Synthetic control: A crash course

PSCI 2301: Quantitative Political Science II

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April 9, 2025

Today's agenda

We've seen diff-in-diff for use with panel data

But what if...

- there's only one treated unit?
- parallel trends is implausible?

Synthetic control designed to deal with this situation

- Find units with similar pre-treatment trends in outcome
- Use them to construct a "synthetic" counterfactual
- Like a comparative case study, but with a statistical selection of comparison

Motivating question: Effects of nonproliferation agreements

Japan 1972: Background

1964: China's first nuclear test

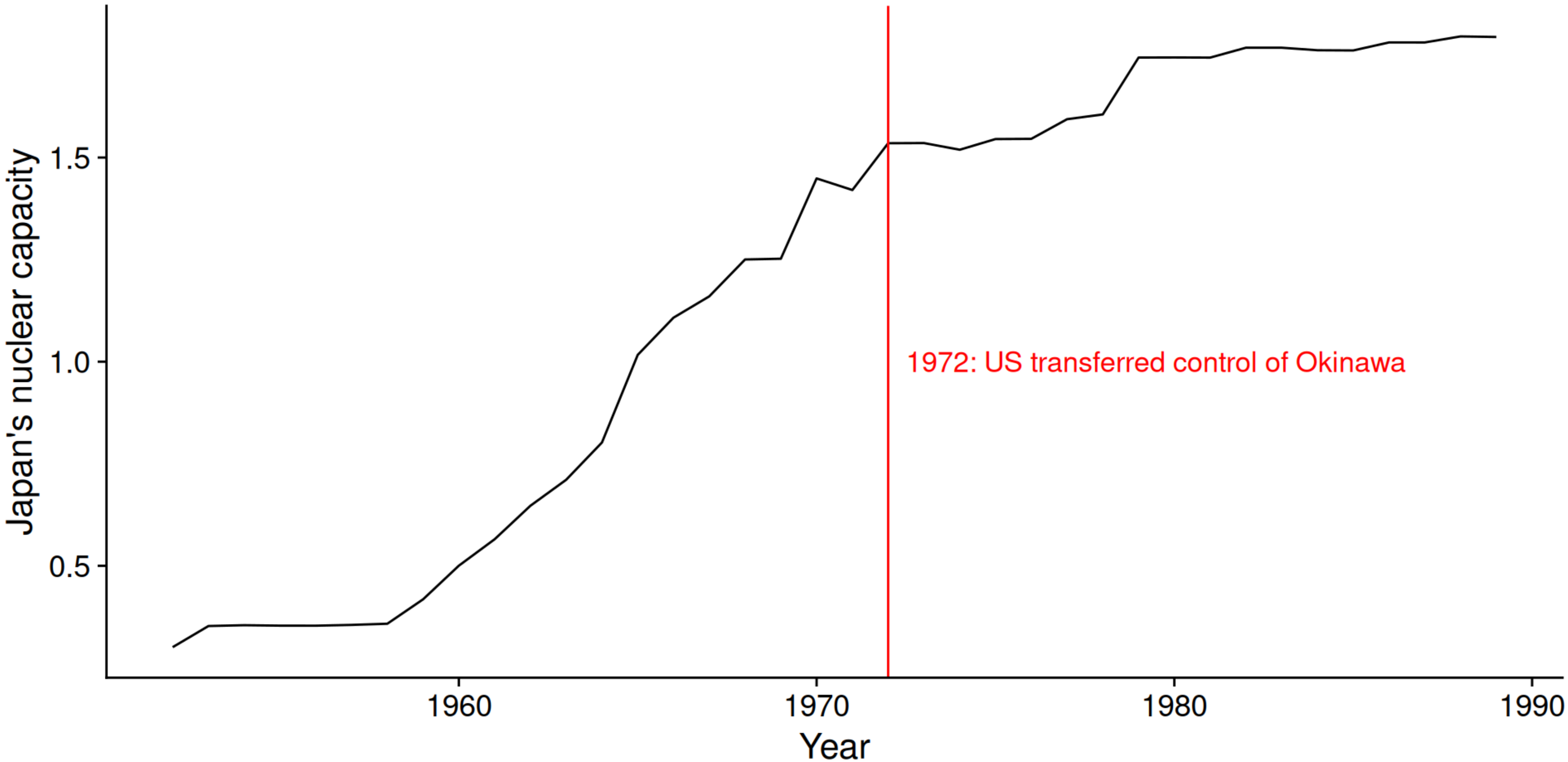
1965: Japanese PM tells LBJ if China has nukes, so should Japan

