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Does the World Cup get the economic ball rolling? Evidence from a synthetic control approach

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Abstract

In this paper we analyze the impact of hosting the FIFA Soccer World Cup on GDP per capita in a worldwide sample of countries using a transparent statistical methodology for data-driven case studies – the synthetic control method. Using country level annual-data covering all events occurring in the period between 1978 (Argentina) and 2006 (Germany), we show that the estimated average treatment effect was either zero or negative for all but one of the countries analyzed. Our results, therefore, support the general claim that World Cups are not statistically associated to development and economic growth.

JEL classification: O4; O5; C50

Keywords: Economic growth; World Cup; Synthetic control method

1. Introduction

In this paper we use country-level annual data on GDP per capita to analyze the impact of hosting the FIFA Soccer World Cup on growth. For that we use the synthetic control method to construct adequate counterfactuals for all countries hosting the event in the period between 1978 and 2006.

The FIFA (Fédération Internationale de Football Association) Soccer World Cup ranks among the three largest events in the world, together with the Olympic Games and the World Expo. These events not only affect the influx of people/tourism in the host country, but also involves publicly financed capital improvement projects that are undertaken to improve infrastructure, such as the construction of new and the improvement of old stadiums (for the particular case of the World Cup), road and airport construction and improvement, among many others. In Uruguay, for instance, which held the first edition of the Cup in 1930, total attendance was little above half million spectators, while this

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Table 1
FIFA World Cups.

Cup year	Year of decision to host	Host	Number of teams	Total attendance
1930	1929	Uruguai	13	590,549
1934	1932	Italy	16	363,000
1938	1936	France	16	375,700
1950	1946	Brazil	13	1,045,246
1954	1946	Switzerland	16	768,607
1958	1950	Sweden	16	819,810
1962	1956	Chile	16	893,172
1966	1960	England	16	563,135
1970	1964	Mexico	16	1,603,975
1974	1966	Germany	16	1,865,753
1978	1966	Argentina	16	1,545,791
1982	1966	Spain	24	2,109,723
1986	1983	Mexico	24	2,394,031
1990	1984	Italy	24	2,516,215
1994	1988	USA	24	3,587,538
1998	1992	France	32	2,785,100
2002	1996	Kora/Japan	32	2,705,197
2006	2000	Germany	32	3,359,439
2010	2004	South Africa	32	3,178,856

Source: FIFA.

number surpassed three millions in two recent editions held in South Africa, with 3.178 millions spectators in 2010, and in Germany, with 3.359 millions in 2006 (see Table 1). The amount of investments has also increased substantially, reaching estimates in the order of €6 billion for both Germany 2006 and South Africa 2010.

Besides the risks and high costs involved in hosting an event of this magnitude, all previous World Cup editions have had large competition between potential host countries (FIFA, 2012). For example, 1930 World Cup had six candidates (Hungary, Italy, Netherlands, Spain, Sweden and Uruguay), while 2018 and 2022 had six and five candidates, respectively. This behavior clearly indicate that countries understand that there are great benefits in hosting such an event. Common arguments cited in favor of such decision include higher economic growth rates, reduction on unemployment rates, increase in touristic activities and government income, increase in capital inflow and an improvement of the image of the country worldwide. The rationale behind these arguments is that the World Cup entails not only investments to build and update stadiums, but also a lot of investment in security, urban mobility and airport infrastructure.

Current literature showing empirically the connection between the World Cup and the variables cited above is scarce, with almost all papers published on the subject focusing on estimating the effect of the event on economic growth. These studies may be divided into two broad categories: ex-ante and ex-post studies. The first of these categories focus on using input-output matrices (ex-ante analysis), while the second focus mainly on time series or differences-in-differences/fixed effects models (ex-post analysis) to estimate the effect of interest.

The results presented for both ex-ante and ex-post studies could not be more diverse. While some ex-post papers find positive, insignificant or even negative effects of World Cups on variables such as GDP, unemployment, government tax income and tourist inflow, ex-ante papers predict large positive effects for these same variables when analyzing the same countries considered on ex-post papers. For example, Bohlmann and van Heerden (2005), using a Computable General Equilibrium (CGE) model developed specifically for the South African economy, predicted that the 2010 World Cup held in South Africa would affect real GDP in excess of R10 billion (about US$1.18 billion), with more than 50,000 jobs being created by the construction of new venues and upgrading of existing infrastructure. Additionally, the authors concluded that the '[e]xpected improvement to the infrastructure of the country, especially the transport sector, would greatly benefit productivity in the longer term and further increase GDP.'

Moving to papers that perform ex-post analysis, Hagn and Maennig (2008, 2009) found insignificant or negative effects of World Cups on unemployment using, respectively, data for the events held in Germany in the years of 1974 and 2006. For the event held in the US, Baade and Matheson (2004), using data at the Metropolitan Statistical Area (MSA) level, found insignificant or negative effects of the World Cup on GDP growth. Finally, Allmers and Maennig (2009) analyzed the effects of the World Cups held in Germany 2006 and France 1998 on overnight stays at hotels, national income from tourism, and retail sales and found that none of the results were statistically significant when using French data. When using German data, however, they estimated an additional 700,000 overnight stays and US$900 million in net national tourism income. One of the main reasons why ex-ante studies tend to report inflated numbers when compared to ex-post studies is that they do not take into account that most of the investment involved in a World Cup is not new money entering the economy, but resources taken from other sectors in which they could have otherwise induced larger economic benefits. In addition, a great percentage of the event attendance include local residents, and this is particularly true for World Cups in countries with great tradition in football. Also, attendance include people who would have visited the host country even if there was no event. Therefore, as argued by Crompton (1995), one ought to expect the boost observed in tourism to be not as large as the numbers predicted by ex-ante models.

Most papers in this literature, however, might suffer from the consequences of the well known ‘fundamental problem of causal inference’ (Holland, 1986), which imposes an additional challenge to empirical researchers when estimating causal effects of policy changes. This problem exists due to the fact that comparisons of two outcomes of interest for the same unit when exposed, and when not exposed, to a treatment is an infeasible task, given the same unit can either participate or not in a program in the same period (Imbens and Wooldridge 2009). In other words, one can never observe a specific country when under and when not under the influence of a World Cup at the same point in time (Sampaio, 2014). Hence, estimates based on input/output matrices or times series models (or even differences-in-differences models under the presence of time-varying unobservable confounders) are only valid under strong assumptions regarding shocks that are correlated to the policy being evaluated.

In this paper, we move away from the methods previously used to study the subject, which for the most part rely on the assumption of selection on observables, and propose to use the synthetic control method (SCM), a technique which gained popularity recently and is well suited to study the problem addressed in this paper. This method, which was developed by Abadie and Gardeazabal (2003) and extended by Abadie et al. (2010), uses data-driven procedures to construct adequate comparison groups/counterfactuals given that, in practice, it is a difficult task to find a single unit/country unexposed to the policy change of interest that approximates the most, relevant characteristics of the treated unit (the country that had a World Cup, for example) and that would provide a good control group. In other words, the method will provide the researcher with an optimal weight for each country such that the weighted average of the variable one is interested in explaining (in our case, GDP per capita) best approximates the value of this variable for the country that had the policy change (in our case, those countries hosting a World Cup). According to Belot and Vandenberghe (2009), the basic intuition behind the SCM is that a combination of countries – a synthetic control – offers a better comparison than any single country alone.

A second advantage of the proposed method, as highlighted by Billmeier and Nannicini (2013), is that, unlike most of the estimators used in the literature of program evaluation and in the literature analyzing effects of world cups, it can deal with endogeneity from omitted variable bias by accounting for the presence of time-varying unobservable confounders. This is a significant improvement considering previous analysis using times series and fixed effects models, which can only account for time-invariant unobservable confounders. This methodology was recently used by Abadie et al. (2010) to analyze the effects of Proposition 99, a large-scale tobacco control program that California implemented in 1988, on tobacco consumption using annual state-level panel data for the period 1970–2000; by Belot and Vandenberghe (2009) to analyze the effects of grade retention on attainment using a reform introduced in 2001 in the French-Speaking Community of Belgium whereby the possibility of grade retention in grade seven was reintroduced; by Billmeier and Nannicini (2013) to analyze the impact of economic liberalization on real GDP per capita in a worldwide sample of countries using annual data covering about 180 countries over the period 1963–2000; and by Sampaio (2014) to analyze the effects of New York state’s law prohibiting handheld cell phone use while driving on fatality rates using annual state-level panel data for the period of 1995–2006. Therefore, given the advantages of the SCM regarding the structure of the data and the institutional framework of the problem being analyzed in this paper, we see the SCM as a promising strategy to overcome some of the shortcomings of previously proposed methods and as a decent instrument to analyze the impact of large sporting events on macroeconomic variables.

Another contribution of our paper relates to the number of events considered in the analysis. With only one exception (Allmers and Maennig, 2009), all papers estimating the effects of world cups look only at one event. In this article, we expand previous research and offer a set of empirical country studies to best analyze the relationship between the events and the pattern of income per capita. We consider a total of 8 events held in 9 countries, covering all World Cups occurring in the period between 1978 (Argentina) and 2006 (Germany).

