Building Capacity for Economic Research on Tobacco Regulation in Low- and Middle-Income Countries: Methodology, Analysis, and Interpreting Evidence

Pre-Congress Session

International Health Economics Association

Bali, Indonesia

July 20, 2025

Goal and Intended Audience

- Describe opportunities for economic research on tobacco regulation.
  - Tobacco regulation includes taxation, place-based smoking bans, and product regulations.
  - New products, including e-cigarettes, have been introduced worldwide.
  - Low- and middle-income countries have adopted a range of regulatory approaches to e-cigarettes. Many countries in sub-Saharan Africa and elsewhere do not regulate e-cigarettes, while India and some other countries ban e-cigarettes entirely.
- The Pre-Congress Session will review new (& old) policies, new products, and state-of-the-art econometric and applied welfare economic methods.
- Intended audience: anyone interested in economic research on tobacco regulation

Discussion Leaders

- Don Kenkel, Cornell University
- Yang Liang, San Diego State University
- James Prieger, Pepperdine University
- Joe Sabia, San Diego State University

- Cornell Research on Tobacco Regulation
  - https://sites.google.com/view/cornellcrtr
  - Virtual Office Hours: Mondays, 7 – 9 a.m. New York time

Schedule/ Outline

- Session I: 1:00 - 2:30 p.m.
    - Introduction and Overview (Kenkel & Prieger)
    - Quasi-Experimental Design in E-Cigarette Policy Research: Evidence from the U.S. and Canada (Sabia & Yang)
    - Discrete Choice Experiments to Inform Tobacco Regulations (Kenkel)
- Refreshment break: 2:30 – 3:00 p.m.
- Session 2: 3:00 – 4:30 p.m.
    - Opportunities for Quasi-Experimental Research on Tobacco Regulations in Low- and Middle-Income Countries (Sabia & Yang)
    - Applied welfare economics & the promise of e-cigarettes to reduce health disparities (Prieger)
    - Cost-Benefit Analysis of Tobacco Regulations (Kenkel)

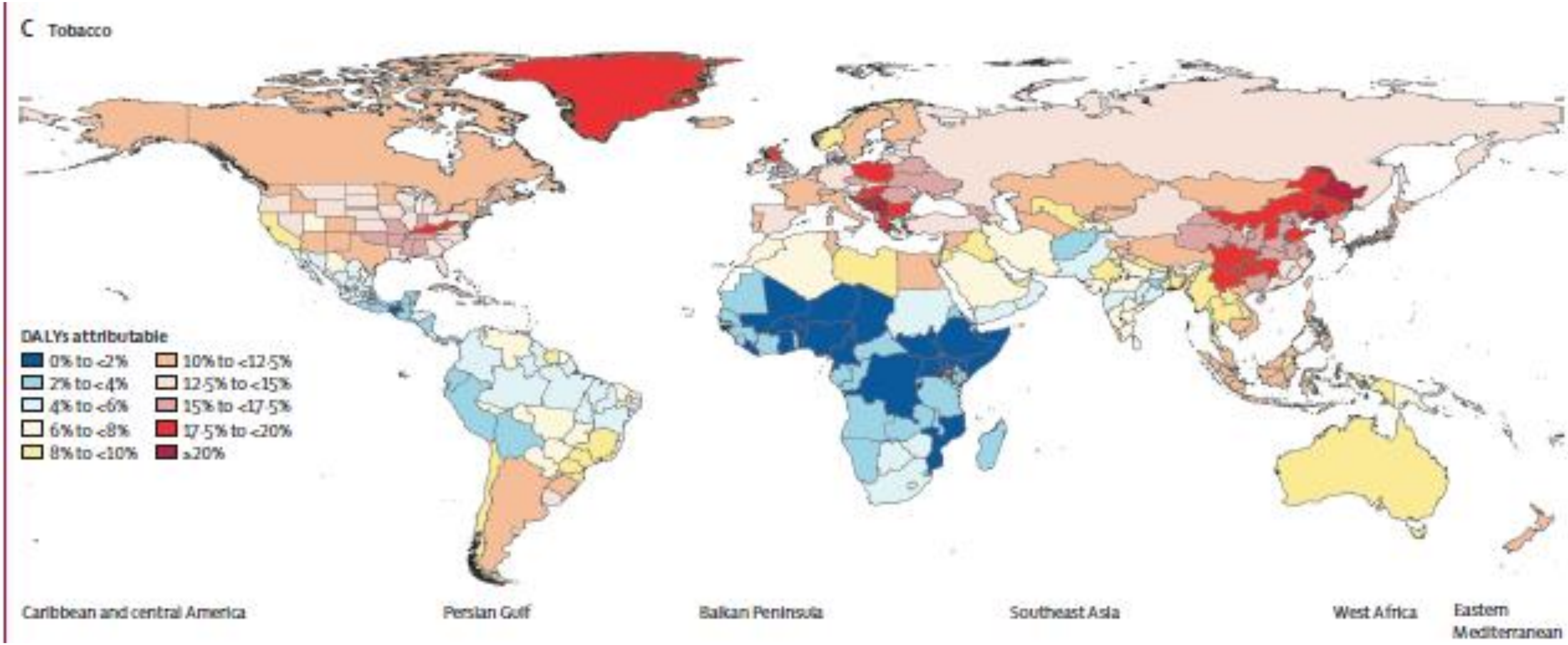
Disclosures

- All opinions and conclusions expressed in this lecture are my own.
- I acknowledge past research support through grants to Cornell University from the National Institutes of Health for my econometric research on alcohol taxation, cigarette taxation, and smoking cessation product advertising.
- I acknowledge past and current research support and support for this pre-Congress session through grants to Cornell University from Global Action to End Smoking (formerly known as Foundation for Smoke-Free World), an independent, U.S. nonprofit 501(c)(3) grantmaking organization. Global Action (GA) played no role in designing, implementing, data analysis, or interpretation of the research results, nor did GA edit or approve any presentations or publications from the study. The contents, selection, and presentation of facts, as well as any opinions expressed, are the sole responsibility of the authors and should not be regarded as reflecting the positions of Global Action. Through September 2023, GA received charitable gifts from PMI Global Services Inc. (PMI), which manufactures cigarettes and other tobacco products. To complement the termination of its agreement with PMI, GA's Board of Directors established a new policy to not accept or seek any tobacco or non-medicinal nicotine industry funding.

Tobacco Harms

- Tobacco use remains a leading cause of death and disease across the globe.
- 1.3 bill. tobacco users
- 8.7 mill. deaths annually
- 230 mill. DALYs

Percent of Global Burden of Disease Attributable to Tobacco



Economic research contributes to the evidence base for tobacco regulation to address the burden of disease attributable to tobacco

- Quasi-experimental methods or DCEs => credible estimates of immediate impacts on smoking, vaping, and quitting.
- Often, lack estimates of longer-term outcomes
  - Research on cost-effectiveness of clinical interventions faces similar lack.
- Use epidemiologic models to predict longer-term outcomes
  - Mendez & Warner developed dynamic population simulation model for long-term smoking outcomes, extended to vaping
  - Jin et al. (2016), Mzhavanadze et al (2025)
- Use results to conduct impact analysis, stake-holder analysis, and applied welfare economic analysis including cost-benefit analysis

Economic research helps build evidence base on multiple impacts of tobacco regulation

- Rate of smoking among youth and adults
- Rate of quitting
- Rates of smoking-related illness and death

Public health impacts

- Medical expenditures on smoking-related illness and death
- Tobacco farming, cigarette & e-cigarette manufacturing, etc.

Other sector impacts

- Consumer welfare
- Tax revenues

CBA

Good research practices for reproducible science

- Center for Open Science: *We envision a future scholarly community in which the process, content, and outcomes of research are openly accessible by default…. All stakeholders are included and respected in the research lifecycle and share pursuit of truth as the primary incentive and motivation for scholarship*
  - Post online documentation of research methods, data, and code in sufficient detail to allow replication.
  - Preregister research plans.
  - Report negative (null) findings.
- These steps address publication bias and bad practices such as data dredging or p-hacking
  - Discussed in context of clinical trials, social psychology research, etc.
- Reference: Munafò, Marcus R., Brian A. Nosek, Dorothy V. M. Bishop, et al. (2017). “A Manifesto for Reproducible Science.” Nature Human Behaviour 1, Article number: 0021.

Good research practices in applied econometrics (taking the con out of econometrics)

- Applied econometrics often uses secondary observational data sets, which raises somewhat different issues.
- Athey & Imbens (2017): *Standard practice in modern empirical work is to present in the final paper estimates of the preferred specification of the model in combination with assessments of the robustness of the findings from this preferred specification. These alternative specifications are intended to convey that the substantive results of the preferred specification are not sensitive to some of the choices in that specification, like using different functional forms of the regression function or alternative ways of controlling for differences in subpopulations.*
- Reference: Athey, Susan, and Guido W. Imbens (2017). "The State of Applied Econometrics: Causality and Policy Evaluation." Journal of Economic Perspectives 31 (2): 3–32.

Research Practices Still Have Room for Improvement

- "Many analysts" studies assign multiple teams of researchers to use the same data to answer the same research question.
- Borjas & Bresnau (2024) report experiment where71 research teams used the same data to answer the same well-defined empirical question about immigration policies.
  - Results ranged from strongly negative to strongly positive.
  - Pro-immigration researchers estimated more positive impacts, while anti-immigration research teams reported more negative estimates.
- Huntington-Klein et al. (2025) report experiment where 146 research teams completed the same causal inference task with the same data, first with few constraints, and then using pre-cleaned data.
  - *…findings underscore the critical importance of data cleaning in shaping applied microeconomic results.*

Cost-Benefit Analysis of Tobacco Regulations: Principles & Practical Examples

Donald Kenkel

Cornell University

Pre-Congress Session

IHEA

July 20, 2025

Outline

- Quick review of basic principles of CBA
- 4 simplified examples of CBAs of tobacco regulations
  - Focus on main concepts: benefits vs. opportunity costs
  - BCA requires evidence-based (not arbitrary) assumptions
  - Simple graphical approach with rigorous foundation
  - Distinguish CBA from stakeholder impact analysis

Principles: CBA and Economic Efficiency of Tobacco Regulations

- CBA is a tool to evaluate whether regulations fix market failures and improves economic efficiency.
  - Economic efficiency requires that societal resources are in their most highly valued use.
- Regulation changes the allocation of resources => winners & losers
- A regulation improves economic efficiency if the winners could potentially compensate the losers, and still be better off themselves.
  - Potential Pareto improvement/ Kaldor-Hicks compensation principle
  - Benefits > Costs ⇔ regulation improves economic efficiency
  - Calculate the sum of the compensating variations in income for everyone who either wins or loses because of the regulation.

Principle: Identifying a policy-significant market failure is the first step in CBA

- First Theorem of Welfare Economics (Invisible Hand Theorem): markets succeed to direct resources to their most highly valued use ⬄ market general equilibrium is economically efficient.
  - Theorem holds depending on a set of assumptions: competitive markets, no externalities, etc.
  - When assumptions don’t hold => market failures.
- “If it ain’t broke, don’t fix it.”
  - If market equilibrium is efficient, change cannot improve efficiency.
  - ⬄ change is not a Kaldor-Hicks improvement⬄ change does not yield B > C
- Unhealthy ≠ market failure (necessarily)

Moving from principles to practice: CBA and policy decisions

- The results of CBA *are informative, but are not dispositive…..* (Katzen 2006)
- Most (all?) tobacco regulations will involve winners & losers.
    - B – C > 0 ⇔ winners can potentially compensate loses.
    - But potential compensation payments are not necessarily (usually?) paid.
- Democratically accountable decision-makers make tradeoffs between economic efficiency and other societal goals like equity, justice, …
    - Tradeoffs involve value judgments.
- Value judgments can be embedded into a Social Welfare Function.
    - Example: generalized utilitarian SWF places greater weight on $ gains and losses experienced by disadvantaged groups.
    - SWF => technocrats make the value judgments, instead of democratically accountable decision-makers making valuing judgments.

Practical Examples

- CBA of tobacco regulations is straight-forward in principle, challenging in practice.
- The rest of the presentation discusses the challenges through a set of simplified examples.
- Example #1: CBA of a clean indoor air policy that reduces non-smokers’ exposure to secondhand smoke.
- Example #2: CBA of a cigarette excise tax when consumers are rational and well-informed.
- Example #3: CBA of a cigarette excise tax when some consumers make systematic mistakes and impose internalities on themselves.
- Example #4: CBA of a nudge regulation that changes tobacco product attributes, when some consumers impose internalities on themselves

Example #1: CBA of regulation that bans smoking in public indoor spaces

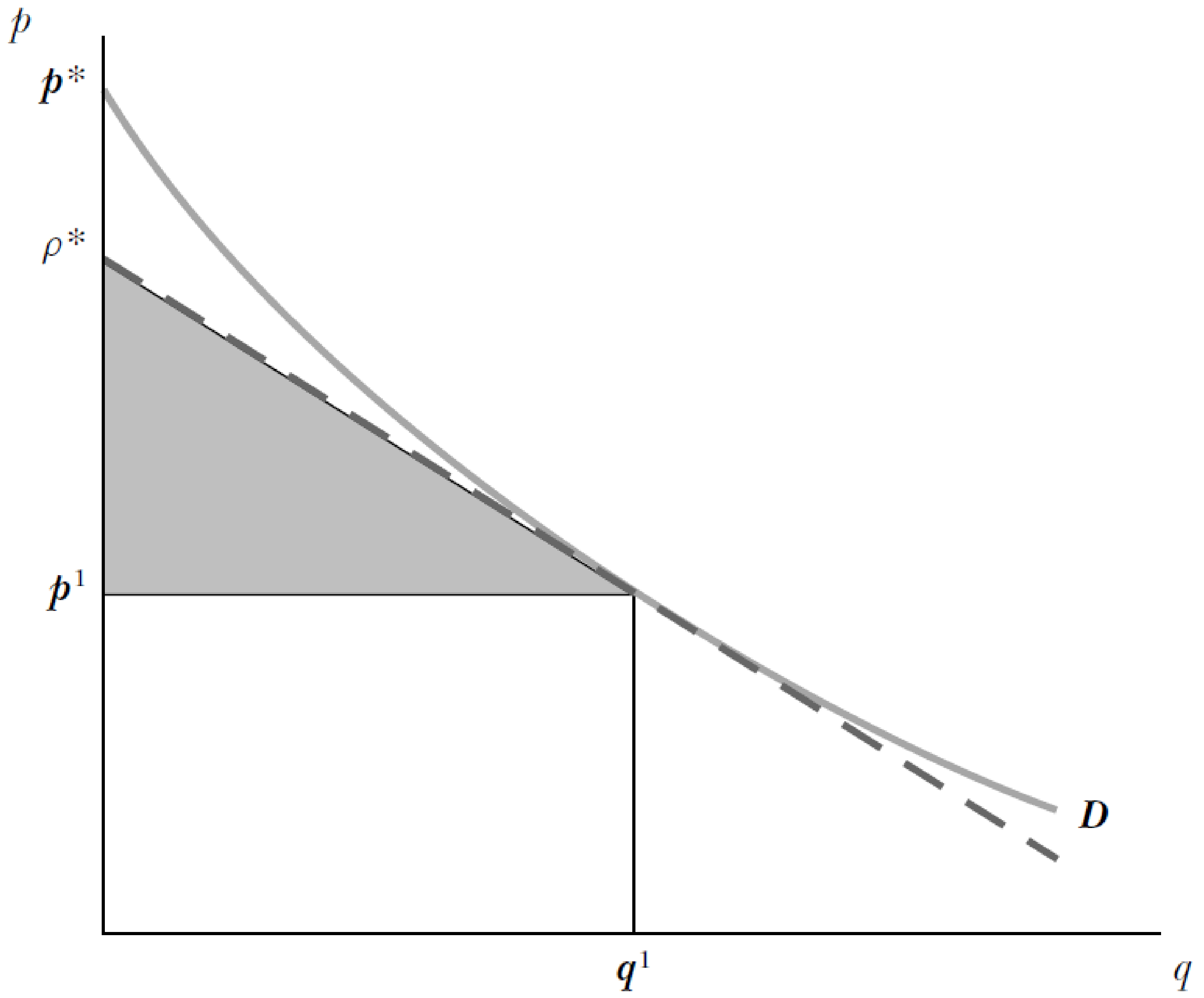
- Market failure: smoking in public indoor spaces imposes a negative externality on non-smokers exposed to secondhand smoke (SHS).
  - FDA (2022) uses an estimate of 41K SHS deaths of U.S. non-smokers annually.
- CBA compares the benefits to non-smokers of reduced SHS exposure to the opportunity costs the ban imposes on smokers.
- Benefits = value of reduction in mortality risks
  - Value of a statistical life summarizes willingness to pay for ↓mortality risks.
  - Risk reduction is probably on the order of magnitude of about 1 in 10,000
  - FDA (2022) uses value of statistical life = $11.8 million

  ⇔ willingness to pay for 1 in 10,000 risk reduction = $1,180 per exposed person

CBA of regulation that bans smoking in public indoor spaces continued

- To find opportunity costs imposed on smokers:
  - Estimate demand curve for smoking in public indoor spaces.
  - Find virtual price p* where the quantity demanded will equal zero.
  - Hausman (2003) suggests that triangular area of consumer surplus gained from a new product/ lost from a banned product is a simple approximation of the value of the product = CV in income for the ban.
- If there are good substitutes for smoking in public indoor spaces, the demand curve will tend to be flat => lower p* required to drive quantity demanded to zero => CV for ban not very large.
  - Possible substitutes include quitting, cutting down, smoking outside, vaping.
  - Unintended consequence: smoking at home (Adda & Cornaglia 2010).
  - Bans often lead to illegal markets; but indoor smoking bans self-enforcing.

New Product



Completing the CBA of bans on smoking in public indoor spaces

- Quasi-experimental estimates of the impact of bans on SHS exposure = ?
  - Adda & Cornaglia (2010) estimate that bans ↑ SHS exposure of nonsmokers
- Retrospective analysis of past reduction in SHS exposure
  - Tsai et al. (2018) estimate that SHS exposure among non-smokers fell from 87.5% to 25.2% from 1988 to 2014.
  - Current annual deaths of 41K due to high exposures in late 1900s
  - Reduced exposure 1988 -2014 => reductions in future SHS deaths.
- If reduced exposure ↓deaths by 30K @ VSL = $11.8 million => benefits = $354 bill./year
- Quasi-experimental estimates of the opportunity costs of the bans = ?
- Break-even calculations => B > C unless opp. costs are over $10K per smoker per year/ $25 per smoker per day.

Example #2: Excise Tax on Cigarettes

- Market failure: none by assumption (to be relaxed later).
  - Goal of the tax is to generate tax revenues for public sector.
- CBA of an excise tax is an analysis of the efficiency cost of taxation.
  - Because there is no market failure, the tax can NOT yield net benefits > 0.
  - Opportunity costs = dollar value (CV) of the utility losses created by the tax.
  - Benefits = Revenues (transferred to other consumers or invested in public goods)
  - Net benefits < 0 => efficiency cost of taxation = deadweight loss of taxation = excess burden of taxation.
- (CBA of how the revenues are used is another question.
  - Example: CBA of an excise tax increase combined with a new government program funded by the tax revenues.)

Sufficient Statistics for Welfare Analysis: A Bridge Between Structural and Reduced-Form Methods (Chetty 2011)

- Static general equilibrium model where consumer is endowed with Z units of numeraire good y and consumes $x_1 \ldots x_J$ other goods; each x_j is produced according to cost function = $c(x_j)$. (Chetty 2011, Annual Review of Econ)

To simplify the exposition, we ignore income effects by assuming that utility is quasi-linear in y. The consumer takes the price vector as given and solves

$$\begin{aligned} &\max_{x,y} u(x_1, \ldots, x_J) + y \\ &\text{s.t. } p \cdot x + t x_1 + y = Z, \end{aligned} \tag{1}$$

where $u(x)$ is strictly quasiconcave. The representative firm takes prices as given and solves

$$\max_x p \cdot x - c(x). \tag{2}$$

Social Welfare = W (t) = Consumer Surplus + Producer Surplus + Tax Revenues

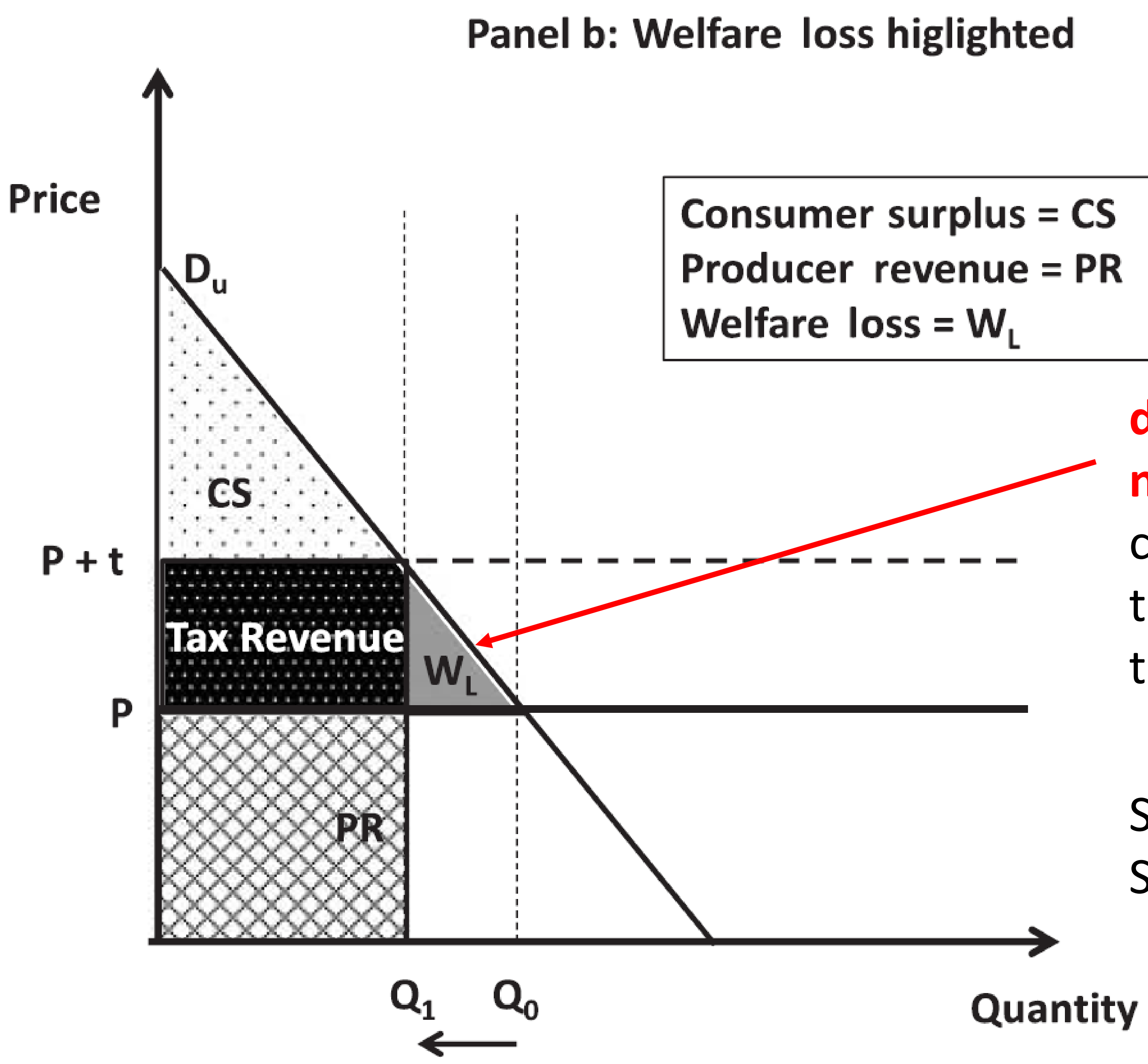
$$
\begin{aligned}
W(t) &= \{\max_x u(x) + Z - tx_1 - p(t)\cdot x\} + \{\max_x p(t)\cdot x - c(x)\} + tx_1 \\
&= \{\max_x u(x) + Z - tx_1 - c(x)\} + tx_1,
\end{aligned}
$$

When calculating dW/dt, the behavioral responses dx/dt in { } can be ignored because of envelope conditions from consumer and firm optimization (substitute in FOCs).

$$
\frac{dW(t)}{dt} = -x_1 + x_1 + t\frac{dx_1}{dt} = t\frac{dx_1(t)}{dt}.
$$

Sufficient Statistic

$$
\Delta W = W(t_2) - W(t_1) = \int_{t_1}^{t_2} t\frac{dx_1}{dt}(t)dt.
$$



dx_1/dt (= dQ/dt in graph's notation) is a sufficient statistic to calculate the size of the "Harberger triangle" of the deadweight loss of the tax t.

Source of graph: Levy, Norton, & Smith, Am J Health Econ 2018

CBA of a Cigarette Excise Tax

- Costs = rectangle + DWL triangle
  - Change in consumer surplus “under” the D curve = CV for the price change
- Benefits = rectangle of tax revenues
- Net Costs = DWL triangle
- Partial equilibrium analysis of the cigarette tax, but use total derivative dx_1/dt

The total derivative $\frac{dx_1}{dt} = \frac{\partial x_1}{\partial p_1}\frac{\partial p_1}{\partial t} + \frac{\partial x_1}{\partial p_2}\frac{\partial p_2}{\partial t} + \ldots + \frac{\partial x_1}{\partial p_J}\frac{\partial p_J}{\partial t}$ measures the effect of an increase in the tax rate on x_1, allowing all prices and equilibrium demands to change endogenously. The simplicity of Harberger's approach stems from estimating $\frac{dx_1}{dt}$ directly rather than estimating its various components, which is effectively what the structural approach requires.

Envelope theorem and pre-existing distortions

- Envelope theorem means that we don't have to worry about general equilibrium effects in the markets for the non-taxed goods x_2, … x_J – they "envelope out."
  - These effects do not have first-order effects on private welfare.
  - Example: As tobacco farming sector contracts, resources of production flow to their next best alternative use, with no first-order welfare loss.
  - Example: Cigarette industry resources flow to next best alternative use.
  - Example: Non-combustible tobacco production increases.
  - Example: medical resources flow to next best alternative use.
- Envelope theorem expression for dW/dt assumes that there are no pre-existing distortions in the markets for the non-taxed goods x_2, … x_J
  - Possible distortions include taxes on other goods, externalities in other markets, internalities, etc.

CBA is NOT the same as stakeholder impact analysis

- Cigarette excise tax has multiple impacts
  - Consumer welfare
  - Tax revenues

  - Rate of smoking among youth and adults
  - Rate of quitting
  - Rates of smoking-related illness and death

  - Medical expenditures on smoking-related illness and death
  - Tobacco farming, cigarette & e-cigarette manufacturing, etc.

CBA

Public health impacts

Other sector impacts

To repeat: predicting stakeholder impacts is not the same as estimating benefits and costs

- **Stakeholder impact analysis**: Predict impacts on major stakeholders including smokers, non-smokers exposed to SHS, tobacco manufacturers & growers, healthcare system, tax revenues.
- **Public health impact analysis**: Predict impacts on smokers' and non-smokers mortality and morbidity risks.
  - Example: dynamic population health simulation model (Mendez & Warner)
- **Cost-benefit analysis: identifies if resources are in their most highly valued use**
- CBA ≠ maximizing tobacco manufacturers' & growers' revenues or profits
- CBA ≠ maximizing government revenue
- CBA ≠ maximizing public health

Example 3: CBA of an excise tax when some consumers make mistakes and impose on internalities on themselves

- Decision-making errors (individual failures to optimize) => internalities
  - Errors could be due to lack of information or decision-making “errors” explored in behavioral economics research
  - Addiction isn’t necessarily irrational, but addiction => past decision-making errors can continue to affect addictive consumption choices through the consumption capital stock (adjacent complementarity)
- One approach is to distinguish decision utility (which reflects biases) from experienced utility (unbiased, “true” preferences).
  - Consumption choices that maximize decision utility fail to maximize experienced utility.
  - Consumers choose “too much” of goods that impose internalities.

Many arguments for tobacco control polcies rely on the existence of internalities

- Whether tobacco control regulation increases or decreases economic efficiency depends on the existence of internalities.
  - A regulation that restricts rational choices creates opportunity costs for consumers and creates economic efficiency losses.
  - A regulation that restricts choices due to behavioral biases reduces the internalities individuals impose on themselves and create economic efficiency gains.
  - In short, internalities turn an opportunity cost into a benefit.
- Whether tobacco control regulation places a disproportionate burden on poor consumers depends on the existence of internalities.
  - Taxes “help” poorer consumers only when their choices to consume tobacco are mistakes.

CBA should require strong evidence of internalities

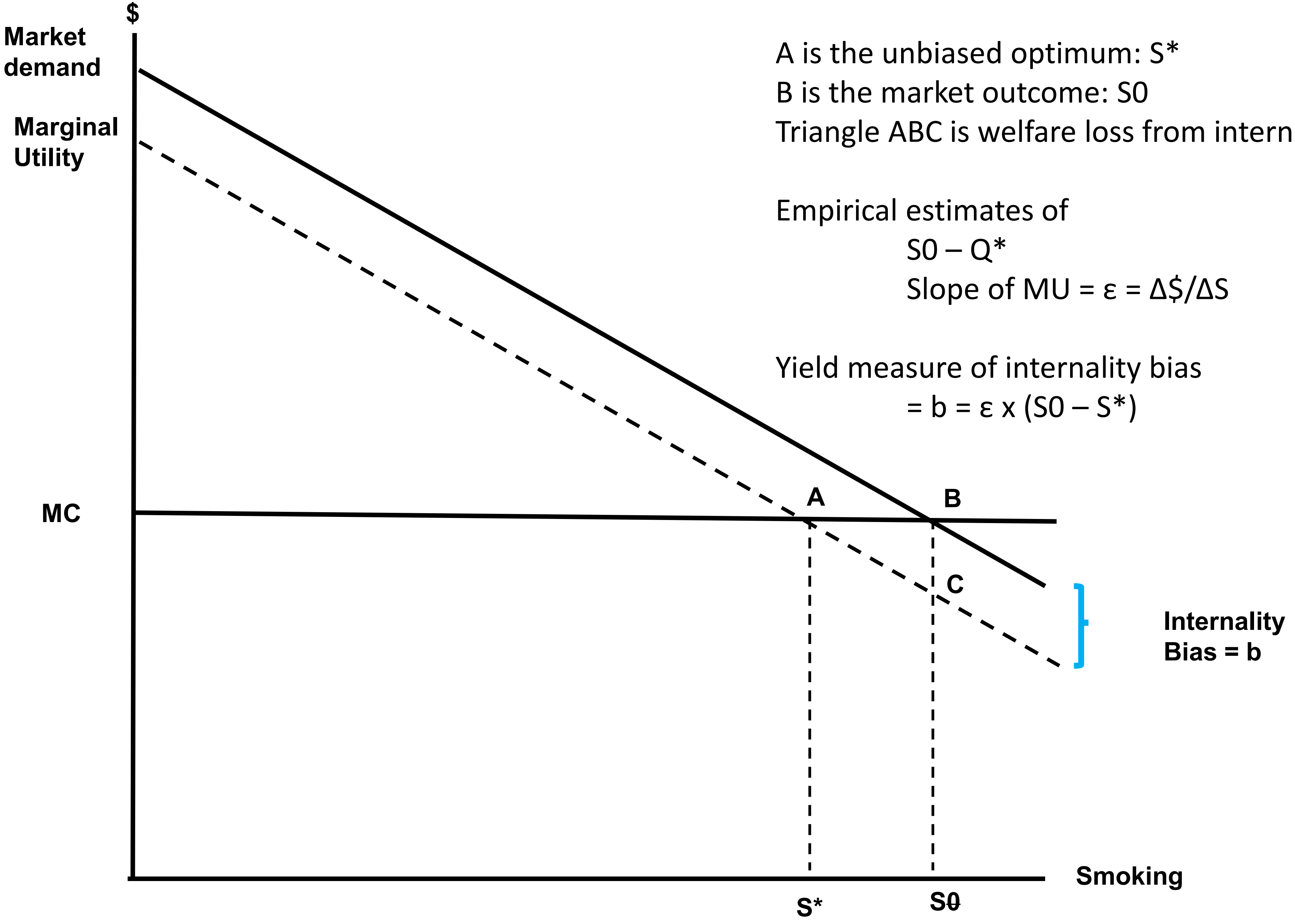
- First step of CBA always requires strong evidence of a market failure.
- Bernheim & Rangel (2005): *[S]tandard welfare analysis is grounded in the doctrine of revealed preference. That is, we infer what people want from what they choose…. if we are to relax the principle of revealed preference when evaluating public policy, it behooves us to set a **high scientific threshold** for reaching a determination, based on objective evidence, that a given problem calls for divergent positive and normative models.*
- Boardman et al. (2022 pp. 1171-1172) propose that the ***rebuttable principle of individual rationality*** should be applied to the possibility that behavioral biases lead to consumer mistakes: *analysts need to present strong empirical evidence that individuals are indeed making serious mistakes….Wherever possible, analysts should look for evidence of the anomalous behavior in markets as well as laboratory experiments.*

Measuring internalities

- Welfare relevant experienced utility from discrete purchase of a good = v
- Decision utility d is biased: d = v + b.
  - Consumers over-estimate utility/ willingness to pay by b because they neglect some or all of the future costs.
- Empirical approach estimates:
  - Market demand from actual purchases based on d.
  - Marginal utility = unbiased demand based on v.
  - Slope of marginal utility curve = ε
- Studies that use this approach include Levy, Norton & Smith (AJHE 2017), Allcott, Lockwood & Taubinsky (QJE 2019, JEP 2019), Allcott et al. (AER 2025).

Approaches to estimate unbiased demand and internalities

- Estimate the unbiased demand of a counter-factual normative consumer.
  - Allcott, et al. (2019) use measures of consumer nutrition information and responses to “I drink soda pop or other sugar-sweetened beverages more often than I should.”
  - Schmaker and Smed (AEJ:EP 2023) use a psych validated self-control scale.
  - Jin et al. (JBCA 2015), Cutler et al. (2015 JBCA) identify demographic sub-groups likely to be able to align behavior with well-informed preferences.
- Use expert estimates to construct unbiased demand.
  - Gruber & Kocegi (QJE 2001) combine their estimate of the health costs of smoking and consensus estimates of β/δ discount rates.
  - Allcott et al. (2025) combine stated preference data on consumer willingness to pay for cars with different gas mileage with EPA estimate of gas mileage
  - Kenkel et al. (in progress) use SPs in DCEs on immediate and 6-month choices



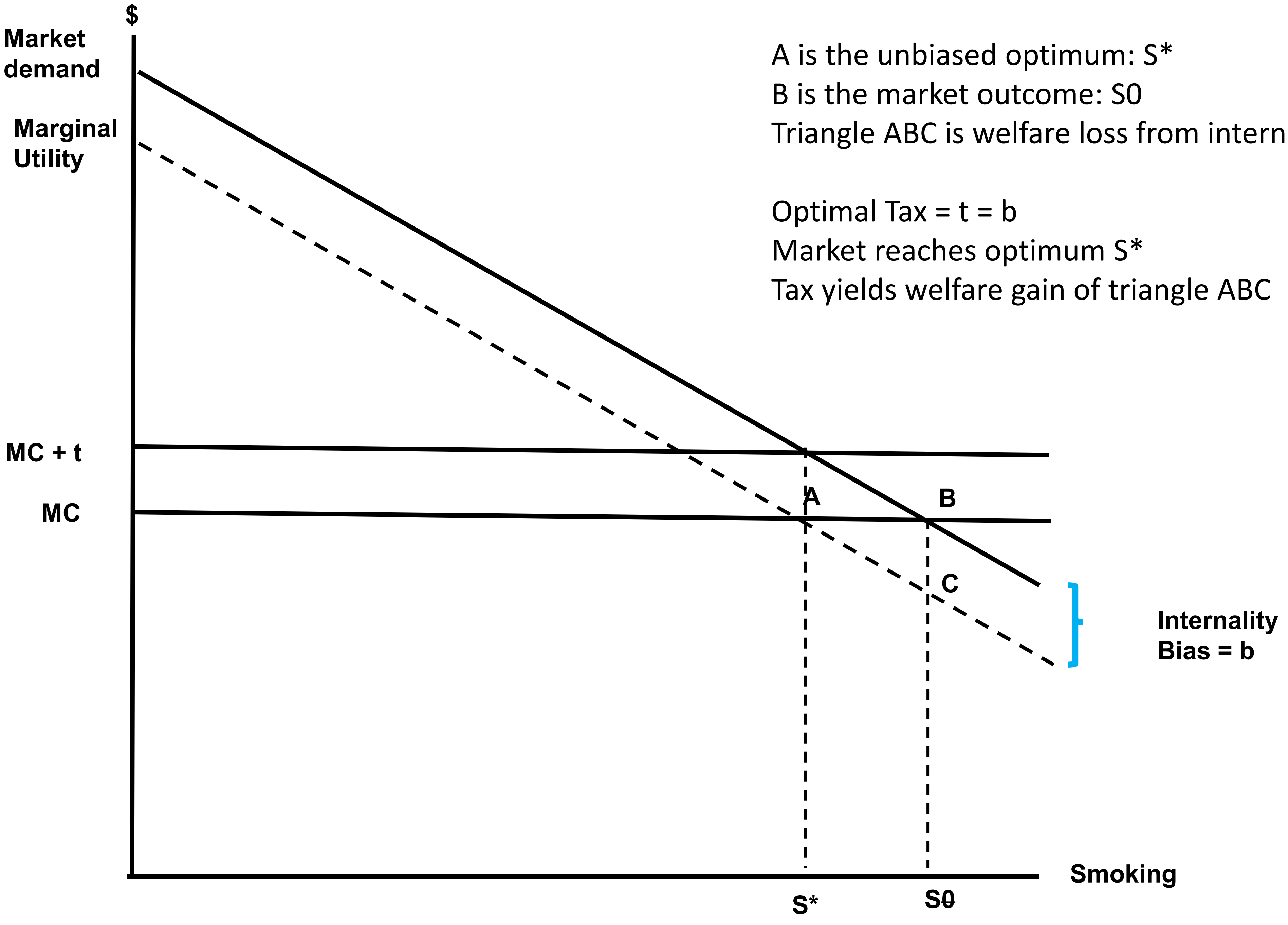
A is the unbiased optimum: S*
B is the market outcome: S0
Triangle ABC is welfare loss from internality

Empirical estimates of
S0 – Q*
Slope of MU = ε = Δ$/ΔS

Yield measure of internality bias
= b = ε x (S0 – S*)

A is the unbiased optimum: S*
B is the market outcome: S0
Triangle ABC is welfare loss from internality

Optimal Tax = t = b
Market reaches optimum S*
Tax yields welfare gain of triangle ABC



Example 4: CBA of a nudge that changes tobacco product attributes, w/ internalities

- Nudge = requiring graphic warning labels on cigarette packages
  - Common in many countries, US reg will take effect in 2026
- Nudge imposes direct costs on consumers
  - Empirical evidence that labels work through fear & disgust, not by providing information => shifts down MU = unbiased demand for cigs
- Kenkel et al. (work-in-progress) use data from Discrete Choice Experiment
  - Estimate average internality = $4.15/pack
  - Estimate average WTP to avoid graphic warning label = $12.20/pack
  - Work-in-progress to capture heterogeneity in internalities & treatment effects

Please select one option.

