Optimal Regulation of E-cigarettes: Theory and Evidence

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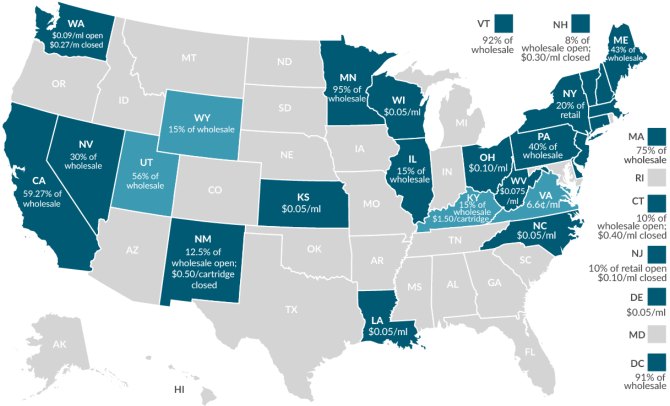
How High are Vapor Taxes in Your State?

State Vapor Excise Tax Rates, as of June 2020



Note: Several states levy general sales taxes in addition to the excise tax. Those are not included on the map. CA's rate will change to 56.93% on July 1. Vapor taxes in UT, VA, and WY take effect on July 1. KY's tax goes into effect on August 1.

Open: An open tank allows the consumer to refill the liquid and allows more freedom in voltage and nicotine levels.

Closed: Normally sold as pods or cartridges. Closed systems typically have higher nicotine levels to allow for consumption of the desired amount of nicotine in shorter sessions.

Source: State Statutes & Bloomberg Tax

Research question

What is the socially optimal tax on e-cigarettes?

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- “Tax”: could be negative (large subsidy) or infinite (complete ban)
- “Optimal”: maximize societal well-being, taking into account consumer surplus, health care costs, and tax revenues

Agenda

1. Optimal tax framework
2. Estimate key parameters
   - Price elasticity (Nielsen scanner data)
   - Effect of e-cigarettes on cigarette smoking (Nielsen and sample surveys)
   - Harms from vaping relative to smoking (expert survey)
3. Optimal tax quantification

Related literature

- Elasticity of demand for e-cigarettes
    - Survey data: Pesko and Warman (2017), Pesko et al. (2018), and Saffer et al. (2018), Cantrell et al. (2019), Pesko, Courtemanche, and Maclean (forthcoming)
    - Scanner data: Stoklosa, Drope, and Chaloupka (2016), Zheng et al. (2017), Huang et al. (2018), Cotti et al. (2020)

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- E-cigarettes as complements vs. substitutes to cigarettes
  - Substitutes: Friedman (2015), Pesko, Hughes, and Faisal (2016), Cooper and Pesko (2017), Pesko and Warman (2017), Saffer et al. (2018), Saffer et al. (2019), Abouk et al. (2019), Cantrell et al. (2019), Dave, Feng, and Pesko (2019), Pesko and Currie (2019), Cotti et al. (2020), Pesko, Courtemanche, and Maclean (forthcoming)
    - Levy et al. (2018): Aggregate smoking accelerated slightly as vaping became popular
    - Smoking cessation RCTs: Bullen et al. (2013), Hajek et al. (2019)
  - Complements: Abouk and Adams (2017), Cotti, Nesson, and Tefft (2018)
    - Plus public health longitudinal studies; see Chatterjee et al. (2016), Soneji et al. (2017), National Academy of Sciences (2018)

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- **Our key contribution**: integrate into optimal tax framework

Related literature

- Optimal sin taxes
  - Gruber and Koszegi (2001, 2004), Bernheim and Rangel (2004), O'Donoghue and Rabin (2006), Allcott and Taubinsky (2015), Allcott, Lockwood, and Taubinsky (2019), Farhi and Gabaix (2020)
- Demographic diff-in-diff
  - Boxell, Gentzkow, and Shapiro (2017), DeCicca et al. (2017)
- Welfare effects of new products
  - Trajtenberg (1989), Hausman (1996), Petrin (2002), Nevo (2003), Goolsbee and Petrin (2004), Gentzkow (2007), Aguiar and Waldfogel (2018)
- Expert elicitation
  - Nutt et al. (2014), DellaVigna and Pope (2018, 2019), Drupp et al. (2018), Pindyck (2019), DellaVigna, Otis, and Vivalt (2020)

Optimal Tax Framework

Economic approach to optimal taxation

- Mathematical model of utility and consumption
- Social welfare function: sum over consumers of utility
- Solve for the tax that maximizes social welfare

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Corrective taxes:

- Externalities: health care costs paid by others, second-hand smoke, etc.
- Internalities: I may not fully consider how vaping/smoking harms my health

Theoretical framework: setup

- Time periods indexed by t
- Goods $j \in \{c, e\}$; numeraire n
- Constant marginal cost, competitive markets
- Government sets taxes $\boldsymbol{\tau} = \{\tau^c, \tau^e\}$, lump-sum transfer T
- $\boldsymbol{p} = \{p^c, p^e\}$: tax-inclusive prices
- Heterogeneous consumers, types θ with measure s_θ
  - $\boldsymbol{q}_t = \{q_t^c, q_t^e\}$: possible consumption
  - $\boldsymbol{q}_{\theta t} = \{q_{\theta t}^c, q_{\theta t}^e\}$: *actual* consumption chosen by type θ
  - Income $z_{\theta t}$, budget constraint $z_{\theta t} + T_t = \boldsymbol{p} \cdot \boldsymbol{q}_t + q_t^n$
  - S_t: consumption capital stock ($\implies$ habit formation)

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- Quasi-linear utility

$$U_\theta = \sum_{t=0}^{\infty} \delta^t \left[u_\theta \left(\boldsymbol{q}_t; S_t \right) + q_t^n \right]$$

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- "Marginal distortion" = marginal bias + marginal externality. $\varphi_\theta^j := \gamma_\theta^j + \phi_\theta^j$.

Social welfare

$$W(\boldsymbol{\tau}) = \sum_{\theta} U_{\theta}$$

Socially optimal taxes

$$\tau^{e*} = \underbrace{\frac{\sum_{\theta,t} \delta^t s_\theta \frac{dq^e_{\theta t}}{dp^e} \varphi^e_\theta}{\sum_{\theta,t} \delta^t s_\theta \frac{dq^e_{\theta t}}{dp^e}}}_{\text{average marginal distortion}} + \underbrace{\frac{\sum_{\theta,t} \delta^t s_\theta \frac{dq^c_{\theta t}}{dp^e} (\varphi^c_\theta - \tau^c_t)}{\sum_{\theta,t} \delta^t s_\theta \frac{dq^e_{\theta t}}{dp^e}}}_{\text{substitution distortion}}$$

Optimal to subsidize e-cigarettes if

- Vaping is not very harmful
- Vaping is a substitute for smoking
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Key statistics:

- $\frac{\partial q^e_\theta}{\partial p^e}$, $\frac{\partial q^c_\theta}{\partial p^e}$: own-price and cross-price elasticities
- φ^e, φ^c: marginal distortions

Price Elasticity

Empirical strategy:

- Data: 2013-2017 Nielsen RMS scanner data aggregated to UPC-cluster-month (k, s, t)
    - "Cluster" $:=$ Montgomery county, rest of MD, Cook county, rest of IL, 46 other states, DC

$$\underbrace{\ln(q^e_{kst})}_{\text{e-cigarette sales}} = \underbrace{\eta \ln(\tilde{p}^e_{kst})}_{\text{e-cigarette price}} + \underbrace{\chi^e \ln(\tilde{p}^c_{st})}_{\text{cigarette price}} + \underbrace{\boldsymbol{\beta X}_{st} + \boldsymbol{\kappa Q}_{kst}}_{\text{controls}} + \underbrace{\nu_{kt} + \mu_{ks} + \xi_{d(s)t}}_{\text{fixed effects}} + \varepsilon_{kst}$$

