available data.

Figure A15: **Substitution Parameters and Robustness Checks**

(a) **Adults**



(b) **Youth**



Notes: These figures present estimates of σ from Equation (19), a regession of smoking on predicted vaping controlling for controlling for linear time trends and other controls. *Control for 2003 smoking* includes additional controls for the 2003 cigarette use in person i's demographic cell and the interaction of that variable with a linear time trend. *Vaping begins in 2012* assumes zero vaping for all years before 2012 (instead of 2013 in the preferred estimate) and imputes vaping beginning in 2012 (instead of 2013). *Demog. cell predictors* uses demographic cells, rather than linear demographic groups, in $\boldsymbol{G}_i$. *Drop race other/missing* drops all observations with “other” or missing race/ethnicity. *No imputed vaping data* uses only observed vaping instead of imputing missing data beginning in 2013. *Predictors excl. age (or race, etc.)* omits age (or race, etc.) from the predictors in Equation (18). *BRFSS (or NHIS, etc.) smoking data only* uses only BRFSS (or NHIS, etc.) data when estimating Equation (4). *Drop race other/missing* drops all youth whose race/ethnicity is not Black, Hispanic, or white from both the predicted vaping and the smoking effects regressions. The confidence intervals reflect the 2.5th and 97.5th percentiles of estimates from 200 bootstrap replications, where we draw bootstrap samples by demographic cell.

E.2 Combined Substitution Estimates

In this appendix, we describe how we form combined estimates of the substitution parameter σ using both the RMS estimates from Section 3 and the sample surveys from Section 4. σ is in units of packs of cigarettes per day vaped.

Beginning with the substitution elasticity χ^e from Table 1, which uses variation in e-cigarette taxes, and using Slutsky symmetry and quasi-linear demand, we have a population average substitution parameter

$$\sigma_1 \coloneqq \frac{\partial q_\theta^c/\partial p^e}{\partial q_\theta^e/\partial p^e} = \frac{\partial q_\theta^e/\partial p^c}{\partial q_\theta^e/\partial p^e} = \frac{\chi^e}{\eta}\frac{\tilde{p}^e\Gamma}{\tilde{p}^c}, \tag{34}$$

where Γ (ml/average day vaped) converts $\tilde{p}^e$ to units of dollars per day vaped. Similarly, beginning with the substitution elasticity χ^c from Appendix Table A3, which uses variation in cigarette taxes, we have

$$\sigma_{\theta 2} = \frac{\partial q_\theta^c/\partial p^e}{\partial q_\theta^e/\partial p^e} = \frac{\chi^c}{\eta}\frac{q_\theta^c}{q_\theta^e}. \tag{35}$$

The empirical estimates are the respective plug-in estimators using $\hat{\chi}^e$, $\hat{\chi}^c$, and $\hat{\eta}$ from Table 1 and A3, and $\hat{q}_\theta^j$, $\hat{\tilde{p}}^j$, and $\hat{\Gamma}$ from Table 3 for $j \in \{c, e\}$. We compute one estimate of $\hat{\sigma}_1$ using the estimates of $\hat{\chi}^e$ and $\hat{\eta}$ from Table 1 with cluster-specific linear trends (column 1), and we compute a second estimate using the estimates without cluster-specific linear trends (column 5). We compute standard errors on $\hat{\sigma}_1$ and $\hat{\sigma}_2$ using the delta method; the variance-covariance matrix is diagonal except for the covariance term between $\hat{\eta}$ and χ^e.

We combine $\hat{\sigma}_1$ and $\hat{\sigma}_2$ using Classical Minimum Distance (CMD) using:

$$\begin{bmatrix}1\\1\end{bmatrix}\sigma_\theta - \begin{bmatrix}\sigma_1\\ \sigma_{\theta 2}\end{bmatrix} = \mathbf{0} \ , \tag{36}$$

noting that

$$\begin{bmatrix}\sigma_1\\ \sigma_{\theta 2}\end{bmatrix} \sim N\left(0, \begin{bmatrix} s_1^2 & s_{12}\\ s_{12} & s_1^2\end{bmatrix}\right). \tag{37}$$

