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The relationship between panel and synthetic control estimators of the effect of civil war.

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Abstract

We examine the relationship between the case-study, synthetic control and large-N panel-data approaches using the costs of conflict as an example. In particular, we show that effects estimated from panel data models and effects estimated by the comparison of a treated case with a synthetic control are closely related. We then illustrate the similarities by studying the impact of civil war on the level and growth rate of GDP and discuss how to overcome some of the methodological challenges involved in quantifying the economic cost of war. We find that the incidence of internal conflicts has an economically significant one-off negative effect on the GDP level, as well as a negative effect on the growth rate of the GPD.

Keywords: Civil war, Counterfactual, Economic growth, Panel analysis, Synthetic control method

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1 Introduction

There has been considerable controversy in political science and economics about the relative merits of qualitative case studies for particular countries and quantitative large-N studies for many countries. Case studies can take account of a lot of country specific history but are a sample of one, often selected for its salience which may make it unrepresentative of other cases. Large-N studies can be generalized but ignore the country specific heterogeneity by, for instance, imposing common coefficients. Abadie *et al.* (2014) note that a widespread consensus has emerged about the necessity of building bridges between the quantitative and qualitative approaches to research in political science. Both case studies and large N studies are done for a variety of different purposes, but one purpose is to measure the effect on some focus variable, an outcome of interest, of some event or intervention. The intervention is often referred to as a "treatment" by analogy with the microeconometric program evaluation literature. In such studies a central issue is the definition of the counterfactual, what would have happened in the absence of the treatment, something which can never be observed. Pesaran & Smith (2014) contains a more general discussion of the issues in the construction of counterfactuals. The event or treatment we will use as an illustration is the occurrence of a civil war and the focus variable, the outcome of interest, will be the level or growth of GDP.

Abadie *et al.* (2014) argue that the synthetic control method not only provides an effective way to define the counterfactual, but provides a way to bridge the quantitative/qualitative divide in comparative politics. The synthetic control method compares the post event trajectory for the variable of interest with a weighted average of the values of that variable from a comparison group chosen on the basis of their pre-treatment similarity to the treated unit. Abadie & Gardeazabal (2003) is a classic example of the synthetic control procedure used to estimate the economic cost of the Basque conflict. Abadie *et al.* (2010) examine the effect of California's smoking control program. Synthetic control methods have typically been used to examine a single case, but since Abadie *et al.* (2010) have made their package Synth available on MATLAB, R and Stata, others have used it to examine multiple cases, in particular Costalli *et al.* (2014) have used it to examine the effect on 20 countries of the economic effects of civil war, the case we are concerned with. There is an alternative, panel time-series based, approach, introduced by Hsiao *et al.* (2012), which can be used to provide a counterfactual. Although this approach seems to have been less widely used, it has a number of attractive features.

In this paper we discuss the relationship between the synthetic control and panel approaches and suggest a method, based primarily on a Chow test, to assess the significance of the measured synthetic control effects. We then compare panel and synthetic control estimates of the economic cost of civil war. Despite an extensive literature on this topic, there is still a lot of debate on the very direction of the effect (whether it is negative or positive), on its size, and on what impact is attributable to the war as against other factors.

We focus on 27 case studies to identify particular responses that are averaged out in large-N quantitative studies, where conflict is assumed to produce the same outcome in very different countries. We provide a range of estimates of the effect of civil war on both the level and growth rate of per capita GDP. Conflict can directly reduce the GDP through a one-off temporary effect, or can bring about a reduction in the growth rate. In the latter case, when conflict causes the growth rate to deteriorate, it can have a permanent negative effect on the output level, and the distance between the actual GDP level and what it would have been in the absence of the conflict increases over time. Using the growth rate as an additional outcome variable mitigates the impact of serial correlation and avoids the problems common to dynamic panel data estimators.

Our case studies suggest that, on average, civil war reduces the GDP level by 9.1% and the growth rate of the GDP by 2.3%. The magnitude of the impact on the GPD level estimated from the panel data analysis is around 8.6% per year, which is very close to what the case-study approach suggests; the permanent losses estimated from the same panel data analysis range from 1.1% to 1.3% of the GDP growth rate, smaller than in the case-studies. Overall, the incidence of internal conflicts has an economically significant one-off negative effect on the GDP level, as well as a negative effect on the growth rate of the GPD, thus suggesting a persistent output loss and a permanent damage to the prospects for economic growth.

The remainder of our paper is organized as follows. Section 2 discusses the relationship between panel and synthetic control estimators. In section 3 we present an application of these methodologies to the estimation of the economic costs of war and provides a short review of the literature. Section 4 discusses the synthetic control method and presents the implemented experiments by region. Section 5 compares the results from the case study methodology with a standard panel data analysis. Section 6 provides concluding remarks.

2 The relationship between panel and synthetic control estimators

The synthetic control approach arises from the microeconometric literature where there are very large samples and it is natural to try and measure the treatment effect by comparing the treated cases with untreated controls who are matched as closely as possible, ideally randomly. The approach fits less well in a time series context where as Abadie *et al.* (2014) note the use of statistical inference is difficult because of the small sample nature of the data, the absence of randomisation, and the fact that probabilistic sampling is not employed to select sample units. Thus rather than giving confidence intervals for their estimates Abadie *et al.* (2014) use what they term placebo studies. Abadie *et al.* (2010) motivate the approach with a factor model. There is a separate approach to measuring the treatment effect used by Hsiao *et al.* (2012), which arises from the panel time-series literature. This also uses a factor model but in a quite different way. Hsiao et *al*'s (2012) remark 9 discusses the relationship between the synthetic control and panel factor representations. Where Abadie *et al.* (2014) ask what was the economic impact on West Germany of the 1990 German reunification?, Hsiao *et al.* (2012) ask what was the economic impact on Hong Kong of the political and economic integration with China? Hsiao *et al.* (2012) exploit the cross-section dependence across units, countries in this case, to construct the counterfactuals. The dependence is attributed to strong factors that drive all units, though their effect on each unit may be different. This procedure allows them to estimate standard errors for the treatment effect and they find that political integration after 1997 had hardly any impact on Hong Kong growth, but economic integration did have a significant effect and raised Hong-Kong's annual real GDP by about 4%. The importance of allowing for cross-section dependence when measuring effects in panels is emphasized by Gaibulloev *et al.* (2014) who examine the impact of terrorism on growth.

The synthetic control method is described in more detail in Abadie *et al.* (2010, 2014), but suppose that we have a sample of $i = 1, 2, ..., N$ units, in time periods $t = 1, 2, ..., T$ with focus variable y_{it}. The target, unit 1, is subject to the intervention at time T_0, with post intervention data $t = T_0 + 1, T_0 + 2, ..., T_0 + T_1$, with $T = T_0 + T_1$. The other $N - 1$ control or "donor" units are not subject to the intervention and are not effected by the consequences of the intervention in unit 1. The effect of the intervention is measured as

$$d_{1,T_0+h} = y_{1,T_0+h} - \sum_{i=2}^{N} w_i y_{i,T_0+h};\ \ h = 1, 2, ..., T_1. \tag{1}$$

To determine the weights w_i let $\mathbf{x}_{1kt}$ be a set of $k = 1, 2, ..., K$ predictor variables for y_{1t}, with the corresponding variables in the other units given by $\mathbf{x}_{jkt}$, $j = 2, 3, ..., N$. These variables are averaged over the pre-intervention period to get $\overline{\mathbf{x}}_{1k}^{T_0}$ and $\overline{\mathbf{X}}_{k}^{T_0}$ the $N-1 \times 1$ vector of predictor k in the control group.[1] Then the $N-1 \times 1$ vector of weights $W = (w_2, w_3, ..., w_N)'$ are chosen to minimize

$$\sum_{k=1}^{K} v_k (\overline{x}_{1k}^{T_0} - W' \overline{X}_{k}^{T_0})^2$$

[1]The predictor variables can be formed from the average of all the available pre-intervention periods, the average of a shorter pre-intervention sub-sample or using particular years.

subject to $\sum_{i=2}^{N} w_i = 1$, $w_i \geq 0$,where v_k is a weight that reflects the relative importance of variable k. The v_k are often chosen by cross-validation, which may be problematic for potentially non-stationary time-series samples. The focus variable may be included in x_{ikt}. Abadie *et al.* (2010) suggest that matching on pre-intervention outcomes helps control for the unobserved factors affecting the outcome of interest. This chooses the comparison units to be as similar as possible to the target along the dimensions included in x_{ikt}.. In the case of German reunification in Abadie *et al.* (2014) the comparison group is Austria, 0.42, US, 0.22, Japan 0.16, Switzerland 0.11 and Netherlands, 0.09. The synthetic West Germany is similar to the real West Germany in pre 1990 pre capita GDP, trade openness, schooling, investment rate and industry share. As they note there may be spillover effects. Since Austria, Switzerland and Netherlands share borders with Germany there is a possibility that their post 1990 values may be influenced by German reunification.