- Exogenous price variation: 11 e-cigarette tax changes from 2013-2017
    - Instrument for $\ln(\tilde{p}^e_{kst})$ and $\ln(\tilde{p}^c_{st})$ with $\ln(\tau^e_{kst} + 1)$ and $\ln(\tilde{\tau}^c_{st} + 1)$, where $\tau =$ (implied) percent tax

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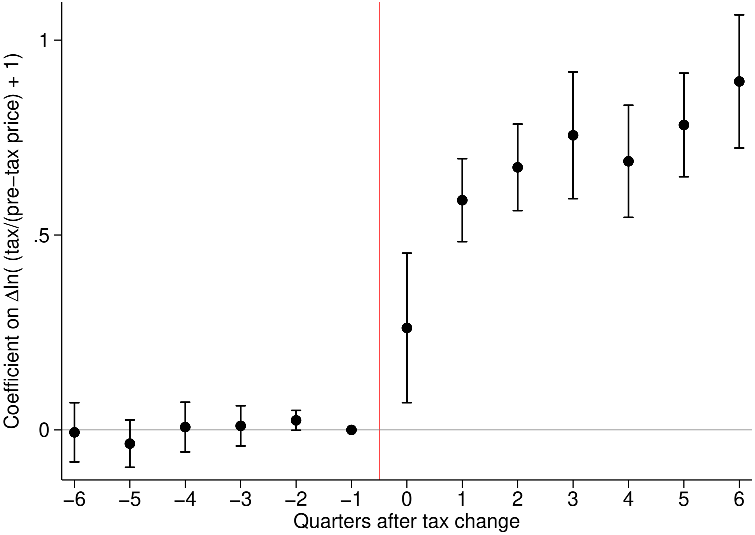
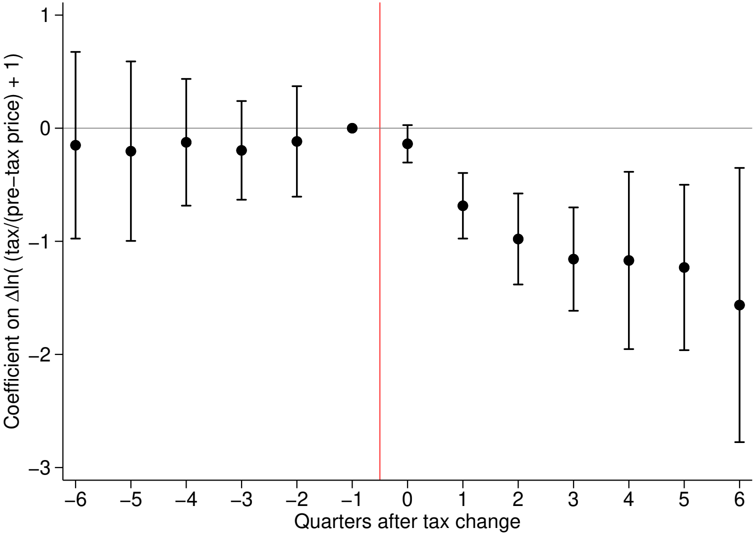
Limitations:

- RMS includes only large retailers covering 2.5% of U.S. e-cigarette sales
  - Different consumer types?
  - Tax avoidance $\implies$ RMS sales more elastic?
- Get medium-run elasticity, but want long-run elasticity
- Taxes raise awareness (Rees-Jones and Rozema 2019)

Event study of e-cigarette tax changes: first stage



Event study of e-cigarette tax changes: reduced form



First stage and reduced form

	(1)	(2)	(3)
Dependent variable:	ln(e-cig price)	ln(cig price)	ln(e-cig units)
ln(e-cig % tax rate + 1)	0.580	0.196	-0.723
	(0.048)	(0.073)	(0.148)
ln(cig % tax rate + 1)	-0.011	0.482	0.115
	(0.043)	(0.102)	(0.228)
Observations	285,985	285,985	285,985

Instrumental variables estimates

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	(1)	(2)	(3)	(4)	(5)
Dependent variable:	ln(e-cig units)	ln(e-cig units)	ln(e-cig units)	ln(e-cig units)	ln(e-cig units
ln(e-cig price)	-1.318	-1.628	-1.203	-1.062	-1.131
	(0.411)	(0.343)	(0.451)	(0.395)	(0.255)
ln(cig price)	0.210	0.721	0.784	0.809	0.819
	(0.463)	(0.620)	(0.635)	(0.612)	(0.381)
UPC-cluster FE	Yes	No	Yes	Yes	Yes
UPC-month FE	Yes	No	No	Yes	Yes
Division-month FE	Yes	No	No	No	Yes
Cluster $\times$ month trend	Yes	No	No	No	No
Quasi-panel	No	No	No	No	No
Time-varying state controls	Yes	Yes	Yes	Yes	Yes
Observations	285,985	286,491	286,303	285,985	285,985

Effect of E-cigarettes on Cigarette Smoking

Data

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	

- 7.4 million observations from 2004-2018
- Weight for national representativeness

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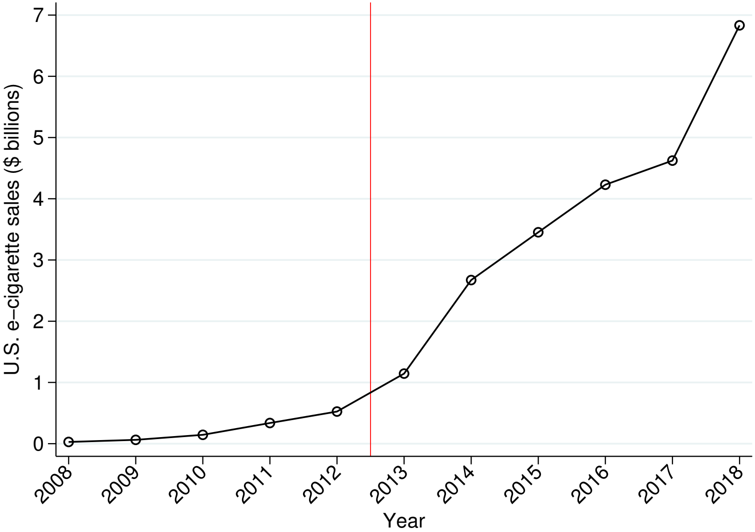
Smoking and vaping self-reports:

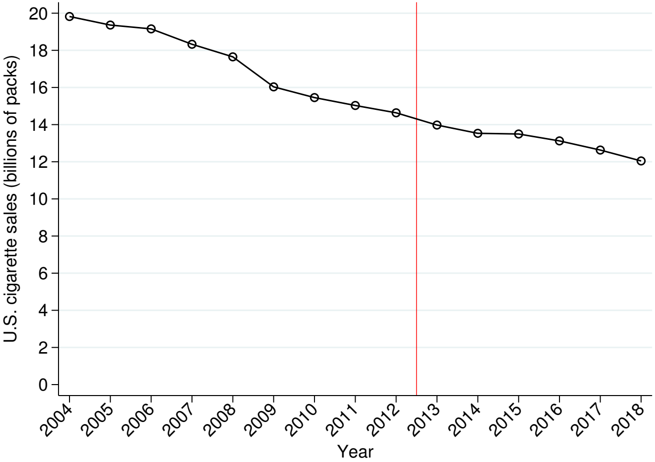
- Vaping: *How many days did you vape in the last 30 days?*
- Smoking: *How many packs per day do you smoke?*
- BRFSS: *Do you smoke/vape every day, some days, or not at all?*