We use $\hat{s}_1^2$ and $\hat{s}_2^2$ from the initial delta method estimation. We estimate s_{12} as follows:

$$s_{12} \coloneqq Cov\left(\frac{\chi^c}{\eta}\frac{q_\theta^c}{q_\theta^e}, \frac{\chi^e}{\eta}\frac{\tilde{p}^e}{\tilde{p}^c}\Gamma\right) \tag{38}$$

$$= \chi^c \frac{q_\theta^c}{q_\theta^e}\frac{\tilde{p}^e}{\tilde{p}^c}\Gamma Cov\left(\frac{1}{\eta}, \frac{\chi^e}{\eta}\right) \tag{39}$$

$$\approx \chi^e \chi^c \frac{q_\theta^c}{q_\theta^e}\frac{\tilde{p}^e}{\tilde{p}^c}\Gamma V\left(\frac{1}{\eta}\right) \tag{40}$$

where the second line follows since the parameters taken outside the covariance are all estimated from separate datasets, and we assume that the covariance between χ^e and $1/\eta$ is small. We estimate $V\left(\frac{1}{\eta}\right)$ from the delta method, and form $\hat{s}_{12}$ using a plug-in estimator.

We also combine $\hat{\sigma}_1$ and $\hat{\sigma}_2$ with our estimates from Section 4 using CMD. Table A6 presents our results.

Table A6: **Estimates of Substitution Parameter σ**

	(1) E-cig cross-price elasticity	(2) E-cig cross-price elasticity (no trends)	(3) Cig cross-price elasticity	(4) Combined RMS	(5) Demo. analysis	(6) Combined RMS and demo.
Adult σ	-0.056	-0.243	0.346	-0.046	0.035	-0.009
	(0.104)	(0.126)	(0.707)	(0.103)	(0.112)	(0.076)
Youth σ	-0.056	-0.243	0.012	0.008	0.013	0.011
	(0.104)	(0.126)	(0.025)	(0.024)	(0.022)	(0.016)

Notes: This table presents estimates of the substitution parameter σ for youth and adults. Column 1 presents $\hat{\sigma}$ from Equation (34) using our estimates of $\hat{\eta}$ and $\hat{\chi}^e$ from Table 1 with cluster-specific linear trends (Panel (b), column 1). Column 2 presents $\hat{\sigma}$ from Equation (34) using our estimates of $\hat{\eta}$ and $\hat{\chi}^e$ from Table 1 without cluster-specific linear trends (Panel (b), column 5). Column 3 presents $\hat{\sigma}$ from Equation (35) using $\hat{\chi}^c$ from Appendix Table A3 (Panel (b), column 1). Column 4 combines the estimates in columns 1 and 3 using Equation (36). Column 5 re-states estimates from the demographic shift-share analysis in Section 4. Column 6 combines estimates from columns 4 and 5 using Classical Minimum Distance.

