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Can the Olympics Spur Local Socioeconomic Development? Evidence From Brazil

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Can the Olympics spur local socioeconomic development? Evidence from Brazil.

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Can the Olympics spur local socioeconomic development? Evidence from Brazil.*

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Abstract

Countries pledge ever increasing budgets and commitments to host the Olympics. The region whose bid emerges victorious puts in motion the reallocation of inputs, labor, and capital to build all the promised infrastructure to run the event, while the remaining areas in country remain largely unaffected by the intervention. This quasi-experiment scenario is proper for the usage of the Synthetic Control Method but few papers have exploited it. This paper fills the gap by being the first to offer an analysis at local level for a developing economy on the impact of the Olympics. Using Rio de Janeiro's winning bid for the 2016 Olympics in 2009, this paper utilizes annual data from 2000 to 2019 to estimate the impact of the intervention when compared to its synthetic control simulating the absence of such. I estimate a statistically significant average increase in income inequality by .026 in the Gini index due to the Olympics. Furthermore, the estimations show no statistically significant impact of the event for per capita GDP and net admissions into the labor market. The results are consistent with the previous literature and also backs the claims of disillusionment with regards to the benefits of the Olympics by citizens.

JEL Classification: C32, O10, L83

Keywords: Mega-events, Regional Development, Sports Economics

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1 Introduction

Countries compete fiercely in conference rooms and offices for hosting the Olympics as they do in track and field, pools, and on the pitch as athletes strive for the gold medal. While Nations awarded with hosting the event pitch and pledge ever increasing commitments and budgets, *ex post* evidence from academics show that the economic benefits to the taxpayer and host city are rather limited. Nonetheless, few studies have exploited the fact that the hosting of the event acts as a quasi-experiment, as the city hosting the event acts receives the "treatment" while the rest of the country remains devoid of the intervention, acting as the control group; thus, a scenario that is proper for the use of the Synthetic Control Method. On October 2, 2009, during the 121st International Olympic Committee Session, Rio de Janeiro was selected as host for the 2016 Summer Olympics. This paper estimates the impacts at state level on GDP per capita, net admissions into the job market, and income inequality measured by the Gini index following the confirmation of Rio de Janeiro as host of the Olympics.

Gauging the causal effects of "mega-events" such as the Olympics is essential in shedding light into the economic and social impacts that are generated by them (or the lack thereof). On one hand, promoters and other interested parties, through *ex ante* analyses, guarantee the positive impacts of the Olympics, generated by global exposure and urban renewal. On the other, constituents from host and bidding countries appear to display a different tone towards the event: in 2013, residents of St. Moritz and Davos rejected the cities joint bid for the 2022 Winter Olympics through referendum; throughout late 2013 and most of 2014, Germany's Munich, Sweden's Stockholm, Poland's Krakow, and Norway's Oslo followed suite and withdrew their bids; the common theme throughout the withdraws was a disillusionment surrounding the windfall generated by the Winter Olympics (see "Norway withdraws Oslo bid" (2014)).

The confirmation of a given city as host of the Olympics green-lights expenditures and real-location of resources that would not have happened otherwise. While the procurement and construction work done for sports venues, roads, airports, and utilities necessary for properly running the Olympics generates demand for inputs, the main concern for the host city and its constituents is whether such investments were able to generate permanent benefits, by attracting investments, creating jobs, increasing trade, boosting productivity, reducing inequality, bringing more tourists and so forth, guaranteeing prosperity beyond the short-run.

However, the *ex post* academic research backs the constituents concerns surrounding the Olympics. The literature is overwhelmingly in consensus regarding the lack of a statistically significant positive correlation between the public provision of sports venues and economic development (see Baade and Dye (1990), Baade (1996), Zimbalist and Noll (1997), and Coates and Humphreys (1999)). Siegfried and Zimbalist (2000) defines three key reasons behind the failure of the public provision of sports venues in promoting economic development: substitution effects, leakages and the multiplier effects, and budgetary impact. Extending the analysis for the Olympics, Baade et al. (2002) claim that the economic impacts of the Olympics are likely transitory if the "...infrastructure for the Games lack synergy, or worse, if it displaces or competes with resident or established capital and labour..." and, due to the intense bidding process, the winning bid, at best, "...would be consonant with a zero economic return on the investment if opportunity costs are included in the bidding calculus." Zimbalist (2016) notes that, following the modest profitability of 1984 Summer Olympics in Los Angeles, budgets pledged for hosting the games have increased as did the number of developing economies participating in the bidding, which bring the following set of problems: as values spent on bids increase – a "winner's curse" as the author points out – they further drive away from the recipe success used on 1984, which was to keep infrastructure costs at a minimum by utilizing the same venues from the 1932 at Los Angeles; developing countries have the added challenge of featuring fragile institutions, which may divert the increased budgets to wasteful spending and embezzlement schemes, further reinforcing the already present patterns of inequality.

Few studies that exploited the fact that cities awarded with the hosting and the rest of their respective countries are actively participants in a quasi-experiment scenario used the Synthetic Control Method (as developed by Abadie and Gardeazabal (2003), Abadie et al. (2010), Abadie (2021)) to gauge the impact of the Olympics on variables outside the sphere of economics, such as air quality in Beijing 2008 (Zhang et al., 2016), COVID-19 cases in Tokyo 2020 (Esaka and Fujii, 2022), or medals obtained (Barbosa et al., 2016); to the knowledge of the author, only Johnson (2020) and Kobierecki and Pierzgalski (2022) gauged the economic impacts of the Olympics, at local level for the last three Olympics on American soil and at country level, respectively. Therefore, this paper fills the gap in the literature by providing an economic assessment at state level for the Olympics in a developing country through the Synthetic Control approach.

This paper utilizes annual data, from 2000 to 2019, for the 26 states plus the Federal District, for per capita GDP, net admissions into labor market, and income inequality through the Gini index and its respective predictors, made available by the Institute of Applied Economic Research in Brazil. The Synthetic Control Method involves constructing the "artificial" treated region, simulating the absence of the intervention, by minimizing the distance between the actual covariates for treated region and a weighted combination of the same covariates for the control regions encompassing the periods prior to the event; such covariates not only include predictors but also pre-intervention lagged outcome variables; thus, the gap for the desired outcome variables post-intervention can be measured by comparing the actual values with the synthetic ones.

The paper is organized as follows: section two offers an overview of the International Olympic Committee, the Games, bidding process, financing and the budgetary structure; section three describes the data that are used; section four delves into the inner workings and assumptions of the Synthetic Control Method; section five highlights the results of my analysis and briefly discusses them; and the final section offers a conclusion and final remarks about the paper.

2 Event Background

The International Olympic Committee, as defined by its Olympic Charter, is a not-for-profit non-governmental international organization, established to act in stewardship over the "Olympic properties" and the principles of "Olympism" as laid out by its charter. Due to the monopoly over the "Olympic brand", countries that are interested in having its designated city host the Olympiad need to engage in the creation of their respective National Olympic Committees, which essentially acts as the franchisee for the International Olympic Committee, by abiding to its Charter. Only then can the National Olympic Committee set up its Organizing Committee of the Olympic Games, which reports directly to the International Olympic Committee Executive Board (Theodoraki, 2007, p. 54-57).

Countries compete amongst themselves by pitching its host city's bid portfolio. The bid's portfolios include, among many other factors, economic guarantees, information on the host city, plans and the legacy of the facilities to be built. The bidding process takes place during an International Olympic Committtee Session between seven and eleven years before the start of the Olympics. The bid selection is not just influenced by technical metrics but also through diplomacy and communication campaigns domestically and abroad as the selection phase reaches its last stages (Theodoraki, 2007, p. 113-114).

The event's budget is divided between the Organizing Committee of the Olympic Games expenditures and the Non Organizing Committee of the Olympic Games expenditures. The former represents expenses associated with the actual running of the event (e.g. torch relay, opening and closing ceremonies, and so forth) and are backed by a mix of money coming from the International Olympic Committee, sponsors, ticket sales, subsidies by the local government and other sources; the latter relates to expenditures associated with the infrastructure surrounding the event (e.g. sports venues, airports, roads, railways, ports, utilities, and so forth), that it's not covered by the International Olympic Committee. The revenues generated by broadcast rights are divided solely between the International Olympic Committee (which is then shared with the National Olympic Committees) and the local Organizing Committee for the Olympic Games (Rio 2016 Bid Committee, 2009).

On October 2, 2009, during the 121st International Olympic Committee Session, Rio de Janeiro's bid for the 2016 Olympics emerged victorious, beating the cities of Madrid (runner-up), Chicago, and Tokyo. Zimbalist (2017) suggests that the Non Organizing Committee of the Olympic Games budget was above \$20 billion , far surpassing the pledged bid of \$14.4 billion, and over the reported

$15 billion for the 2012 Games in London (McCarthy, 2021). Little over month heading into the event, the governor of Rio de Janeiro declared state of financial emergency (Watts, 2016).

