Synthetic Control (Sam's Version)

ILRST/INFO/STSCI 3900: Causal Inference

12 Nov 2024

Learning goals for today

At the end of class, you will be able to:

1. Explain the intuition behind synthetic control
2. Understand how synthetic control relates to other causal inference methods

Logistics

- This week, read Ch 10 of The Causal Inference Mixtape
- Problem Set 5 peer reviews due Nov 15
- Task 3 and 4 Check-in (assigned Nov 5, due Nov 17)
- In class project check-ins next week
- Problem Set 6 (assigned Nov 14, due Nov 21)

What is the effect of personal events on google searches?

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- Who was the last celebrity you googled?
- What do you usually google about celebrities?

NFL Top 100

Before the start of each season, all current NFL players vote on the top players

(1) Mahomes

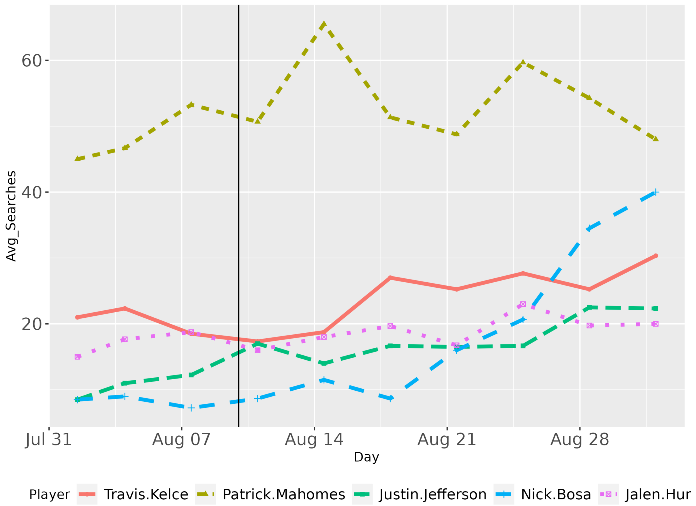
(2) Jefferson

(3) Hurts

(4) Bosa

(5) Kelce

Google searches for NFL players



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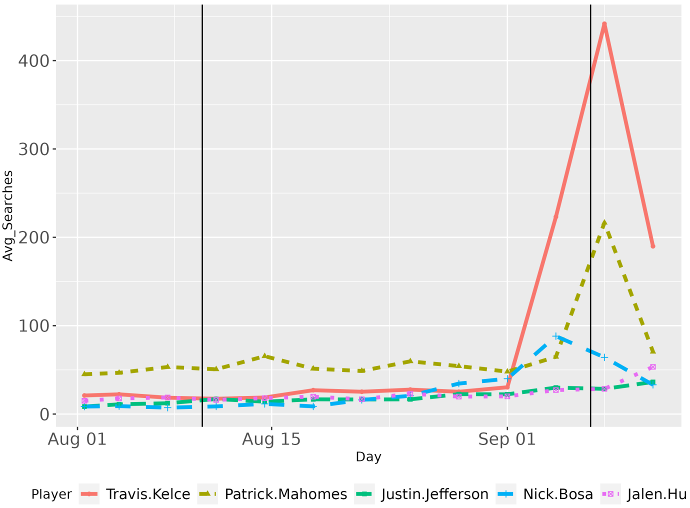

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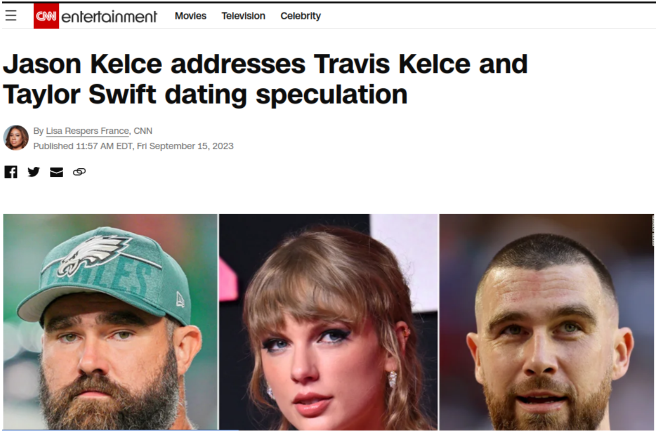
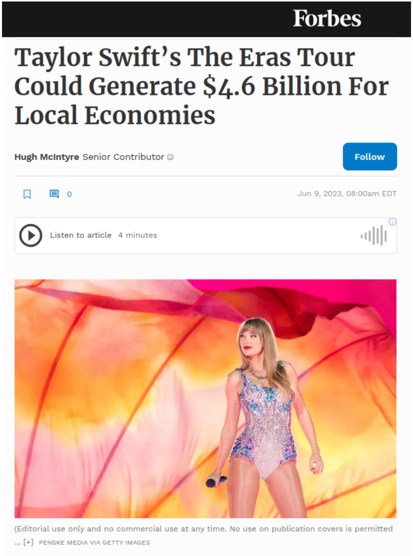


