

# ORIE 5355

## Lecture 15: Synthetic control

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# Announcements

- HW 4 due tomorrow
- Quiz 4 tomorrow through Friday
- Guest lecture this evening, 7:30pm – 8:30pm over zoom

Experimentation culture

# General pipeline of launching a product

- Come up with idea, iterate on design
- Code it up, and evaluate on simulator
- Test in real experiment in one city/market
- If that goes well over time, roll out in multiple markets
- Continue rolling out in more and more markets
- Eventually, will have rolled out everywhere



THE INVENTION OF CLINICAL TRIALS

[xkcd: Clinical Trials](#)

# Universal holdout

Downsides of standard approaches:

- Test one product at a time
- Usually enroll as few users as possible (don't want to waste sample size)
- Experiments are usually short → Don't observe long-term metrics

What if you want to know, “What is the total effect on everything I launched last quarter on customer retention?”

Solution: **Universal holdout**

- Each quarter (or month or year...), hold out same set of users from *every product* you launch that quarter
- End of quarter, compare metrics for that group to all other users; re-enroll a new set of universal holdout for next quarter

# Experimentation summary so far

- Classic A/B Test
- In social networks and marketplaces, *interference* ruins tests
  - Social networks: Social effect; Me getting treatment effects you
  - Marketplaces: Competition and scarcity introduces interference
- Experiments in the face of interference:
  - (Spatial or Graph-based) Cluster randomized assignment
  - Time-based experimentation: Switchbacks
- Causal inference without experiment: Synthetic control
- Naïve peeking in experimentation is bad, but can be done smartly

# Experimentation summary so far

## Several different experimental designs

- Classic, individual level A/B testing
- Graph cluster randomization
  - More generally, *spatial* randomization
- Switchbacks: randomization over time

## These experimental techniques are not workable sometimes

- Product is “public-facing” – hard to roll back
- Interference really network/city wide, so spatial randomization less effective
- Sensitive change, so can’t launch in many cities at once
- It takes a long time for effect to occur

Today: “synthetic control”

Synthetic control



# Synthetic control is important

“The gold standard for drawing inferences about the effect of a policy is a randomized controlled experiment.”

“However, in many cases, experiments remain difficult or impossible to implement, for financial, political, or ethical reasons, or because the population of interest is too small.”

Synthetic control “is arguably the most important innovation in the policy evaluation literature in the last 15 years”

# Recently used to study...

**In academia:** gun laws, immigration policy, minimum wage, taxation, organized crime...

- What is the effect of a minimum wage increase?
- What is the effect of more immigration into a city?

**Outside academia:** “multi-lateral organizations, think tanks, business analytics units, governmental agencies, and consulting firms”

- Bill & Melinda Gates Foundation
- Tech companies

“Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspect.” Alberto Abadie, 2021

# Synthetic control: Setting

Suppose running standard experiments is hard:

- Product is “public-facing” – hard to roll back
- Interference really network/city wide, so spatial randomization less effective
- Sensitive change, so can’t launch in many cities at once
- It takes a long time for effect to occur

So, you decide to launch in just 1 city

- This is the treatment city... so what is the control?
- Why do we need a control?

want to measure global treatment effect:  $Y_1 - Y_0$

“what would have happened to this city if I didn’t launch the treatment?”

# Possible controls

**Example:** Suppose you're launching a product at time  $T$  in Miami, and your platform also has users in Houston, Atlanta, and Orlando

What are possible controls? ( $Y_0$ )

- The same city (Miami) from time  $0$  to time  $T$   
Problem: seasonality!
- Seasonality-adjusted Miami  
Problem: unforeseen events (Covid)
- Pick one of: Houston, Atlanta, Orlando from time  $T$  to time  $2T$   
Hope: Seasonality/Covid affects control city similar to how it affects Miami  
Challenge: Which city do I pick?  
Problem: No city is perfect analogue



# Main Idea

**Problem with using past Miami (from time 0 to time T):** Time matters; future might be different than past, for reasons nothing to do with treatment