3 Data

Yearly data was obtained from the Institute of Applied Economic Research, from 2000 to 2019, for all 26 states plus the federal district. The outcome variables being analyzed are: per capita GDP (thousand of Brazilian Reals), net admissions into labor market (generated from data available for admissions and layoffs), and Gini index. Predictors for per capita GDP were sectoral shares of GDP, openness index (imports plus exports as share of GDP), human capital indicators (percentage of individulals with regards to illiteracy and high school diploma, percentage of households with electricity, access to adequate water supply and treatment, and trash service), and credit applications (thousand of Brazilian Reals); for Gini index analysis, the social vulnerability index, per capita income, and population; and for net admissions, human capital indicators already mentioned, per capita GDP, credit applications, and population. Additionally, lagged values for all pre-intervention periods were used as covariates when estimating the outcome variables. Table 1 displays the summary statistics for the outcome variables.

4 Empirical Strategy

4.1 Synthetic Control Method

The idea behind comparative case studies resides on gauging the impact of an event, intervention, or policy on the treated region between two states: with it and without it. The latter is a factually impossible event; thus, the impact is gauged by comparing the treated region with a neighboring area, a region that display similarity with the treated, or the average of selected areas. The Synthetic Control Method – as developed in Abadie and Gardeazabal (2003), Abadie et al. (2010), and Abadie (2021) – approaches the selection of the control regions differently by using a weighted combination of the control regions, therefore, creating a control region that artificially resembles the treated region without the treatment.

In general terms, suppose we have $J+1$ regions, so that: $j = 1,2,\ldots,J+1$. Assuming the first one is the exclusive target of a certain intervention, we shall have the remaining units as the "donor pool", the untreated regions not affected by the intervention. Let us also assume that there are T time periods, and that T_0 is the amount of periods before the intervention. For each unit j, we have a set of k predictors, $X_{1j}, X_{2j}, \ldots, X_{kj}$, which may include pre-intervention values for the dependent variable. Then, the $k \times 1$ vector $\mathbf{X_1}$ will contain the predictors for the treated region, while the $k \times J$ vector $\mathbf{X_0} = [\mathbf{X_2}...\mathbf{X_{J+1}}]$ is its counterpart for the "donor pool".

For each unit j, at time period t, we can define the outcome variable without the treatment as Y^N_{jt}. For the treated region, for periods $t > T_0$ after the intervention, we define the outcome variable as Y^I_{1t}. Then, the effect of the intervention for the post-treatment periods is:

$$\tau_{1t} = Y^I_{1t} - Y^N_{1t}.$$

The question then is how to estimate Y^N_{1t} for both the pre and post-intervention periods. As mentioned previously, the unit of comparison used in the Synthetic Control Method is the "synthetic" treated region, by using the weighted average of the regions present in the "donor pool". The weights are chosen so that the dependent variable pre-intervention values for the "synthetic" region closely match the actual pre-intervention values. Thus, given a set of non-negative constants $v_1, ..., v_k$, the synthetic control $J \times 1$ vector $\mathbf{W}^* = (w^*_2, ..., w^*_{J+1})'$ is chosen such that it minimizes:

$$||\mathbf{X_1} - \mathbf{X_0}\mathbf{W}|| = [\textstyle\sum_{h=1}^{k} v_h (X_{h1} - w_2 X_{h2} - ... - w_{J+1} X_{hJ+1})^2]^{1/2}$$

subject to the restriction that the weights are non-negative and $w_2 + ... + w_{J+1} = 1$. The estimated treatment effect for the treated unit for the post-intervention periods is:

$$\hat{\tau}_{1t} = Y^I_{1t} - \textstyle\sum_{j=2}^{J+1} w^*_j Y_{jt}$$

The $k \times 1$ vector $\mathbf{V} = (v_1, ..., v_k)$ weigh in the importance of the synthetic control in reproducing the values for each of the k predictors for the treated unit, $\mathbf{X_{11}}, ..., \mathbf{X_{k1}}$. Selecting the optimal values for $v_1, ..., v_k$ – as suggested by Abadie and Gardeazabal (2003) and Abadie et al. (2010) – involve minimizing the mean square prediction error for the pre-intervention periods with respect to Y_{1t}^N:

$$\sum_t^{T_0}(Y_{1t} - w_2(\mathbf{V})Y_{2t} - ... - w_{J+1}(\mathbf{V})Y_{J+1t})^2$$

and which is the approach I shall be using in this paper.

4.2 Inference

Abadie et al. (2010) and Abadie (2021) suggest a mode of inference through a series of placebo tests, where the synthetic control is applied to the control regions. If the unaffected areas showcase similar magnitudes in the gaps for the considered outcome variables when compared to the treated region, then the analysis of the latter does not produce significant evidence of the impact of the intervention. The authors created a test statistic in order to gauge for all regions the goodness-of-fit for the pre-intervention periods and the magnitude of the impact post-intervention through the following:

$$R_j(t_1,t_2) = (\tfrac{1}{t_2-t_1+1}\sum_{t_1}^{t_2}(Y_{jt} - \hat{Y_{jt}}^N)^2)^{1/2}$$

which is the root mean square prediction error. Then, it is possible to calculate the quality of the fit post-intervention with regards to quality of fit pre-intervention by:

$$r_j = \frac{R_j(T_0+1,T)}{R_j(1,T_0)}.$$

A *p-value* for the inference, based on the permutation distribution of r_j, is given by:

$$p = \tfrac{1}{J+1}\sum_1^{J+1} I_+(r_j - r_1)$$

where I_+ represents an indicator function that returns the value of one for non-negative values of $(r_j - r_1)$ and zero otherwise. In order to better gauge inference, the authors suggest removing from the donor pool the units that feature a bad fit for the synthetic control in the pre-intervention periods.

4.3 Assumptions

Abadie (2021) highlights the following contextual requirements that must hold in order for the Synthetic Control be an appropriate approach for intervention evaluation. The effect of the intervention, regardless of how large it is, can be difficult to detect if one does not account for the volatility that may be present in the outcome variable of choice. The availability of a suitable control group, by avoiding including regions that feature similar interventions such as the one in the treatment or may have suffered from idiosyncratic shocks which would have not occurred in the absence of the intervention and, moreover, restricting the "donor pool" to regions with characteristics similar to the treatment region. Anticipation effects by forward-looking agents should be avoided by backdating the period in which the intervention comes into play. Spillover effects should be accounted for by either discarding units that may be affected by such from the "donor pool" or by the research actively accounting for the bias coming from the control regions also affected by the treatment. The pre-intervention values for the outcome variable in the treatment region must be closely tracked by the synthetic control. Lastly, the need for a suitable amount of post-treatment periods in order to accurately gauge the intervention.

5 Results

5.1 Synthetic Control Estimates

Figure 1 shows the trends for per capita GDP between Rio de Janeiro and the average of the rest of Brazil. Figure 2, likewise, shows the trajectories between Rio de Janeiro and the average of the "donor pool" for net admissions, and one can observe the dramatic contraction in the labor market faced by the former for the year of 2015. Figure 3, similarly, displays the trends between the treatment region and the average of the control regions for income inequality measured by the Gini index. Visually, it is possible to notice that the average of the remaining Brazilian states does not closely match the trend shown by the state of Rio de Janeiro for the periods prior to 2009.

Through the synthetic control it is possible to generate a counter factual that closely follows for the pre-intervention periods.

As mentioned in the previous section, the synthetic control chooses the weights as to minimize the distance between the covariates for the treated and control regions. Table 3 shows that the per capita GDP trends simulating the absence of the intervention were best reproduced by a combination of the states of Amapá, Espírito Santo, Mato Grosso, and São Paulo. For net admissions, Table 4, the synthetic best reproduced the actual pre-intervention values from a combination of the states of Ceará, Paraná, and São Paulo. For Gini index, Table 5 displays that the synthetic control is best constructed by the combination of the states of Alagoas, Paraná, Rondônia, Santa Catarina, and the Federal District. Table 2 displays the average values for the outcome variables, before and after the time of the intervention, for Rio de Janeiro and the "donor regions".

Figure 4 shows the trends of the actual per capita GDP values and its synthetic counterpart. After the intervention it is possible to observe how per capita GDP faced a reversal of fortunes, peaking in 2014 (about 1000 Brazilian Reals higher) and, for the remaining periods, the synthetic shows that per capita GDP would be higher in the absence of the Olympics (for 2016, per capita GDP was estimated as approximately 2750 Brazilian Reals lower). On average, for all post-intervention periods, per capita GDP decreased by 650 Brazilian Reals. Figure 5 shows more clearly the gap between actual and synthetic values. Inference is gauged through the placebo test, as explained in the previous section, by applying the synthetic control for the control regions. Figure 6 show the gap trends for the treated and control regions and it can be observed that the trajectory of the former cannot be easily distinguished from the rest of units being analysed; furthermore, the root mean squared prediction error for the pre-intervention periods for the treatment showcased a goodness-of-fit that was worse than the values for the placebo runs in the donor pool; thus, we cannot reject the null hypothesis of zero impact on per capita GDP due to the intervention.

