

Heterogeneity-Robust Spatial Synthetic Controls

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Table of Contents

1. The Idea
2. Generating Synthetic Controls
3. Heterogeneous Treatment Effects
4. Heatwave Application
5. Conclusion and Discussion

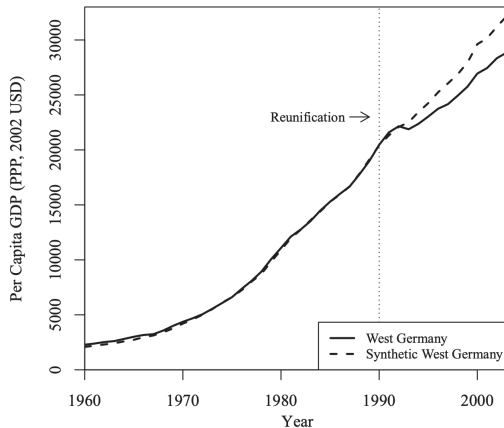
The Idea

Disclaimer

- This is a collection of preliminary ideas.
- The purpose of this presentation is to receive constructive criticism on many of these thoughts!
- My goal is to develop this project into a paper in graduate school!

Conventional Synthetic Controls

- Recover causal effects when no/ few untreated comparison units are available.
- Construct synthetic control units via pre-treatment/ exogenous characteristics
- Relies on parallel trends assumption



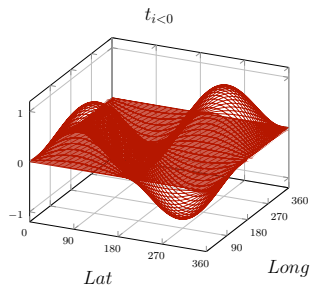
[Abadie et al., 2015]: German Reunification

A Three-Dimensional Extension

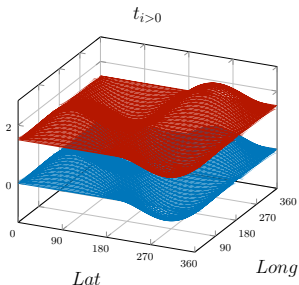
- **Hypothesis:** The GDP effect of German reunification is not uniform across every state
 - Treatment effect heterogeneity?
 - Complex spatial relationships?
 - Information loss during data aggregation?
- Spatial Synthetic Controls (SSC) adds a spatial dimension to the *conventional* Synthetic Controls (SC) method
 - Disaggregation of information in the spatial dimension
 - Refine the average (ATE) to conditional (CATE) treatment effects
 - Causal inference in high-dimensional space

A Three-Dimensional Extension: Visualization

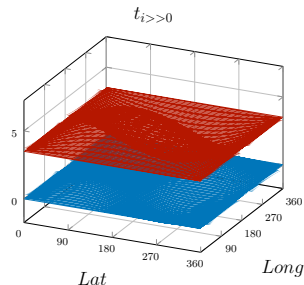
Treatment occurs at $t_i=0$. Let us consider three scenarios:



Pre-treatment, no treatment
response



Post-treatment,
homogeneous response

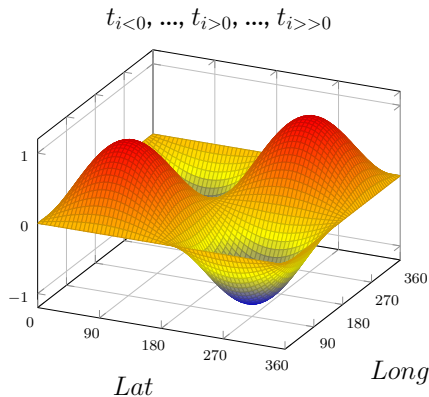


Post-treatment,
heterogeneous response

Generating Synthetic Controls

Requirements for the Prediction Algorithm

1. Model non-linear relationships well
2. Robust to unobservables ("heterogeneity-robust") across spatial and temporal dimensions
3. Suitable for high-dimensional space



Note: This problem is currently at the forefront of statistical research. If I had a definitive solution, I would be resting on my laurels right now.

Solutions?

Machine Learning	Non-Parametric	Dimensionality Reduction
Strong predictive performance in non-linear relationships	Robust to violations of functional form assumptions	Absorb temporal dimension into fixed effect.

