Hosting Olympics: The Secret to a Country's Economic Prosperity?[1]

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[1] Code for the paper can be found in this repository: https://github.com/AbdullahKhurram30/Olympics-prosperity. The dataset is also linked in the code.

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Abstract

This research examines the economic impact of hosting the Olympics on a country, focusing on Australia as the treatment unit and GDP-per-capita as the outcome. Using a Synthetic Control method, the study compares the economic performance of Australia to its counterfactual, a synthetic control unit. The results suggest that while there may be a temporary boost in GDP per capita during the year of hosting, there is a subsequent decline in the years following the event. The study also finds no evidence of spillover effects on other countries in the donor pool or anticipation effects prior to hosting. However, the study acknowledges limitations in the scope and external validity of the findings due to the use of a specific country and limited variables. Nonetheless, the results add to the growing body of evidence suggesting that hosting the Olympics may not lead to sustained economic benefits for a country. The study recommends further research using more robustness checks and alternative causal inference methods to enhance the generalizability of the findings.

Introduction

Countries eagerly compete to host the olympics (McBride and Manno, 2022), with China going as far as cladding a hillside with steel and adding fake snow to construct an Olympic ski jump, costing it billions of dollars (Bradsher , 2022). Many papers associate hosting the Olympics with economic prosperity, however, the literature remains divided. Thus, this paper attempts to answer the causal question “What is the effect of hosting the Olympics on Australia's GDP-Per-Capita?” Utilizing one of the most robust methodologies to date, the Synthetic Control method, this paper found that there is only a temporary increase in GDP per capita and that is during the year the games take place in the country. In subsequent years, a decline in GDP-per-capita is observed, suggesting that there maybe no economic benefit in hosting the Olympics, rather, the opposite.

Literature review

Existing literature is divided into two clear groups, with one appreciating the Olympics for the positive effects it has on the economic prosperity of a country, and the other, vehemently denying the former’s claims. The supporters of the Olympics cite reasons such as the development of non-sports related infrastructure in preparation for the games (Baumann & Matheson, 2013; Fowler, 2008), the increased tourism potential that the country gains (Taylor, 2012), increased investor and consumer confidence (Ponomarenko & Plekhanov, 2014), and an increase in employment levels (Prynn, 2012). However, skeptics refute these claims with results from empirical studies which have concluded that there is no positive effect of hosting the Olympics on a country’s economic prosperity (Billings and Halladay, 2011), supplementing their arguments with literature that proves the increased employment is only temporary (Baumann et al., 2010). It was also found that the average cost of hosting the olympics, for each olympics after 1976, was overrun by atleat 252% (post adjustment for inflation) (Flyvbjerg & Stewart, 2012), making bailouts, especially for developing countries a frequent occurrence for the Olympics Committee (McBride and Manno, 2021). Critiquing the research assessing the economic impact of the Summer Olympics in 2000 in Sydney, Matheson & Baade (2004), highlight the role of the ‘substitution effect’ wherein, they mention that the analyses presenting a net gain for the country are actually net gains for the city as, it was found that while hotel booking increased within Sydney where the olympics were being held, it came at a cost of decreased bookings in Adelaide and other regional cities, begging the question: was there an actual net increase in tourism or just a redirection of crowd flow into other cities?

From a purely empirical standpoint, Huang et al., (2022), utilizing a Regression Model, attempted to find the difference between the host country's GDP per capita growth rate pre and post-hosting the Olympics, conditioning on independent variables: a binary variable indicating the development status of the country, forecasted budget cost, actual cost, over-budget rate, and revenue generated. They concluded that the Olympic games have a little positive impact, if any, and the analysis itself showed that when actual spending increases, especially in lesser developed countries, the economic boost is mostly diminished and sometimes even reversed. Giving a relatively novel finding, Brückner & Pappa (2015) concluded that bidding for and hosting the Olympic Games have significant positive effects on the macroeconomic variables of the hosting country, however, this is true only ex-ante, largely due to the 'anticipation effect' which increases government spending and increases the private sector's productivity. The study utilized a panel data regression, for the time period 1950-2009, to arrive at this conclusion, with fixed-country and year effects, controlling for government expenditures and lagged GDP growth, and clustering the error term at the country level. The dependent variables utilized were the exchange rate, price levels, government consumption expenditures, private consumption, investment, real-per-capita GDP, and output growth, while the independent variables were bidding for and hosting the Olympic Games, government expenditure, and GDP growth.