Hsiao *et al.* (2012) measure the effect in the same way using (1), but choose the w_i by regression of y_{1t}, growth in Hong Kong on a subset of y_{jt}, $j = 2, 3, ..., N$, growth in the control countries during the pre-intervention period. The subset is chosen by a model selection procedure. The control group they select contains Japan, Korea, USA, Philippines and Taiwan. They emphasize that Hong Kong is too small for the effects of integration with China to influence any of these countries. There are positive weights on USA and Taiwan and negative weights on the other three. Abadie *et al.* (2014) criticize regression methods because they can give negative weights, but the object of the two exercises is different. The Abadie *et al*'s (2014) procedure is designed to build a synthetic control which is very similar to the target. This is sensible in a microeconometric context when the units are only subject to weak factors. The Hsiao *et al.* (2012) procedure is designed to construct a good prediction of the focus variable in the target taking advantage of the strong factors present in macro-economic time-series. This is sensible in a macroeconometric context, because very different countries can be driven by the same common trends. Hsiao *et al.* (2012) include the US in the controls, not because the US is like Hong Kong, but because US growth is a good predictor of Hong Kong growth. No other country is like Hong Kong, not even Singapore, the closest comparison. Hong Kong lies outside the support of the data for the other countries, which raises a problem for the synthetic control method, which relies on finding an average that is similar, but not for the prediction method. Abadie *et al.* (2014) criticize the fact that regression methods can give negative weights, but this is to be expected if one interprets the procedure as involving prediction using global factors. Suppose Hong Kong before integration is largely driven by global factor A, the US by factors A and B, and Japan largely by factor B; then the US minus Japan provides an estimate of factor A, which drives Hong Kong.

Following Abadie *et al.* (2010, p.495) we can write the model in (1)

$$y_{it} = d_{it}c_{it} + y_{it}^N$$

where y_{it}^N is the estimated value in the absence of intervention, equal to the actual value in the absence of intervention, and $c_{it} = 1$ if $i = 1$ and $t > T_0$, zero otherwise. Were we to then model y_{it}^N by a country specific intercept and global factors, $\mathbf{f}_t$ plus an idyosyncratic error, we would obtain

$$y_{it} = d_{it}c_{it} + \alpha_i + \lambda_i' \mathbf{f}_t + \varepsilon_{it} \tag{2}$$

which is a standard heterogeneous factor augmented panel model. There are a variety of ways of estimating the unobserved factors, $\mathbf{f}_t$. Conditional on estimates of the factors, the d_{it} can be obtained as the prediction errors from estimates of (2) for each country up to T_0. The significance of the d_{it} can then be estimated by the usual Chow predictive failure test. We can allow for more countries to be subject to intervention, by defining $c_{it} = 1$, if a civil war is in progress and $c_{it} = 0$ if not.

In their study of terrorism using a model like (2) Gaibulloev *et al.* (2014) use a modified projected principal component estimator. Another estimator is the Pesaran (2006) correlated common effect estimator which proxies the unobserved $\mathbf{f}_t$ by the cross section averages (weighted or unweighted) of the observed variables. This involves estimating

$$y_{it} = d_{it}c_{it} + \alpha_i + \delta_{1i}\overline{c}_t + \delta_{2i}\overline{y}_{tt} + \varepsilon_{it} \tag{3}$$

This brings out the similarities to the synthetic control and Hsiao *et al.* (2012) approaches, where the cross-section averages like (1) are used to provide the predicted counterfactual. Where it differs is that $\overline{c}_t$, the average prevalence of conflict is included, which allows for contagion effects. The averages may be weighted or unweighted, and if weighted may give zero weights to some countries like the synthetic control.

If we assume homogeneity of λ_i' in (2) we get

$$y_{it} = d_{it}c_{it} + \alpha_i + \alpha_t + \varepsilon_{it}$$

with $\alpha_t = \lambda'\mathbf{f}_t$. This is a two way fixed effect model, a static version of equation (1) of Gaibulloev *et al.* (2014).[2] If we further assume that the effects of conflict are homogeneous over time and country so that $d_{it} = \beta$, we have a standard panel model of the cost of conflict

$$y_{it} = \beta c_{it} + \alpha_i + \alpha_t + \varepsilon_{it}$$

In our example, which we discuss in more detail below, we will consider a balanced panel $i = 1, 2, ..., N$ and $t = 1, 2, ..., T$ with data for y_{it} which is either log per-capita real GDP or the growth rate in per-capita real GDP and $c_{it} = 1$ if a civil war is taking place in country i in year t and $c_{it} = 0$ otherwise. The sample is made up of those that had civil wars (but not other sorts of wars) and those that had no wars at all.[3] There is an issue about whether other covariates should be included, since the civil war may have effects on these other variables and attributing this effect to variations in the other covariates may

[2] We confine ourselves to static models to bring out the similarity between the panel and synthetic control approaches, since the latter does not include lagged dependent variables of the treated cases.

[3] We exclude cases where the country was subject to interstate or extra-systemic wars.

"over-control" and under-estimate the total impact effect of civil war. Pesaran & Smith (2014) discuss this issue. We do not include other covariates although the argument can be extended to allow for them.

3 Economic costs of war

We now explore the relationship between these two methods in an analysis of the economic impact of civil wars, the dominant form of violence in the contemporary international system. From 1960 to 2010, more than 20% percent of nations experienced at least ten years of civil war. The number of active conflicts peaked in the 1980s and 1990s, following the collapse of the Soviet Union and the outbreak of conflict across Sub-Saharan Africa, where a third of countries had active civil wars during the mid-1990s. Civil war is more frequent in poor countries and can further weaken their prospects for economic development. An extensive literature has investigated the effects of civil war on economic growth across countries. Surveys on the economic costs of conflict are provided by Gardeazabal (2010), Skaperdas (2011), World Bank (2011), Brück & De Groot (2012) and De Groot *et al.* (2012). A recent survey by Smith (2014) examines the methodological difficulties involved in quantifying the economic costs of conflict.

Seminal empirical studies by Organski & Kugler (1977) and Organski (1981) analyze the economic effects of WWI and WWII on European Countries. Among the studies on the cost of civil war, Collier (1999) has definitely had the greatest impact and continues to do so (see Brück & De Groot, 2012). He finds that during civil wars GDP per capita declines at an annual rate of 2.2%. The decline is partly because war directly reduces production and partly because it causes a loss of the capital stock due to destruction, dissaving, and portfolio substitution of foreign investors. Blomberg *et al.* (2004) use a their structural VAR model to show that negative shocks to GDP due to internal or external conflicts yield much larger and longer-lived effects than those obtained from a negative shock due to terrorism.

Later articles also investigate the spillover effects on neighboring countries and trading partners (e.g. Murdoch & Sandler, 2002; Fosu, 2003; Kang & Meernik, 2005; Butkiewicz & Yanikkaya, 2005; Koubi, 2005; De Groot, 2010). Using an event-study methodology, Chen *et al.* (2008) analyze a cross-section of 41 countries and find a substantial drop in per capita income in conflict countries during war and a failure to make subsequent progress in key areas of social and political development comparable to countries that did not experience civil war. Cerra & Saxena (2008) use impulse response functions and show that the immediate effect of a civil war induce a reduction of 6% points in GDP, although almost half of that loss is recovered after about 6 years.[4] Yet, the long-run estimates are imprecise and allow for the possibility of a zero long-run effect. Moreover, in the event of a long civil war, such as in Angola or Sri Lanka, the negative effects on growth can be expected to compound over time and it is not clear to what extent output can be expected to partially recover in the long run, as it does in the impulse response to a theoretical one-time shock (see Skaperdas, 2011). Country experiences in terms of growth of course vary widely. While event studies are very informative, they also conceal a deal of heterogeneity and suffer from predictable omitted variable bias concerns (see Blattman & Miguel, 2010; Skaperdas, 2011).[5]

Case studies are particularly useful in this respect as it is not always clear-cut whether civil wars (and the subsequent level of anarchy and statelessness) has a negative effect on the economic performance of conflict-ridden countries. Most of the civil wars breaks out in countries with dysfunctional states that are not only unable to provide basic public goods, such as infrastructures and schools, but may themselves be a major hurdle to economic development. Oppressive and exploitative governments can in fact depress economic development below a level achievable without any government at all. Leeson (2007) and Powell *et al.* (2008) compare Somalia's relative economic performance when

[4]Similarly, Auray *et al.* (2014) study the impact of conflicts on macroeconomic aggregates of 9 countries from 1870 onwards, including the GDP.

