Discussion

This morning

A brief practical introduction to the

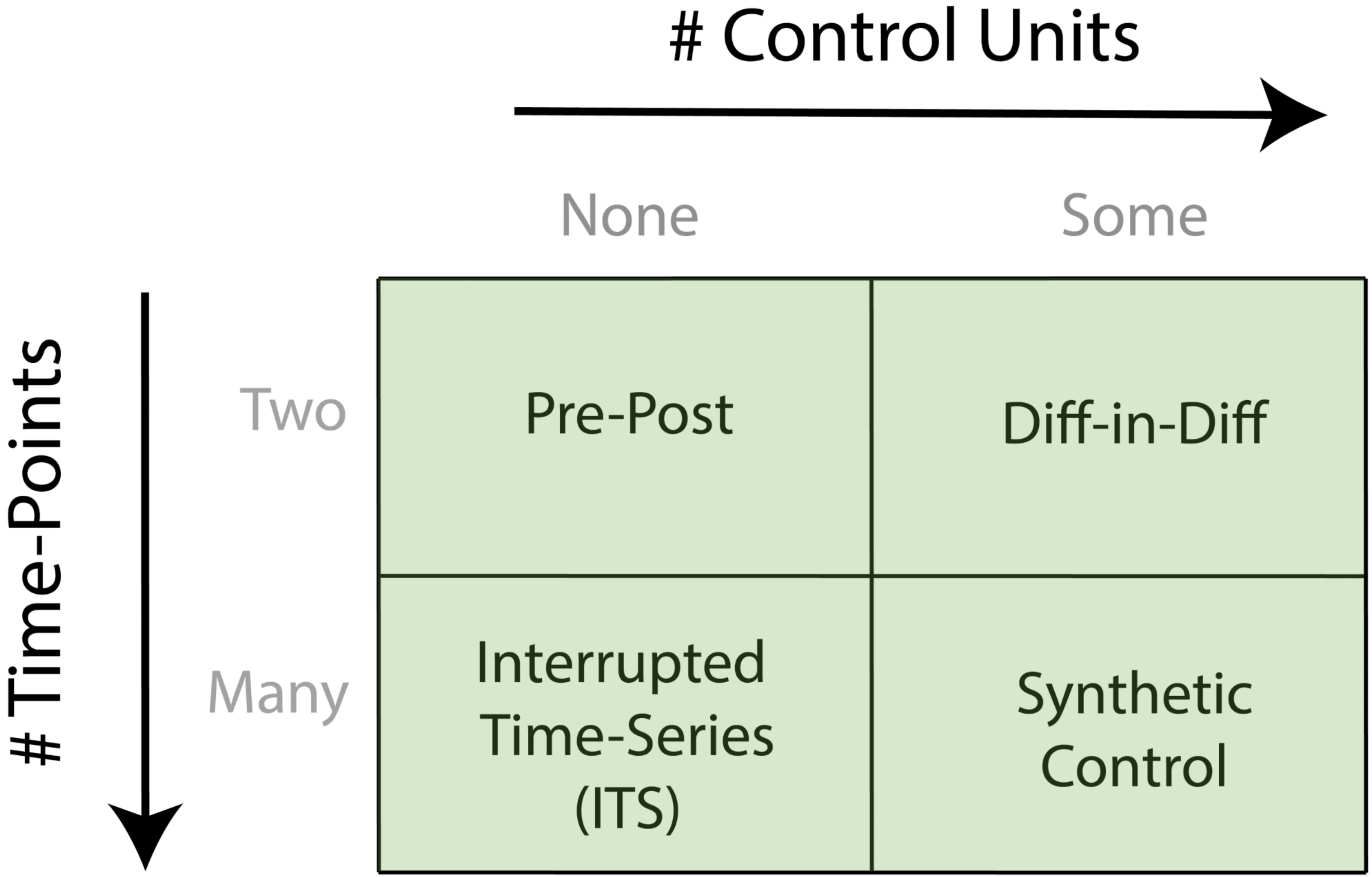
- Core concepts
- Key assumptions
- Different statistical methods

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

Disclaimer:

We took a “wide” instead of “deep” view

Many details / extensions / advanced topics omitted!