Data

The World Bank DataBank and OECD Data were the primary sources of data for the study. These sources provide a range of measures of economic and financial indicators over multiple time periods for different countries, which are the units of observation considered in the study. The final published dataset is provided here.[2]

The treatment (Australia hosting the Olympics) occured in the year 2000, and so to generate the dataset for the causal inference, we consider data ranging from 1986 to 2005. This longer span of data allows us to observe the trends of the treatment unit and synthetic control unit. In synthetic control studies, we expect the outcome variable trends of the treatment and synthetic control unit to be as similar as possible pre- treatment, and so more data allows us to more accurately verify this expectation, as well as to more accurately determine the weights of each unit in the donor pool. Additionally, more post-treatment data allows us to more effectively estimate the treatment effect.

Besides GDP per capita, which represents the outcome variable, and the 'year' variable, which defines our pre- and post-treatment time periods, we consider a several other covariates that would be relevant to the outcome, and potentially even the treatment. These variables include: population (in millions), Consumer Price Index, exchange rate, land area, international tourism expenditures, percentage of exports, labor force, percentage of national expenditures, percentage capital formulation, adjusted national income, percentage trade, unemployment, percentage urban population, and urban population. The table below shows the full list of variables included in the generated dataset, along with their descriptions, classification, and means of measurement.Figure 1 also shows the summary statistics for each of the variables included in the data. Furthermore, the DAG shown in Figure 2 depicts the expected relationships between the identified variables, treatment, and outcome.

[2] Dataset link: https://tinyurl.com/ss154-final

Variable	Description	Classification	Measurement
country	Country (units of observation)	Treatment unit (Australia) / Donor pool units	-
year	Year	Time (Pre-/post-treatment indicator) variable	years
gdp_per_capita	GDP per capita	Outcome/Dependent variable	current US$
million_population	Country population	Covariate	million persons
cpi	Consumer Price Index (Inflation indicator)	Covariate	annual growth rate (%)
exchange_rate	Currency exchange rate	Covariate	national currency per US dollar
land_area	Total area of land	Covariate	sq. km
tourism_expenditures	International tourism expenditures	Covariate	% of total imports
exports_percentage	Exports of goods and services	Covariate	% of GDP
labor_force	Total labor force	Covariate	persons
national_expenditures_percentage	Gross national expenditures	Covariate	% of GDP
capital_formulation	Gross capital formation	Covariate	current US$
capital_formulation_percentage	Gross capital formation	Covariate	% of GDP
adj_national_income	Adjusted net national income	Covariate	current US$
trade_percentage	Total trade	Covariate	% of GDP

unemployment	Total country unemployment	Covariate	% of total labor force
urban_pop_percentage	Urban population	Covariate	% of total population
urban_pop	Urban population	Covariate	persons