1968–1970: Non-Proliferation Treaty signing and ratification

1972: US concedes control over Okinawa to induce Japan's compliance with NPT

Causal question: Did this slow Japan's progress toward a weapon?

Japan’s progress toward a nuclear weapon



Problems for causal inference

Before vs after: Japan's progress slowed after 1972

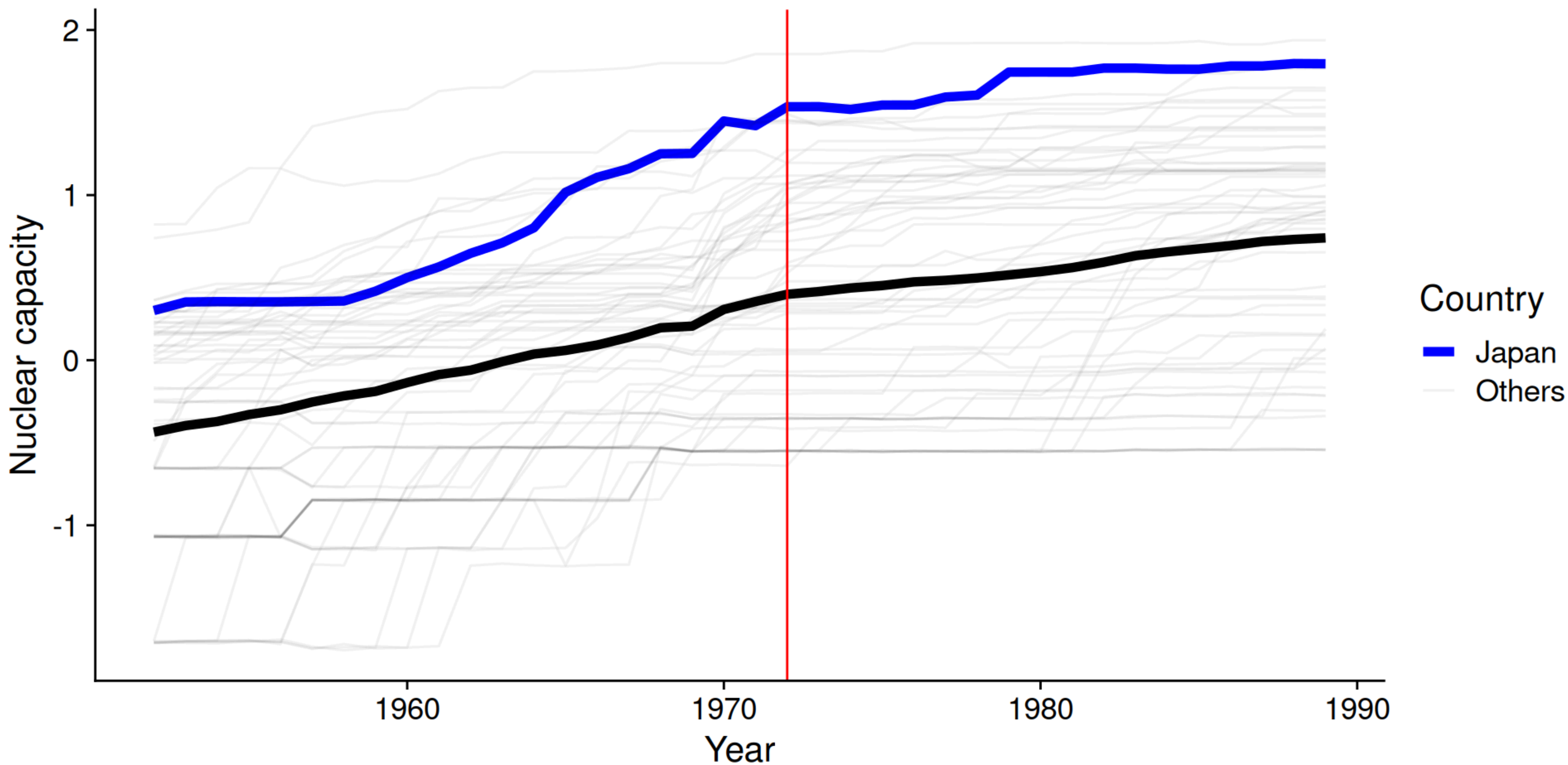
But remember — before-after comparisons aren't causal effects