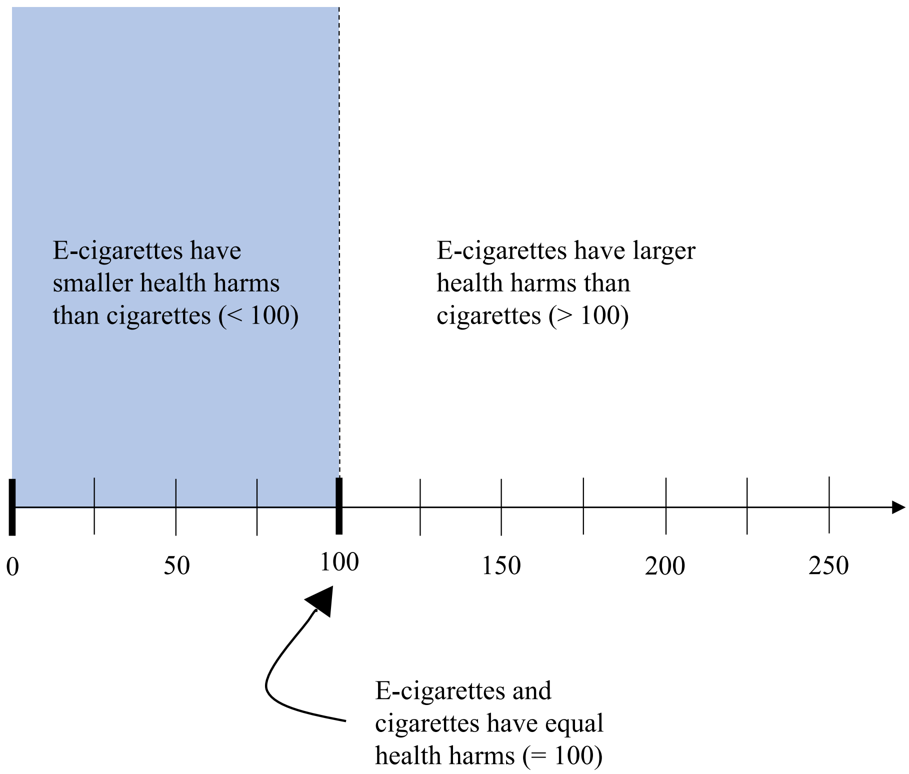
F Expert Survey Appendix

Table A7: **Expert Survey Response Rates**

	(1) Public health experts	(2) Economists
Invited to participate	432	50
Have valid email	417	50
Did not unsubscribe due to expertise	400	47
Opened survey	175	27
Consented	165	25
Finished reading RCT description	134	22
Finished survey	115	22

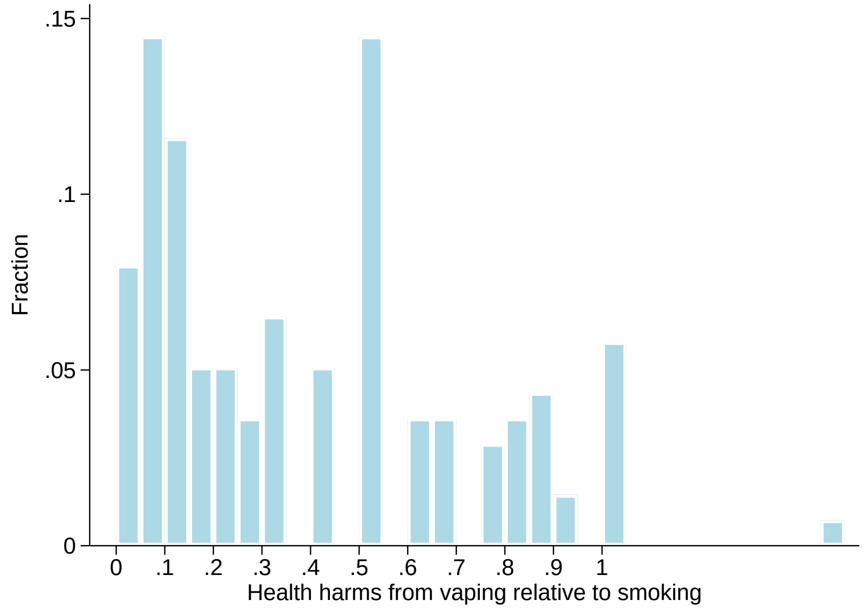
Notes: This table presents the number of experts at each point in the survey response funnel.

Figure A16: **Expert Survey: Graphical Illustration of Relative Harms Elicitation**



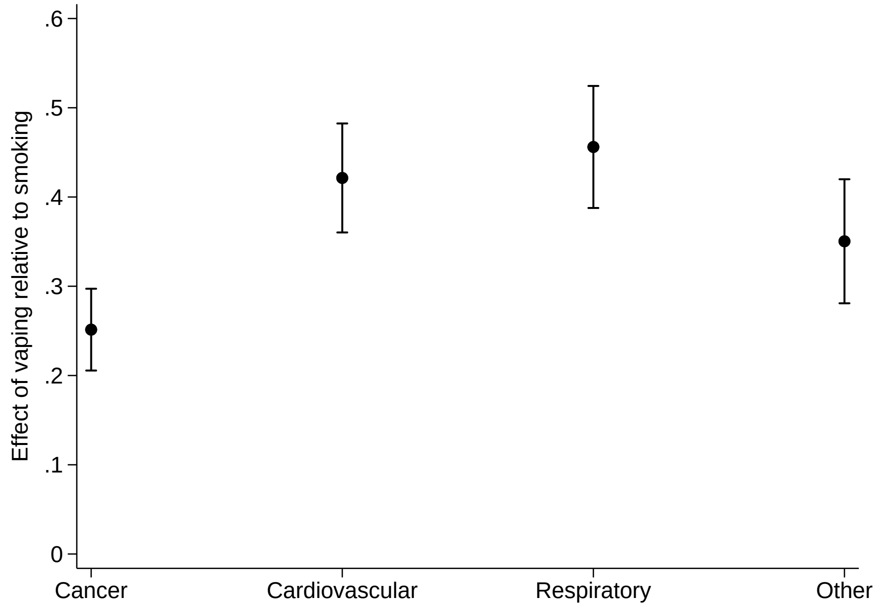
Notes: Our expert survey included this graphical illustration when eliciting experts' beliefs about the relative health harms from vaping compared to smoking cigarettes.