Table 1: Table showing the variables included in the generated dataset, their definitions, classifications, and units of measurement

```
data <- read.csv("https://tinyurl.com/ss154-final")
summary(data)

Out:
      id           country         year       gdp_per_capita
 Min.   : 1.0   Argentina: 20   Min.   :1986   Min.   : 1546
 1st Qu.: 4.0   Australia: 20   1st Qu.:1991   1st Qu.: 4738
 Median : 7.5   Brazil   : 20   Median :1996   Median :15009
 Mean   : 7.5   Denmark  : 20   Mean   :1996   Mean   :17510
 3rd Qu.:11.0   Japan    : 20   3rd Qu.:2000   3rd Qu.:27644
 Max.   :14.0   Korea    : 20   Max.   :2005   Max.   :56243
                (Other)  :160
 million_population      cpi           exchange_rate        land_area
 Min.   :  2.519    Min.   :  -1.600   Min.   :   0.000   Min.   :    670
 1st Qu.:  7.064    1st Qu.:   1.258   1st Qu.:   1.409   1st Qu.:  96460
 Median : 28.341    Median :   2.684   Median :   2.483   Median : 346525
 Mean   : 44.836    Mean   :  43.936   Mean   :  79.628   Mean   :1694043
 3rd Qu.: 58.060    3rd Qu.:   6.127   3rd Qu.:   7.126   3rd Qu.:1943950
 Max.   :184.991    Max.   :2947.733   Max.   :1403.183   Max.   :8358140

 tourism_expenditures exports_percentage  labor_force
 Min.   : 2.587       Min.   :  6.598    Min.   : 1281793
 1st Qu.: 5.039       1st Qu.: 17.789    1st Qu.: 3900290
 Median : 7.210       Median : 26.050    Median :10662472
 Mean   : 7.728       Mean   : 40.690    Mean   :20545776
 3rd Qu.: 8.970       3rd Qu.: 40.076    3rd Qu.:28968040
 Max.   :89.009       Max.   :225.160    Max.   :90599384

 national_expenditures_percentage capital_formulation
 Min.   : 71.25                   Min.   :6.790e+09
 1st Qu.: 94.85                   1st Qu.:2.598e+10
 Median : 98.58                   Median :5.990e+10
 Mean   : 97.11                   Mean   :1.634e+11
 3rd Qu.:100.56                   3rd Qu.:1.242e+11
 Max.   :110.99                   Max.   :1.720e+12
```

```
capital_formulation_percentage adj_national_income trade_percentage
Min.   :10.85                  Min.   :1.530e+10   Min.   : 13.75
1st Qu.:19.75                  1st Qu.:9.682e+10   1st Qu.: 35.51
Median :23.07                  Median :2.280e+11   Median : 51.61
Mean   :24.67                  Mean   :5.068e+11   Mean   : 78.09
3rd Qu.:28.23                  3rd Qu.:4.392e+11   3rd Qu.: 76.18
Max.   :43.64                  Max.   :4.300e+12   Max.   :420.43

 unemployment    urban_pop_percentage   urban_pop
Min.   : 1.558   Min.   : 46.67       Min.   :  2719750
1st Qu.: 3.408   1st Qu.: 73.70       1st Qu.:  5200098
Median : 5.240   Median : 79.62       Median : 17334652
Mean   : 6.780   Mean   : 78.36       Mean   : 34274701
3rd Qu.: 8.520   3rd Qu.: 85.07       3rd Qu.: 45497351
Max.   :21.194   Max.   :100.00       Max.   :155000000
```

Figure 1: Summary statistics dataset variables outputted using R.

Generation of the synthetic control unit requires careful and well-planned considerations of units to include in the donor pool. These units should be fairly similar to the treatment unit, as significantly different donor units in terms of the covariates specified can weaken the synthetic control unit or flaw the inference and lead to biased results. For this study, we considered 12 donor pool units that we estimated to be fairly similar to the treated unit, Australia, in terms of economic, political, and financial indicators, based on pre-existing and general knowledge of the field. These countries are: New Zealand, United Kingdom, Sweden, Denmark, Switzerland, Brazil, South Africa, Mexico, Japan, Argentina, Singapore, and Malaysia. Several other units were considered for the donor pool, but were dropped as they did not meet the requirements for a satisfactory donor pool unit. For instance, although Canada might have been generally similar to Australia, the country was treated (hosted the Olympics) in 1988, which lies within the pre-treatment period. Therefore, including Canada could bias the effect estimate by “corrupting” the synthetic control unit.

Finally, although efforts were made to choose variables with available and accessible data and to effectively compile data from multiple sources, the generated dataset had some missing values due to the absence of complete data from the sources used in generating the dataset, especially for earlier time periods. These missing data points could be problematic for the libraries used in the inference procedure, and could also affect the overall inference results by introducing bias to the dataset due to reduction in the its size. As a result, we took measures to effectively “impute” values for these missing data points. This was done by observing the general trend of the data for the specified country and estimating reasonable values for these data points. While the estimated values might not perfectly match the true unobserved values of the variables at the specified time, this imputation technique allows us to fill up the data, and the relatively small number of missing values implies a very little effect of the imputation on the model results.