[5]A small body of recent works compare outcomes between neighboring areas within the same country with different exposure to conflict, using micro level data (Davis *et al.* , 2002; Miguel & Roland, 2011; Brakman *et al.* , 2004; Lopez & Wodon, 2005).

the country had a government with its extended period of post-1991 war and anarchy. They both find that a number of Somalia's development indicators have improved during its period of statelessness. The results are explained by the existence of public corruption and government rent-seeking in the pre-war period. The emergence of anarchy opened up opportunities for advancement not possible before the collapse of the state.

To tackle some of the theoretical and empirical issues involved in the quantification of the costs of war, we now compare fairly standard panel estimators and a case study methodology, the synthetic control method, using the same set of countries. This is the issue considered next.

4 Case studies

Consider an outcome such as per capita GDP, which has been observed before during and after a conflict. We want to compare the observed outcome for the conflict years with a hypothetical counterfactual, which gives the country's per capita GDP in absence of a conflict. To compare the trajectory of the GDP for a country affected by a civil war with the trajectory of a control group, we need a suitable control unit with the same characteristics of the unit exposed. Yet, when the units of analysis are aggregate entities, like countries, a suitable single control often does not exist, and therefore a combination of control units offers a better compromise.

As shown in section 2, the synthetic control method is based on the premise that in absence of a civil war, the evolution in terms of GDP per capita of the treated region would be given by a weighted average of the potential comparison units that best resemble the characteristics of the case of interest. The gap between the conflict-ridden country and its artificial counterfactual and the cumulative stream of gaps can identify the yearly effect as well as the cumulative effects of civil war on subsequent economic performances over extended periods of time. To select the countries into the donor pool, we focus only on the outcome variables in the pre-treatment period. Therefore the vectors of pre-conflict characteristics for the country at war and the treated units include only pre-treatment levels of per capita GDP and their growth rates.

We use civil war data from the UCDP/PRIO Armed Conflict dataset. Accordingly, a civil war is defined as “a conflict between a government and a nongovernmental party”. We use both cases where there is no interference from other countries and civil wars where “the government side, the opposing side, or both sides, receive troop support from other governments” since these instances are very frequent in modern internal conflict. We exclude countries with extra-systemic armed conflicts - i.e., conflict between a state and a non-state group outside its own territory, and interstate armed conflicts - i.e., between two or more states. Real per capita GDP and the GDP growth rates are taken from Penn World Table dataset.

Our pool of experiments is made up of countries meeting the following conditions: (i) the treated country and the control group have no missing information on the outcome variable in the 25-year-long sample period as we require 15-year pre-war observations to calibrate the synthetic control and 10-year post-war observations to forecast the long-run effect of the civil war; (ii) the treated country experienced a civil war at the latest in 2002, as we focus on a 10-year post-war window;[6] (iii) in case of multiple and subsequent civil wars, we select the first one in chronological order. By imposing the above conditions, we end up with 27 case studies.

The pool of potential comparison economies consists of countries which did not experience any civil war in the 25-year-long sample period (i.e., between 15 years before and 10 years after the onset of a civil war). As one valid concern in the context of this study is the potential existence of spillover effects, we exclude from this pool the countries sharing borders with the treated units.

Given the potential of heterogeneity across regions, we divide our 27 treated countries into six groups i.e. Asia, Middle East and North Africa (MENA), Sub-saharan Africa, Latin America and Europe.[7] For the sake of brevity, this section will only briefly cover

[6] With the exception of the Ivory Coast, where we only have 8 years post civil war onset

[7] Given its level of development and its aspiration to join the European Union, we have treated Turkey

four case studies, one in Asia (i.e., Nepal), one in Latin America (i.e, Peru), one in the MENA region (i.e., Algeria) and one in Sub-Saharan Africa (i.e., Uganda). We refer the reader to the online appendix for the remaining countries.

Section A in the appendix display the weights of each state in the synthetic control. For example, the weights reported indicate that per capita GDP in Algeria prior to the civil war in 1991 is best reproduced by a combination of the Bahamas (0.023), Albania (0.048), Iceland (0.023), Sao Tome and Principe (0.155), Jordan (0.132), Oman (0.025), China (0.128), Mongolia (0.061), Bhutan (0.067), Brunei Darussalam (0.008), Vanuatu (0.226) and Samoa (0.103).

Figures 1 and 2 show the real GDP per capita trends in levels and growth rates respectively for the treated country and for its synthetic control. The estimated effect of a civil war on real per capita GDP is the difference between per capita GDP (solid line) and in its synthetic version (dotted line) after the onset of the civil war. As we can see, the real per capita GDP in the synthetic very closely tracks the trajectory of this variable in the treated countries for the entire 15-year pre-war period. This suggests that the synthetic provides a sensible approximation to the GDP that would have been achieved in the treated country in the post-war period in the absence of a war. While the treated countries and the synthetic control behave similarly in the pre-treatment period, the divergence between the solid and the dotted lines after the outbreak of the conflict indicates that civil war has a negative impact on their subsequent GDP levels (see Figure 1). Algeria shows the case of a level shift, which suggests a one-off temporary effect on the GDP. Nepal, Peru and Uganda display a situation in which there is a steady divergence from their artificial counterfactual following the onset of the civil war.

When we use the growth rate as the outcome variable (see Figure 2), the synthetic control predicts the treated country less well in the years before the civil war than when the level of per capita GDP is used. This is to be expected as the growth rate series are less smooth than the corresponding levels, which are likely to be non-stationary. The

as European.

results are not homogeneous: while Uganda illustrates a situation in which conflict causes the growth rate to deteriorate,[8] in Algeria, Nepal and Peru the GDP growth rate in some years ends up higher than it would have been in absence of the conflict. In fact, a visual inspection of the discrepancies between solid and dotted lines suggest a succession of negative and positive gaps (i.e., the country at war outperforms its synthetic counterpart).

[Figures 1 and 2 about here]

The appendix contains the remaining cases. In particular, Figure A1 and A8 include Papua New Guinea, Sri Lanka and Thailand. The Middle East and North Africa sample in Figures A2 and A9 includes Egypt, Morocco and Syria. Sub-saharan Africa is the region with the largest number of civil wars in the post-WWII history and the question of why Africa has seen more wars has been examined by a number of scholars.

Our sample of Sub-Saharan countries is very rich and includes Djibouti, Guinea, Guinea Bissau, the Ivory Coast, Liberia, Mauritania, Niger, the Republic of Congo, Mozambique, Rwanda, Senegal and Sierra Leone (Figures A3 to A5 and A10 to A12). Latin America countries, El Salvador and Nicaragua, are in Figures A6 and A13, while Europe (Figures A7 and A14) includes Spain, Turkey and the United Kingdom.[9] Overall, the divergence between the solid and the dotted lines after the outbreak of the conflict indicates that civil war has for most countries a negative effect on the GDP level, while its effect on the economic growth is very heterogeneous, and varies across countries and over time for each country.

To assess whether there is a significant difference between the outcomes of the treated, y_{it}, and the control group, $\bar{y}_{it}^{S}$, during civil war years, we perform a Chow test to estimate d_{ih}, the wartime forecast error in

[8]In Uganda the civil war seems to have caused an output loss prior to the official start date of the war; in these cases, the time of the civil war could be redefined to be the first period in which the outcome reacts to the treatment.

[9]The start date of the treatment in Spain and the UK corresponds to heightened tensions between the governments and the ETA and IRA, respectively, in terms of battle related deaths, as coded by the PRIO/UPPSALA dataset. The results we obtain with the case study on Spain are consistent with early findings by Abadie & Gardeazabal (2003), who however measure the effects of ETA on the economy of the Basque region only.

$$y_{it} - \bar{y}^S_{it} = \sum_h d_{ih} c_{ih} + w_{it} \tag{4}$$

where c_{ih} are separate dummies for each of the war years,

$$h = T_{0i+1}, T_{0i+2}, ..., T_{0i+T_{1i}}.$$

The d_{ih} are the prediction errors for the war years, the w_{it} will be the pre-intervention differences between the treated case and the synthetic control and will be zero for the war years, when the errors will be captured by d_{it}.