Figure A17: **Expert Survey: Effects of Vaping on Life Expectancy**



Notes: Our expert survey asked, "If smoking one pack per day reduces life expectancy (compared to Control) by 100 units, by how many units do you think vaping every day would reduce life expectancy (compared to Control)?" This figure presents the distribution of responses across experts, after dividing by 100.

Figure A18: **Expert Survey: Effects of Vaping on Specific Health Conditions**



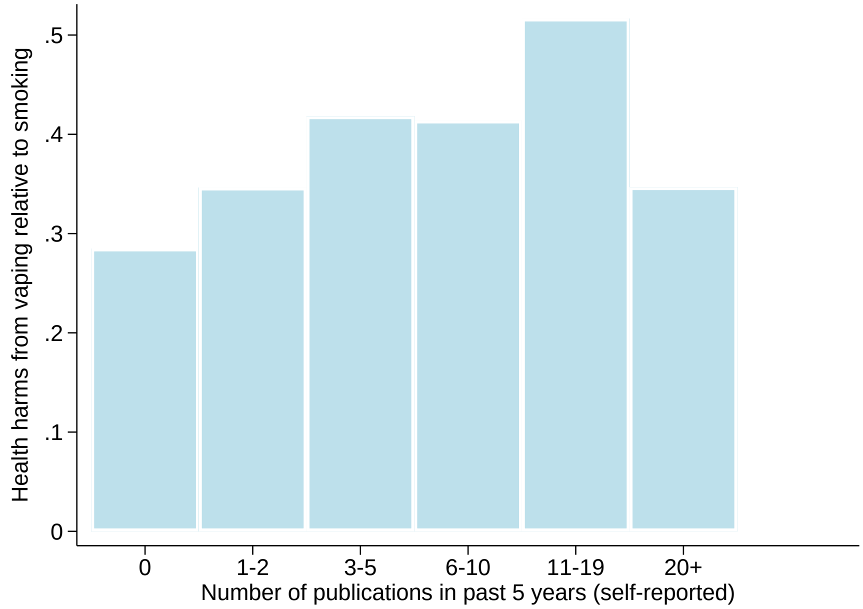
Notes: Our expert survey asked, "For each type of disease below, if smoking one pack per day increases lifetime prevalence by 100 units (compared to Control), by how many units do you think vaping every day would increase lifetime prevalence (compared to Control)?" This figure presents the mean and 95 percent confidence interval of the estimate of the mean for each of the four health conditions the survey asked about.

Table A8: **Expert Survey: Effects on Individual Diseases Predict Effects on Morbidity and Mortality**

	(1) Quality-adjusted life expectancy	(2) Life expectancy
Cardiovascular	0.222	0.309
	(0.0908)	(0.0780)
Respiratory	0.321	0.195
	(0.146)	(0.103)
Cancer	0.337	0.369
	(0.122)	(0.0982)
Other	0.0390	0.0643
	(0.0853)	(0.0930)
Observations	134	138
R^2	0.800	0.811