Our empirical findings show that for all the countries considered in the analysis (Germany, Japan, Korea, France, United States, Italy, Mexico, Spain and Argentina), the World Cup had a null or a negative effect on income per capita. We should emphasize that pre-treatment adjustment between real and synthetic control for the majority of countries cited above was quite good, with real GDP time series almost overlapping that of synthetic GDP time series, which validates de exercise being carried out. For Spain, however, the synthetic control presented a poor pre-treatment fit, which implies that a suitable counterfactual was not found and this reduces the inferential value of this specific experiment. Therefore, our results support the general conclusion that World Cups are not statistically associated to economic growth.

Looking at its most recent edition (2014 World Cup in Brazil), Crespo (2014) estimated that total foreseen cost of the Cup would be about R$ 26 billion, with 'only' R$ 8 billion spent in stadiums (31% of the total expenses) and R$ 13 billion (50% of the total) spent in urban mobility and airport infrastructure. Nevertheless, despite these large absolute numbers, total foreseen cost of the 2014 World Cup is still a drop on the ocean when compared to the huge public budget of Brazil (for example, it represents only 9% of total annual costs on public education, as noted by Patu et al., 2014). Therefore, besides the Cup being a huge sporting event, it appears not to have the economic importance as many argue to have. Moreover, as input-output studies tend to forget, most of these so called investments that arise once the country is assigned as host are not new resources, but are in fact reallocated resources. Therefore, these two aspects taken together cast serious doubt on the possible benefits of hosting such an event.

After this introduction, the rest of the paper is organized as follows. Section 2 describes in detail the synthetic control approach to comparative case studies of aggregate events. In Section 3 the data used is presented and in Section 4 results are discussed. Finally, a few concluding remarks are drawn in Section 5.

2. Methodology

In this section we present the empirical strategy used to identify the causal effect of hosting a World Cup on the outcomes of interest. Let Y_{ct} be the outcome for country $c$at time t, WC_{ct} be a dummy variable that assumes value equal to 1 for the years following the occurrence of a World Cup (or following the announcement of the hosting country), and ε_{ct} be unobserved determinants of the outcome variable. The parameter of interest, β_1, which represents the effect of the World Cup on the outcome, may be estimated via the following model

$$Y_{ct} = \beta_0 + \beta_1 * WC_{ct} + \varepsilon_{ct} \tag{1}$$

One can easily verify that by estimating equation 1 using data only for the country that had a World Cup, the parameter of interest would equal the average of the outcome variable after the World Cup (when $WC_{ct} = 1$) minus the average of the outcome variable before the World Cup (when $WC_{ct} = 0$). It is hard to argue, however, that such difference represent the causal effect of the World Cup, given that other confounding factors not controlled for that might compromise identification, that is, it might be that $COV\,(WC_{ct}, \varepsilon_{ct}) \neq 0$.

To overcome the problems described above, the usual practice in this literature has been to use data on another country (or many other countries) that did not host any World Cup during the years before or after the country currently hosting the World Cup. These countries would then be used as counterfactuals for the country being analyzed and the parameter of interest would be identified via a difference-in-differences (DID) setup. This strategy would remove bias that might result from permanent differences between the country hosting the World Cup and other countries used as counterfactuals, as well as bias from comparison over time in the country that had the World Cup that could be the result of time trends unrelated to the World Cup itself (Imbens and Wooldridge, 2009). In this case, the equation to be estimated is given by

$$Y_{ct} = \alpha_0 + \alpha_1 * WC_{ct} + \Theta X_{ct} + \lambda_c + \lambda_t + \mu_{ct} \tag{2}$$

where X_{ct} is a vector of controls, and λ_c and λ_t are, respectively, country and year fixed effects to control for country time-invariant unobservable characteristics and for yearly differences between the outcome of interest. The parameter of interest, α_1, equals the average gain over time in the countries not hosting a World Cup minus the average gain over time in the country hosting the World Cup. One main hypothesis required for the validity of this approach in identifying the World Cup effect, is that both treated and control countries must have exactly the same time trend in the absence of the World Cup, and it is not clear why this should be the case. If, for example, the countries not hosting a World Cup have different trends compared to the country hosting the World Cup, the researcher will be unable to differentiate between the World Cup effect and the trend difference.

This shortcoming is exactly what we aim to overcome in the present paper by using the synthetic control method to construct a combination of countries that best describes pre-treatment variables for the country hosting the World Cup, i.e., this artificially constructed group is similar to the treated country in the pre-treatment periods than any of the control country on their own.

2.1. The synthetic control method (SCM)

In this section we describe the synthetic control method (SCM) developed by Abadie and Gardeazabal (2003) and extended in Abadie et al. (2010). We also discuss its advantages and limitations when compared to other methodologies used in the literature, paying particular attention to DID strategies. Suppose there are $J+1$ regions/countries and that only the first region is exposed to the policy change (the country hosting the World Cup), so that there are J remaining regions as potential controls (all other countries not hosting World Cups in the period near the one being analyzed). Let Y_{ct}^{N} be the outcome that would be observed for region c at time t in the absence of the intervention, for units $c=1, \ldots,$ $J+1$, and time periods $t=1, \ldots, T$. Let Y_{ct}^{I} be the outcome that would be observed for unit c at time t if unit c is exposed to the intervention in periods T_0+1 to T, where T_0 is the number of pre-intervention periods such that $1 \leq T_0 < T$. It is assumed that the intervention has no effect on the outcome of interest before the implementation period, such that for $t \in 1, \ldots, T_0$ and all $c \in 1, \ldots, N$ we have that $Y_{ct}^{I} = Y_{it}^{N}$.

Now let $\alpha_{ct} = Y_{ct}^{I} - Y_{ct}^{N}$ the effect of the intervention for unit c at time t, and let D_{ct} be an indicator that takes value one if unit c is exposed to the intervention at time t, and zero otherwise. In this case, the observed outcome for unit c at time t is given by $Y_{ct} = Y_{ct}^{N} - \alpha_{ct} D_{ct}$. For region one, which is the only region exposed to the intervention after period T_0, it follows that $D_{ct}=1$ for $t > T_0$ and zero otherwise.

Our objective is to estimate $(\alpha_1 T_{0+1})$, which is given by $\alpha_{1t} = Y_{1t}^{I} - Y_{1t}^{N} = Y_{1t} - Y_{1t}^{N}$. The problem in estimating α's in this case is that Y_{ct}^{N} is never observed for the treated region once $t > T_0$. Thus, one must estimate its value. To see how a control group might be obtained from the set of untreated regions, suppose as in Abadie et al. (2010) that Y_{ct}^{N} is given by the following model

$$Y_{ct}^{N} = \delta_t + \theta_t Z_c + \lambda_t \mu_c + \varepsilon_{ct} \tag{3}$$

where δ_t is an unknown common factor with constant factor loadings across units, Z_c is a vector of observed covariates (not affected by the intervention), θ_t is a vector of unknown parameters, λ_t is a vector of unobserved common factors, μ_c is an vector of unknown factor loadings, and the error terms ε_{ct} are unobserved transitory shocks at the region level with zero mean.

Now consider a $(J \times 1)$ vector of weights $W = (w_2, \ldots, w_{J+1})'$ such that $w_j \geq 0$ for $j=2, \ldots, J+1$ and $w_2 + \ldots + w_{J+1} = 1$. Each value that W might take represents a synthetic control group for region one. For example, if $w_2 = 1$ and $w_j = 0$ for $3, \ldots, J+1$, then region 2 works as control for region one (the treated one). If, on the other hand, one sets a subset $J' \subset J$ to have equal weights, such that $w'_j = \frac{1'}{J}$ *for* $j \in J$ and 0 otherwise, the comparison would be between the treated region and the average of all other regions that belong to the group J'.