Even if the mean of the errors was zero, $\beta_i = T_1^{-1} \sum_h d_{ih} = 0$, the variance may be changed by the war, producing significant forecast errors. In fact, we estimate model 4 and assuming that the errors are normally distributed we test the restriction $d_{ih} = 0$. This is the same null as a Chow predictive failure test. Tables 1 and 2 display the Chow test for our four case studies, while Tables A1 - A7 contain the Chow tests for the remaining 23 countries. In all Tables we also report the t-statistics and p-values for each war-time dummies. We detect significant negative effects of the civil war on real per capita GDP. These effects start materialising one year after the onset of the conflict for Algeria and Peru, while two and eight years after for the case of Nepal and Uganda respectively. When the focus variable is the growth rate of per capita GDP, we find significant economic downturn in Algeria and Peru for the whole of the war period, but the initial two years. The negative effect on Nepal's growth rate is significant at conventional level only during the period 1998-2000, while the difference between Uganda GDP growth and its synthetic counterpart is in all but one year statistically insignificant.

[Tables 1 and 2 about here]

Table 3 summarizes the results from the case study analysis. The mean effect is the coefficient of the civil war dummy (which takes on the value 1 when a country has a conflict, and 0 otherwise) in an equation where the dependent variable is the log GDP gap between the country at war and its artificial counterpart. In fact, we run an equation similar to 4, but we do not use separate civil war year dummies, which allows us to obtain a mean effect. We also report the p-value of this mean effect and the p-value of the Chow test, which corresponds to the one displayed at the bottom of each panel containing the individual Chow test. Finally, we report the Standard Error of the Regression (SER), to show how well the pre-war model fits the data.

[Table 3 about here]

We find that 17 of the 27 cases show a negative effect of war on the GDP level, of which 15 are statistically significant at conventional levels. Moreover, 18 out of 27 show a negative effect on the growth rate, of which only one is insignificant. In terms of magnitude, Table 3 suggests that the average impact of conflict on the GDP level is around -9.1%. This is different from the 17% drop found in the study of Costalli *et al.* (2014), which uses a different sample (20 case studies), a different pre-intervention period (10 years) and additional predictor variables to construct the synthetic control (i.e., investment share, trade openness, population growth rate and secondary school enrollment rate). However, considering common cases only, we obtain an average impact of 12.8% against the 17.2% of Costalli *et al.* (2014). Finally, the effect on the growth rate is estimated to be around -2.3%. which is virtually identical to the -2.2% estimated by Collier (1999).

As we demonstrated in Section 2, models estimated from panel data and models where treatment effects are estimated by comparison of a treated case with a synthetic control are very closely related. Therefore, we should expect to find results of similar magnitude when we move form the synthetic control method to the panel data analysis.

5 Panel data analysis

To link the results obtained from the synthetic control method to the panel data analysis, we now estimate the economic costs of war using the empirical specification in equation (3). In particular, we assume that the effects of conflict are homogenous over time and across country. The model takes the following form

$$y_{it} = \beta c_{it} + a_i + \delta_1 \bar{c}_t + \delta_2 \bar{y}_t + u_{it} \tag{5}$$

where y_{it} is the (log) of real per capita GDP or the per capita GDP growth rate in a country i at time t.

In order to compare the output gaps obtained from the synthetic control method with the panel data estimation, we use the same pool of control units (i.e., countries with no civil war in the 25-year-long sample period). We also use a restricted sample, with models (ii) and (iv) estimating equation (5) only for the 27 countries who experienced civil wars. In this case the control group will be made up of cases not yet treated but that will be treated later on.

The first two models in Table 4 are semi-logarithmic regression, in which the dependent variable is the natural logarithm of the real per capita GDP, therefore the interpretation of the estimated coefficients of the control variable is that of a percentage change in per capita GDP. The estimated impact of a civil war in model (i) is around -8.6%. The magnitude of the impact is almost 3% points higher than the one estimated by Cerra & Saxena (2008). The model in column (ii) shows that civil war is insignificant at conventional level. One of the most striking result is the similarity of this result, -8.6%, to the average impact estimated by means of the synthetic control, i.e., -9.1% (see Table 3).

To investigate the possibility that conflict may also affect the pace at which the per capita GDP evolves over time, we estimate a growth equation. Our results show that reduce the growth rate of GDP rather than just its level. In fact, civil war incidence over the period 1960s-2000s, is associated with a drop in average growth rate in the range of 1.1% to 1.3%, smaller than the 2.2% estimated by Collier (1999), and smaller than the -2.3% estimated in Table 3.

Note that the model estimated by Collier (1999) takes the following form $y_{i,d} = \beta c_{id} + \delta X_{i,d} + u_{id}$ where d stands for decade and $y_{i,d}$ is the decade average per capita GDP growth rate of each country between 1960 and 1989. $X_{i,d}$ includes a number of explanatory variables: dummies for all three decades and continent dummies in lieu of the constant; the initial value (at the start of the decade) of the level of secondary schooling and the level of per capita income; the degree of ethno-linguistic fractionalization; and a dummy for landlocked countries. The effect of civil war is captured by the number of months of warfare during the decade, and two postwar variables to explore the effects on the first five years of subsequent peace. Only the first one expresses the concurrent effect of war, and thus is directly comparable with our estimate. There are many reasons behind this small discrepancy. Growth models tend to be sensitive to specification and most of the classical predictors of economic growth, such as education or investment, are directly influenced by war. This implies that some of the effects of war work through them. Therefore the inclusion of covariates that are themselves negatively affected by civil war may create a post-treatment bias. Our parsimonious model specification may be safer. Moreover, the growth average over long periods fails to capture the short-term response of the economic growth.[10]

[Table 4 about here]

Given that we use a large dataset from 1960 to 2011, and $T = 51$ is large, we can estimate individual separate effects of civil war for each country and relax the homogeneity restrictions, while allowing for common factors influencing all countries and use the Pesaran (2006) Correlated Common Effect, CCE, estimator. For the countries who experienced civil wars we estimate the following model

$$y_{it} = \beta_i^c c_{it} + a_i^c + \delta_{1i}^c \bar{c}_t + \delta_{2i}^c \bar{y}_t + u_{it}$$

and then look at the distribution of the least squares estimator $\hat{\beta}_i^c$. We summarise the results of this exercise in Figure 3(a), which presents the distribution of the estimated coefficients of civil war, $\hat{\beta}_i^c$, of the per capita GDP equation and Figure 3(b), which shows

[10] Collier (1999) performs also a robustness check and runs a fixed effects model, whose results are very close to the main specification.

the distribution of the coefficients in the per capita GDP growth equation. As we can see, there is a wide range of possible responses to conflict shocks, ranging from -33% (Sierra Leone) to +30% (Liberia) in the GDP level and between -13% (Guinea-Bissau) to +6% (Djibouti) in the GDP growth rate. We then graph in Figure 4 on the x-axis the estimated coefficients (c_{it}) of the growth equation of our sample of 27 countries, and on the y-axis the coefficients of per capita GDP in levels. The fitted line suggests a very small positive correlation between temporary and permanent effects of war on the GDP. The coefficient of civil war in the per capita GDP growth equation is negative for the majority of countries, while roughly fifty percent display a positive temporary response to conflict.

[Figures 3 and 4 about here]

6 Conclusions

This paper attempts to link panel data analyses, case studies and synthetic control methods, establishing the relation between them and illustrating the discussion with various estimates of the effect of civil war on the level and the growth of economic activity. Civil war is the prevailing form of war and has spurred a growing academic debate on its effect on economic performance, in particular on economic growth.

We first use a counterfactual approach and compare the evolution of the real per capita GDP for countries affected by a conflict with the evolution of an artificial control group. We find that in many cases, civil wars did not have an obvious negative impact on the economic growth of exposed countries every year. On average, however, we find that civil war reduces the GDP level by 9.1% and the growth rate of the GDP by 2.3%. We then compare these results with a panel data analysis. We find that the incidence of internal conflicts has an economically significant one-off negative effect on the GDP level, as well as a negative effect on the growth rate of the GPD, thus suggesting a persistent output loss and a permeant damage to the prospects for economic growth. The estimated losses range from 1.1% to 1.3% of the GDP growth rate while the magnitude of the (temporary) impact on the GPD level is around 8.6% per year. Overall, the models estimated from panel data and the synthetic control are closely related and give particularly similar results when looking at the effect of war on the GDP level.

References

Abadie, Alberto, & Gardeazabal, Javier. 2003. The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review*, **93**(1), 113–132.

Abadie, Alberto, Diamond, Alexis, & Hainmueller, Jens. 2010. Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, **105**(490), 493–505.

Abadie, Alberto, Diamond, Alexis, & Hainmueller, Jens. 2014. Comparative politics and the synthetic control method. *American Journal of Political Science*.