	Cigarettes	E-Cigarettes	Neither
PRODUCT			
PRICE	20.00 USD	2 USD	
NICOTINE CONTENT	You will inhale between 22-38 mg of nicotine per pack of typical cigarettes if you smoke regulars, or between 12-20 mg of nicotine per pack if you smoke so-called mild or light cigarettes.	Various nicotine levels available, up to 20mg	**I will quit smoking cigarettes and not use e-cigarettes.**
FLAVOR	Your current cigarette flavor	Available flavors are tobacco, menthol, fruit/sweet/candy	
WARNING MESSAGE		This product contains nicotine, nicotine is an addictive chemical	

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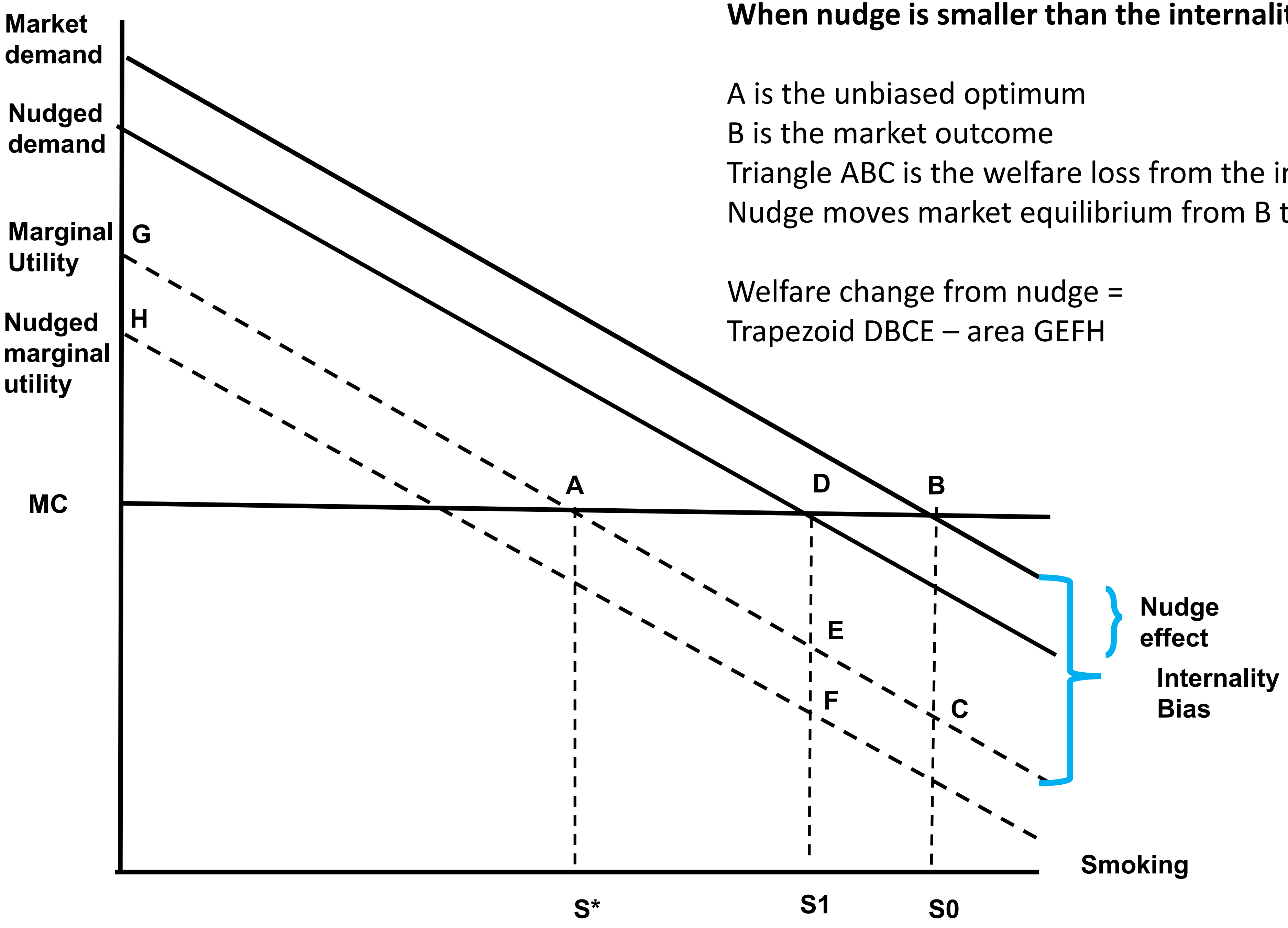


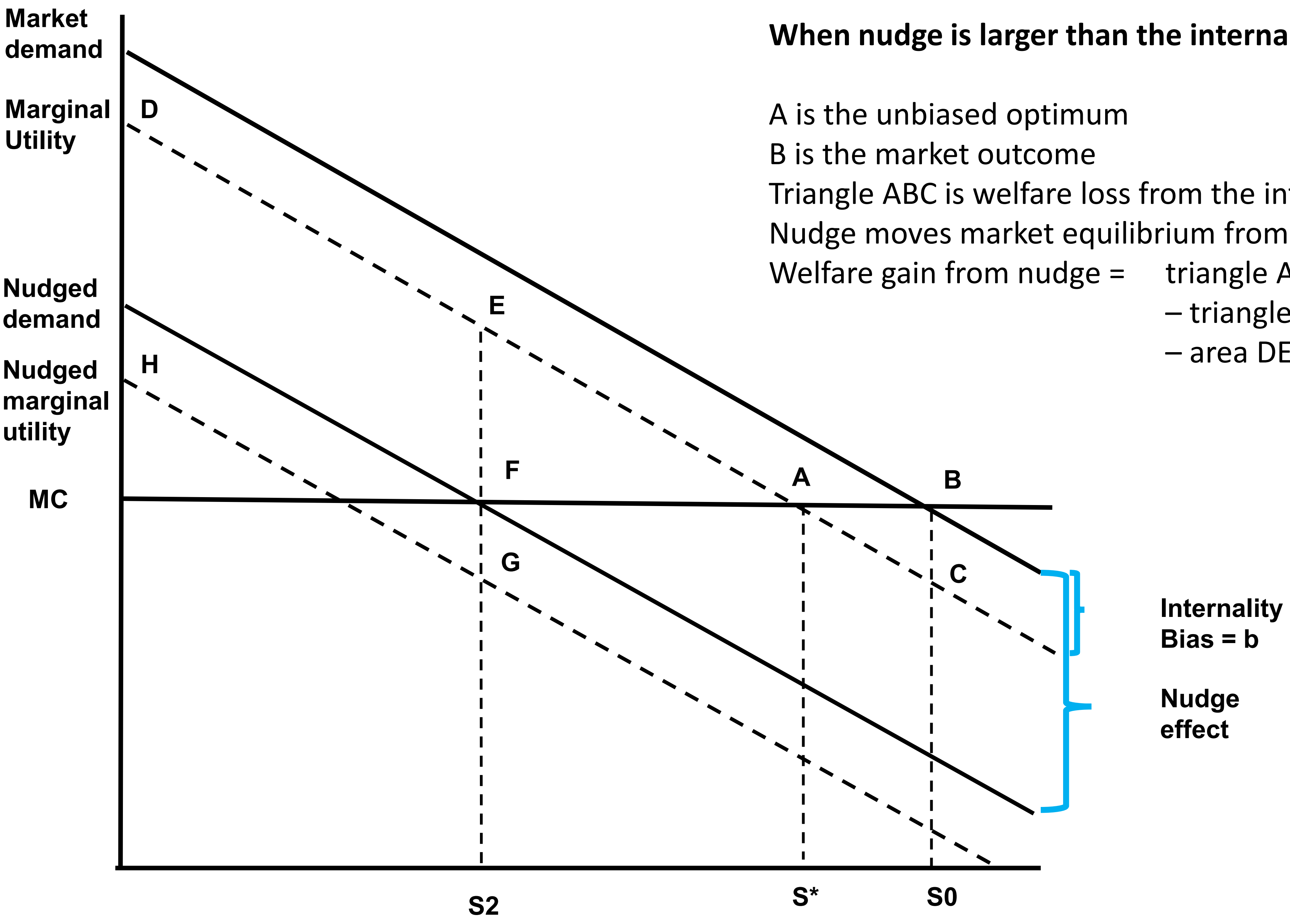
When nudge is smaller than the internality

A is the unbiased optimum
B is the market outcome
Triangle ABC is the welfare loss from the internality
Nudge moves market equilibrium from B to D

Welfare change from nudge =
Trapezoid DBCE – area GEFH

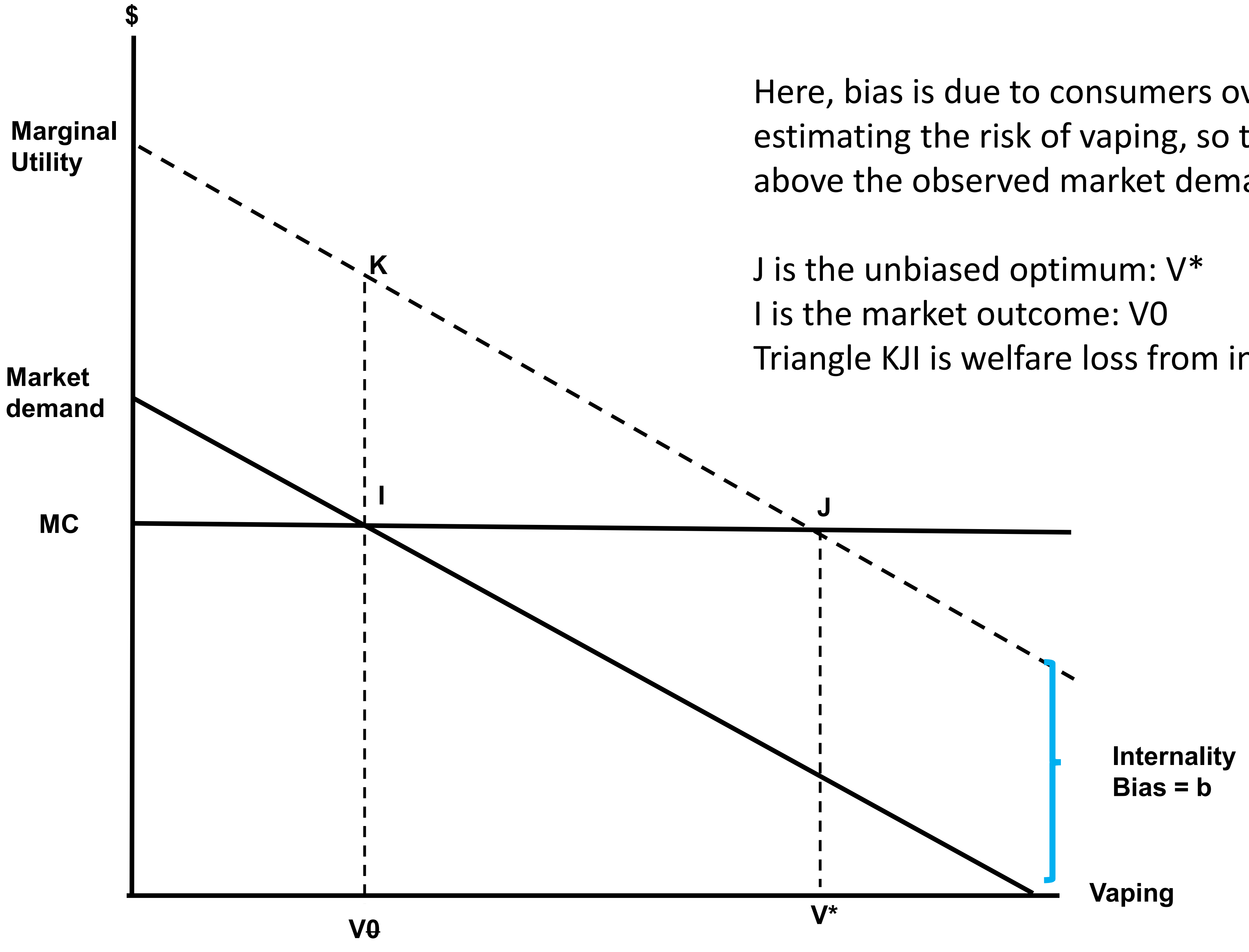
When nudge is larger than the internality

A is the unbiased optimum
B is the market outcome
Triangle ABC is welfare loss from the internality
Nudge moves market equilibrium from B to F
Welfare gain from nudge = triangle ABC
– triangle EAF
– area DEGH



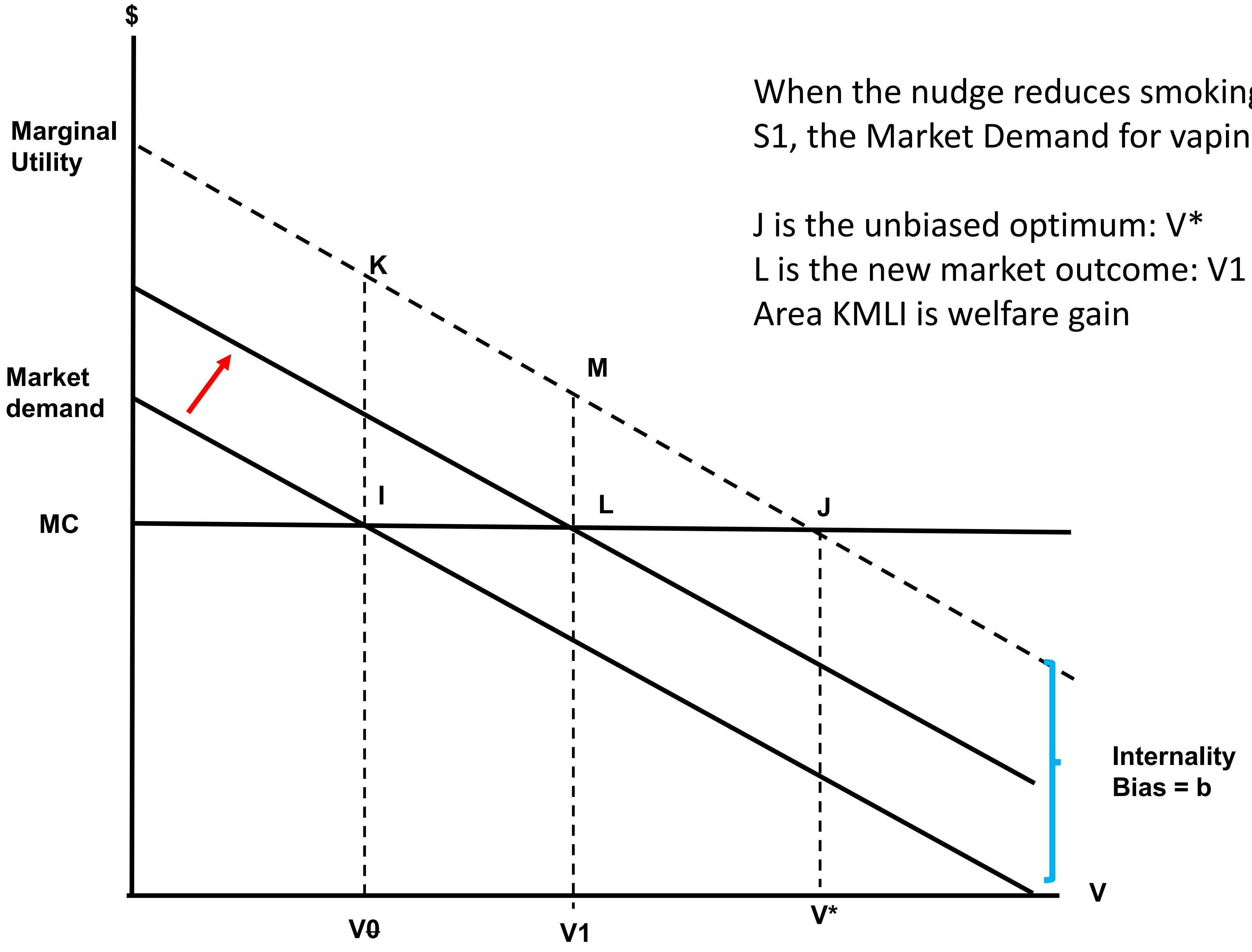
Preliminary Cost-Benefit Analysis

- Size of U.S. cigarette market = 10.688 billion packs
- Benefit of graphic warning labels = $0.39 billion
- Cost of graphic warning labels = $3.3 billion
- Benefits – Costs = -$2.94 billion
- Heterogenous treatment effects => graphic warning labels are poorly targeted because consumers with internalities don't respond
  - I.e. graphic warning labels impose costs on rational consumers and don't correct the behavior of consumers w/ internalities.
- Next step: extend analysis to include extra benefit of shifting smokers to vaping
  - Additional benefit because e-cig market is distorted by misinformation



Here, bias is due to consumers over-estimating the risk of vaping, so true MU is above the observed market demand.

J is the unbiased optimum: V*
I is the market outcome: V0
Triangle KJI is welfare loss from internality



When the nudge reduces smoking from S0 to S1, the Market Demand for vaping shifts up.

J is the unbiased optimum: V*
L is the new market outcome: V1
Area KMLI is welfare gain

Discrete Choice Experiments for Economic Research on Tobacco Regulation

Donald Kenkel

Cornell University

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Tasks of Empirical Analysis in Economics

- "Evaluating the impacts of public policies, forecasting their effects in new environments, and predicting the effects of policies never tried are three central tasks of economics." (Heckman & Vytlacil, Econometrica, May 2005).
- Quasi-experimental methods focus on the first task: evaluating the impacts of public policies
  - Retrospective policy evaluation
  - Back-of-the-envelope forecasts of effects in new environments
  - Sometimes more formal forecasts.
- What about predicting effects of policies never tried?
  - Prospective policy evaluation
  - Lab and field experiments
  - Discrete choice experiments gather data on subjects' stated preferences, which can be used to predict the effects of policies in new environments and to predict the effects of policies never tried.

Stated preference methods

- **Stated preference (SP)** research *involves asking the same individuals to state their preferences in hypothetical (or virtual) markets.*
- ***DCEs** are an attribute-based approach to collect SP data. They involve presenting respondents with a sequence of hypothetical scenarios (choice sets) composed by two or more competing alternatives that vary along several attributes, one of which may be the price of the alternative or some approximation for it.*
  - Ryan et al., Using Discrete Choice Experiments to Value Health and Health Care, Springer 2008
- **Contingent valuation** asks respondents about their willingness to pay.
  - A dichotomous choice study -- Are you WTP $X? – is sometimes called a DCE.
- **Conjoint analysis** is a related broad set of techniques to elicit preferences. Use of the terms varies, but Louivre, et al. stress that only DCEs are linked to and consistent with economic demand theory.
  - Louivre, Flynn, and Carson, "Discrete Choice Experiments are Not Conjoint Analysis," Journal of Choice Modelling, 3(3), pp 57-72.

DCEs are a well-established tool for causal inference in empirical microeconomics

- DCEs are commonly used in marketing research and economics
  - Marketing and pharmacoeconomic research use DCEs and conjoint analysis to provide predictions of consumer demand for new products or combinations of attributes.
- Examples of DCEs include economic studies of consumer demand in policy-relevant scenarios that are not yet observed in actual markets:
  - Kesternich, Heiss, McFadden, & Winter (*JHE* 2013) study consumer choices of Medicare Part D Rx insurance plans, before launch of Part D.
  - Blass, Lach, & Manski (*IER* 2010) study preferences for electricity reliability
  - Moshary, Shapiro, & Drango (NBER Working Paper 2023) study consumer preferences for firearms and the implications for regulation

Other Uses of DCEs in Economics

- DCEs also provide a way to test economic hypotheses that are hard to study with other approaches
  - Mas & Pallais (*AER* 2017) study workers' preferences for alternative work arrangements
  - Wiswall and Zafar (*QJE* 2018) study prospective workers' preferences for work flexibility, job stability, and high earnings growth potential.
  - Alex Chan (Stanford PhD dissertation, conditionally accepted at *AER*) used a discrete choice experiment to study patient discrimination against Black and Asian doctors.
- Environmental economics uses stated preference methods including contingent valuation and DCEs to estimate consumer willingness to pay for non-market goods like environmental quality.

Recent Tobacco Product DCEs in Economic Journals and at IHEA

Authors	Year	Journal
Buckell, Hensher, and Hess	2021	Health Economics
Buckell and Hess	2019	Journal of Health Economics
Guindon, Mentzakis, and Buckley	2024	Economics & Human Biology
Kenkel, Peng, Pesko, and Wang	2020	Health Economics
Kenkel et al.	2024	Annals of Public and Cooperative Economics
Kenkel, et al.	2025	Health Economics
Marti, Buckell, Maclean, and Sindelar	2019	Economic Inquiry
Farandy et al.	2025	IHEA: Tuesday 3:30 – 5 pm
Deng et al.	2025	IHEA: Tuesday 3:30 – 5 pm

DCE research: strengths and limitations

- Strengths
  - Strong internal validity: Experimental design identifies causal effects and overcomes challenges researchers face when using observational data.
  - Flexible & timely
  - Tightly linked to economic theory/useful for cost-benefit analysis
- Limitations
  - Important to follow good practices in DCE methodology
  - Important to tailor DCE to market/regulations under study
  - External validity – Is it valid to extrapolate results from experiment to predict results of real-world regulations?

Research on DCE External Validity

- In a narrative review of research, McFadden (2017) concludes that there is a “sharp reliability gradient”
  - “Forecasts that are comparable in accuracy to RP [revealed preference] forecasts can be obtained from well-designed SP studies for familiar, relatively simple goods that are similar to market goods purchased by consumers, particularly when calibration to market benchmarks can be used to correct experimental distortions. However, studies of unfamiliar, complex goods give erratic, unreliable forecasts.”
- Penn and Hu (2018) conduct meta-analysis of “calibration factors” (CFs) which shows the ratio of willingness to pay estimated from SP data to the willingness to pay estimated from RP data.
  - About one quarter of the CFs are between 0.81 and 1.2 (close to 1 is good!)
  - Distribution of CFs is skewed right (=> SP over-estimates WTP).
  - Estimates for private goods are more reliable

Calibrating SP Estimates from DCEs

- “Revealed preference data have the advantage that they reflect actual choices…. However, RP data are limited to the choice situations and attributes of alternatives that currently exist or have existed historically. Often a researcher will want to examine people’s responses in situations that do not currently exist…RP data are simply not available for these new situations.”
- “Stated-preference data complement revealed-preference data…. The limitations of SP data are obvious: what people say they will do is often not the same as what they actually do. People might not know what they would do if a hypothetical situation were real. Or they might not be willing to say what they would do.”
- By combining RP and SP data, “the advantages of each can be obtained while mitigating the limitations. The SP data provide the needed variation in attributes, while the RP data ground the predicted shares in reality.” (Train, 2002, pp. 174-175).

Key stages in developing a DCE

- As used by Johnson et al, **Experimental Design = *the process of generating specific combinations of attributes and levels that respondents evaluate in choice questions*.** Experimental design should reflect:
  - **Research Objectives** refer to the object of choice for which preferences will be quantified, e.g. tobacco products.
  - **Attributes and Levels** are the features that comprise the research object, among which the survey will elicit trade-offs, **e.g. price, legality of sale, flavor**
  - **Choice Question Format** describes how a series of sets of alternatives from among all possible profiles will be presented to respondents.
  - **Analysis Requirements** for the intended model specification

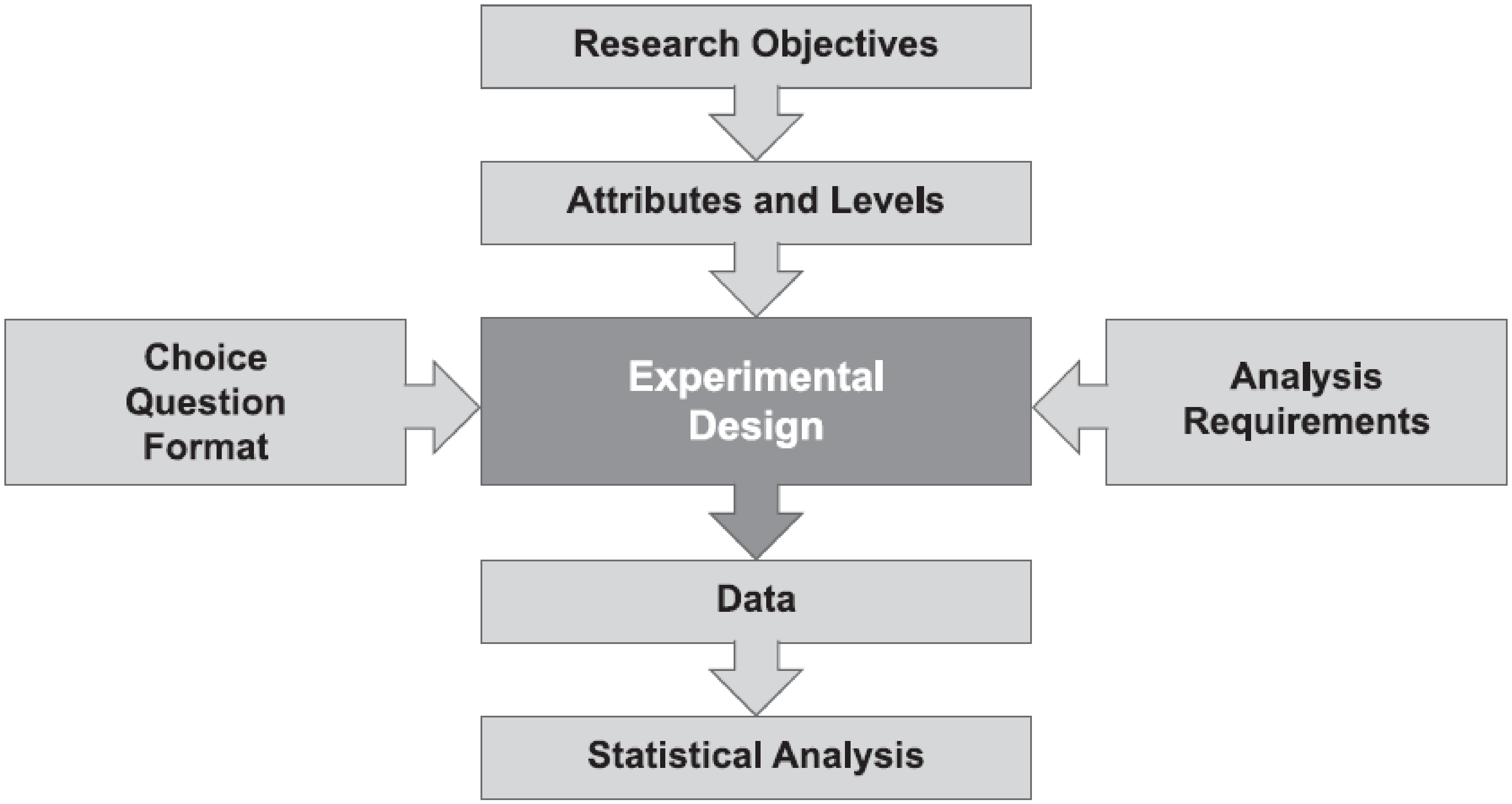

Fig. 1 – Key stages for developing a discrete-choice experiment.

Source: Johnson, Lancsar, Marhall, et al. (Value in Health, 2013), Constructing Experimental Designs for Discrete-Choice Experiments: Report of the ISPOR Conjoint Analysis Experimental Design Good Research Practices Task Force.

Examples: Cornell DCEs

- Method: collect and analyze primary data from online DCEs
- In Fall 2021 we completed **Round 1** of the DCEs: Australia, China, Indonesia, Japan, Sweden, UK, US; in January 2023 we added Malaysia
  - Hypothetical choices between cigarettes, e-cigarettes (Japan: heated tobacco), quitting
  - Attributes: price, flavor, nicotine (Australia: Rx), health messages
- **Round 2**: DCEs of illegal markets
  - April 2022: US proposed prohibition of menthol
  - January – February 2023: Australian e-cigarette Rx requirement
China e-cigarette flavor ban
- **Round 3**: research collaborations with
  - Alan Farandy and colleagues, Indonesian Development Foundation
  - Asena Caner and colleagues, TOBB University of Economics and Technology, Ankara, Türkiye

Türkiye DCE: Product Attributes and Levels

OPTIONS

ATTRIBUTE

	Packaged Cigarette	Roll Your Own (RYO)	E-Cig or HTP	Quit
Price	0,5 P P (actual price paid) 2P	30 TL	20 TL 40 TL 80 TL	-
Sale Type	Legal with banderole	Illegally sold	Legal with banderole Illegally sold Strictly Banned	-
Flavor	Tobacco only Menthol available	Tobacco	Tobacco only Variety of Flavors	-

Türkiye DCE Choice Task Screen

	Option 1	Option 2	Option 3	Option 4
	 **(Packed Cigarettes)**	 **(Roll Your Own)**	 **(E-cigarette or a heated tobacco product)**	None
PRICE	3 Levels	1 Level	3 Levels	
SALE TYPE	1 Level	1 Level	3 Levels	I will quit smoking cigarettes and not use e-cigarettes.
FLAVOR	2 Levels	1 Level	2 Levels	
Please select one option.	O	O	O	O

Choice of levels

- Depends on research question
  - E-cigarette manufacturer might want to know if consumers prefer mint flavor over menthol flavor.
  - Health economist (and maybe also manufacturer) might want to test economic model that predicts consumers care about e-cig health effects, or effectiveness of e-cigs for smoking cessation
- **Türkiye DCE** (and other Cornell DCEs) use levels to correspond to regulatory policies that already vary across countries or are under consideration: price, flavor, nicotine, **health messages**, legality
  - Policies affect the **availability** of flavors and nicotine levels
  - Policies can mandate health messages on warning labels but cannot mandate how consumers react to those messages.

Other DCEs of tobacco product choices have used different approaches to define levels

- Example study by Buckell et al.: Subjects presented with choice between products with specific flavors, life year losses
  - Ex: regular cigarette, fruit flavored e-cig, sweet-flavored e-cig
  - Some subjects, e.g. menthol smokers, unhappy with all the alternatives
  - Subjects can opt out (“none of the above”) but interpretation is ambiguous: do they plan to quit, or to get their preferred product somewhere else?
- Choice task is not a realistic description of choices presented in real markets
  - Also not a realistic description of how regulations would change real markets
- Study’s model does provide estimates of the Δ utility from flavors, so model can predict choices in status quo markets and under alternative regulatory regimes
- Study’s model also provides estimates of the Δ utility per life-year lost
  - Regulations can influence but can’t exactly determine consumers’ perceptions of life-year loss

Option 1: Tobacco Cigarette	Option 2: Tobacco Cigarette
 • Flavor: **Tobacco** • Nicotine level: **High** • Die earlier: **10 Years** • Price: **$4.99**	 • Flavor: **Tobacco** • Nicotine level: **High** • Die earlier: **10 years** • Price: **$13.99**
Option 3: E-cigarette	Option 4: E-cigarette
 • Flavor: **Fruit** • Nicotine level: **High** • Die earlier: **2 Years** • Price: **$13.99**	 • Flavor: **Sweet** • Nicotine level: **High** • Die earlier: **Unknown** • Price: **$4.99**

Source: Buckell, Marti, & Sindelar (2019, Tobacco Control)

Also note: Option 1 dominates Option 2.

Table 1
Discrete Choice Experiment (DCE) Attributes and Levels

	Cigarettes[a]	Vape pen
Less harmful to health than cigarettes		Yes [left blank]
Effective for helping people quit		Effective Not effective Unknown
Nicotine strength	12 mg per stick	None (0 mg) Low (1-12 mg) Medium (13-17 mg) High (18 mg or higher)
Flavor	Tobacco[b] Menthol[b]	Tobacco Menthol Fruit/candy/sweet/other flavors
Price	Price per pack[b]	Starter Kit: $30[c] Refill Price: $3 $5 $7

Source: Shang et al, Tobacco Regulatory Science 2020.

These attributes can not be directly manipulated by regulatory policy

Not a realistic description of product availability in markets; for example, consumers never see only high nicotine products or only fruit/candy flavored products

Identification in DCEs

- Random assignment of attributes => clean identification of the causal effects of the attribute on product choice.
- But the DCE needs to be carefully designed to allow for identification of every parameter of interest with enough degrees of freedom.
  - Review of health care literature found: *some studies had one or more effects that were perfectly confounded with other effects, meaning that the effects could not be independently identified….* (Johnson et al. 2013)
- Simple example: suppose choice set is between #1 a Tx that has no pain and a risk of heart attack vs #2 a Tx with mild pain and a risk of infection.
  - If subjects choose #2, is it because they found mild pain acceptable, or because they wanted to avoid the side-effect risk of a heart attack?
  - For identification, DCE needs to include more alternatives in the choice set: #3 no pain & infection risk, and #4 mild pain & heart attack risk

Intended model specification

A critical issue in all discrete choice models is the specification of the "representative" (i.e. estimated) utility function $V(X_{in}, \beta)$, that relates the observed attributes of the alternatives to the utility U_{in} derived from alternative i. It is common to assume linear-*in*-parameters function as shown in Equation 1.6.

$$V_{in} = \mathrm{ASC}_i + \beta_1 x_{i1} + \ldots + \beta_K x_{iK} \qquad (1.6)$$

where there are $k = 1, 2, \ldots, K$ attributes (possibly including price) with generic coefficients (to be estimated) β_k across alternatives.[7] An alternative-specific constant (ASC_i) captures the mean effect of the unobserved factors in the error terms for each of the alternatives.[8]

Source: Ryan et al., Using Discrete Choice Experiments to Value Health and Health Care

Intended model specification continued

- **Linear in parameters** model
  - β_K parameters capture the **main effects** of each attribute on utility, i.e. if attributes continuous, the marginal utility of the attribute level.
  - **Interaction effects** when marginal utility of one attribute depends upon the level of one or more other attributes.
- **Non-linear main effects**: when the marginal utility of attribute K depends on the level of attribute K
  - Only two levels: linear marginal utility
  - Three levels: generally suffice to identify non-linearities (Ryan et al.)
- **Discrete levels:** estimate Δ utility instead of marginal utility

Türkiye DCE example specification

- Linear main effects, no interaction effects
  - We estimate marginal utility of price = - marginal utility of income
    - Three price levels so we could estimate non-linearities
    - For most consumers, changes in tobacco product prices are small relative to income => marginal utility of income approximately constant in range
  - We estimate Δ utility for different levels of legality
  - We estimate Δ utility for different levels of flavor availability
- Sub-sample analysis allows are parameters to vary across age sub-groups

Empirical analysis of DCE data

- Cross-tabulations
  - If balanced, orthogonal design, cross-tabs provide unbiased estimates of the differences in choices across different attribute levels
- Linear probability models
  - OLS is a marginal effect generator: *The upshot of this discussion is that while a nonlinear model may fit the CEF [conditional expectation function] for LDVs [limited dependent variables] more closely than a linear model, when it comes to marginal effects, this probably matters little. This optimistic conclusion is not a theorem, but…it seems to be fairly robustly true*. (Angrist & Pischke Mostly Harmless Econometrics 2009, p. 107)
- Logit or probit models of 0-1 choices
- Conditional logit model of multinomial choices
- **Structural models of utility function**

		All		Ages 18-30		
		Mean	**Std.Dev.**	**Mean**	**Std.Dev.**	**M**
ASC (Base: Quit)						
Cigarette	**Estimate**	5.572 ***	3.356 ***	4.943 ***	3.057 ***	6
	(SE)	(0.275)	(0.265)	(0.303)	(0.290)	(
RYO	**Estimate**	2.906 ***	4.147 ***	2.386 ***	2.914 ***	2
	(SE)	(0.352)	(0.232)	(0.318)	(0.283)	(
Vape	**Estimate**	2.326 ***	3.662 ***	2.885 ***	2.257 ***	2
	(SE)	(0.495)	(0.424)	(0.332)	(0.392)	(
Price	**Estimate**	-0.033 ***	0.040 ***	-0.022 ***	0.027 ***	-
	(SE)	(0.003)	(0.003)	(0.003)	(0.003)	(
Legal status of vapes (Base: Legal with banderole)						
Illegally Sold	**Estimate**	-0.767 ***	1.057 **	-0.407 ***	0.720 ***	-
	(SE)	(0.199)	(0.468)	(0.167)	(0.257)	(
Strictly Banned	**Estimate**	-1.038 ***	1.123 ***	-0.615 ***	0.865 **	-
	(SE)	(0.197)	(0.288)	(0.190)	(0.422)	(
Flavor availability (Base: Tobacco only)						
Menthol cigarettes	**Estimate**	-0.523 ***	1.326 ***	-0.091	0.834 ***	-
	(SE)	(0.113)	(0.245)	(0.129)	(0.209)	(
Vape in various flavors	**Estimate**	-0.148	0.916 ***	-0.193	1.141 ***	-
	(SE)	(0.119)	(0.207)	(0.198)	(0.347)	(
N		13452		5136		

Türkiye DCE: Predicted Market Shares

	Cigarettes	*RYO*	*Vapes*	*Quit*
Scenario 1: Baseline + Double vape price	52.39 ↑	27.35 ↑	10.84 ↓	9.42 ↑
Scenario 2: Baseline + Vapes legally available	48.56 ↓	25.08 ↓	19.43 ↑	6.93 ↓
Scenario 3: Baseline + Vapes legally available + Double vape price	50.50	26.82 ↑	13.75 ↓	8.93 ↑
Scenario 4: Baseline + Vapes strictly banned	51.44 ↑	26.16 ↑	14.55 ↓	7.85 ↑
Scenario 5: Baseline + Vapes strictly banned+ Double vape price	53.80 ↑	27.79 ↑	8.61 ↓	9.79 ↑
Baseline Scenario: Cigarettes legal, RYO under-the-counter, vapes under-the-counter, only tobacco flavor for cigarettes and RYO, various flavors for vapes (prices: current average prices for all product options)	50.96	25.77	15.57	7.71

Estimating Willingness to Pay

- Because α_i is the marginal utility of income, WTP for attribute is $\frac{\beta_i}{\alpha}$
- Because β_i is lognormal, with α fixed, WTP is lognormally distributed.
  - Alternative approach (not reported) is to estimate model in WTP space: specify convenient distributions for WTPs
- Note: WTP for an attribute ≠ Compensating Variation
  - Small & Rosen (1981 *Econometrica*) “log-sum” expression for CV weights the utility associated with each alternative by the probability of selecting that alternative
- We assume SP choices are free from behavioral biases and estimate CVs w.r.t. experienced utility.
  - SP quit rate > RP quit rate, possibly reflecting behavioral biases in decision utility

Willingness to Pay Estimates for Illegally Sold and Banned Vapers

	All	Ages 18–30	Ages 31–45	Ages 46–6
Legal status (Base: Legal with Banderole)				
Illegally Sold	-23.31	-18.81	-10.08	-69.19
(illegal retail/ under-the-counter)	**-37%**	**-30%**	**-16%**	**-110%**
Strictly Banned	-31.53	-28.38	-18.03	-109.84
(illegal street)	**-50%**	**-45%**	**-29%**	**-174%**

In each legal status category, the first figure is the WTP estimate in Turkish liras, while the second one shows the estimate as a % of average price of a pack of cigarettes (63 TL/pack) at the time of the survey

Menthol DCE: Predicted Market Shares

Policy Scenario	Menthol Cigs	Menthol-flavored E-cigs	Non-menthol Cigs	Tabacco-flavored E-cigs	Quit Attempt
Status quo					
1. Status quo legality & prices	0.455	0.253	0.065	0.066	0.162
Illegal Retail Market for Menthol Cigs					
6. 50% lower price for illegal products	0.420	0.274	0.077	0.072	0.156
7. No price change	0.330	0.306	0.085	0.082	0.197
8. 50% higher price for illegal products	0.270	0.328	0.093	0.088	0.221
Illegal Street Market for Menthol Cigs					
12. 50% lower price for illegal products	0.372	0.294	0.084	0.078	0.172
13. No price change	0.290	0.322	0.092	0.087	0.210
14. 50% higher price for illegal products	0.236	0.342	0.099	0.093	0.231

Source: Kenkel, et al., (2025). "Understanding the Demand-side of an Illegal Market: The Case of Menthol Cigarettes," Health Economics.

Re-capping

- DCEs allow researchers to collect data on consumers’ stated preferences in realistic market-like situations not yet observed.
  - Experimental design provides strong internal validity
  - Research suggests DCEs for familiar goods purchased in private markets yield reliable predictions, which can be enhanced by calibrating with RP data
- DCEs have and can explore the impact of regulations that:
  - Increase product prices
  - Provide information (or misinformation!) to consumers about product risks
  - Change availability of desirable attributes like flavors
  - Lead to illegal markets for prohibited products

Econometrics Approaches for Tobacco Policy Evaluation in LMICs

Yang Liang[1]

July 20, 2025

IHEA Pre-Congress Session on Tobacco Regulation

[1]San Diego State University

Motivation and Challenge

Scott Cunningham's bumper sticker

- At first glance, low- and middle-income countries (LMICs) often lack subnational policy variation (no 'natural' control groups from spatial rollouts)
- Because many LMICs do not have a federalist government structure and set e-cigarette policy nationally, does this mean that staggered adoption DiD is irrelevant to researchers studying LMICs?

But this might not always be so...

- Just because the nature of local and federal governments may be different in LMICs, does not mean that there is no variation in local policies
- A researcher may just need to be *more industrious* and *more creative* in identifying local policy variation
  - This may require a fair amount of work, but it is also potentially high reward because of a higher degree of internal validity (causal inference)
- For instance, localities may implement national regulations at different times due to differences in local expertise, infrastructure, and resources
- In addition, *enforcement* of national policies and *monitoring* of national policies may differ across jurisdictions
- These are all important potential sources of “staggered adoption” of local policies

International Journal of Drug Policy
Volume 124, February 2024, 104307

Research Paper

Quasi-experimental study on the impact of local smoke-free policies on smoking among Indonesian adults: Evidence from repeated national health surveys

Wahyu Septiono

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Abstract

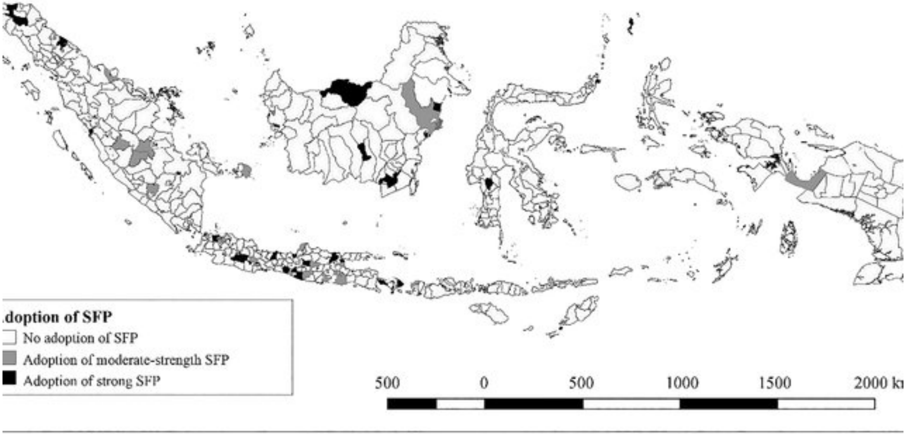
Background

Smoke-free policies (SFPs) have been effective in reducing smoking prevalence, but evidence remains limited for low- and middle-income countries. Due to decentralized governance in Indonesia, SFPs are adopted in different ways in different locations. This study aims to assess the impact of local smoke-free policies (SFPs) on current smoking among Indonesian adults.

Example: Quasi-Experimental Impact of Local Smoke-Free Policies in Indonesia

- A recent public health study (Septiono 2024) leverages variation in local smoke-free policy adoption across Indonesian municipalities
- Quasi-experimental study on the impact of local smoke-free policies on current smoking among Indonesian adults
- Municipalities adopted smoke-free policies at different times; DiD estimates the effect on adult smoking prevalence
- Significant declines in smoking rates due to SFP

Variation in Smoke-Free Policy Adoption (Indonesia, 2007–2013)



Source: Septiono et al. (2024). District-level map of smoke-free policy adoption. Darker shading indicates earlier and/or stronger policy presence.