Using W as weights to construct a weighted average of Eq. (3), one obtains the following expression

$$\sum_{J=2}^{j+1} w_j Y_{jt} = \delta_t + \theta_t \sum_{J=2}^{j+1} w_j Z_j + \lambda_t \sum_{J=2}^{j+1} w_j \mu_c + \sum_{J=2}^{j+1} w_j \varepsilon_{jt} \tag{4}$$

If one assumes that exists weights $\left(w_2^*, \ldots w_{J+1}^*\right)$ such that the following holds, $\sum_{J=2}^{j+1} w_j Y_{jt} = Y_{11}, \ldots, \sum_{J=2}^{j+1} w_j^* Y_{jT_0} = Y_{1T_0}$ and $\sum_{J=2}^{j+1} w_j^* Z_j = Z_1$ then Abadie et al. (2010) prove that the following equation is true

$$Y_{1t}^N - \sum_{J=2}^{j+1} w_j^* Y_{jt} = \sum_{J=2}^{j+1} w_j \sum_{s=1}^{T_0} \lambda_t \left(\sum_{n=1}^{T_0} \lambda_n' \lambda_n \right)^{-1} \lambda_s' \left(\varepsilon_{js} - \varepsilon_{1s} \right) - \sum_{J=2}^{j+1} w_j^* \left(\varepsilon_{jt} - \varepsilon_{1t} \right) \tag{5}$$

and that its right hand side will be close to zero if the number of pre-intervention periods is large relative to the scale of the transitory shocks. This implies that $Y_{1t}^N = \sum_{J=2}^{j+1} w_j^* Y_{jt}$ which suggests the following estimator for the α vector:

$$\hat{\alpha} = Y_{1t} - \sum_{J=2}^{j+1} w_j^* Y_{jt} \tag{6}$$

To obtain the vector of optimal weights W, let $X_1 = \left(Z_1', Y_{11}, \ldots, Y_{1T_0}\right)'$ be a vector of pre-intervention characteristics for the treated region an X_0 be a matrix that contains the same variables for the untreated regions, such that the jth column of X_0 is $\left(Z_j', Y_{ij}, \ldots, Y_{jT_0}\right)'$. Then W^* is chosen to minimize the distance $\|X_1 - X_0 W\|_V = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)}$ between X_1 and $X_0 W$ subject to $w_j \geq 0$ and $w_2 + \ldots + w_{J+1} = 1$, where V is symmetric and positive semidefinite matrix chosen in a way that the resulting synthetic control region approximates the trajectory of the outcome variable of the affected region in the pre-intervention periods.

The model described above has several advantages when compared to other approaches used in the literature. As pointed out by Billmeier and Nannicini (2013), the model is transparent, given the weights $\left(w_2^*, \ldots, w_{J+1}^*\right)$ identify the regions that are used to construct counterfactuals for the treated region, and the model is flexible, as the set of potential control regions can be appropriately restricted to make the comparisons sensible. Also, the model relaxes the assumption that confounding factors are time invariant (fixed effects) or share a common trend (differences-in-differences), given the effect of unobservable confounding factors is allowed to vary with time.

On the other hand, this approach has the limitation that it does not allow one to assess the significance of the results using standard inferential techniques, given the number of untreated regions and the number of periods considered are small. Abadie et al. (2010) suggest that inference should be carried out by implementing placebo experiments. In this case, inference is based on comparisons between the magnitude of the gaps generated by the placebo studies and the magnitude of the gap generated for the treated state. Thus, if the gap estimated for the treated state is large compared to the gap estimated for the placebo experiments, then the analysis would suggest that the treatment had an effect on the outcome of interest and is not driven by chance.

3. Data

We use country-level data covering most FIFA World Cups occurring in the period between 1978 (Argentina) and 2006 (Germany).[1] Our data comes from three different sources. The main variable of interest (GDP per capita) and three of the covariates included in the vector of pre-intervention characteristics (population, investment (gross total investment/GDP), government final consumption expenditure (% of GDP) and consumer spending (% of GDP)), were obtained from the Penn World Tables 7.1. Additionally, we obtained data from Marshall et al. (2014) and from Barro and Lee (2010) on a politics index and on secondary school enrollment, respectively, to use as additional covariates in the vector of pre-intervention characteristics.[2] We should emphasize that, following Abadie et al. (2010), we augmented

[1] Selection of World Cups to be analyzed was based on data availability.

[2] We thank an anonymous referee for suggesting these additional covariates.

Table 2
Data description and sources.

Variable	Description	Source
RGDPL	Real gross domestic product per capita in PPP 2005 dollars	Penn World Table 7.1 (rgdpl)
Pop. Gro.	Population growth	Penn World Table 7.1 (POP)
Inv./GDP	Investment share of PPP converted GDP per capita at 2005 constant prices	Penn World Table 7.1 (ki)
Gov./GDP	Government consumption share of PPP converted GDP per capita at 2005 constant prices	Penn World Table 7.1 (kg)
Con./GDP	Consumption share of PPP converted GDP per capita at 2005 constant prices	Penn World Table 7.1 (kc)
Sec.Enroll	Sencondary enrollment in thousands	Barro and Lee (2010)
Politics	Index from −10 (Autocracy) to 10 (Full Democracy)	Marshall et al. (2014)

Table 3
Descriptive statistics.

Group of countries	Variables	Mean	S.D.	Min	Max	Median
All countries	RGDPC	8.45	11.01	0.16	136.31	4.03
	Pop. Gro.	0.02	0.04	−0.56	3.58	0.02
	Inv./GDP	22.93	11.24	−11.50	93.64	21.68
	Gov./GDP	11.86	8.97	0.31	67.19	8.89
	Con./GDP	70.67	19.18	3.56	219.12	70.86
	Sec.Enroll	5.33	27.88	0.00	492.74	0.47
	Politics	0.25	7.47	−10.00	10.00	−1.00
OECD[a]	RGDPC	19.17	11.79	1.24	80.22	17.27
	Pop. Gro.	0.01	0.10	−0.02	3.58	0.01
	Inv./GDP	24.25	8.12	1.75	80.39	23.10
	Gov./GDP	8.07	3.71	1.66	28.40	7.55
	Con./GDP	66.69	9.59	29.27	96.05	67.62
	Sec.Enroll	2.75	3.70	0.00	19.65	1.28
	Politics	6.79	6.33	−10.00	10.00	10.00
Latin America	RGDPC	4.97	2.53	1.17	12.53	4.57
	Pop. Gro.	0.02	0.01	−0.10	0.05	0.02
	Inv./GDP	19.96	7.73	−11.50	52.13	19.52
	Gov./GDP	9.72	6.28	1.18	49.37	8.10
	Con./GDP	74.21	10.60	29.22	110.98	75.51
	Sec. Enroll	1.75	4.22	0.01	44.96	0.49
	Politics	1.64	6.69	−10.00	10.00	5.00

Source: research data.
[a] It also includes Taiwan and Singapore, while excludes Czech Republic, Estonia, Iceland, Israel, Slovakia, Slovenia, besides the countries that hosted the World Cup.

our vector of pre-intervention characteristics to allow for the inclusion of lagged GPD per capita to improve pre-intervention adjustment. Tables 2 and 3 provides a brief explanation and descriptive statistics for all the variables used in our analysis.

As we briefly explain above, there are two possible definitions for the treatment assignment period (T_0). One possibility is to use the year in which the world cup really occurred. In this case, we would consider the years presented in column 1 of Table 1. The second possibility is to use the year in which FIFA announced the hosting country for the following event (presented in column 2 of Table 1). For this paper, we decided to use in our main specification the year of announcement, because most investments in infrastructure (new construction projects like stadiums, etc.) happen before the actual cup happens. We do, however, consider using the year in which the World Cup is realized. As it will be shown in the next section, quantitative results are quite similar regardless of what definition is used.

Another important point regarding the application of the synthetic control method is the choice of countries that will be included as potential control units for the treated countries. In that sense, a first limitation comes directly from the available data. Although Penn World Tables contain data on 188 countries since 1950, other data sources have unavailable data for some countries (for example, starting after 1950) or are incomplete, such as Barro and Lee's

(2010) data, which are only available over five-year intervals.[3] Also, the starting year T_0 is different for each of the countries analyzed, therefore, we must exclude from the list of potential control units recent hosting countries which might still be under the effect of the event. Our final set of potential controls, therefore, vary within hosting countries. For instance, Germany 2006 has more than 70 potential controls while Argentina 1978 has only 34.[4]

In Table 4 we present summary statistics for the 9 countries that hosted a World Cup in the period analyzed. Note that for each country we present two sets of statistics, labeled as 1 and 2. Label 1 refers to the case in which treatment assignment is based on the date the hosting country was announced, while label 2 refers to the case in which treatment assignment is the year the event occurred. For example, Argentina before announcement (Argentina 1) had an average gross total investment/GDP of 22.31, while Argentina before the World Cup occurred (Argentina 2) had an average gross total investment/GDP of 23.91.

4. Results

We start by presenting results that consider in our donor pool all countries with available data (unconstrained donor pool). Then, according to the usual practice in this literature, we restrict our donor pool to be composed of countries with similar characteristics (for instance, only OECD countries are considered as donors for USA and European countries).

4.1. Unconstrained donor pool

Before looking at the estimated effects of the World Cups, let us first look at the countries that compose the synthetic country for each of the treated countries and how their pre-treatment characteristics compare to the pre-treatment characteristics of the real hosting country. Table 5 presents the estimated weights for each country in the set of potential control countries.[5] Synthetic Argentina and synthetic France, for example, are convex combinations of many other countries, while synthetic Germany is composed of only Austria, Belgium, Bulgaria and Switzerland. Hence, as we highlight above, the model is transparent as the weights clearly identify the countries that are used to construct the counterfactuals.