Figure 7 displays the trajectories for both Rio de Janeiro and its synthetic control, showcasing how the method constructs a closely-matching counterfactual for the pre-interention periods. After the intervention, again, there is a crossing point between the trends, with the year of 2016 being particularly evident (as shown in Figure 8) on the contraction of the labor market, estimating that the intervention actually cut an additional 134,000 job positions. On total, the additional aggregate contraction was estimated at 286,102 posts approximately. Figure 9 display the placebo test, showing a very distinct trajectory of the treated unit in comparison with the control regions for the post-intervention periods; however, when analysing for the goodness-of-fit in the pre-intervention periods, the treatment displayed a value that was above most of the placebo runs in the donor pool; thus, this subpar fit places a caveat on the statistical significance of the analysis.

Lastly, Figure 10 presents the trends for the actual and the synthetic values for the Gini index. Following the intervention, the trends for the synthetic control and the treated diverges, estimating higher income inequality levels for all post-intervention periods. Figure 11 shows that the gap between the treatment and synthetic peaks at approximately a .06 in inequality. Figure 12 shows the placebo test; with a root mean squared prediction error of .004963 and .029 for the pre and post-intervention periods, respectively, the treatment displayed the second-to-best fit and the synthetic trend for it was significant for a 10% level (the p-value is approximately .076), thus offering evidence for income inequality being generated by the intervention.

5.2 Difference-in-Differences Robustness Checks

As further backing to the estimation done through the Synthetic Control Method, I also run the simple canonical difference-in-difference model to estimate the impact of the intervention for the outcome variables through the following model:

$$OutcomeVariable_{it} = \beta_0 + \beta_1 * Olympics_{it} + \beta_2 * Post2009_{it} + \beta_3 * Interaction_{it} + e_{it}$$

where i indexes the variables between the two regions considered, Rio de Janeiro and the Synthetic Rio de Janeiro, while t indexes the years in the sample, from 2000 to 2019; $Olympics_{it}$ is a dummy variable that takes the value of one if the intervention took place, zero otherwise; $Post2009_{it}$ is a dummy variable that equals one for all periods after the year 2009; $Interaction_{it}$, as the name implies, is the product of the aforementioned dummies, capturing the effect of the intervention, after controlling it for time and location. Table 6 reports the result of the regression and the estimates reported match the synthetic control analysis: for both per capita GDP and net admissions, the effect of the intervention was correlated to an average contraction of 645 Brazilian Reals, roughly 4.6% of the average per capita GDP reported, and little under 29,500 jobs, a decrease of 113.5% of the average number of positions for the sample,; nonetheless, the parameters were not statistically significant in order to reject the null hypothesis; for income inequality, the intervention is correlated to an average effect of increasing the Gini index .026, and was statistically significant for a 5% level, offering a strong argument for the Olympics actually increasing the disparity in the host region.

5.3 Discussion

The statistically insignificant results for the impact of the Olympics on both per capita GDP and net admissions reflect the consensus shown by the previous literature. Vartanian and Garbe (2019) reports that the Brazilian economy faced eleven consecutive quarters of economic contraction, from the second quarter of 2014 to the fourth quarter of 2016; due fiscal rules arrangement between states and the federal government in Brazil, crises that affect the balance-of-payments of the country spillover to the regional balance, the state of Rio de Janeiro being definitely affected. The big dent in public budgets due to the Olympics, thus, may have been only one of the many nails in the coffin of the state's fiscal health, as Bonomo et al. (2021) report Rio de Janeiro being a traditionally reckless spender.

The year of 2015 is one of particular note when observing the figures, as both per capita GDP and net admissions faced significant contraction. The reasoning behind the results is due to the fact that the macroeconomic readjustment period began in 2015, the first full year of contraction, and policies such as short-term interest rates hikes (325 basis points, from the fourth quarter of 2014 to the second quarter of 2015), austerity measures for the accumulation of trade surpluses, alongside the reaction by the market, such as decreased credit rating (Vartanian and Garbe, 2019). All events contribute to a deflationary and contraction period for the economy, with companies cutting on inventories, investing less, and hiring fewer workers, if not contracting their staff. Thus, the downturn shown in per capita GDP and net admissions from 2014 and 2016 was more likely due to the recession faced by the country, instead of the intervention.

The significance of the estimates surrounding the increased income inequality raises then the question of what might be the chain of causation for such phenomena. I suggest one of the reasons behind such shifts in wealth may lie in the displacement of lower-income populations, as households and business are required to move from their original location in order to make space for the construction work required for the planned infrastructure for the Olympics. Zimbalist (2017) reports how 77,000 individuals had to be evicted from their houses and businesses for the construction of a bus rapid transit line; in short, at a single stroke, thousands may lose asset ownership and source of income, regardless of how small they might be. The displacement might as well "hollow-out" the middle income jobs in favor of reallocation towards the lower-skill spectrum, such as construction work, and while the construction of all the infrastructure may demand that type of labor, the excess of low-skill laborers in the Brazilian workforce might drive down returns. The dent on public budgets may also exert a negative impact on income transfers and access to government pension schemes, further restricting sources of income for the lower spectrum of the population.

6 Conclusion

This paper explores the effects that arise when a country is selected as the host of the Olympics on per capita GDP, net admissions into the labor market, and income inequality through Gini index by analysing the winning bid of Rio de Janeiro for the 2016 Summer Games.

By using the Synthetic Control Method, I find that the intervention increased income inequality in the state of Rio de Janeiro, through an average increase .026 units in the Gini index, and was statistically significant for a 5% level. Additionally, effects on per capita GDP and net admissions were found to be negative but statistically insignificant. All results match the consensus found previously in the literature but this body work represents, to the best of the author's knowledge, the first to gauge the economic effects of the Olympics at a regional level for a developing economy through the aforementioned method. Equally as important, this paper also offers further backing to the disillusionment surrounding the benefits of the Olympics as shown by citizens in polls and referendums, effectively stopping the bidding for hosting the event.

References

ABADIE, A. (2021): "Using synthetic controls: Feasibility, data requirements, and methodological aspects," *Journal of Economic Literature*, 59, 391–425.

ABADIE, A., A. DIAMOND, AND J. HAINMUELLER (2010): "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program," *Journal of the American statistical Association*, 105, 493–505.

ABADIE, A. AND J. GARDEAZABAL (2003): "The economic costs of conflict: A case study of the Basque Country," *American Economic Review*, 93, 113–132.

BAADE, R. A. (1996): "Professional sports as catalysts for metropolitan economic development," *Journal of urban affairs*, 18, 1–17.

BAADE, R. A. AND R. F. DYE (1990): "The impact of stadium and professional sports on metropolitan area development," *Growth and change*, 21, 1–14.

BAADE, R. A., V. MATHESON, ET AL. (2002): "Bidding for the Olympics: Fool's gold," *Transatlantic sport: The comparative economics of North American and European sports*, 54, 127.

BARBOSA, A., J. H. VIANA, B. SAMPAIO, AND G. R. SAMPAIO (2016): "The Olympic Spirit Boost: A Synthetic Control Approach," *Available at SSRN 3151894*.

BONOMO, M. A., C. R. FRISCHTAK, AND P. RIBEIRO (2021): "Public investment and fiscal crisis in Brazil: Finding culprits and solutions," Tech. rep., IDB Working Paper Series.

COATES, D. AND B. R. HUMPHREYS (1999): "The growth effects of sport franchises, stadia, and arenas," *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management*, 18, 601–624.

ESAKA, T. AND T. FUJII (2022): "Quantifying the Impact of the Tokyo Olympics on COVID-19 Cases Using Synthetic Control Methods," *Available at SSRN 4030457*.

JOHNSON, C. (2020): *The impact of the Olympic games on employment growth: A synthetic control approach*, West Wirginia University. https://web. holycross. edu/RePEc/fek/Session03.

KOBIERECKI, M. M. AND M. PIERZGALSKI (2022): "Sports Mega-Events and Economic Growth: A Synthetic Control Approach," *Journal of Sports Economics*, 23, 567–597.

MCCARTHY, N. (2021): "The Massive Costs Behind The Olympic Games [Infographic]," *Bloomberg*.

"NORWAY WITHDRAWS OSLO BID" (2014): "Norway withdrawls Oslo bid for 2022 Winter Games," *Reuters*.

