Causal Inference analysis: Effect of Prison Construction on Crime Rate in Brazil

Synthetic Control, Robustness Check, Placebo Test

Executive Summary

We attempted to replicate Prof. Cunningham's findings from Chapter 10.2: *Causal Inference* and extended your analysis with a robustness check and placebo test. Although the graphs for the effect of prison expansion on black male incarceration look similar, the weights for synthetic controls are different. Thus, we invited him to re-evaluate his calculations, and we extended the paper using leave-one-out and in-time placebo robustness tests to show his findings are robust. Our analysis using the synthetic control method and additional robustness checks has shown that the prison construction bill passed in Texas in 1993 minimised incarceration rates of African-American men. We can therefore confidently conclude that this legislation had decreased incarceration rates for this demographic.

Introduction

In 1993, Texas Governor Ann Richards announced a $1 billion prison construction bill. The chapter details how prison capacity expansion led to increasing incarcerations. The incarceration rate of black men in Texas doubled in 3 years, deviating from the general trend of other US states.

This paper first created a synthetic control with a similar pre-treatment trend to Texas but divergence in the post-treatment period. The gap between actual and synthetic control reached 25000 in 1995, 2 years post-treatment.

The data and code provided by Cunningham are accessed via this link. Our replication and extension code is attached in the Appendix as a GitHub link.

Replication

We attempted to replicate Figures 10.9 and 10.10 from Cunningham et al. (2021). These figures show the difference between Texas's actual outcome and its synthetic control's potential outcome.

The synthetic control method is a way to compare the outcomes of a treatment group to what might have happened if there had been no intervention. This is done by creating a hypothetical control group and using it to predict outcomes the treatment group would have had without the intervention. This approach is often used in comparative case studies to evaluate the impact of an intervention.

In this scenario, the synthetic control group is constructed by finding control group units (other US States) with similar characteristics (alcohol, poverty, etc.) as the treatment group (Texas). Each of these units is given a weight, representing its similarity level to the treated state. The units with higher weights are more similar to Texas. These units are summed together (synthetic control group) with their weights to generate a predicted outcome (counterfactual) for Texas had the prison construction not happened in 1993.

There is a difference in synthetic control weights between ours and Cunningham's results, as shown in Table A. In our calculations, Louisiana is more weighted by 0.238, Florida is more by 0.189, California is less by 0.067, and Illinois is not included in the synthetic control.

Cunningham et al.'s calculations		**Our calculations**	
State Name	Weights	State Name	Weights
California	0.408	California	0.341
Florida	0.109	Florida	0.298
Illinois	0.36	Illinois	0.000

Louisiana	0.122	Louisiana	0.360

Table 2: Cunningham et al. and our Synthetic Control Weights

Figure 1A (Original) and Figure 1B (Replication) (see Appendix) are very similar when trying to compare Texas versus Synthetic Texas after prison expansion. However, in 1990, there is a smaller difference in "bmprison" between actual and synthetic outcomes in Figure 1B. This is further evidenced by Figures 2A and 2B, where the actual and synthetic gap touches the zero dashed line in Figure 2B and not in 2A.

Extension

We extended the findings of this paper by doing leave-one-out and in-time placebo tests for the synthetic control used. The robustness test aims to assess the reliability of the synthetic control group that has been created. The in-time placebo test is designed to examine whether any false treatment effects can be detected in the years preceding the actual start of the intervention period. This is done by artificially setting a start date for the intervention. If any false treatment effects are found, it raises concerns about the validity of the primary treatment effect.

To begin the robustness test, we remove the highest-weighted state, Louisiana, from the synthetic control donor pool. Then we compare the results to see if they are consistent with the plots containing Louisiana in the donor pool. This consistency can help increase the credibility that the synthetic control group is a reliable estimate of Texas' counterfactual.

Top 4 Synthetic Control Weights after taking Louisiana out of the donor pool	
State Name	Weights
California	0.487
Mississippi	0.270
New York	0.208

Michigan	0.003

Table 2: Top 4 new synthetic control weights after taking out Louisiana

After excluding Louisiana from the group of potential donor states, the top 4 weights have changed to the weights in Table 2 above (see the full table of weights in Table 3 in the Appendix). However, the new synthetic control path and gap plots (Figures 3 and 4) show similar results to our original graph. This similarity is seen in the gap plot where, after prison expansion, the gap between actual and synthetic still rose to 25000. Therefore, our treatment effect result from the previous analysis is fairly robust to excluding Louisiana from the synthetic control donor pool. This robustness increases our treatment effect's credibility.