- Want to know the counterfactual, what if US hadn't intervened?
- Could look at trends in other countries
- … but Japan wasn't chosen for "treatment" at random

Think about the problem from DiD perspective

- Would need to assume parallel trends for causal inference
- Pretty sketchy when "treatment group" is just one observation!

Pre-treatment trends are not parallel



The synthetic control method

Data requirements

Observe outcome $Y_{j,t}$ in $J + 1$ units over T time periods

Unit 0 is eventually treated, units 1 through J are never treated

Treatment happens at time t^*, in the middle of observation period

Causal question: At each time $t > t^*$, how much more/less is $Y_{0,t}$ compared to counterfactual world where treatment wasn't applied?

Key problem: Constructing no-treatment counterfactual for treated unit

The synthetic control method

How to construct the no-treatment counterfactual?

- Use a **weighted average** of never-treated units
- Want to focus on most similar never-treated units (akin to matching)

How to select weights on each never-treated unit?

- Look at pre-treatment observed confounders + trend in outcomes
- Select weights to make these match as closely as possible
- (There's a *lot* of math we're skipping over)

Implementing synthetic control in R

Data

Using subset of Smith and Spaniel's replication data

- "Smith" = Vandy prof Brad Smith, you might have learned about game theory from him
- See Quarto source code for obtaining + cleaning

```
df_nuclear
```

```
# A tibble: 2,356 × 9
  ccode state_abb  year nuclear_capacity democracy log_urban_pop log_gdp openness Country
  <dbl> <fct>     <int>            <dbl>     <int>         <dbl>   <dbl>    <dbl> <chr>
1     0 JPN        1952            0.301        10          1.68    3.46     22.2 Japan
2     0 JPN        1953            0.352        10          1.69    3.48     21.4 Japan
3     0 JPN        1954            0.354        10          1.69    3.50     20.2 Japan
4     0 JPN        1955            0.353        10          1.70    3.52     20   Japan
5     0 JPN        1956            0.353        10          1.70    3.55     22.6 Japan
# i 2,351 more rows
```

Setting up the synthetic control analysis in R

Using the `tidysynth` package

```
library("tidysynth")
```

Start by telling it the data source + key elements of analysis

```
synth_base <- df_nuclear |>
  synthetic_control(
    outcome = nuclear_capacity,   # outcome variable
    unit = state_abb,             # unit ID
    time = year,                  # time ID
    i_unit = "JPN",               # which unit ID is treated?
    i_time = 1972                 # when does treatment start?
  )
```

Constructing the synthetic control

Matching on democracy, urbanization, development, trade openness in pre-1972 period

Also matching on nuclear capacity as of 1955 and 1965

```
synth_final <- synth_base |>
  generate_predictor(
    time_window = 1952:1971,
    democracy = mean(democracy, na.rm = TRUE),
    log_urban_pop = mean(log_urban_pop, na.rm = TRUE),
    log_gdp = mean(log_gdp, na.rm = TRUE),
    openness = mean(openness, na.rm = TRUE)
  ) |>
  generate_predictor(time_window = 1955, nuke55 = nuclear_capacity) |>
  generate_predictor(time_window = 1965, nuke65 = nuclear_capacity) |>
  generate_weights() |>
  generate_control()
```