CNN entertainment Movies Television Celebrity

Jason Kelce addresses Travis Kelce and Taylor Swift dating speculation

By Lisa Respers France, CNN
Published 11:57 AM EDT, Fri September 15, 2023

Google searches for NFL players



Forbes

Taylor Swift's The Eras Tour Could Generate $4.6 Billion For Local Economies

Hugh McIntyre Senior Contributor

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Jun 9, 2023, 08:00am EDT

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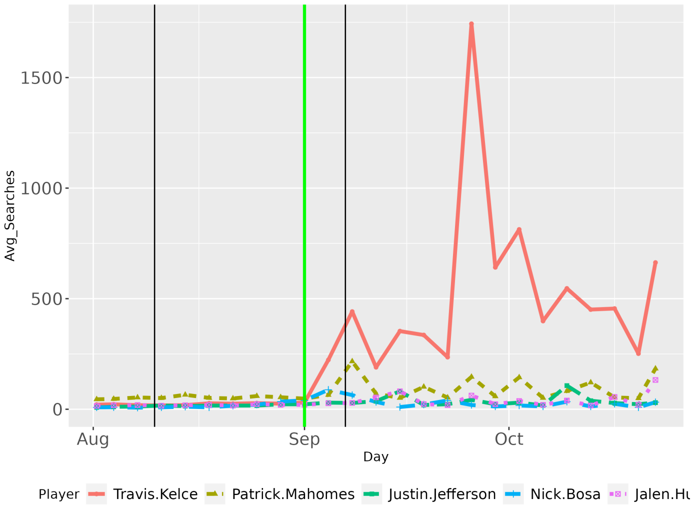
Google searches for NFL players



Google searches for NFL players

What is the causal effect of dating Taylor Swift on google searches?

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- Causal effect may vary over time

Google searches for NFL players

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- Causal effect at time t

$$\tau_{t,Kelce} = Y_{t,Kelce}^{\text{Swift}} - Y_{t,Kelce}^{\text{NoSwift}}$$

- For notation, let T_0 denote the time that the treatment occurs
- We observe $Y_{t,Kelce}^{\text{S}}$ for $t > T_0$ and $Y_{t,Kelce}^{\text{NS}}$ for $t < T_0$, but not at the same time!

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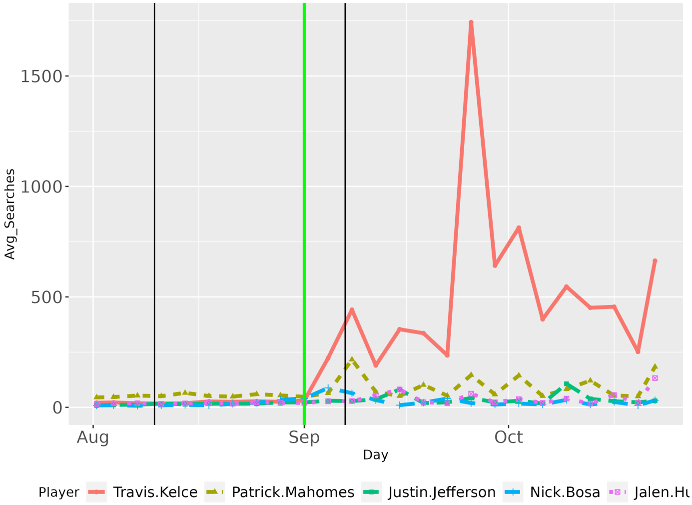
- Blank space in our data

Google searches for NFL players



- Kelce and Mahomes play for the same team
- Kelce and Jefferson play similar positions
- Kelce and Bosa both went to college in Ohio

Synthetic Control

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- Estimating the effect far away from the treatment seems iffy
- Kelce doesn't quite match any individual player exactly, but is similar to other players in different ways

Synthetic Control

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- We do observe $Y^{\mathrm{NS}}_{t,Mahomes}$, $Y^{\mathrm{NS}}_{t,Hurts}$, etc.