DiD Evidence: Local Smoke-Free Policies Reduce Smoking in Indonesia

- **Data:** Indonesia Basic Health Survey (Riskesdas), 1.6 million adults from 515 districts (years: 2007, 2013, 2018)
- **Method:** DiD/logistic regression at individual level
- **Specification:**

$$Y_{idt} = \alpha + \delta \cdot (\mathsf{SFP}_{dt} \times \mathsf{Post}_t) + \lambda_d + \gamma_t + X_{idt}\beta + \varepsilon_{idt}$$

  - Y_{idt}: current smoking status for individual i in district d and year t
  - SFP_{dt}: indicator for district d adopting moderate/strong smoke-free policy
  - Post_t: post-treatment year indicator (2013 or 2018)
  - X_{idt}: controls (age, gender, education, employment)
  - λ_d, γ_t: district and year fixed effects
- **Results (converted from odds ratios):**
  - **Moderate SFP (2007–2013):** approx. 9.4% reduction in smoking
  - **Strong SFP (2007–2013):** approx. 11.5% reduction in smoking
  - Effects persist through 2018: moderate SFP → 6.1% lower; strong SFP → 5.1% lower smoking prevalence

Do Not Give Up on "Staggered Adoption"

- Researchers studying e-cigarette policy in LMICs should not give up in using local policy variation for identification
- You can make important contribution to the literature on the intended and unintended effects of e-cigarette policy implementation
- And as experts in your nation's regulatory environment, you are in a better position than anyone to conduct this sort of credible policy analysis

Difference-in-Differences Across Countries

- Joe presented research in the U.S. and Canada on using DiD to estimate the effects of state and provincial policies on nicotine vaping
- These analyses required a panel of states and years
- But there is no reason why one could not consider staggered adoption of policies across different countries, perhaps in a similar region of the world
- Before one rejects this out of hand, one could argue that Malaysia and Indonesia are more similar than Mississippi and California!
- One could spend some time establishing common trends (and maybe even levels) in tobacco outcomes of interest

Hypothetical Example: "DiD on MLPA = 18"

- Applies only to individuals under 18 (i.e., e-cigarette in China)
- No spatial variation — policy implemented uniformly nationwide; But we can still use DiD by comparing:
  - Treated group: 15–17-year-olds (illegal to purchase post-2022)
  - Control group: 18–20-year-olds (legal both pre/post)

$$Y_{it} = \alpha + \beta \cdot \text{Post}_t + \gamma \cdot \text{Treated}_i + \delta \cdot (\text{Post}_t \times \text{Treated}_i) + \varepsilon_{it}$$

  - $\text{Treat}_i = 1$ for 15–17-year-olds
  - $\text{Post}_t = 1$ for 2022–2025
  - $\delta =$ DiD estimate: impact of MLPA policy

Another Hypothetical Example: ”Indoor Vaping Ban in Middle Schools”

- Policy bans vaping in all indoor spaces of *middle schools* starting in 2023
- Implemented nationally with no spatial variation — but still usable in DiD framework
- Compare outcomes for:
  - Treated group: 11–13-year-olds (middle school students directly affected)
  - Control group: 14–18-year-olds (in high school, not affected by school-specific ban)

$$Y_{it} = \alpha + \beta \cdot \text{Post}_t + \gamma \cdot \text{Treated}_i + \delta \cdot (\text{Post}_t \times \text{Treated}_i) + \varepsilon_{it}$$

- $\text{Treat}_i = 1$ for 11–13-year-olds
- $\text{Post}_t = 1$ for 2023–2025
- $\delta =$ DiD estimate: impact of indoor vaping ban on young students

Shift-Share Design

- Core Idea: Even if a policy hits everyone, the bite can vary across regions, based on baseline exposure.

$$Y_{it} = \alpha + \beta(\mathit{Policy}_t \times \mathit{Share}_i) + X_{it}\Gamma + \epsilon_{it}$$

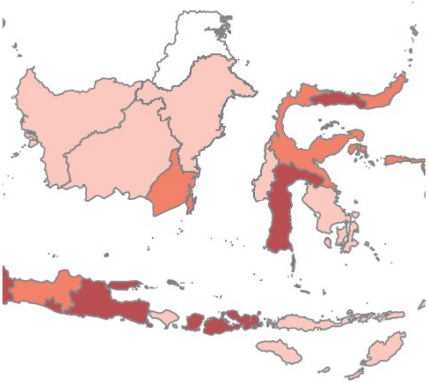
where *share*$_i$ is **pre-treatment** intensity (e.g., % smokers in region *i*)

- Identification Assumption: $\mathit{Share}_i \perp$ other shocks

- More generally: a weighted sum of a common set of shocks , with weights reflecting heterogeneous exposure shares: $z_{it} = \sum_n \mathit{Policy}_{nt} \times \mathit{share}_{in}$
- We want to use z_{it} to estimate parameter β of the previous model

Hypothetical Example

- National policy shock: Indonesia Tobacco Tax hike in 2018/2021
- Share: Construct an exogenous measure of policy bite across provinces — e.g., regions with higher expected price sensitivity, greater tax pass-through, or more exposure to enforcement shocks



Synthetic Control Method(SCM) Method: (one treated jurisdiction)

- SCM is ideal when a policy is implemented in a single country (or unit), and you want to estimate its causal impact.
- Instead of using one control country, SCM constructs a **synthetic counterfactual** — a weighted average of multiple comparison countries that didn't adopt the policy.
- **LMIC Example:**
  - Suppose Indonesia raises tobacco taxes in 2021.
  - Countries like Vietnam, Malaysia, China, or Bangladesh **did not** — they form your donor pool.
  - SCM builds a synthetic Indonesia that matches trends in cigarette sales *before* 2021.
  - You compare Indonesia's outcomes post-2021 to this synthetic version.

Synthetic Control Method(SCM) Method: (one treated jurisdiction)

- SCM Method: California's Proposition 99 (**Abadie et al., 2010**)
- **Policy:** In 1988, California passed Proposition 99, a comprehensive anti-smoking initiative
  - Raised cigarette tax by 25 cents per pack
  - Funded public health and media campaigns
  - It's considered one of the first comprehensive statewide tobacco control initiatives in the U.S.
- **Treated unit:** California
- **Donor pool:** 38 U.S. states without major tobacco interventions
- **Method:** Abadie et al., 2010 construct a synthetic California using a weighted average of control states to match pre-1988 outcomes

How Well Does Synthetic California Match the Real One? Real vs. Synthetic California

Variable	California (Real)	California (Synthetic)	Average of 38 Control States
Ln(GDP per capita)	10.08	9.86	9.86
Percent aged 15–24	17.40	17.40	17.29
Retail price (cents)	89.42	89.41	87.27
Beer consumption per capita	24.28	24.20	23.75
Cigarette sales per capita (1988)	90.10	91.62	114.20
Cigarette sales per capita (1980)	120.20	120.43	136.58
Cigarette sales per capita (1975)	127.10	126.99	132.81

Table 1 from Abadie et al. (2010): Predictor means used to match synthetic California. The match is very close on demographics, price, and lagged outcomes.

Where Does Synthetic California Come From? Donor State Weights

Table 2. State weights in the synthetic California

State	Weight	State	Weight
Alabama	0	Montana	0.199
Alaska	–	Nebraska	0
Arizona	–	Nevada	0.234
Arkansas	0	New Hampshire	0
Colorado	0.164	New Jersey	–
Connecticut	0.069	New Mexico	0
Delaware	0	New York	–
District of Columbia	–	North Carolina	0
Florida	–	North Dakota	0
Georgia	0	Ohio	0
Hawaii	–	Oklahoma	0
Idaho	0	Oregon	–
Illinois	0	Pennsylvania	0
Indiana	0	Rhode Island	0
Iowa	0	South Carolina	0
Kansas	0	South Dakota	0
Kentucky	0	Tennessee	0
Louisiana	0	Texas	0
Maine	0	Utah	0.334
Maryland	–	Vermont	0
Massachusetts	–	Virginia	0
Michigan	–	Washington	–
Minnesota	0	West Virginia	0
Mississippi	0	Wisconsin	0
Missouri	0	Wyoming	0

Treatment Effect: California vs. Synthetic California After Prop 99

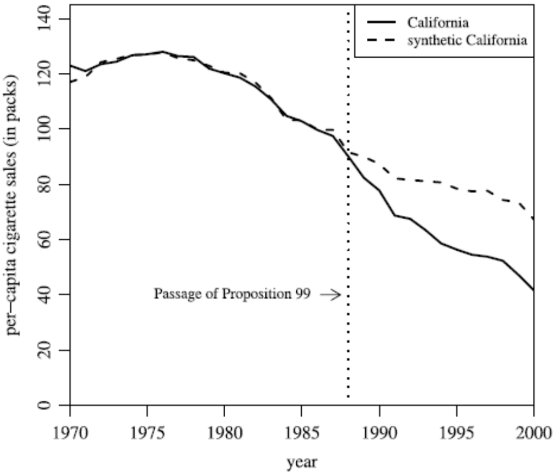


Figure 2. Trends in per-capita cigarette sales: California vs. synthetic California.

Placebo Test

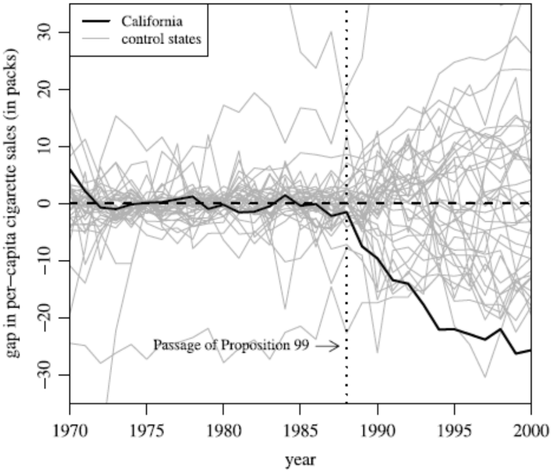


Figure 4. Per-capita cigarette sales gaps in California and placebo gaps in all 38 control states.

Hypothetical Example

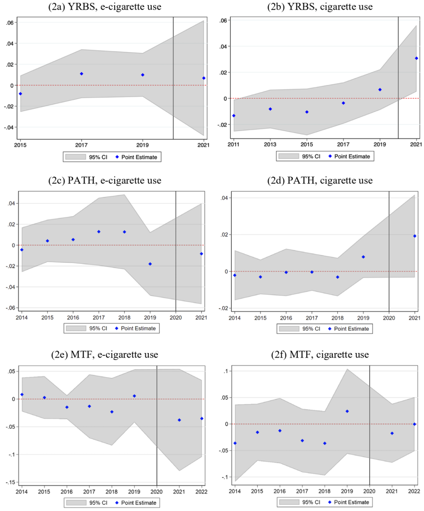
- Indonesia is the treated country (treatment date: 2021 tax hike)
- Donor Pool: select nearby or similar LMICs (Vietnam, Thailand, Malaysia, Bangladesh) – These countries did not raise taxes during this period
- Pre-treatment matching: match Indonesian's cigarette consumption trend using a weighted average of donor countries (also match covariates such as GDP per capita, % urban, educaiton level, etc)
- Construct synthetic weights and estimate the causal effect

SDiD: Combining Synthetic Control and Difference-in-Differences

- SCM provides good pre-trend fit, **but**:
  - No standard errors
  - No covariate adjustment
  - Often limited to single treated unit
- **What is SDiD?** A method that blends:
  - **SCM**: chooses unit weights to match treated unit pre-policy
  - **DiD**: adds time weights and regression framework to estimate ATT
- **Why use it?** SDiD retains SCM's match quality **and** allows:
  - Panel regressions with covariates
  - SEs, p-values
  - Multi-unit and staggered adoption settings, event studies
- **Use case**: Saffer et al. (2025) on e-cigarette flavor bans

Visualizing SDiD: Event Studies of Flavor Ban Impact on Youth E-Cigarette and Cigarette Use

Figure 2.
Synthetic difference-in-differences event study plots for youth



RDD-in-Time (RDiT): Sharp Rollout in Time

- **Core Idea:** Treat time like a running variable in RDD. When a policy kicks in at time t_0, estimate its immediate effect by comparing observations just before and after.
- **Model:**

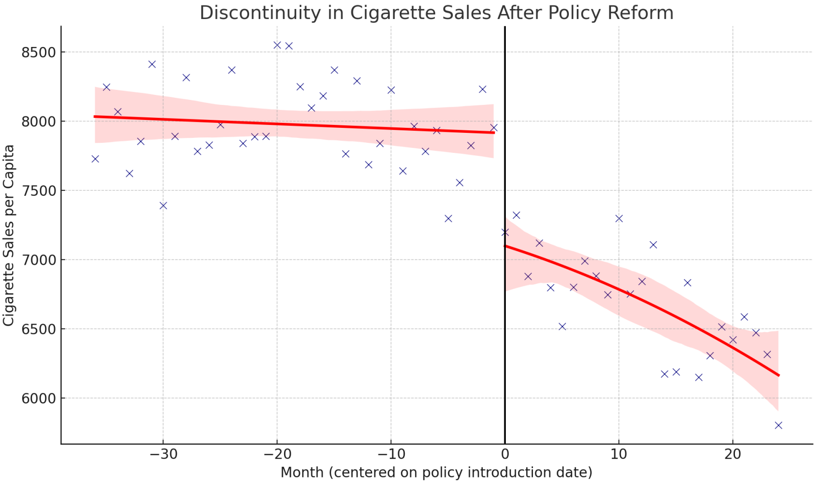
$$Y_t = f(t) + \beta \cdot \mathbf{1}(t \geq t_0) + \varepsilon_t$$

  - $f(t)$: smooth trend function (e.g., polynomial, splines)
  - t: running variable (time)
  - β: treatment effect at the cutoff
- **Assumptions:**
  - No other discontinuous shock at t_0
  - Sufficient data close to cutoff for credible estimation
- **Interpretation:** Captures short-run, immediate causal effect of the policy

Hypothetical Example: Philippines Sin Tax Reform (2013)

- Policy: In January 2013, the Philippines implemented a large increase in cigarette excise taxes (Sin Tax Reform Act)
- This provides a clean RDiT opportunity with monthly data availability
- Estimate impact by comparing sales trends in months just before and just after Jan 2013
- Control for seasonality via a flexible time trend $f(t)$

RDiT with Simulated Data



Stylized RDiT plot: visible jump at cutoff shows treatment effect

Thank you!

`yang.liang@sdsu.edu`

X: @yangliangecon **Bluesky**: @yangliang.bsky.social

Tobacco products and their regulation

James E. Prieger

PROFESSOR OF PUBLIC POLICY
PEPPERDINE UNIVERSITY
SCHOOL OF PUBLIC POLICY
MALIBU, CA

SENIOR ECONOMIST
BOTEC ANALYSIS

Disclaimer: same as Don's, with grant support from Global Action to BOTEC Analysis.

Tobacco and nicotine today
A plethora of products

- Traditional tobacco products
  - Western/Global: Cigarettes, cigars, pipes, chewing tobacco, snuff, etc.





Tobacco and nicotine today
A plethora of products

- Traditional tobacco products
  - Western/Global: Cigarettes, cigars, pipes, chewing tobacco, snuff, etc.
  - Non-Western: water pipes, bidis, paan, gutkha, kreteks, betel quid & tobacco







Tobacco and nicotine today
A plethora of products *and a continuum of risk*

- Novel products: Reduced risk products (RRPs)
  - Note: Some of these are "tobacco products" only in a regulatory sense. E-cigs & pouches have no tobacco leaf and the nicotine may be synthetic.
  - E-cigarettes/Electronic nicotine delivery systems: Juul, Vuse, Elf Bar, Blu…

Tobacco and nicotine today
A plethora of products and a continuum of risk

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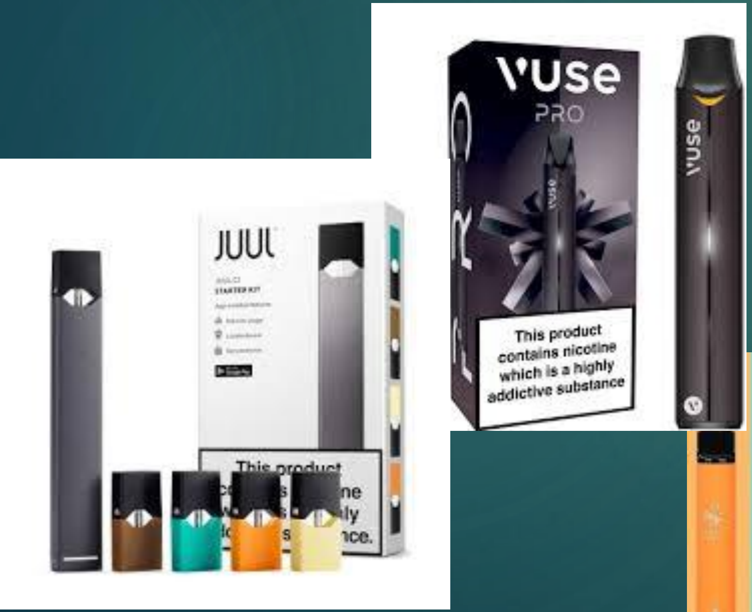

Tobacco and nicotine today
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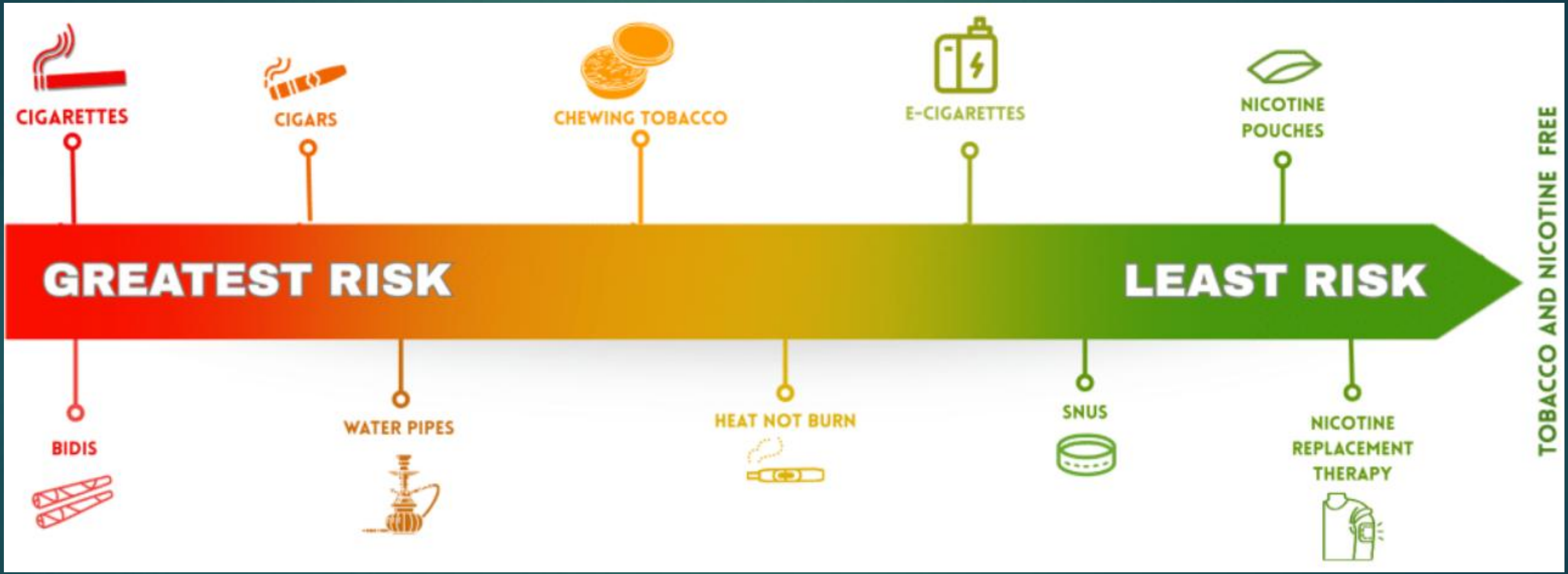
  - E-cigarettes/Electronic nicotine delivery systems: Juul, Vuse, Elf Bar, Blu…
  - Heat-not-burn/heated tobacco products (HNB/HTP): IQOS, glo, Ploom, lil
  - Nicotine pouches: Zyn, On!, Velo.

Harms differ among products

- It is important to focus on how to best improve public health
- Foundational premises affect public health messaging, regulation, and health outcomes.
- Premise Option 1: *No tobacco product is risk-free*.
  - Binary, absolutist
  - Leads to prohibitionist or abstinence-only stances.
  - In other words, "business as usual" for tobacco control developed for smoking: "quit or die"
- Premise Option 2: *Some products have reduced risk*
  - Continuum of risk
  - Leads to harm-reduction approach (as in other areas of public health): encourage switching to RRPs through differential taxation, etc. (see my later session this afternoon)
  - Less common, with UK as notable example

A continuum of risk

- Risks are not fully known, but a rough sketch may look like this:



- The fact that there *exists* a continuum of risk is more important than knowing exactly where each product is located along it – don't get sidetracked (e.g. PHE's "e-cigarettes are 95% safer")

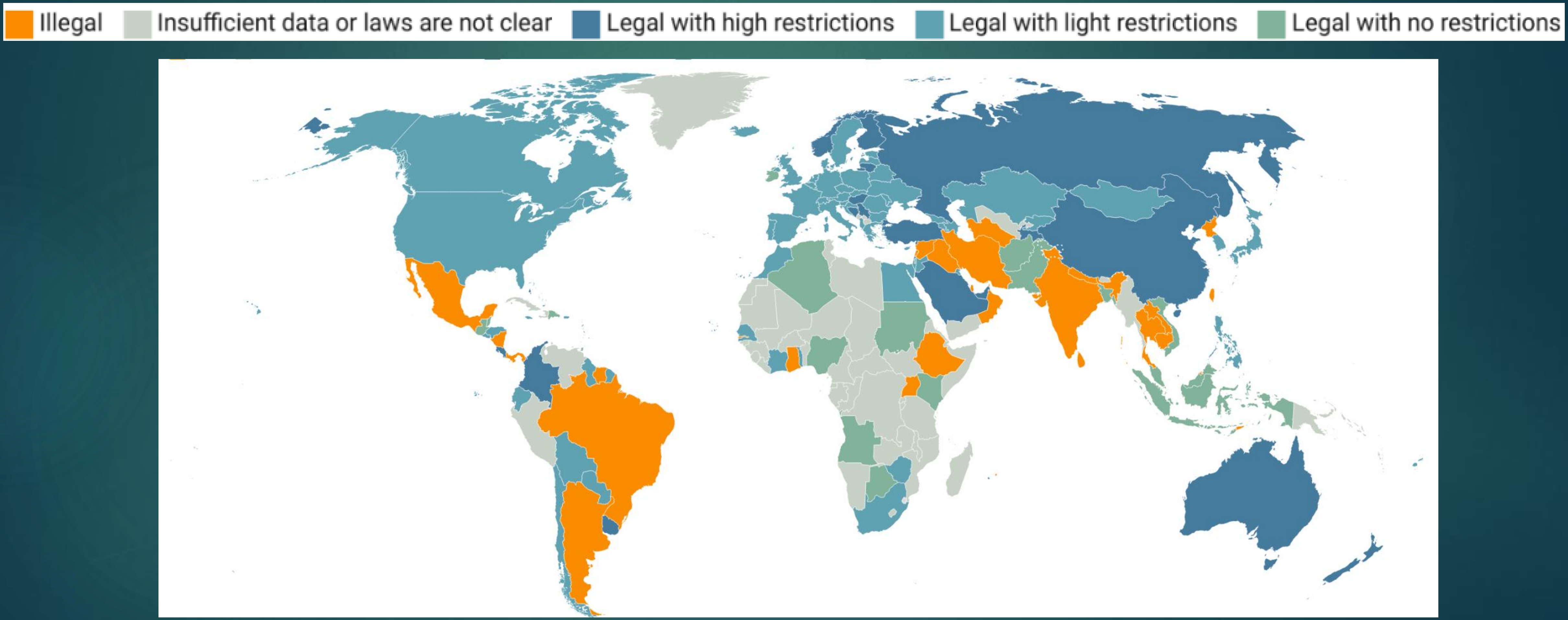
Regulation of e-cigarettes

- Leading forms of regulation
  1. Prohibition. India, Brazil, Singapore
     - Enforcement issues, problems with illicit markets…
  2. Medical approach: Prescription or therapeutic use only. Australia, S. Africa
     - In practice, may be similar to a ban. See Japan (no e-cigs approved for Rx)
     - Requires smokers to see themselves as "sick"
  3. Tobacco regulation: "Deem" and treat as tobacco products. USA, Indonesia, Russia
  4. Specific regulation: Separate category, separate rules. EU (Tobacco Products Directive (TPD II)), UK, Canada
  5. No or minimal regulation. Most common in Africa and SE Asia.
- How about your country?

What can be regulated?

- Age of sale, purchase, or use
- Sales and distribution
  - anywhere? vending machines?
  - specialist shops only? Internet?
- Advertising
  - Where, which media, to whom (kids)?
- Where can they be used?
  - Indoor vaping bans, private spaces with children present
- Product notification to authorities and public
- Tank capacity/e-liquid refill capacity
- Nicotine concentration
- Restricted ingredients
  - caffeine, energy supplements
- Flavors
- Medicinal vs. consumer vs. tobacco product
- Taxation
  - Level (high vs. low vs. none)
  - Structure (ad valorem, specific, combined taxes; see WHO tax manual)
- Health warnings
- Plain packaging
- Refillable vs. disposable products

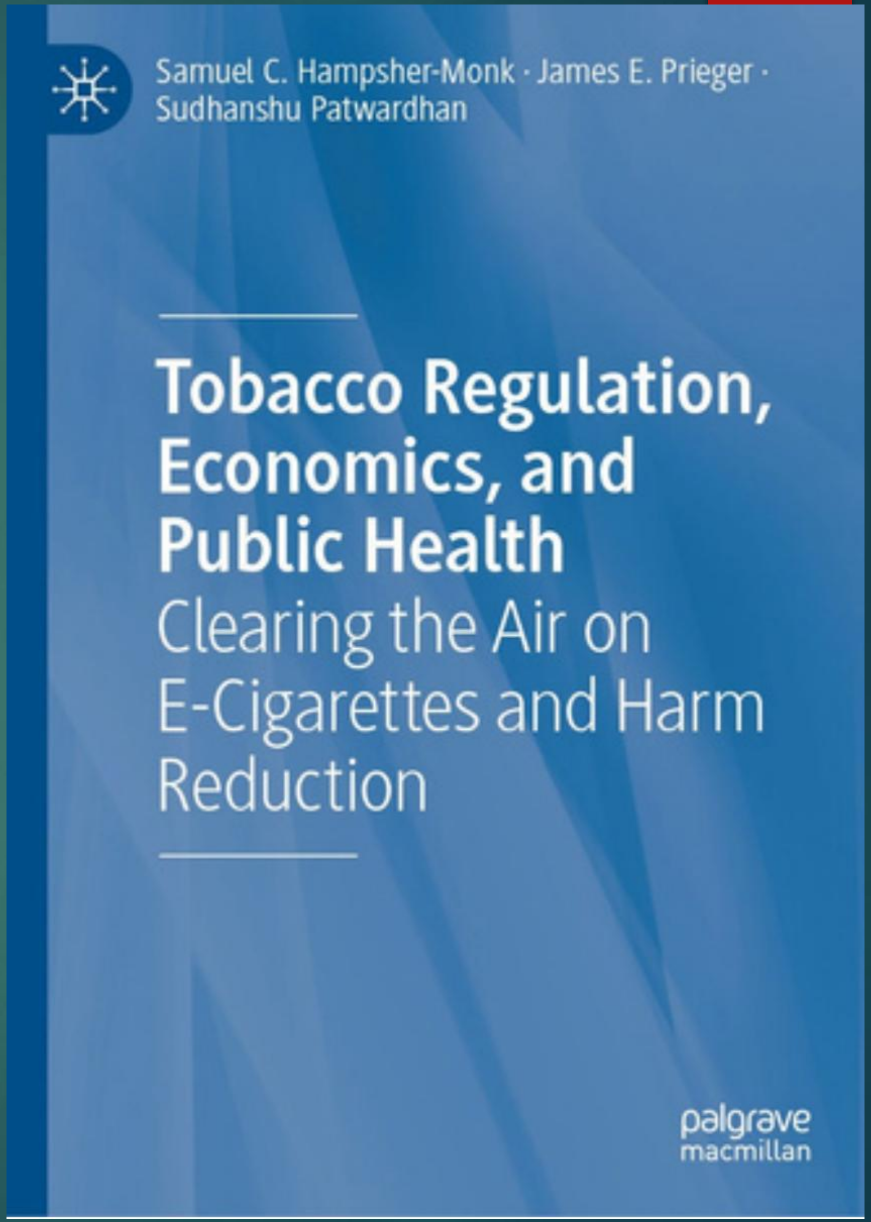
Variation in regulation of e-cigarettes



Source: MIST UK Electronics, 2023

Need a comprehensive resource?

Covering most topics discussed today, and more



On Optimal Taxes for Cigarettes and E-cigarettes

Applied Welfare Economics

JAMES PRIEGER

PEPPERDINE UNIVERSITY

SCHOOL OF PUBLIC POLICY

JAMES.PRIEGER@PEPPERDINE.EDU

IHEA CONFERENCE JULY 2025

This research was funded by the Reason Foundation

Prieger JE. Optimal Taxation of Cigarettes and E-Cigarettes: Principles for Taxing Reduced-Harm Tobacco Products. *Forum for Health Economics & Policy*. 2023 Dec 15;26(2):41-64.

The issue

- Should ENDS be taxed?
  - How much?
  - Relative to cigarettes?
- There are many motives and rationales for taxing tobacco products
- The main conclusion for optimal taxes does not depend on the rationale:
  taxes on ENDS and other harm-reduced products would be relatively *lower*, and likely *much lower*, than those on cigarettes

Three facts about ENDS underlying the results

1. ENDS are not risk-free products, but they are (almost certainly) not as harmful as cigarettes. National Academy of Science, 2018:
   - there is "substantial evidence" that vaping exposes users to **significantly lower levels of toxic substances** than smoking
   - switching from smoking to ENDS results **in improved short-term health outcomes**
   - Long-term health effects unknown, but hard to imagine could be as bad as smoking

Three important facts about ENDS

1. ENDS are not risk-free products, but they are (almost certainly) not as harmful as cigarettes.
2. ENDS can help some smokers quit
    - Review of 90 RCTs and other studies: using ENDS to help quit smoking led to better success rates than NRT, counseling, or willpower alone (Cochrane Review, Lindson et al, 2025)

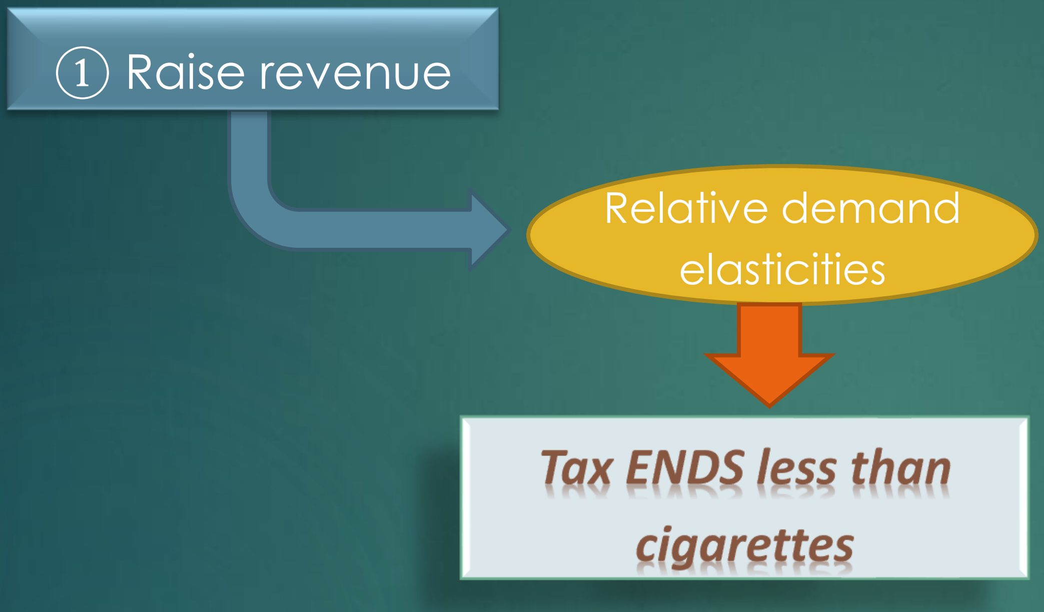
Three important facts about ENDS

1. ENDS are not risk-free products, but they are (almost certainly) not as harmful as cigarettes.
2. ENDS can help some smokers quit
3. ENDS and cigarettes are economic substitutes in demand. (Do, Shang, Huang et al., 2025; Pesko, 2023; Allcott & Rafkin, 2021; Cotti et al. 2022; Huang et al., 2014; Saffer et al., 2020; Stoklosa et al., 2016; Yao et al., 2020; Zheng et al., 2017)
    - Thus taxing ENDS will lead to increased demand for cigarettes

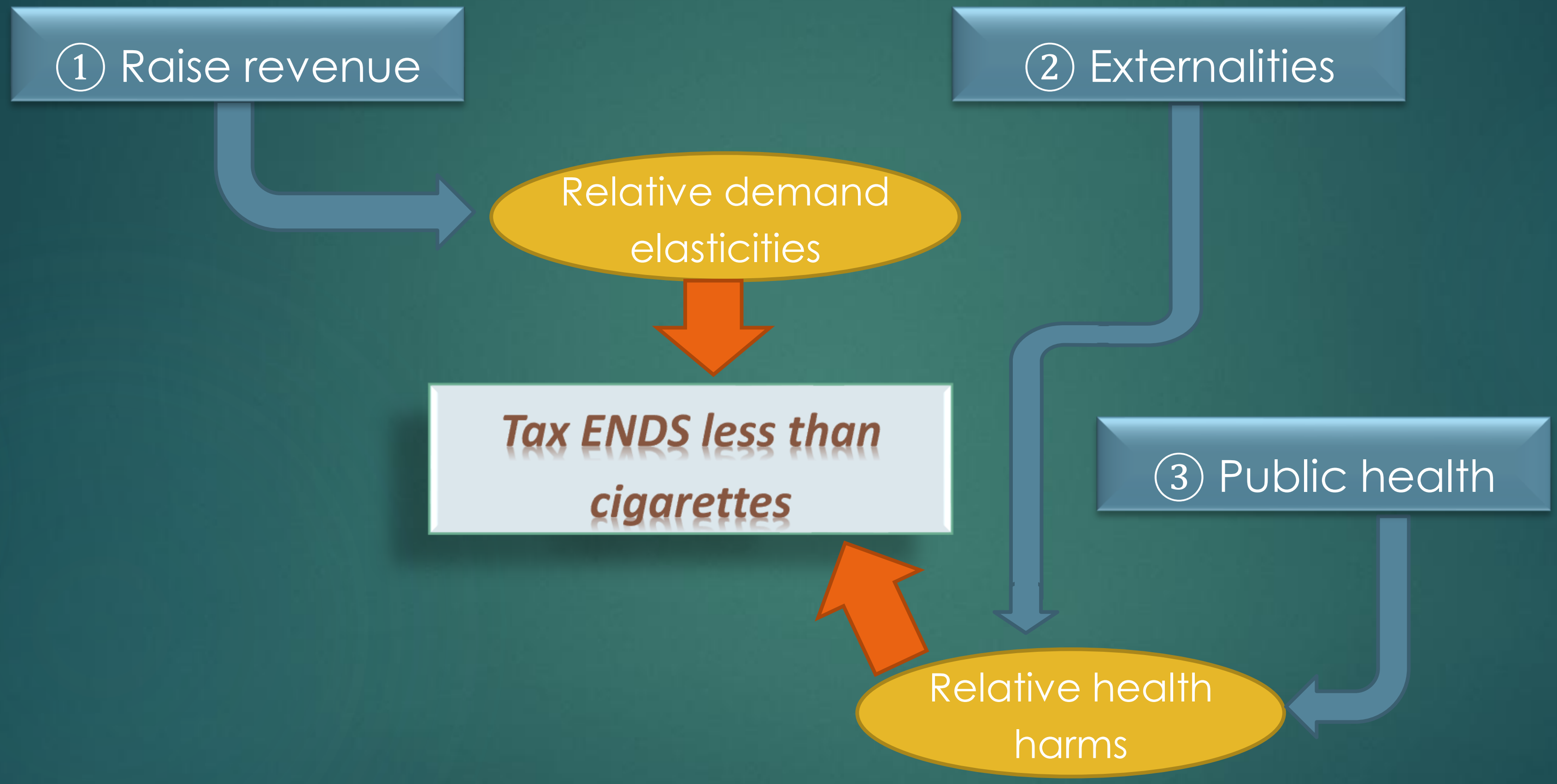
Motivations for taxing ENDS

- There are many motives and rationales for taxation
  1. Raise revenue
  2. Correct a market failure (Externalities)
  3. Improve public health
  4. Correct for behavioral irrationality ("Internalities")

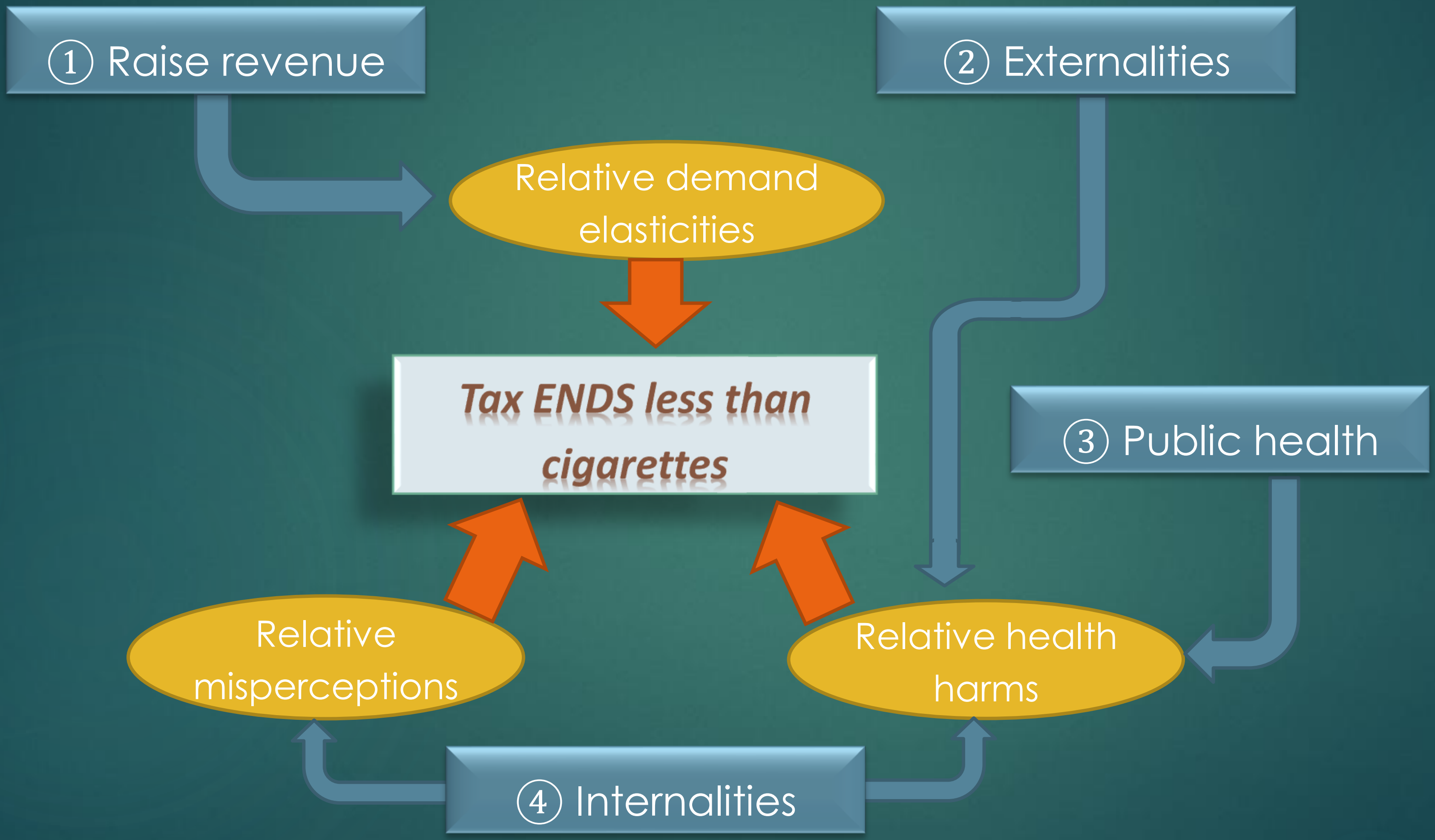
The main results



The main results



The main results



Rationale #1: Tax to raise revenue

- The (economist's) objective function with K tax rates

$$\max_{\tau_1,\ldots,\tau_K} TotalSurplus(\tau_1, \ldots, \tau_K) \;\; \text{s.t.} \; \sum_{k=1}^{K} \tau_k P_k Q_k(P_k) = \bar{R}$$

Rationale #1: Tax to raise revenue

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$$\max_{\tau_1,\ldots,\tau_K} TotalSurplus(\tau_1, \ldots, \tau_K) \;\text{ s.t. } \sum_{k=1}^{K} \tau_k P_k Q_k(P_k) = \bar{R}$$

- Solution: the *Ramsey Rule* for optimal commodity taxes
- Goods with *more elastic demand* are taxed *less*
- Under simplest assumptions (no cross-price effects in D), all taxes are proportional to the inverse elasticity of demand:

$$\tau_k \propto \frac{1}{|\varepsilon_k|}$$

Application to cigarettes and ENDS

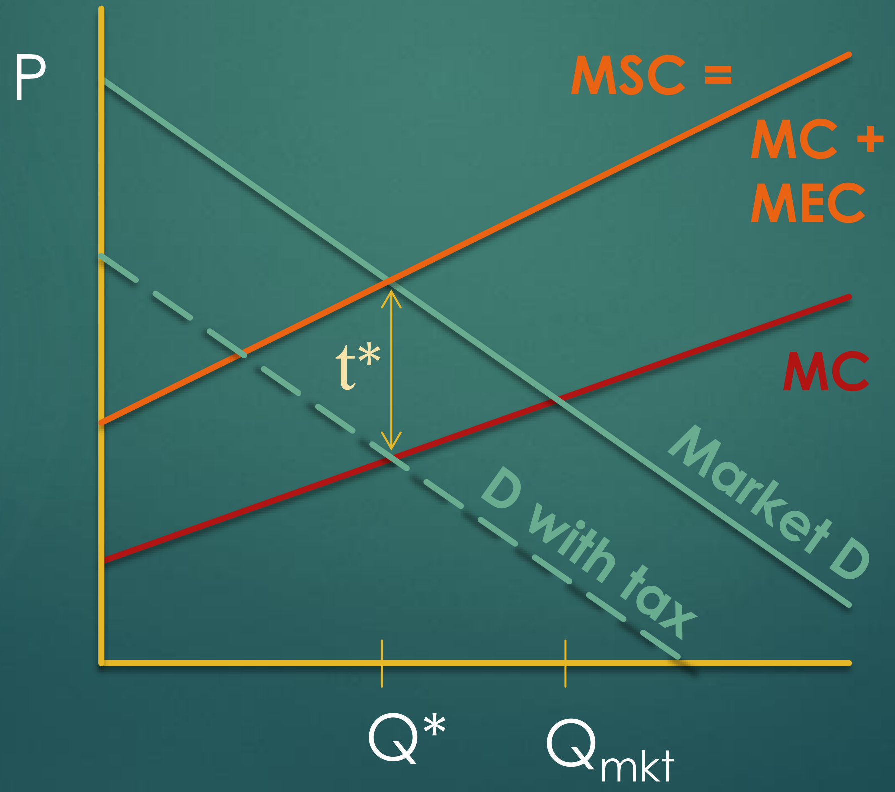
- Econometric evidence: $\varepsilon_{cigs} = -0.4 \qquad \varepsilon_{ecigs} = -2.3 \text{ to } -1.3$
- So the Ramsey Rule implies: $\frac{\tau_{cigs}}{\tau_{ecigs}} = \frac{|\varepsilon_{ecigs}|}{|\varepsilon_{cigs}|} = 3\frac{1}{4} \text{ to } 5\frac{3}{4}$
  - Cigarette taxes should be around **4.5** times the tax rate on ENDS

Application to cigarettes and ENDS

- Econometric evidence: $\varepsilon_{cigs} = -0.4 \qquad \varepsilon_{ecigs} = -2.3 \text{ to } -1.3$
- So the Ramsey Rule implies: $\dfrac{\tau_{cigs}}{\tau_{ecigs}} = \dfrac{|\varepsilon_{ecigs}|}{|\varepsilon_{cigs}|} =$ 3¼ to 5¾
  - Cigarette taxes should be around **4.5** times the tax rate on ENDS
  - Ramsey Rule with cross-price and income effects $\Rightarrow$ cigarette taxes should be **1¾** times the tax rate on ENDS

Rationale #2: Pigovian taxes to correct for externalities

- Optimality requires MSB = MSC.
- So the *optimal tax ratio* depends on the ratio of *marginal external harms* (MEC).