In Table 4 we provide the numerical comparison by explanatory variable between each treated country and the constructed synthetic control. Again, note that we have two synthetic controls for two different countries in each case study. Also, the matrix V was chosen to minimize the mean squared prediction error produced by the weights $W^*(V)$ during the validation period (eight years before treatment year, T_0). A first point we look at is how different are countries and their synthetic control characteristics when using label 1 (announcement year) or label 2 (World Cup year). In most countries, there are significant differences between the two. Synthetic Argentina 1 has an average investment/GDP ratio of 21.11, while for Synthetic Argentina 2 this number equals 22.83. A general conclusion, however, is that the synthetic countries seem to provide a better control group than only comparing the treated country with the average characteristics of all other countries in the donor pool or with a single country. This advantage will become clearer in the graphs below.

As stated above, the convex set of weights that composes the synthetic control unit is chosen by the minimization of the vectors V and W(V). Reliable causal synthetic control estimators require that the counterfactual unit resemble the main characteristics of the treated country in the period before the intervention. In particular, the choice of countries that compose the synthetic units highlight an important feature of the SCM since the treated and synthetic units are reasonably comparable, by excluding those units that do not present similar characteristics in the pre-treatment period.

The graph on the left-hand side of Figs. 1 and 2 represent the time series of the outcome variable, real GDP per capita, for the treated unit (solid line) and the synthetic control unit (dashed line), both in the entire pre-treatment period and for ten years after the period the event occurred. The dotted vertical line represent the year FIFA announced the hosting country. The comparison between the solid and dashed line before treatment shows the quality of adjustment in the time series of the outcome variable for the country hosting the World Cup and the time series of the outcome

[3] Data for in-between years were obtained via interpolation, as is common in the literature.

[4] We emphasize that the list of potential controls do not include any of the countries that hosted a World Cup during the sample we analyze.

[5] In this table we report only countries that received weights larger than 0.005. For instance, the synthetic control for Germany is composed of 78 countries, most with very small weights. For the sake of space limitation, we only report those with representative weights.

Table 4
Treated states, synthetic states and control unit mean predictors.

Country	Pop. Gro.	Inv./GDP	Gov./GDP	Con./GDP	Sec. Enroll	Politics
Argentina 1	0.017	21.11	10.06	70.59	1.15	−3.94
Synthetic Argentina 1	0.017	22.23	10.06	70.60	1.16	1.77
Control Countries 1	0.023	22.43	8.51	73.61	1.29	2.49
Argentina 2	0.017	22.83	9.21	68.52	1.62	−4.50
Synthetic Argentina 2	0.019	22.71	8.86	68.52	7.19	−2.37
Control Countries 2	0.021	23.61	8.82	72.22	2.12	1.83
Spain 1	0.009	21.82	5.76	71.69	0.42	−7.00
Synthetic Spain 1	0.009	20.70	2.88	71.68	0.41	−5.66
Control Countries 1	0.023	22.43	8.51	73.61	1.29	2.49
Spain 2	0.010	23.89	5.39	69.65	1.08	−3.72
Synthetic Spain 2	0.009	25.46	6.06	64.73	0.79	0.04
Control Countries 2	0.021	23.88	9.01	71.91	2.57	1.88
Mexico 1	0.026	24.40	3.82	73.68	2.25	−4.50
Synthetic Mexico 1	0.026	24.57	11.66	67.50	2.20	−4.38
Control Countries 1	0.021	24.78	10.50	70.64	2.80	−1.29
Mexico 2	0.026	23.38	3.97	73.75	2.71	−4.24
Synthetic Mexico 2	0.025	23.56	5.07	73.73	2.65	−4.18
Control Countries 2	0.021	24.27	10.60	70.74	3.15	−1.19
Italy 1	0.004	25.83	6.43	67.06	9.01	10.00
Synthetic Italy 1	0.004	25.80	8.36	67.01	5.36	9.84
Control Countries 1	0.021	24.59	10.54	70.72	2.90	−1.31
Italy 2	0.003	27.01	6.47	67.51	10.76	10.00
Synthetic Italy 2	0.003	27.06	6.67	65.95	2.27	9.16
Control Countries 2	0.021	23.69	10.66	70.74	3.72	−0.86
USA 1	0.010	19.04	9.50	72.75	77.04	10.00
SyntheticUSA 1	0.010	24.65	7.72	61.83	3.24	8.51
Control Countries 1	0.021	23.64	10.82	71.24	3.37	−1.15
USA 2	0.011	19.02	9.27	72.89	76.95	10.00
Synthetic USA 2	0.011	20.90	7.31	66.60	6.09	10.00
Control Countries 2	0.020	23.03	10.86	71.24	4.28	−0.33
France 1	0.006	21.97	7.44	70.92	8.48	8.30
Synthetic France 1	0.006	21.97	8.45	70.92	2.13	8.48
Control Countries 1	0.021	23.13	10.91	71.37	3.99	−0.46
France 2	0.006	21.40	7.53	71.07	10.54	8.45
Synthetic France 2	0.006	23.09	7.56	70.01	2.90	7.51
Control Countries 2	0.020	22.89	10.72	71.28	4.95	0.25
Korea 1	0.014	33.41	7.55	63.91	7.63	−1.56
Synthetic Korea 1	0.015	29.73	15.48	57.19	29.56	−4.19
Control Countries 1	0.020	22.97	10.79	71.30	4.58	0.01
Korea 2	0.014	33.41	7.55	63.91	7.63	−1.56
Synthetic Korea 2	0.015	29.73	15.48	57.18	29.67	−4.19
Control Countries 2	0.020	22.97	10.79	71.30	4.58	0.01
Japan 1	0.007	32.95	5.62	62.05	30.87	10.00
Synthetic Japan 1	0.008	27.97	8.07	62.13	0.75	9.12
Control Countries 1	0.020	22.97	10.79	71.30	4.58	0.012
Japan 2	0.007	32.95	5.62	62.05	30.87	10.00
Synthetic Japan 2	0.008	30.93	7.38	59.34	7.36	8.72
Control Countries 2	0.020	22.82	10.82	71.37	4.62	0.07
Germany 1	0.002	23.54	7.48	68.95	15.93	10.00
Synthetic Germany 1	0.002	25.28	7.13	67.66	2.57	9.70
Control Countries 1	0.020	22.78	10.66	71.26	5.32	0.47
Germany 2	0.002	23.08	7.19	69.01	19.81	10.00
Synthetic Germany 2	0.004	23.05	7.18	68.37	9.73	9.83
Control Countries 2	0.019	22.66	10.54	71.26	6.51	1.05

Source: research data.

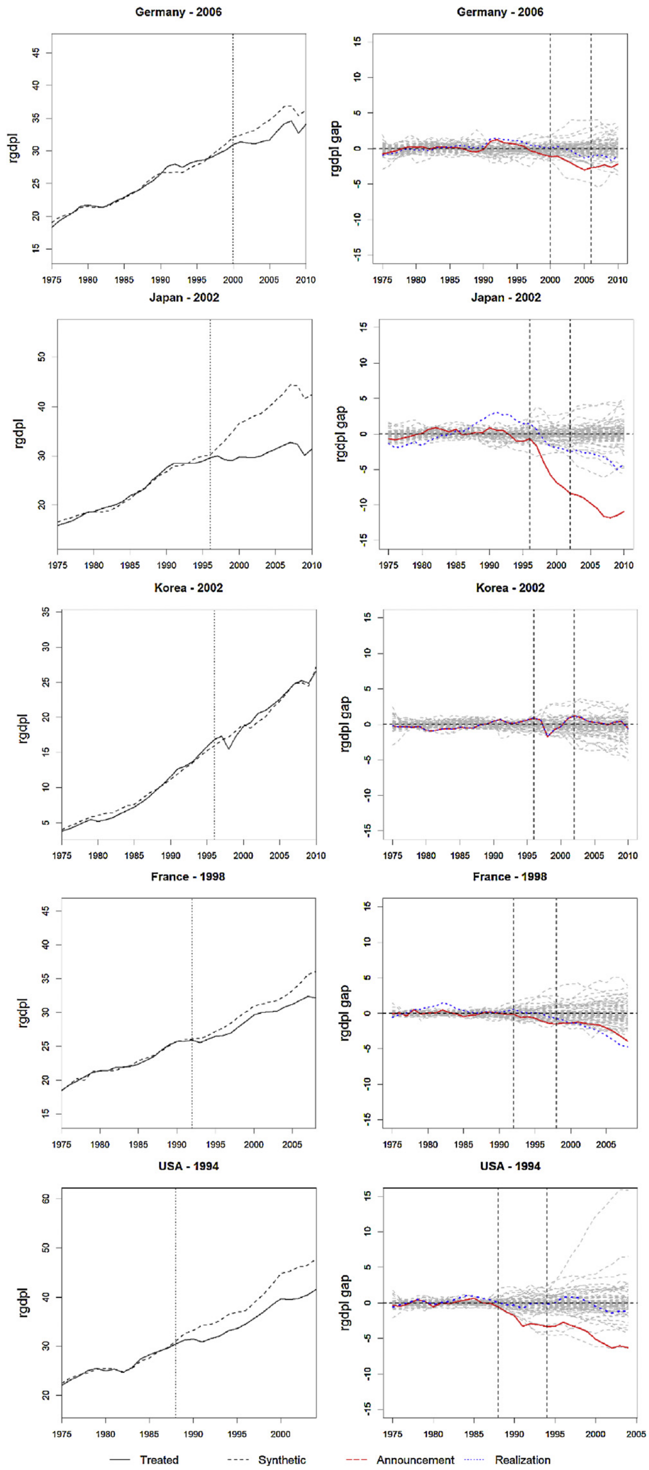

Fig. 1. Synthetic control analysis for the 1994–2006 FIFA's World Cup.

