Discussion

Today's Goal

A brief survey and practical introduction to the

- Core concepts
- Key assumptions
- Different statistical methods

used to evaluate the **causal effects** of **policy interventions**

Disclaimer:

We took a "wide" instead of "deep" view

Many details / extensions / advanced topics omitted!

Control Units

# Time-Points	0	1	Many
2	Post - Pre (inference only with multiple treated units)	Diff-in-Diff (inference only with multiple treated units)	Synthetic Diff-in-Diff, Matching DID
Few (>2)	Regression Discontinuity Design, Post - Pre	Diff-in-Diff (inference based on time-averages)	Synthetic Control
Many	Interrupted Time Series (ITS)	Controlled Interrupted Time Series (CITS)	Synthetic CITS Synthetic Control

Connections to other methods

Synthetic Control type methods are conceptually and practically similar to **matching techniques**

- Often used in causal inference; match similar treated and untreated units

DiD analysis often applied with **multiple treated units** (averages)

Synthetic Diff-in-Diff (Arkhangelsky et al. 2021)

- combines DiD and Synthetic Control

Advanced Topics / Open Questions

How to deal with interventions which are not “sharp”?

- E.g. policy may be gradually introduced / rolled out
- Some policies may have an “anticipatory” effect; people stop smoking because cigarettes are about to get more expensive
- Here fuzzy-RDD type analyses may be helpful. OR explicit modelling of intervention effect.

How to deal with multiple treated units?

- Aggregating vs not-aggregating
- Classic approach is to take means, estimate ACEs. Less data + assumption “hungry” but information is lost
- If you have enough data to perform, e.g., synthetic control analysis, may be better to first estimate unit-level effects, then summarize

Advanced Topics / Open Questions

What questions / problems do you run into, that we didn't manage to cover in class?

https://app.wooclap.com/ZHSIPT

Summary

Many different methods have been developed to answer these types of research questions

These methods differ in terms of:

- The **amount** and **type** of information they use
    - Amount of time-points and amount of potential “control” units
- The specific **statistical approach** they take
- The types of **assumptions** they make

So, which method should I use?

So which method should I use?

In this workshop we took a rather statistical view of this question

- The answer **in part** depends on what type and amount of data you have
- But this is the **easy part**

The answer in practice depends on **domain knowledge**

- The **hard part** is to figure out which **assumptions** you need for causal inference and whether they are reasonable in your particular use case
- <u>It may simply not be possible in some cases!</u>
- E.g. DiD won't work if trends are not parallel; synthetic control won't work if there is interference between units (no matter how much data you have!)
- Often, methods which are "data hungry" can relax some assumptions, but:

<u>There is no free lunch!</u>

Other dimensions to keep in mind

Interpretability of the model

- Nice to know/ understand where inferences are coming from
- Some methods better than others (e.g. synthetic control more understandable than CausalImpact)

Sensitivity / Robustness / Researcher Degrees of Freedom

- How many arbitrary choices do you have to make?
- How much do the results change if you make a different choice?
- In practice, perform sensitivity checks whenever you can

Useful References

Difference in Differences

Angrist, J. D., & Krueger, A. B. (1999). Empirical strategies in labor economics. In Handbook of labor economics (Vol. 3, pp. 1277-1366). Elsevier.

Angrist, J. D., & Pischke, J. S. (2009). Mostly harmless econometrics: An empiricist's companion. Princeton university press.

Caniglia, E. C., & Murray, E. J. (2020). Difference-in-difference in the time of cholera: a gentle introduction for epidemiologists. *Current epidemiology reports*, *7*, 203-211.

Interrupted Time Series

Bernal, J. L., Cummins, S., & Gasparrini, A. (2017). Interrupted time series regression for the evaluation of public health interventions: a tutorial. International journal of epidemiology, 46(1), 348-355.

Bernal, J.L, Cummins, S., & Gasparrini, A. (2019). Difference in difference, controlled interrupted time series and synthetic controls. International journal of epidemiology, 48(6), 2062-2063.

Useful References

Synthetic Control

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), 493-505.

Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. Journal of Economic Literature, 59(2), 391-425.

CausalImpact

Brodersen, K. H., Gallusser, F., Koehler, J., Remy, N., & Scott, S. L. (2015). Inferring causal impact using Bayesian structural time-series models. The Annals of Applied Statistics, 247-274.

Linden, A. (2018). Combining synthetic controls and interrupted time series analysis to improve causal inference in program evaluation. Journal of evaluation in clinical practice, 24(2), 447-453.

http://google.github.io/CausalImpact/CausalImpact.html

Useful References

Synthetic DiD

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., & Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review*, *111*(12), 4088-4118.

More on Causal Policy Evaluation

Free online course materials made by Andrew Heiss

Program Evaluation for Public Service

https://evalf22.classes.andrewheiss.com/content/

Thanks!

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