Looking at the weights

What combination of units will we use to construct the counterfactual?

```
grab_unit_weights(synth_final) |>
  arrange(desc(weight))
```

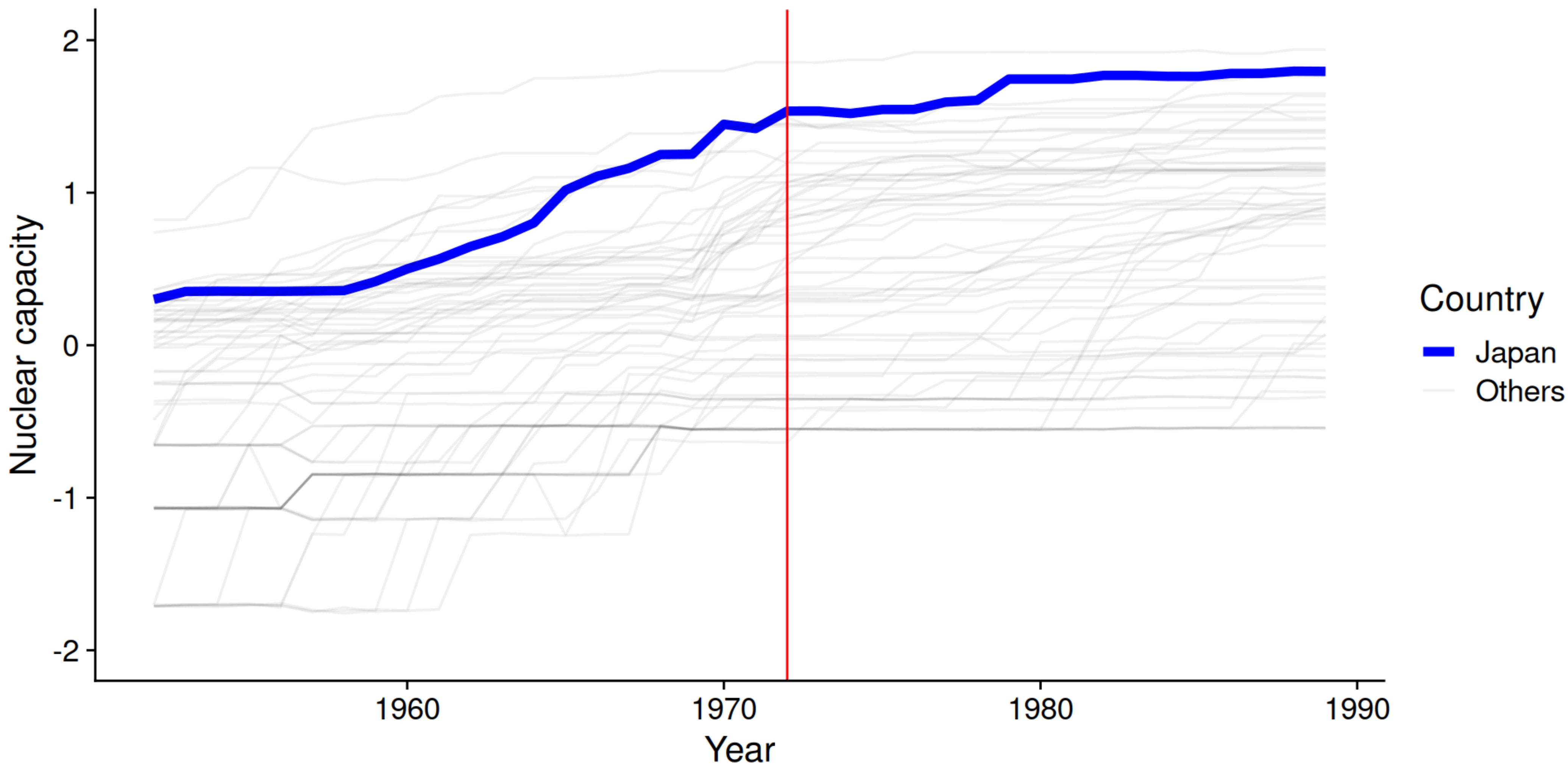
```
# A tibble: 61 × 2
  unit      weight
  <chr>      <dbl>
1 ITA   0.813
2 IND   0.137
3 FRN   0.0493
4 SPN   0.00000632
5 CHN   0.00000626
# i 56 more rows
```

Which variables were most relevant in coming up with the unit weights?