Methodology

In order to evaluate the effect of hosting the Olympics on the host country (Australia) we have decided to use the Synthetic Control method. The Synthetic control method is well suited to these cases where we have a small number of treated units (only one here) and a higher number of control units. It is better than Matching because we won't find a perfect match for the unit and since the sample size is small, we can't even match distributions. Most other causal inference methods also tend to rely on large sample sizes in the treated and control groups in order to make inferences about the treatment effect. Synthetic control doesn't suffer from this and is thus well suited to the causal question at hand.

Synthetic control is a statistical method used in program evaluation and policy analysis to estimate the causal effect of an intervention or policy change on an outcome of interest, such as economic growth or public health outcomes. The method constructs a synthetic control group by combining weighted observations from a pool of potential control units that closely resemble the treated unit prior to the intervention. The weights are chosen to minimize the difference between the treated and synthetic control group prior to the intervention, allowing for a comparison of post-intervention outcomes between the two groups.

The biggest advantage associated with Synthetic controls is that it allows for Counterfactual estimation through the creation of a "synthetic" control that closely resembles the treated unit. Synthetic control is also data efficient and can be used in cases where the number of variables is small as long as they are measured in time-series format and over an interval of time. Synthetic controls also offer robustness estimates with well-defined methods.

The method doesn't come without limitations. We are assuming that the control group would have followed the same trajectory as the treated group in the absence of an intervention i.e. the path that we trace out with the synthetic control would be very similar to what Australia would have followed in the absence of the treatment. Moreover, Synthetic control methods can be quite sensitive to the variables that we chose, and the donor pool. Finally, calculating the treatment effect of Synthetic controls can be hard as well since the estimate of the outcome is a weighted sum, and most interpretations in the past have been done only on the path plot.

Given all the considerations above, we do believe that Synthetic control is suitable for the question at hand and can perform quite well. We will now discuss a causal diagram to show how the variables that we have measured interact with the treatment and outcome as well as with each other.

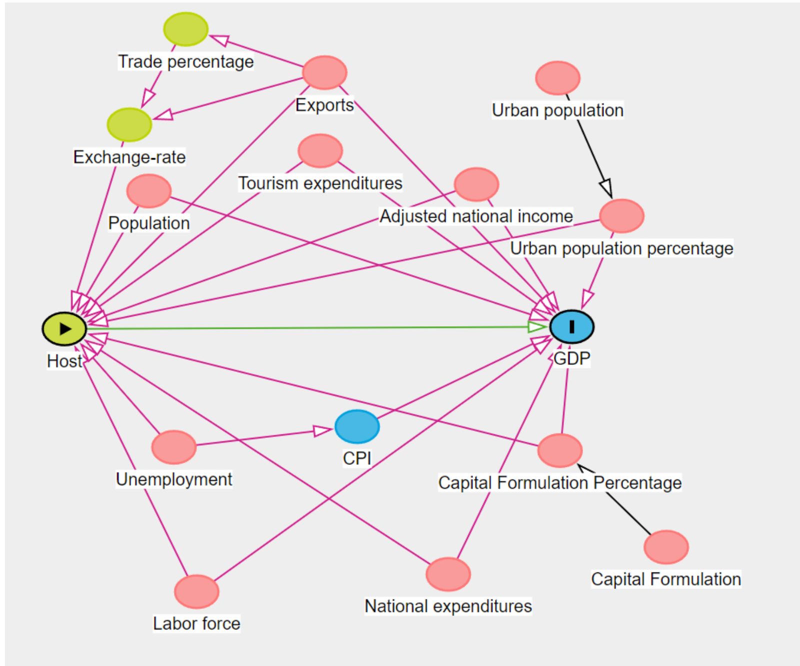

Figure 2: Directed Acyclic Graph representing the relationship between the variables that we have measured, the treatment (Host), and the outcome (GDP per capita).

Looking at the graph above, we can see that the variables are interlinked with both the treatment and the outcome. Some of the relationships are quite straight forward e.g. a higher labor force means higher GDP and also a higher chance of hosting. Similarly, national expenditures, capital formulation percentage, urban population percentage, tourism expenditures, and population have a direct link. The interesting link here would the one between exports, trade percentages, and exchange rates. Higher exports would mean a bigger influence on trade which in turn leads to an appreciation of the exchange rate. However, the exchange rate is a collider and if we were to control for the exchange rate, we would open up additional paths that would need to be blocked. Thus, if we run a regression of any sort on this dataset, one must be careful so as not to control for the exchange rate.