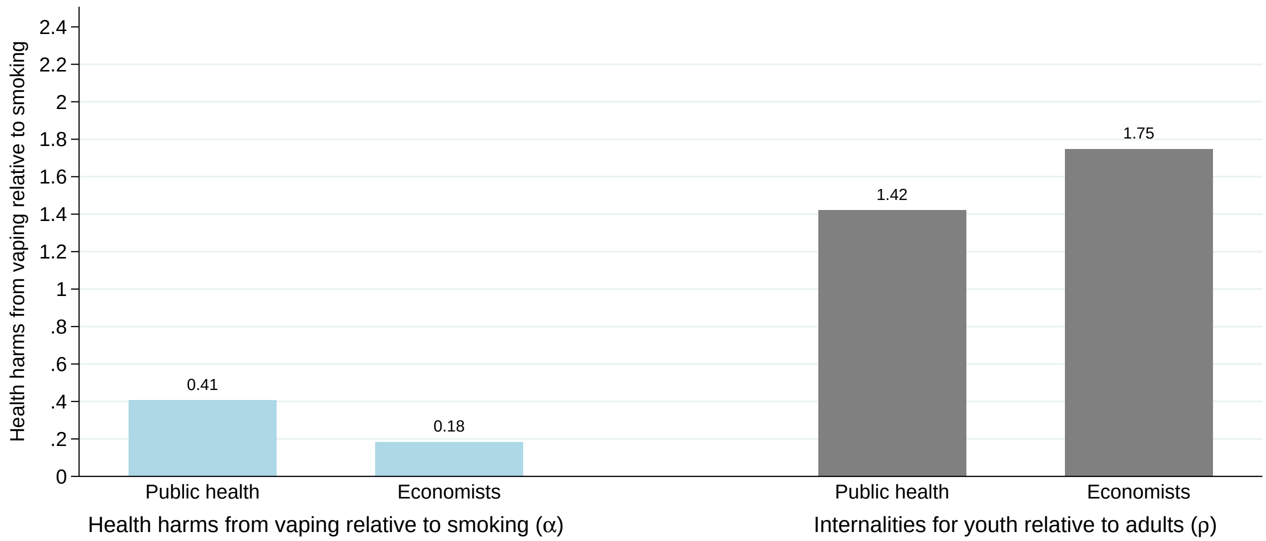
Notes: This table presents regressions of experts' predictions of the relative effects of vaping (compared to smoking) on life expectancy and quality-adjusted life expectancy on cardiovascular disease, respiratory disease, cancer, other health conditions. Robust standard errors are in parentheses.

Figure A19: **Expert Survey: Beliefs about Health Harms by Number of Publications**



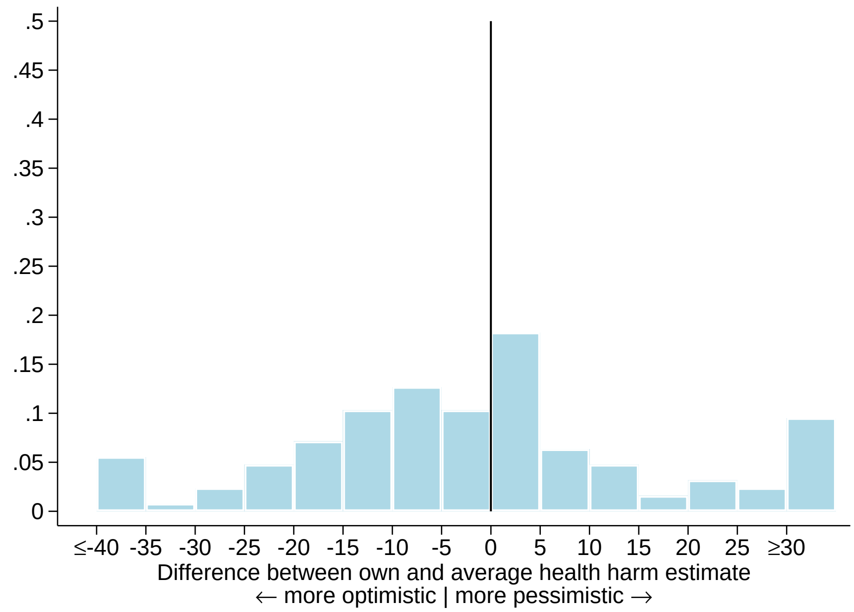
Notes: Our expert survey asked, "Over the past five years, approximately how many peer-reviewed research papers have you published on the health effects of e-cigarettes or combustible cigarettes?" This figure presents experts' average belief about the relative effect of vaping on quality-adjusted life expectancy after grouping experts by number of publications. There is no statistically significant relationship.