- Optimal tax: t* = MEC(Q*).

Application to cigarettes and ENDS

- Externalities from cigarettes: mostly 2^{nd} hand smoke.
  - Second hand smoke causes about 40,000 deaths per year in the U.S. (1.5% of all deaths)

Application to cigarettes and ENDS

- ENDS:
  - Amounts of potentially harmful substances in secondhand vapor are a *small fraction of pollutants* found in secondhand smoke (Ruprecht et al., 2014; Schripp et al., 2013)
    - Typical finding: Palmisani et al. (2019): 20 mins vaping indoors creates 1-2 orders of magnitude *less* ultrafine particles (UFPs) than **1** cigarette.
  - Vaping within a closed, small room: air quality exceeds WHO or EU air-quality standards (O'Connell et al., 2015)
  - Any health risk from exposure to others' vapor is likely to be less harmful than secondhand smoke (lit review: Hess et al. (2016); National Academies of Science (2018))

Application to cigarettes and ENDS

- Conclusion: taxes on ENDS would be low under this rationale (Pigovian externalities)

Skip to Rationale #4:
To correct for internalities

- Behavioral economics
- Rests on one or both of two assumptions:
  - People misperceive (underestimate) the risks
  - People have time-inconsistent preferences

Rationale #4: To correct for internalities

- Regarding misperceptions:
  - For smoking, perceptions are fairly accurate: 87% of U.S. adults in 2022-23 believed that cigarettes are “very harmful” or “extremely harmful”. Only 1.0% thought smoking was “not at all harmful” (Path Wave 7).
  - ENDS, perceptions are not at all accurate, but people **OVER**estimate risk:
    - 69% think ENDS are as harmful as cigarettes,
    - 16% think ENDS are *more* harmful, and
    - only 14% think ENDS are less harmful.
  - Behavioralist prescription: *subsidize* ENDS?

Rationale #4: To correct for internalities

- Regarding time inconsistent preferences
  - The present self wants to smoke. The future self wishes one hadn't smoked
  - Intrapersonal market failure ⇒ "behavioral wedge" between true marginal cost of consumption and the true marginal benefits
  - Optimal tax: height of the wedge
  - Wedge is smaller for e-cigarettes, due to lower ignored health harms
- So, once again: optimal taxes would be lower for e-cigarettes than cigarettes

Summary: Regardless of motivation for taxation, optimal e-cigarette taxes are *lower* than optimal cigarette taxes

For the full presentation of these issues, see the journal article

- Prieger JE. Optimal Taxation of Cigarettes and E-Cigarettes: Principles for Taxing Reduced-Harm Tobacco Products. *Forum Health Econ Policy*. 2023 Dec 15;26(2):41-64.

How does e-cigarette use affect smoking-related socioeconomic disparities in the US?

With emphasis on income levels

James E. Prieger
Pepperdine University

Samuel Hampsher
BOTEC Analysis

1

IHEA Conference
Bali, Indonesia
July 2025

Disclaimer

- TLDR: This research is funded by *Global Action to End Smoking.* All results and opinions are those of the authors, not GA. GA used to receive funding from PMI but were independent. They no longer receive funding from the tobacco industry.
- TL: This research was supported by a grant to BOTEC Analysis from Global Action to End Smoking (GA; formerly known as Foundation for Smoke-Free World), an independent, U.S. nonprofit 501(c)(3) grantmaking organization. GA played no role in the research design, implementation, data analysis, or interpretation of the results, nor did GA edit or approve any presentations or publications from the study. The contents, selection, and presentation of facts, as well as any opinions expressed, are the sole responsibility of the authors and should not be regarded as reflecting the positions of GA. Through September 2023, GA received charitable gifts from PMI Global Services Inc. (PMI), which manufactures cigarettes and other tobacco products. To complement the termination of its agreement with PMI, GA's Board of Directors established a new policy to not accept or seek any tobacco or non-medicinal nicotine industry funding.

Introduction

- Smoking prevalence is often concentrated among disadvantaged groups in a country
  - Lower income, less education, other SES
  - Racial or ethnic minorities
  - Disabled and mentally ill
- As noted earlier today, high-quality evidence indicates that e-cigarettes aid cessation from smoking (Hartmann-Boyce et al., 2022; Lindson et al., 2025).
- However, there is little conclusive direct evidence on how e-cigarette use may affect smoking-related health inequality
  - Lucherini et al (2019): systematic review => evidence is “somewhat inconsistent”.
  - Of poor econometric quality

Research questions

- Does use of e-cigarettes aid cessation from smoking (among US adults)?
- If so, is that also true for disadvantaged groups?
  - And to the same extent?
  - Can e-cigarettes help close socioeconomic gaps in smoking/cessation?

Empirical approaches

- Key empirical problem: The use of e-cigs may be endogenous with smoking/cessation behavior
  - Common liabilities in nicotine use at the individual level: genetic, environmental, etc.
  - Omitted variables: local tobacco control policies, etc.
- We’ve already seen today how panel data + Diff-in-diff estimation can allow causal inference

Empirical approaches using observational data

- What if you only have a cross-sectional survey?
  - What you should *not* do (which much of the public health literature does): treat use of e-cigarettes as exogenous and just run regressions

Empirical approaches using observational data

- Potential statistical solutions *if you only have a cross-sectional survey*
  - IV regression. Requires an instrument that determines e-cigarette use but does not independently (apart from e-cig use) affect smoking or cessation.
    - Works well with a strong instrument
    - Ignoring the binary nature of e-cig use and cessation may be problematic.
    - The selection-in-ecig-use is inherently nonlinear (e.g. probit or logit), and IV corrects for *linear* selection bias.
  - Many other possibilities (ignoring the doubly-binary nature of the problem)
    - Matching methods, Control functions, etc.

Empirical approaches using observational data

- Take the double-binary nature of selecton and outcome seriously: Model a continuum of "types" with a model for selection into use of e-cigarettes.
  - Triangular (doubly binary) bivariate system
  - *D* = e-cig use. Treated as a causal variable.
  - *Y* = cessation from smoking. The outcome.
  - Selection: *u* and *ε* are correlated.
  - ID: parametric (bivariate normal, copulas), seminonparametric (De Luca, 2008; Gallant & Nychka, 1987), "less parametric" moment based (Wooldridge)
  - Do not *need* an instrument in *z*, but it helps a lot if you have one

$$D_i = \begin{cases} 1 & \text{if } z_i'\gamma + u_i \geq 0 \\ 0 & \text{else} \end{cases}$$

$$Y_i = \begin{cases} 1 & \text{if } \alpha_0 + \tau D_i + x_i'\beta + \varepsilon_i \geq 0 \\ 0 & \text{else} \end{cases}$$

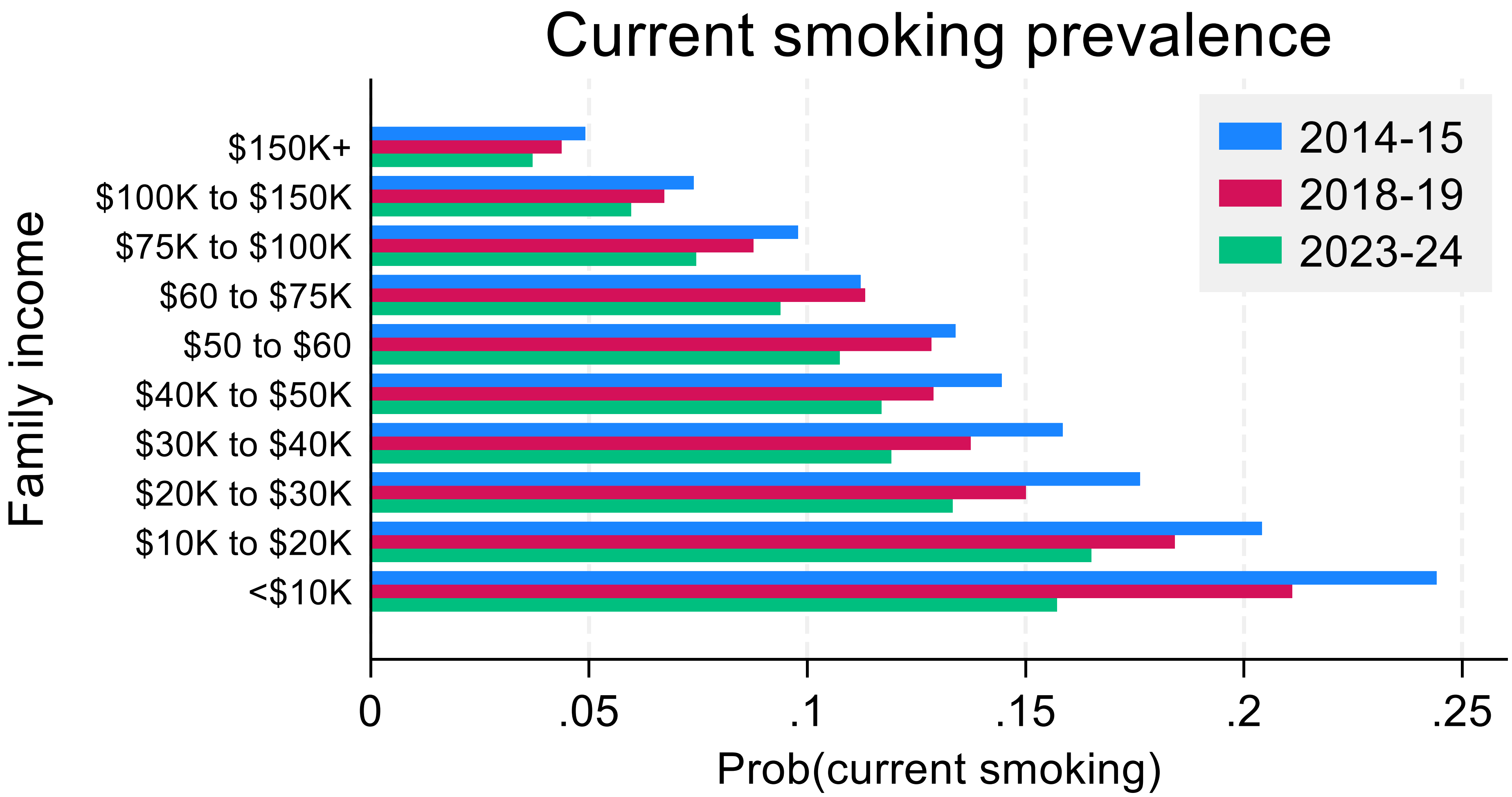
- Prieger & Choi (2024), *J. Consumer Policy*

Brief description of our study

- CPS-Tobacco Use Supplement (TUS), 2014-2023 (3 waves)
- Examine people who were smoking 12 months before taking the survey.
  - Some were still smoking at time of survey
  - Some had quit (cessation)
  - Some used e-cigarettes during the past year, others did not
- All estimates will use survey weights
- SEs will account for complex survey design effects

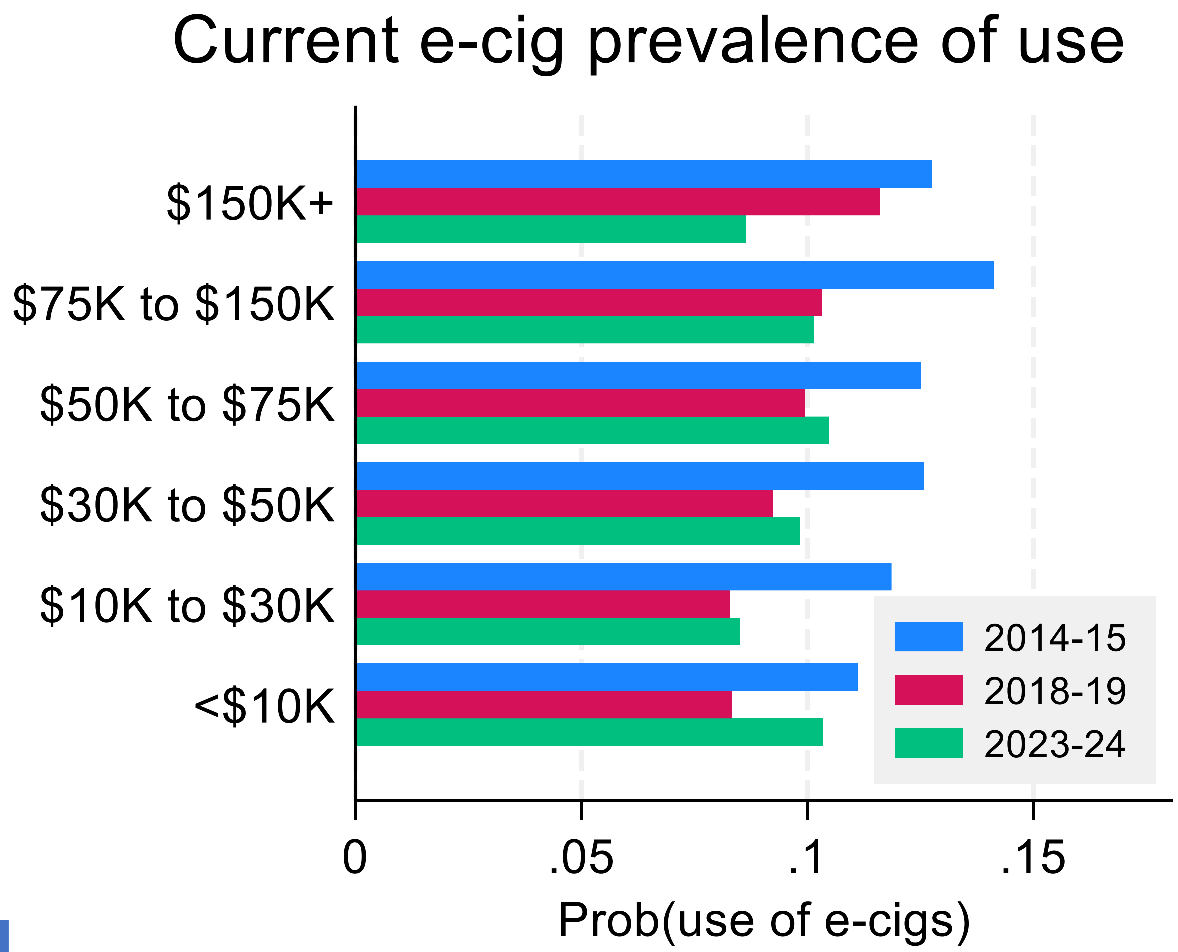
TUS: Who is still smoking?

The socioeconomic gradient in smoking



TUS: Among adult smokers, who is using e-cigarettes?

- Answer:
  people of all income levels, roughly equally



χ^2 *p*-value for differences among income levels: 0.557

Past 12M smokers

BOTEC ANALYSIS

Regression-adjusted results for cessation

- Recall the outcome equation for Y = cessation from smoking as a function of D = uses/used e-cigarettes in the past year is

$$Y_i = \begin{cases} 1 & \text{if } \alpha_0 + \tau D_i + x_i'\beta + \varepsilon_i \geq 0 \\ 0 & \text{else} \end{cases}$$

  Estimate this first treating D as exogenous
    - OLS/LPM
    - Logit
- Then estimate the double-binary triangular system
    - Bivariate probit, for initial results.

$$D_i = \begin{cases} 1 & \text{if } z_i'\gamma + u_i \geq 0 \\ 0 & \text{else} \end{cases}$$

$$Y_i = \begin{cases} 1 & \text{if } \alpha_0 + \tau D_i + x_i'\beta + \varepsilon_i \geq 0 \\ 0 & \text{else} \end{cases}$$

BOTEC ANALYSIS

Impact of e-cigs on past-year cessation

Y = Past year cessation	Est. 0 LPM
E-cig use	0.086***
Add'l controls?	No
χ^2 (p-value)	0.000
R squared	0.026
N	50,934

** 5% significance *** 1% significance

Note that all regressions include individual controls and state & year fixed effects

- Personal Controls:
  - Family income
  - Sex, Race/ethnicity
  - Education
  - Married, Children in HH
  - Metro/nonmetro
  - Labor force status
  - Occupation & industry
  - Native-born
  - Addiction: time to 1st cig., cigs/day

Impact of e-cigs on past-year cessation

Y = Past year cessation	Est. 0 LPM	Est. 1 LPM
E-cig use	0.086***	0.086***
Add'l controls?	No	Yes
χ^2 (p-value)	0.000	0.000
R squared	0.026	0.026
N	50,934	50,934

- The effect size persists with add'l controls

- Personal Controls: income, sex, race/ethnicity, education, married, children, metro, working, occupation, industry, native-born, addiction
- Regulatory Controls:
  - Cig taxes, sales licensing, smoke-free policies, Medicaid coverage of cessation treatments, alcohol taxes, cannabis laws
  - All lagged one year from survey
- Economic Controls:
  - GDP growth, per cap. income, UE (all lagged)

BOTE

Impact of e-cigs on past-year cessation

Y = Past year cessation	Est. 0 LPM	Est. 1 LPM	Est. 2 Logit
E-cig use	0.086***	0.086***	0.773***
Add'l controls?	No	Yes	Yes
χ^2 (p-value)	0.000	0.000	0.000
R squared	0.026	0.026	
N	50,934	50,934	50,934

- The effect persists with logit. OR ≈ 2.2

- Personal Controls: income, sex, race/ethnicity, education, married, children, metro, working, occupation, industry, native-born, addiction
- Regulatory Controls:
  - Cig taxes, sales licensing, smoke-free policies, Medicaid coverage of cessation treatments, alcohol taxes, cannabis laws
  - All lagged one year from survey
- Economic Controls:
  - GDP growth, per cap. income, UE (all lagged)

Impact of e-cigs on past-year cessation

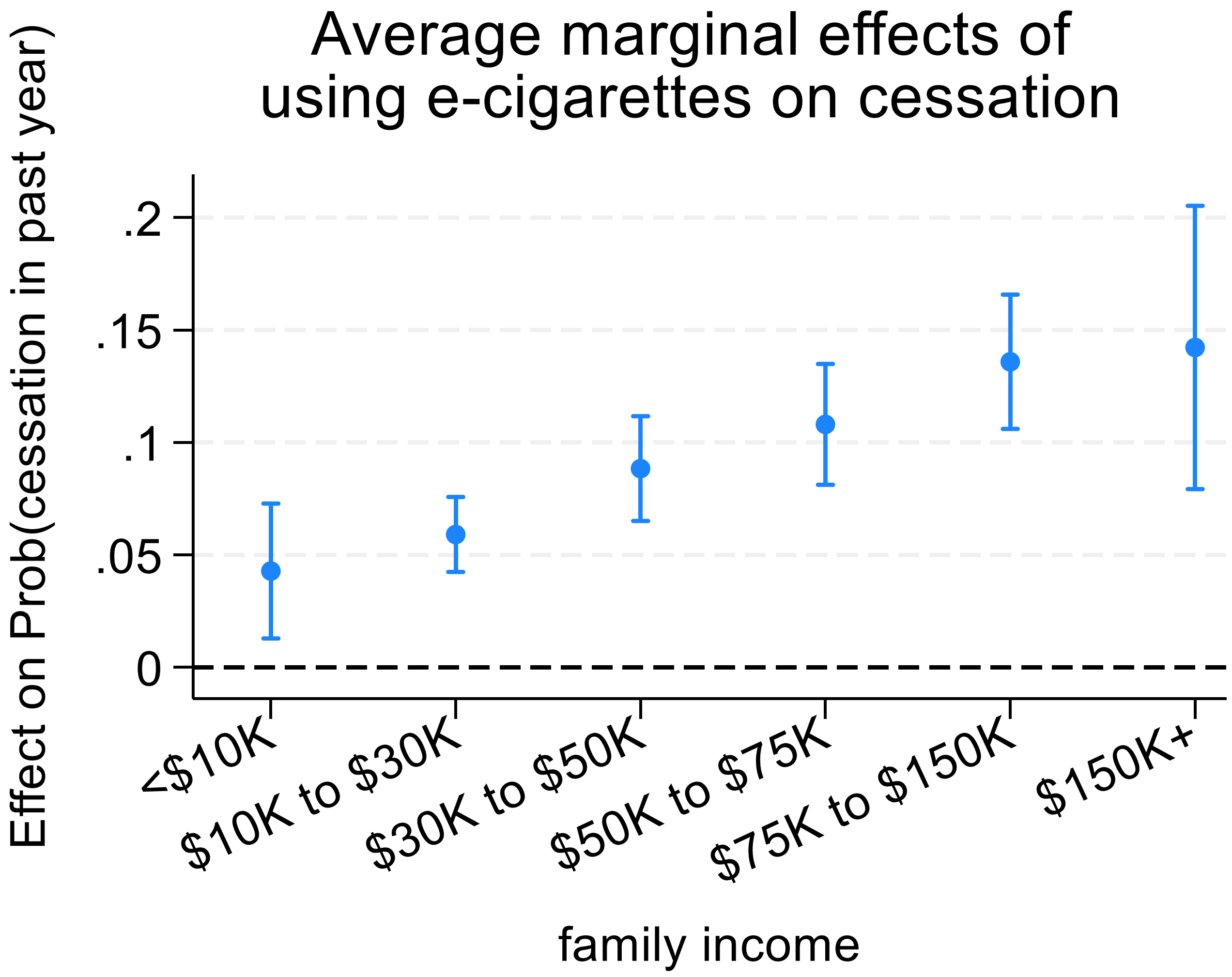
Y = Past year cessation	Est. 0 LPM	Est. 1 LPM	Est. 2 Logit	Est. 3 LPM
E-cig use	0.086***	0.086***	0.773***	0.048***
Use (2015)				0.057***
Use (2018)				0.067***
Use (2019)				0.105***
Use (2022)				0.123***
Use (2023)				0.161***
Add'l controls?	No	Yes	Yes	Yes
χ^2 (p-value)	0.000	0.000	0.000	0.000
R squared	0.026	0.026		0.029
N	50,934	50,934	50,934	50,934

- The effect size grows over time

- Personal Controls:
  Family income, sex, education, race/ethnicity, married, children in household, Labor force status, metro/nonmetro, occupation, industry, native-born
- Regulatory Controls:
  - Cig taxes, sales licensing, smoke-free policies, Medicaid coverage of cessation treatments, alcohol taxes
  - All lagged one year from survey
- Economic Controls:
  - GDP growth, per cap. income, UE (all lagged)

Impact of e-cigarettes by income group

- Regression: as before, but interact e-cigarette use with year *and* income
  - There are 36 relevant coefficients for the effect of e-cigs (6 income levels × 6 years)
  - summarize with the average marginal effects in the graph (ave. treatment effect on the treated: ATT)
- E-cigarettes are effective for cessation *for all incomes*
- However: effectiveness of e-cigs for cessation *increases with income* (*p*-value for equal effects = 0.000)

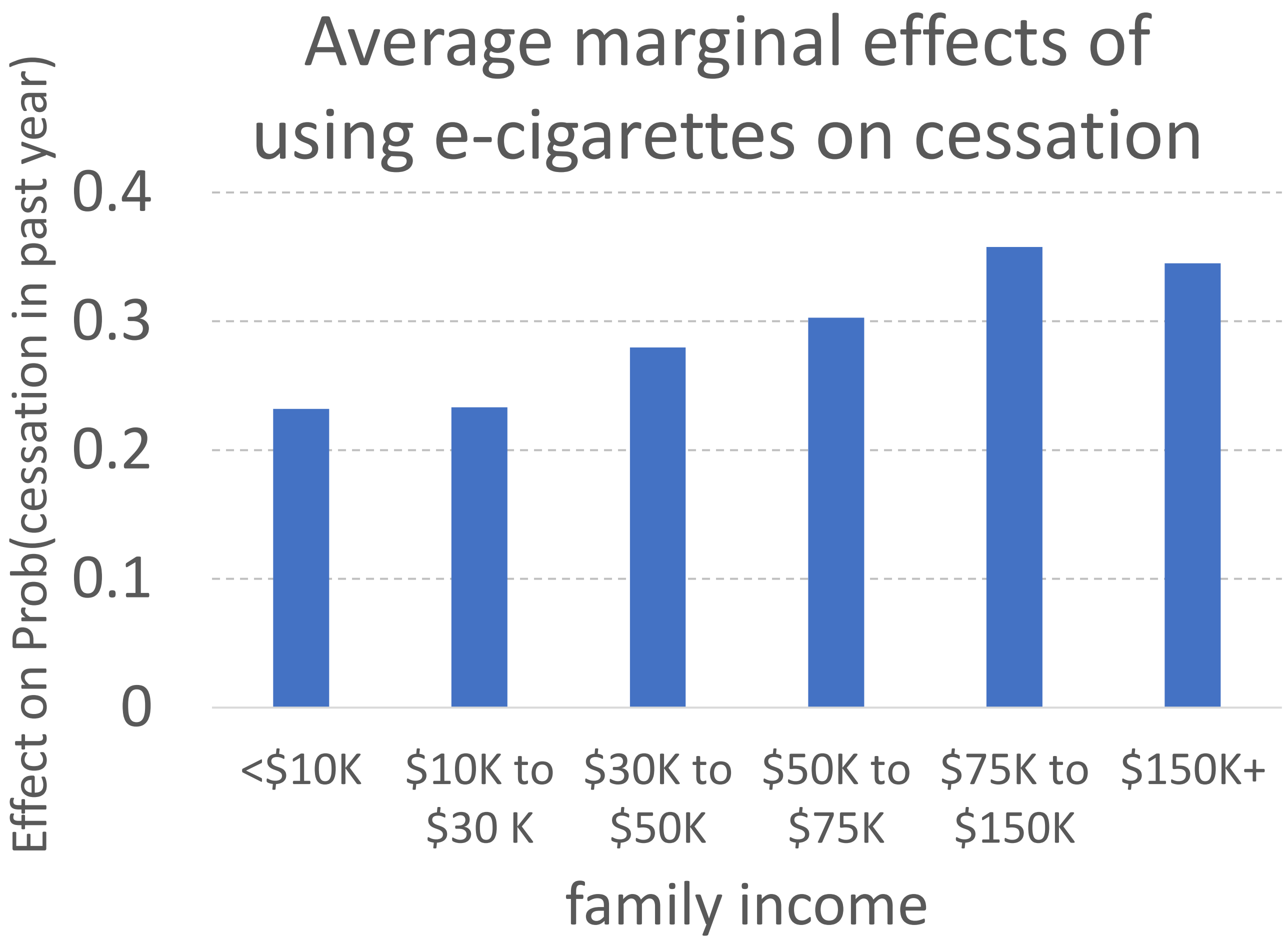


Impact of e-cigarettes by income, accounting for endogeneity of e-cigarette use

- Bivariate probit binary treatment effects model
  - Refer to the triangular model described earlier
- Excluded instruments in the equation for e-cigarette use:
  - E-cig taxes, e-cig retail licensing laws, the individual's workplace vaping rules, did anyone vape at work recently, state vape-free laws
  - Chi-squared statistic for their *relevance*: 109; *p*-value = 0.000

Impact of e-cigarettes by income, accounting for endogeneity of e-cigarette use

- Bivariate-probit binary treatment effects model
- Excluded instruments in the e-cig use equation:
  - E-cig taxes, e-cig retail licensing laws, the individual's workplace vaping rules, did anyone vape at work recently, state vape-free laws
  - Chi-squared stat on them: 109; p-value = 0.000
- There is sig. *negative* correlation between the cessation and e-cig use errors
  - Unobserved factors making e-cig use more likely (e.g. strong addiction) make cessation less likely
- Results for ATT are as before, *but even larger effects* (all are significant)



Conclusions

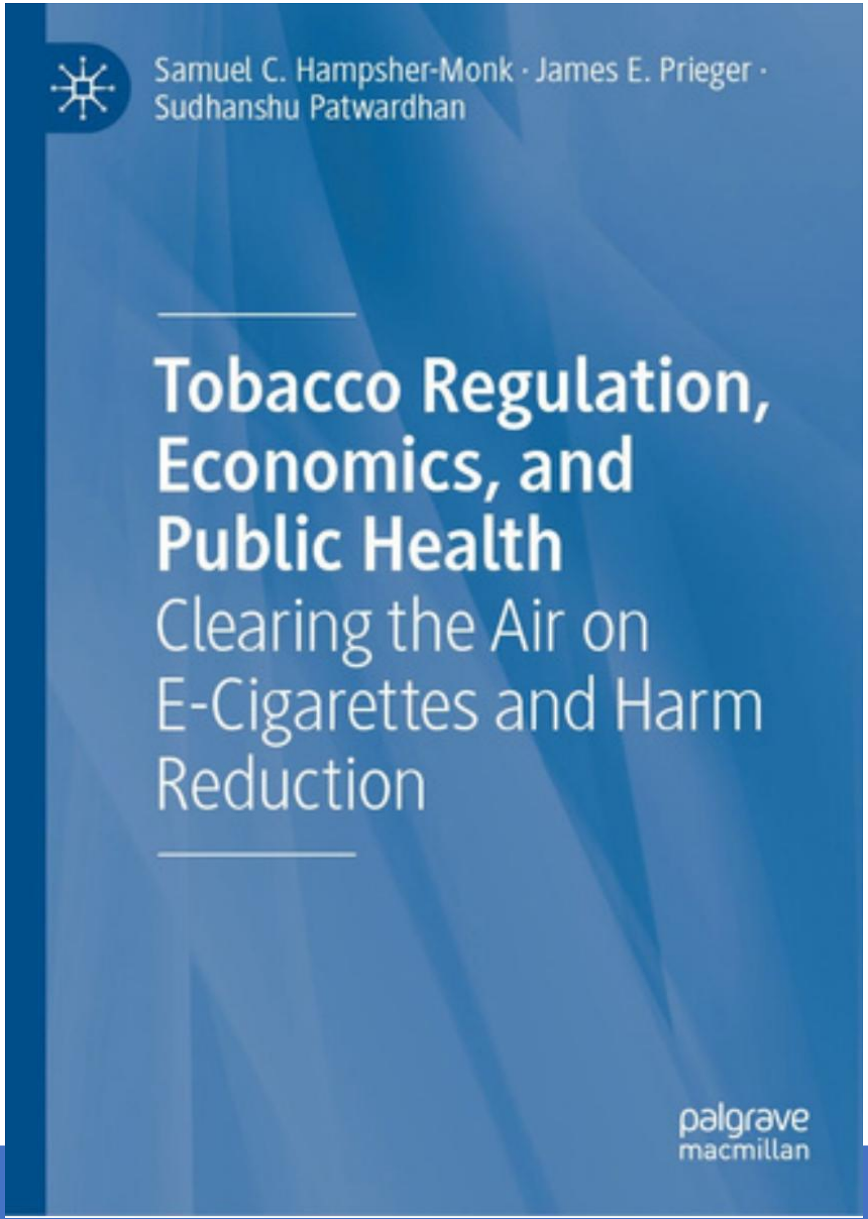
- E-cigarettes appear to aid cessation: +8.7** pp quitting in past year; 3x that after accounting for endogeneity of using e-cigarettes.
- Lower-income smokers' use of e-cigarettes *is as likely* as higher-income's
- But: Lower-income smokers benefit *less* from e-cigarettes for cessation
  - But still benefit: +4.3** pp for income <$10K vs. +14.2** pp for income ≥$150K
  - E-cigs may *absolutely* help low-income smokers quit, while *relatively* exacerbating inequities in prevalence of smoking
- Motivations for using e-cigarettes matter (from results not shown here)
  - E-cigs' efficacy for cessation is much greater when they are used for that purpose: +13.8** pp vs. +2.1** pp.
  - Potential policy implication: physician and public health messaging should consider encouraging their use for cessation (as in UK)

**Significant at 1% level

Final thoughts

- If e-cigarettes aren't helping disadvantaged groups to quit smoking as much as for high-income smokers, why not?
  - It isn't because lower income smokers are less likely to use e-cigarettes
  - Supplementary work: it isn't because they are less likely to use e-cigs for purposes of cessation
  - It is because they see less benefit for cessation (why?)
  - Requires continued investigation

Thank you!


Samuel C. Hampsher-Monk · James E. Prieger · Sudhanshu Patwardhan
Tobacco Regulation, Economics, and Public Health
Clearing the Air on E-Cigarettes and Harm Reduction
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Quasi-Experimental Design in E-Cigarette Policy Research:
Evidence from the U.S. and Canada

Joseph J. Sabia

Center for Health Economics & Policy Studies

San Diego State University & Institute of Labor Economics

Disclosure

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Electronic Nicotine Delivery Systems

- Electronic nicotine delivery systems (ENDS) are devices in which nicotine and other ingredients (e.g., flavors) are heated into a vapor and inhaled
  - First developed in China and entered US tobacco market in 2006

- Increased ENDS access could improve public health via harm reduction
  - Cigarette smoking is the leading cause of preventable death in US
    - Smoking responsible for 480,000 deaths each year, increase risk of a myriad of cancers, heart disease, stroke, and respiratory disease; annual cost $600B (CDC 2023)

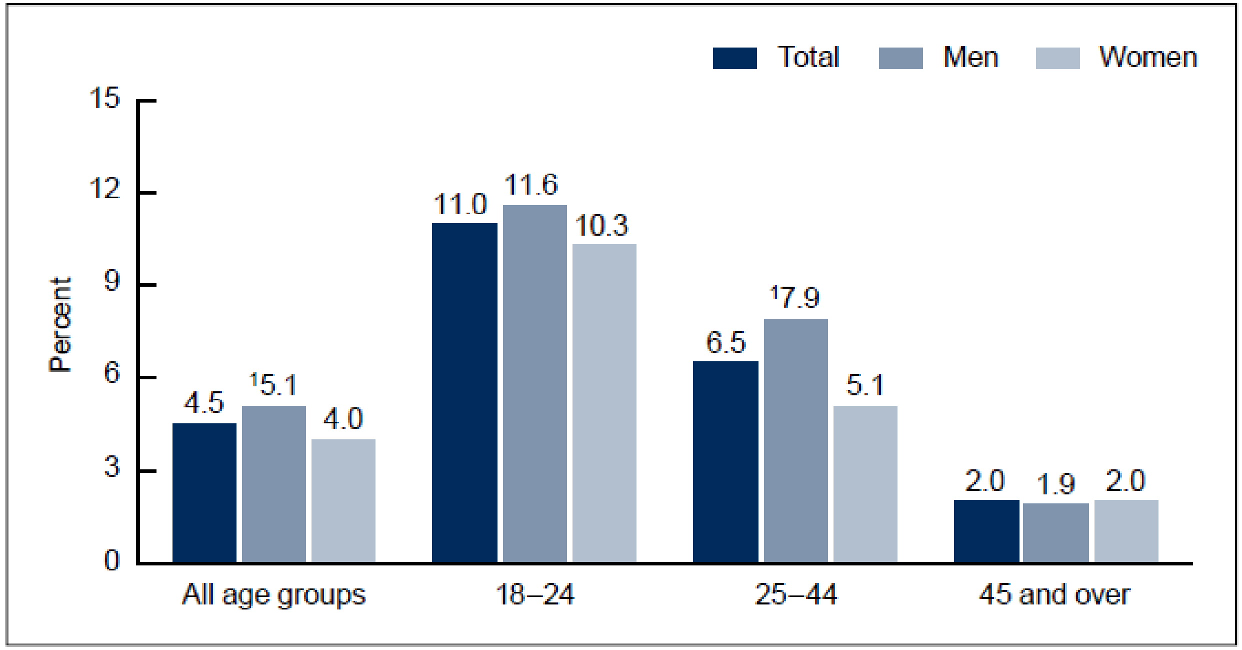
  - In sharp contrast, National Academies of Sciences (2018) concludes that while ENDS use appears to cause respiratory and heart-related health harm:

    "...e-cigarettes appear to pose less risk to an individual than combustible tobacco cigarettes ...e-cigarette aerosol contains fewer numbers and lower levels of toxicants than smoke from combustible tobacco cigarettes."

  - Expert reviews suggest that e-cigarettes carry 5-37% of the harm of cigarettes (Allcott and Rafkin 2022; Public Health England 2015)

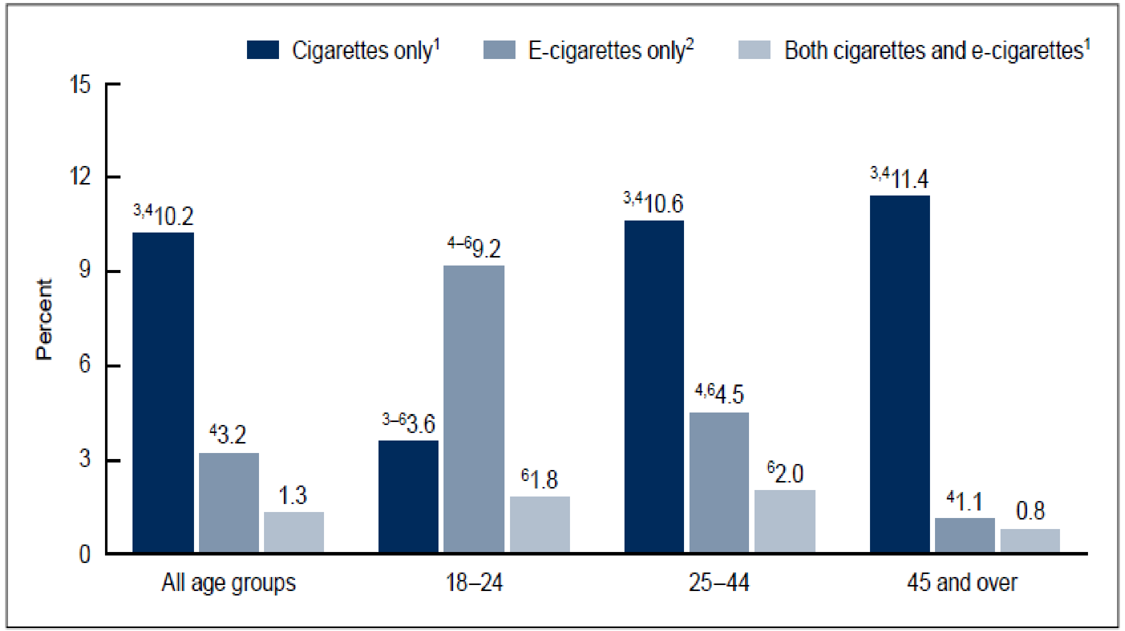
E-Cigarette Use Among U.S. Adults, by Age

Figure 1. Percentage of adults aged 18 and over who currently use e-cigarettes, by age group and sex: United States, 2021



[1]Significantly different from women ($p < 0.05$).
NOTES: Men, women, and total men and women had a significant linear trend by age ($p < 0.05$). Current e-cigarette use was based on responses of "every day" or "some days" to the question, "Do you now use e-cigarettes or other electronic vaping products every day, some days, or not at all?" This question was asked of adults who had ever tried an e-cigarette, even one time. Estimates are based on household interviews of a sample of the U.S. civilian noninstitutionalized population. Access data table for Figure 1 at: https://www.cdc.gov/nchs/data/databriefs/db475-tables.pdf#1.
SOURCE: National Center for Health Statistics, National Health Interview Survey, 2021.

Figure 4. Percentage of adults aged 18 and over who currently smoke cigarettes and use e-cigarettes, by age group: United States, 2021



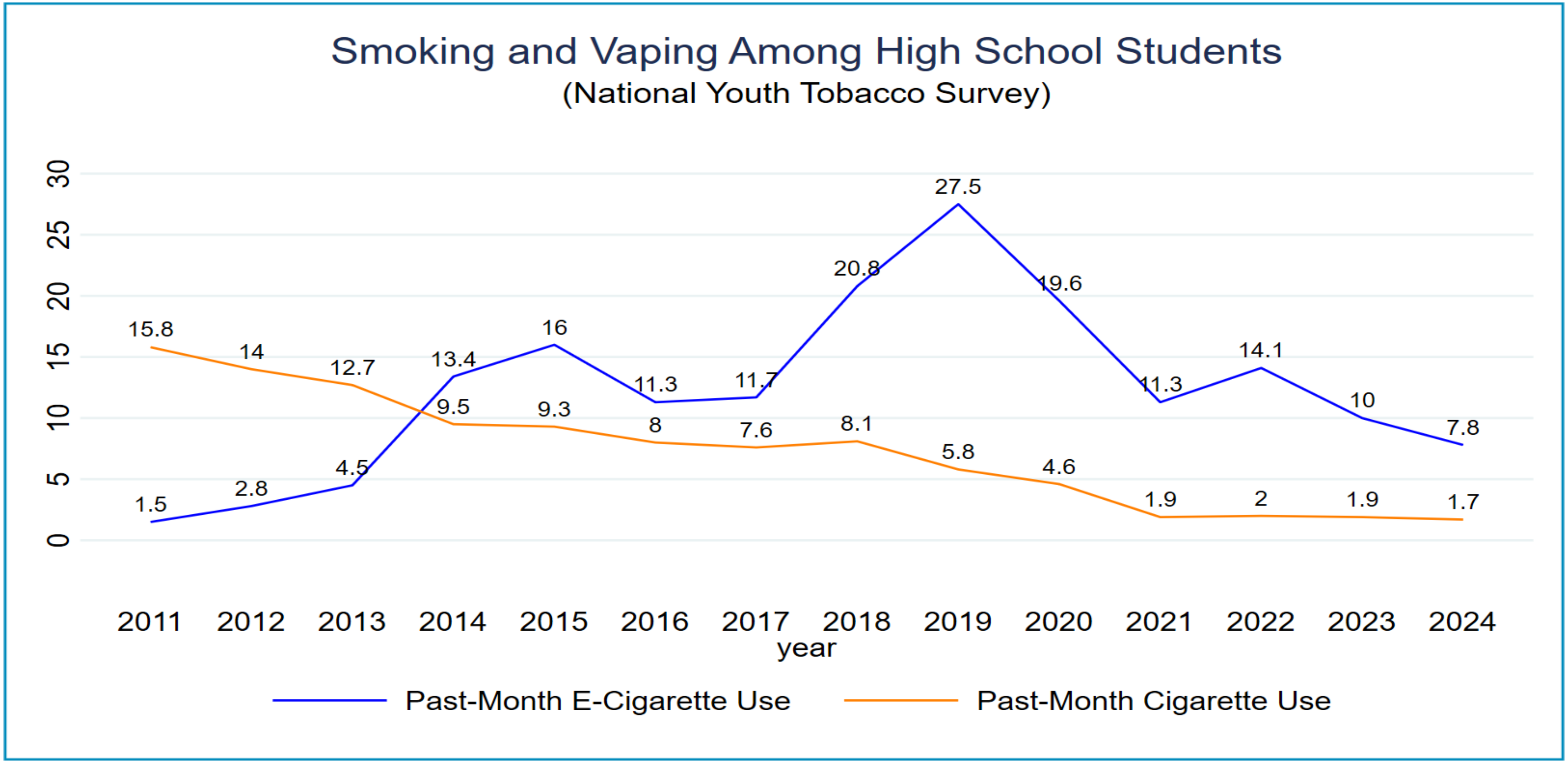
[1]Significant quadratic trend by age ($p < 0.05$).
[2]Significant linear trend by age ($p < 0.05$).
[3]Significantly different from e-cigarettes only ($p < 0.05$).
[4]Significantly different from both cigarettes and e-cigarettes ($p < 0.05$).
[5]Significantly different from adults aged 25–44 ($p < 0.05$).
[6]Significantly different from adults aged 45 and over ($p < 0.05$).
NOTES: Current e-cigarette use was based on responses of "every day" or "some days" to the question, "Do you now use e-cigarettes or other electronic vaping products every day, some days, or not at all?" This question was asked of adults who had ever tried an e-cigarette, even one time. Adults were asked if they had smoked at least 100 cigarettes in their lifetime and, if yes, whether they currently smoked cigarettes every day, some days, or not at all. Those who smoked every day or some days were classified as current cigarette smokers. The sum of e-cigarettes only and both cigarettes and e-cigarettes may not equal total e-cigarette use due to rounding. Estimates are based on household interviews of a sample of the U.S. civilian noninstitutionalized population. Access data table for Figure 4 at: https://www.cdc.gov/nchs/data/databriefs/db475-tables.pdf#4.
SOURCE: National Center for Health Statistics, National Health Interview Survey, 2021

Policymakers concerned about youths

- Could ENDS serve as a gateway to combustible tobacco for youth?
  - Tobacco control advocates worry that increased access to ENDS products, especially flavored ENDS, could “lure” teens into riskier health behaviors
  - Are e-cigarettes and combustible cigarettes economic complements or substitutes for teens?