The causal diagram above might look complicated but Synthetic controls are independent of functional forms and are not sensitive to specific relationships assumed between the variables. The main assumptions that we associate with synthetic controls are that of parallel trends i.e. the outcome variable of the treated unit and the synthetic control would have followed parallel trends in the absence of the intervention. We also assume that the synthetic control and the treated unit are similar in terms of observed and unobserved variables. In terms of treatment effects, we assume that there are no spillover effects on other units in the donor pool as well as no anticipation effect i.e. the behavior of the treated unit is not affected by the treatment prior to its implementation.

Analysis

Synthetic control results can be hard to interpret but the method is also known for "hiding no truth" i.e. it is very clear in terms of how the weight assignment is done as well as which units in the donor pool contribute the most to the synthetic control. The weights of variables are also explicit. First, we shall look at the weight allocation to each of the countries in the donor pool and see what the synthetic control unit is composed of.

Country	Weight
Argentina	0.009
Brazil	0.002
Denmark	0.004
Japan	0.003
South Korea	0.003
Malaysia	0.002
Mexico	0.002
New Zealand	0.472
Singapore	0.004
South Africa	0.006
Sweden	0.020
Switzerland	0.008
United Kingdom	0.465

Table 2: Table showing weights of the countries in the donor pool as to how much they contribute to the synthetic control.

As we see in the table above, the main contributors to synthetic control are the United Kingdom and New Zealand. This was to be expected as we see that the countries are quite similar in reality too with Australia & New Zealand have been British colonies in the past while they also share a common language and many other characteristics such as being developed countries. Table 2 shows that synthetic Australia is not very different from what we expected it to be in terms of composition from our donor pools. Next, we will look at the mean values and how they differ for Australia vs "synthetic" Australia.

Variable	Treated	Synthetic	Weight
Population (millions)	1.76e+01	3.04e+01	0.002
CPI	4.12	5.76	0.104
Exchange rate	1.405	4.223	0.182

Land Area	7.6823e+06	3.028956e+05	0
Tourism Expenditures	10.03	10.67	0
Exports percentage	17.19	27.44	0
Labor Force	8.7834e+06	1.5206e+07	0
National Expenditures Percentage	1.0128e+02	1.0129e+02	0.376
Capital Formulation	3.903e+10	3.892e+10	0.329
Adjusted National Income	2.586e+11	5.255e+11	0
Trade Percentage	35.5	54.0	0
Unemployment	8.23	7.72	0
Urban Population	1.4964e+07	2.3920e+07	0.008

Table 3: Table representing the variable balance between the treated unit and the synthetic control unit. The values shown are the mean values of the covariates measured over time. The last column represents the respective weights of each variable in estimating the outcome variable.

Looking at the table above, we see that synthetic Australia is not perfectly the same as Australia in terms of variable balance which is an important consideration in Synthetic controls. The variables that do seem to be quite similar across the two units are “National Expenditures Percentage”, “Capital Formulation”, “Unemployment”, and “Tourism Expenditure”. However, this might not be that big of an issue if we can determine which variables are important in estimating the outcome variable (GDP per capita). Synthetic control methods are also explicit about these weights. These weights are shown in the right-most column of the table above. As we can see, “National Expenditures Percentage” and “Capital Formulation” are the most important variables in predicting the outcome. Both of them are quite similar across the two units in our analysis which shows that our Synthetic control might be able to match “Actual” Australia quite well.

