Is China's Comprehensive Smoke-free Policy Effective? A Synthetic Difference-in-Differences Analysis in Beijing

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Disclosures

- This work is not supported by any funding.
- The authors have received no tobacco-related funding over the past 10 years.
- The present study has not yet published, and is currently undergoing revision. Please feel free to raise any questions or comments throughout the presentation and I will pause for questions after finishing each section of the presentation. We will appreciate feedbacks in any form so that we can make our study stronger.

Motivation

1. Tobacco has been considered one of the leading causes of death worldwide that is highly addictive.[1].
2. Many interventions or policy has been implemented to reduce tobacco consumption. In particular, comprehensive smoke-free policies (CSFP) have been recognized as one of the most effective tools to reduce smoking behaviors.[2].

Gaps in Knowledge

No rigorous smoke-free policy evaluation has been conducted in China, the country with one of the highest smoking prevalence.

[1] World Health Organization. (n.d.) Tobacco. Retrieved February 13, 2022, from https://www.who.int/news-room/fact-sheets/detail/tobacco

[2] Centers for Disease Control and Prevention. (2021, June 30) Tobacco Control Interventions — Health Impact in 5 Years — Health System Transformation — AD for Policy — CDC. https://www.cdc.gov/policy/hst/hi5/tobaccointerventions/index.html

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Comprehensive smoke-free policy

What is a comprehensive smoke-free policy?

- Policies enacted to achieve a complete smoking ban in indoor public places, workplaces and public transport, with no buffer period and smoking rooms, and clear law enforcement bodies and penalties. [1]

[1] China University of Political Science and Law. (2023). Healthy China smoke-free legislation in progress. Caixin.Com. https://datanews.caixin.com/interactive/2020/smokefree-digital-map/

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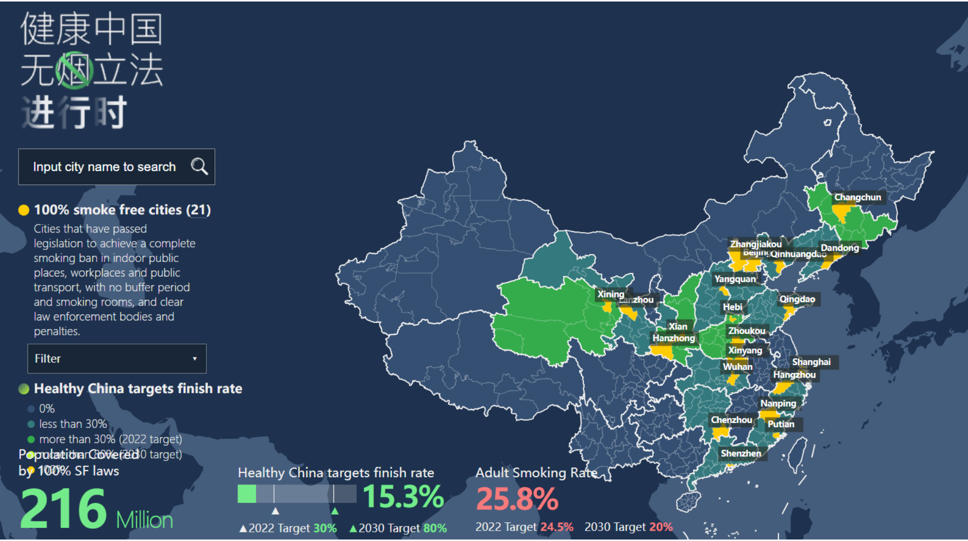
Smoke-free Legislation in China



Objectives

Fortunately, Beijing is among the first places to witness a CSFP implementation in 2015, right in the middle of 2010 to 2020 where we have the panel data, thus granting us enough pre-treatment and post-treatment period and to finally get a glimpse of the true policy effect on the early adopters.