Figure A20: **Expert Survey: Responses from Public Health Researchers and Economists**



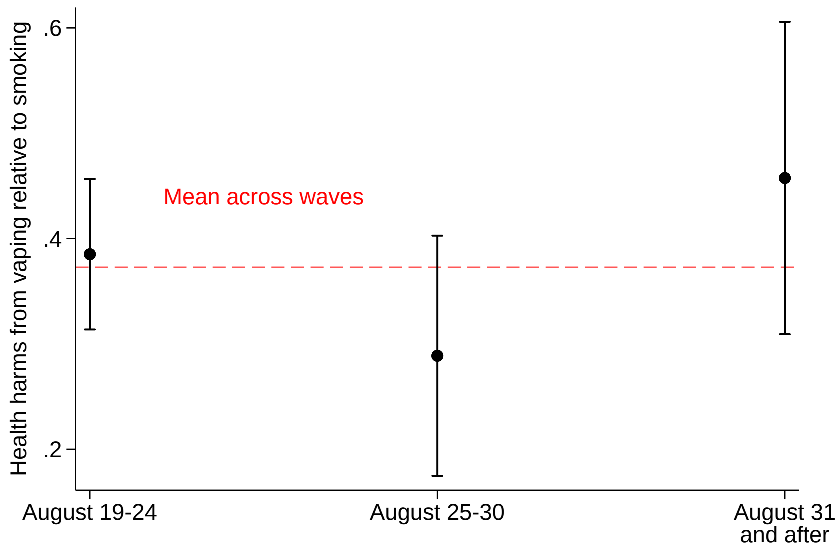
Notes: This figure presents the average belief about the relative effects of vaping on quality-adjusted life expectancy and the misperceived harms from vaping for youth relative to adults, separately for public health researchers and economists.

Figure A21: **Expert Survey: Distribution of Perceived Disagreement with the Average Expert**



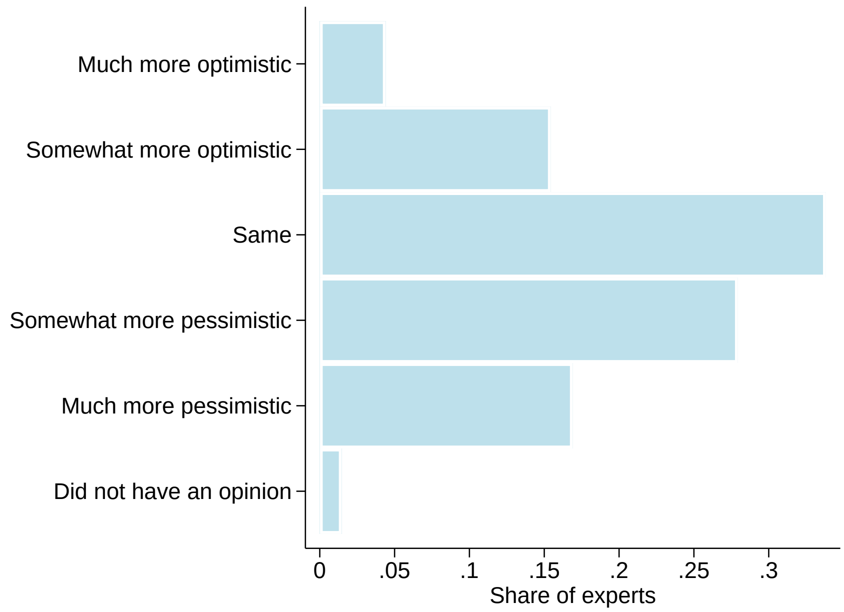
Notes: Our expert survey asked, "You predicted that the relative effect of vaping onr quality-adjusted life expectancy was [$\alpha \times 100$] units, i.e. [$\alpha \times 100$] percent of the effect of smoking. What do you think the average expert would report?" This figure presents the distribution of the difference between each expert's own α and his or her response to that question.