Table 5
Country weights for synthetic controls considering the year of announcement as the treatment year.

Control country	Argentina	Spain	Mexico	Italy	USA	France	Korea	Japan	Germany
Australia								0.006	
Austria			0.007	0.394		0.087		0.012	0.435
Bahrain			0.106		0.058				
Bangladesh			0.014						
Belgium						0.139			0.495
Bolivia	0.306								
Bulgaria						0.006		0.015	0.022
Canada			0.012	0.027	0.348	0.006			
China	0.063	0.008	0.018				0.196		
Cuba			0.048						
Cyprus								0.238	
Denmark						0.017		0.006	
Dom. Republic	0.006								
Egypt	0.012								
El Salvador	0.007								
Finland				0.278		0.019		0.284	
Ghana	0.010								
Greece						0.007			
Guatemala	0.007								
Honduras	0.006								
Hungary			0.009			0.011			
India				0.086					
Iran		0.078							
Iraq			0.023						
Ireland	0.012					0.006			
Jordan		0.013							
Lesotho			0.007			0.012			
Luxemburg	0.194				0.338	0.139		0.302	
Malawi	0.022								
Morocco	0.006								
Netherlands						0.007		0.007	
Nicaragua	0.011								
Norway			0.015	0.066	0.172	0.012		0.040	
Paraguay	0.010		0.006						
Poland			0.009						
Portugal	0.029	0.730				0.009			
Sierra Leone			0.016						
Singapore			0.199						
Sudan			0.144						
Sweden						0.412		0.006	
Switzerland		0.170	0.006		0.035			0.011	0.034
Syria			0.153						
Taiwan	0.080						0.804		
Trini. & Tobago			0.008						
UK	0.009			0.142		0.010			
Uruguay	0.105								

Source: own elaboration.
Note: in this table, we report only countries that received weights larger than 0.005.

variable for the synthetic country. This same comparison for the periods after treatment year represent estimates of the dynamic treatment effect of interest.

We plot these differences on the graphs on the right-hand side of Figs. 1 and 2. These represent the gap between the outcome variable of the country hosting the event (solid line of the graph on the left-hand side) and the outcome variable of the synthetic control (dashed line of the graph on the left-hand side). Note that for these graphs, we plot two dashed vertical lines and two colored (blue and red) lines. The two dashed vertical lines represent, in chronological

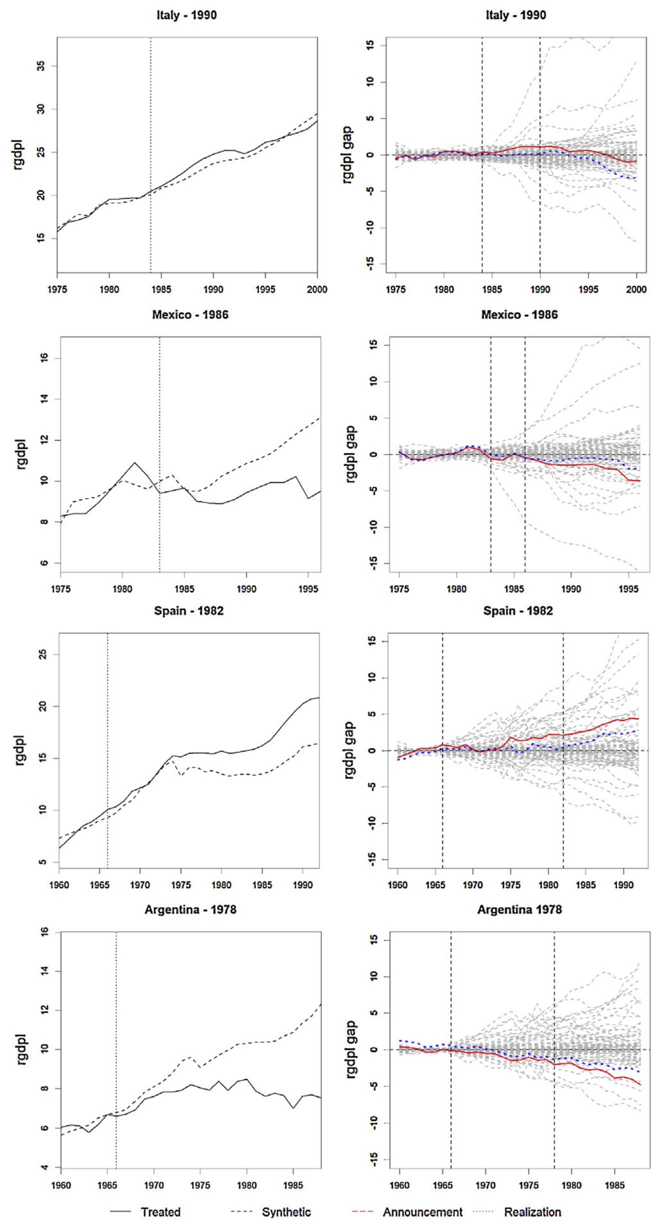

Fig. 2. Synthetic control analysis for the 1978–1990 FIFA's World Cup.

order, the year of announcement and the year the event occurred, respectively. The two colored lines represent the gaps estimated for the two treatment definitions considered: the announcement year (red solid line) and the World Cup year (blue dotted line). As mentioned above, the motivation for considering the first definition arises from the fact that most investments and international exposition occur before event occurrence. The year of realization, on the other hand, could capture a boost in tourism, which presumably would last from a few months/years due to international exposition.

As pointed out by Abadie et al. (2010) and by Abadie and Gardeazabal (2003), one must 'evaluate the significance' of the estimates using the SCM, given 'results could be driven entirely by chance.' Thus, they propose that the SCM should be applied to all other countries that did not impose any ban during the period analyzed (donor pool) and inference is based on comparisons between the magnitude of the gaps generated for the placebo studies and the magnitude of the gap generated for the real treated country.

Table 6
Mean squared prediction error for the host countries.

Host country	Unconstrained pool	Constrained pool
Germany	0.32	0.29
Japan	0.34	0.40
Korea	0.28	0.49
France	0.06	0.07
USA	0.13	0.17
Italy	0.14	0.13
Mexico	0.34	1.53
Spain	0.31	0.29
Argentina	0.08	0.05

Source: research data.

Accordingly, we implement this idea and add placebo gaps, which are represented by grey lines, to the graphs on the right-hand side. Note that these placebo gaps consider only our baseline specification, i.e., that treatment is defined as the announcement year. We should emphasize also that we discarded placebo countries with pre-intervention mean squared prediction error – MSPE (the average of the squared discrepancies between GDP per capita in the treated country and in its synthetic counterpart during the pre-intervention period) five times higher than the hosting country. This is because placebo countries with poor fit prior to the World Cup do not provide information to measure the relative 'rarity' of estimating a large post-event gap for a country which is well fitted prior to the intervention (Abadie et al., 2010). The MSPE values for all estimations are reported in Table 6 considering both unconstrained and constrained donor pools. In general, pre-treatment adjustment between real and synthetic countries per capita GDP was quite good, especially considering the constrained estimation. We now describe in more detail the results for each World Cup considered and provide some contextual background to justify potential heterogeneities.

The results for 2006 are presented graphically in Fig. 1. The pre-treatment adjustment between real and synthetic Germany was very good for the entire period, with real GDP time series almost overlapping that of the synthetic GDP time series. The estimated treatment effects depend on what definition of treatment is used in the estimation, with no effect found when using the event definition (blue line) and a possibly negative effect when using the announcement definition (red line). This negative effect, however, does not seem to provide sufficient evidence that the World Cup affected GDP negatively, given that several of the placebo experiments in the potential controls are larger (in absolute value) than the effect estimated for Germany. Therefore, our results for Germany provide weak support for the theory that the event affected GDP, which is in accordance to the conclusions derived in Hagn and Meannig (2009) but contrary to several studies done before the World Cup, which predicted increases in income growth varying from 2 to 10 billion euros (see, for example, Ahlert, 2001).

The results for the World Cup that occurred in Japan and Korea in 2002 are presented in Fig. 1, respectively. Surprisingly, the two countries experience two different World Cup effects. For Japan, we found a strong negative effect when using the announcement definition (red line) and a weaker negative effect when using the host definition (blue line). Note that the gap estimated for Japan after announcement is a lower bound for all placebo tests, which seems to provide sufficient evidence that the income decline experience in Japan, in comparison to the synthetic Japan, was strongly related to the World Cup. For Korea, we found null effects using both the year of announcement and the year of the World Cup, with both curves in the middle of the majority of the placebo gaps. Despite their similarities, both countries (Japan and Korea) were experiencing completely different economic realities. According to data provided by the World Bank,[6] while Japan was going through a recession, growing at an average of 1.6% from 1998 to 2002, Korea was growing at an average of 4.42%, busted by a series of structural reforms under the command of the International Monetary Fund (IMF).