Smoking and vaping trends

Rapid rise in vaping

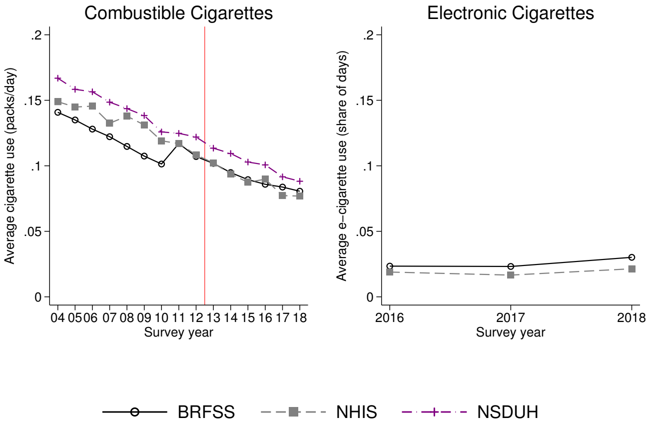


Continued decline in smoking



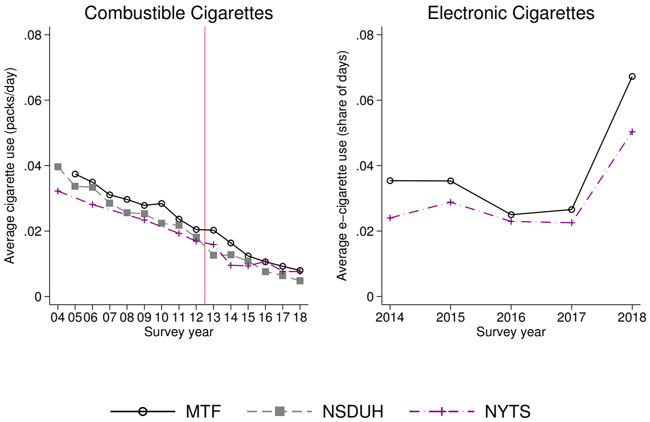
- Perfect complements (substitutes) $\Longrightarrow$ cigarette sales $\uparrow$ ($\downarrow$) by 1.5 billion packs/year

Smoking and vaping trends (adults)



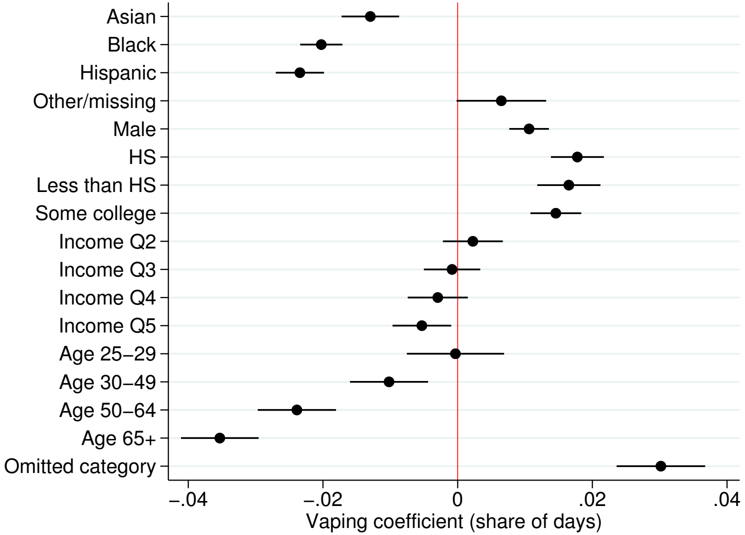
- Perfect complements (substitutes) $\implies$ smoking $\uparrow$ ($\downarrow$) by 0.0125 packs/day

Smoking and vaping trends (youth)



- Perfect complements (substitutes) $\implies$ smoking $\uparrow$ ($\downarrow$) by 0.03 packs/day

Demographic predictors of vaping (adults)



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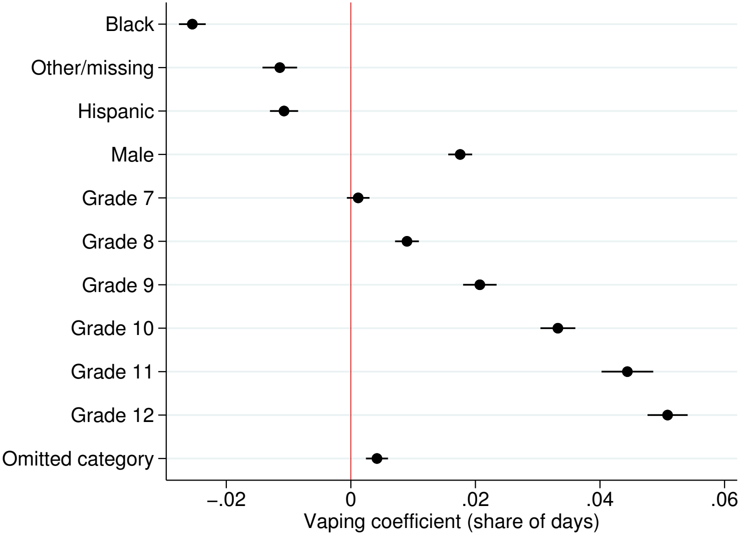
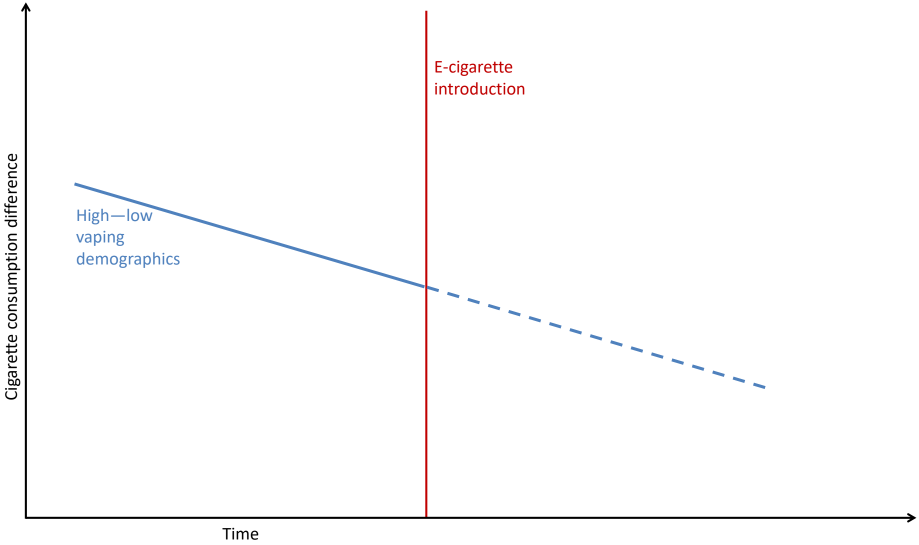