**Problem with using Houston (from time T to time 2T):** Geography also matters; Houston is not Miami

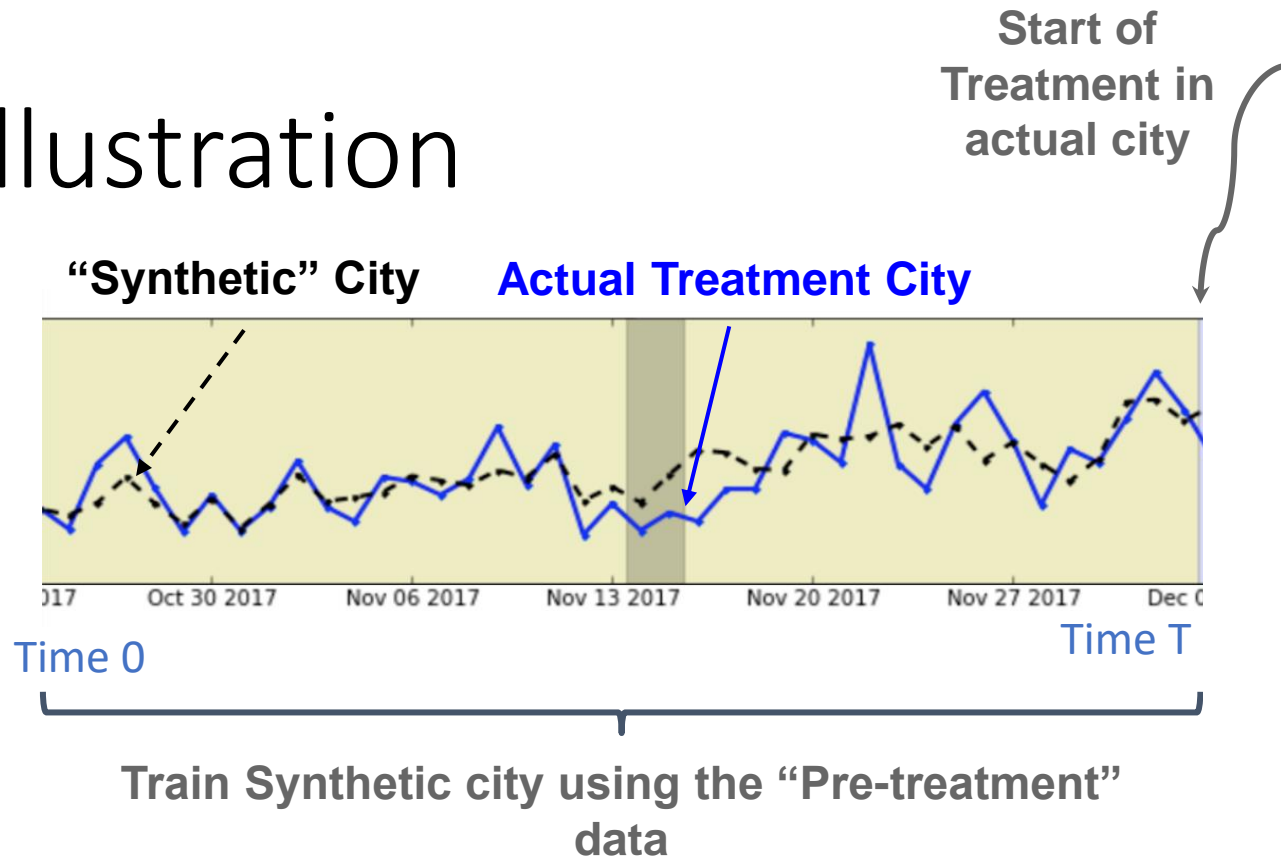
(differs from Miami even in observed past, from time 0 to T)

**Synthetic control main idea:** Use a weighted average of Houston/Orlando/Atlanta, from **time T to time 2T**

Design weights such that “Synthetic Miami” matches real Miami in past (**0 to T**)