RIO 2016 BID COMMITTEE (2009): "Rio 2016 Candidate City: Candidature File for Rio de Janeiro to Host the 2016 Olympic and Paralympic Games," Tech. rep.

SIEGFRIED, J. J. AND A. ZIMBALIST (2000): “The economics of sports facilities and their communities,” *Journal of Economic Perspectives*, 14, 95–114.

THEODORAKI, E. (2007): *Olympic Event Organization*, Elsevier Ltd.

VARTANIAN, P. R. AND H. D. S. GARBE (2019): “The Brazilian economic crisis during the period 2014-2016: is there precedence of internal or external factors,” *Journal of International and Global Economic Studies*, 12, 66–86.

WATTS, J. (2016): “Rio de Janeiro governor declares state of financial emergency ahead of Olympics,” *The Guardian*.

ZHANG, J., C. ZHONG, AND M. YI (2016): “Did Olympic Games improve air quality in Beijing? Based on the synthetic control method,” *Environmental Economics and Policy Studies*, 18, 21–39.

ZIMBALIST, A. (2016): *Circus Maximus: The Economic Gamble Behind Hosting the Olympics and the World Cup*, Brookings Institution Press.

——— (2017): *Rio 2016: Olympic Myths, Hard Realities*, Brookings Institution Press.

ZIMBALIST, A. AND R. G. NOLL (1997): “Sports, Jobs, & Taxes: Are New Stadiums Worth the Cost?” *The Brookings Institution*.

Figure 1: Trends in per capita GDP: Rio de Janeiro vs. rest of Brazil

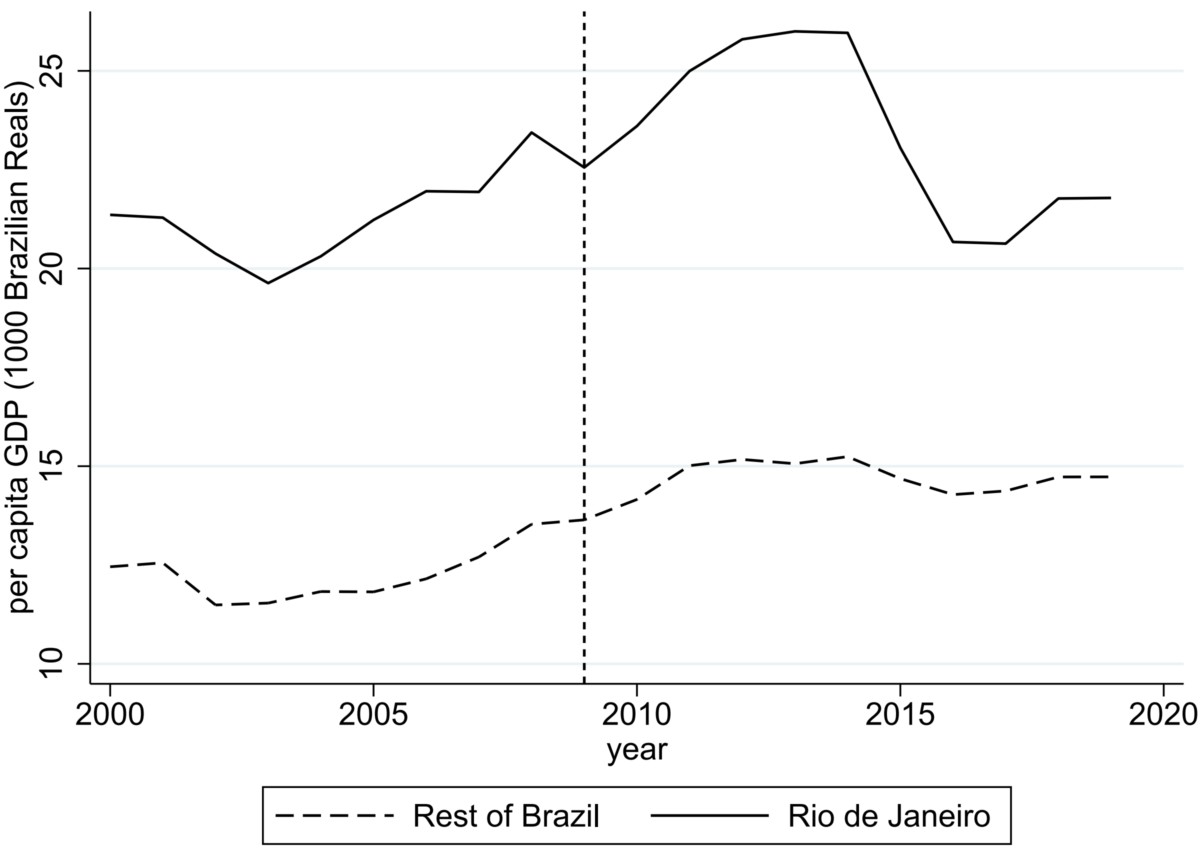

Figure 2: Trends in net admissions into job market: Rio de Janeiro vs. rest of Brazil

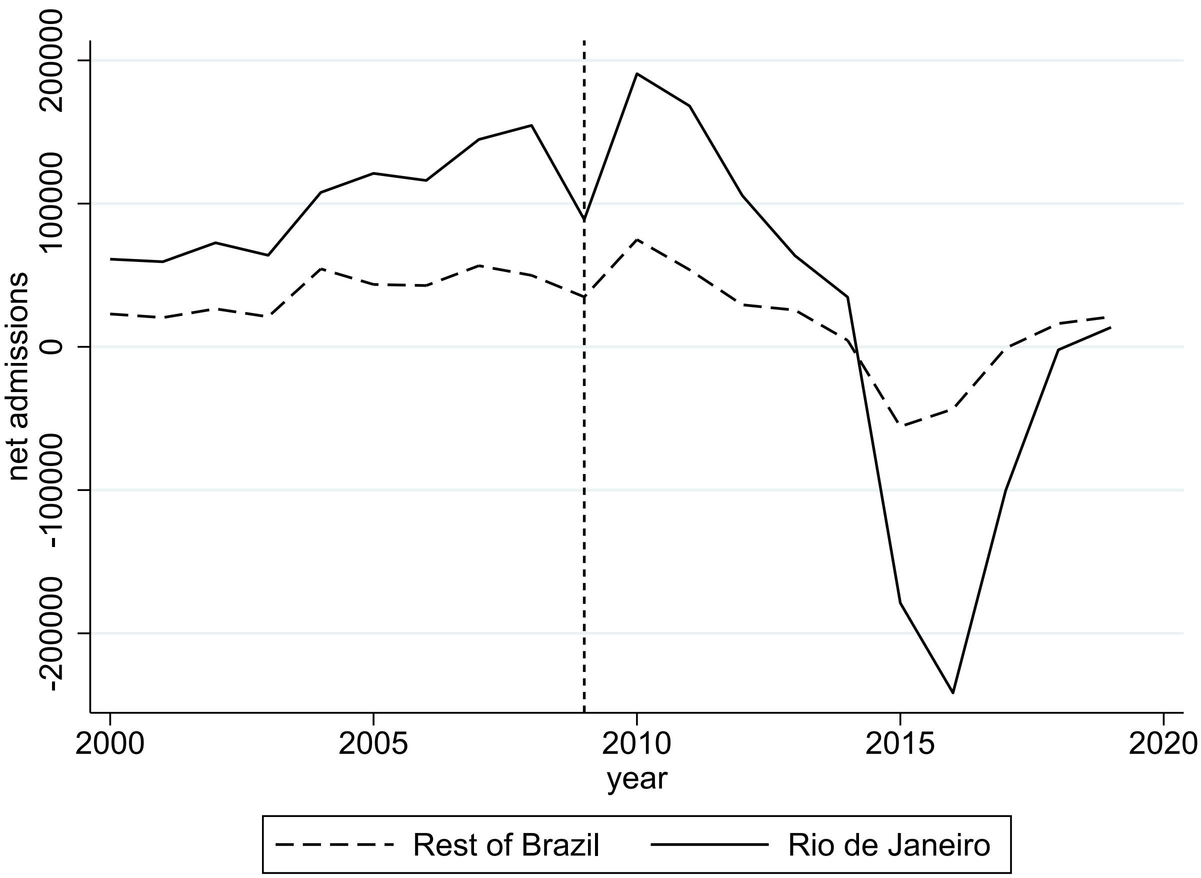

Figure 3: Trends in inequality by the Gini index: Rio de Janeiro vs. rest of Brazil