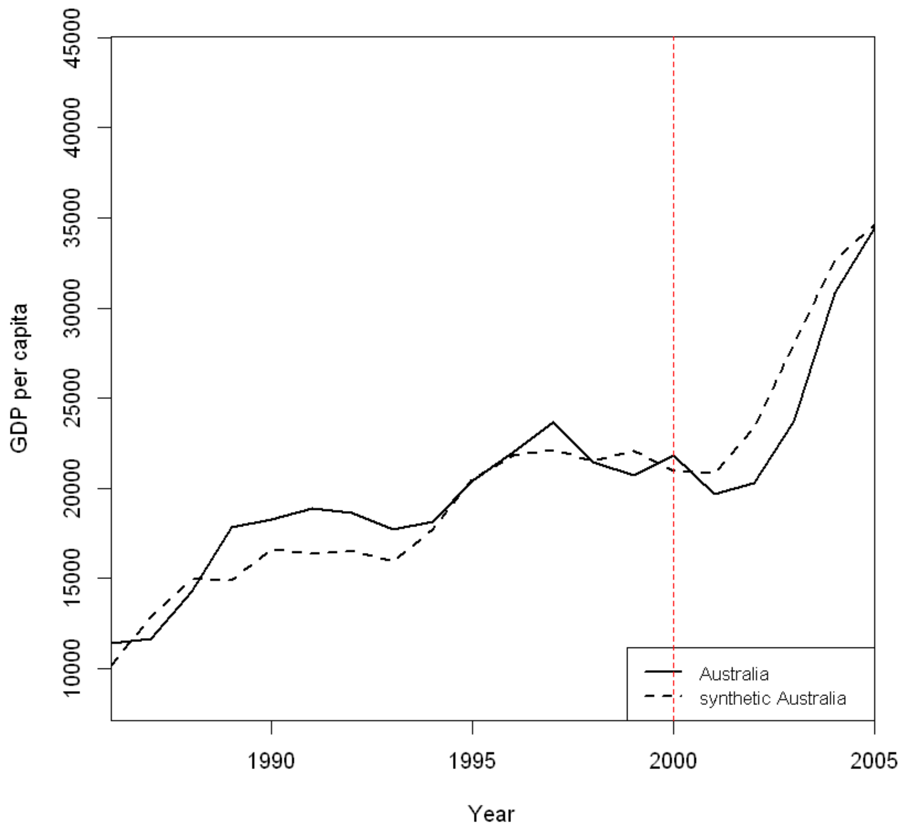

Figure 3: Path plot of Australia vs "Synthetic Australia" over the course of 20 years. The red line shows the point where the treatment was administered.

Looking at the plot above, we see that the "synthetic" control unit follows the treatment unit quite well throughout that period. After the treatment is administered i.e. Australia hosts the Olympics in 2000, we see a sudden drop in GDP per Capita which seems to stay for a few years before finally returning to the pre-treatment trend estimate from the Synthetic Control in 2005. This is an interesting finding since our findings indicate that hosting the Olympics might cause an initial negative effect on the economic prosperity ,measured through GDP per capita in this case, but over a longer period of time these negative effects seem to disappear and the economy returns to normal levels.