For the in-time placebo tests, we arbitrarily set the fake intervention year to 1990 and observed its trend up to 1993, the actual treatment year. If we find any false treatment effects, then the reliability of our main treatment effect is questionable. Since treatment has not yet occurred in 1990, we should not detect any treatment effects between actual and synthetic Texas.

Figure 5's path plot shows that Texas and synthetic Texas are very similar before and after the hypothetical treatment, which is good. The gaps plot in Figure 6 also helps us to see this further. However, it seems there is an increasing treatment effect as we approach the actual 1993 treatment year. This could be the effect of anticipating a policy change: expecting the governor to increase prison capacity may lead people in authority to increase incarceration rates. Therefore, we can reasonably conclude that the gap between Texas and synthetic Texas is minor, which favours the reliability of our primary treatment effect.

Conclusion

In this paper, we attempted an exact replication study to run experiments directly on the dataset available from Cunningham et al. Cunningham et al.'s results are not reproducible given different synthetic weights, however, since the graphs are very similar, the conclusions drawn are not incorrect and is conceptually similar.

Based on our robustness checks for the synthetic control method in our extension, we can reasonably conclude that there is a positive treatment effect of the prison construction bill passed in Texas in 1993 on African-American male incarceration rates.

References

Cunningham, S. (2021). *Causal Inference The Mixtape - 10 Synthetic Control*. Mixtape.scunning.com. Retrieved December 16, 2022, from https://mixtape.scunning.com/10-synthetic_control#prison-construction-and-black-male-incarceration

Appendix

Link to the dataset:

https://github.com/scunning1975/mixtape/blob/master/Texas/Data/texas.dta

Paper:

https://mixtape.scunning.com/10-synthetic_control#prison-construction-and-black-male-incarceration

Code for replication and extension:

https://gist.github.com/SomtochiUmeh/15855b7c01d10222d8e35a2ed6f5e5e1

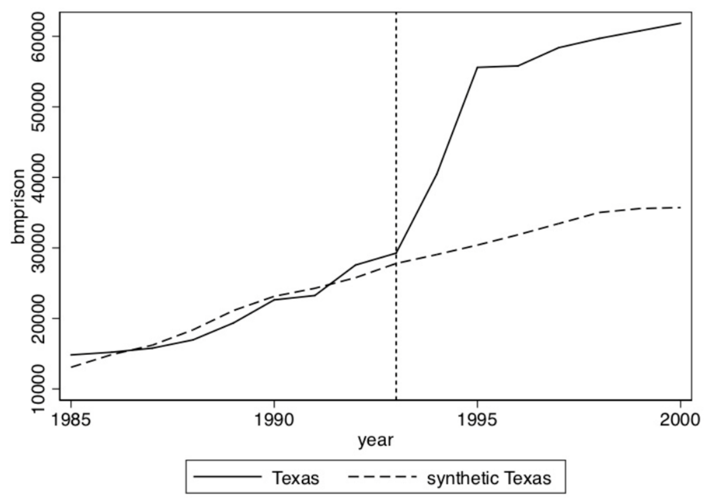

Figure 1A: Cunningham et al. "African-American male incarceration"

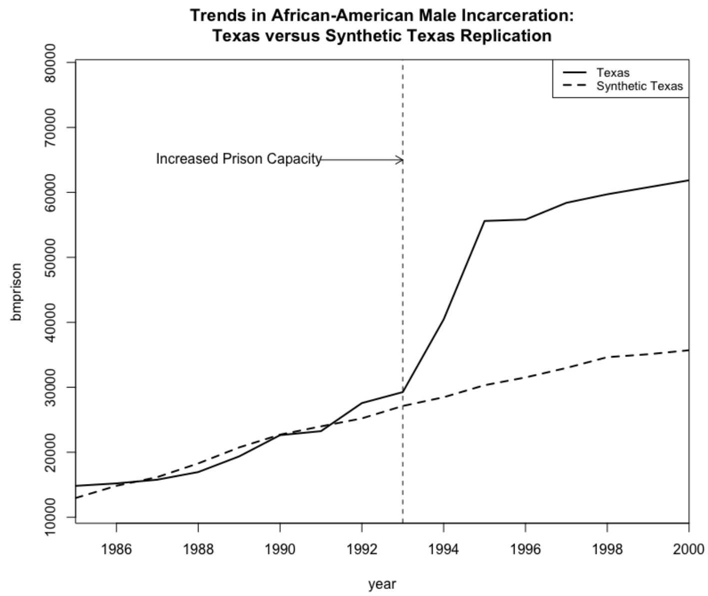

Figure 1B: Replication of "African-American male incarceration"