- Youths may deserve special attention by policymakers for regulation
  - Asymmetric information
  - Prefrontal cortexes not fully developed, making “rational” decision-making more difficult and responses to negative emotional shocks less measured
  - Time-inconsistent preferences that could generate internalities

National Youth Tobacco Survey (U.S.)



Common Policy strategies to reduce ENDS use

- Minimum legal purchasing ages for e-cigarettes
    - Now Federal “Tobacco-to-21” Law
- Restricting sales of flavored ENDS products
- Extend clean indoor air laws to cover e-cigarette aerosol
- ENDS retail licensure laws
- Restricting the delivery of ENDS products purchased online
- ENDS taxes

Importance of Causal Inference in Policy Analysis

- In the absence of a randomized controlled trial (RTC), credible quasi-experimental research design is needed to establish causal effect of policy
  - Disentangle selection effects and reverse causality from causal impact
- We need credibly policy analysis to understand the intended and unintended effects of public policies (positive analysis)
  - These estimated policy parameters can then be used as part of a cost-benefit analysis (normative analysis)
- Concern with Observational Data: Policy adoption is not random
  - Jurisdictions that adopt stricter ENDS policies may have stronger anti-vaping sentiment or, alternatively, higher vaping rates than controls
- Credible quasi-experimental econometric methods are necessary to mimic conditions of a (localized) experiment

Common quasi-experimental methods used

- **Difference-in-differences (DiD)**
  - Exploit staggered adoption of local policies to identify their effects on health
    - Compare trends in vaping (smoking) before and after policy change in treatment jurisdictions vs counterfactual jurisdictions

Common quasi-experimental methods used

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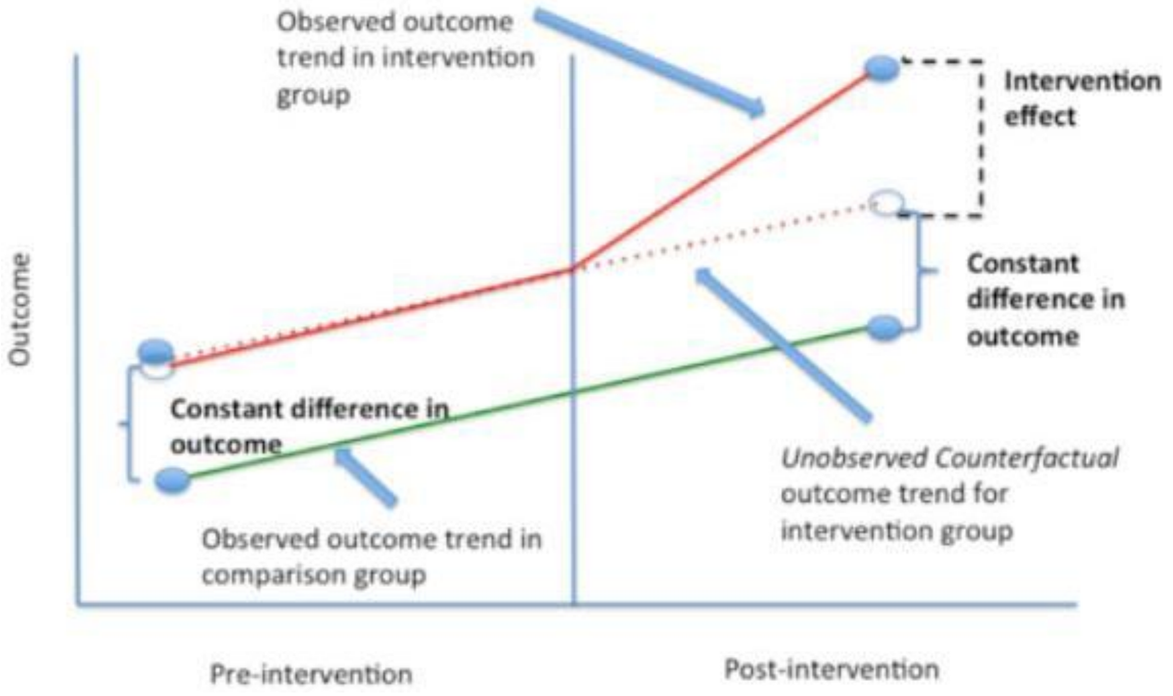

Source: https://www.publichealth.columbia.edu/research/population-health-methods/difference-difference-estimation

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  - Exploit staggered adoption of local policies to identify their effects on health
    - Compare trends in vaping (smoking) before and after policy change in treatment jurisdictions vs counterfactual jurisdictions
  - Dynamic DiD (event-study analysis)
    - decompose the treatment effect over time
    - explore whether prior to policy adoption, vaping (smoking) in treatment and control states were trending similarly and any diversion happens post-treatment
  - Two-way fixed effects (TWFE) vs Alternate DiD Estimators
    - Stacked DiD (Cengiz et al. 2019); Sun and Abraham (2021); Callaway and Sant'Anna (2021); Gardner (2021); de Chaisemartin and D'Haultfoeuille (2020; 2023)

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- **Regression discontinuity design (RDD)**
  - Assignment variable (e.g. age) has discrete value where the treatment is felt by those on one side of a cutoff and not felt on the other side of the cutoff
  - For example, a minimum legal sales age for e-cigarettes of age 18
    - If you are 17.9 years-old, it is illegal, but if you are 18.1, it is legal

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Journal of Health Economics

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Intended and unintended effects of e-cigarette taxes on youth tobacco use

Rahi Abouk [a], Charles Courtemanche [b c d], Dhaval Dave [c d e], Bo Feng [f], Abigail S. Friedman [g], Johanna Catherine Maclean [c d h], Michael F. Pesko [d i], Joseph J. Sabia [d j], Samuel Safford [j k]

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Abstract

Over the past decade, rising youth use of e-cigarettes and other electronic nicotine delivery systems (ENDS) has contributed to aggressive regulation by state and local governments. Between 2010 and mid-2019, ten states and two large counties adopted ENDS taxes. We use two large national surveys (Monitoring the Future and the Youth Risk Behavior Surveillance System) to estimate the impact of ENDS taxes on youth tobacco use.We find that ENDS taxes reduce youth ENDS consumption, with estimated ENDS tax elasticities of -0.06 to -0.21. However, we estimate sizable *positive* cigarette cross-tax effects, suggesting economic substitution between cigarettes and ENDS for youth. These substitution effects are particularly large for frequent cigarette smoking. We conclude that the unintended effects of ENDS taxation may considerably undercut or even outweigh any public health gains.

ENDS Taxes

- Popular policy tool in U.S. to restrict access to ENDS (via higher prices) is through the adoption of ENDS taxes
- As of December 2024, 32 states and the District of Columbia had adopted ENDS taxes
- The first such tax was adopted in 2010 in Minnesota, with an effective tax rate of $1.24 per mL of e-liquid (in 2023$)
- In 2023, the highest ENDS taxes were in Minnesota ($2.89 per mL of e-liquid) and Vermont ($2.79 per mL of e-liquid)

Why might ENDS taxes reduce ENDS use?

- Cotti et al (2022) find that 90% of e-cigarette taxes are passed along to consumer retail prices
  - IV approach finds e-cigarette own-price elasticity of -2.2

- ENDS taxes could serve as an informational signal about the risk of nicotine vaping
  - Or relative risk of vaping as compared to other tobacco products

- Heterogeneity in Tax Sensitivity for Youths vs Adults
  - Possible that youths are more price sensitive due to more limited disposable income
  - Very different reasons for consumption (adults more likely to use as smoking cessation aid)

Data

- **National and State Youth Risk Behavior Surveys** (2015-2019; 2015-2023)
  - Nationally representative (and in case of State YRBS, state representative as well) school-based survey of US high school students
  - Detailed information on health and health behaviors, including prior-month ENDS use and combustible tobacco product (cigarettes, cigars) use
  - Coordinated by the Centers for Disease Control and Prevention and administered by States Department of Health & Human Services and Education

- **Monitoring the Future** (2014-2019)
  - Nationally representative survey of 8^{th}, 10^{th}, 12^{th} grade students
  - Information on ENDS use, combustible tobacco product use

- **Behavioral Risk Factor Surveillance Survey** (2016-2022)
  - Nationally representative phone-based survey (includes landlines and smartphones) of those aged 18 and older
  - Includes information on health and health behaviors, including past 30-day ENDS use and cigarette use

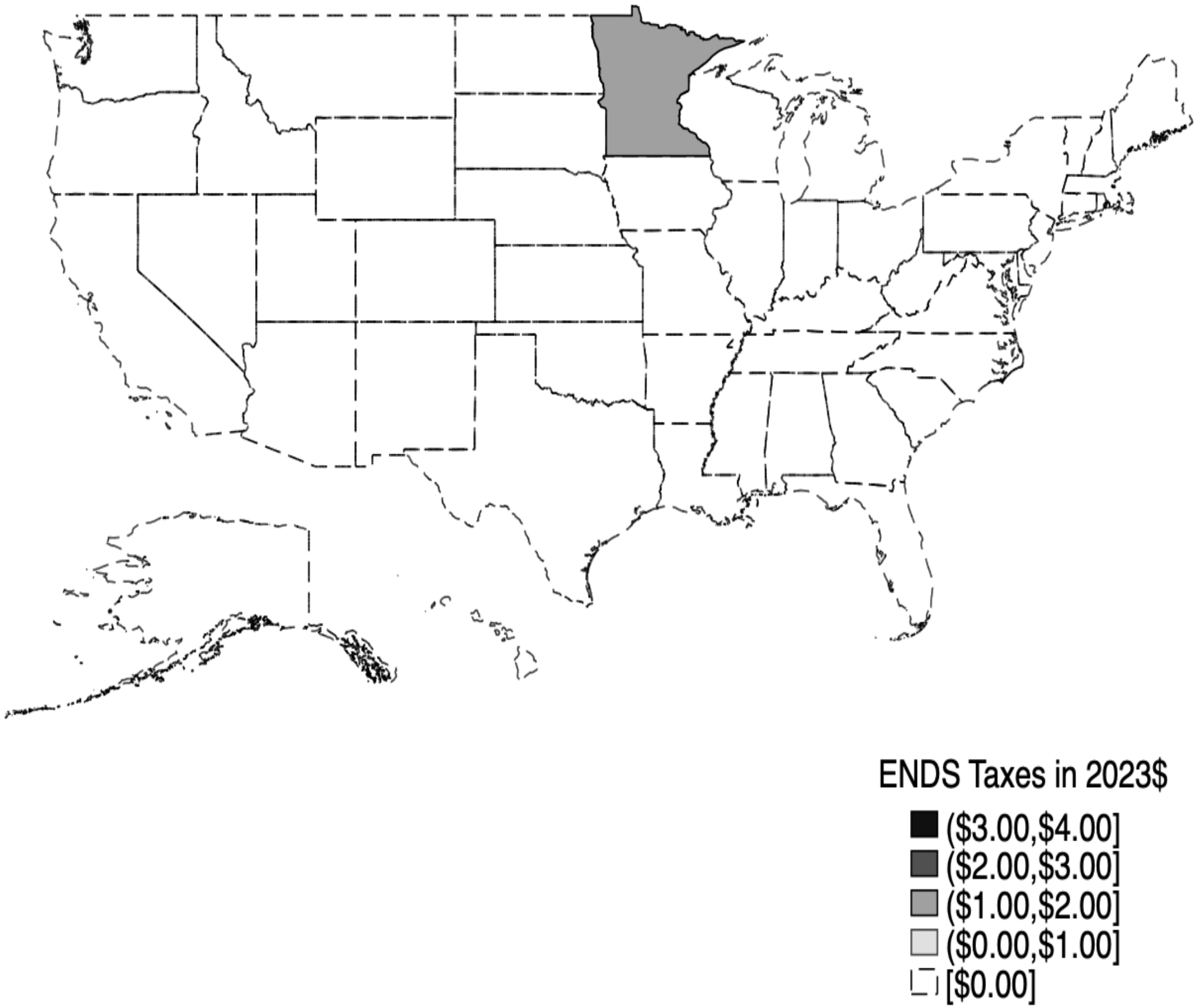
Empirical Approach

- Two-way fixed effects (TWFE) DiD Regression:

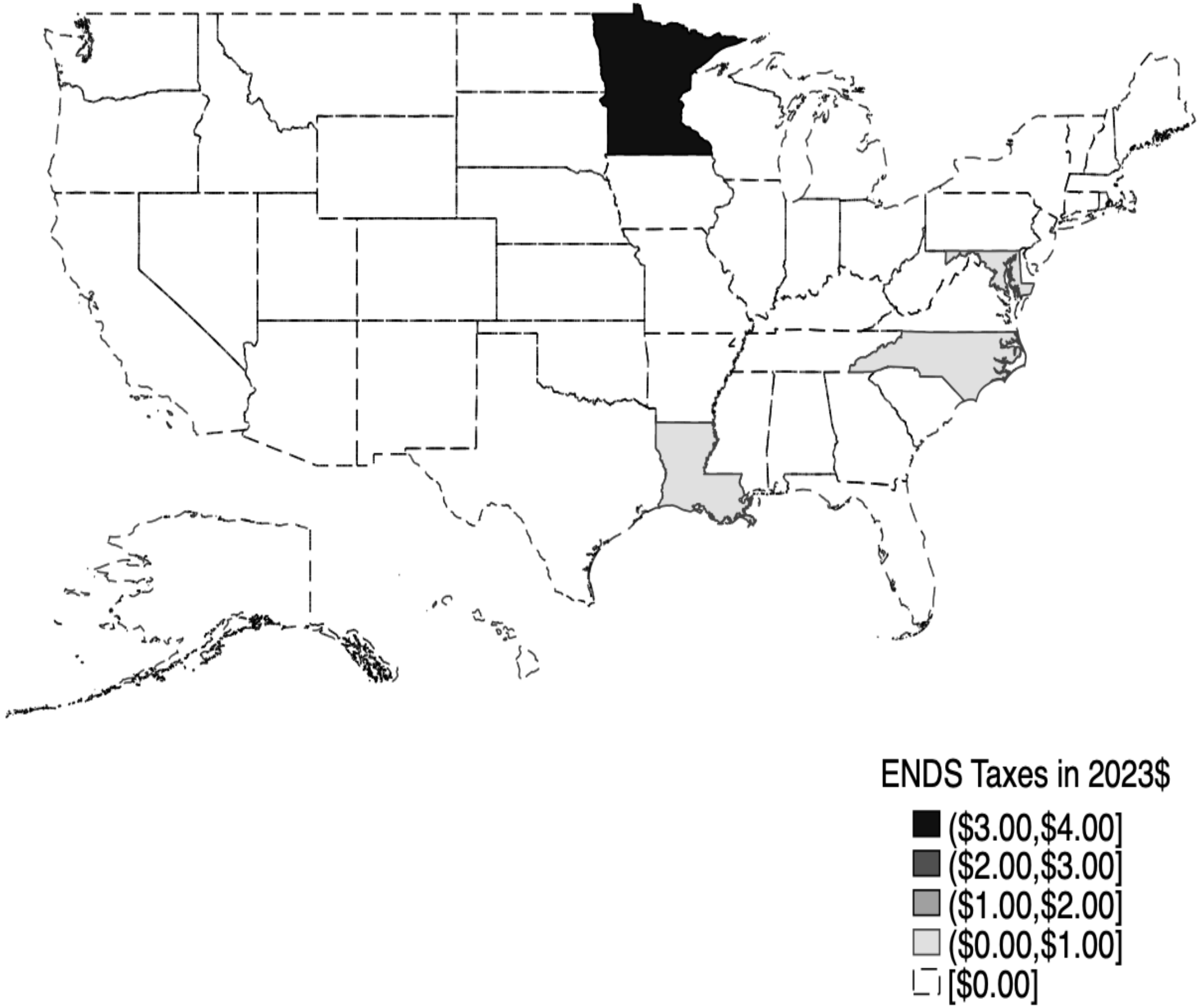
$$Y_{ist} = \gamma_0 + \gamma_1 ENDS\ Tax_{st} + \boldsymbol{X}_{st}\,\boldsymbol{\beta} + \boldsymbol{Z}_{it}\boldsymbol{\kappa} + \alpha_s + \theta_t + \varepsilon_{ist}$$

- Y_{ist} measures current ENDS use, combustible cigarette use
- **macroeconomic conditions** (unemployment rate, poverty rate)
- **tobacco control policies** (the presence of an ENDS MLSA, cigarette tax indoor ENDS use restriction in restaurants, bars, or workplaces, indoor smoking restriction in restaurants, bars, or workplaces, Tobacco-21 laws, vertical license laws, ENDS flavor bans, ENDS licensure laws)
- **alcohol and marijuana policies** (beer tax per, medical & recreational MJ laws)
- **individual demographic controls** (in the YRBS & MTF: gender, age, race/ethnicity, and grade; in the BRFSS: gender, age, educational attainment, race/ethnicity)