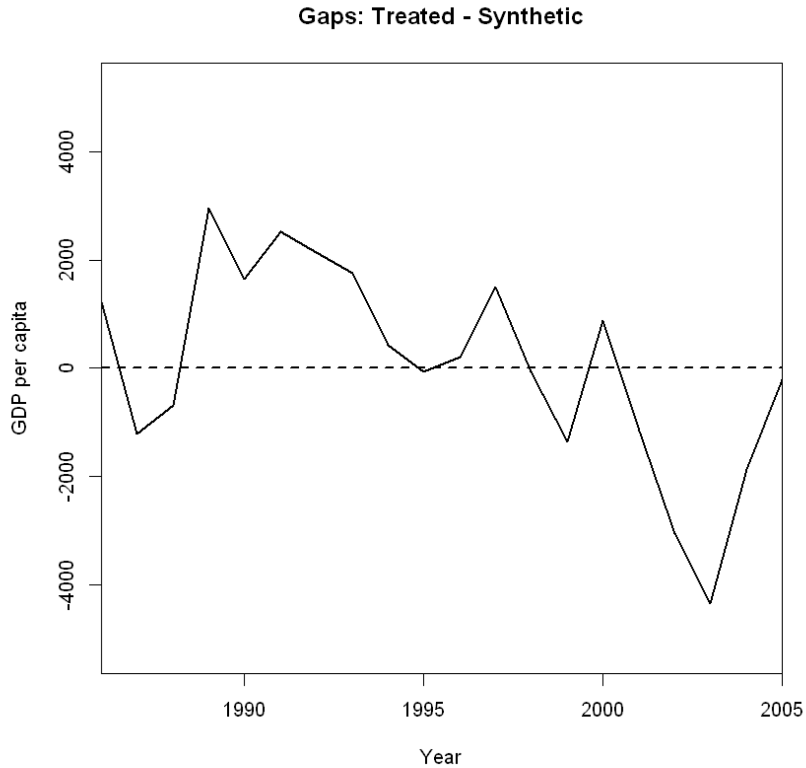

Figure 4: Gap plot showing how far the synthetic control unit is from the treated unit at each point in time. The horizontal line on y = 0 is the synthetic unit and the solid line is the deviation from that at each point in time.

Looking at the Gap plot we can see that the synthetic control stays quite close to the treated unit throughout the period and after an initial big deviation, the rest of the plot is quite close to zero up until 2000 when the treatment is administered. At that point, there is a sudden drop in the treated unit values as shown by the big valley that grows up until about 2003. Synthetic controls can give an estimate of the treatment effect for every interval in time after the treatment as they take the difference from the value of the treated unit. Doing the same analysis on our synthetic control gives us an average value of $-1617.34. This can be interpreted as "Hosting the Olympics in 2000 caused the GDP per capita of Australia to fall by $1617 on average over the next five years. Breaking these numbers down by the year, we see an initial positive increase in GDP per capita of $881.59 in 2000 when the Olympics were held which could be explained by the increase in tourists coming into the country and the corresponding increase in income. However, after that, the GDP per capita keeps falling below the "synthetic" estimate by $1157 in 2001, 3039 in 2002, and 4331 in 2003. After this, Australia starts recovering from the downturn in the economy being $1857 below the estimate and just 200 dollars below the estimate in 2005.

The final step in the discussion of the results is robustness tests. Robustness tests allow us to evaluate the strength of our results and see whether or not we can be confident in our results or not. We will run two placebo tests to evaluate the sensitivity of our results. The first is an in-place placebo test where we assume that the treatment took place in a different country from the donor pool and use the rest of the countries as the donor pool for that. The second is an in-time placebo test where we assume that the treatment took place at a different time before the treatment and see whether we observe a treatment effect or not. If our results are robust, we should not see any treatment effect in both of these cases.