Figure 2A: Cunningham et al. "Gap between actual Texas and synthetic Texas"

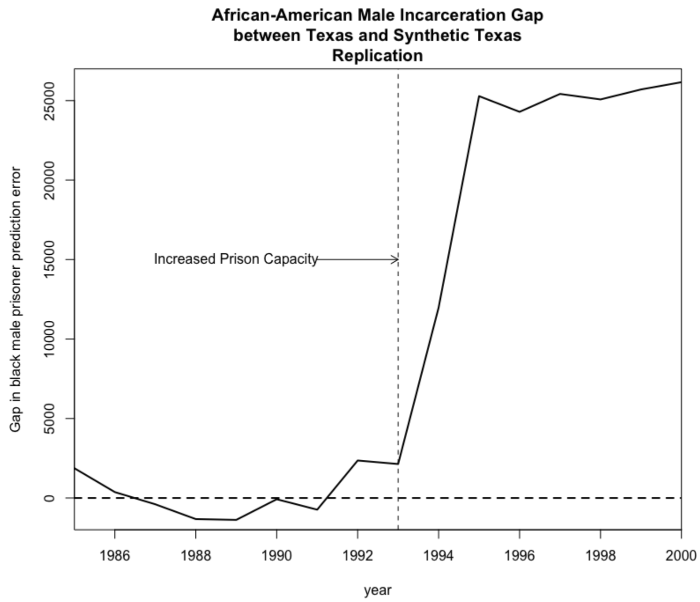

Figure 2B: Replication: "Figure 10.10: Gap between actual Texas and synthetic Texas"

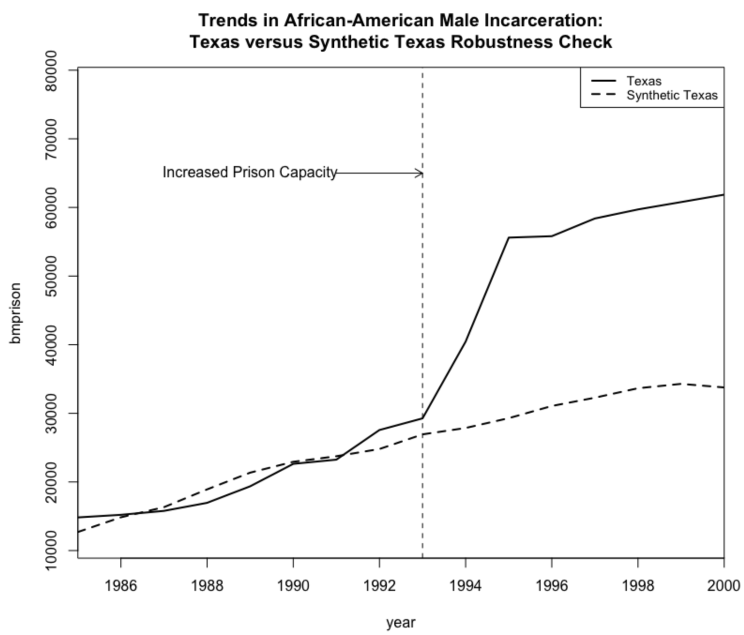

Figure 3: Leaving highest weight state, Louisiana, out from control donor pool path plot

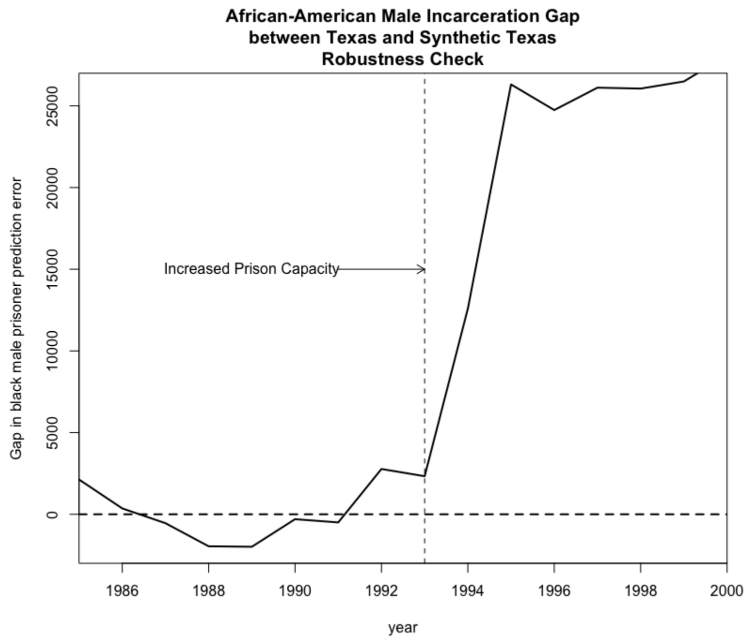

Figure 4: Leaving highest weight state, Louisiana, out from control donor pool gaps plot