Therefore, This study intends to evaluate the impact of CSFP on:

1. smoking rate
2. cigarette consumption

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Difference in Differences (DiD), Revisit

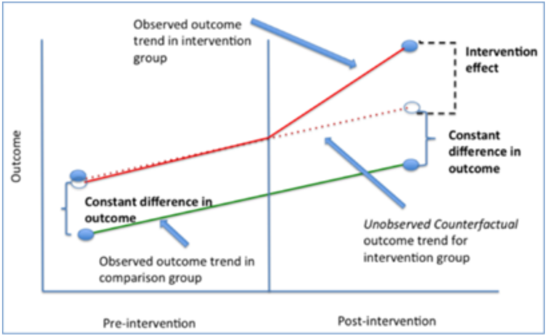

Figure: Difference-in-Differences estimation, visual[1]

[1] Columbia Public Health. (2022, April 15). *Difference-in-Difference Estimation — Columbia Public Health*. https://www.publichealth.columbia.edu/research/population-health-methods/difference-difference-estimation

Synthetic Control (SC), Revisit

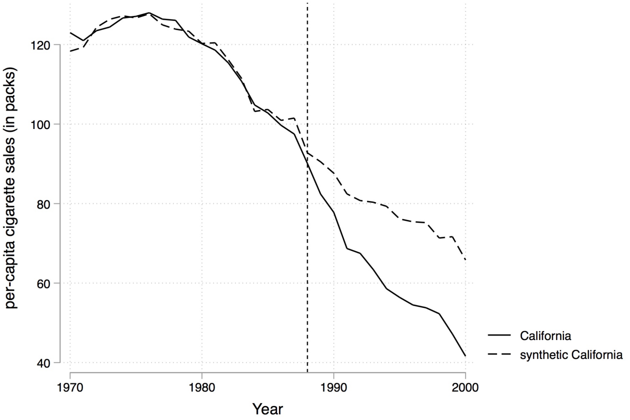

Figure: Synthetic Control estimation, visual[1]

[1] Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, 105(490), Article 490. https://doi.org/10.1198/jasa.2009.ap087466

Similarities between the DiD and SC Method

- DiD estimator can be recast it into the Two-Way Fixed-Effects formulation where we fit unit (α_i) and time averages (β_t), alongside the treatment indicator.

$$(\hat{\tau}^{did}, \hat{\mu}, \hat{\beta}) = \underset{\mu, \alpha, \beta, \tau}{argmin} \{\sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2\} \tag{1}$$

- Synthetic Control estimator can also be recast as solving the following optimization problem which looks similar to the one in DiD. The weights ($\hat{\omega}^{sc}$) for the control units are estimated through optimization as well.[1]

$$(\hat{\tau}^{sc}, \hat{\mu}, \hat{\beta}) = \underset{\mu, \beta, \tau}{argmin} \{\sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \beta_t - W_{it}\tau)^2 \hat{\omega}_i^{sc}\} \tag{2}$$

[1] Facure, Matheus. (2022) *Causal Inference for The Brave and True*. https://matheusfacure.github.io/python-causality-handbook/landing-page.html

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Synthetic Difference in Differences (SDiD)

Figure: Both Pills[1]

[1] Facure. (2022). *Causal Inference for The Brave and True.* https://matheusfacure.github.io/python-causality-handbook/landing-page.html

Synthetic Difference in Differences (SDiD), Cont'd

- Difference in Differences

$$(\hat{\tau}^{did}, \hat{\mu}, \hat{\beta}) = \underset{\mu,\alpha,\beta,\tau}{argmin} \{\sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2\} \tag{3}$$

- Synthetic Diff-in-Diff

$$(\hat{\tau}^{sc}, \hat{\mu}, \hat{\beta}) = \underset{\mu,\beta,\tau}{argmin} \{\sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \beta_t - W_{it}\tau)^2 \hat{\omega}_i^{sc}\} \tag{4}$$

- SDiD model added back the unit fixed effects (α_i) while keeping the unit weights ($\hat{\omega}^{sdid}$). Time weights $\hat{\lambda}_t^{sdid}$ were introduced into the equation.