Identification strategy in pictures

Identification strategy



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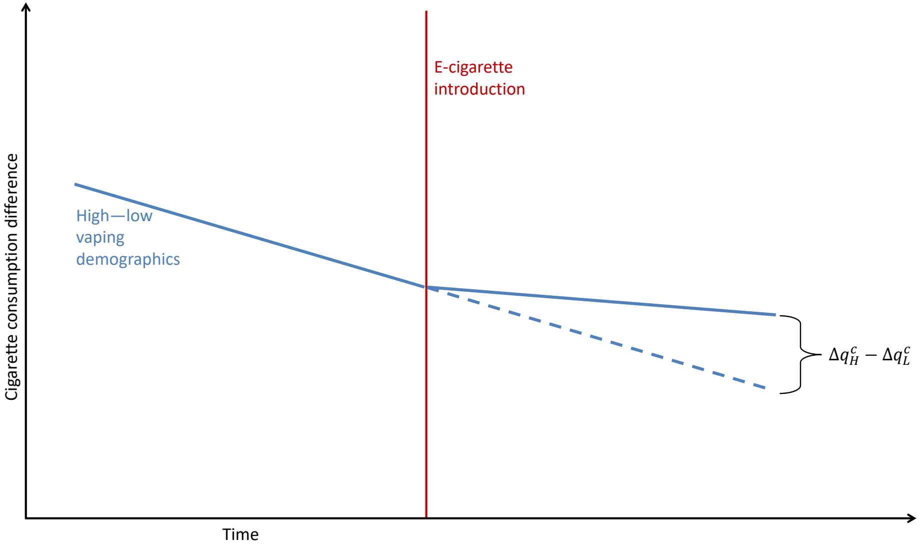

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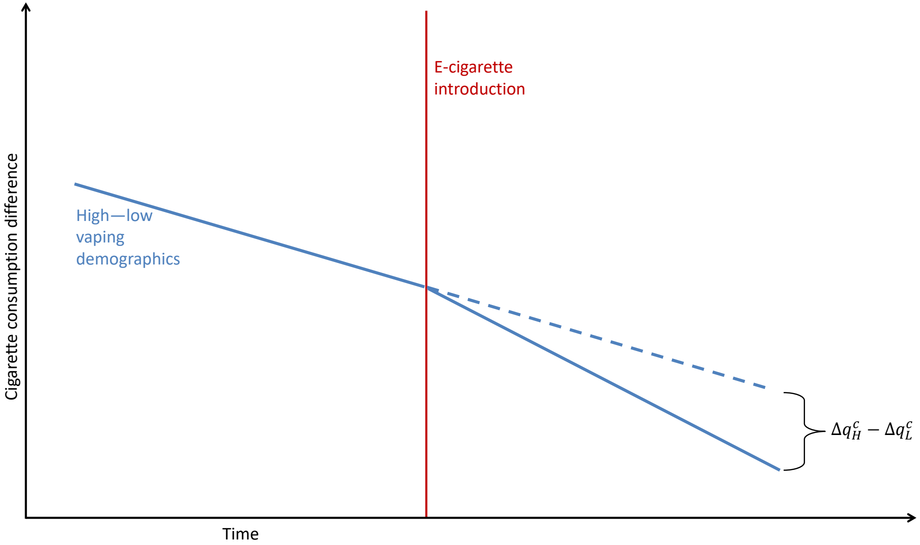


Identifying assumption

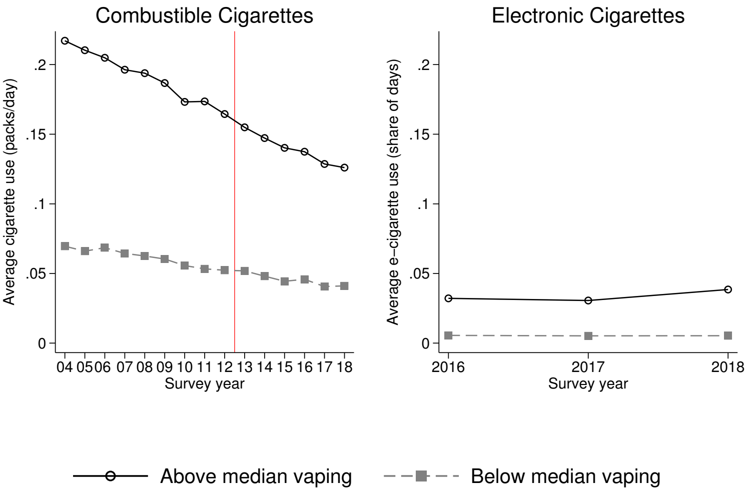
Identifying assumption:

- Without e-cigarettes, there would have been no systematic changes in cigarette consumption (conditional on trends, year effects, etc.) for higher- vs. lower- vaping demographic groups

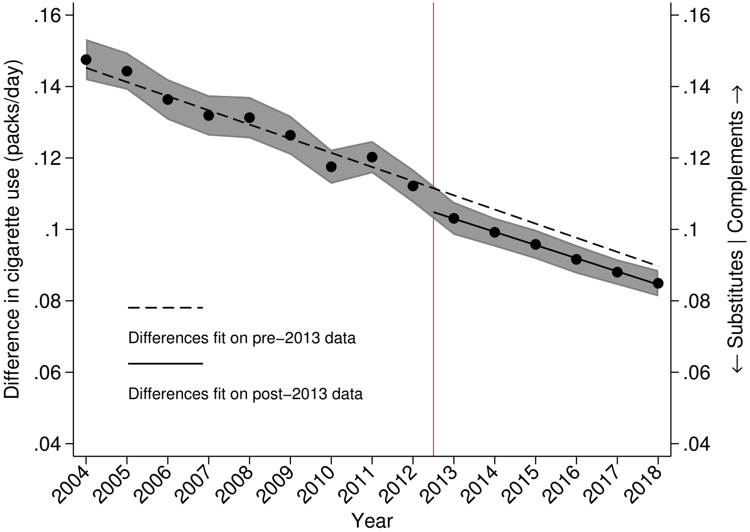
Suggestive tests:

- Pre-event trends
- Overidentification

Smoking and vaping trends for high vs. low vaping demographics (adults)



Difference in smoking trends for high vs. low vaping demographics (adults)



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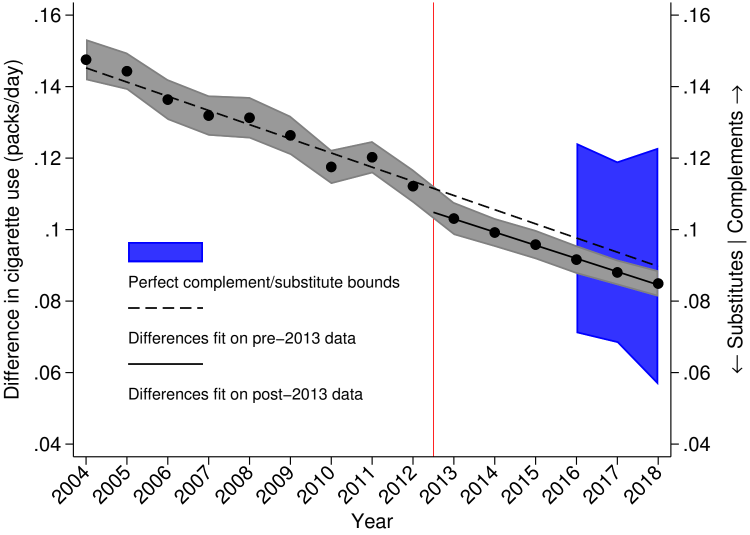

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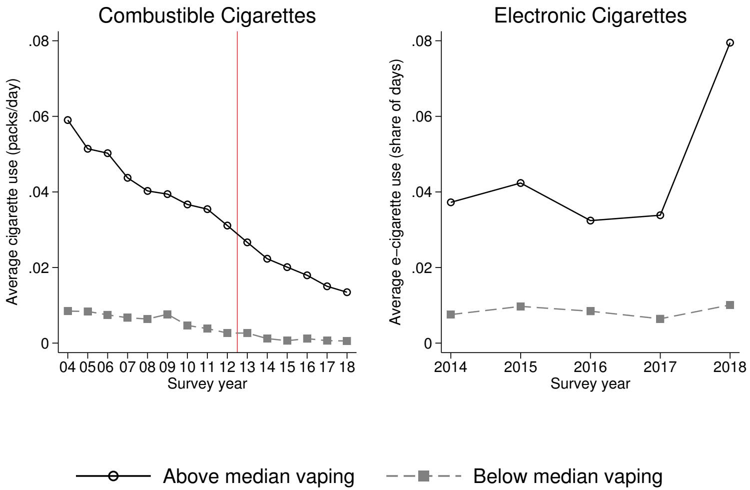