Results for the 1998 and 1994 World Cup that occurred in France and USA are also presented in Fig. 1. The pre-treatment fit was excellent for both announcement and World Cup year in both cases. For France, the estimated treatment effect was null (or slightly negative) using both treatment definitions, although one can argue that the effect is

[6] At the World Bank website http://data.worldbank.org/.

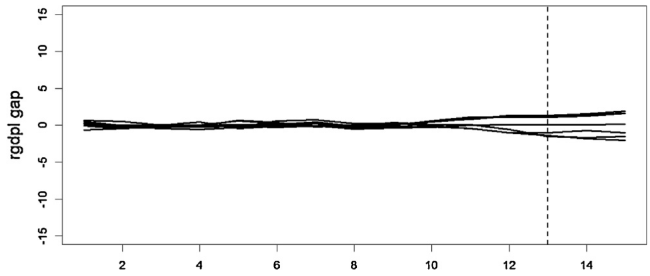

Fig. 3. Rgdpl gaps for Germany, Japan, France, USA, Italy, Spain and Argentina.

slightly more negative when using the announcement definition. The synthetic controls constructed for the USA were more peculiar, as the synthetic controls gaps strongly diverged between the one based on the announcement definition and the one based on the host definition. One possible explanation is that the announcement definition correlates with the recession experienced by the USA in the early 90s, which is evident in the left panel of Fig. 1. The announcement definition implied a negative effect, while the host definition implied a null effect. However, even the definitions of treatment years differed in the effects they implied; there is still enough evidence to assert that the 1994 World Cup had no positive effect on the USA economy. The stronger effect when using announcement as treatment observed for France and more noticeable for the USA was also observed for the German and the Japanese cases. The common explanation for this is that when we use the announcement year the effect starts before the effect measured using the hosting definition, so for each year after the realization of the cup the cumulative effect of the first will be greater in absolute terms than the second.

Results for Italy 1990 up to Argentina 1978 are reported in Fig. 2. Synthetic countries present fits that varies more between contries when compared to the cases presented in Fig. 1. In particular, despite the small RMSE for Spain, its synthetic control had only one point of contact with the real trajectory of Spain, as can be seen in the left panel of Fig. 2, which hinders any attempt to conclude in favor of a positive effect of the 1982 World Cup. Furthermore, this uncertainty about any positive effect of the World Cup in Spain is reinforced by the null effect implied by the host definition, which, by the way, had a better pre-treatment fit.

The World Cup held in Mexico, on the other hand, have an even poorer pre-treatment fit, but still we find suggestive evidence of a negative effect on the Mexican economy. However, the Mexican case presents two peculiar characteristics. The first refer to the country that was initially assigned to host the event, which was Colombia and not Mexico. Due to major economic problems, Colombia was unable to comply with the technical requirements imposed by FIFA, and withdrew on November 5, 1982, less than four years before the event was scheduled to start. Second, the economic situation of Mexico in the period close to the occurrence of the World Cup was quite complicated. The country not only experienced a series of earthquakes (the largest reaching 8.1 on the Richter scale) eight months before the event started, but, similar to other Latin-American countries, the international oil crisis coupled with high interest rates, inflation, deterioration in the balance of payments and large capital outflow led the country to declare an involuntary moratorium on debt payments in August 1982 (Edwards, 1996). This complicates further interpretations regarding our estimates.

Finally, regarding the World Cup hosted by Argentina in 1978 in Fig. 2, the synthetic Argentina fits quite well with the real Argentina on the pre-treatment period, which indicates that the counterfactual seems to provide a good description of the outcome variable in the period before announcement or occurrence of the World Cup. The estimated gaps are negative for both red and blue lines; however, they do not differ substantially from all placebo experiments. This is a good indication that our results support that general conclusion that World Cups are not statistically associated to economic growth.

One problem that might compromise identification of our parameter of interest is if countries faced pre-treatment trends in the outcome variable. This could, for example, be the result of anticipatory investments decisions even before announcement. To test for this possibility we perform a placebo exercise by estimating the same models as above but considering treatment starting two years before announcement. If there exists anticipatory effects, then we should observe significant changes in the outcome variable precisely a couple of years before announcement. Fig. 3 present estimates for our treated countries. The dashed line represent the two-year-before cutoff. As show in the figure, there are no clear jumps in the outcome variable before announcement. Therefore, our results appear not to suffer from pre-treatment macroeconomic decisions.

4.2. Constrained donor pool

The results presented on the previous section considered all countries with available data as potential donors for each treated country considered in the analysis. However, Abadie et al. (2010) and Billmeier and Nannicini (2013) draw attention that this huge and very diverse pool could result in overfitting of the synthetic control, therefore assigning large weights to countries that differ substantially from the country one is trying to construct the synthetic control. To check if our results are affected by this sort of problem, we follow the literature and estimate all the synthetic controls using restricted pools of countries.

Specifically, for USA and European hosts, we restricted the pool of countries to those belonging to the OECD. For Japan and Korea, given they were the only Asian countries belonging to the OECD, we restricted their donor pool to OECD countries plus Taiwan and Singapore. Finally, for the World Cups hosted in Latin America (Argentina and Mexico) we restricted the donor pool to only Latin American countries. Table 3 presents the descriptive statistics for these subgroups.

The results for the estimations with restricted pool of donors are shown in Figs. 4 and 5. For most countries, results are precisely the same as those obtained using the unrestricted donor pool. The only two exceptions are Mexico and Spain. For the Mexican case, the effect appears to be slightly positive but pre-treatment adjustment was so poor that any conclusions derived from this empirical exercise are weak. On the other hand, for Spain the (doubtful) positive effect obtained considering the unconstrained case is now convincingly null, therefore sustaining our main conclusion that world cups are not statistically associated to positive economic growth.

4.3. Robustness checks

Although original placebo procedures like RMSE provide useful information about the likelihood of estimated effects under the null hypothesis of no effect, plausible p-values area not readily available due to the limited number of placebo units in some case studies and the existence of unit-specific transitory shocks that should be zero mean but not averaged out in SCM estimators. Ando (2015) provides two test statistics aimed to access the significance of the intervention impact. We use such tests to access the effect of the Word Cup on host countries' GDP per capita.

The first test consists in comparing the average treatment effects sizes relative to the distribution of average placebo effects for all placebo units, in all case studies, where the total number of average placebo effects are increased by summing placebo trials in different case studies. It consists in estimating all treatment effects, $\hat{\alpha}_{gt}$, and placebo effects, $\hat{\eta}_{git}$, for all case studies, with g indicating one specific World Cup edition, i representing a control unit in donor pool and $t \in \{T_{0+1}, \ldots, T\}$. Then, we calculate the average treatment effects for the treated units, $\bar{\hat{\alpha}}_g$, and for the placebo units, $\bar{\hat{\eta}}_{gi}$, over time for all case studies in the post-intervention period. We use the distribution of $\bar{\hat{\eta}}_{gi}$ for significance tests on $\bar{\hat{\alpha}}_g$, assuming that they follow common distribution under the null hypothesis.

The second test proposed by Ando (2015) checks whether the overall average treatment effect is sufficiently large in comparison to the distribution of corresponding placebo estimates that are calculated with randomly chosen placebo units. The first step consists in estimating the overall treatment effect, $\tilde{\alpha} = \sum_{g=1}^{G} \bar{\hat{\alpha}}_g / G$, and the overall placebo effects, $\tilde{\gamma} = \sum_{g=1}^{G} \bar{\hat{\gamma}}_{gi} / G$, by randomly choosing a control unit i in each g, where G is the number of World Cup editions. Then, we replicate the previous step M times to create a distribution of overall average placebo effects, $\tilde{\gamma}_m$, with $m = 1, \ldots, M$. Finally, the distribution of $\tilde{\gamma}_m$ is used for significance tests on $\tilde{\alpha}$.