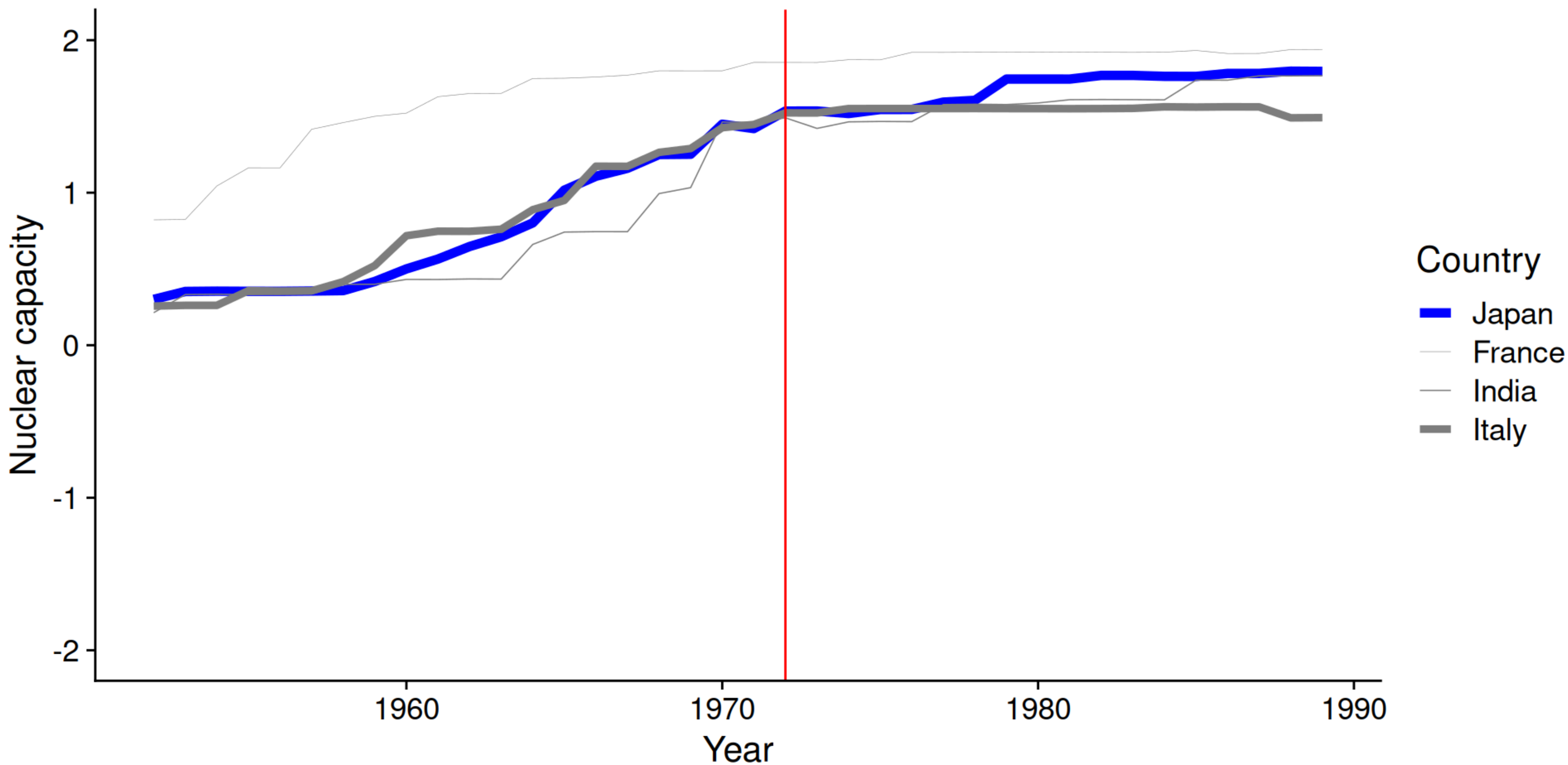
```
grab_predictor_weights(synth_final) |>
  arrange(desc(weight))
```

```
# A tibble: 6 × 2
  variable      weight
  <chr>          <dbl>
1 democracy     0.655
2 nuke65        0.148
3 openness      0.0547
4 log_gdp       0.0544
5 nuke55        0.0476
6 log_urban_pop 0.0406
```