Auray, Stéphane, Eyquem, Aurélien, & Jouneau-Sion, Frédéric. 2014. Wars and capital destruction. *Journal of Economic Dynamics and Control*.

Blattman, Christopher, & Miguel, Edward. 2010. Civil War. *Journal of Economic Literature*, **48**(1), 3–57.

Blomberg, S Brock, Hess, Gregory D, & Orphanides, Athanasios. 2004. The macroeconomic consequences of terrorism. *Journal of Monetary Economics*, **51**(5), 1007–1032.

Brakman, Steven, Garretsen, Harry, & Schramm, Marc. 2004. The strategic bombing of German cities during World War II and its impact on city growth. *Journal of Economic Geography*, **4**(2), 201–218.

Brück, Tilman, & De Groot, Olaf J. 2012. The Economic Impact of Violent Conflict. *Defence and Peace Economics*, 1–5.

Butkiewicz, James L, & Yanikkaya, Halit. 2005. The impact of sociopolitical instability on economic growth: analysis and implications. *Journal of Policy Modeling*, **27**(5), 629–645.

Cerra, Valerie, & Saxena, Sweta Chaman. 2008. Growth dynamics: the myth of economic recovery. *The American Economic Review*, **98**(1), 439–457.

Chen, Siyan, Loayza, Norman V, & Reynal-Querol, Marta. 2008. The aftermath of civil war. *The World Bank Economic Review*, **22**(1), 63–85.

Collier, Paul. 1999. On the economic consequences of civil war. *Oxford economic papers*, **51**(1), 168–183.

Costalli, Stefano, Moretti, Luigi, & Pischedda, Costantino. 2014. The Economic Costs of Civil War: Synthetic Counterfactual Evidence and the Effects of Ethnic Fractionalization. *HICN working paper.*

Davis, Donald R, Weinstein, David E, Eeckhout, Jan, Jovanovic, Boyan, Case, Anne, Lubotsky, Darren, Paxson, Christina, Johnson, Simon, McMillan, John, Woodruff, Christopher, *et al.* . 2002. Bones, Bombs, and Break Points: The Geography of Economic Activity. *American Economic Review*, **92**(5), 1269–1289.

De Groot, Olaf, Brück, Tilman, & Bozzoli, Carlos. 2012. How many Bucks in a Bang: on the Estimation of the Economic Costs of Conflict. *Oxford Handbook of the Economics of Peace and Conflict.*

De Groot, Olaf J. 2010. The spillover effects of conflict on economic growth in neighbouring countries in Africa. *Defence and peace economics*, **21**(2), 149–164.

Fosu, Augstin Kwasi. 2003. Political instability and export performance in sub-Saharan Africa. *Journal of Development Studies*, **39**(4), 68–83.

Gaibulloev, Khusrav, Sandler, Todd, & Sul, Donggyu. 2014. Dynamic panel analysis under cross-sectional dependence. *Political Analysis*, **22**(2), 258–273.

Gardeazabal, Javier. 2010. Methods for Measuring Aggregate Costs of Conflict. *DFAEII 2010.09.*

Hsiao, Cheng, Steve Ching, H, & Ki Wan, Shui. 2012. A panel data approach for program evaluation: measuring the benefits of political and economic integration of Hong kong with mainland China. *Journal of Applied Econometrics*, **27**(5), 705–740.

Kang, Seonjou, & Meernik, James. 2005. Civil war destruction and the prospects for economic growth. *Journal of Politics*, **67**(1), 88–109.

Koubi, Vally. 2005. War and economic performance. *Journal of Peace Research*, **42**(1), 67–82.

Leeson, Peter T. 2007. Better off stateless: Somalia before and after government collapse. *Journal of Comparative Economics*, **35**(4), 689–710.

Lopez, Humberto, & Wodon, Quentin. 2005. The economic impact of armed conflict in Rwanda. *Journal of African Economies*, **14**(4), 586–602.

Miguel, Edward, & Roland, Gerard. 2011. The long-run impact of bombing Vietnam. *Journal of Development Economics*, **96**(1), 1–15.

Murdoch, James C, & Sandler, Todd. 2002. Economic growth, civil wars, and spatial spillovers. *Journal of conflict resolution*, **46**(1), 91–110.

Organski, Abramo FK. 1981. *The war ledger*. University of Chicago Press.

Organski, AFK, & Kugler, Jacek. 1977. The costs of major wars: the Phoenix factor. *The American Political Science Review*, **71**(4), 1347–1366.

Pesaran, M Hashem. 2006. Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, **74**(4), 967–1012.

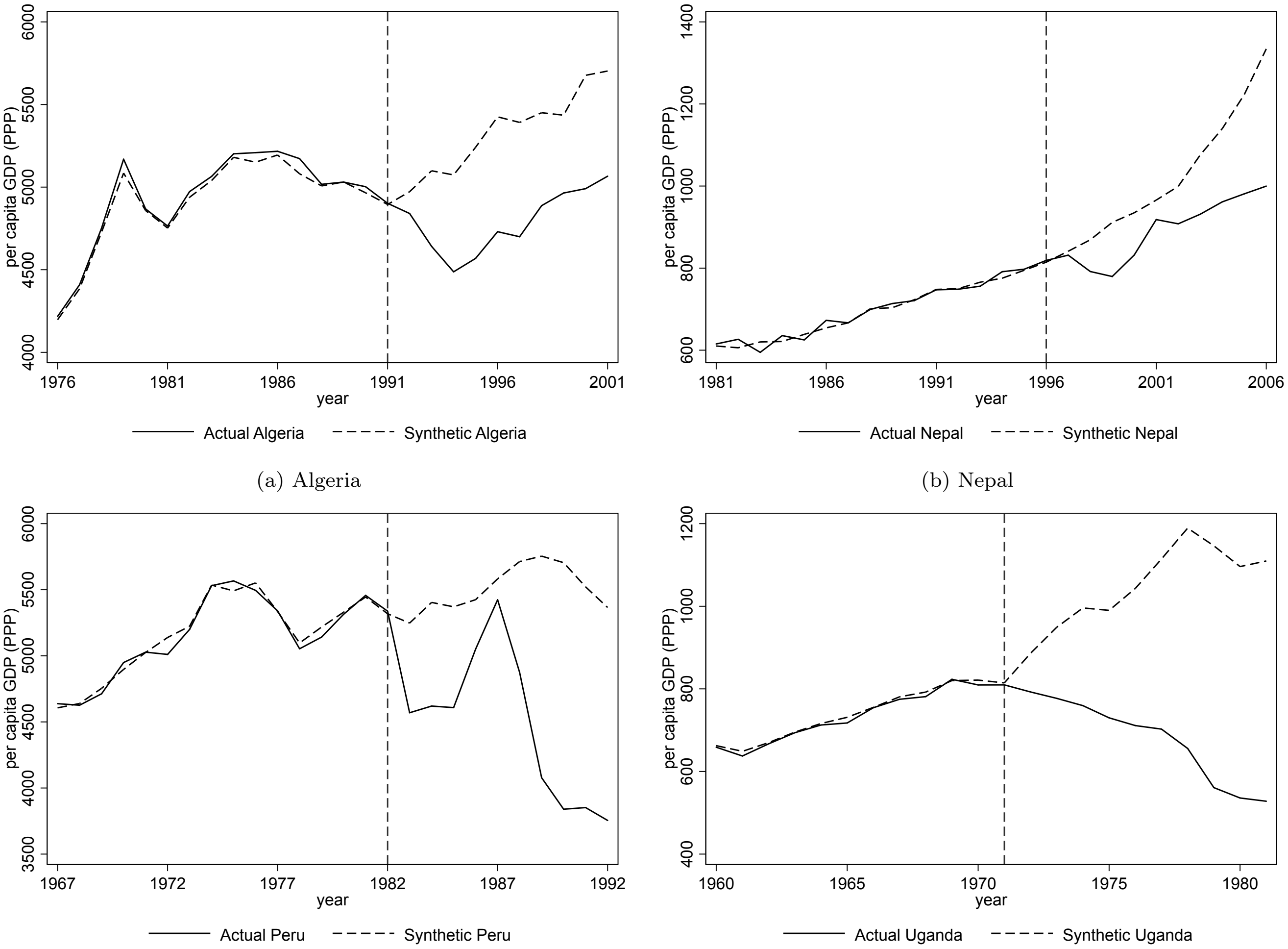
Pesaran, M Hashem, & Smith, Ronald Patrick. 2014. Counterfactual Analysis in Macroeconometrics: An Empirical Investigation into the Effects of Quantitative Easing. *Birkbeck Working Papers in Economics and Finance*.