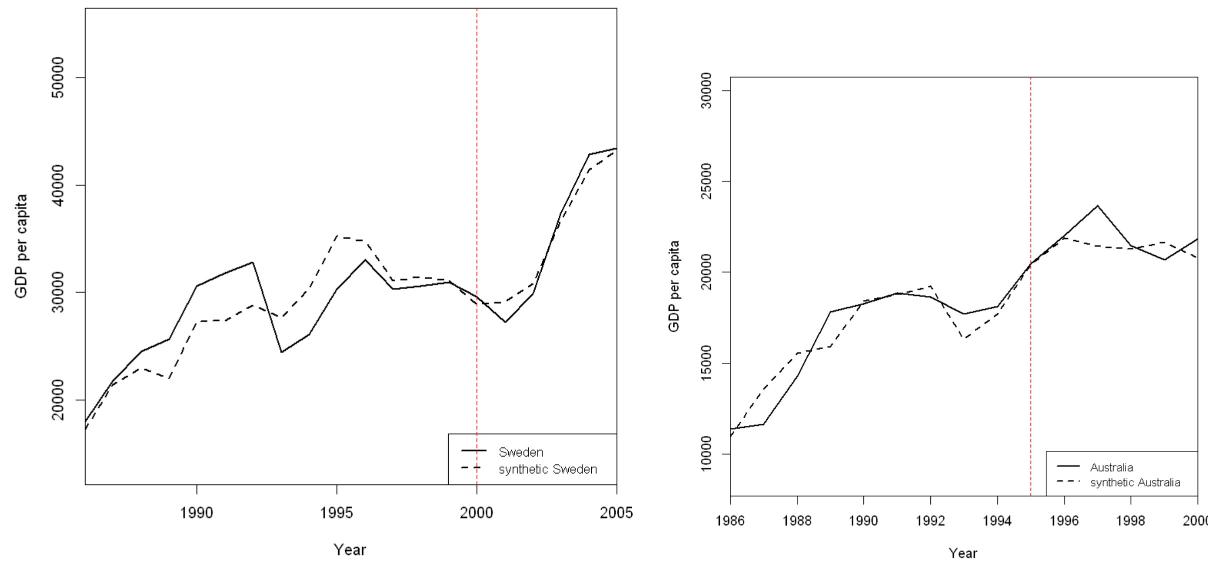

Figure 5: Path plots generated from the placebo tests that were run. On the left is the in-place placebo test which uses Sweden as the treatment group and makes a synthetic control for Sweden. On the right is an in-time placebo test which assumes that the treatment occurred in Australia in 1995.

Looking at the plots above, we see no treatment effect in both placebo tests which gives more confidence to our predictions of the treatment effect. The plots above can also be used to test the three assumptions that we detailed earlier. The parallel trends assumption can be checked using the path plot (Figure 3) for synthetic Australia or the Gaps plot (Figure 4) both of which indicate that the synthetic control and the treated unit do indeed follow similar trends and paths. The similarities in terms of covariates can be seen in Table 3 where we showed that the variables that are important in predicting the outcome (GDP per capita) are indeed similar across the two units. Finally, we can check the assumption of spillover effects by referring to the in-place placebo test that used Sweden as the treated unit but showed no treatment effect. This shows that there was no effect of hosting the Olympics in Australia on the country in the donor pool. Finally, we also check that there was no anticipation effect in Australia as we see no treatment effect in the in-time placebo test which indicates that the treatment effect is due to hosting the Olympics.

Limitations

This analysis, while covering a lot of countries, is still limited in scope. We have only used data for 20 years and limited variables. The list of variables can be expanded to potentially improve the causal estimate by accounting for more confounders, but the research is limited due to a lack of publicly available data. This absence of data is further portrayed in the mising data values that were imputed. The quality of the data and analysis can thus be improved through more robust and advanced imputation or missing data management methods. The “synthetic” control is also not a perfect fit and there are deviations so one would expect that including more variables over a longer period of time would solve that problem.

Another limitation of our analysis is the external validity of our findings. Our findings are very specific to Australia and since Synthetic controls use estimates specific to a country, the results are not generalizable to the broader list of host countries. It does strengthen the argument against hosting the Olympics but can only be used as a case study. We might find similar results in the other host countries too but we would need to do an analysis on each of them or use an alternative causal inference method that allows us to generalize our results.

Conclusion

From our analysis, we found that hosting the Olympics might bring temporary economic prosperity measured by GDP per capita to a country in the year of hosting but Australia suffered a downfall in GDP per capita in the years following. This gives more evidence to research where the Olympics are expected to have a negative impact on the economy of a host country. This research can be complemented further by using more robustness checks and using a Bayesian Synthetic control method as extensions to this paper. Moreover, alternative methods like Differences-in-Differences could be used to estimate the effect of hosting the Olympics on Australia. In order to generalize the results, a method like Matching or Regression Analysis through Panel data could also be used to find more generalizable effects.

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Statement of contribution

Abdullah: I wrote the sections on the Analysis and Results and wrote the code for the Synthetic controls. Further, I wrote the limitations of the analysis and testing of assumptions along with the conclusions. Finally, I made the DAG for the paper and wrote the explanation for that as well. I also reviewed the paper at the end before submission and made sure that there were no errors and that the paper met the standards highlighted in the instructions.

Jessey: I constructed the donor pool by identifying potential candidates and eliminating dissimilar or unqualified units. I identified the relevant variables for the dataset, I generated the dataset used for the synthetic control inference by pooling data from multiple sources on the internet. I wrote descriptions for the how the data was sourced and processed, constructed a table explaining the variables used. Finally, I described the limitations of the data and how they can be improved.

Nabeeha: I wrote the Literature review and then helped identify the variables that we would need to find in order to conduct a meaningful analysis. Moreover, I wrote the abstract and introduction sections of the paper along with the formatting as well. I also reviewed the paper's grammar and made sure the sections all combined together well.