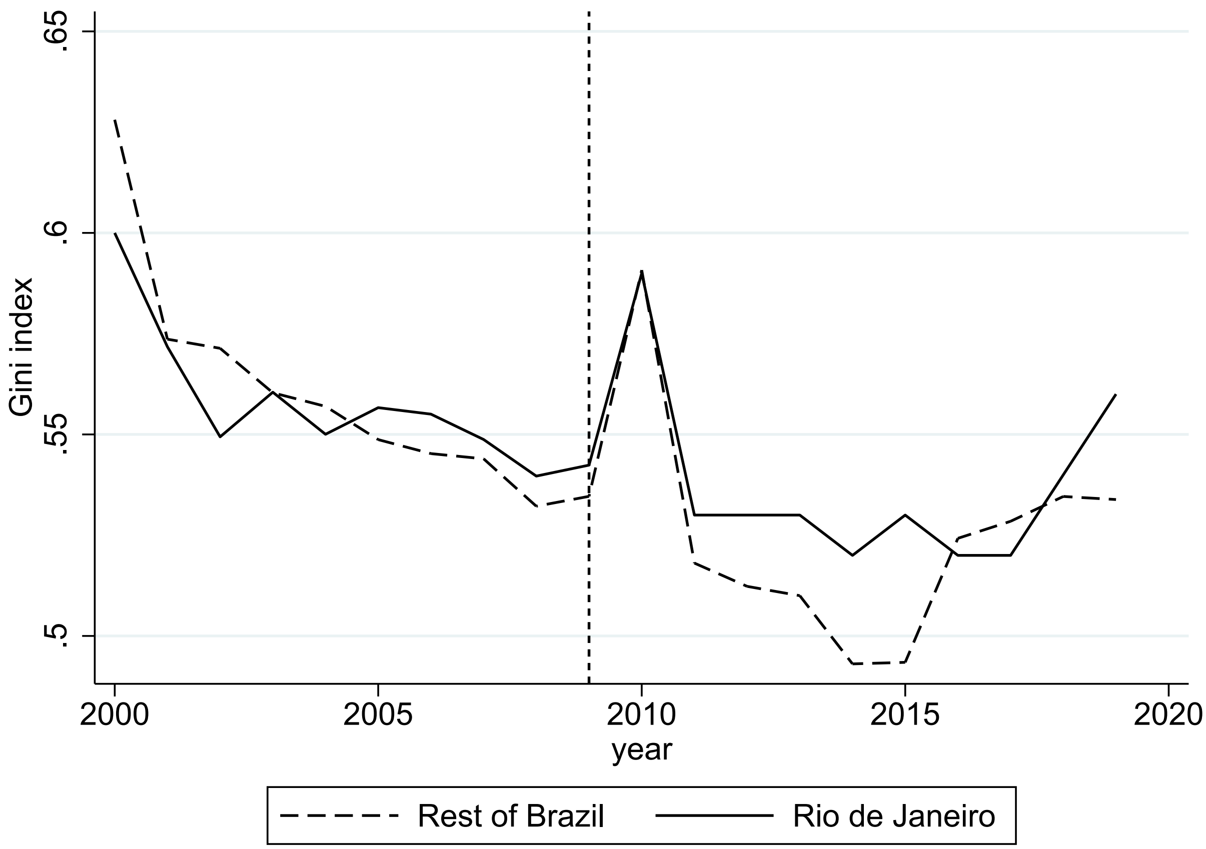

Figure 4: Trends in per capita GDP: Rio de Janeiro vs. synthetic Rio de Janeiro

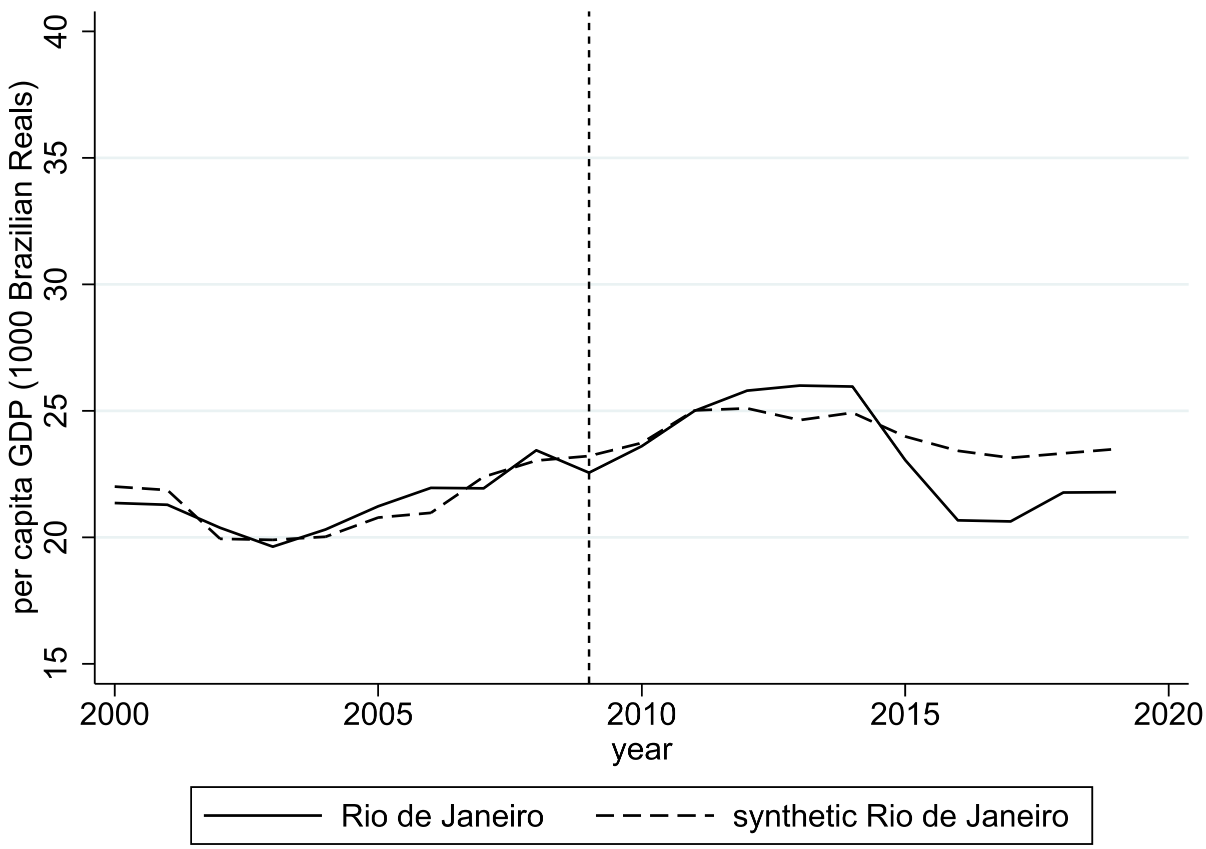

Figure 5: Per capita GDP gap between Rio de Janeiro and its synthetic control

Figure 6: Per capita GDP gap in Rio de Janeiro and placebo gaps for the rest of Brazil