Powell, Benjamin, Ford, Ryan, & Nowrasteh, Alex. 2008. Somalia after state collapse: Chaos or improvement? *Journal of Economic Behavior & Organization*, **67**(3), 657–670.

Skaperdas, Stergios. 2011. The costs of organized violence: a review of the evidence. *Economics of Governance*, **12**(1), 1–23.

Smith, Ron P. 2014. The economic costs of military conflict. *Journal of Peace Research*, **51**(2), 245–256.

World Bank, Group. 2011. *World Development Report 2011: Conflict, Security, and Development*. World Bank: Washington, DC.



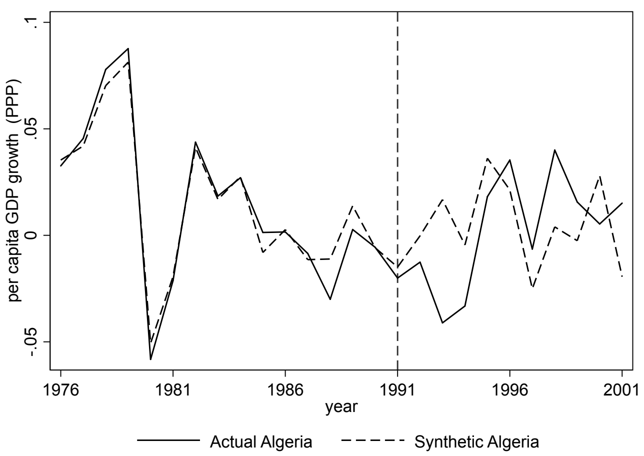
(a) Algeria

(b) Nepal

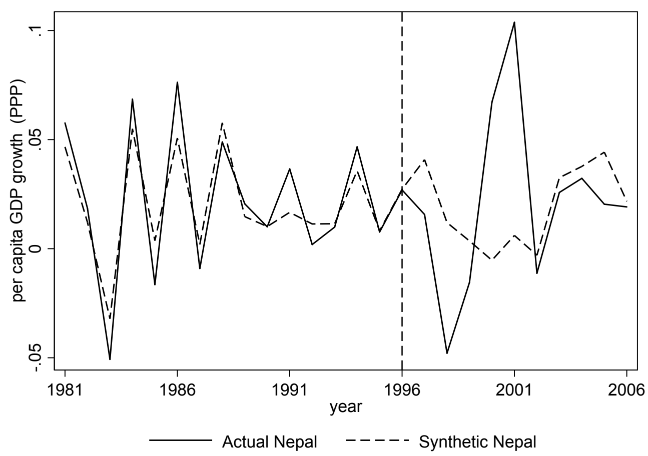
(c) Peru

(d) Uganda

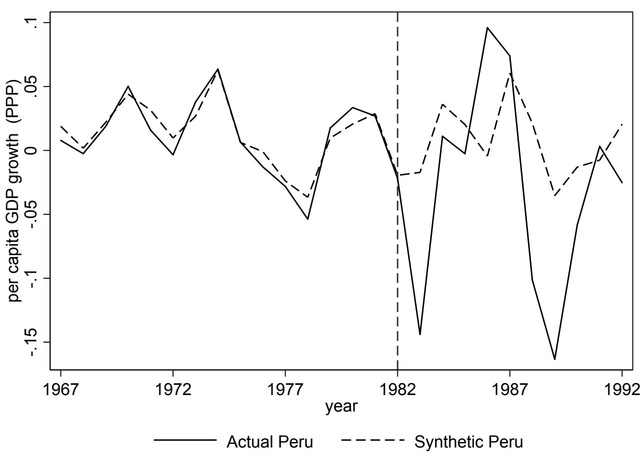
Figure 1: Per capita GDP trends, Treated Country vs. Synthetic Control



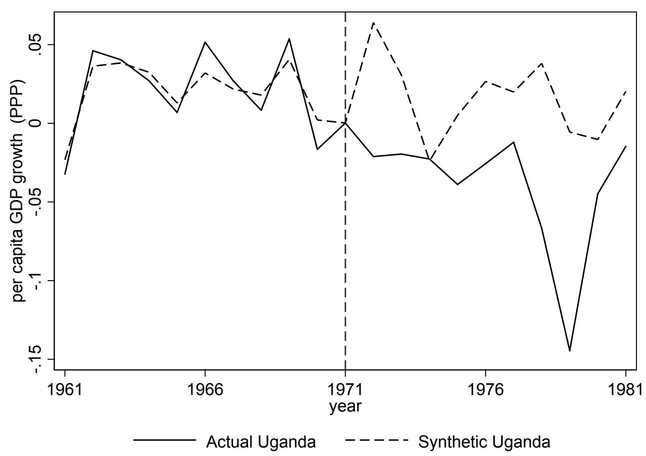
(a) Algeria



(b) Nepal



(c) Peru



(d) Uganda

Figure 2: Per capita GDP growth trends, Treated Country vs. Synthetic Control

Table 1: Chow test for case studies. Dependent variable is per capita GDP.

	stat	p-value
Algeria		
1991	-0.891	0.388
1992	-5.945	0.000
1993	-17.771	0.000
1994	-22.455	0.000
1995	-25.587	0.000
1996	-26.403	0.000
1997	-26.286	0.000
1998	-21.584	0.000
1999	-18.265	0.000
2000	-26.070	0.000
2001	-24.277	0.000
F-test	308.428	0.000
Nepal		
1996	0.163	0.873
1997	-0.896	0.385
1998	-6.109	0.000
1999	-10.323	0.000
2000	-8.091	0.000
2001	-3.824	0.002
2002	-7.205	0.000
2003	-11.289	0.000
2004	-13.908	0.000
2005	-18.793	0.000
2006	-25.920	0.000
F-test	115.284	0.000
Peru		
1982	0.659	0.521
1983	-12.624	0.000
1984	-14.634	0.000
1985	-14.229	0.000
1986	-6.833	0.000
1987	-2.720	0.017
1988	-15.676	0.000
1989	-31.617	0.000
1990	-35.208	0.000
1991	-31.486	0.000
1992	-30.373	0.000
F-test	346.255	0.000
Uganda		
1971	0.583	0.568
1972	0.095	0.926
1974	-0.692	0.499
1979	-2.612	0.020
1980	-2.474	0.026
1981	-2.592	0.020
F-test	3.152	0.033

Table 2: Chow test for case studies. Dependent variable is per capita GDP growth

	stat	p-value
Algeria		
1991	-0.590	0.565
1992	-1.536	0.147
1993	-7.505	0.000
1994	-3.675	0.002
1995	-2.278	0.039
1996	1.932	0.074
1997	2.528	0.024
1998	4.818	0.000
1999	2.469	0.027
2000	-2.888	0.012
2001	4.619	0.000
F-test	14.223	0.000
Nepal		
1996	-0.133	0.896
1997	-1.912	0.077
1998	-4.401	0.001
1999	-1.472	0.163
2000	5.086	0.000
2001	6.892	0.000
2002	-0.702	0.494
2003	-0.595	0.561
2004	-0.501	0.624
2005	-1.817	0.091
2006	-0.292	0.774
F-test	9.993	0.000
Peru		
1982	0.043	0.966
1983	-12.514	0.000
1984	-2.241	0.042
1985	-2.019	0.063
1986	10.443	0.000
1987	1.647	0.122
1988	-12.106	0.000
1989	-12.644	0.000
1990	-4.297	0.001
1991	1.388	0.187
1992	-4.342	0.001
F-test	55.418	0.000
Uganda		
1971	0.554	0.589
1972	-1.954	0.071
1974	0.590	0.565
1979	-3.539	0.003
1980	-0.461	0.652
1981	-0.475	0.642
F-test	2.863	0.049