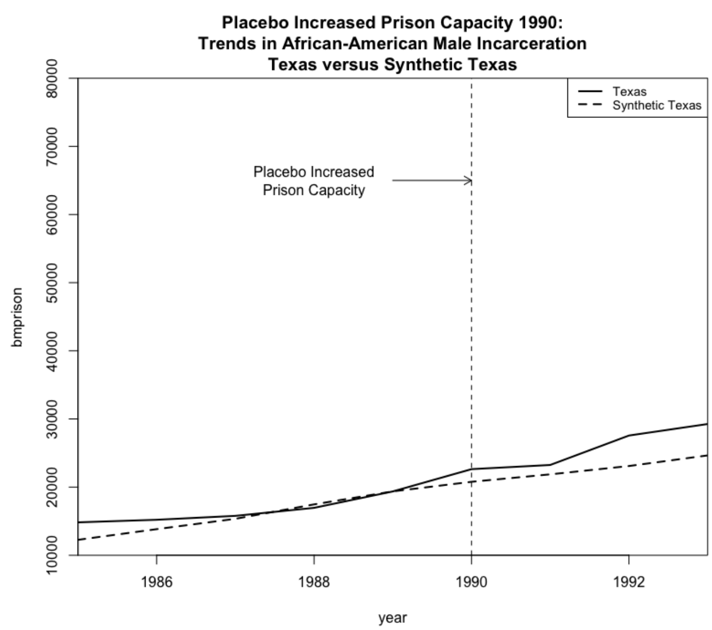

Figure 5: Placebo Increased Prison Capacity in 1990 Path Plot: Texas versus Synthetic Texas

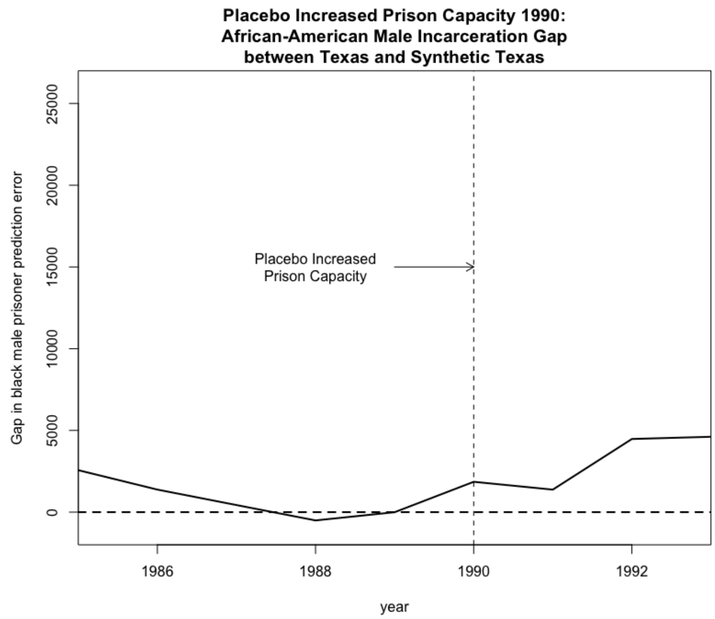

Figure 6: Placebo Increased Prison Capacity in 1990 Gaps Plot: Texas versus Synthetic Texas

State numbers	State names	weights
6	California	0.487
9	Connecticut	0.001
12	Florida	0.002
13	Georgia	0.002
17	Illinois	0.002
18	Indiana	0.001
19	Iowa	0.001
20	Kansas	0.001
21	Kentucky	0.001
24	Maryland	0.001
26	Michigan	0.003
28	Mississippi	0.270

29	Missouri	0.001
34	New Jersey	0.001
36	New York	0.208
37	North Carolina	0.001
39	Ohio	0.003
40	Oklahoma	0.001
42	Pennsylvania	0.002
45	South Carolina	0.001
47	Tennessee	0.001
49	Utah	0.001
51	Virginia	0.001
54	West Virginia	0.001

Table 3: New synthetic control weights after taking out Louisiana