Constructing the counterfactual

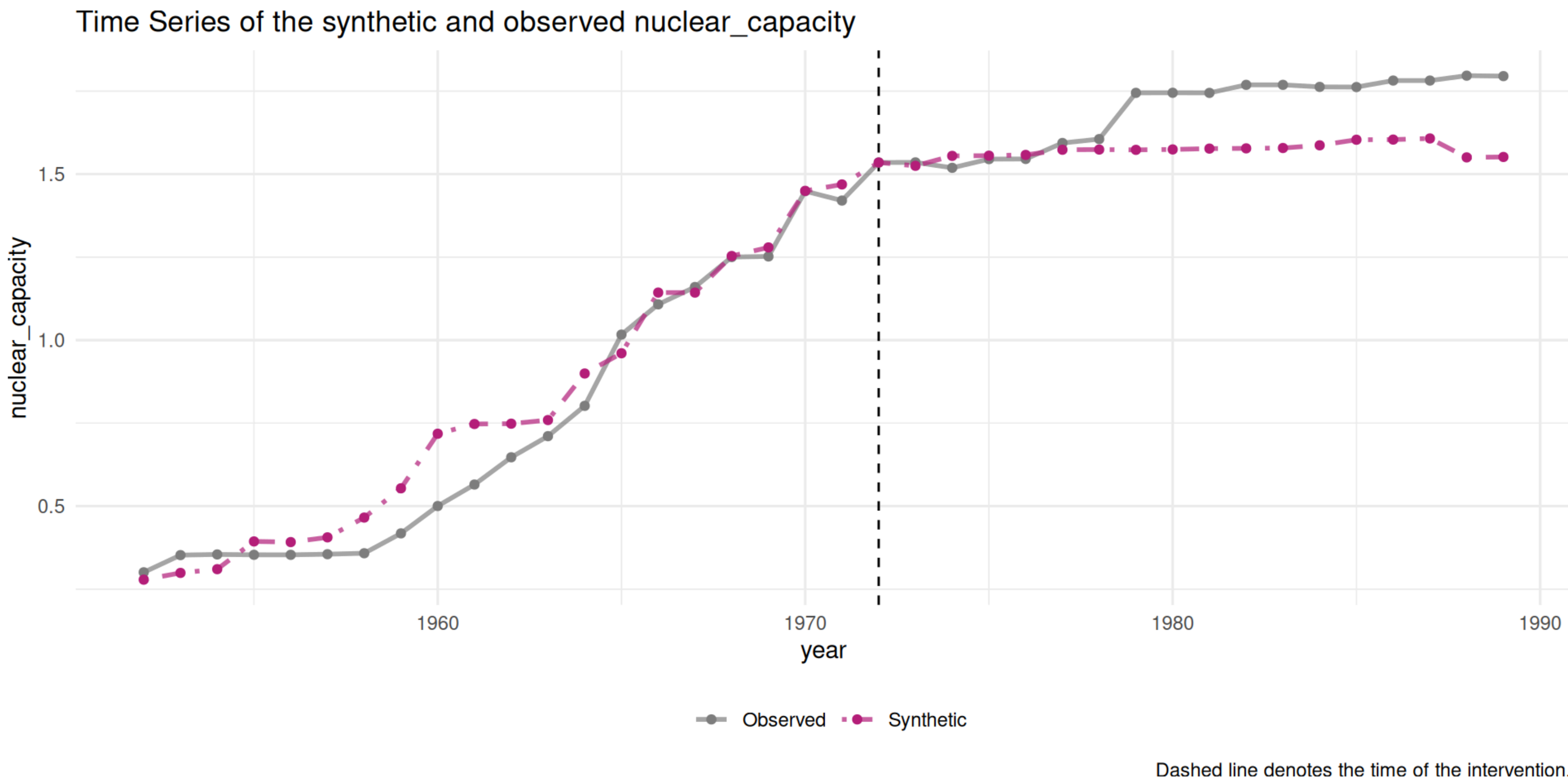


Constructing the counterfactual



Estimating the effect of treatment

```
plot_trends(synth_final)
```



Checking balance

```r
grab_balance_table(synth_final)
```

```
# A tibble: 6 × 4
  variable          JPN synthetic_JPN donor_sample
  <chr>           <dbl>         <dbl>        <dbl>
1 democracy     10              9.71        0.268
2 log_gdp        3.74           3.74        3.52