The results for both tests are presented in Figs. 6 and 7, respectively. In Fig. 6 we observe that the distribution of the average effect for all units have mean around zero, indicating that the treatment assignment has no systematic effects on the control units. Regarding the magnitude of the average effects, all the World Cup editions fail to reject the null hypothesis of no impact on GDP per capita. Fig. 7 presents the result for the overall average treatment effect test. It

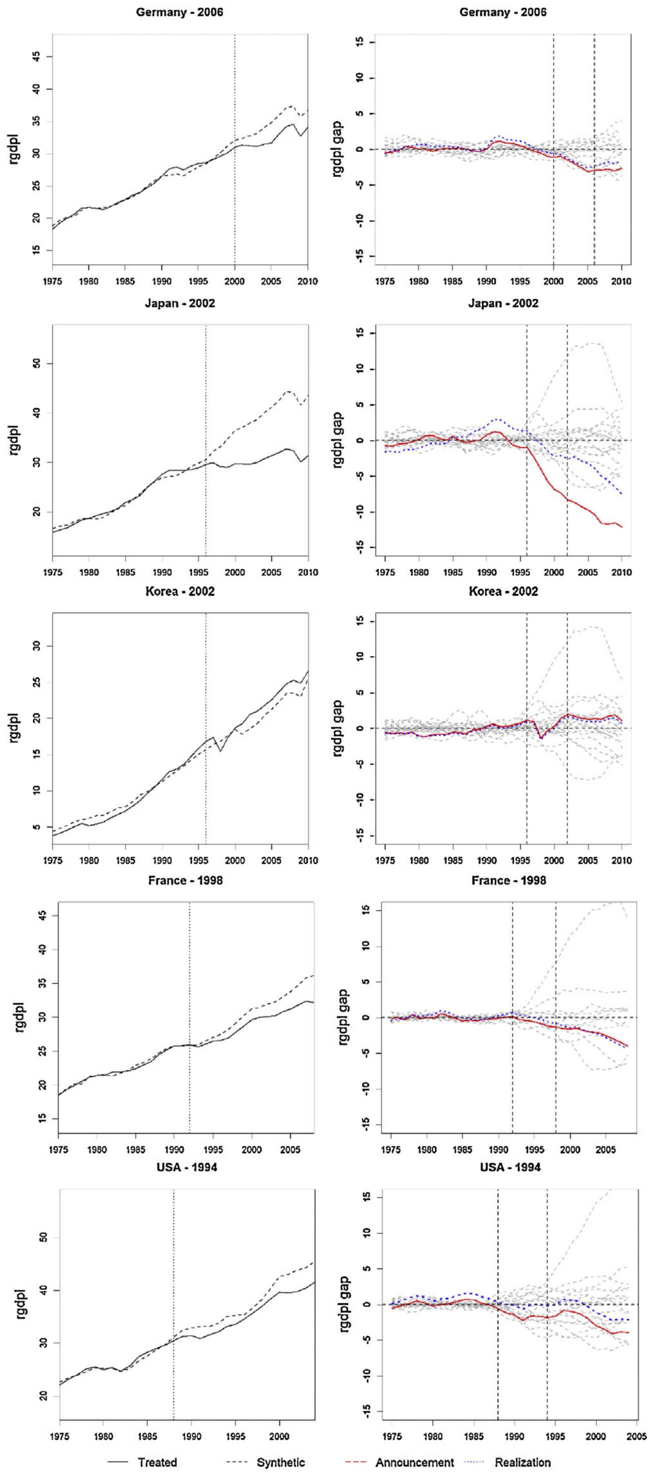

Fig. 4. Synthetic control analysis (restricted pool of donors) for the 1994–2006 FIFA's World Cup.

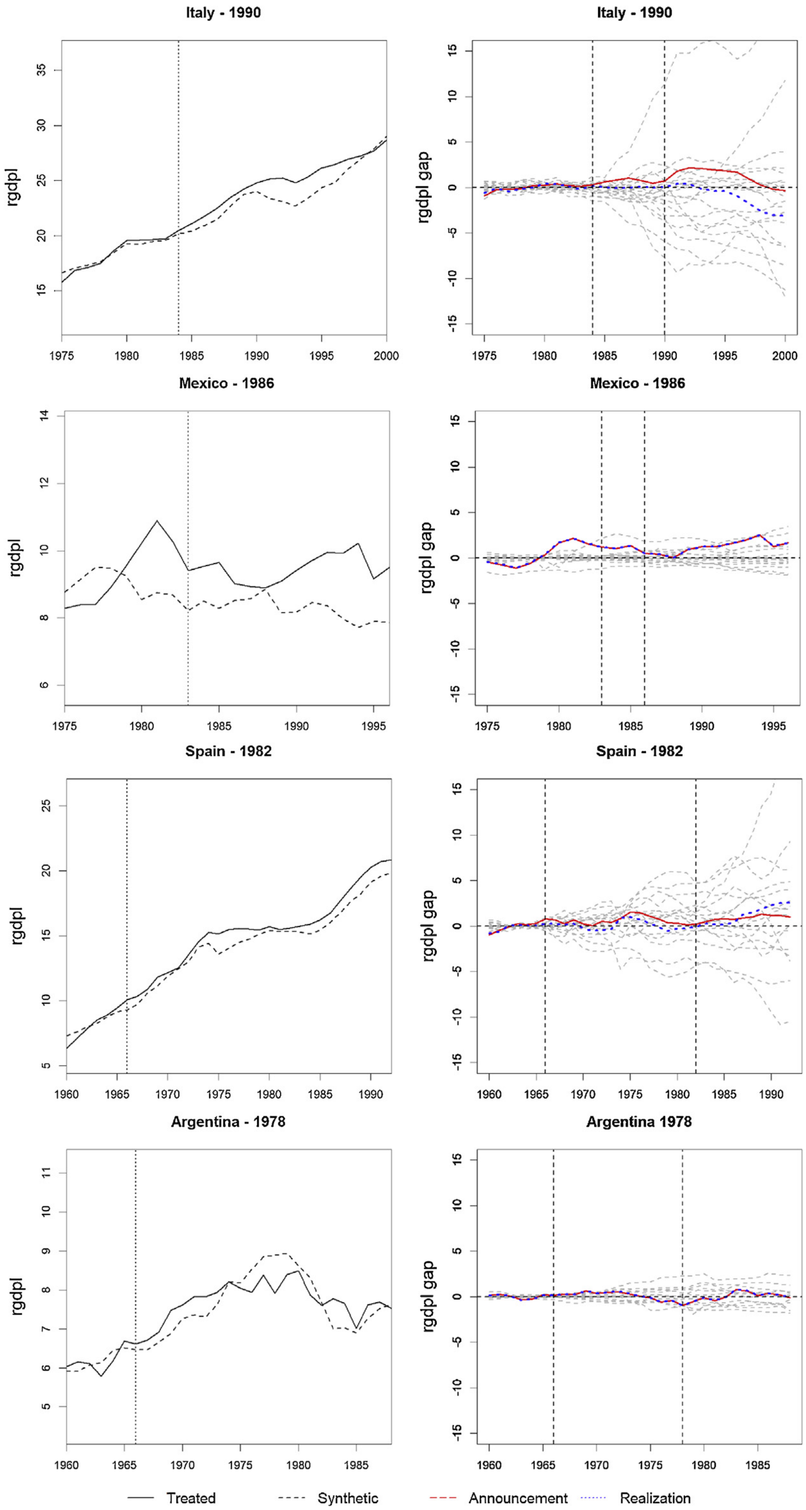

Fig. 5. Synthetic control analysis (restricted pool of donors) for the 1978–1990 FIFA's World Cup.

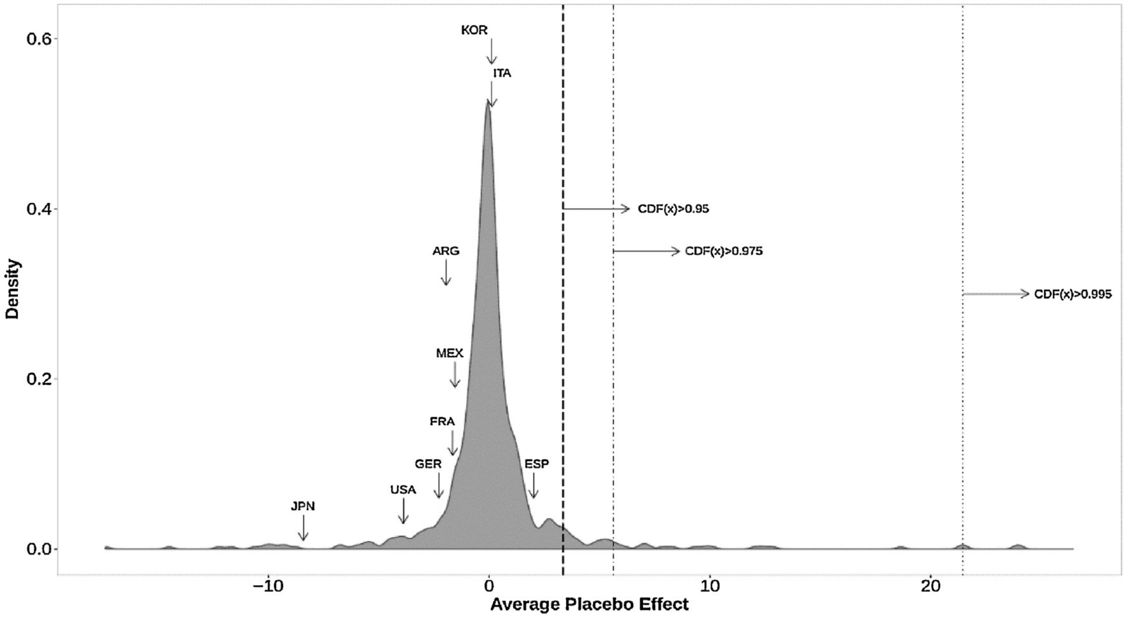

Fig. 6. Density of average placebo effects. *Note*: CDF(x) is the empirical cumulative distribution function of average placebo effects.