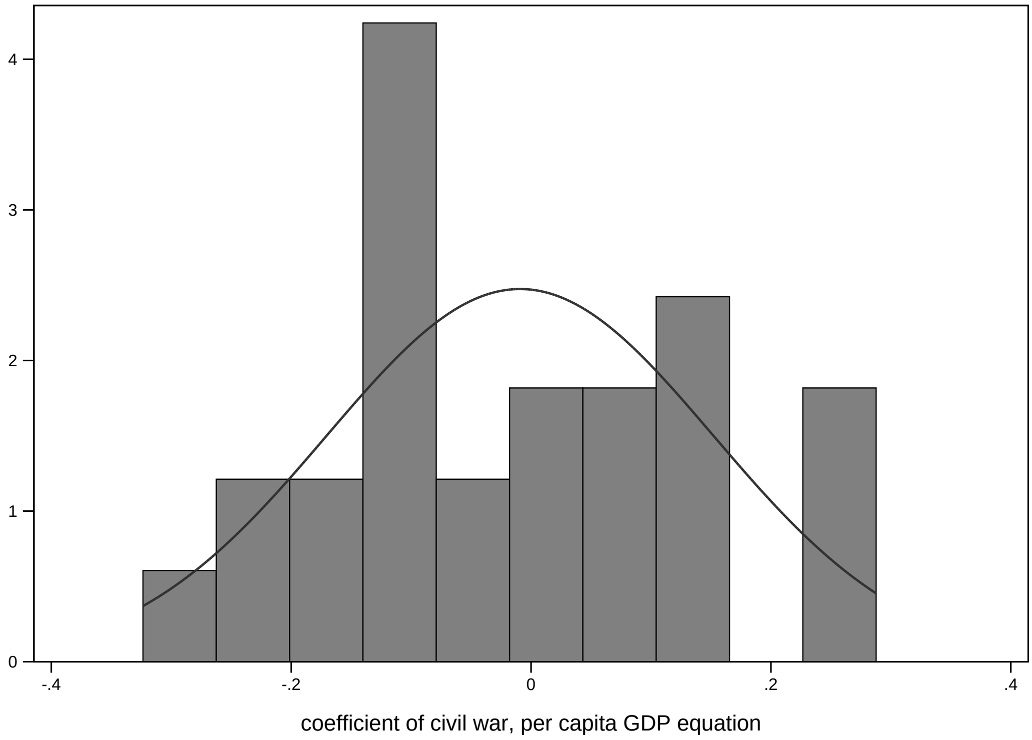
Table 3: Summary of results from case study analysis

Country		Mean effect	Mean effect (p-value)	years	Chow test (p-value)	SER
Nepal	level	-0.125	0.000	96-06	0.000	12.6
	growth	0.000	0.987		0.000	0.014
Papua New Guinea	level	0.164	0.000	89-90;92-96	0.000	121.1
	growth	0.047	0.121		0.000	0.034
Sri Lanka	level	0.025	0.043	84-94	0.017	32.2
	growth	0.010	0.543		0.593	0.041
Thailand	level	0.042	0.001	74-82	0.001	45
	growth	0.007	0.479		0.000	0.009
Algeria	level	-0.106	0.000	91-01	0.000	26.6
	growth	-0.001	0.853		0.000	0.007
Egypt	level	-0.032	0.451	93-98	0.979	413.3
	growth	-0.009	0.513		0.324	0.027
Morocco	level	0.024	0.421	71; 75-85	0.840	124.4
	growth	0.018	0.576		0.235	0.068
Syria	level	0.057	0.284	79-82	0.400	244.8
	growth	0.026	0.605		0.891	0.096
Djibouti	level	-0.163	0.346	91-94; 99	0.836	1134.15
	growth	0.092	0.002		0.001	0.044
Guinea	level	0.058	0.514	00-01	0.807	111.1
	growth	0.022	0.164		0.214	0.021
Guinea-Bissau	level	-0.100	0.500	98-99	0.820	190.7
	growth	-0.095	0.045		0.002	0.052
Ivory Coast	level	-0.011	0.844	02-04	0.914	133.5
	growth	-0.024	0.102		0.100	0.021
Liberia	level	0.151	0.741	89-90	0.651	290.5
	growth	-0.217	0.203		0.191	0.222
Mauritania	level	0.133	0.112	75-78	0.449	206.4
	growth	-0.016	00.818		0.829	0.133
Mozambique	level	-0.670	0.000	77-87	0.000	33
	growth	-0.032	0.074		0.005	0.029
Niger	level	0.027	0.767	91-92;94-95;97	0.921	125.5
	growth	-0.024	0.410		0.706	0.060
Rep of Congo	level	-0.010	0.800	93; 97-99; 02	0.662	186.5
	growth	-0.017	0.525	0.518	0.518	0.053
Rwanda	level	0.007	0.900	90-94; 96-00	0.046	67.5
	growth	-0.119	0.173		0.426	0.21
Senegal	level	-0.180	0.005	90; 92-93; 95; 97-98; 00	0.002	155.5
	growth	-0.045	0.039		0.072	0.043
Sierra leone	level	-0.583	0.001	91-00	0.053	367.3
	growth	-0.068	0.041		0.000	0.033
Uganda	level	-0.300	0.017	71-72; 74; 79-81	0.033	176.3
	growth	-0.030	0.135		0.049	0.033
El Salvador	level	-0.260	0.000	79-89	0.000	78.6
	growth	-0.012	0.157		0.000	0.010
Nicaragua	level	-0.210	0.000	77-79; 82-87	0.000	284.8
	growth	-0.086	0.050		0.016	0.080
Peru	level	-0.194	0.000	82-92	0.000	51
	growth	-0.033	0.082		0.000	0.010
Spain	level	-0.108	0.002	78-82; 85-87	0.100	1350.6
	growth	-0.008	0.289		0.032	0.013
Turkey	level	-0.083	0.000	84-94	0.000	50
	growth	0.001	0.971		0.000	0.017
the UK	level	-0.013	0.015	71-81	0.177	155
	growth	-0.015	0.030		0.000	0.000
Mean of the means	level	-0.091				
	growth	-0.023				

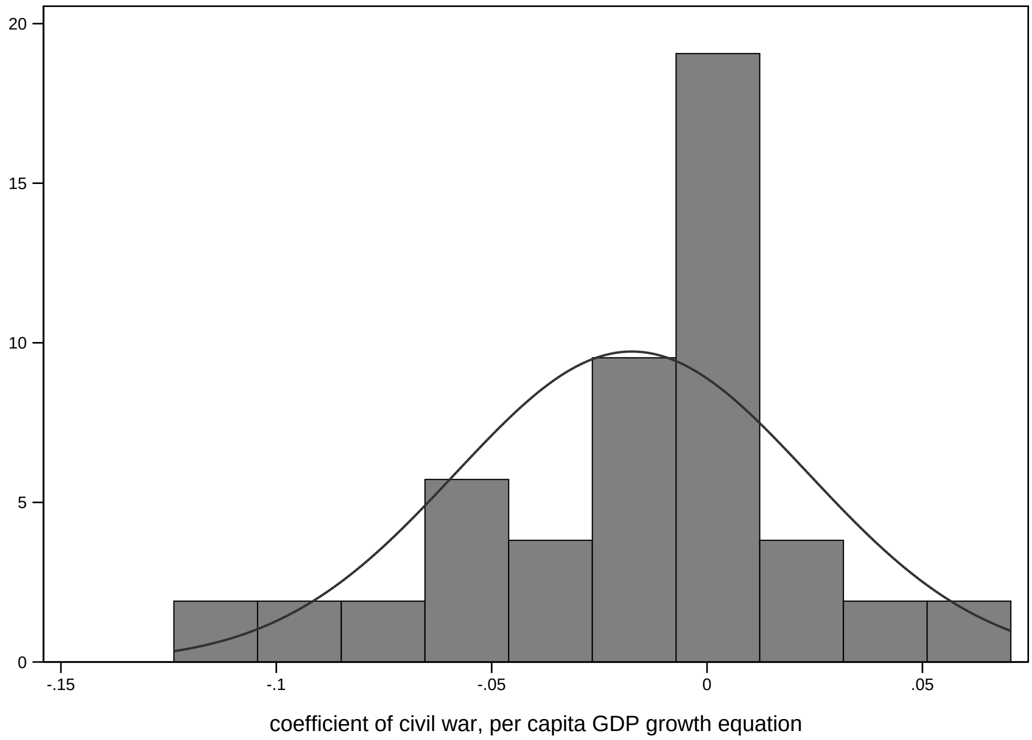
Table 4: The impact of civil war (c_{it}) on log per capita GDP and per capita GDP growth (y_{it})

	per capita GDP		per capita GDP growth	
	(i)	(ii)	(iii)	(iv)
c_{it}	-0.086*	-0.008	-0.011**	-0.013*
	(0.044)	(0.045)	(0.006)	(0.007)
$\bar{y_{it}}$	0.976***	0.704***	1.000***	0.832**
	(0.109)	(0.147)	(0.148)	(0.313)
$\bar{c_{it}}$	-0.028	-0.573	0.017	0.023
	(0.307)	(0.439)	(0.051)	(0.089)
constant	0.205	1.788	-0.000	-0.000
	(0.892)	(1.219)	(0.007)	(0.013)
RMSE	0.300	0.282	0.069	0.074
Countries	92	27	92	27
Observations (N $\times$ T)	4461	1356	4369	1329

NOTE. - Ordinary least squares estimates given. Robust standard errors (in parenthesis) allow for arbitrary correlation of residuals within each country. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



(a)



(b)

Figure 3: Distribution of the estimated coefficient of civil war (c_{it}) of the per capita GDP equation (a) and per capita GDP growth equation (b).