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\beta}) = \underset{\mu,\alpha,\beta,\tau}{argmin} \{\sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \hat{\omega}^{sdid} \hat{\lambda}_t^{sdid}\} \tag{5}$$

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Statistical Analysis Plan

Primary Analysis: *Synthetic Difference-in-Differences Design (SDID)*

1. **Short-term effect:** using donors that did not enact a CSFP between 2010 to 2015.
2. **long-term effect:** use never-adopters as donors.
3. Statistical significance assessed through placebo tests

Sensitivity Analyses

1. **Fixed-effect regression:** we identified the correlation between the proportion of the population covered by the CSFP within a province and outcomes of interest.
2. **Leave-one-out analyses:** an iterative process where a weighted donor was removed from the pool, a new synthetic control was generated, and treatment effects estimated.

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Data

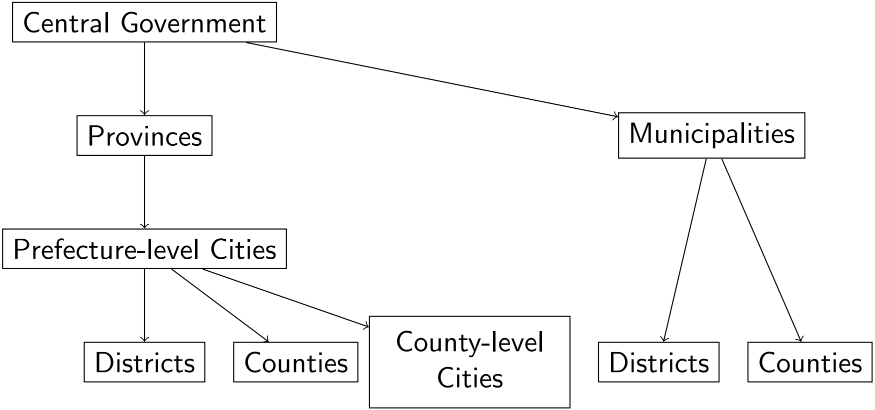
Data Source: China Family Panel Studies (CFPS) from 2010 to 2020 (a biennial survey)

Outcome: smoking rate and smoking amount

Treated unit: a surveyed district in Beijing (the name of the district is indexed given the privacy protection policy with the CFPS data)

Donor units: Chinese district/county level units with over 100 participants surveyed who has not been treated with CFPS. In this study, we included 72 donors for short-term and 63 donors for long-term estimation.

Administrative Structure



CFPS sampled at the **district-level** in Beijing (a municipality)
Therefore, we chose donors at this administrative level

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Spaghetti Plots

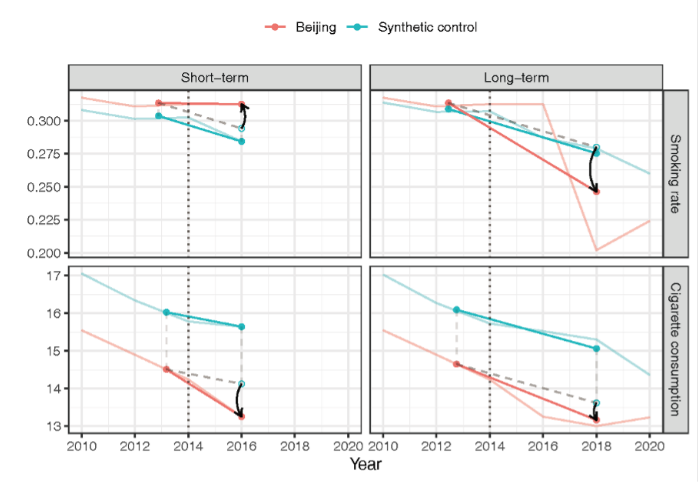

Figure: Summary of spaghetti plots for all SDID models

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Summary of Results

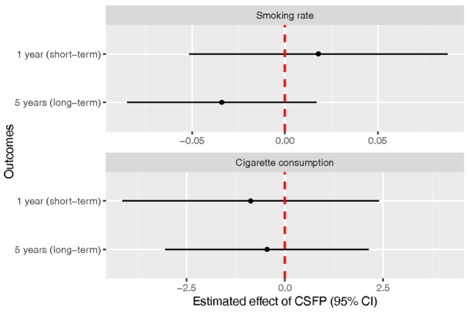

Figure: CSFP policy impact on the smoking rate and cigarette consumption over time