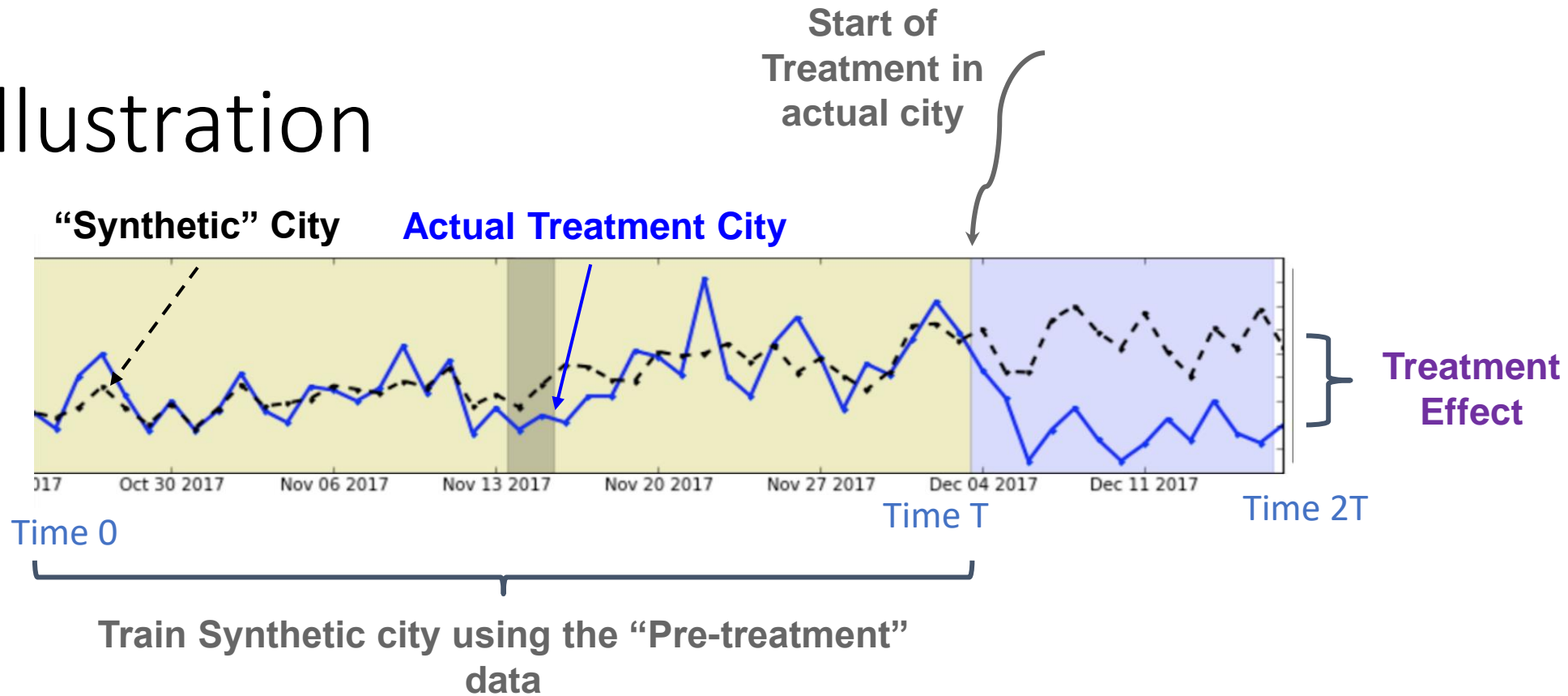
Hope: That Synthetic Miami in future (**T to 2T**) behaves like what Miami would have behaved like if you didn't launch the treatment

# Illustration



**Step 1:** Train a synthetic city using past data, such that synthetic city and actual treatment city match when *neither* is in treatment