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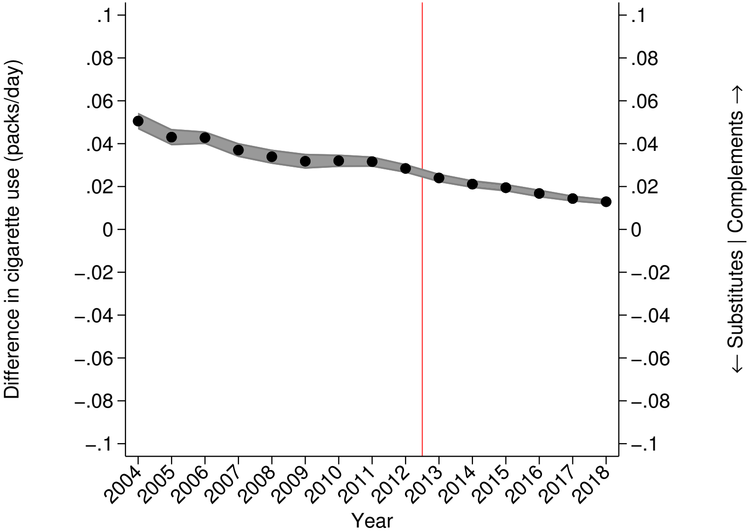

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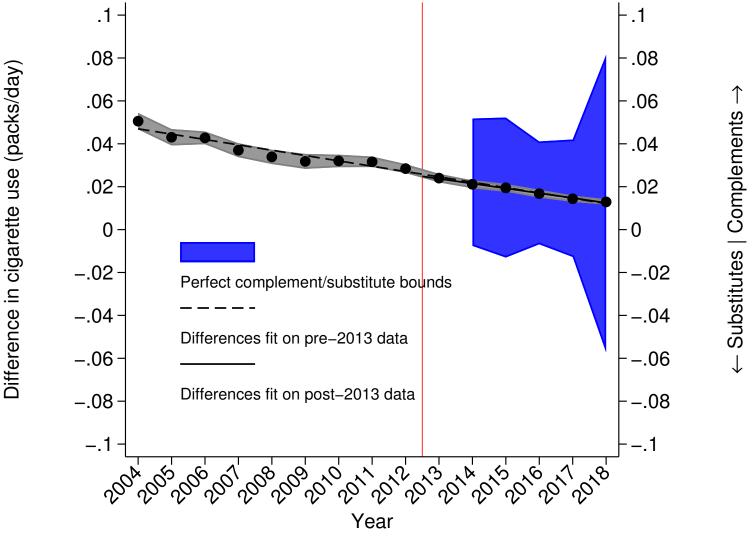


Parameter estimates

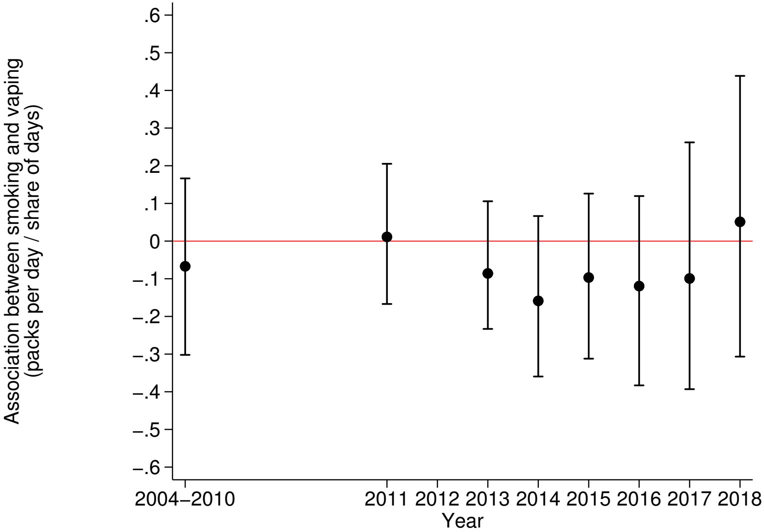
Identification strategy: implementation

- i = person, d = dataset, g = demographic cell, t = year
- ν_t = year indicators; μ_{dgt} = dataset controls
- $\boldsymbol{G}_i$ = vector of demographic group indicators (male, race, gender, age bins, etc.)
- Estimating equation

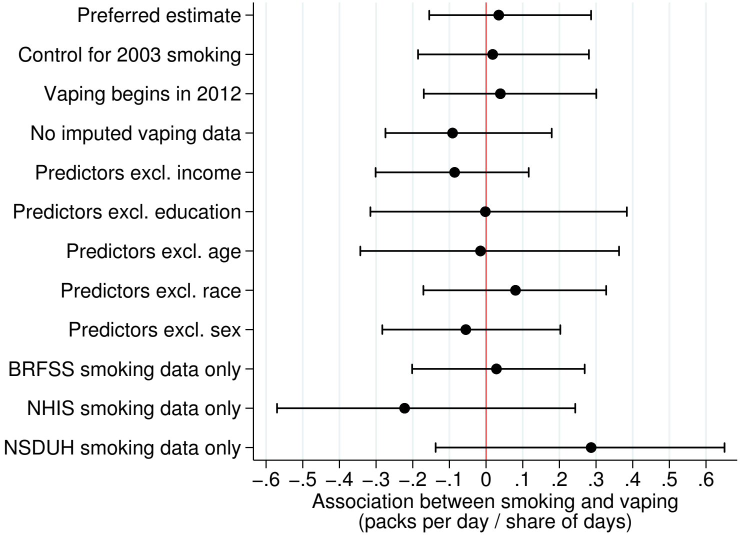
$$q^c_{it} = \sigma \hat{q}^e_{it} + \boldsymbol{\lambda} \boldsymbol{G}_i + \boldsymbol{\omega}(t - 2004)\boldsymbol{G}_i + \nu_t + \mu_{dgt} + \varepsilon_{it}.$$

- Instrument for q^e_{it} with $\boldsymbol{G}_i \cdot 1[t \geq 2013]$, $\boldsymbol{G}_i \cdot 1[t \geq 2013] \cdot (t - 2012)$, and $\boldsymbol{G}_i \cdot 1[t = 2018]$

Event study of e-cigarette introduction (adults)



Substitution parameters and robustness checks (adults)



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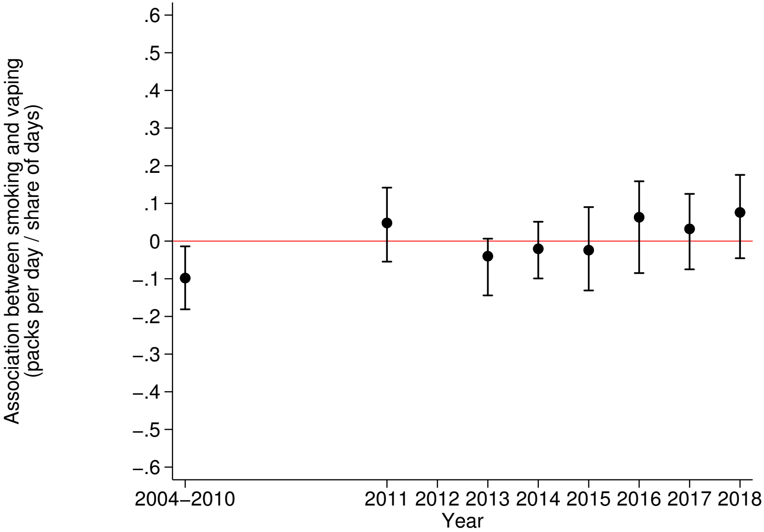