Figure A22: **Expert Survey: Average Reported Relative Health Harms by Response Time**



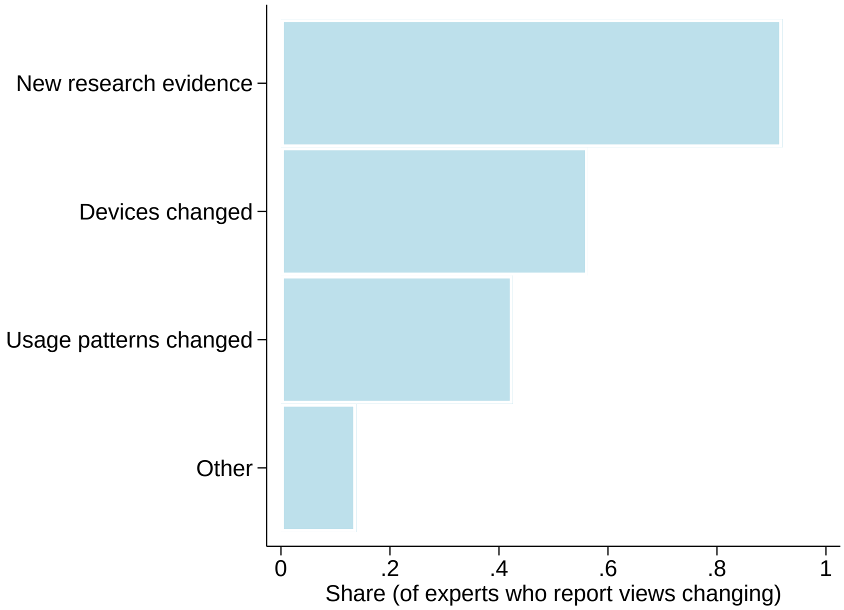
Notes: We sent three survey invite emails spaced six days apart, and almost all responses came within two days of an email being sent. This figure reports the average belief about the effect of vaping relative to smoking on quality-adjusted life years for responses in different time windows. The spikes are 95 percent confidence intervals on the estimate of the mean.

Figure A23: **Expert Survey: Personal Change in Beliefs about Health Effects of Vaping in Past Five Years**



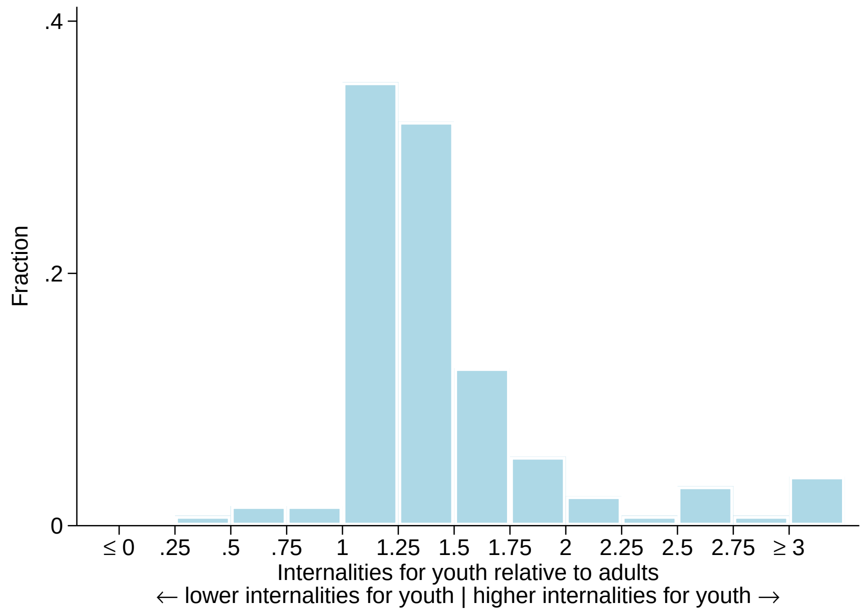
Notes: Our expert survey asked, "How optimistic or pessimistic are you about the health effects of vaping now, compared to five years ago?" This figure presents the distribution of responses to that question.

Figure A24: **Expert Survey: Reasons for Changes in Beliefs about the Health Effects of Vaping**



Notes: For experts who reported being more optimistic or pessimistic about the health effects of vaping now, compared to five years ago, our expert survey asked, "Why have your views changed?" This figure presents the distribution of responses to that question.