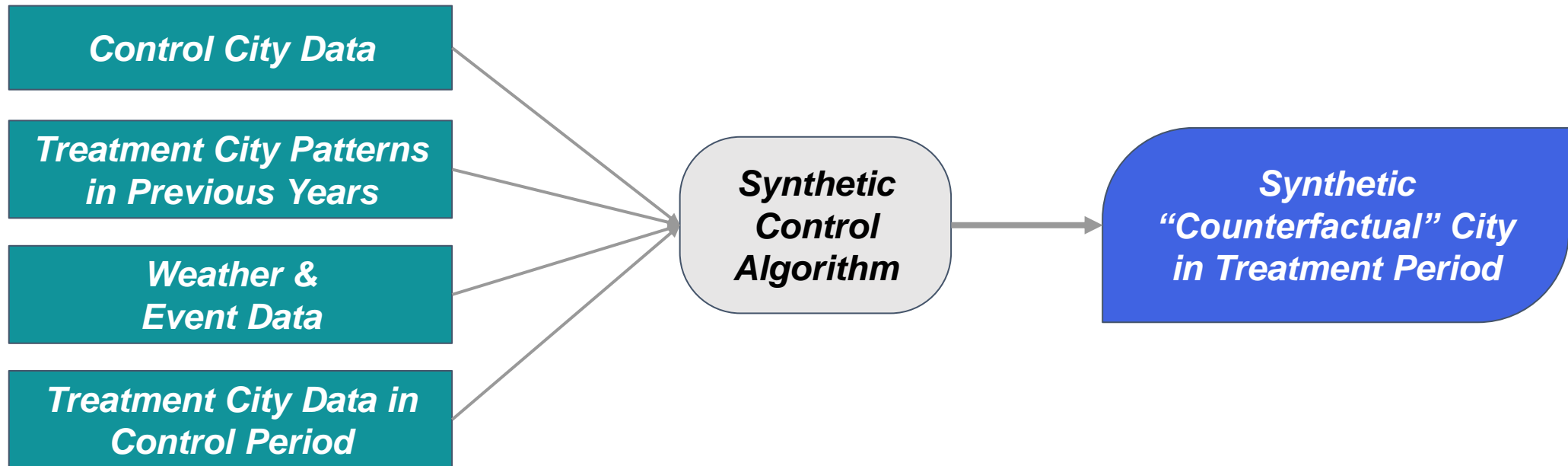
# Illustration



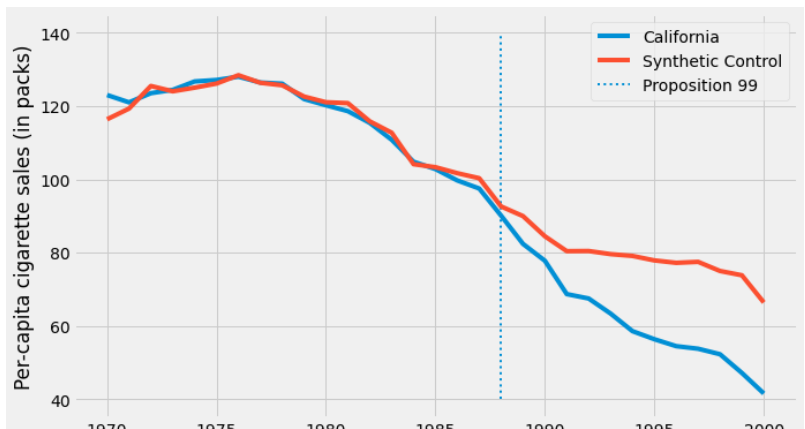
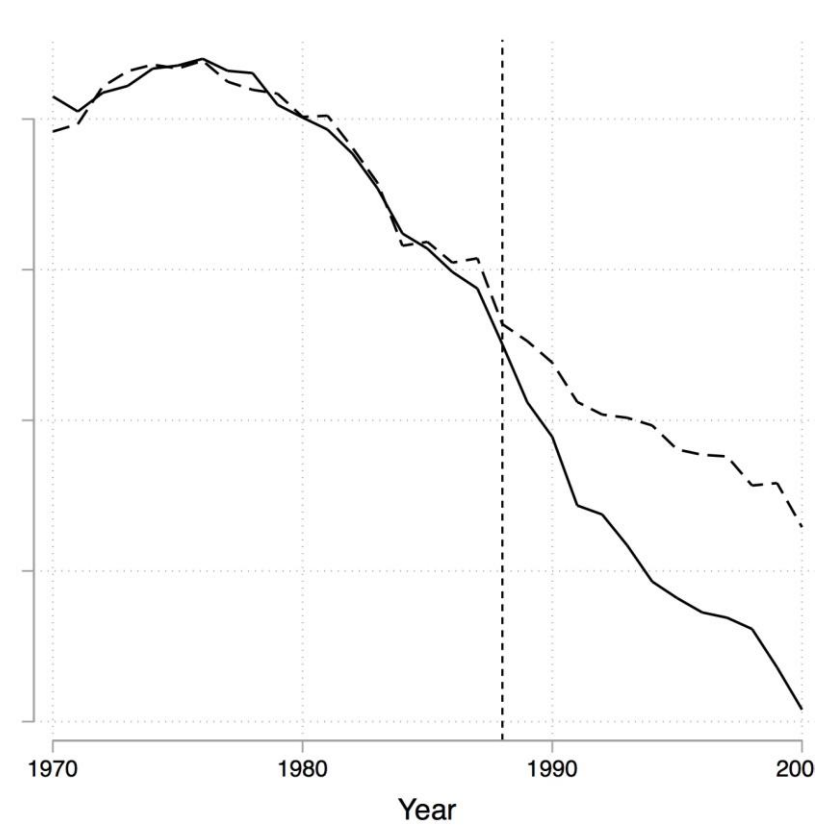
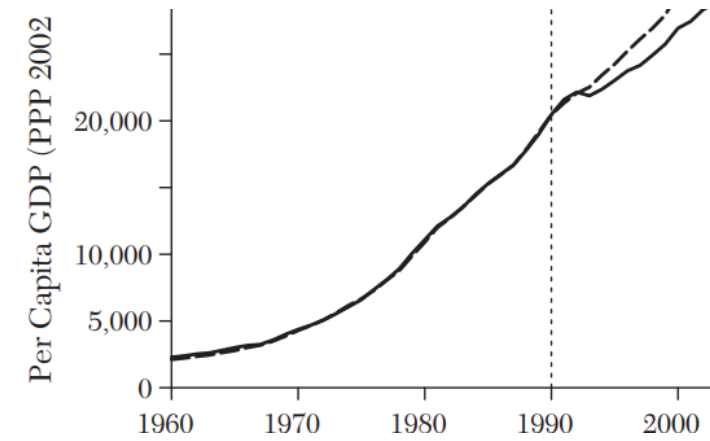
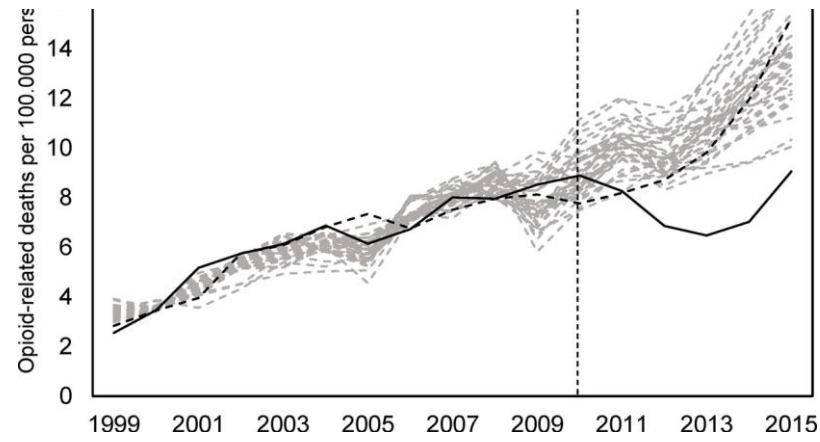