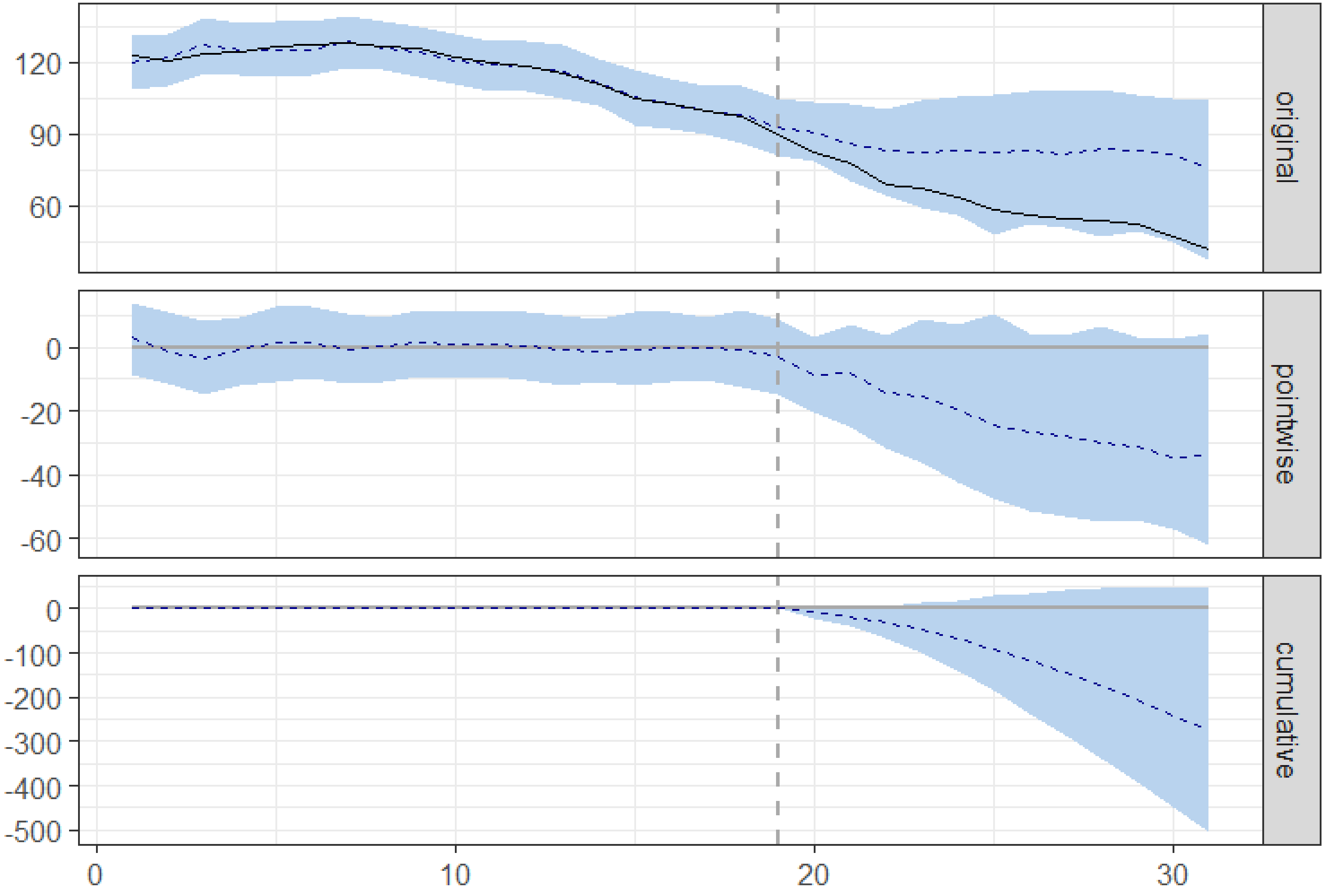


Control Units
None
Some
Time-Points
Two
Many
Pre-Post
Diff-in-Diff
Interrupted Time-Series (ITS)
Synthetic Control

Combining ITS & Synth. Control

- Controlled Interrupted Time Series

- CausalImpact



Advanced Topics / Open Questions

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

- Policy may be gradually introduced / rolled out
- Policy may have an “anticipatory” effect;
  stop smoking because cigarettes will get more expensive
- “Fuzzy” regression discontinuity analysis OR explicit modelling of intervention effect.

How to deal with multiple treated units?

- Aggregating vs not-aggregating
- Classic approach is to take means, estimate ACE.
- Enough data for synthetic control, first estimate unit-level effects, then summarize?

So, which method should I use?

In this session we took a statistical view of this question

- **in part** depends on type and amount of data
- 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
- It may simply not be possible in some cases!
- 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:

There is no free lunch!

Stay in touch!

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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/