SDID Group	Smoking Rate (95% CI)	Smoking Amount (95% CI)
Short-term (one year after policy)	0.018 (-0.052 to 0.088)	-0.872 (-4.138 to 2.394)
Long-term (five years after policy)	-0.034 (-0.085 to 0.017)	-0.454 (-3.043 to 2.135)

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Sensitivity Analysis

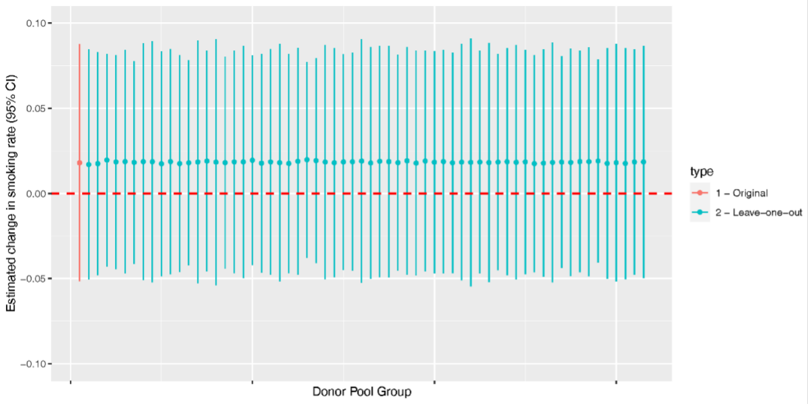

Figure: Leave-one-out SDID estimation of change in short-term smoking rate

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Sensitivity Analysis, Cont'd

Fixed-effects regression across time found **statistically significant correlations** between the provincial-level smoking rate ($p<0.001$) / cigarette consumption ($p<0.01$) and the percentage of the population covered by the CSFP in each province.

Intuition

That is, if the CSFP coverage moves from 0 to 100% of a province, the change is associated with:

1. a reduced smoking rate of 5.8%
2. a reduction of 2.16 cigarettes per smoker smoked per day

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Insights from the analyses

- Combining the SDiD model and regression resuts, we noticed that the limited policy effect in Beijing compared to late adopters may be due to its previous partial smoke-free policy.
- CSFP may lack the capacity to affect "stubborn smokers" given the decrease in smoking rate but not the smoking amount among the smokers.

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Strengths and Limitations

Strength

1. By adding weights to both units and time via an SDiD design, we constructed a valid counterfactual for policy impact evaluation.
2. Studying smoking-related topics in China is difficult given the limited data access. Nevertheless, this research leverages the best smoking-related open-access data to implement a quasi-experimental design.

Limitations

1. County level data collected were not self-representative by the survey design, hampering internal validity.
2. This study only analyzed six time points (three pre-intervention) hence, the estimate via SDID could be less precise.
3. Finally, while using the county-level CSFP-free donor pool is appropriate given the basic requirements by the SDID methodology, the SDID model may yield less valid comparisons due to the highly unbalanced development across China.

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Conclusion

Although no statistically significant result was identified with SDID models, we found **some suggestive evidence that the policy impact on long-term smoking rate.** The validity of this estimation is backed by:

1. substantial numerical reduction in smoking rate
2. consistent estimates in leave-one-out analyses
3. statistically significant negative correlations found between provincial CSFP coverage and both the smoking rate and cigarette consumption in the fixed-effect regressions

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Future

1. A national-level CSFP is recommended for improving population health.
2. Future studies with more detailed and higher quality data to confirm the comprehensive smoke-free policy impact found in this study and further investigation into its implementation status in China are warranted.

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