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- We don't observe $Y_{t,Kelce}^{\mathrm{NS}}$ after T_0
- We do observe $Y_{t,Mahomes}^{\mathrm{NS}}$, $Y_{t,Hurts}^{\mathrm{NS}}$, etc.
- Create a "synthetic" version of of Kelce by weighting other players

$$Y_{t,Kelce}^{\mathrm{NS}} \approx w_1 Y_{t,Mahomes}^{\mathrm{NS}} + w_2 Y_{t,Hurts}^{\mathrm{NS}} + w_3 Y_{t,Bosa}^{\mathrm{NS}} + w_4 Y_{t,Jefferson}^{\mathrm{NS}}$$

where $w_j \geq 0$ and $\sum w_j = 1$

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- So perhaps, Synthetic Kelce is
  - 50% Patrick Mahomes
  - 25% Justin Jefferson
  - 25% Nick Bosa
  - 0% Jalen Hurts

Synthetic Control

- Estimate counterfactual Travis Kelce $Y^{NS}_{t,Kelce}$ by using Synthetic Kelce

$$Y^{NS}_{t,Synthetic} = .5 \times Y_{t,Mahomes} + .25 \times Y_{t,Bosa} + .25 \times Y_{t,Jefferson}$$

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- Straightforward approach boils down to picking "good" weights

Picking Weights

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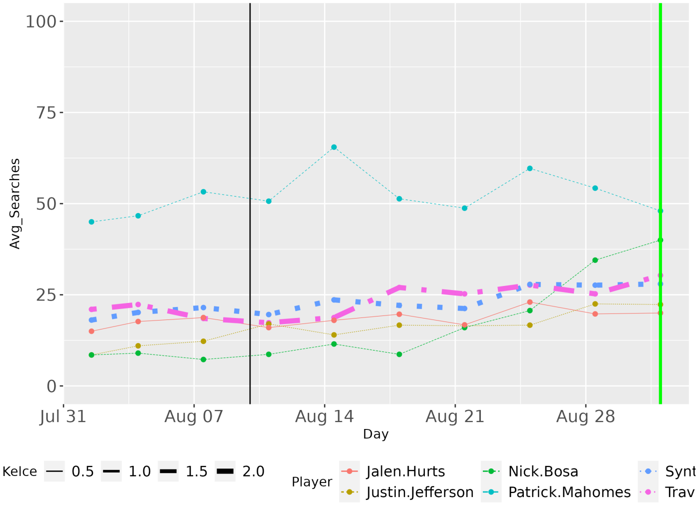
- Can also be selected to minimize discrepancy between other pre-treatment covariates (preview of discussion)

Synthetic Control



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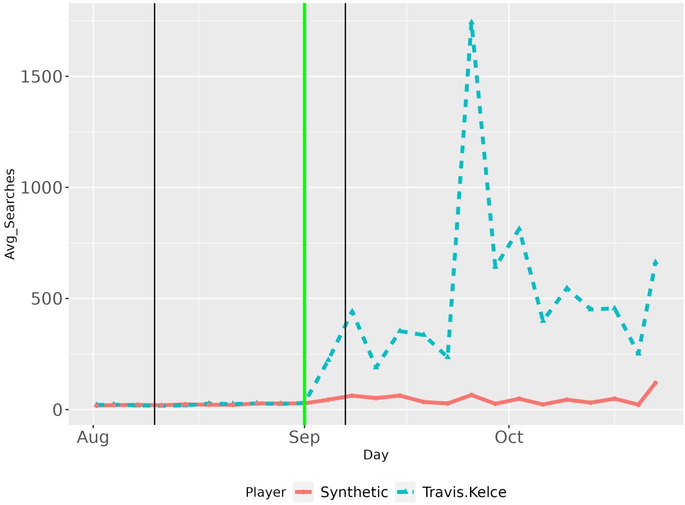

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Examples:

- What is the effect of political instability on the economy in Basque country in the 1960-70s?
  (Abadie and Gardeazabal 2003)
- What is the effect of a cigarette tax on smoking in California?
  (Abadie, Diamond, Hainmueller 2010)

Synthetic control and Matching

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In some ways, synthetic control can be seen as a specific form of matching

- Predict unobserved potential outcome using observed outcome of “similar” units
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- Synthetic control differs in how weights are chosen
- Data across time (longitudinal) so we also observed untreated outcomes of (eventually) treated unit
- Can directly match to minimize pre-treatment fit

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- Both have observations pre and post treatment
- Diff-in-Diff requires parallel trends assumption
- In synthetic control, we have a similar assumption, but parallel trends holds for synthetic unit
- Generally, Diff-in-Diff has fixed set of comparison units using prior knowledge (i.e., NJ vs PA)
- Synthetic control, we can start with a large "donor pool" and select weights using data

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