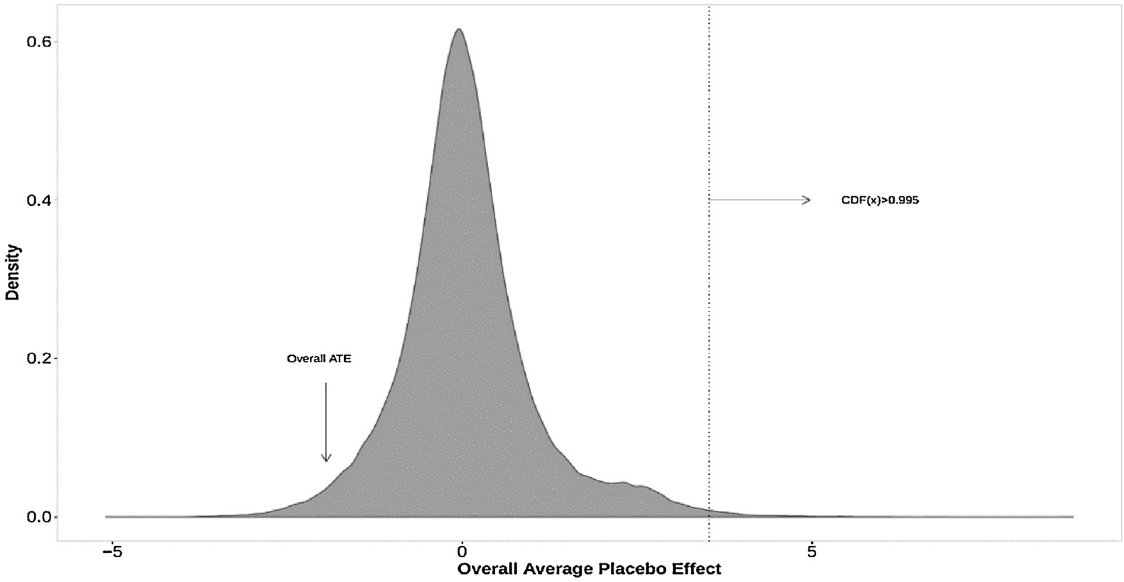

Fig. 7. Density of overall placebo effects.
Note: number of Monte Carlo repetitions M = 100,000. CDF(x) is the empirical cumulative distribution function of overall average placebo effects.

shows that the overall effect is lower than the threshold line at CDF = 99,5% when we run $M = 100{,}000$ Monte Carlo simulations. In this sense, it is unlike that the magnitude of this overall effect is generated by random errors.

5. Concluding remarks

The FIFA (Fédération Internationale de Football Association) Soccer World Cup ranks among the three largest events in the world. It not only affect the influx of people/tourism in the host country, but also involves publicly financed capital improvement projects that are undertaken to improve infrastructure, such as the construction of new stadiums and the improvement of old ones, road and airport construction and improvement, among many others. The risks and costs involved in hosting an event of this magnitude are large; however, in all previous World Cup editions there has been large competition to host the event. This, in part, is due to the common belief that host countries will experience higher economic growth rates, reduction on unemployment rates, increases in touristic activities and government income, increase in capital inflow and an improvement of the image of the country worldwide.

Current literature on this subject is scarce and inconclusive, specially considering the methods used so far, which might suffer from severe identification problems. In this paper we move away from the methods previously used to study the subject and propose to use the synthetic control method (SCM), a technique which gained popularity recently and is well suited to study the problem addressed in this paper. The main advantage lies on the fact that, unlike most of the estimators used in the literature of program evaluation and specially in the literature analyzing the effects of world cups, the SCM deals in some degree with time-varying unobservable confounders.

A second contribution of our paper relates to the number of events considered in the analysis. Unlike most papers in the literature which consider only one world cup in their analysis, our paper expands previous research and offer a set of empirical case studies to best analyze the relationship between the events and the pattern of income. We consider a total of 8 events held in 9 countries, covering all World Cups occurring in the period between 1978 (Argentina) and 2006 (Germany).

Our empirical findings show that for the majority of the countries considered in the analysis (Germany, Japan, Korea, France, United States, Italy, Mexico and Argentina), the World Cup had a null or a negative effect on income per capita. With the exception of Spain and Mexico, in which the synthetic control presented a poor pre-treatment fit with real GDP time series, all other countries presented a quite good pre-treatment adjustment between real and synthetic control series. This is quite comforting because the inferential value of this experiment increases when the method delivers a suitable counterfactual to the analysis.

The general conclusion of the paper points in the direction that hosting a World Cup leads to no economic benefit. We emphasize, however, that our paper looks only at GDP per capita. Hence, any other benefits related to economic well-being of the population, trade (see, for example, the work of Rose and Spiegel, 2011), or gains related to the image of the country and future touristic activities are not captured in our analysis. However, despite the potential positive benefits in terms of well being in hosting the World Cup, our paper suggests that countries under economic turmoil might suffer from hosting a World cup, instead of boosting their economy, as most believe.

Acknowledgements

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References

Abadie, A., Gardeazabal, J., 2003. The economic costs of conflict: a case study of the Basque Country. Am. Econ. Rev. 93, 113–132.

Abadie, A., Diamond, A., Hainmueller, J., 2010. Synthetic control methods for omparative case studies: estimating the effect of California's tobacco control program. J. Am. Stat. Assoc. 104, 493–505.

Ahlert, G., 2001. The economic effects of the Soccer World Cup 2006 in Germany with regard to different financing. Econ. Syst. Res. 13, 109–127.

Allmers, S., Maennig, W., 2009. Economic impacts of the FIFA soccer world cups in France 1998, Germany 2006, and outlook for South Africa 2010. East. Econ. J. 35, 500–519.

Ando, M., 2015. Dreams of urbanization: quantitative case studies on the local impacts of nuclear power facilities using the synthetic control method. J. Urban Econ. 85, 68–85.

Baade, R.A., Matheson, V.A., 2004. The quest for the cup: assessing the economic impact of the world cup. Reg. Stud. 38, 343–354.

Barro, R.J., Lee, J-W., 2010. A new data set of educational attainment in the world, 1950–2010. NBER Working Paper 15902.

Belot, M., Vandenberghe, C., 2009. Grade retention and educational attainment: exploiting the 2001 Reform by the French-Speaking Community of Belgium and Synthetic Control Methods. Discussion Paper 2009-22, *mimeo*, Catholic University of Louvain, Louvain.

Billmeier, A., Nannicini, T., 2013. Assessing economic liberalization episodes: a synthetic control approach. Rev. Econ. Stat. 95, 983–1001.

Bohlmann, H.R., van Heerden, J.H., 2005. The Impact of Hosting a Major Sport Event on the South African Economy. University of Pretoria Working Paper 2005-09, University of Pretoria, Pretoria.

Crespo, Silvio Guedes, 2014. Copa custa R$ 8 bi em estádios e R$ 16 bi em outras obras; falta acabar 18%. Available at http://achadoseconomicos.blogosfera.uol.com.br/2014/07/14/copa-custou-r-8-bi-em-estadios-e-r-16-em-outras-obras-falta-terminar-18/. (Accessed 10 January 2015).

Crompton, John L., 1995. Economic impact analysis of sports facilities and events: eleven sources of misapplication. J. Sport Manage. 9, 14–35.

Edwards, S., 1996. A Tale of two Crises: Chile and Mexico. NBER Working Paper 5794.

Hagn, F., Maennig, W., 2008. Employment effects of the football world cup 1974 in Germany. Labour Econ. 15, 1062–1075.

Hagn, F., Maennig, W., 2009. Large sport events and unemployment: the case of the 2006 soccer World Cup in Germany. Appl. Econ. 41, 3295–3302.

Holland, P., 1986. Statistics and causal inference. J. Am. Stat. Assoc. 81, 945–970.

Imbens, G., Wooldridge, J.M., 2009. Recent developments in the econometrics of program evaluation. J. Econ. Lit. 47, 5–86.

Marshall, M.G., Gurr, T.R., Jaggers, K., 2014. Polity IV Project. Political Regime Characteristics and Transitions 1800–2013. http://www.systemicpeace.org/inscrdata.html.

Patu, G., Amora, D., Coutinho, F., 2014 Custo da Copa Equivale a um mês de gastos com educação. Available at http://www1.folha.uol.com.br/fsp/poder/167243-custo-da-copa-equivale-a-um-mes-de-gastos-com-educacao.shtml. (Accessed 10 January 2015).

Rose, A.K., Spiegel, M.M., 2011. The olympic effect. Econ. J. 121, 652–677.

Sampaio, B., 2014. Identifying peer states for transportation policy analysis with an application to New York's handheld cell phone ban. Transportmetrica A: Transp. Sci. 10, 1–14.