Figure A25: **Expert Survey: Uninternalized Harms from Vaping for Youth Relative to Adults**



Notes: Our expert survey asked, "Imagine that vaping every day causes 100 units of actual harms on adults. How many units do you think the average adult perceives?" and "Now imagine that vaping every day causes 100 units of actual harms on youth. How many units do you think the average youth perceives?" This figure presents the distribution of 1 – (youth perceived harms – adult perceived harms)/100.

G Welfare Analysis Appendix

The version of Equation (14) for empirical implementation is

$$\tau^{e*} = \frac{\sum_{\Theta} s_\theta q_\theta^e \Gamma \left[\varphi_\theta^e + (\sigma_\theta/\Gamma)\left(\varphi_\theta^c - \tau^c\right)\right]}{\sum_{\Theta} s_\theta q_\theta^e \Gamma}. \tag{41}$$

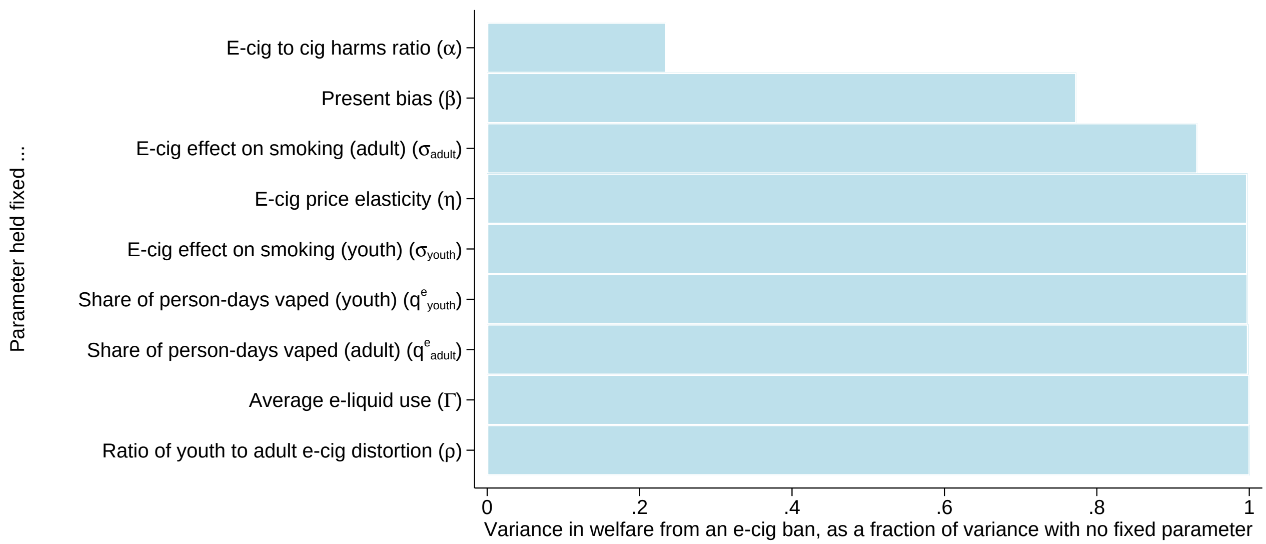
Vaping quantity q_θ^e is in units of share of days, σ_θ is in units of packs of cigarettes per day vaped, and Γ is in units of ml fluid/day vaped. τ^{e*} and φ_θ^e are in units of \$/ml.

The version of Equation (15) for empirical implementation is

$$\Delta\overline{W} = 365 \times \sum_{\theta\in\{a,y\}} s_\theta \left[\underbrace{q^e_\theta \Gamma \frac{\tilde{p}^e}{-2\eta}}_{\text{perceived CS change}} - \underbrace{\left(-q^e_\theta \Gamma\right)\left(\varphi^e_\theta - \tau^e\right)}_{\text{e-cigarette distortion change}} - \underbrace{q^e_\theta \Gamma \cdot \left(-\sigma_\theta/\Gamma\right)\left(\varphi^c - \tau^c\right)}_{\text{cigarette distortion change}} \right], \tag{42}$$

where $\Delta\overline{W}$ is in units of dollars per person-year.

Figure A26: **Contribution of Parameters to Policy Uncertainty**



Notes: This figure presents the variance across Monte Carlo simulations of the welfare effects of an e-cigarette ban from Equation (15), holding the reported parameter fixed at its mean.