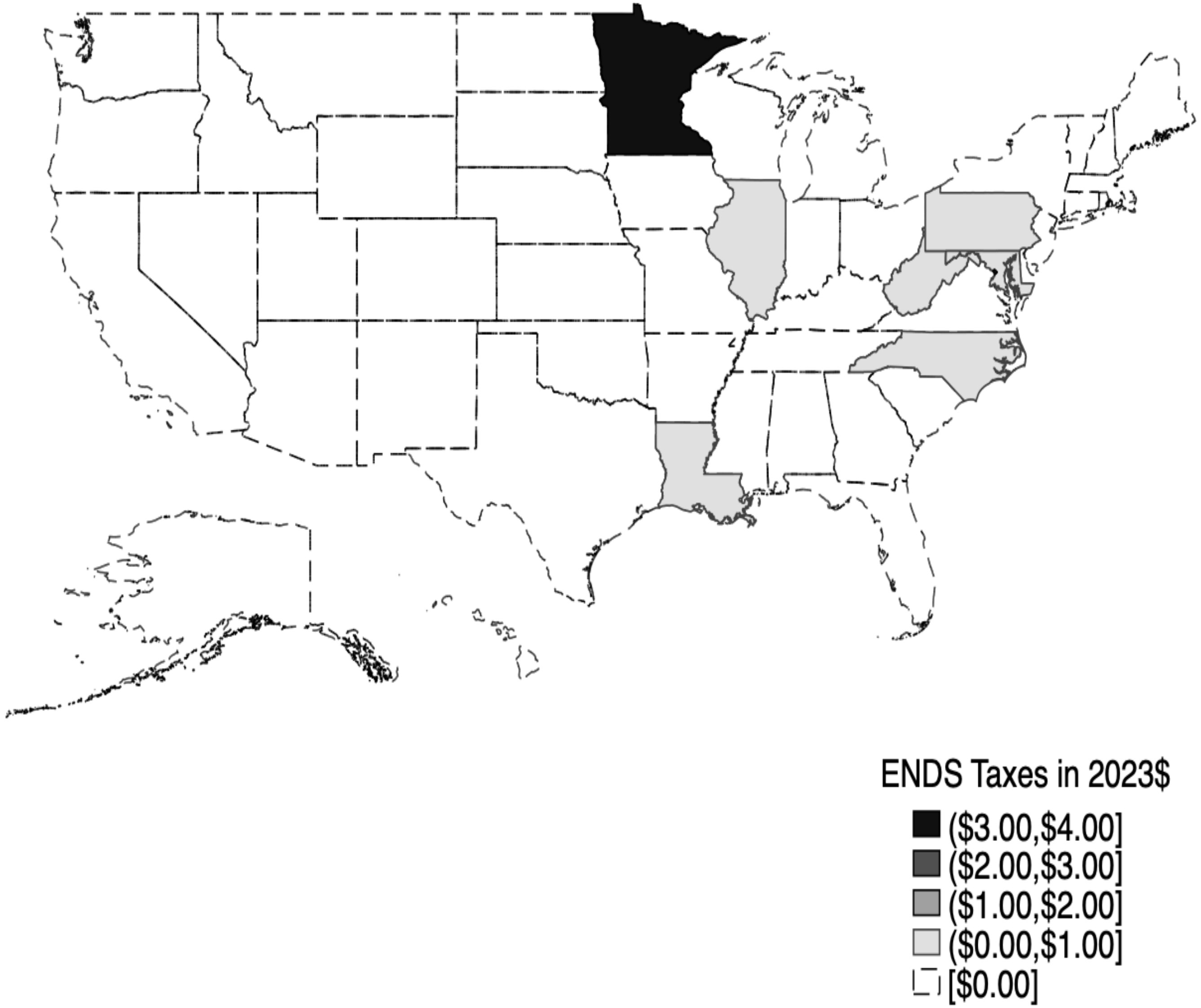
2010



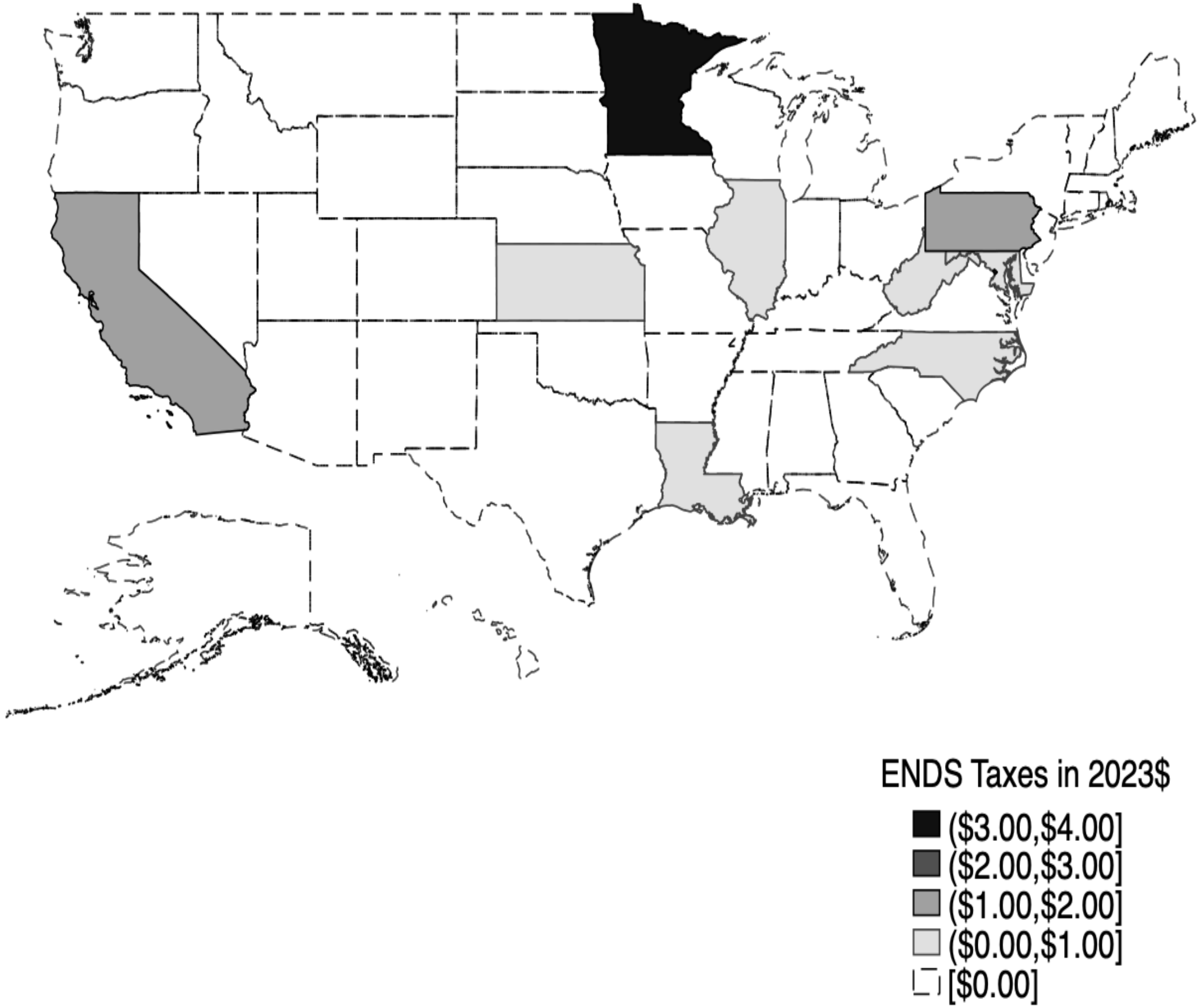
2015



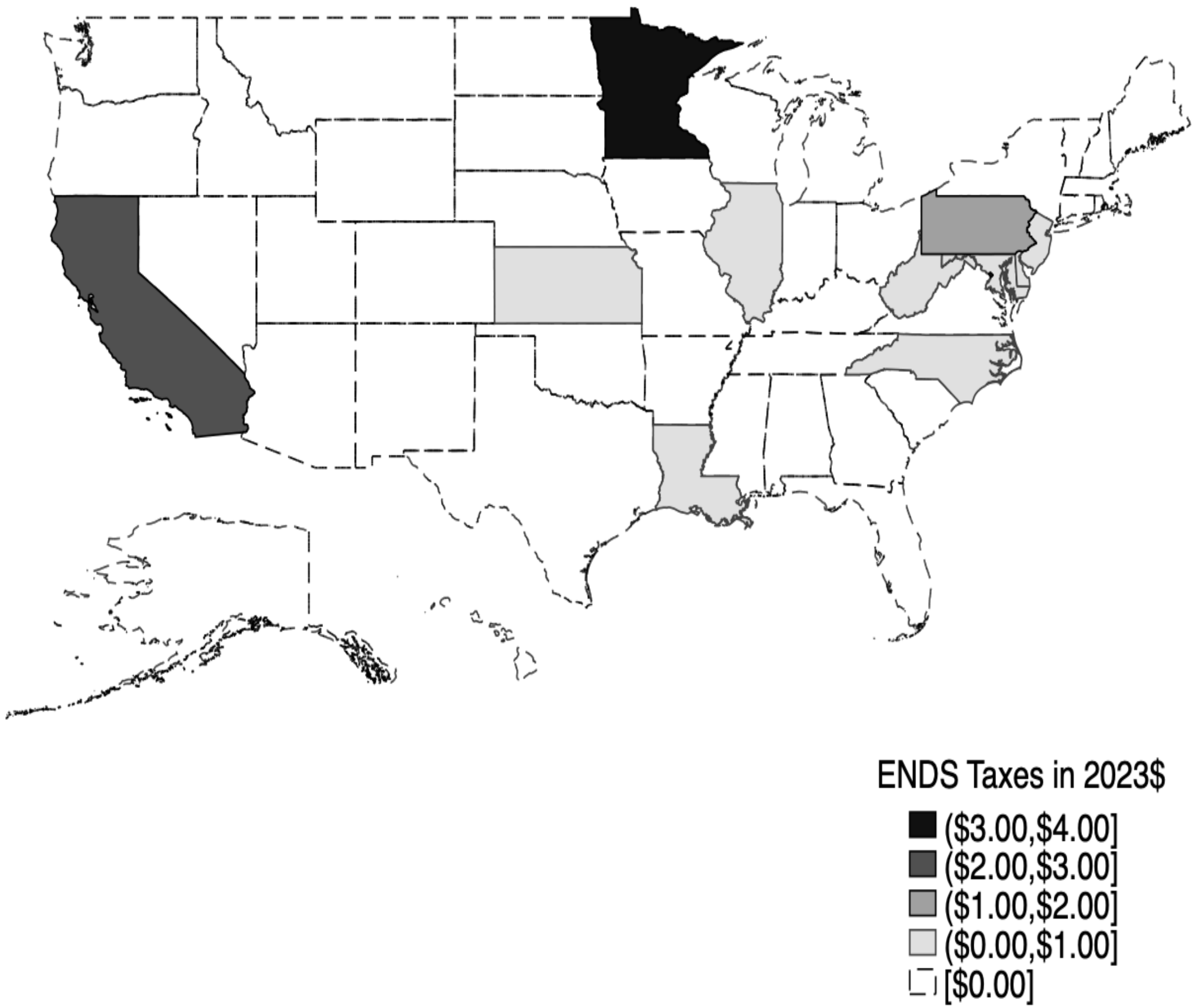
2016



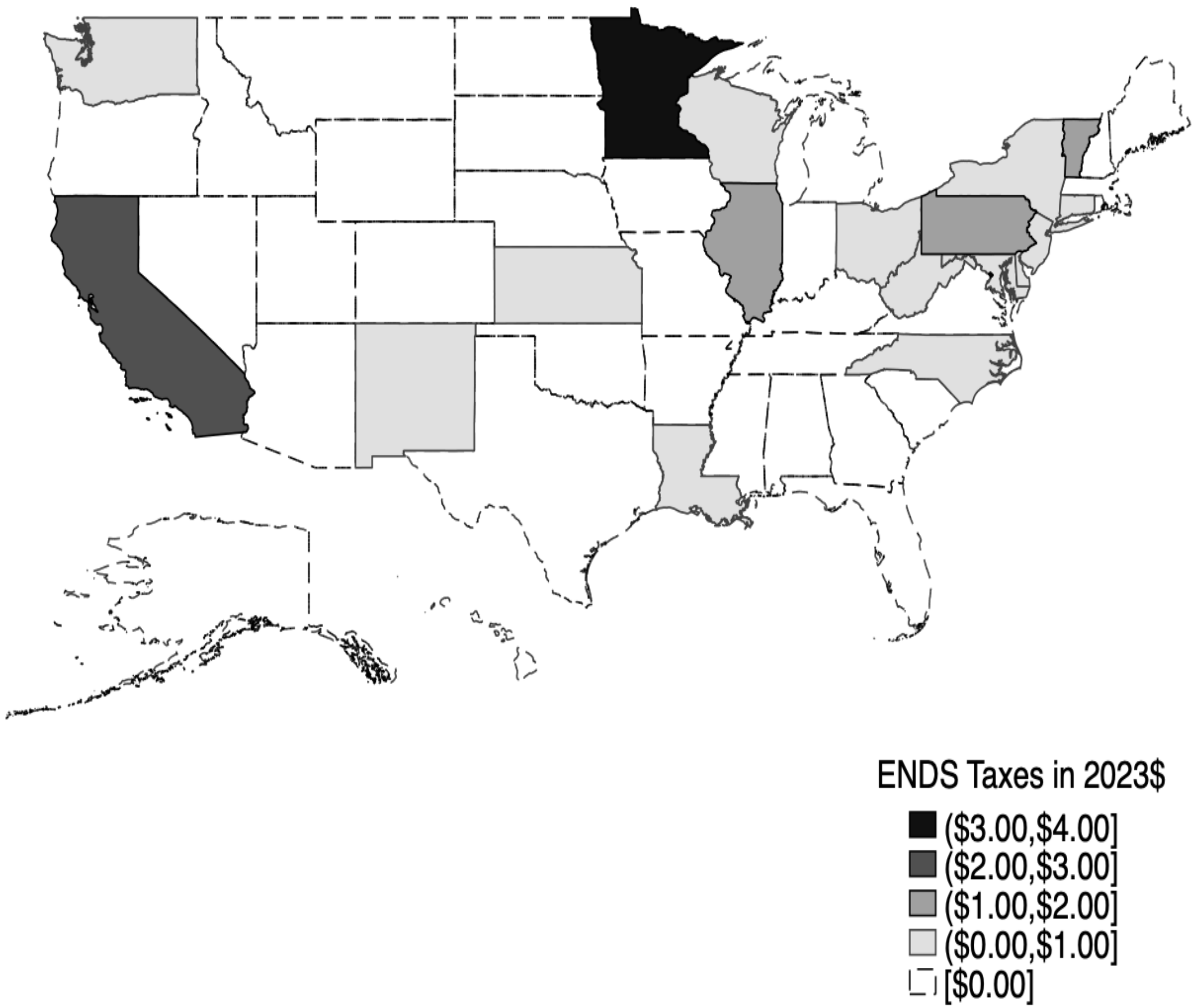
2017



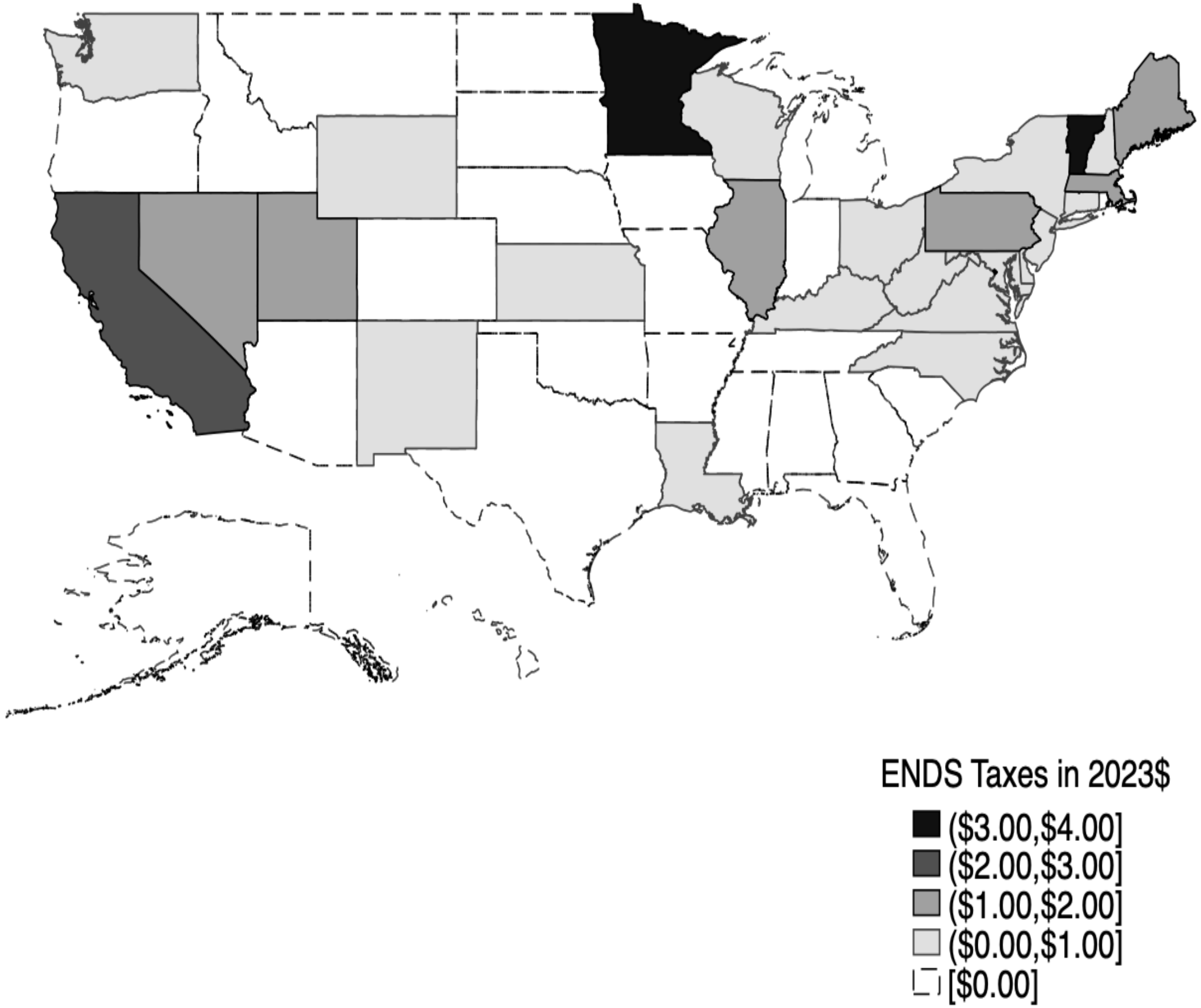
2018



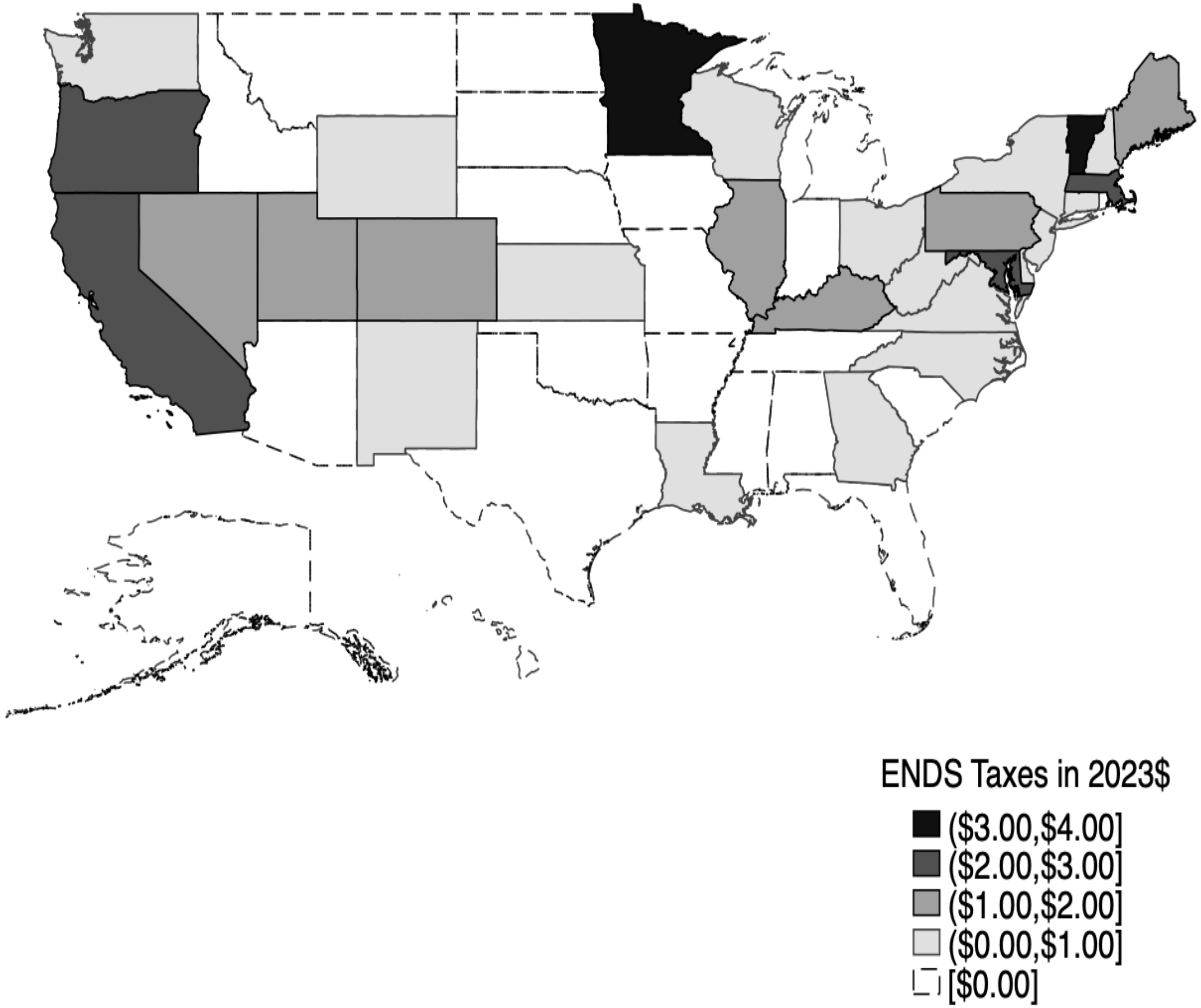
2019



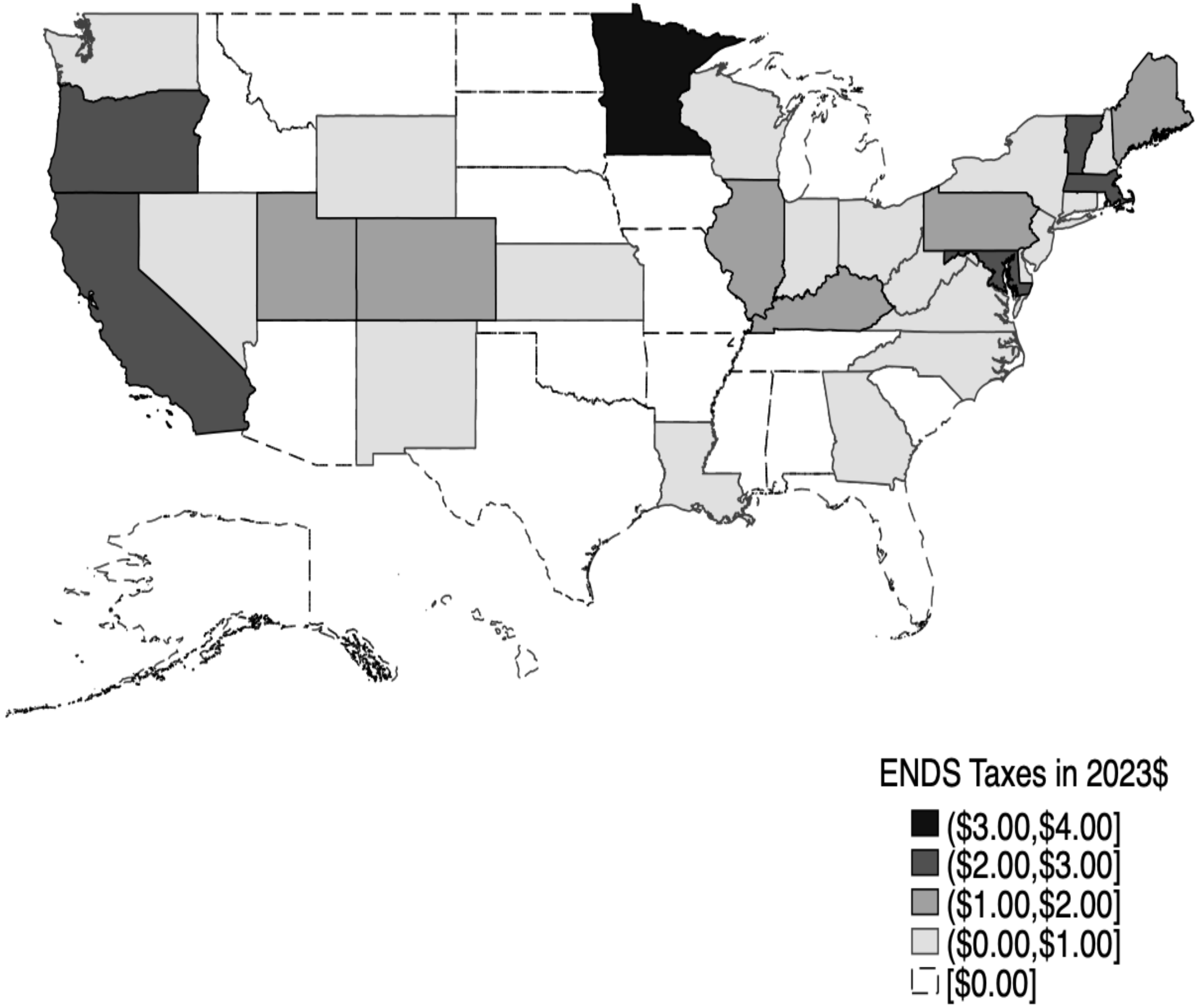
2020



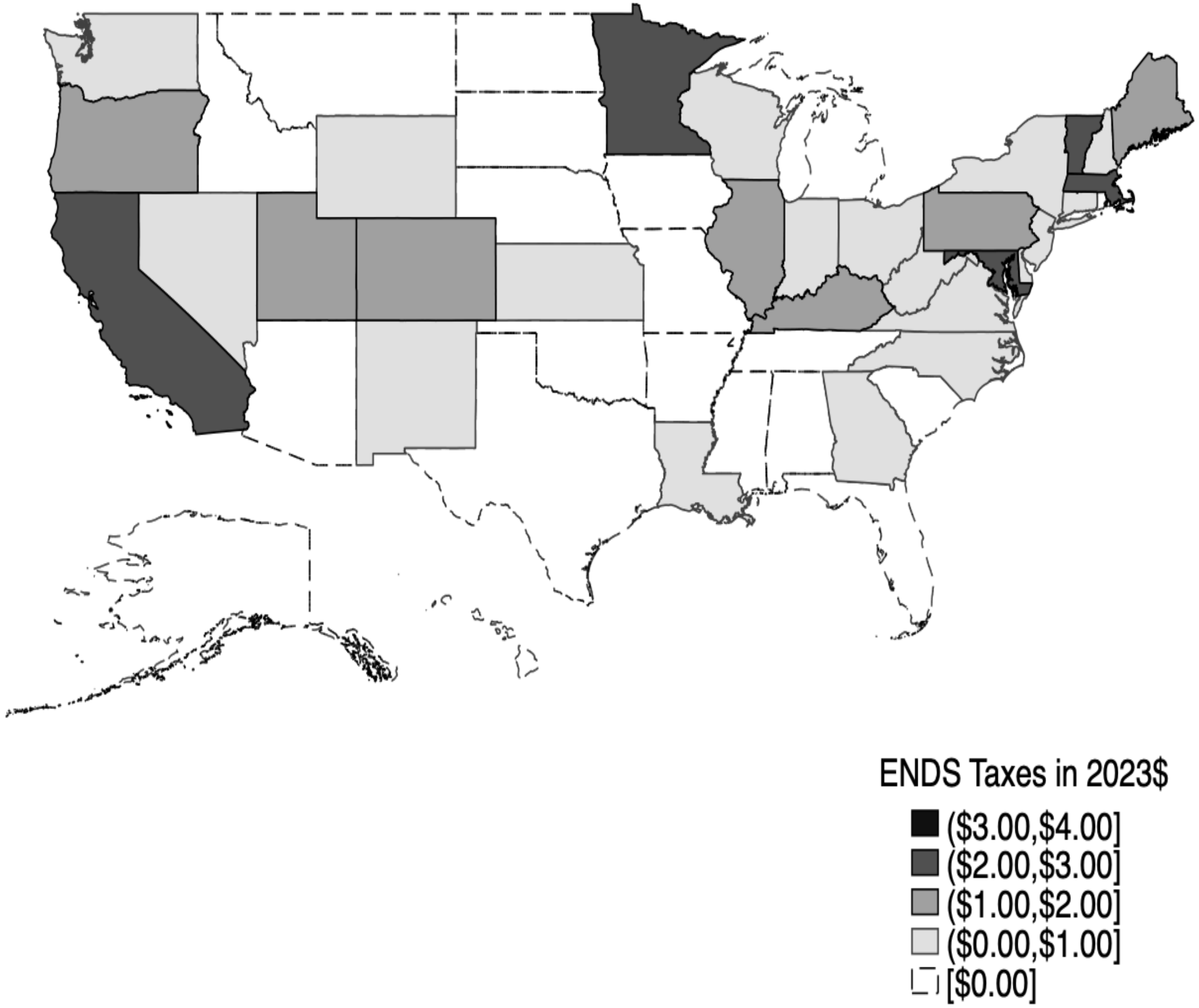
2021



2022



2023



Identification Assumptions of TWFE DiD

- Common Trends Assumption
  - In the absence of treatment, youth vaping trends in the treatment states would have evolved as the control states did

<u>This means</u>:

- No state-specific time-varying unobservables correlated with ENDS tax adoption and youth vaping (smoking)
- No reverse causality whereby youth vaping causes ENDS tax increases

<u>In addition, bias may arise through</u>:

- Negative weighting of treatment states due to timing of adoption
- Using earlier adopters as controls for later adopters in the presence of heterogeneous and dynamic treatment effects

Effects of ENDS Taxes on Youth ENDS Use, YRBS (2015-2019) and MTF (2014-2019)

	Current ENDS User	Regular ENDS User	Ever Use ENDS	Current ENDS User
ENDS Tax Rate per ml (2019 $)	-0.019*	-0.013*	-0.052***	-0.071***
	(0.010)	(0.007)	(0.010)	(0.025)
N	126,306	126,306	85,541	538,992
Dependent Variable Mean	0.152	0.038	0.287	0.213
Dataset	MTF	MTF	MTF	YRBS
ENDS Tax Elasticity	-0.095	-0.712	-0.127	0.568

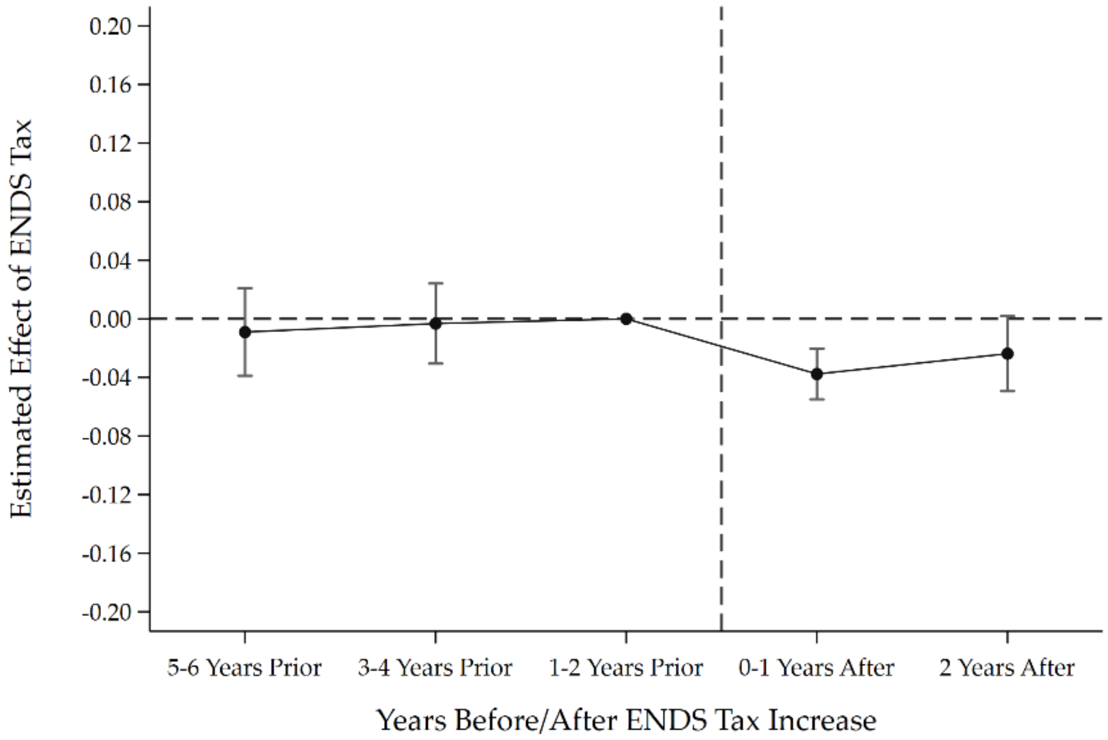
***p < .01 **p < .05 *p< .10

Intended Effects Persist in YRBS, 2015-2023

ENDS Tax (2023$)	-0.018***	-0.016***	-0.029**	-0.029**	-0.028**	-0.029**
	(0.004)	(0.005)	(0.012)	(0.012)	(0.011)	(0.011)
N	735109	735109	735109	735109	735109	735109
Pre-Treat Mean of Dep Var	0.179	0.179	0.179	0.179	0.179	0.179
State, Year, and Semester FE?	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic Control?	No	Yes	Yes	Yes	Yes	Yes
Tobacco Policy Controls?	No	No	Yes	Yes	Yes	Yes
Alcohol Policy Control?	No	No	No	Yes	Yes	Yes
Marijuana Policy Controls?	No	No	No	No	Yes	Yes
Non-MJ Drug Policy Controls?	No	No	No	No	No	Yes

***p < .01   **p < .05   *p< .10

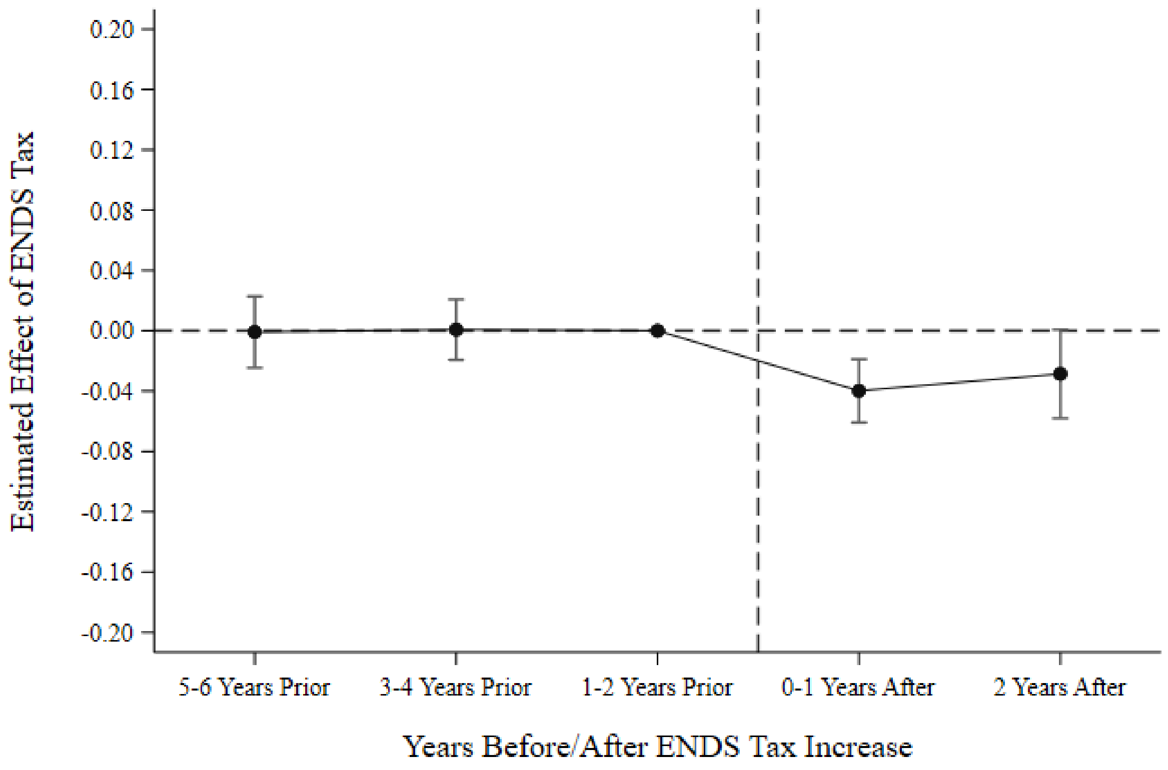
Event-Study Analysis, TWFE Estimates



95% CI reported on coefficients

Event-Study Analysis, Stacked DD Estimates

[Never and not-yet adopters as counterfactuals]



95% CI reported on coefficients

Intended Effects of ENDS Taxes for Adults, BRFSS

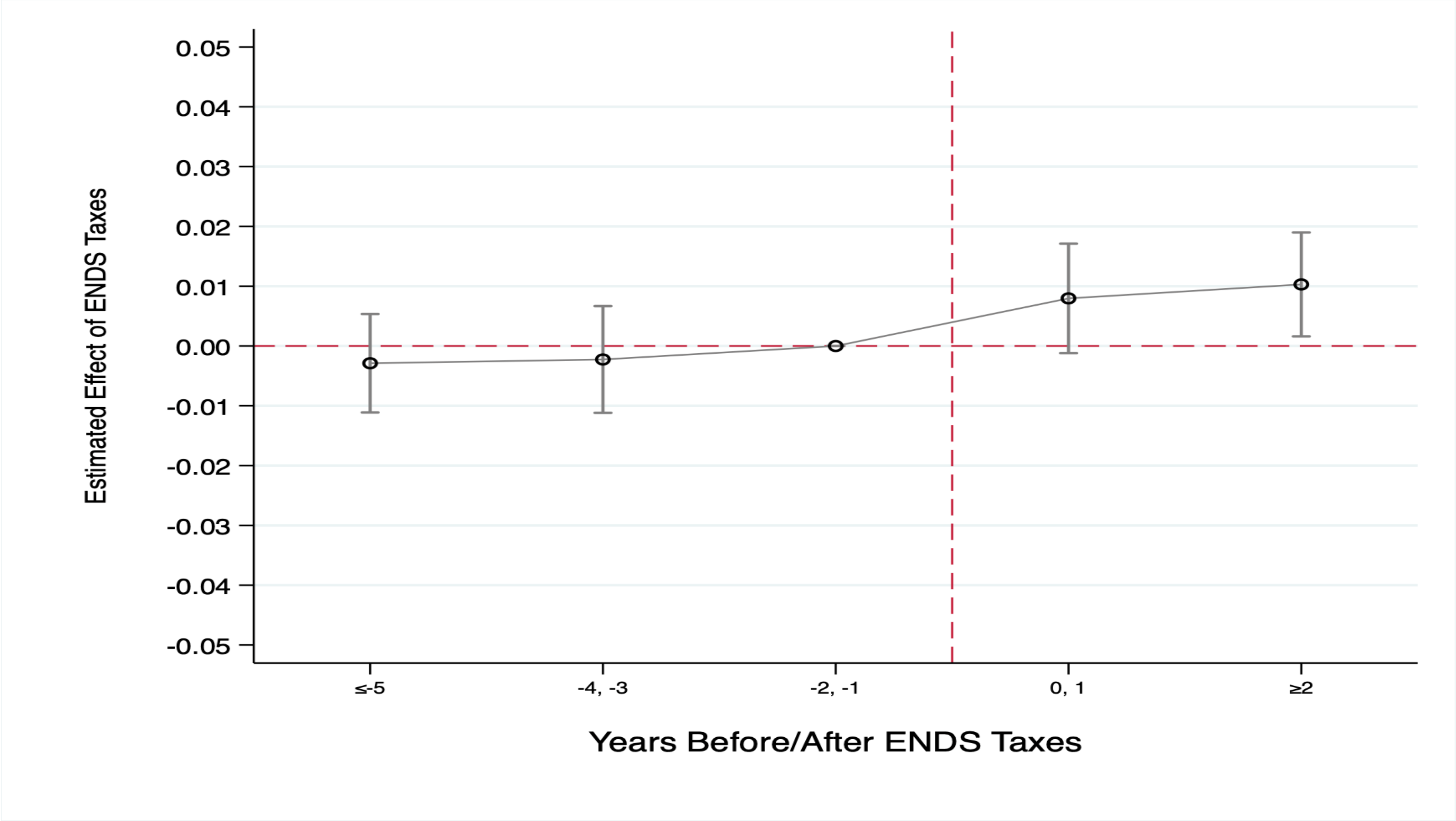
	Panel I: Ages 18-20					
ENDS Tax (2022$)	-0.0166***	-0.0162***	-0.0097*	-0.0104*	-0.0082	-0.0079
	(0.0043)	(0.0042)	(0.0057)	(0.0057)	(0.0060)	(0.0057)
N	47633	47633	47633	47633	47633	47633
Pre-Treatment Mean of DV	0.147	0.147	0.147	0.147	0.147	0.147
	Panel II: Ages 21-30					
ENDS Tax (2022$)	-0.0083***	-0.0075**	-0.0093**	-0.0078*	-0.0070*	-0.0089**
	(0.0030)	(0.0030)	(0.0041)	(0.0039)	(0.0041)	(0.0038)
N	193762	193762	193762	193762	193762	193762
Pre-Treatment Mean of DV	0.116	0.116	0.116	0.116	0.116	0.116
	Panel III: Ages 31 and older					
ENDS Tax 2022($)	0.0019	0.0021	0.0022	0.0019	0.0021	0.0015
	(0.0019)	(0.0017)	(0.0013)	(0.0020)	(0.0020)	(0.0022)
N	1,746,778	1,746,778	1,746,778	1,746,778	1,746,778	1,746,778
Pre-Treatment Mean of DV	0.0406	0.0406	0.0406	0.0406	0.0406	0.0406

Effect of ENDS Taxes on Teen Combustible Tobacco Use (2014-2019)

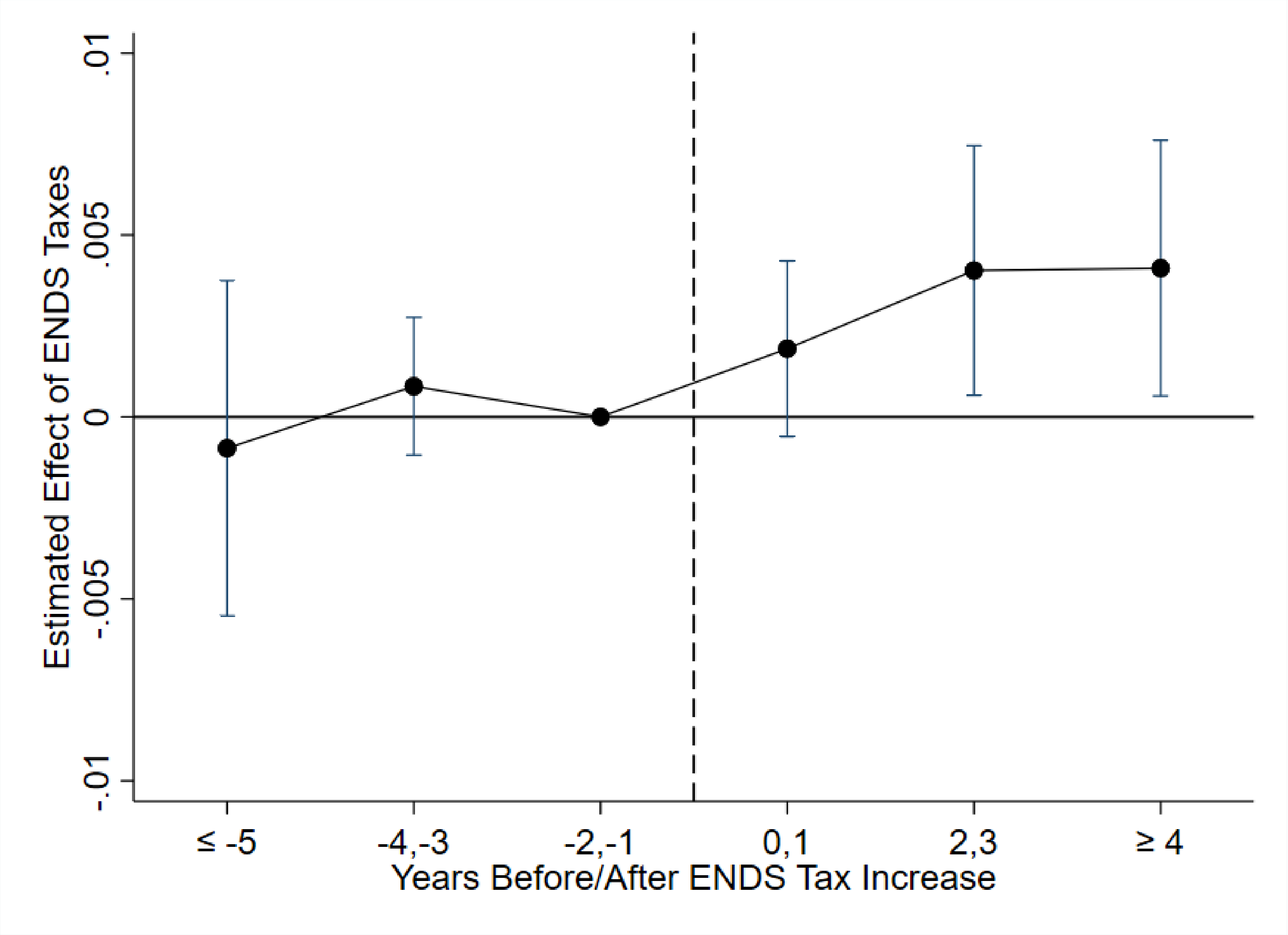
	Current Cigarette Use	Cigarette Half Pack a Day	Current Cigarette or Cigar	Current Cigarette Use	Regular Cigarette Use	Daily Cigarette Use	Current Cigarette or Cigar
ENDS Tax Rate per ml (2019$)	0.013** (0.006)	0.006** (0.002)	0.012* (0.006)	0.008 (0.013)	0.016 (0.014)	0.014 (0.012)	0.007 (0.016)
N	244,360	244.630	246,192	580,788	580,788	580,788	504,639
Dependent Var Mean	0.066	0.012	0.080	0.080	0.019	0.014	0.107
ENDS Tax Elasticity	0.123**	0.341**	0.089*	0.041	0.336	0.412	0.031
Dataset	MTF	MTF	MTF	YRBS	YRBS	YRBS	YRBS

***p < .01 **p < .05 *p< .10

Event-Study Analysis of ENDS Taxes and Teen Cigarette Smoking, 2015-2023



Event-Study Analysis of ENDS Taxes and Adult Everyday Cigarette Smoking, 2016-2023



Spillover Effects of ENDS Taxes:

Alcohol, Marijuana, Obesity, and Mental Health

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Journal of Health Economics
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The Effect of E-Cigarette Taxes on Substance Use *

Dhaval Dave [a b c], Yang Liang [d], Johanna Catherine Maclean [b c e], Caterina Muratori [d f], Joseph J. Sabia [b d]

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Abstract

Public health advocates warn that the rapid growth of legal markets for electronic nicotine delivery systems (ENDS) may generate a "gateway" to marijuana and harder drug consumption, particularly among teenagers. This study explores the effects of ENDS taxes on substance use. Analyses are based on difference-in-differences and event-study methods applied to both survey (Youth Risk Behavior Surveillance System and Behavioral Risk Factor Surveillance System) and administrative (Treatment Episode Data Set) data. Our results imply that a one-dollar increase in ENDS taxes (2023$) is associated with a 1.0 to 1.5 percentage point decline in teen marijuana use and in co-use of ENDS and marijuana. This result is consistent with e-cigarettes and marijuana being economic complements. We also find that youth responses to ENDS taxes, in terms of their ENDS

Do Vaping Taxes Tip the Scale? The Effect of E-Cigarette Taxation on Obesity

Charles J. Courtemanche, Tessie Krishna, Yang Liang, Joseph J. Sabia & Anthony Chuo

WORKING PAPER 33890 DOI 10.3386/w33890 ISSUE DATE June 2025

A large literature documents that quitting cigarette smoking may lead to weight gain because nicotine is an appetite suppressant and metabolic stimulant. However, researchers in this literature emphasize that the health benefits of smoking cessation exceed the harms from the weight typically gained. New products, such as electronic nicotine delivery systems (ENDS), that deliver nicotine with a lower health risk than combustible cigarettes could conceivably alter this tradeoff in favor of nicotine use. Accordingly, this study asks whether a leading policy tool to curb ENDS use –

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Nicotine Vaping and Youth Mental Health: New Evidence from E-Cigarette Regulations

Chad D. Cotti, Tessie Krishna, Johanna Catherine Maclean, Erik T. Nesson & Joseph J. Sabia

WORKING PAPER 33917 DOI 10.3386/w33917 ISSUE DATE June 2025

The confluence of a youth mental health crisis and high rates of teenage nicotine vaping has led some U.S. tobacco control advocates to argue that reducing access to electronic nicotine delivery systems (ENDS) — through policies such as ENDS taxation — may improve youth and young adult mental health. Using data from several nationally representative surveys (Youth Risk Behavior Survey, Behavioral Risk Factor Surveillance System, and Population Assessment of

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Can Anti-Vaping Policies Curb Drinking Externalities? Evidence from E-Cigarette Taxation and Traffic Fatalities

Dhaval M. Dave, Yang Liang, Johanna Catherine Maclean, Joseph J. Sabia & Matthew Braaksma

WORKING PAPER 30670 DOI 10.3386/w30670 ISSUE DATE November 2022 REVISION DATE April 2024

Teenage drinking is a major public health concern, generating social costs of over $28 billion per year, including substantial external costs associated with alcohol-related traffic fatalities. At the same time, the high rate of electronic nicotine delivery systems (ENDS) use among teenagers has been deemed "an epidemic" by the U.S. Surgeon General, with state and local policymakers

ELSEVIER

Journal of Health Economics

Volume 102, August 2025, 103013

The effect of e-cigarette flavor bans on tobacco use *

Chad Cotti [a], Charles Courtemanche [b], Yang Liang [c], Johanna Catherine Maclean [d], Erik Nesson [e], Joseph J. Sabia [f]

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Abstract

Advocates for sales restrictions on flavored e-cigarettes argue that flavors appeal to young people and lead them down a path to nicotine addiction. Using data from a variety of surveys (Youth Risk Behavior Surveys, Behavioral Risk Factor Surveillance Survey, and Population Assessment of Tobacco and Health), this study is among the first to examine the effect of state and local restrictions on the sale of flavored electronic nicotine delivery system (ENDS) products on youth and young adult tobacco use. We find robust evidence

Are flavors luring teenagers to vape nicotine?

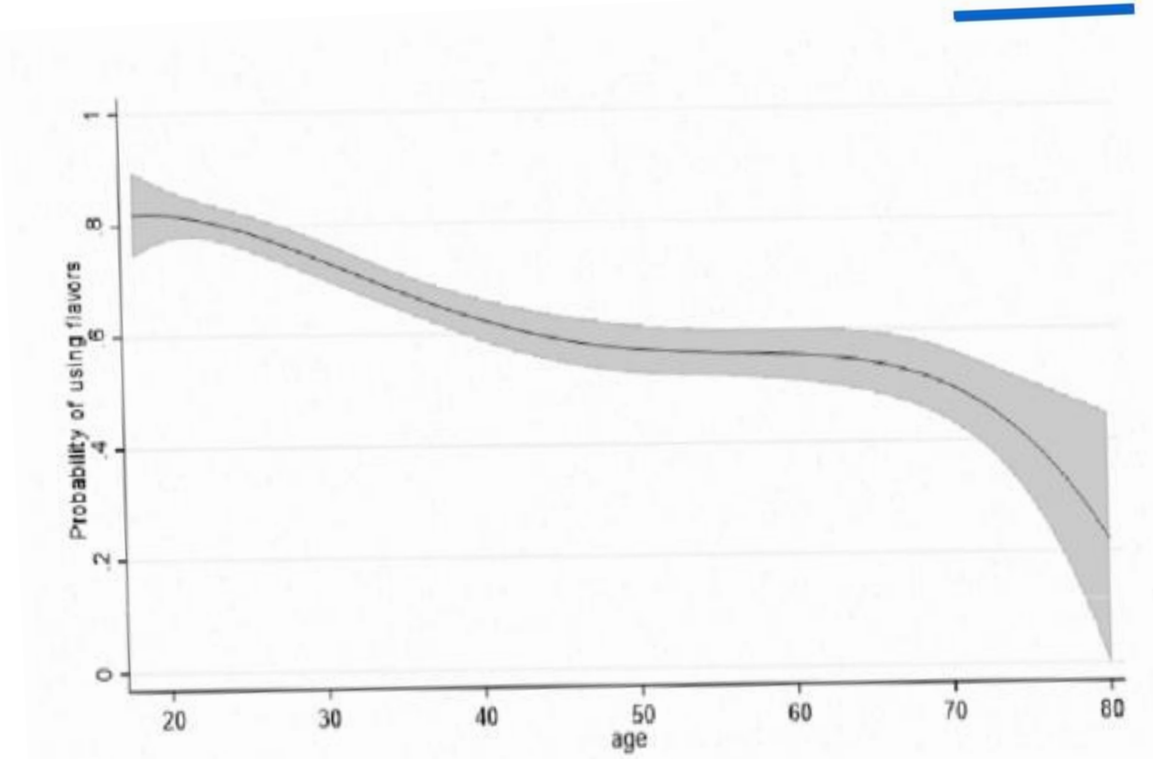
"The tobacco industry is well aware that flavors appeal to and attract kids, and that young people are uniquely vulnerable to nicotine addiction… [W]e all must work with even greater urgency to protect our nation's youth from all flavored e-cigarettes, including disposables."

-Truth Initiative (2023)

ENDS Flavor Restrictions

- According to the 2023 National Youth Tobacco Survey, 89% of youths who vape report using flavors
  - Most common are fruit (63%), candy, desserts, other sweets (35%), mint (28%), menthol (20%) (Birdsey et al., 2023)

BUT FLAVORS ARE NOT JUST FOR TEENS



Source: Hampsher-Monk et al (2024)

Data

- **National and State Youth Risk Behavior Surveys (YRBS)**
  - Biennial School-based surveys (2015 -2023) coordinated by CDC
  - Representative of tobacco use among high school students at state and national levels
  - Outcomes: prior-month e-cigarette and combustible tobacco use (any, frequent, everyday)

- **Behavioral Risk Factor Surveillance Survey (BRFSS)**
  - Telephone-based survey of adults aged 18 and older (2016-2023) coordinated by CDC
  - Nationally representative survey of adults (young adults 18-20 years and 21+ years)
  - Outcomes: prior-month e-cigarette and combustible cigarette use

- **Population Assessment of Tobacco and Health (PATH)**
  - Individual-level panel dataset of youths and adults
  - Detailed information on types of ENDS used

Empirical Approach

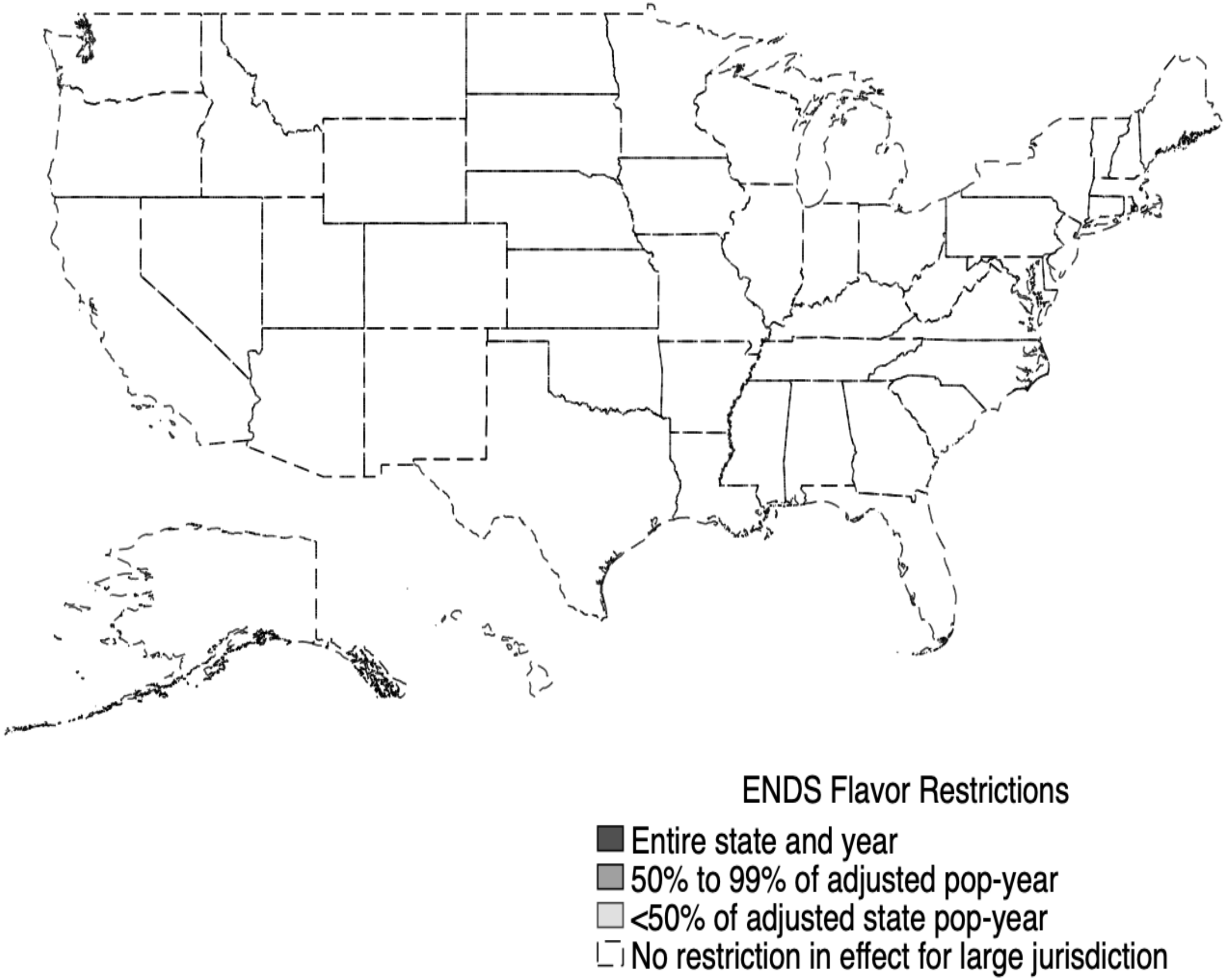
- Two-way fixed-effects model estimated via logit and OLS:

$$\mathbf{Y}_{ist} = \beta_0 + \beta_1\,\mathbf{FlavorBan}_{st} + \mathbf{X'}_{ist}\beta_2 + \mathbf{P'}_{st}\beta_3 + \alpha_s + \lambda_p + \varepsilon_{ist}$$

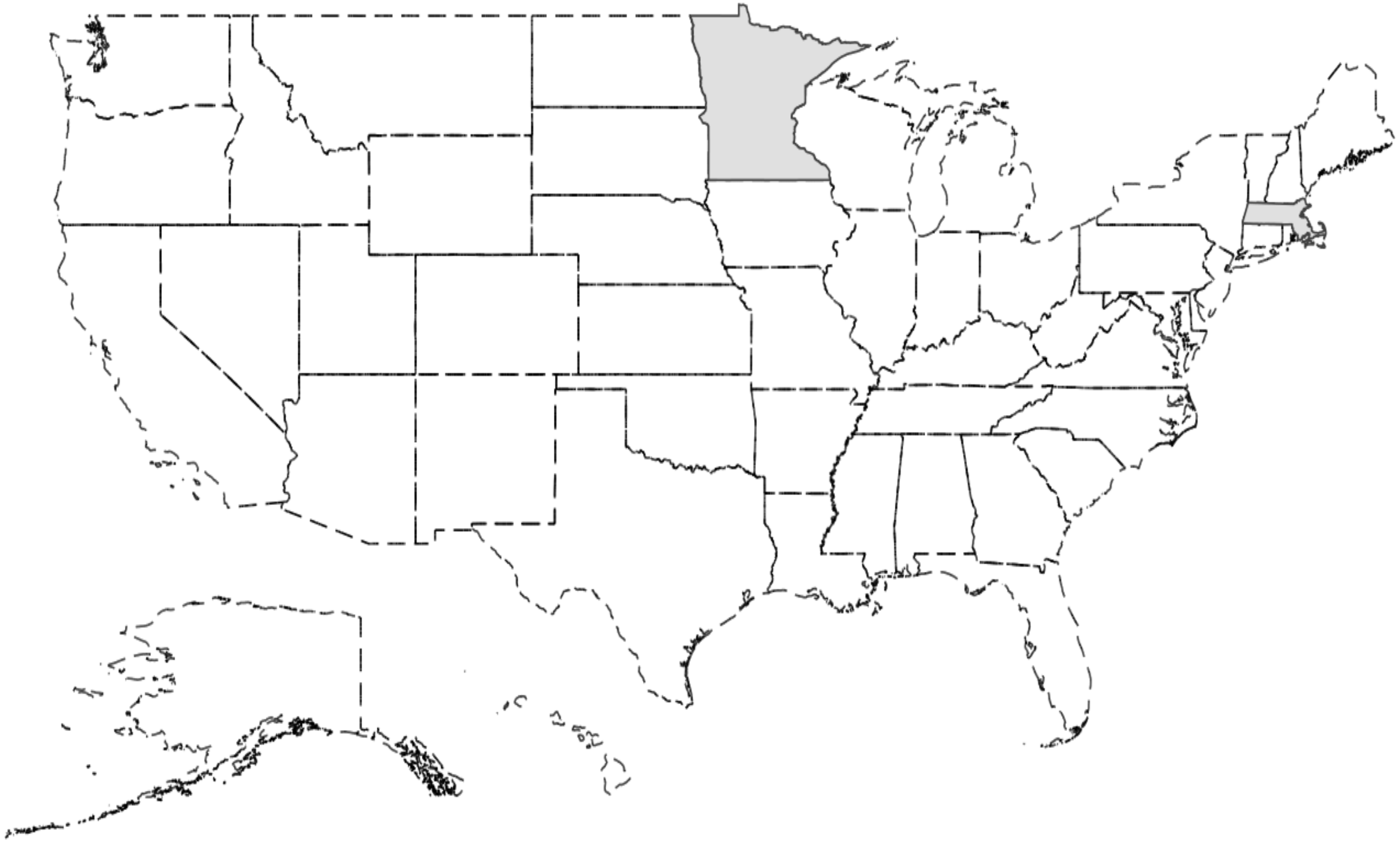
- $\mathbf{Y}_{ist}$: tobacco use (prior-month e-cigarette use, combustible cigarette smoking)
- $\mathbf{FlavorBan}_{st}$: ENDS Flavor Restriction
- $\mathbf{X}_{ist}$: Individual characteristics (e.g., gender, age, race, ethnicity, grade)
- $\mathbf{P}_{st}$: State Combustible tobacco and ENDS policy controls (Tobacco-21 Laws, ENDS Tax, Cigarette Tax, Menthol Cigarette Ban, ENDS Licensure Laws, ENDS Online Sales Delivery Ban, Clean Indoor Air Laws, MLPAs), Unemployment Rate, COVID-19 Death Rate, Beer Taxes, Medical and Recreational MJ Laws
- $\boldsymbol{\alpha}_s$: State fixed effects
- $\boldsymbol{\tau}_t$**:** Year-semester fixed effects
- Standard errors clustered at state level and regressions are weighted