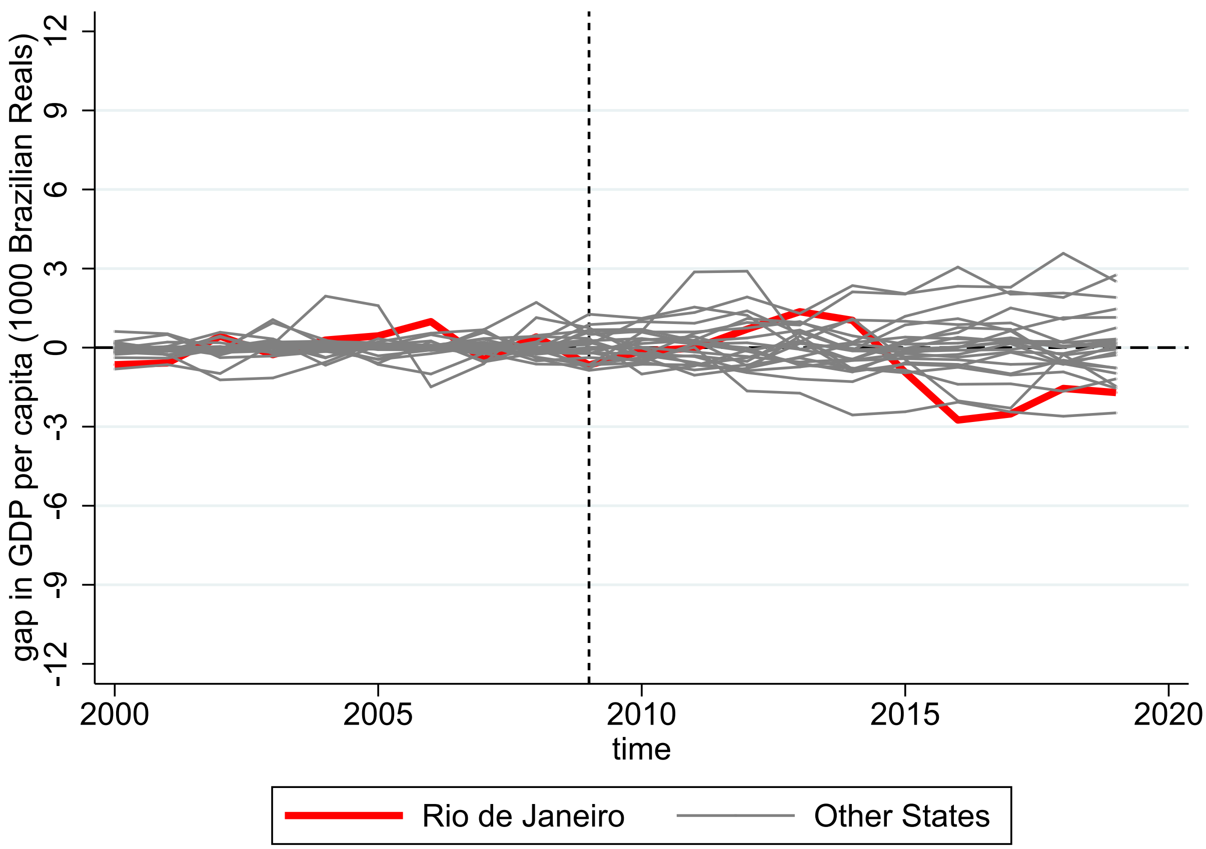

Figure 7: Trends in net admissions: Rio de Janeiro vs. synthetic control

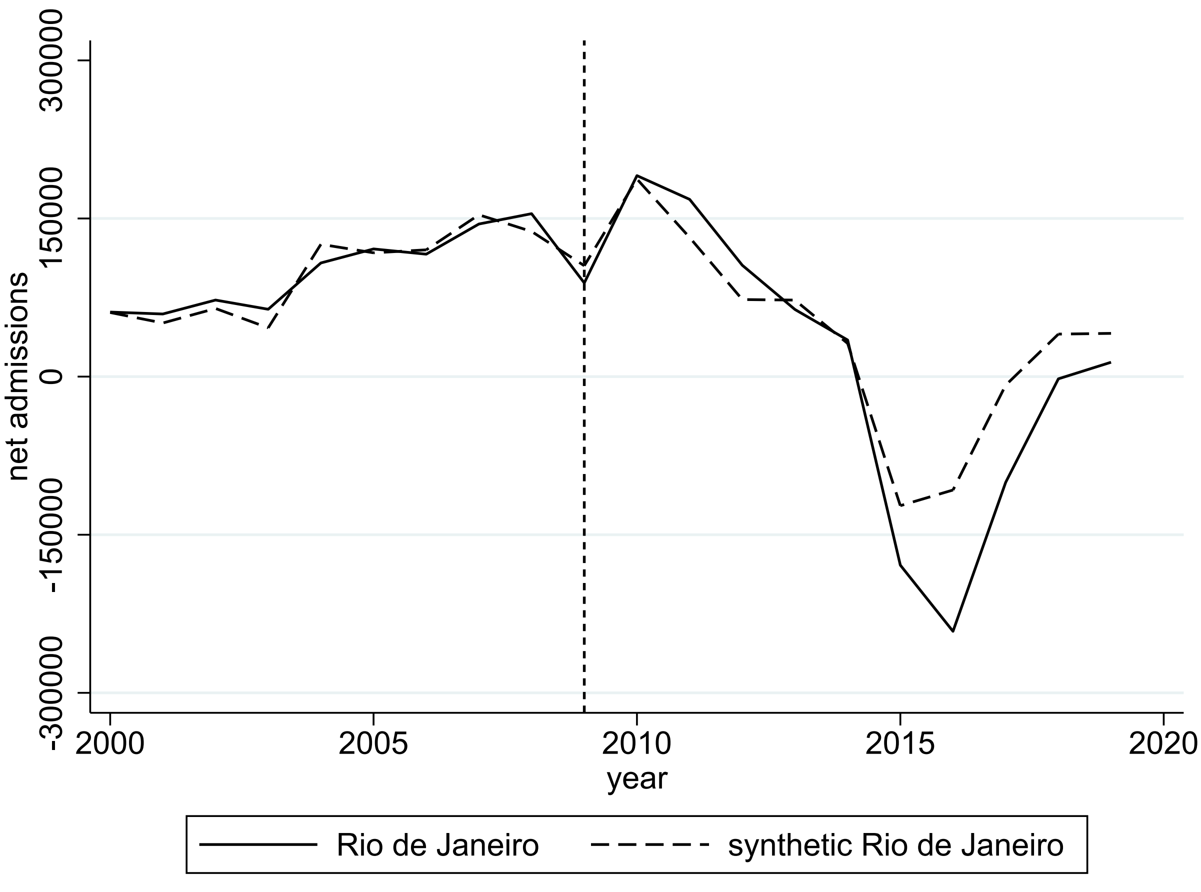

Figure 8: Net admissions gap between Rio de Janeiro and its synthetic control

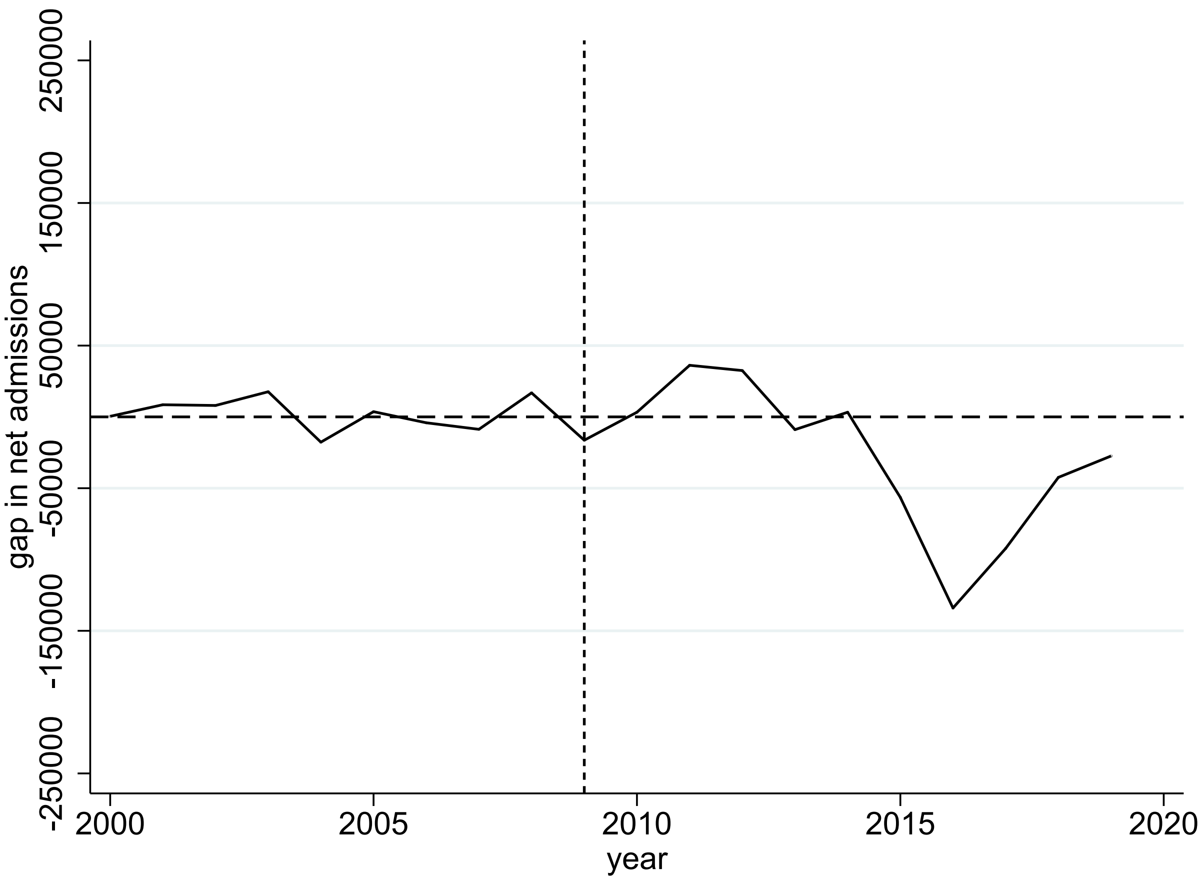

Figure 9: Net admissions gap in Rio de Janeiro and placebo gaps for the rest of Brazil