3 log_urban_pop  1.72           1.64        1.35
4 openness      20.2           23.5        38.6
5 nuke55         0.353          0.394      -0.329
6 nuke65         1.02           0.961       0.0591
```

Is the effect significant?

Inherently hard to calculate statistical significance when there's only one treated unit

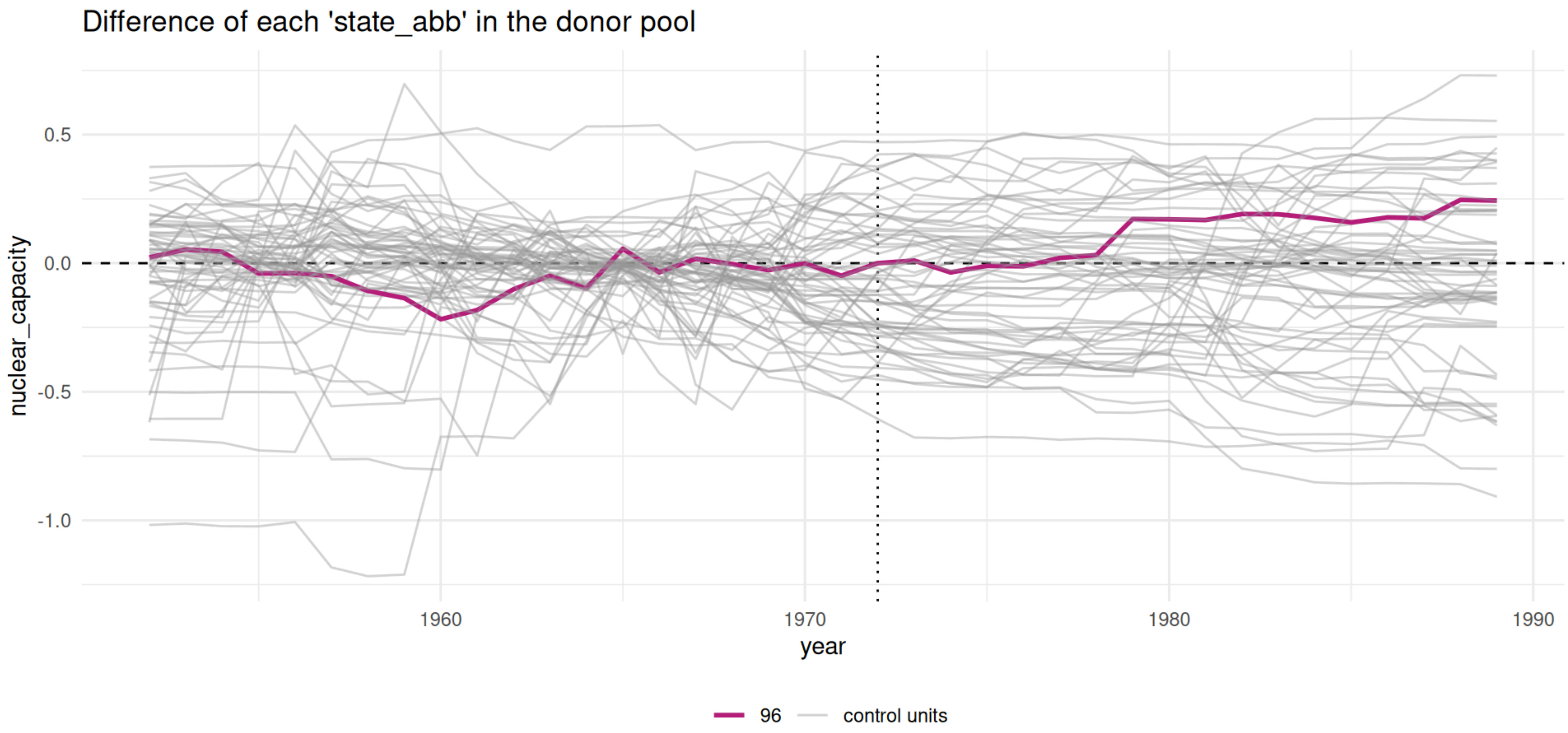
Traditional hypothesis test: How big is the effect, vs what we'd expect just due to random chance?