- Machine learning (LASSO) approach to select controls

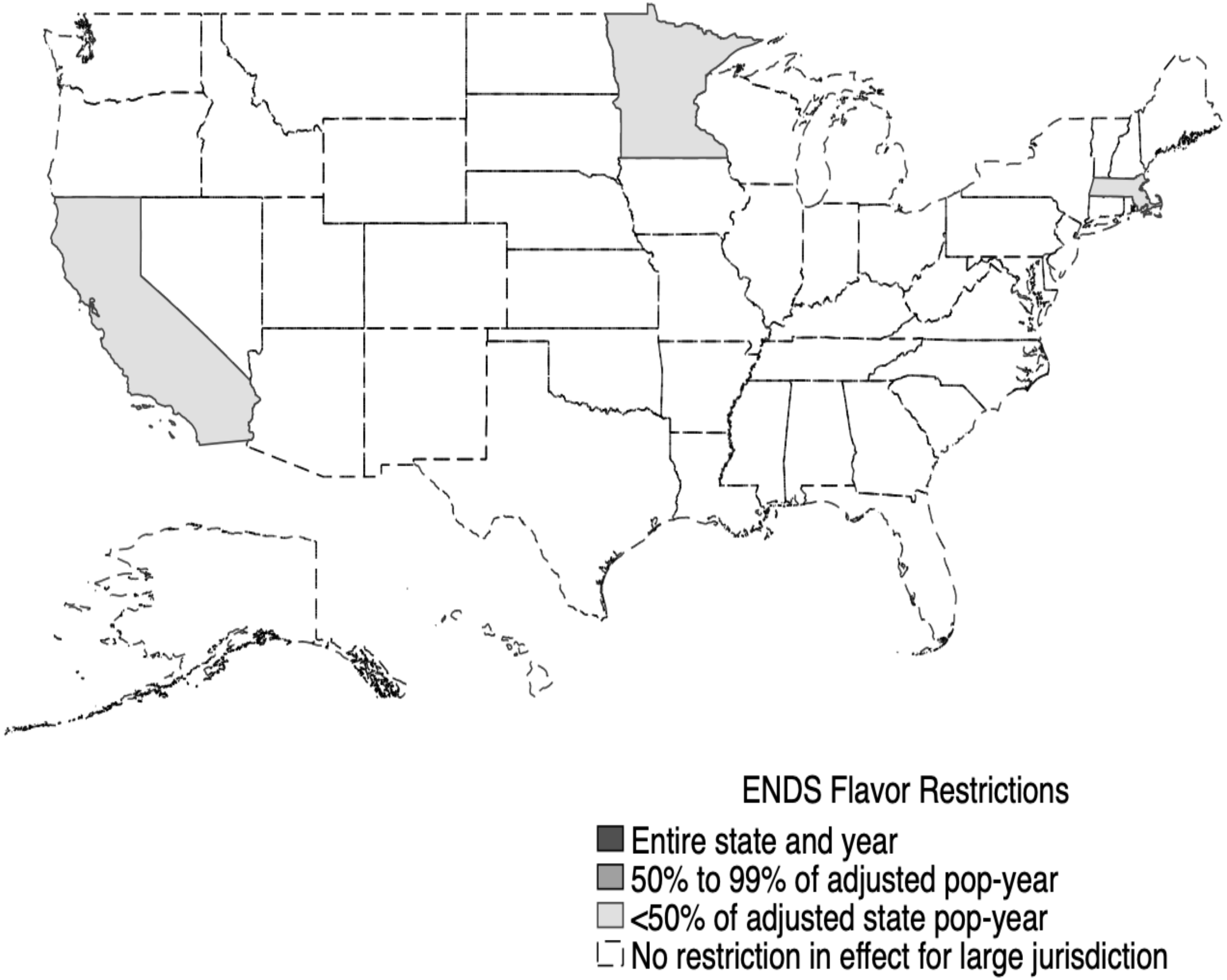
2015


ENDS Flavor Restrictions
Entire state and year
50% to 99% of adjusted pop-year
<50% of adjusted state pop-year
No restriction in effect for large jurisdiction

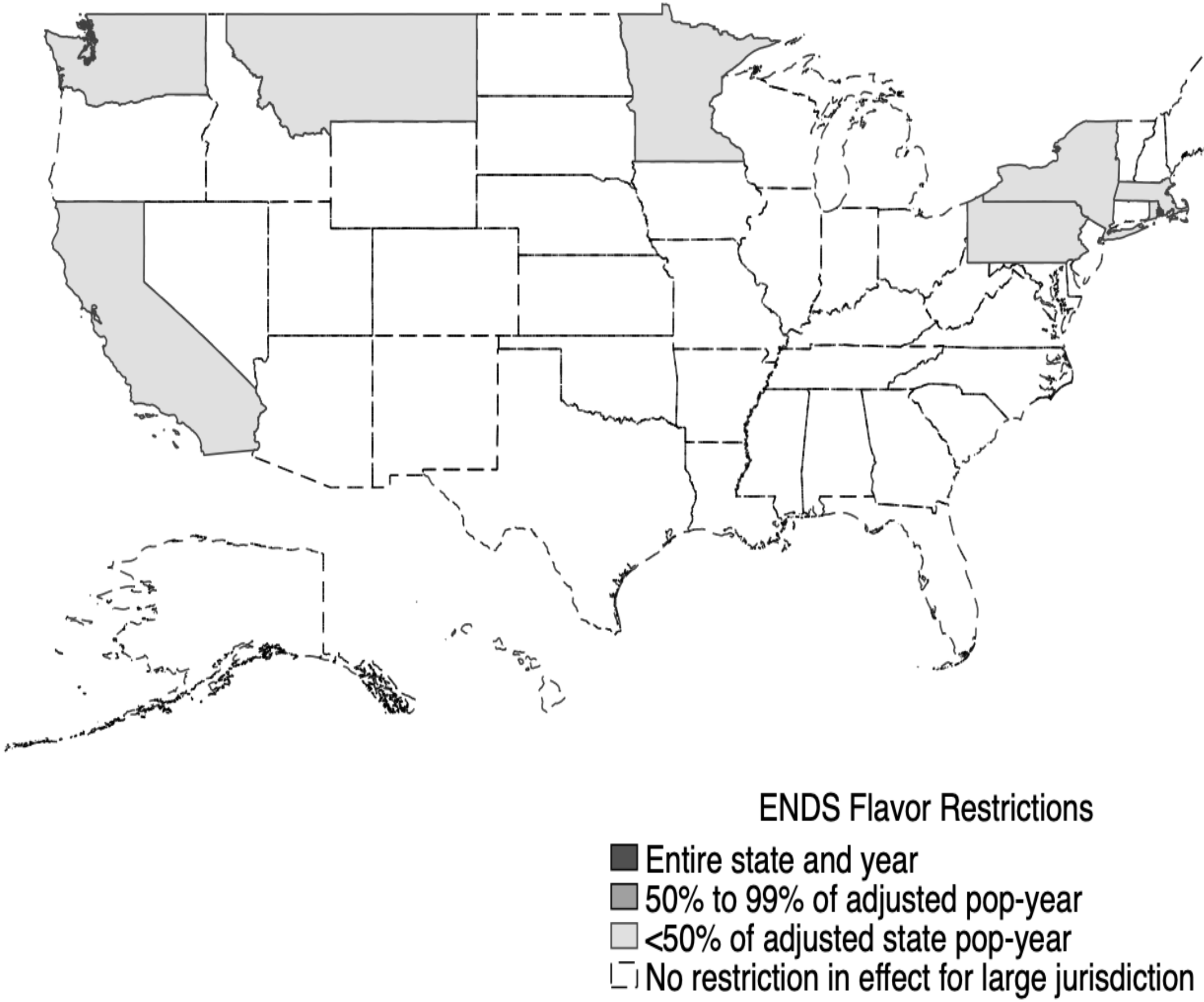
2017


ENDS Flavor Restrictions
Entire state and year
50% to 99% of adjusted pop-year
<50% of adjusted state pop-year
No restriction in effect for large jurisdiction

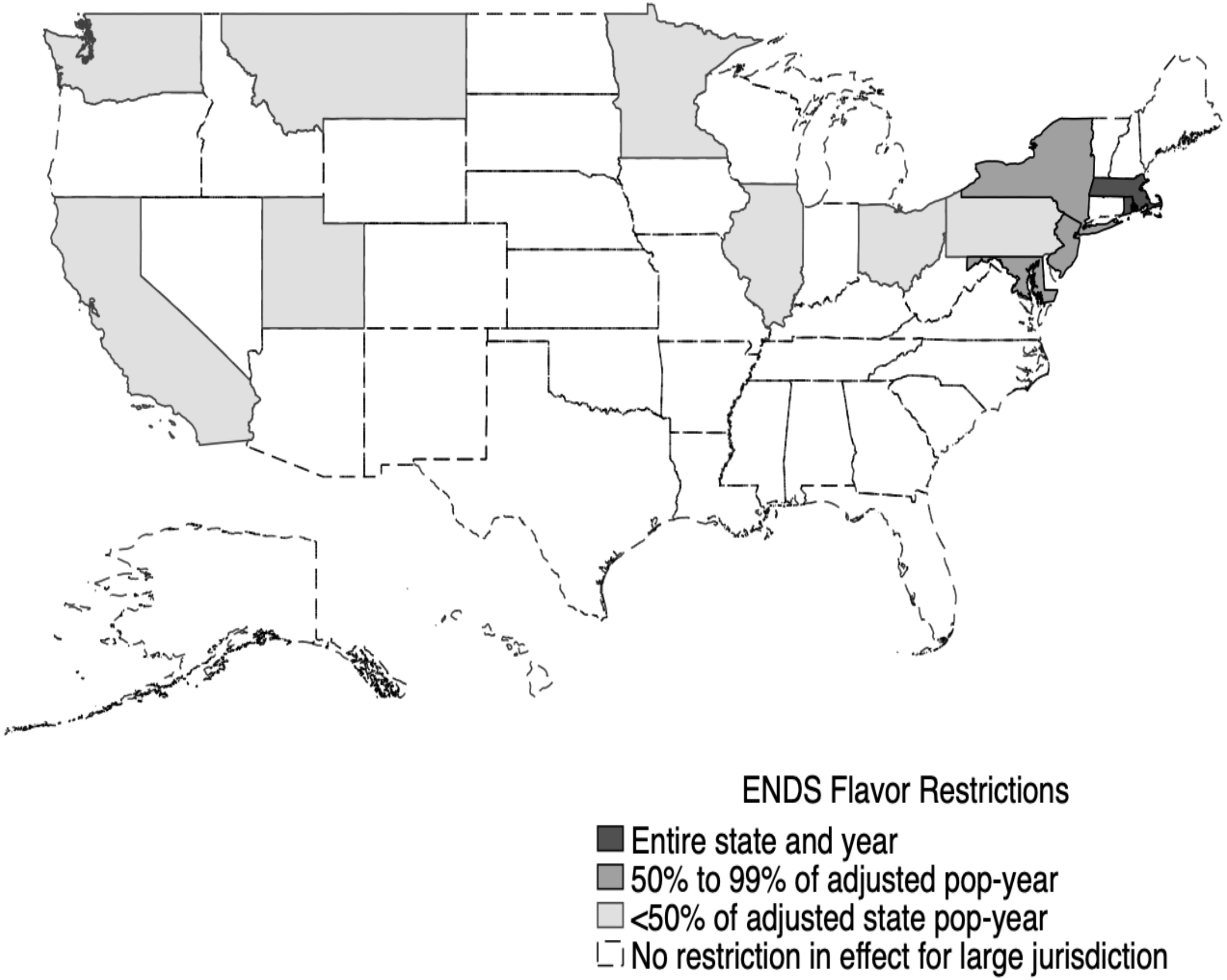
2018


ENDS Flavor Restrictions
Entire state and year
50% to 99% of adjusted pop-year
<50% of adjusted state pop-year
No restriction in effect for large jurisdiction

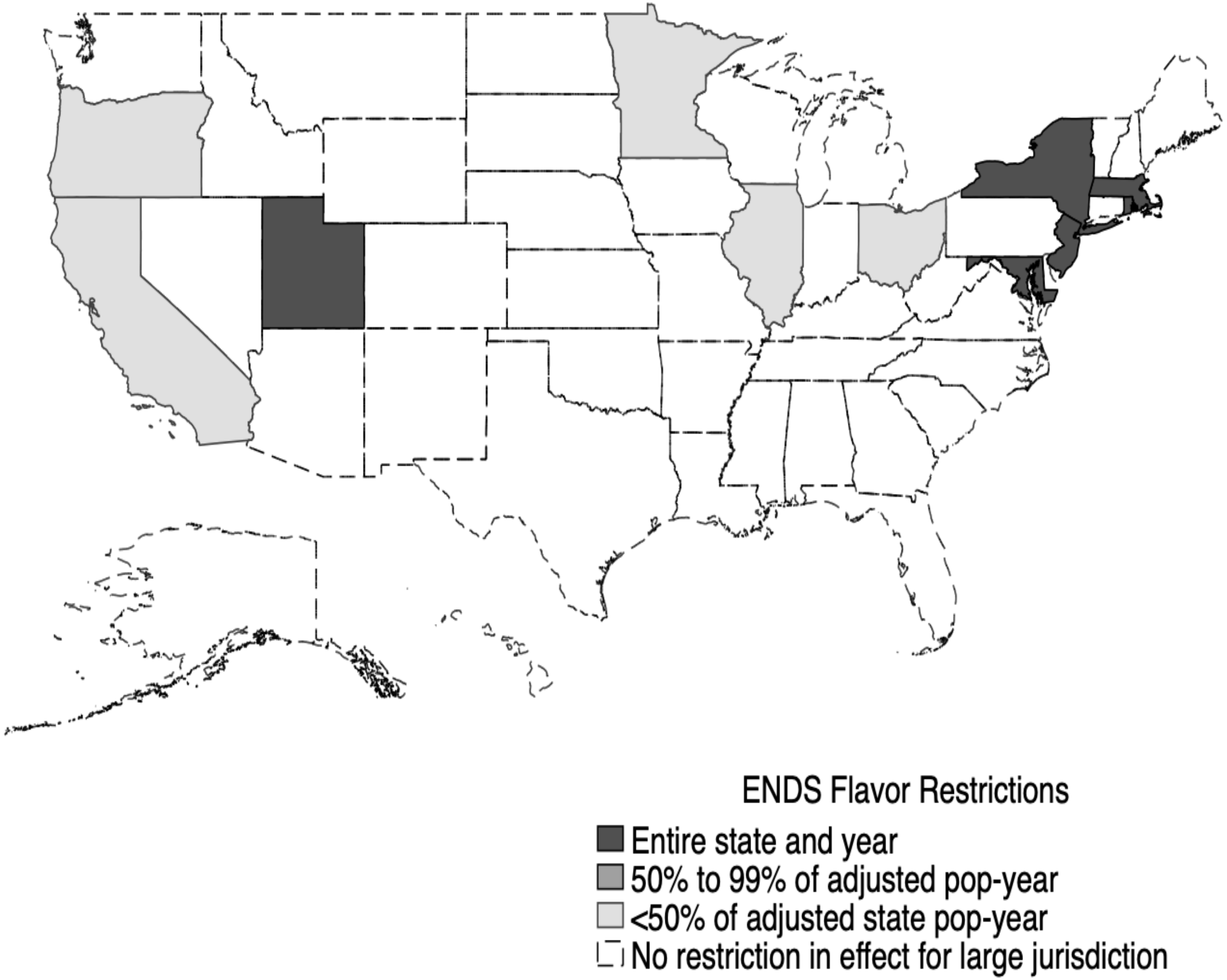
2019


ENDS Flavor Restrictions
Entire state and year
50% to 99% of adjusted pop-year
<50% of adjusted state pop-year
No restriction in effect for large jurisdiction

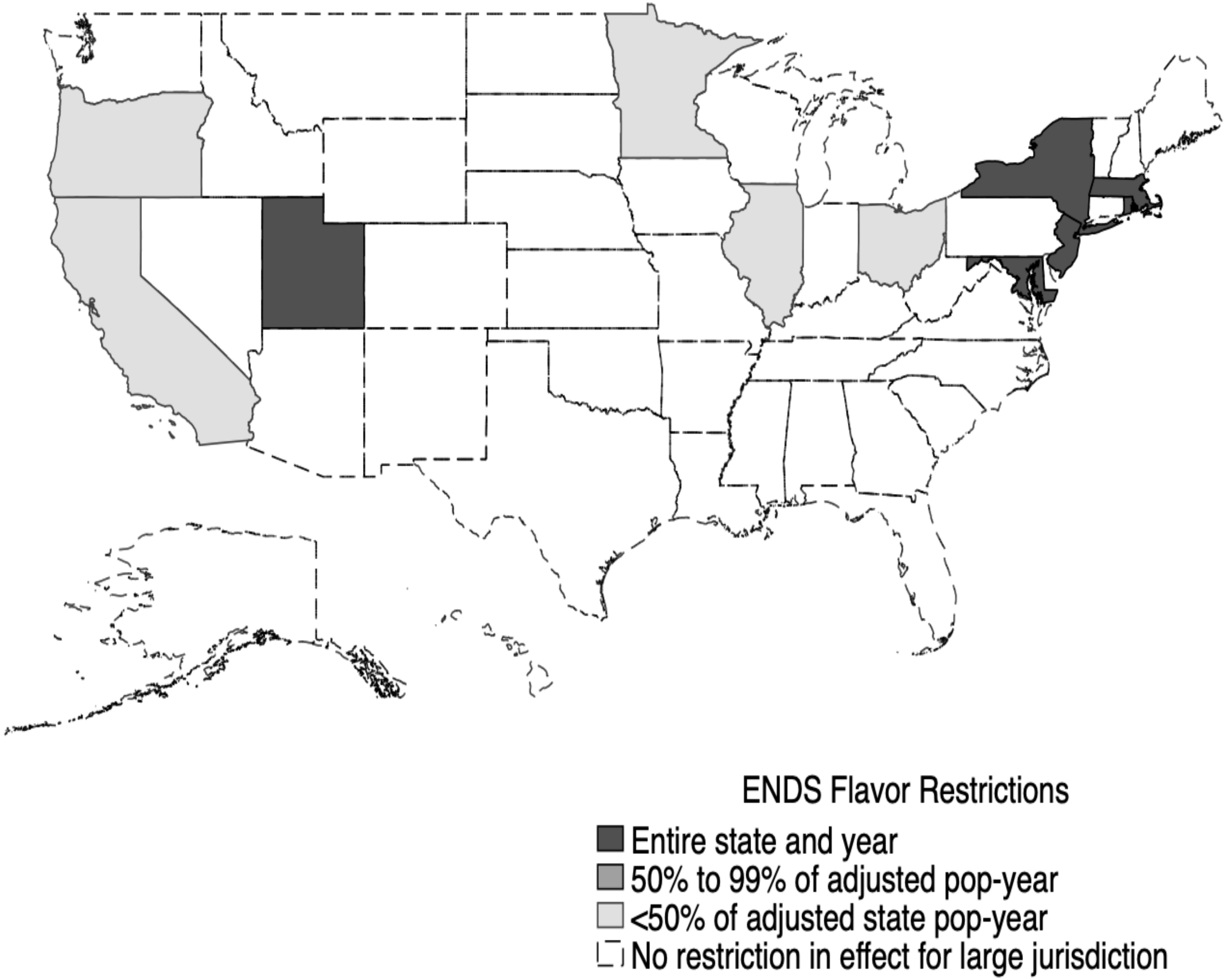
2020


ENDS Flavor Restrictions
Entire state and year
50% to 99% of adjusted pop-year
<50% of adjusted state pop-year
No restriction in effect for large jurisdiction

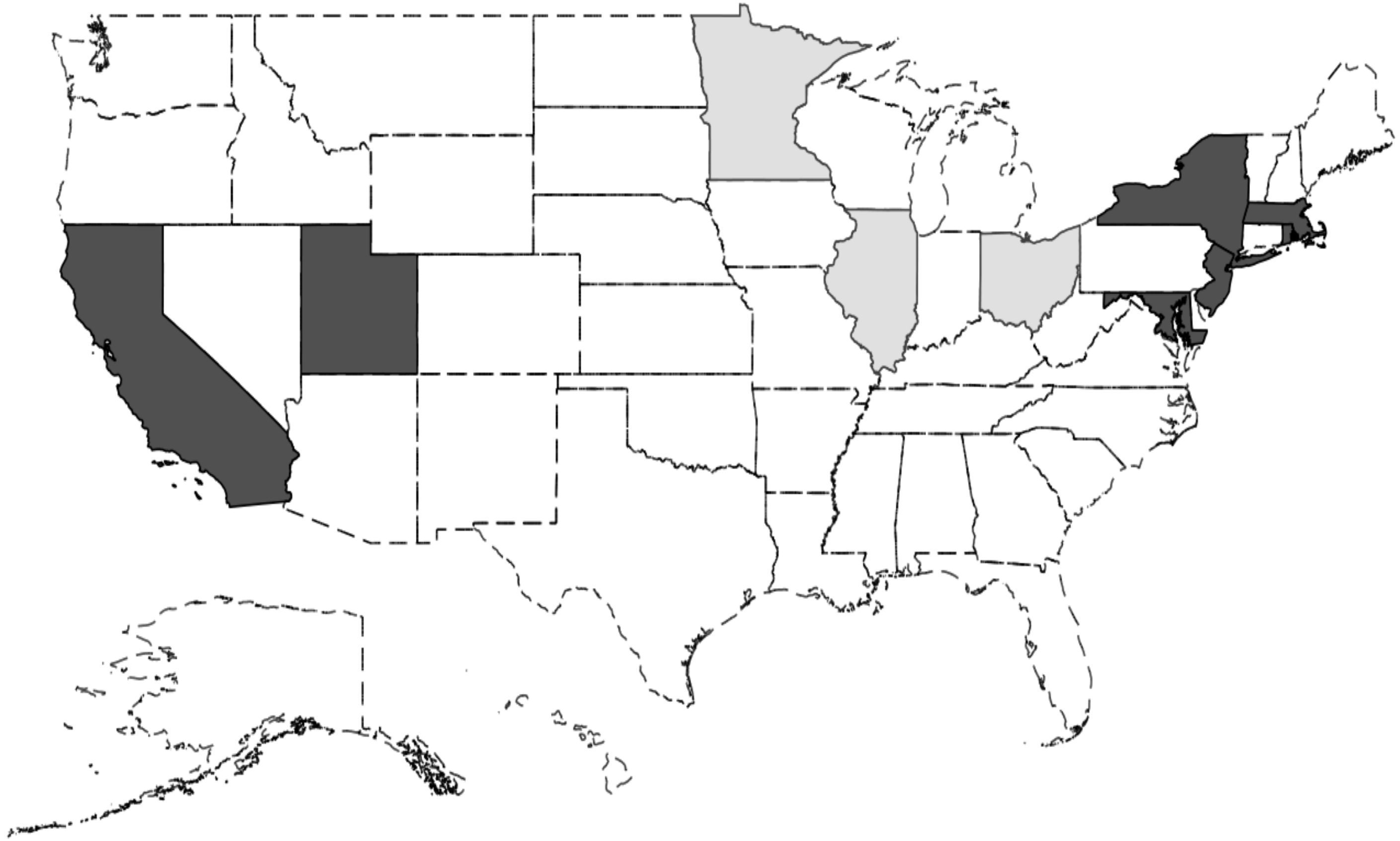
2021


ENDS Flavor Restrictions
Entire state and year
50% to 99% of adjusted pop-year
<50% of adjusted state pop-year
No restriction in effect for large jurisdiction

2022


ENDS Flavor Restrictions
Entire state and year
50% to 99% of adjusted pop-year
<50% of adjusted state pop-year
No restriction in effect for large jurisdiction

2023



ENDS Flavor Restrictions
Entire state and year
50% to 99% of adjusted pop-year
<50% of adjusted state pop-year
No restriction in effect for large jurisdiction

Effect of Flavor Bans on Current ENDS Use

	(1)	(2)	(3)
		Panel I: Overall Treatment Effect	
ENDS Flavor Restriction	-0.0094	0.0058	0.0064
	(0.0097)	(0.0189)	(0.0188)
		Panel II: Lagged Effects	
0-1 Years After ENDS Flavor Restriction	-0.0077	-0.0037	-0.0028
	(0.0140)	(0.0226)	(0.0226)
2+ Years After ENDS Flavor Restriction	-0.0102	0.0114	0.0119
	(0.0109)	(0.0200)	(0.0200)
Pre-Treatment Mean DV	0.2164	0.2164	0.2164
N	789921	789921	789921
Control Variables:			
Baseline Controls?	Yes	Yes	Yes
Extended Controls?	No	Yes	Yes
Double-selection LASSO	No	No	Yes

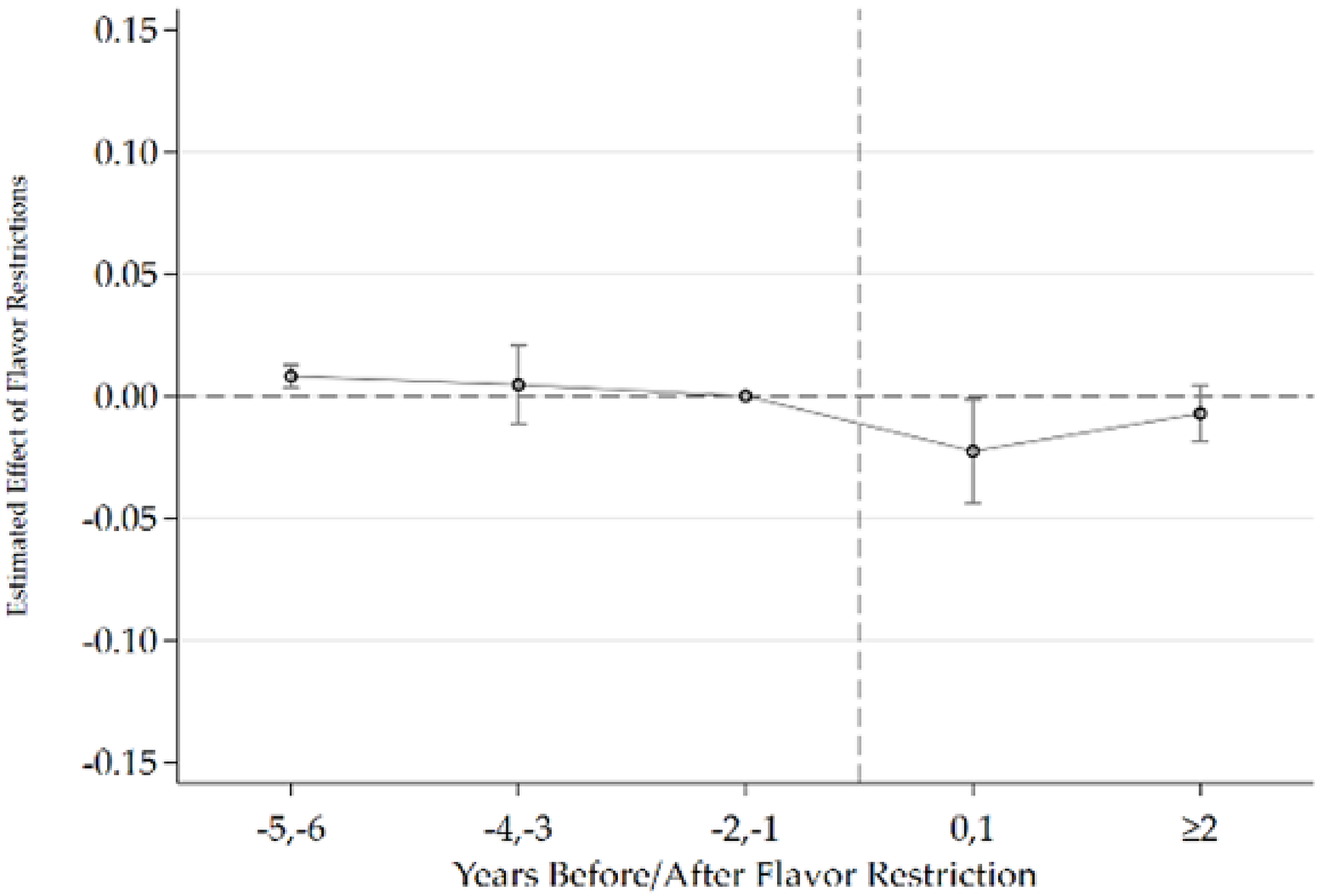
* $p<.1$, ** $p<.05$, *** $p<.01$

Effect of Flavor Bans on Everyday ENDS Use

	(1)	(2)	(3)
	Panel I: Overall Treatment Effect		
ENDS Flavor Restriction	-0.0137**	-0.0110	-0.0101
	(0.0057)	(0.0076)	(0.0074)
	Panel II: Lagged Effects		
0-1 Years After ENDS Flavor Restriction	-0.0220**	-0.0240**	-0.0225**
	(0.0088)	(0.0111)	(0.0107)
2+ Years After ENDS Flavor Restriction	-0.0095	-0.0035	-0.0027
	(0.0062)	(0.0083)	(0.0083)
Pre-Treatment Mean DV	0.0292	0.0292	0.0292
N	789921	789921	789921
Control Variables:			
Baseline Controls?	Yes	Yes	Yes
Extended Controls?	No	Yes	Yes
Double-selection LASSO	No	No	Yes

* $p<.1$, ** $p<.05$, *** $p<.01$

Dynamic DiD Estimates on Everyday Use



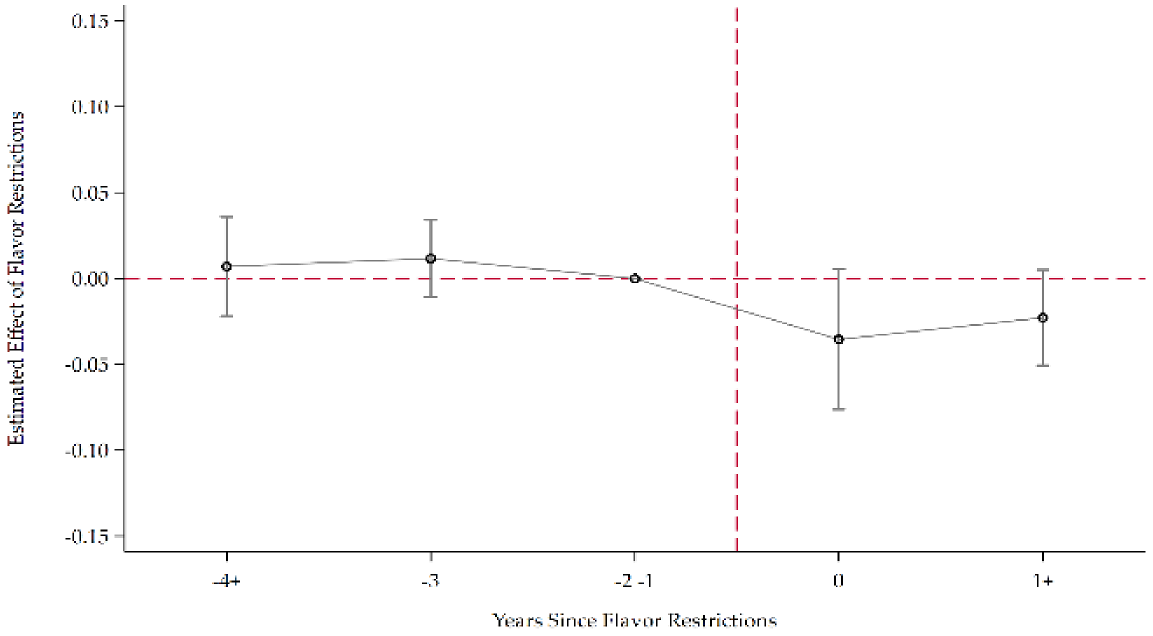
Why might effects (especially on extensive margin) be a muted?

Population Assessment of Tobacco & Health

	Current ENDS Use	Everyday ENDS Use	Flavored ENDS	Unflavored ENDS
Panel A. Current Treatment Effect				
ENDS Flavor Restriction	-0.009	-0.023**	-0.014	0.021***
	(0.021)	(0.011)	(0.020)	(0.006)
Panel B. Lagged Treatment Effect				
0-1 Years After ENDS Flavor Restriction	-0.001	-0.017*	-0.004	0.020***
	(0.020)	(0.010)	(0.019)	(0.006)
2+ Years After ENDS Flavor Restriction	-0.026	-0.035**	-0.034	0.022***
	(0.029)	(0.014)	(0.027)	(0.007)
Pre-Treatment Mean DV	0.143	0.037	0.128	0.013

Event-Study Analysis, 18-20-Year Olds

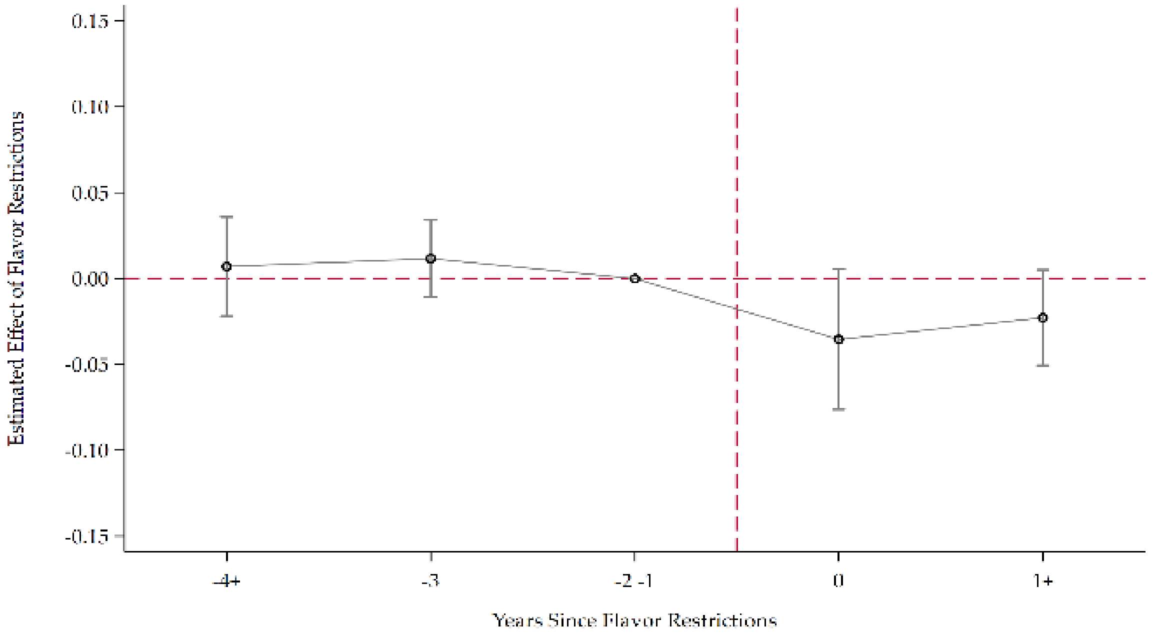
ENDS Use



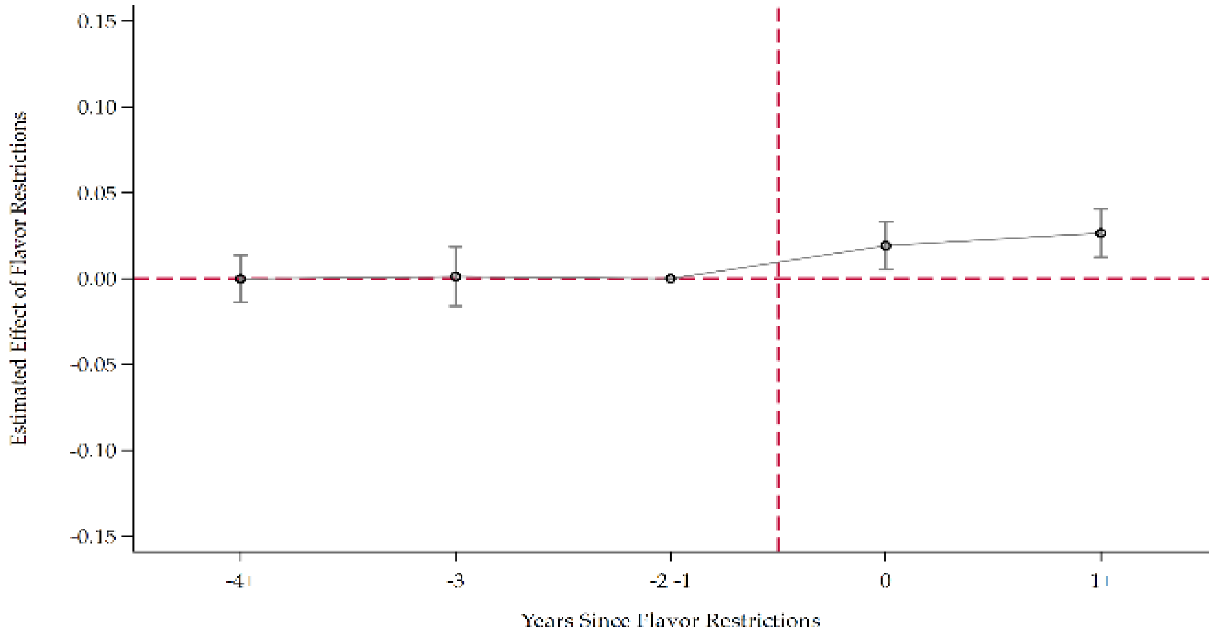
Adoption of an ENDS flavor restriction is associated with a 3 percentage-point reduction in young adult ENDS use

Event-Study Analysis, 18-20-Year Olds

ENDS Use



Cigarette Smoking



Adoption of an ENDS flavor restriction is associated with a 3 percentage-point reduction in young adult ENDS use, but a **1 percentage-point increase in cigarette smoking**

ELSEVIER

Journal of Health Economics

Volume 98, December 2024, 102919

Do e-cigarette retail licensure laws reduce youth tobacco use?

Charles Courtemanche [a], Yang Liang [b], Johanna Catherine Maclean [c], Caterina Muratori [d], Joseph J. Sabia [e]

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https://doi.org/10.1016/j.jhealeco.2024.102919

Abstract

E-cigarette licensure laws (ELLs) require retailers to obtain a state license to sell e-cigarettes over the counter. This study is the first to comprehensively explore the effect of ELL adoption on youth tobacco product use. Using data from the State Youth Risk

E-Cigarette Retail Licensure Laws

- While many policies designed to curb youth ENDS use have focused on demand-side approaches — such as using taxes to raise prices faced by consumers — this study explores the impact of a prominent supply-side policy strategy: e-cigarette licensure laws (ELLs)

- Since 2011, 33 states and the District of Columbia have adopted ELLs, which require tobacco sellers to obtain a state license to sell e-cigarettes over the counter (Public Health Law Center, 2023)

- Minimum license fees range from trivial amounts (e.g., $5 in Montana) to more substantial fees (e.g., $800 in Connecticut), and penalties for noncompliance include suspension or revocation of a firm's license to sell e-cigarettes, license, fines up to $25,000, even criminal sanctions

What are ELLs designed to do?