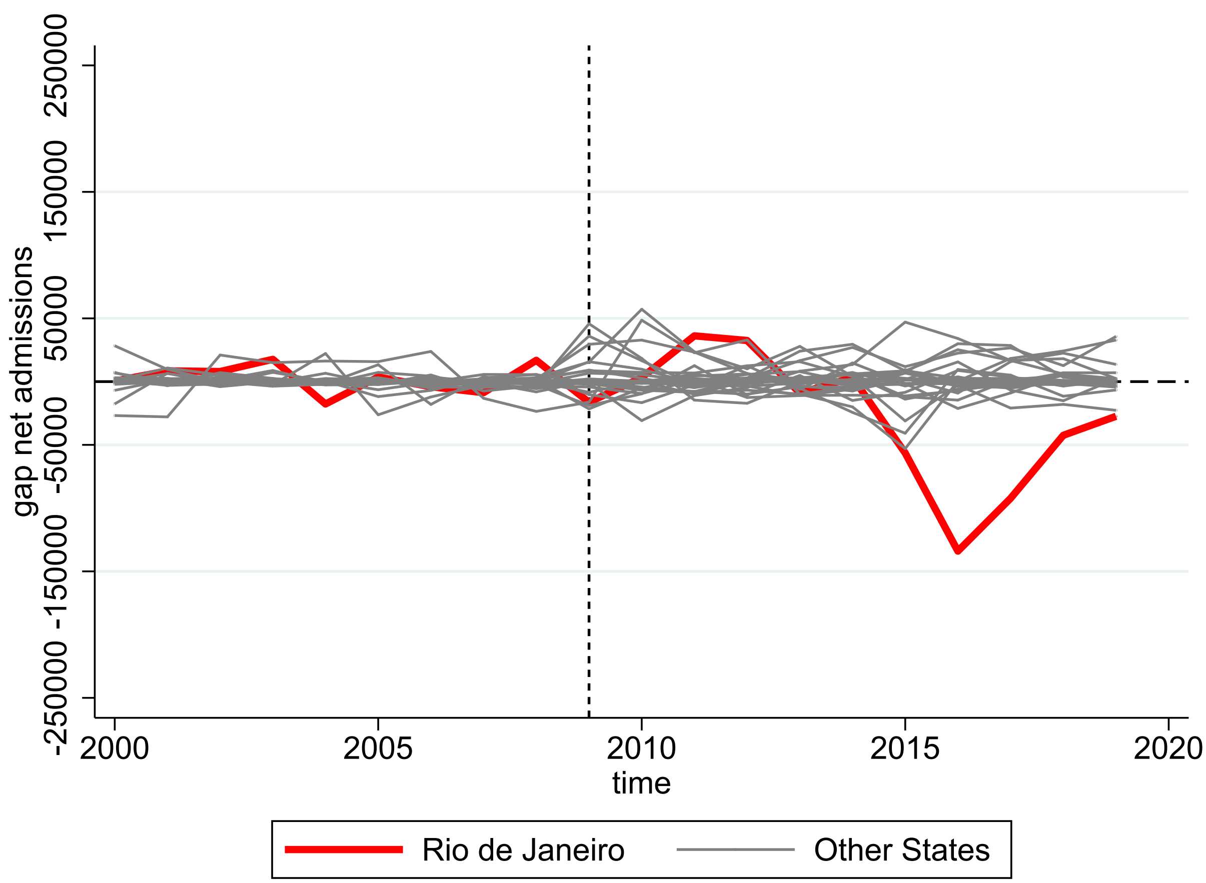

Figure 10: Trends in inequality by Gini index: Rio de Janeiro vs. synthetic Rio de Janeiro

