Econometrics Approaches for Tobacco Policy Evaluation in LMICs

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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

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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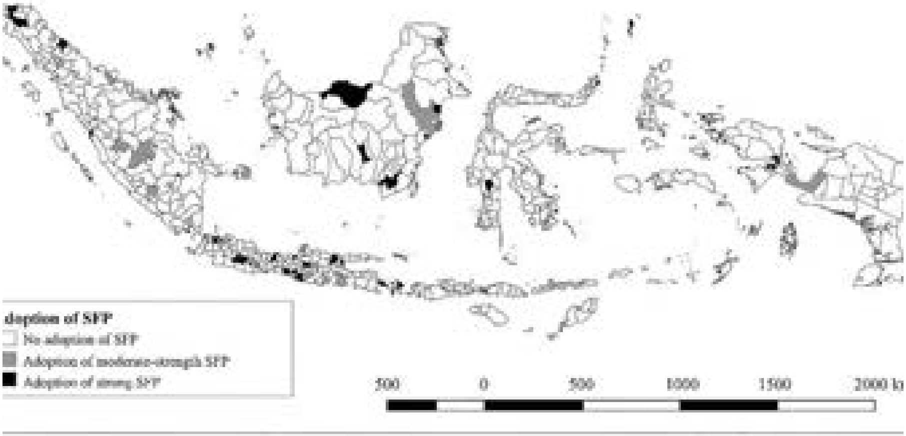
Abstract

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



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.

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

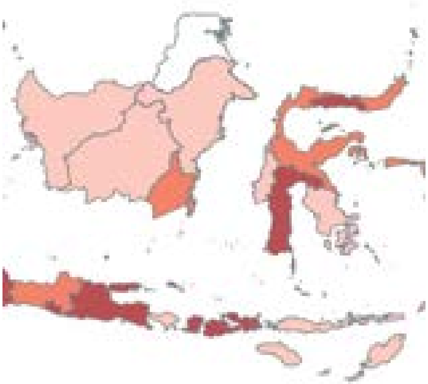
where *share*$_i$ is **pre-treatment** intensity (e.g., % smokers in region *i*)

- 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

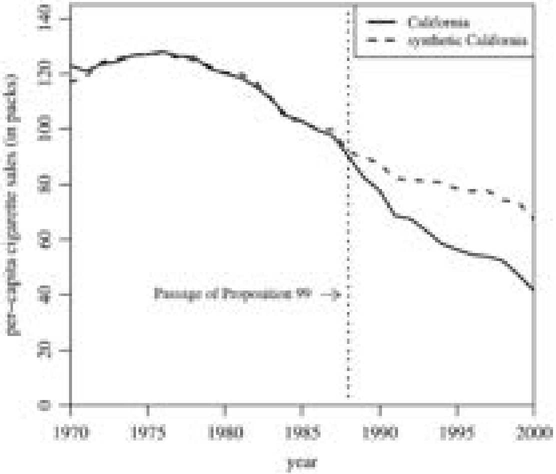


Figure 2. Trends in per-capita cigarette sales: California vs. synthetic California.

Placebo Test

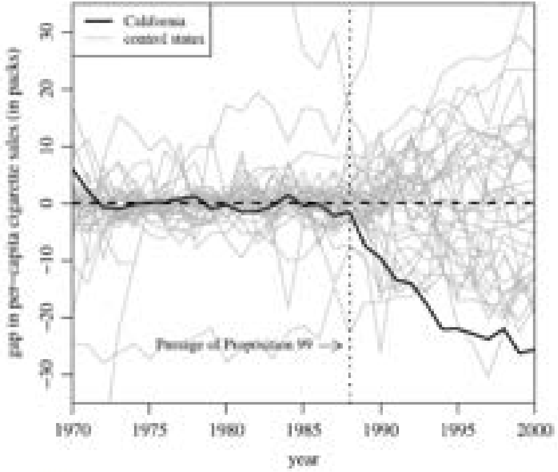


Figure 4. Per-capita cigarette sales gaps in California and placebo gaps in all 38 control states.

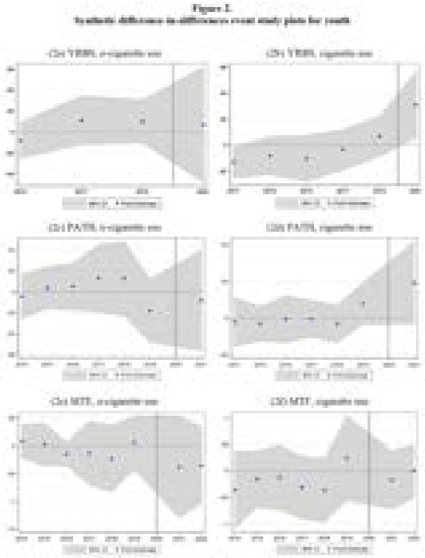
Hypothetical Example

- 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



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:**

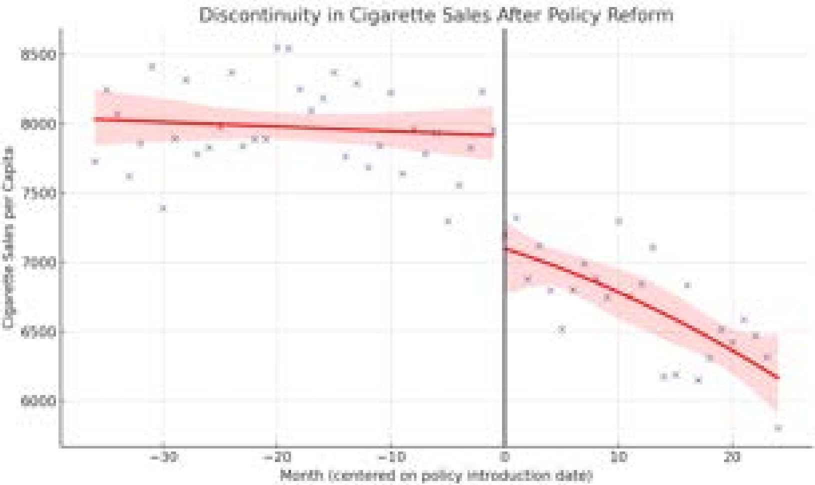
$$Y_t = f(t) + \beta \cdot \mathbf{1}(t \geq t_0) + \varepsilon_t$$

  - $f(t)$: 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!

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