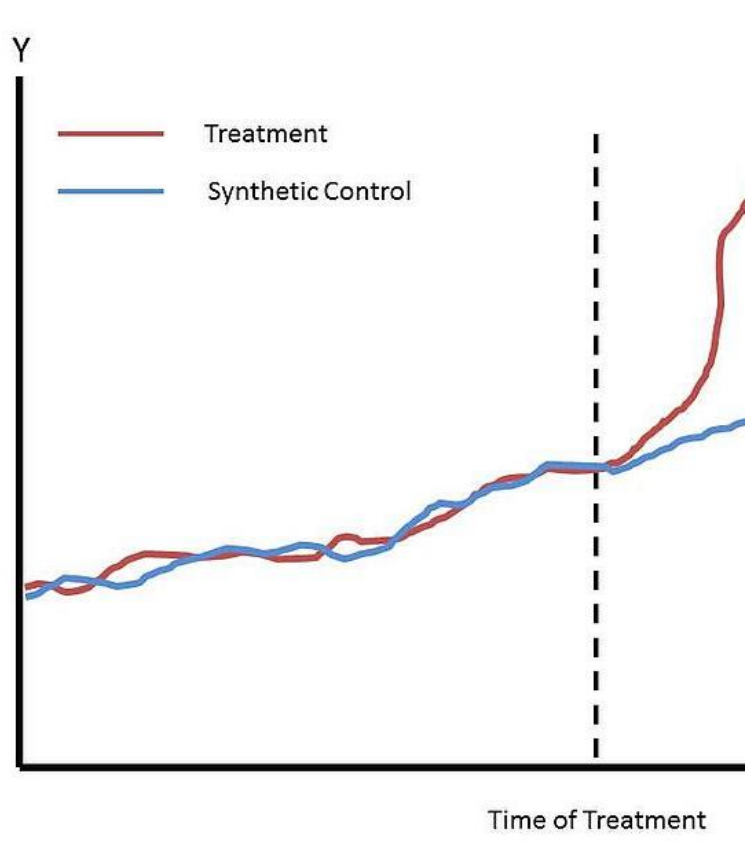
**Step 2:** Launch experiment in just 1 city, and calculate treatment effect as difference between synthetic city and the actual measurement in treatment city