- ELLs are designed to regulate sales, increase compliance with state tobacco regulations (i.e., minimum legal purchasing ages, scanner ID laws), and reduce the supply of e-cigarettes available to local consumers, in particular youth

- ELLs also offer "support" to retailers, with some ELLs encouraging vendors to meet with onsite inspectors to ask questions about selling e-cigarettes and ensuring proper signage

- Many public health advocates see ELLs as a vital anti-vaping policy tool (Tobacco Control Legal Consortium, 2016)
    - In 2018, the U.S. Surgeon General issued an advisory recommending that states and localities adopt ELLs as part of a comprehensive approach to curbing youth vaping (U.S. Surgeon General, 2018)

Datasets

- Main: 2015-2021 State Youth Risk Behavior Survey (State YRBS)
  - State representative surveys of 9th through 12th grade high school students
  - Can be made nationally representative of 14-18-year-olds
  - Information from 2015-2021 on prior-month ENDS use (including number of days of nicotine vaping)
  - Also includes information on combustible cigarette or cigar smoking
  - Supplement analysis using National YRBS

- Auxiliary: 2016-2021 Behavioral Risk Factor Surveillance System Survey (BRFSS)
  - Includes information on ENDS and combustible cigarette use among adults
  - Explore effects for teens ages 18-20 and 21+ (at or above MLPA)

Estimation Strategy

- Begin with TWFE Estimation

$$Y_{ist} = \gamma_0 + \gamma_1 E\,L\,L_{st} + X_{ist}\,\beta + Z_{st}\,\delta + \alpha_s + \Theta_t + \epsilon_{ist}$$

Y_{ist} : ENDS use

$E\,L\,L_{st}$: ENDS licensure law

X_{imt} : Vector of individual demographic controls: gender, age, grade and race dummies

Z_{smt} : Vector of state-level covariates

Macroeconomic conditions & COVID-19: unemployment rate, per capita income, COVID-19 cumulative death rate (experimented with Oxford COVID-19 indexes)

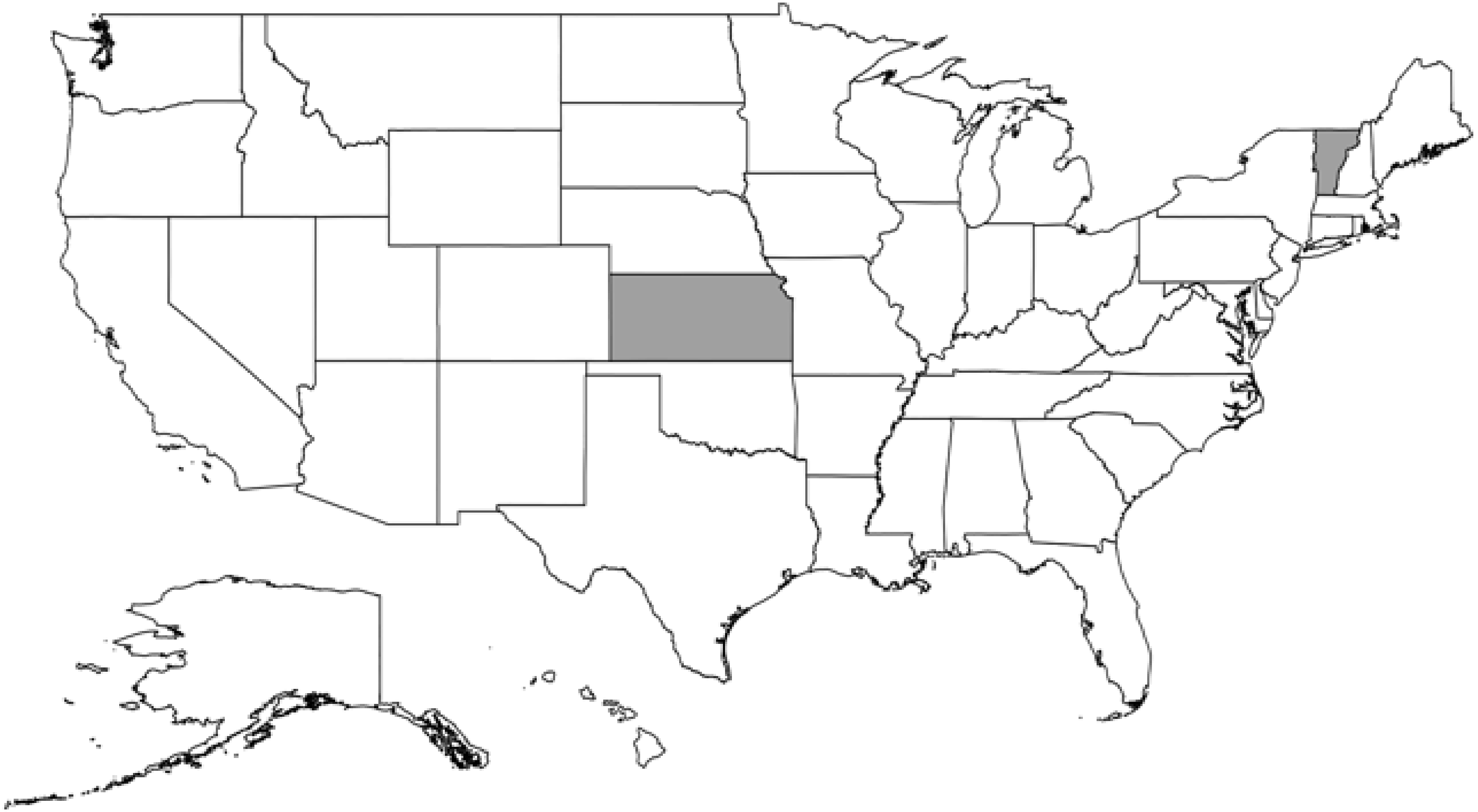
Tobacco policies: Tobacco-21 law, cigarette tax, e-cigarette tax, ENDS MLPA, indoor smoking/ENDS restrictions, combustible tobacco licensure law, ENDS flavor restrictions, menthol cigarette ban, online sales delivery ban

Substance use policies: recreational marijuana law, medical marijuana law, beer tax

2011

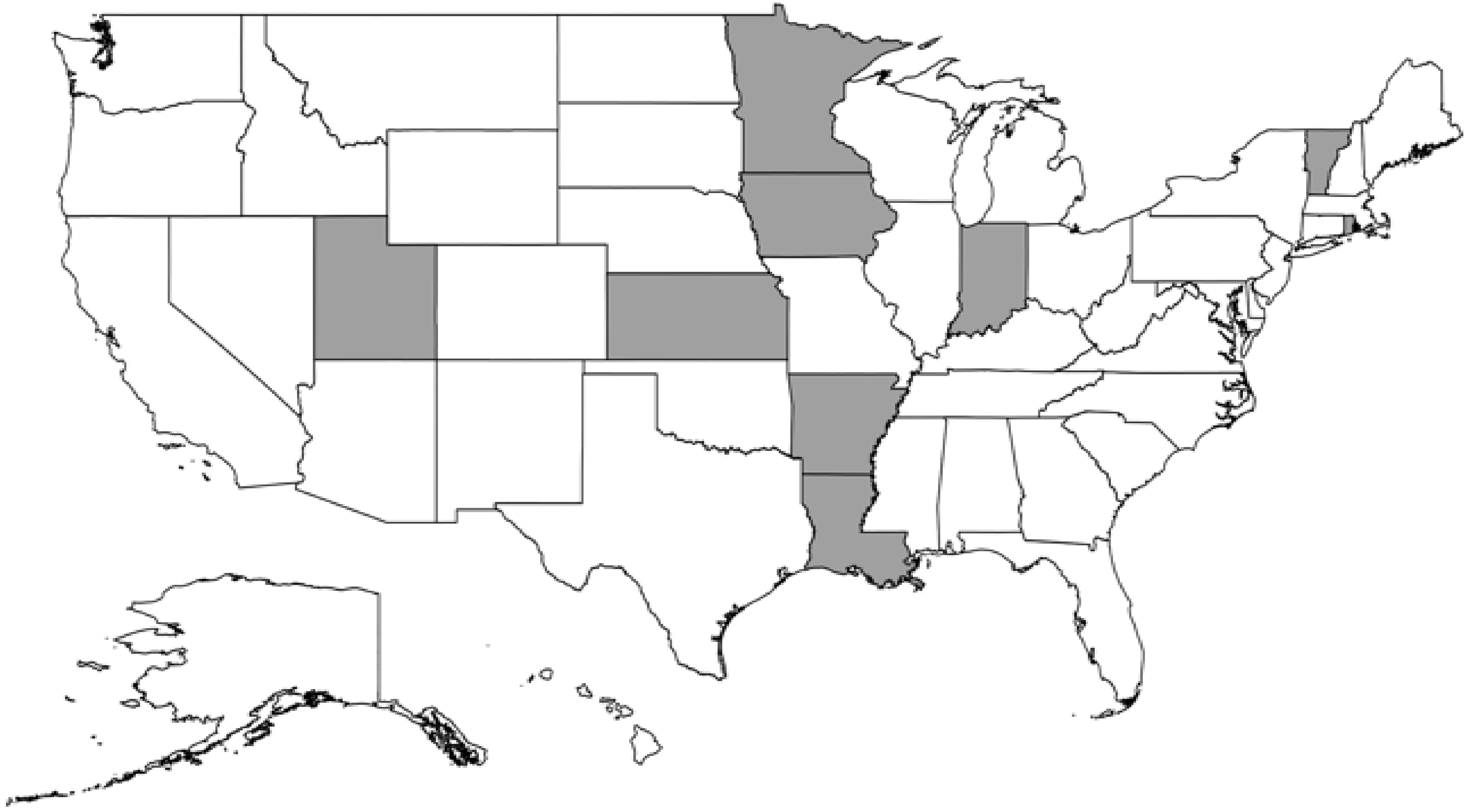
ENDS Licensure Laws

2013



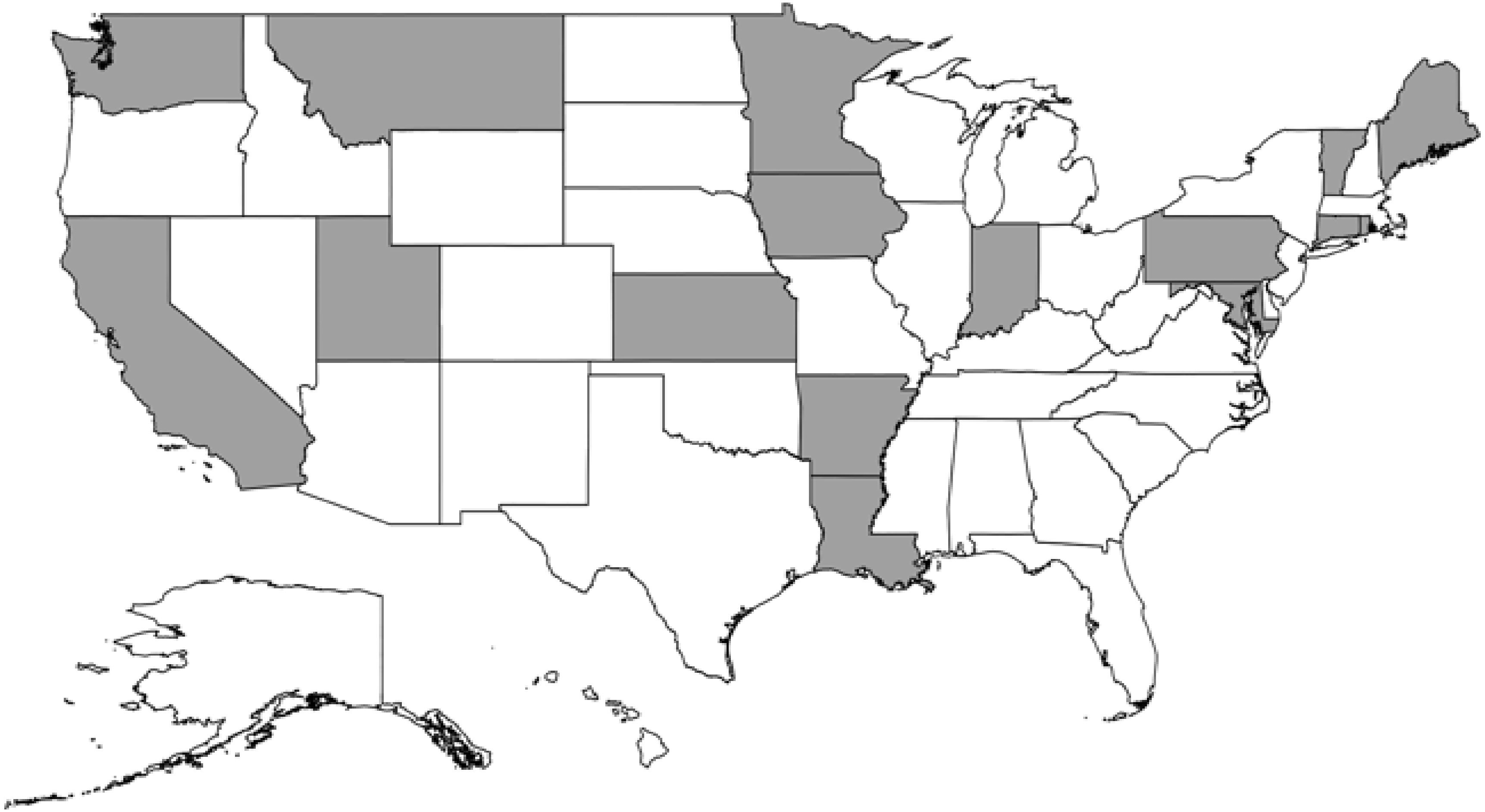
ENDS Licensure Laws

2015



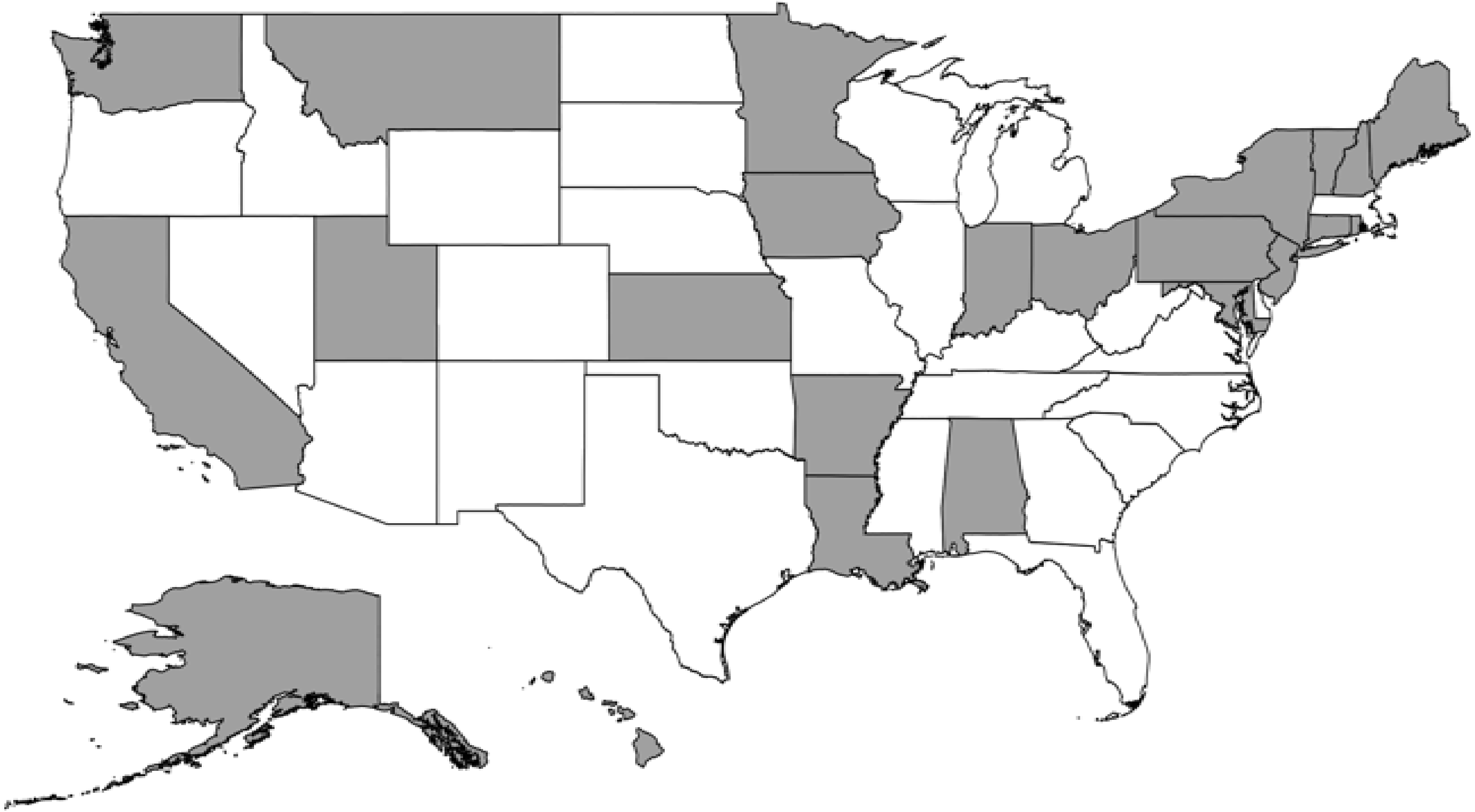
ENDS Licensure Laws

2017



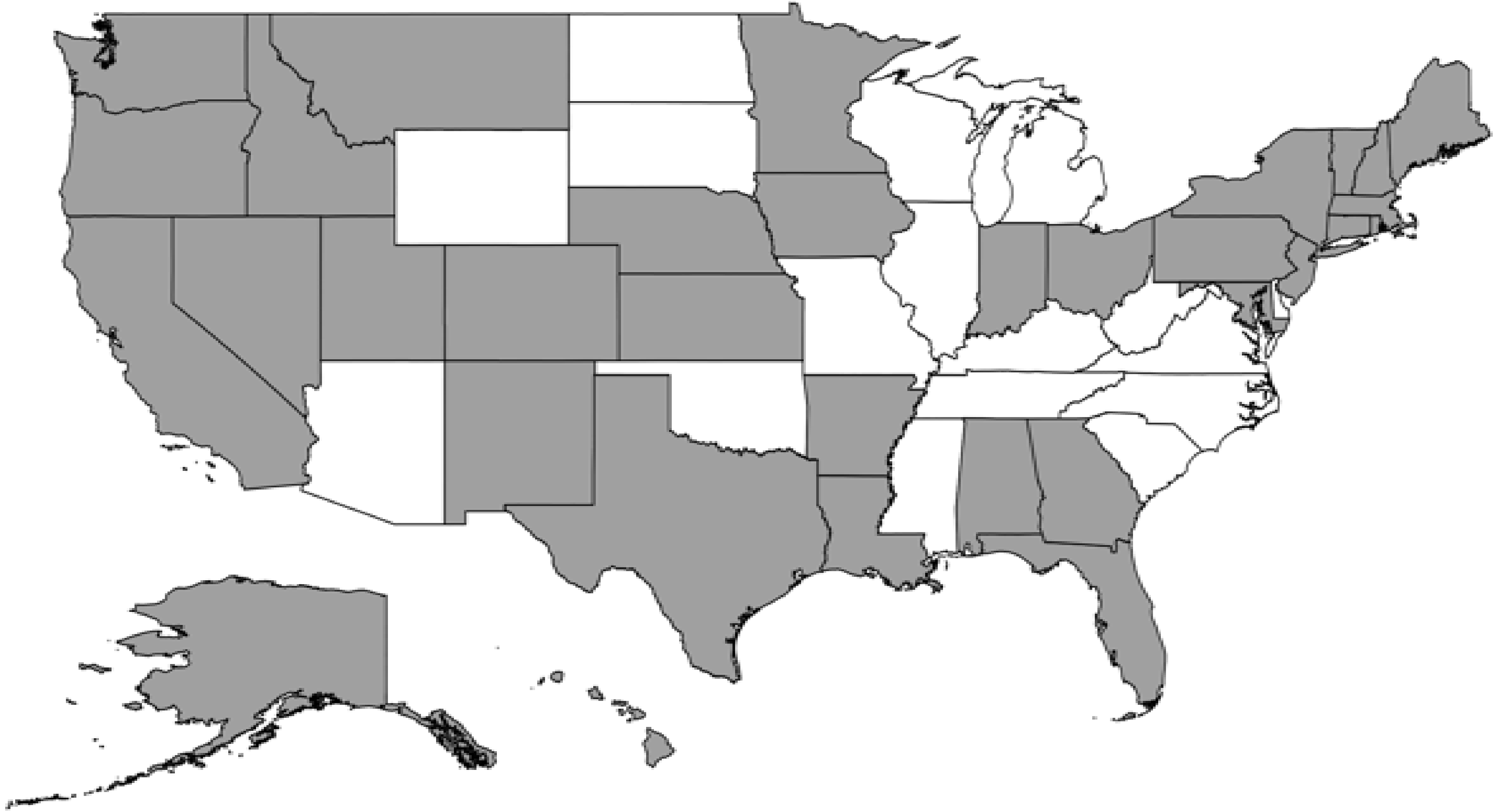
ENDS Licensure Laws

2019



ENDS Licensure Laws

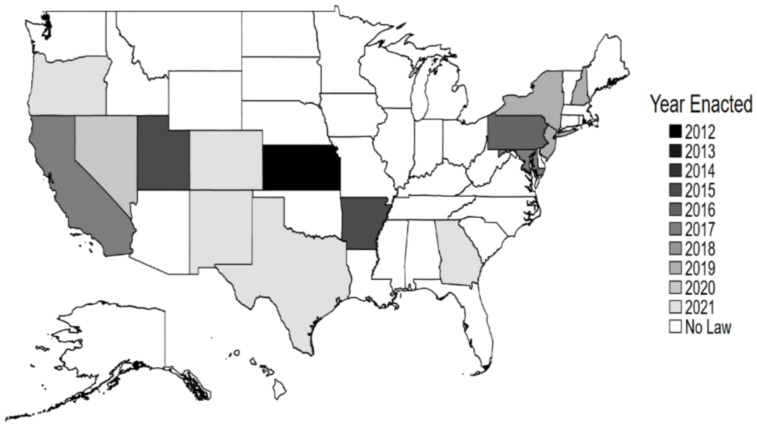
2021



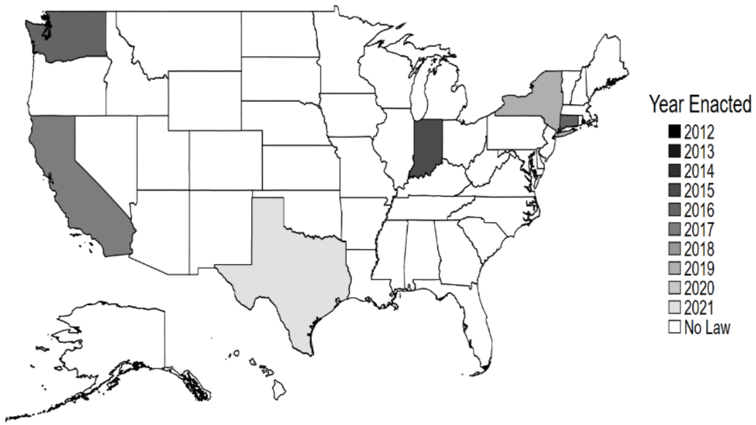
ENDS Licensure Laws

Heterogeneity by Law Intensity

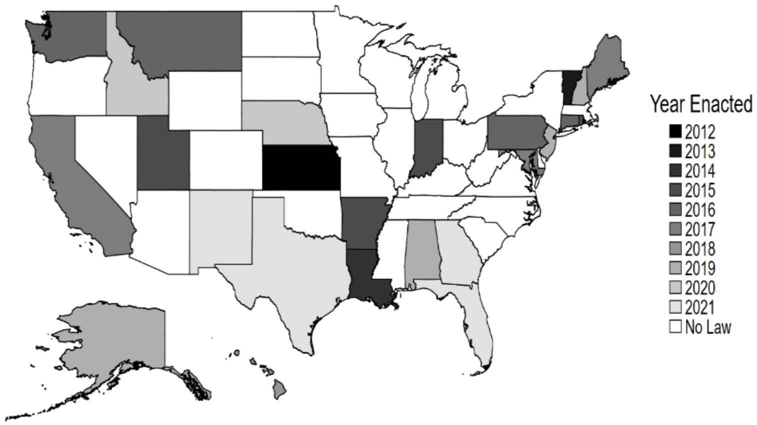
Higher Fines



Higher Renewable Fees



Criminal Penalty



Effects of ENDS Taxes (2021$) on Youth ENDS Use, YRBS

Panel II: Current ENDS Use	.009	.014	.014	.013
	(.011)	(.011)	(.011)	(.010)
Pre-Treat. Mean of DV	*0.198*	*0.198*	*0.198*	*0.198*
Panel II: Frequent ENDS Use	-.001	.002	.008	.007
	(.006)	(.005)	(.005)	(.005)
Pre-Treat. Mean of DV	*0.040*	*0.040*	*0.040*	*0.040*
Panel III: Daily ENDS Use	-.002	.001	.005	.004
	(.004)	(.004)	(.004)	(.004)
Pre-Treat. Mean of DV	*0.028*	*0.028*	*0.028*	*0.028*
N	622122	622122	622122	622122
Controls:				
State and Wave FE & Demographics?	Yes	Yes	Yes	Yes
Region-by-wave FE, Macro & COVID?	No	Yes	Yes	Yes
Tobacco Policy Controls?	No	No	Yes	Yes
Other Substances Policy Controls?	No	No	No	Yes

0 is a number too!

Editorial Statement on Negative Findings

The Editors of the health economics journals named below believe that well-designed, *well-executed empirical studies that address interesting and important problems in health economics, utilize appropriate data in a sound and creative manner, and deploy innovative conceptual and methodological approaches compatible with each journal's distinctive emphasis and scope* have potential scientific and publication merit regardless of whether such studies' empirical findings do or do not reject null hypotheses that may be specified. As such, the Editors wish to articulate clearly that the submission to our journals of studies that meet these standards is encouraged.

We believe that publication of such studies provides properly balanced perspectives on the empirical issues at hand. Moreover, we believe that this should reduce the incentives to engage in two forms of behavior that we feel ought to be discouraged in the spirit of scientific advancement:

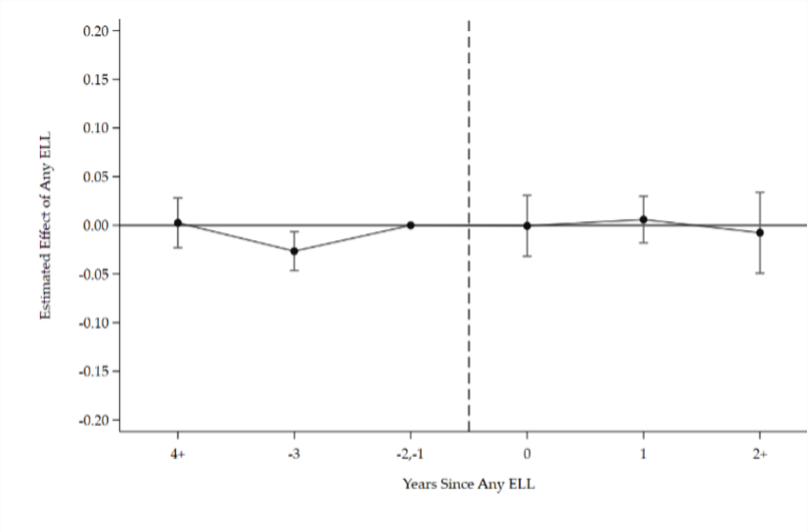
1. Authors withholding from submission such studies that are otherwise meritorious but whose main empirical findings are highly likely "negative" (e.g. null hypotheses not rejected).
2. Authors engaging in "data mining," "specification searching," and other such empirical strategies with the goal of producing results that are ostensibly "positive" (e.g. null hypotheses reported as rejected).

Henceforth we will remind our referees of this editorial philosophy at the time they are invited to review papers. As always, the ultimate responsibility for acceptance or rejection of a submission rests with each journal's Editors.

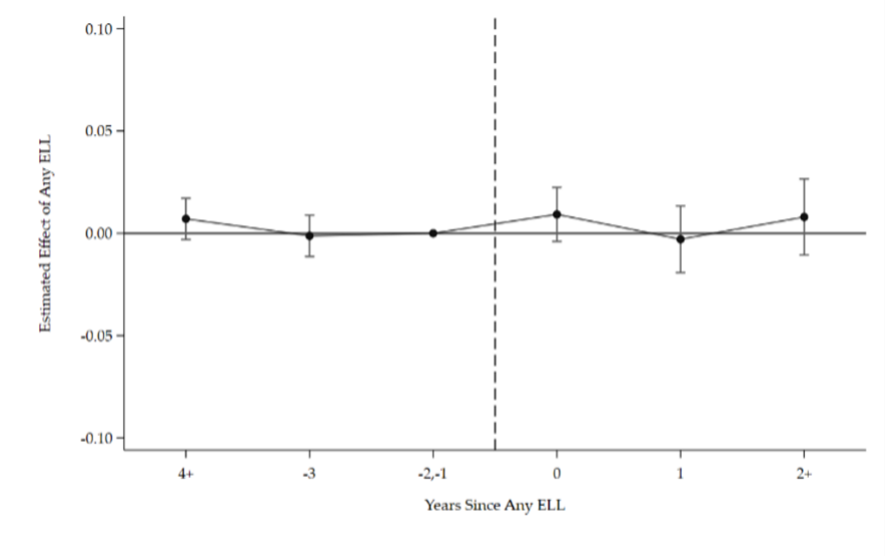
American Journal of Health Economics
European Journal of Health Economics
Forum for Health Economics & Policy
Health Economics Policy and Law
Health Economics Review
Health Economics
International Journal of Health Economics and Management
Journal of Health Economics

Event-Study Analysis, TWFE Estimates

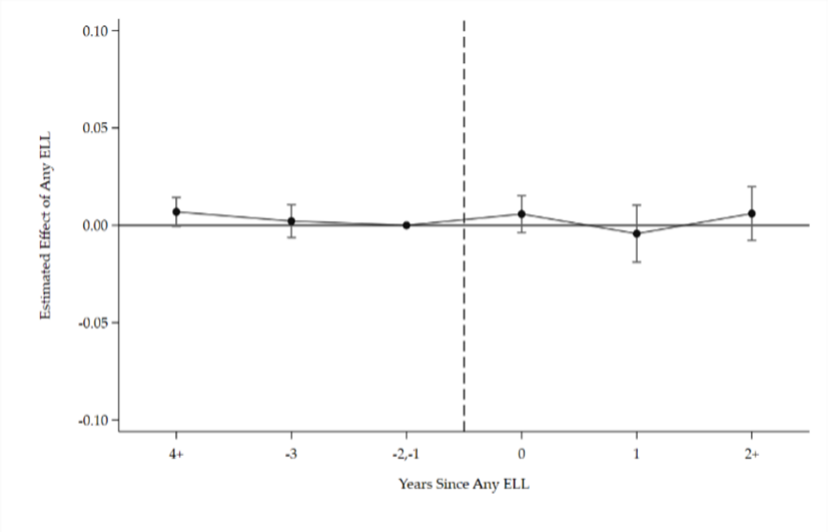
Current ENDS Use



Frequent ENDS Use

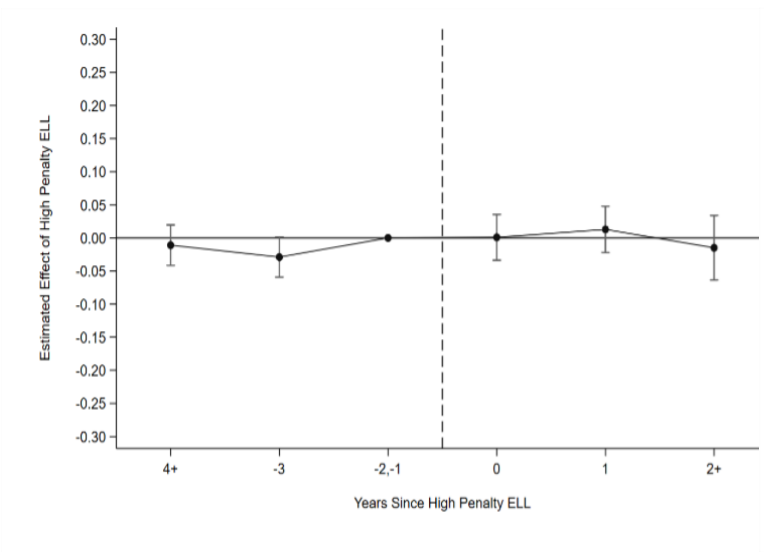


Everyday ENDS Use

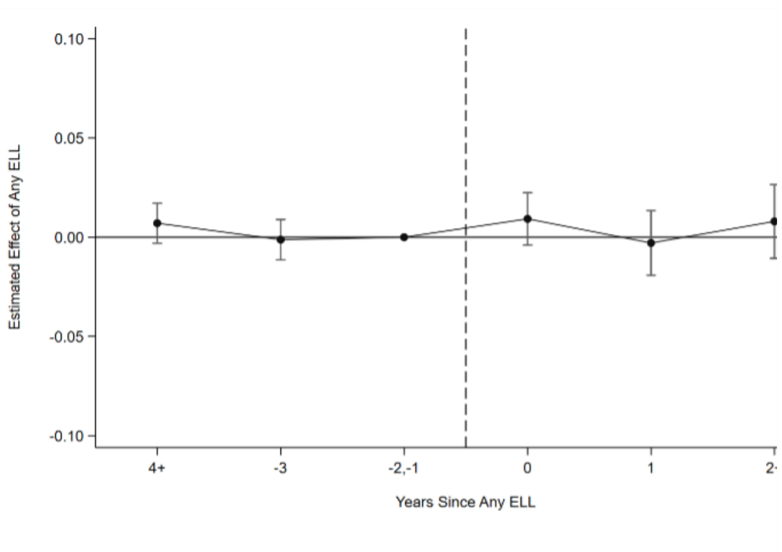


Higher Penalty Licensure Laws

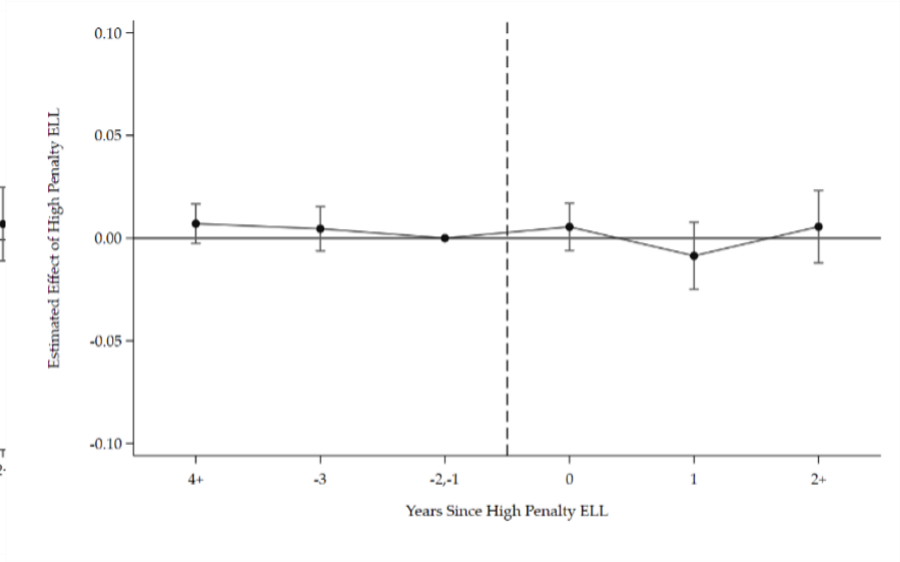
Current ENDS Use



Frequent ENDS Use



Everyday ENDS Use



Auxiliary Findings on Adults (BRFSS)

	(1)	(2)	(3)	(4)
	Aged 18-20	Aged 21+	Aged 18-20	Aged 21+
	Any ENDS Use		Daily ENDS Use	
ELL	.021	-.002	-.005	-.0003
	(.021)	(.002)	(.007)	(.001)
Pre-Treat. Mean of DV	*0.135*	*0.048*	0.043	*0.019*
N	38086	1548893	38086	1548891

American Journal of Health Economics > Volume 9, Number 3

PREVIOUS ARTICLE

Details Figures References Cited by

Regression Discontinuity Evidence on the Effectiveness of the Minimum Legal E-cigarette Purchasing Age

Jeff DeSimone, Daniel Grossman, and Nicolas Ziebarth

PDF | PDF PLUS | Abstract | Full Text | Supplemental Material

Abstract

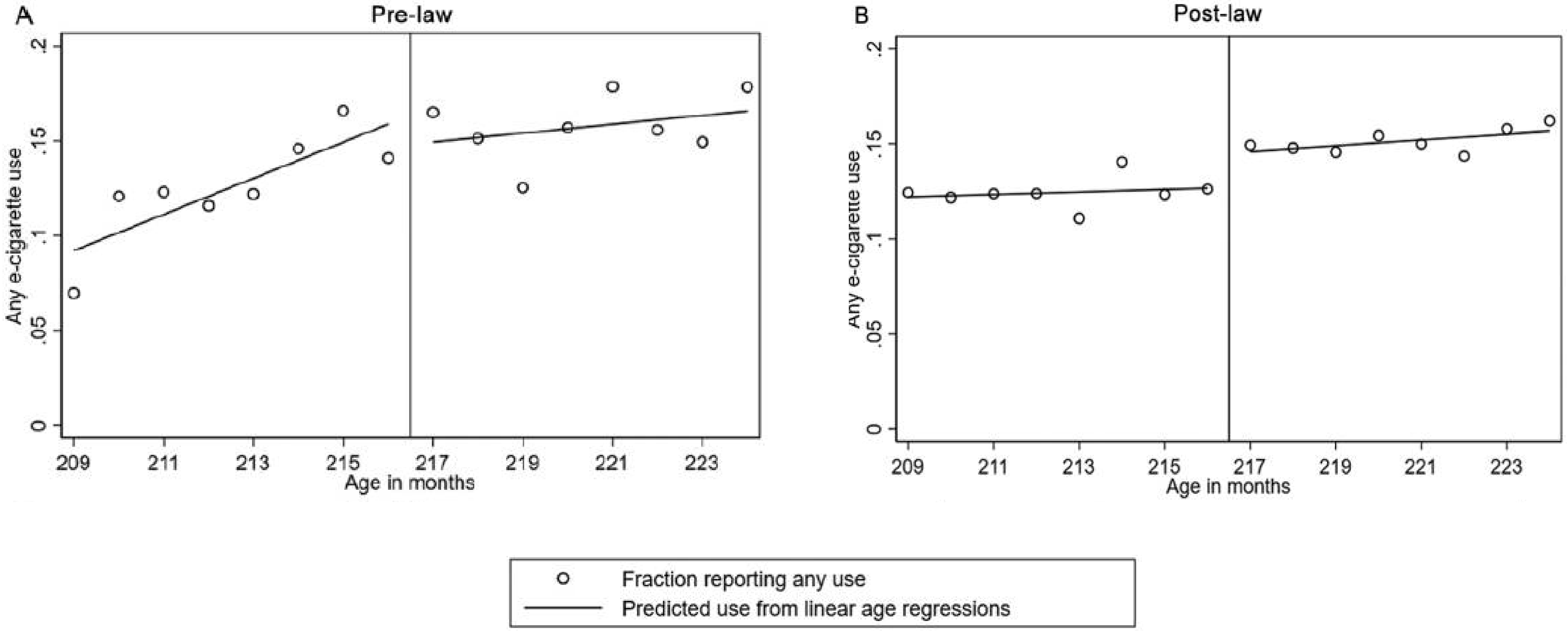
Increases in youth vaping rates and concerns of a new generation of nicotine addicts recently prompted an increase in the federal minimum legal purchase age (MLPA) for tobacco products, including e-cigarettes, to 21 years. This study presents the first regression discontinuity evidence on the effectiveness of e-cigarette MLPA laws. Using data on 12th graders from Monitoring the Future, we obtain robust evidence that federal and state age 18 MLPAs decreased underage e-cigarette use by 15–20 percent and frequent use by 20–40 percent. These findings suggest that the age 21 federal MLPA could meaningfully reduce e-cigarette use among 18- to 20-year-olds.

American Journal of Health Economics
Volume 9, Number 3
Summer 2023

Identification with RDD

- Continuity of Potential Outcomes
  - In absence of treatment, the estimated treatment effect around the cutoff of the assignment variable would be 0
- Discontinuity in Treatment Assignment
  - Sharp vs Fuzzy RDD
- No Manipulation of Treatment Variable
- Other Covariates Should Trend Smoothly around Assignment Cutoff

Do E-Cigarette MLPA Laws Work?



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Association of Canada's Provincial Bans on Electronic Cigarette Sales to Minors With Electronic Cigarette Use Among Youths

Hai V. Nguyen, PhD[1]

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Key Points

Question To what extent and through what channels did Canada's provincial bans on electronic cigarette (e-cigarette) sales to minors reduce their e-cigarette use?

Findings This quasi-experimental difference-in-differences and triple-differences study found that, between 2013 and 2017, e-cigarette use by youths increased in all provinces but less rapidly in provinces with a ban on e-cigarette sales to minors. Youths in provinces with a ban on e-cigarette sales to minors had better perception of harm from e-cigarette use and greater difficulty obtaining e-cigarettes but also higher use of social sources for e-cigarettes.

Difference-in-difference-in-differences (DiDiD)

- Can add a third difference to DiD models if there is, for instance, a within-state control group

- Studies of MLPA-18 laws could evaluate 15-17-year-olds in a DiD framework
  - Then, can estimate the effect of MLPA-18 laws on 18-25-year-olds

- DiDiD is the difference in DiD for treatment and control ages

- Advantages
  - Nets out incidental vaping trend difference among 18-25-yo in treated vs control states
  - Controls for unmeasured state-specific shocks commonly affecting 15-17- and 18-25-yo

- Identifying Assumptions
  - No youth specific, state shocks correlated with MLPA-18 and youth vaping
  - No reverse causality

Table 1. Dates of Bans on e-Cigarette Sales to Minors Across Canada

Province	Date in Effect	Target Age, y
Nova Scotia	May 31, 2015	19
New Brunswick	July 1, 2015	19
Prince Edward Island	October 1, 2015	19
Quebec	November 26, 2015	18
Ontario	January 1, 2016	19
Newfoundland and Labrador	June 7, 2016	19
British Columbia	September 1, 2016	19
Manitoba	October 1, 2017	18
Alberta	No ban	NA
Saskatchewan	No ban	NA
Canada-wide	May 23, 2018	18

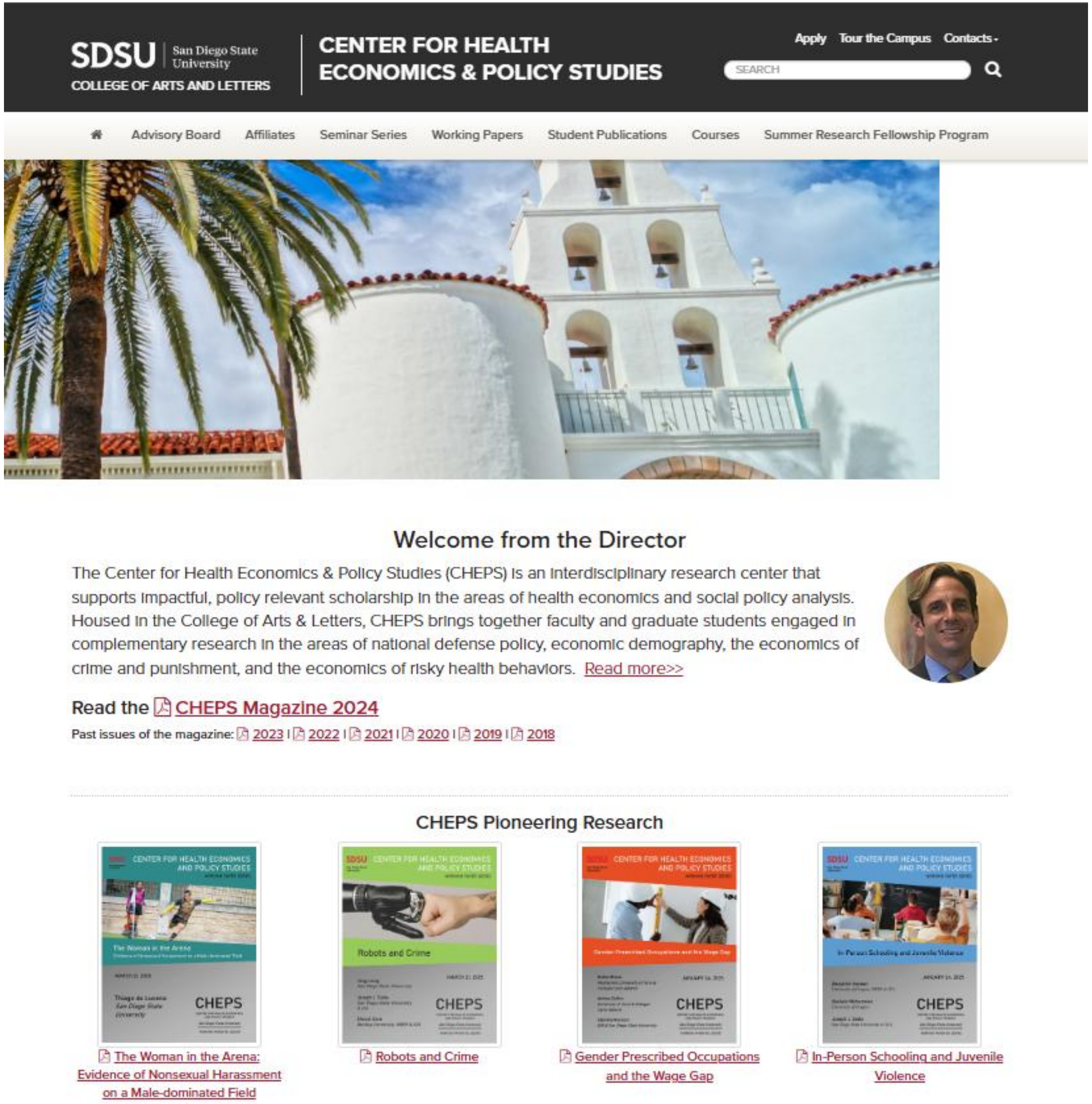
Abbreviations: e-Cigarette, electronic cigarette; NA, not applicable.

Table 4. Changes in Past 30-Day e-Cigarette Use, Use of Social Source, Harm Perception, and Access Difficulty After Ban[a]

Outcome	Percentage Point Change After Ban (95% CI)	*P* Value	Data Source	Study Sample Age, y
Base Case Analysis				
Past 30-d e-cigarette use				
DD (n = 8212)	−4.3 (−6.8 to −1.7)	.004	CTADS 2013-2017	15-17 or 18
DDD (n = 20 934)	−3.1 (−6.0 to −0.2)	.04	CTADS 2013-2017	15-25
Obtain e-cigarettes through social sources: DD (n = 2798)	17.3 (5.2 to 29.4)	.01	CTADS 2017	15-25 (e-cigarette users)
No harm in regular e-cigarette use: DD (n = 78 650)	−2.6 (−3.7 to −1.5)	.001	CSTADS 2014-2017	15-17 or 18
Difficult to access e-cigarettes: DD (n = 74 894)	6.2 (1.1 to 11.4)	.02	CSTADS 2014-2017	15-17 or 18

Conclusions

- In order to (1) evaluate the intended and unintended impacts of public policies, and (2) assess the broader social welfare effects of public policies, credible quasi-experimental design is needed
- In the U.S. and Canada, the most common methods used to estimate the economic impact of e-cigarette regulations are difference-in-differences (DiD) and regression discontinuity design (RDD)
- In a presentation later today from Yang Liang, we will discuss how these and other methods are being and/or can be used in low- and middle-income counties to evaluate impacts of e-cigarette regulations



<u>Website & X:</u>

http://cheps.sdsu.edu

X: @SDSUCHEPS

<u>Reach me at:</u>

jsabia@sdsu.edu

<u>Office Hours:</u>

Beginning in August

Tuesdays/Wednesdays

5:30PM-6:45PM PT

(8:30AM-9:45AM local time)

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