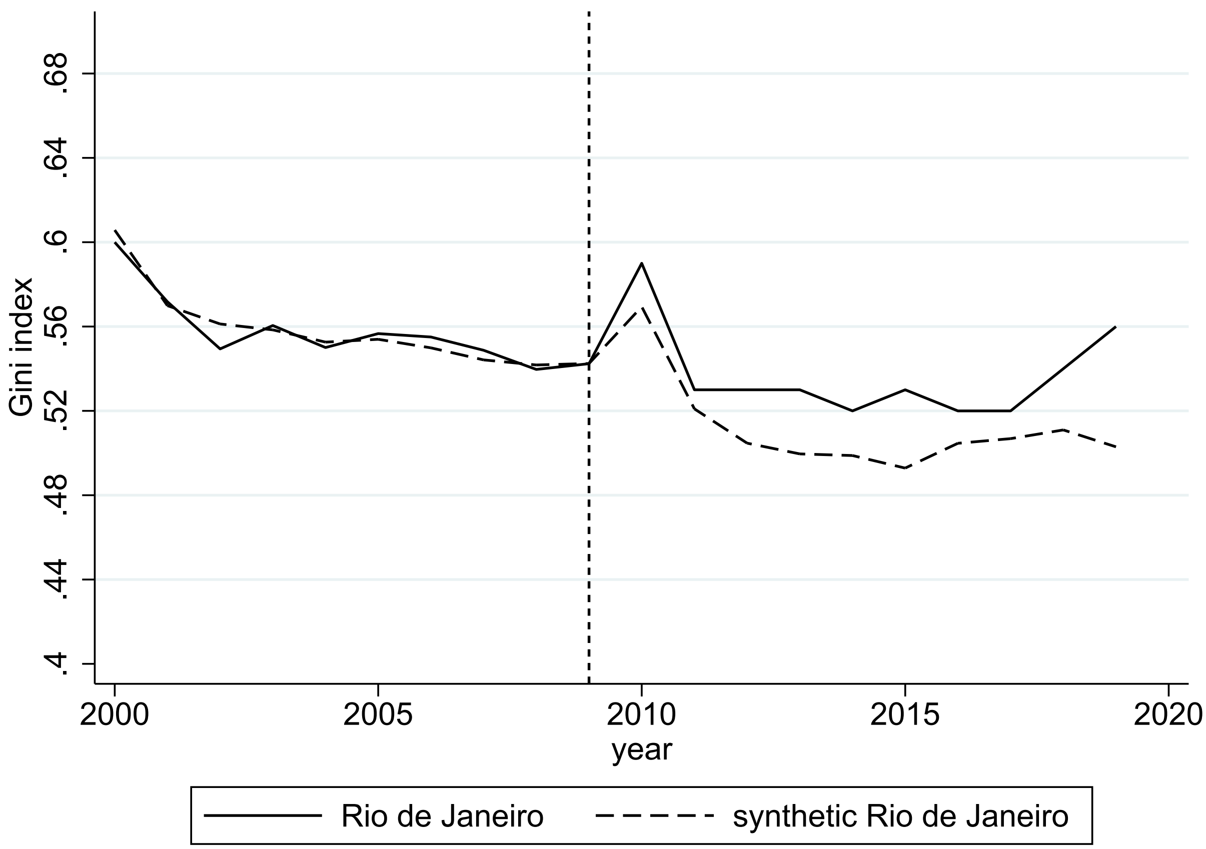

Figure 11: Gini index gap between Rio de Janeiro and its synthetic control

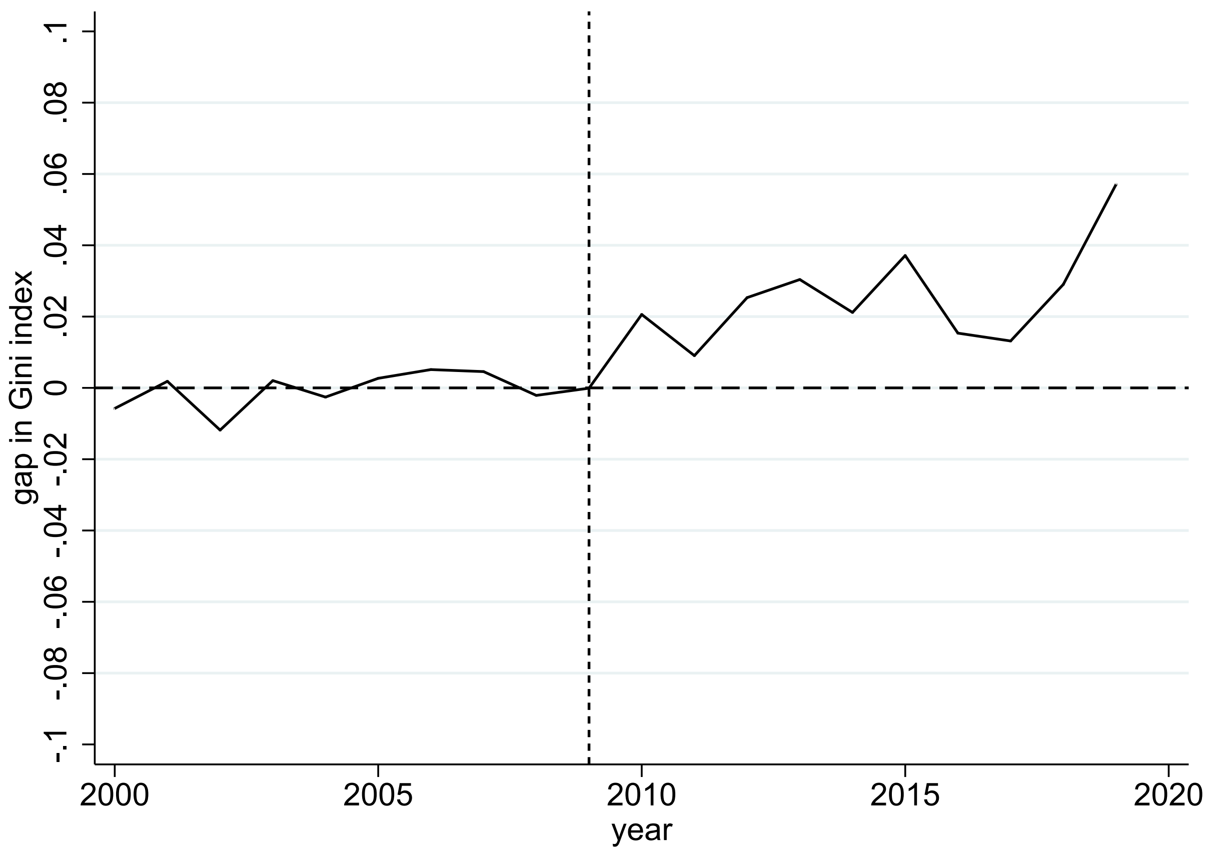

Figure 12: Gini index gap in Rio de Janeiro and placebo gaps for the rest of Brazil

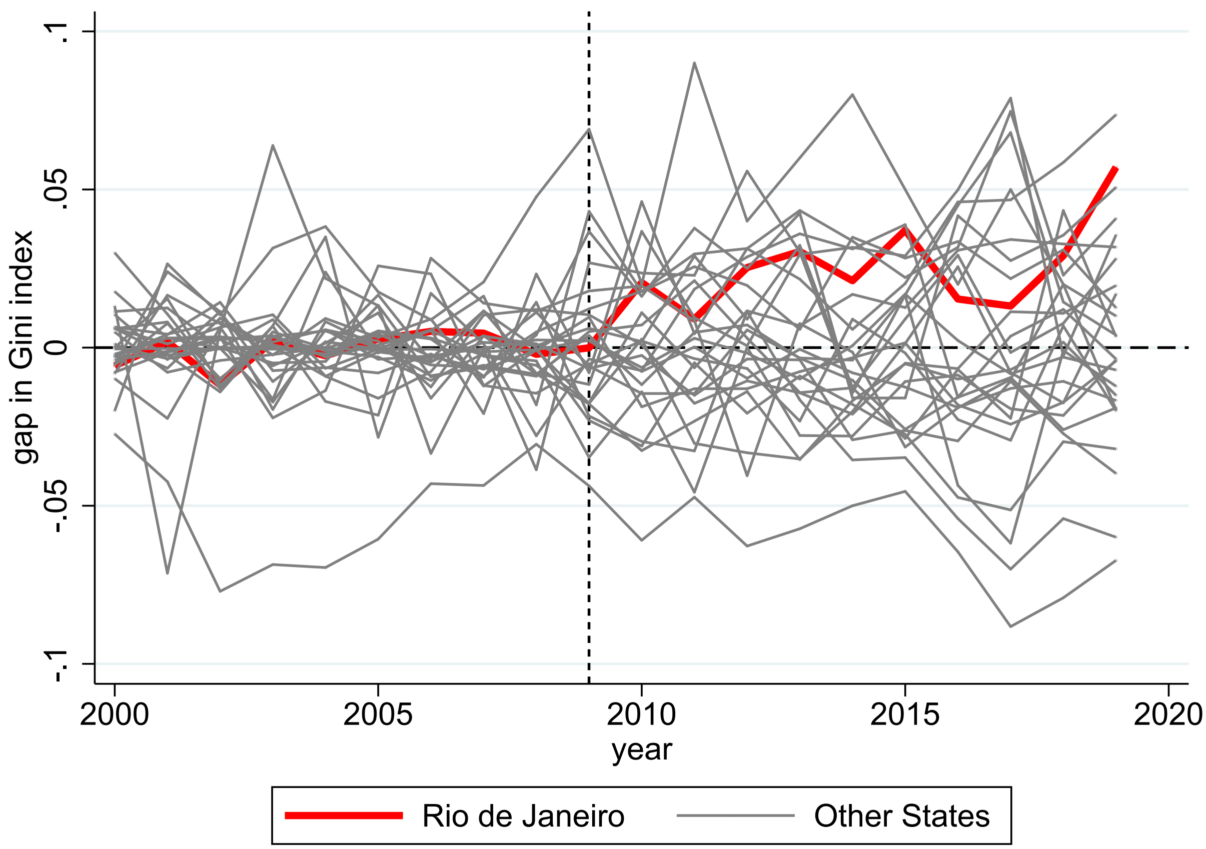

Table 1: Summary statistics for the outcome variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Per Capita GDP (1000 Brazilian Reals)	540	13.887	7.795	4.134	8.600	16.806	47.997
Gini Index	540	0.542	0.047	0.420	0.510	0.570	0.680
Net Admissions	540	25,938.300	80,839.540	−477,956	974	30,966.2	653,242

Table 2: Averages for the outcome variables, before and after the intervention, for the “donor locations and Rio de Janeiro

Variable	Average Rio Pre-2009	Average Rio Post-2009	Average Donor Pool Pre-2009	Average Donor Pool Post-2009
Per Capita GDP	21.409	23.428	21.306	24.001
Net Admissions	99,054.100	5,378.200	157,992.900	50,219.630
Gini Index	0.557	0.537	0.555	0.503

Table 3: State weights in synthetic Rio de Janeiro for per capita GDP analysis

State	Weight
Acre	0.000
Alagoas	0.000
Amapa	0.051
Amazonas	0.000
Bahia	0.000
Ceara	0.000
Distrito Federal	0.030
Espirito Santo	0.058
Goias	0.000
Maranhao	0.000
Mato Grosso	0.115
Mato Grosso do Sul	0.000
Minas Gerais	0.000
Para	0.000
Paraiba	0.000
Parana	0.000
Pernambuco	0.000
Piaui	0.000
Rio Grande do Norte	0.000
Rio Grande do Sul	0.000
Rondonia	0.000
Roraima	0.000
Santa Catarina	0.000
Sao Paulo	0.745
Sergipe	0.000
Tocantins	0.000

Table 4: State weights in synthetic Rio de Janeiro for net admissions analysis

State	Weight
Acre	0.000
Alagoas	0.000
Amapa	0.000
Amazonas	0.000
Bahia	0.000
Ceara	0.748
Distrito Federal	0.000
Espirito Santo	0.000
Goias	0.000
Maranhao	0.000
Mato Grosso	0.000
Mato Grosso do Sul	0.000
Minas Gerais	0.000
Para	0.000
Paraiba	0.000
Parana	0.062
Pernambuco	0.000
Piaui	0.000
Rio Grande do Norte	0.000
Rio Grande do Sul	0.000
Rondonia	0.000
Roraima	0.000
Santa Catarina	0.000
Sao Paulo	0.190
Sergipe	0.000
Tocantins	0.000

Table 5: State weights in synthetic Rio de Janeiro for Gini index analysis

State	Weight
Acre	0.000
Alagoas	0.044
Amapa	0.000
Amazonas	0.000
Bahia	0.000
Ceara	0.000
Distrito Federal	0.379
Espirito Santo	0.000
Goias	0.000
Maranhao	0.000
Mato Grosso	0.000
Mato Grosso do Sul	0.000
Minas Gerais	0.000
Para	0.000
Paraiba	0.000
Parana	0.125
Pernambuco	0.000
Piaui	0.000
Rio Grande do Norte	0.000
Rio Grande do Sul	0.000
Rondonia	0.210
Roraima	0.000
Santa Catarina	0.243
Sao Paulo	0.000
Sergipe	0.000
Tocantins	0.000

Table 6: Differences-in-Differences estimates (standard errors in parentheses)

	Dependent variable:		
	Per Capita GDP	Net Admissions	Gini Index
	(1)	(2)	(3)
Olympics	-0.006	827.615	-0.001
	(0.638)	(40,046.980)	(0.009)
Post-2009	2.664^{***}	$-64{,}238.000$	-0.047^{***}
	(0.638)	(40,046.980)	(0.009)
Interaction	-0.645	$-29{,}437.900$	0.026^{**}
	(0.903)	(56,634.990)	(0.013)
Constant	21.415^{***}	$98{,}226.490^{***}$	0.558^{***}
	(0.451)	(28,317.490)	(0.006)
Observations	40	40	40
R^2	0.437	0.187	0.499
Adjusted R^2	0.390	0.119	0.457
Residual Std. Error (df = 36)	1.427	89,547.780	0.020
F Statistic (df = 3; 36)	9.321^{***}	2.762^{*}	11.957^{***}
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$