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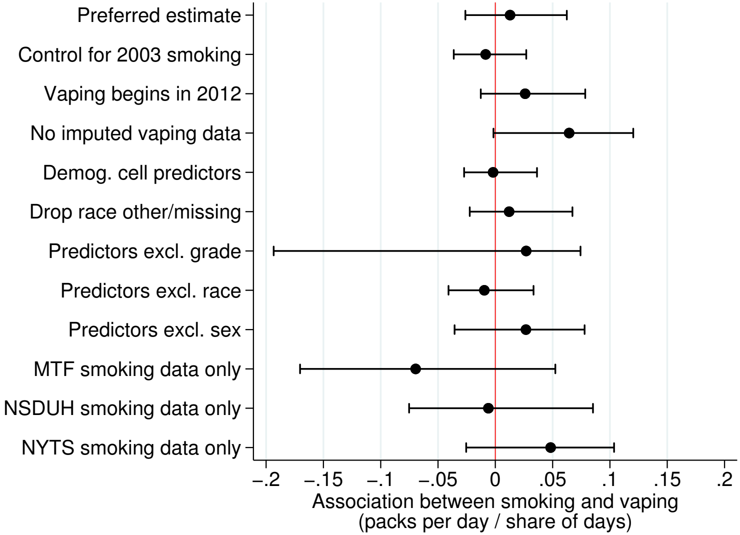

Effects of e-cigarettes on smoking

	Adults	Youth
$\hat{\sigma}$ (packs per day/share of days)	0.03	0.01
95% confidence interval	(-0.16, 0.29)	(-0.03, 0.06)
2018 average vaping (share of days)	0.024	0.053
Effect of vaping on smoking (packs/day)	0.00083	0.00068
95% confidence interval	(-0.00374, 0.00690)	(-0.00138, 0.00329)
2018 average smoking (packs/day)	0.082	0.006
Effect of vaping on smoking (%)	1.0	10.6
95% confidence interval	(-4.5, 8.4)	(-21.4, 51.2)
2018 implied total smoking (million packs)	7,495	58.7
Effect of vaping on smoking (million packs)	76.0	6.2
95% confidence interval	(-340.9, 629.7)	(-12.6, 30.0)
2004–2018 smoking decrease (packs/day)	0.071	0.030
Effect of vaping on smoking (% of decrease)	-1.2	-2.3
95% confidence interval	(-9.8, 5.3)	(-11.1, 4.7)

Harms from Vaping Relative to Smoking

Expert survey: harms from vaping relative to smoking

Motivation for expert survey:

- Disagreement among experts
- Rapidly evolving research
- E-cigarette products
- Need *quantitative* estimates of relative harms

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Fielded August 2020

Expert survey sample frame

1. The 13 committee members, 13 reviewers, and 122 corresponding authors of papers on the health impacts of e-cigarettes from the landmark National Academy of Sciences (2018) report
2. The 113 editors, contributing authors, and reviewers of the 2020 Surgeon General Report on smoking cessation
3. The 91 editors, contributing editors, contributing authors, and reviewers of the 2016 Surgeon General Report on e-cigarettes
4. The 34 people who served on the FDA Tobacco Product Scientific Advisory Committee between 2017 and 2020
5. The 65 people who have been honored as Fellows of the Society for Research on Nicotine and Tobacco
6. The 70 editors, senior editors, and senior associate editors at three leading academic journals (Tobacco Regulatory Science, Tobacco Control, and Nicotine and Tobacco Research), as well as the 62 associate editors at the latter two journals
7. The 55 authors of papers about cigarettes or e-cigarettes cited in Cutler et al. (2015), Chaloupka, Levy, and White (2019), and our September 2019 draft

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Completion rate: 137/447 $\approx$ 31%

Expert survey introduction

To be concrete, we'll ask you to predict the effects of a ***hypothetical*** *randomized control trial with a* ***random sample of people in the U.S. who currently smoke or vape or might do so in the future****. Participants would be assigned one of three groups:*

1. "Smoking group": Smoke one pack of typical cigarettes every day

2. "Vaping group": Vape every day using ***typical e-cigarettes currently available in the U.S.****, consuming a* ***comparable amount of nicotine*** *as the smoking group*

3. "Control group": Not vape or smoke at all

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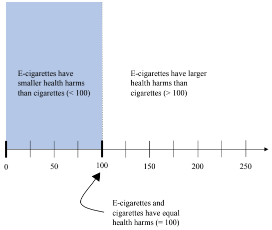
- *Please assume there is no dual use: the smoking group does not vape, and the vaping group does not smoke cigarettes.*
- *Please assume the experiment starts next year and continues for a long time, with **full compliance**.*
- *Please assume that participants in the experiment do not use illegal products and do not vape or smoke THC/marijuana. (This is because we want to evaluate regulations that only affect the use of legal products.)*
  - *The 2019 outbreak of e-cigarette product use-associated lung injury (EVALI) was largely linked to use of e-liquids containing THC. We ask you to **ignore any EVALI or other health effects that you think are caused by illegal products or THC**.*

Predicted effects on health outcomes

If smoking one pack per day reduces quality-adjusted life expectancy (compared to Control) by 100 units, by how many units do you think vaping every day would reduce quality-adjusted life expectancy (compared to Control)?

- *If vaping and smoking have equal effects on morbidity and mortality, your answer would be 100 units.*
- *If vaping is much more harmful than smoking, your answer might be much larger than 100.*
- *If vaping is much less harmful than smoking, your answer might be close to 0.*



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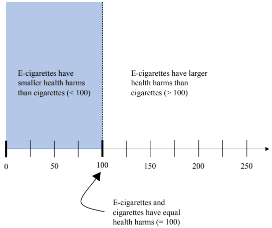
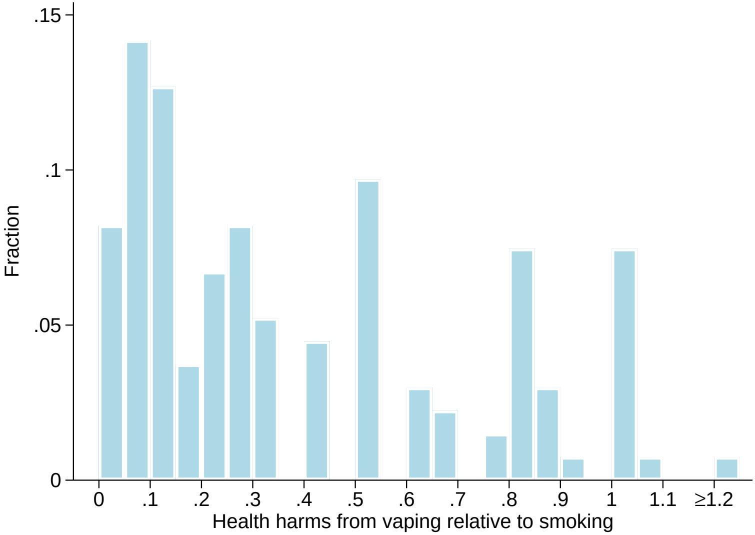


- Parallel questions for cardiovascular disease, respiratory disease, cancer, other health