Inspiration from Literature

- [Pouliot, 2022]
 - Krig-and-regress method for spatially misaligned data
 - Introduces Kriging (prediction) method into spatial econometrics
 - Relevant discussion on interpolation, aggregation, and spatial filtering techniques
- [Serra-Burriel et al., 2020]
 - Estimate the effects of wildfires on vegetation
 - An application of spatial synthetic controls, though treatment is discrete and units are static
 - Use of Nuclear Norm Matrix Completion Method (see, [Athey et al., 2021])

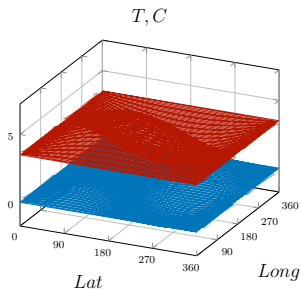
Heterogeneous Treatment Effects

A Set of Spatial Treatment Effects

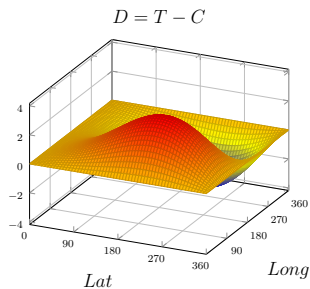
- Assume we have finite spatial grid which is divided in $i*j$ grids, where $i \in Lat$ and $j \in Long$.
- Then, we can obtain a set of treatment effects $D = \{\delta_{1,1}, \delta_{2,1}, \delta_{1,2}, \dots, \delta_{i,j}\}$ by subtracting synthetic untreated outcomes in observed treated outcomes at position i, j .
- Commonly, it is assumed that all elements of D are constant over space. This assumption does not hold in spatially heterogeneous settings.

Reporting Heterogeneous Treatment Effects

The set of treatment effects D at time t_i may be spatially heterogeneous:



Treated (T), Control (C)



Treatment Effects (D)

Reporting Heterogeneous Treatment Effects

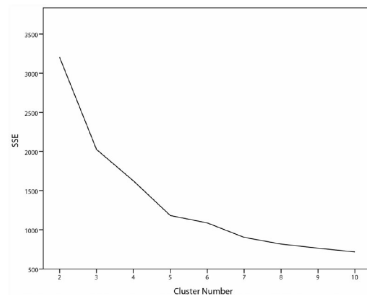
- How do we report these heterogeneous treatment effects?
 - Individual Treatment Effect: We report $\delta_{i,j}$ for $\forall i, j$.
 - Average Treatment Effect: We report $\frac{1}{n} * \sum(\delta_{i,j}) \forall i, j$.
- The options are unrealistic and uninformative, respectively. Therefore, can we find a good middle ground?

Formally: We are looking to report the average of k subsets of D , where $1 < k < n$ in a plane with n grids.

The Clustering Problem

Rather than pre-define the reporting veracity (e.g., zip code), a clustering approach may allow the data to tell the whole story.

- How do we find the optimal k ?
- Problem: As n increases, the error function monotonically decreases
- Formally: $\nexists k$ s.t. $\operatorname{argmin}_k(\text{Error})$, outside of $k = n$.

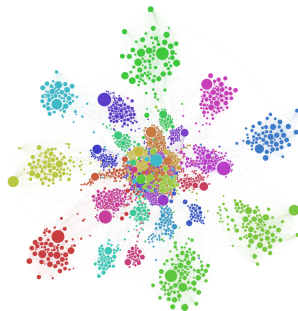


Trade-Off: SSE vs. Cluster

A Solution?

Rather than pre-define the reporting veracity (e.g., zip code), a clustering approach may allow the data to tell the whole story.

- Methods to find k : Elbow, Silhouette, etc.
- Problem: Curse of dimensionality!
- Uncertain: Is time really that important in short time horizons?

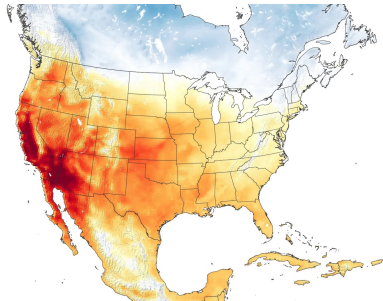


High-dimensional Clustering

Heatwave Application

Motivation

- Measuring the effect of climate disasters
 - Experimental approaches - if not unethical - are nearly impossible
 - Researchers are stuck with observational data
 - Recovering robust causal effects is critical policy input

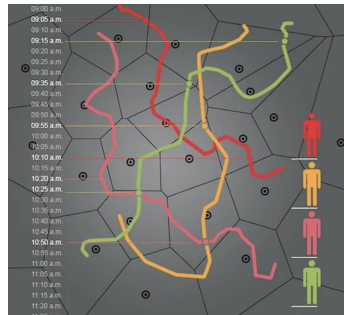


Application: How do we measure the effect of heat waves on community health?

U.S. Cell Phone Ping Data

Access to cell phone ping data: Unique opportunity to analyze spatial settings where units are not bound to spatial location.

- Consider a densely populated area:
- Idea 1: Measure whether individuals visit hospitals via cell phone pings (Problem: Ping Irregularity)
- Idea 2: Measure the *dispersion effect* of heat waves





Conclusion and Discussion




Further Extensions

- Continuous treatment (consider [Callaway and Sant'Anna, 2021])
- Recent advances in spatial treatments (see, M. Pollmann)
- Digging into high-dimensional prediction and clustering

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