Placebo test approach for synthetic control

1. Rerun analysis repeatedly, as if each control unit were treated at t^*
2. Look at distribution of estimated "effects" where truth should be 0
3. Compare our main effect estimate to this distribution
    - Main estimate is an outlier $\rightsquigarrow$ significant
    - Main estimate is in middle of dist $\rightsquigarrow$ not significant

Distribution of placebo effects

```r
plot_placebos(synth_final, prune = FALSE)
```



Formal significance test

```
grab_significance(synth_final) |>
  arrange(desc(unit_name == "JPN"))
```

```
# A tibble: 62 × 8
  unit_name type    pre_mspe post_mspe mspe_ratio  rank fishers_exact_pvalue z_score
  <fct>     <chr>      <dbl>     <dbl>      <dbl> <int>                <dbl>   <dbl>
1 JPN       Treated  0.00722    0.0236       3.27    18               0.290   0.0911
2 SAF       Donor    0.0146     0.245       16.7      1               0.0161  4.14
3 DOM       Donor    0.0329     0.483       14.7      2               0.0323  3.53
4 NTH       Donor    0.00615    0.0715      11.6      3               0.0484  2.60
5 VEN       Donor    0.0194     0.169        8.74     4               0.0645  1.74
# i 57 more rows
```

(Take this more as a gut check than as a super precise test)

Wrapping up

Treatment effect estimation: Comparing the options

You've learned about a lot of different ways to do causal analyses!

Method	Key assumptions	Pros	Cons
Difference in means	Random assignment	No fancy adjustments needed, small standard errors	Expensive or infeasible for many causal questions
Matching	All confounders measured	Easy to calculate and to assess balance	Many ways to match, curse of dimensionality, unlikely to measure all confounders
Regression	All confounders measured, linear relationship b/w them and outcome	Flexible, easy to interpret	Linear extrapolation can be problematic, unlikely to measure all confounders

Treatment effect estimation: Comparing the options

Method	Key assumptions	Pros	Cons
Instrumental variables	Instrument not confounded, doesn't directly affect outcome	Can leverage random influence on nonrandom treatment	Assumptions very stringent, standard errors large if instrument weak, effective sample (compliers) not necessarily representative
Regression discontinuity	Treatment "jumps" with running variable, confounders don't	Easy to assess balance, easy to see where causal estimate comes from	Possible sensitivity of estimate to bandwidth, effective sample (running $\approx$ 0) not necessarily representative
Difference in differences	Parallel trends in potential outcome if untreated	Widely applicable with panel data, easy to see where causal estimate comes from	Requires repeated observation of same units, parallel trends sketchy if other things changing when treatment is switched on

Plan for the rest of the semester

- Mon 4/14: Presentations of final projects
  - → Should be 10-12 minutes each
  - → Main points to hit: your causal question, your data, how you identify a causal effect, your main findings
- Weds 4/16: Likely no class
- Weds 4/23: Final paper and revision memo due