Expert survey: effects of vaping on quality-adjusted life expectancy



Part 2: Reasons for disagreement with prior assessments

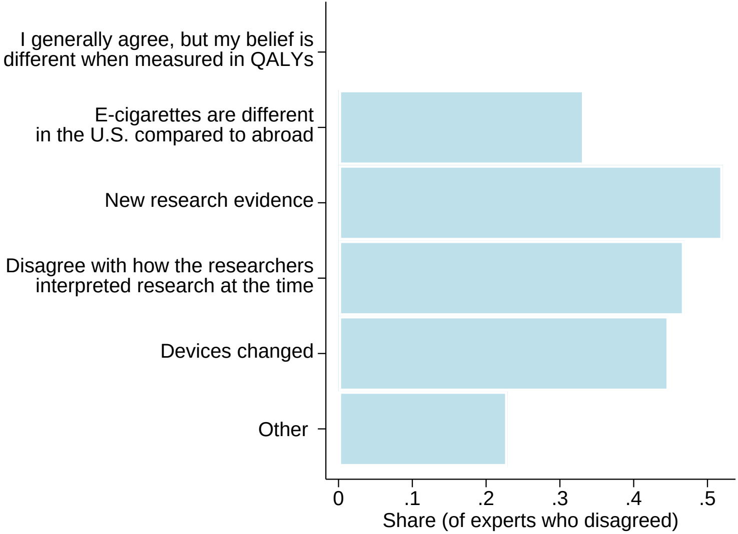
What do you think the average expert would report?

How optimistic or pessimistic are you about the health effects of vaping now, compared to five years ago?

Public Health England (2018) concluded that “Based on current knowledge, stating that vaping is at least 95% less harmful than smoking remains a good way to communicate the large difference in relative risk.” A paper by Nutt et al. (2014) came to a similar conclusion.

... you are more [pessimistic / optimistic] about vaping than Nutt et al. (2014) and Public Health England (2018). Why?

Expert survey: reasons for disagreement with prior assessments



Expert survey: comments

- Extensive confirmation checks $\implies$ unlikely that experts misunderstood
- No relationship between α and number of publications
- Public health experts report higher α than economists
- Sample selection bias does not explain why our experts disagree with prior assessments
    - Our experts report being more *optimistic* than average
    - No relationship between α and response date
    - Even if all non-respondents believe $\alpha = 0$, the average α is still 0.11

Optimal Tax Quantification

Formulas for empirical implementation

Optimal e-cigarette tax:

$$\tau^{j*} = \frac{\sum_{\theta} s_{\theta} q_{\theta}^{j} \left[\varphi_{\theta}^{j} + \sigma_{\theta} \left(\varphi_{\theta}^{-j} - \tau^{-j} \right) \right]}{\sum_{\theta} s_{\theta} q_{\theta}^{j}}$$

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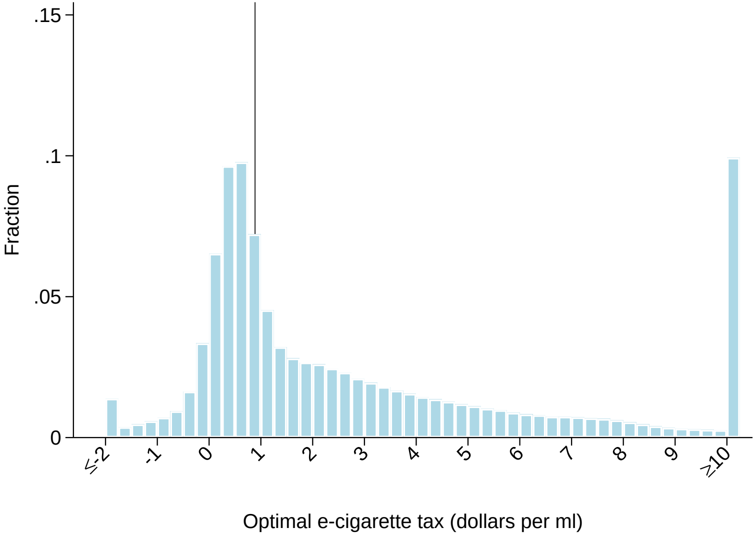
Welfare effect of e-cigarette ban:

$$\Delta \overline{W} = \textstyle\sum_\theta s_\theta \left[\underbrace{\Delta q_\theta^e \frac{\tilde{p}^e}{-2\eta}}_{\text{perceived CS change}} - \underbrace{\sum_j \Delta q_\theta^j \left(\varphi_\theta^j - \tilde{\tau}^j\right)}_{\text{uninternalized distortion change}} \right]$$

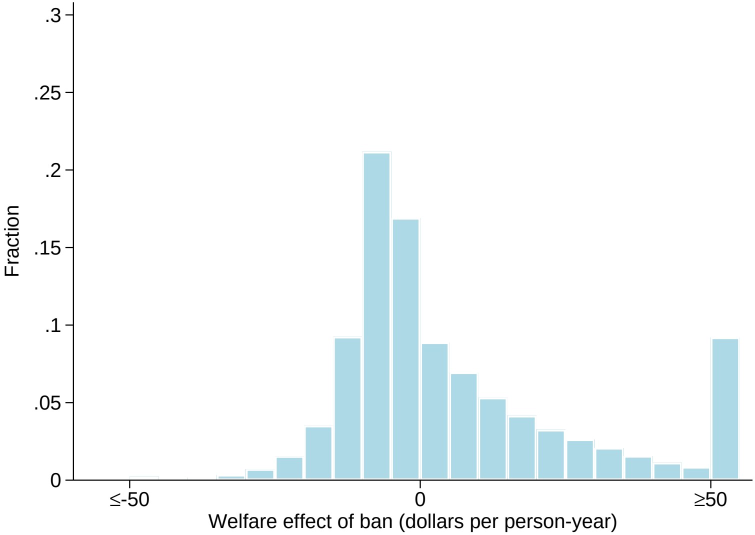
Parameters for policy analysis

Object	Description and units	Mean	Data source
η	E-cigarette own-price elasticity	-1.318	RMS (Table **??**)
σ_{adult}	E-cig effect on smoking (packs/day vaped)	0.035	Figure **??**
σ_{youth}	E-cig effect on smoking (packs/day vaped)	0.013	Figure **??**
s_{adult}	Population share adults	0.910	2018 American Community Survey
s_{youth}	Population share youth	0.090	2018 American Community Survey
$\tilde{p}_e$	E-liquid price ($/ml)	3.90	E-cigarette User Survey
$\tilde{\tau}^c$	Average cigarette tax ($/pack)	2.92	Tax Policy Center (2019), ACS
$\tilde{\tau}^e$	Average e-liquid tax ($/ml)	0.233	Tax Foundation, RMS, Census
q^e_{adult}	Share of person-days vaped	0.024	BRFSS, NHIS 2018
q^e_{youth}	Share of person-days vaped	0.053	MTF, NYTS 2018
Γ	Average e-liquid use (ml/day vaped)	0.58	E-cigarette User Survey
Λ	Nicotine in e-liquid relative to cigarettes (ml/pack)	0.7	CDC (2020)
ϕ^c	Smoking externality ($/pack)	0.64	Sloan et al. (2004)
α	Health harms from vaping relative to smoking	0.373	E-cigarette Expert Survey
α	Health harms from vaping relative to smoking	0.05	McNeill et al. (2018)
H^c	Private health cost of smoking ($/pack)	44.4	Gruber and Kőszegi (2001)
β	Present focus	0.670	Chaloupka et al. (2019)
β	Present focus	0.9	Gruber and Kőszegi (2001)
ρ	Internalities for youth relative to adults	1.474	E-cigarette Expert Survey