# How does Uber form their synthetics?

They use a model to “forecast” outcomes in our target treatment city, using only data from control cities, weather and events, and previous year’s data in that city:







Classic synthetic control plot

# Warning

“At the same time, the **validity of synthetic control** estimators **depends on important practical requirements**. **Perfunctory applications** that ignore the context of the empirical investigation and the characteristics of the data **may miss the mark, producing misleading estimates.**”

“Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspect.” Alberto Abadie, 2021

## Challenges

- Overfitting during training period (have a “validation” period)
- What if something happens during treatment? (hurricane in Miami)

Miscellaneous topics in  
experimentation

# Ethics and Communication

When is an experiment unethical to run?

What if your strong intuition is that the new product is bad?

- Challenge trials in medicine: very controversial, especially during Covid
- Can you purposely degrade your product to evaluate how it usually performs?

What if Uber purposely broke surge during New Years?

What if your strong intuition is that the old product is bad?

Should you launch the replacement product immediately, or can you experiment first?

"Objecting to experiments that compare two unobjectionable policies or treatments" PNAS, Michelle Meyer et al. 2019

# Various treatment effects

- So far we've discussed the “Global Average Treatment Effect” (GATE)  
How does the world where *everyone* receives the treatment, compare to the world where *everyone* receives the control?
- If there is no interference (and 1 more condition; SUTVA), this is equal to the “Average Treatment Effect” (ATE)  
On average, if *I* receive the treatment, how does that compare to if *I* received the control?
- “Local Average Treatment Effect” (LATE) or “Complier ATE” (CATE)  
Example: if treatment is *access to vaccine*, CATE only counts as treated those who *take* the vaccine; ATE would count everyone given *access*
- *Heterogeneous treatment effect:*
  - *What if the treatment effect differs for different sub-populations?*
  - Example: Giving students coupons to Broadway shows vs giving professors coupons