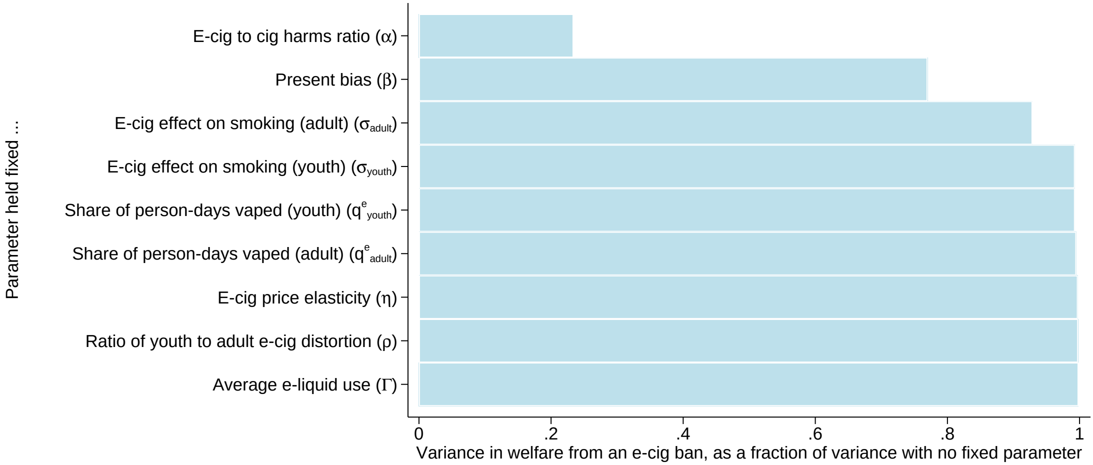
Optimal e-cigarette tax across Monte Carlo simulations



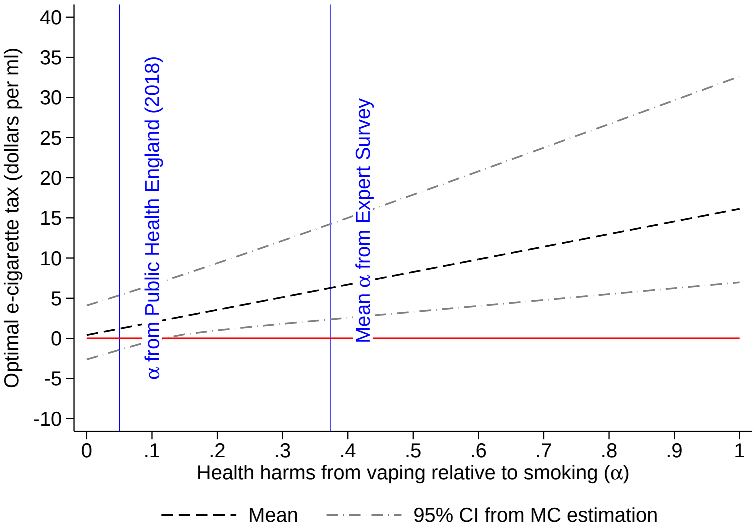
Welfare effect of a ban across Monte Carlo simulations



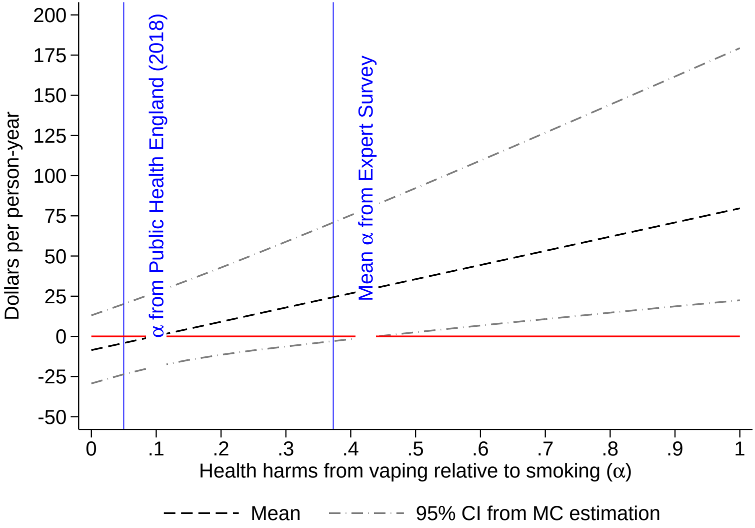
Sources of uncertainty in welfare effect of ban



Optimal tax as a function of health harms



Welfare effect of ban as a function of health harms



Optimal tax under alternative assumptions

Parameter assumptions	(1) $\alpha = 0.05$ (McNeill et al. 2018)	(2) $\alpha = 0.37$ (mean, Expert Survey)
1. Primary	1.20	6.27
2. Present focus only, $\beta = 0.9$	0.51	3.03
3. Present focus only, $\beta = 0.670$	1.87	9.50
4. Belief bias only	-37.64	-16.86
5. Jin et al. (2015) internality only	0.48	2.85
6. Rescale distortions so $\varphi^c = \tilde{\tau}^c$	0.23	1.68
7. $\sigma_\theta = \hat{\sigma}$ from Nielsen RMS	0.30	5.37
8. σ_θ and η from Nielsen RMS without time trends	-2.64	2.43
9. $\sigma_\theta =$ combined $\hat{\sigma}_\theta$	0.72	5.80
10. Perfect complements	6.58	11.65
11. Perfect substitutes	-5.00	0.07
12. $\sigma_\theta = 0$	0.79	5.86
13. $\tilde{\tau}^c$ set optimally	0.80	5.87
14. $s_{\text{adult}} = 0$, $s_{\text{youth}} = 1$	1.32	8.11
15. $s_{\text{adult}} = 1$, $s_{\text{youth}} = 0$	1.17	5.87

Welfare effect of ban under alternative assumptions

Parameter assumptions	(1) $\alpha = 0.05$ (McNeill et al. 2018)	(2) $\alpha = 0.37$ (mean, Expert Survey)
1. Primary	-4.10	24.39
2. Present focus only, $\beta = 0.9$	-7.91	6.24
3. Present focus only, $\beta = 0.670$	-0.32	42.54
4. Belief bias only	-222.29	-105.54
5. Jin et al. (2015) internality only	-8.13	5.21
6. Rescale distortions so $\varphi^c = \tilde{\tau}^c$	-9.53	-1.34
7. $\sigma_\theta = \hat{\sigma}$ from Nielsen RMS	-9.09	19.41
8. σ_θ and η from Nielsen RMS without time trends	-26.26	2.29
9. $\sigma_\theta =$ combined $\hat{\sigma}_\theta$	-6.74	21.75
10. Perfect complements	25.76	54.24
11. Perfect substitutes	-38.55	-10.07
12. $\sigma_\theta = 0$	-6.39	22.11
13. $\tilde{\tau}^c$ set optimally	-6.32	22.20
14. $s_{\text{adult}} = 0$, $s_{\text{youth}} = 1$	-6.77	68.60
15. $s_{\text{adult}} = 1$, $s_{\text{youth}} = 0$	-3.84	20.00
16. $\eta = -.5$	-16.50	11.98
17. $\eta = -1$	-5.56	22.92

Conclusion

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- Optimal tax framework: optimal tax (or subsidy) depends on health harms, substitution with smoking, and uninternalized harms from smoking
- Estimates of key parameters
    - E-cigarette demand is price elastic
    - Vaping neither a significant complement nor substitute for smoking over the medium term
    - Experts believe that vaping is more harmful than prior assessments had suggested
- Optimal tax quantification
    - In our model, the optimal e-cigarette tax to correct plausible levels of present bias is probably higher than the current norm
    - Monte Carlo simulations highlight substantial uncertainty
    - More research on internalities and externalities would be very valuable