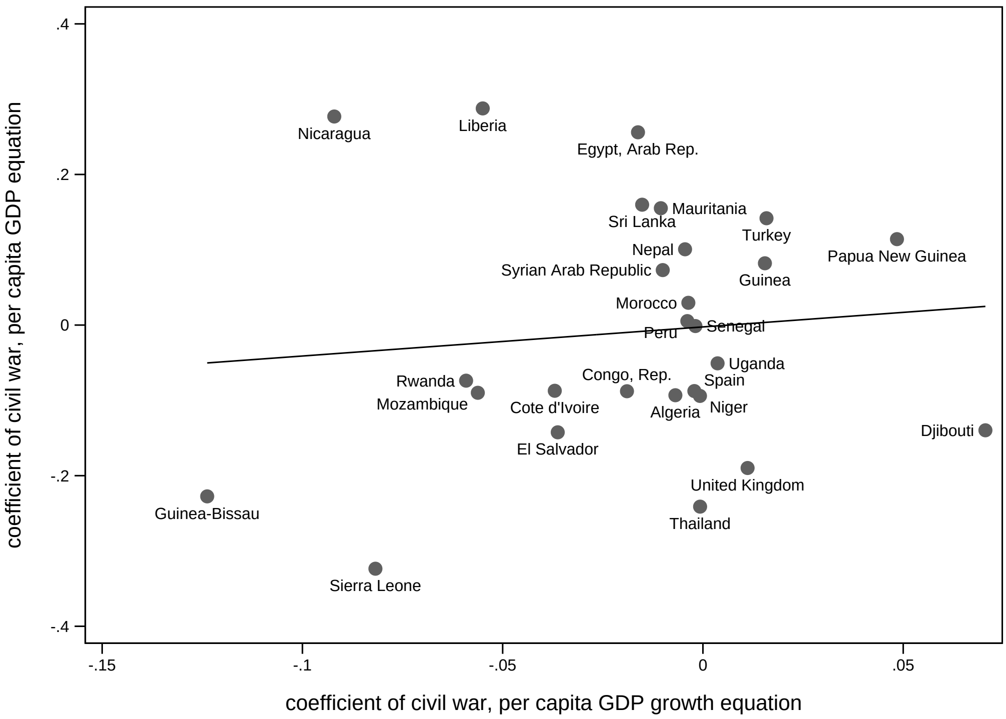


Figure 4: Correlation between the estimated coefficient (c_{it}) of the per capita GDP and per capita GDP growth equation.

A Estimated unit weight for donor countries

A.1 Dependent variable is per capita GDP

Algeria: The Bahamas (0.023), Albania (0.048), Iceland (0.023), Sao Tome and Principe (0.155), Jordan (0.132), Oman (0.025), China (0.128), Mongolia (0.061), Bhutan (0.067), Brunei Darussalam (0.008), Vanuatu (0.226), Samoa (0.103).

Djibouti: Guyana (0.456), Equatorial Guinea (0.333), Gabon (0.067), Kiribati (0.144).

Egypt: St. Vincent and the Grenadines (0.004), Cyprus (0.013), Botswana (0.074), Swaziland (0.006), China (0.748), Rep of Korea (0.019), Maldives (0.048), Singapore (0.011), Vanuatu (0.049), Tonga (0.028).

El Salvador: USA (0.074), Iceland (0.009), Equatorial Guinea (0.285), Niger (0.062), Zambia (0.205), Mauritius (0.301), Australia (0.011), New Zealand (0.053).

Guinea: Guyana (0.013), Uruguay (0.002), Albania (0.022), Equatorial Guinea (0.006), Zambia (0.032), Zimbabwe (0.52), Malawi (0.151), Madagascar (0.183), China (0.031), Bhutan (0.039).

Guinea Bissau: Bulgaria (0.038), Zimbabwe (0.559), Malawi (0.156), Madagascar (0.209), Rep of Korea (0.011), Solomon Islands (0.01), Marshall Islands (0.013), Palau (0.003).

Ivory Coast: Cuba (0.002), Barbados (0.018), Albania (0.018), Sao Tome and Principe (0.094), Togo (0.234), Zimbabwe (0.014), Malawi (0.227), Swaziland (0.039), Madagascar (0.349), Palau (0.006).

Liberia: Central African Republic (0.036), Zambia (0.204), Malawi (0.435), Madagascar (0.306), Bahrain (0.009), Kiribati (0.009).

Mauritania: Togo (0.259), China (0.681), Japan (0.06).

Morocco: Greece (0.031), Niger (0.01), Lesotho (0.734), Comoros (0.181), Seychelles (0.017), Japan (0.027).

Mozambique: Guinea (0.051), China (0.949).

Nepal: Albania (0.005), Tanzania (0.332), Zambia (0.005), Zimbabwe (0.286), Malawi (0.154), Madagascar (0.052). China (0.152), Solomon Islands (0.013).

Nicaragua: Sweden (0.104), Iceland (0.012), Equatorial Guinea (0.308), Zambia (0.426), Mauritius (0.15).

Niger: Equatorial Guinea (0.049), Malawi (0.949), Brunei Darussalam (0.001).

Papua New Guinea: Brazil (0.046), Cape Verde (0.136), Benin (0.021), Zambia (0.615), Malawi (0.008), Vanuatu (0.069), Kiribati (0.052), Samoa (0.054).

Peru: Barbados (0.018), Mexico (0.006), Finland (0.033), Sweden (0.034), Iceland (0.018), Gabon (0.047), Central African Republic (0.061), Rep of Congo (0.099), Zambia (0.545), Namibia (0.076), New Zealand (0.063).

Rep of Congo: Cuba (0.07), Benin (0.604), Jordan (0.067), Mongolia (0.173), Tonga (0.087).

Rwanda: Benin (0.045), Central African Republic (0.393), Malawi (0.514), China (0.005), Bhutan (0.043).

Senegal: Equatorial Guinea (0.138), Benin (0.458), Gabon (0.003), Malawi (0.015), Madagascar (0.234), Mauritius (0.016), Bhutan (0.123), Brunei Darussalam (0.001), Kiribati (0.004), Marshall Islands (0.007).

Sierra Leone: Albania (0.028), Equatorial Guinea (0.062), Benin (0.358), Malawi (0.284), China (0.269).

Spain: Brazil (0.058), Finland (0.231), Norway (0.095), Equatorial Guinea (0.019), Japan (0.256), Singapore (0.21), New Zealand (0.131).

Sri Lanka: Ecuador (0.001), Benin (0.054), Gabon (0.004), Malawi (0.053), Lesotho (0.322), Jordan (0.095), China (0.445), Nepal (0.004), Singapore (0.022).

Syria: Jamaica (0.018), Trinidad and Tobago (0.068), Brazil (0.003), Sweden (0.005), Equatorial Guinea (0.305), Guinea (0.439), Mauritius (0.161).

Thailand: Barbados (0.005), Panama (0.078), Malawi (0.201), Namibia (0.005), Comoros (0.243), China (0.268), Rep of Korea (0.192), Japan (0.006).

Turkey: USA (0.01), Puerto Rico (0.202), Denmark (0.07), Equatorial Guinea (0.633), Gabon (0.001), Rep of Korea (0.08), Australia (0.004).

Uganda: Equatorial Guinea (0.056), Guinea (0.041), Burkina Faso (0.318), Togo (0.068), Lesotho (0.396), Turkey (0.006), China (0.059), Rep of Korea (0.049), New Zealand (0.007).

The UK: USA (0.215), Luxembourg (0.081), Switzerland (0.024), Senegal (0.052), Mauritius (0.134), Seychelles (0.207), New Zealand (0.288).

A.2 Dependent variable is per capita GDP growth rate

Algeria: The Bahamas (0.097), Albania (0.034), Iceland (0.173), Sao Tome and Principe (0.027), Benin (0.032), Jordan (0.011), Mongolia (0.062), Bhutan (0.005), Brunei Darussalam (0.107), Vanuatu (0.244), Solomon Islands (0.09), Samoa (0.116).

Djibouti: Albania (0.282), Equatorial Guinea (0.042), Gabon (0.257), Zambia (0.357), Kiribati (0.062).

Egypt: Jamaica (0.111), Antigua and Barbuda (0.251), Equatorial Guinea (0.003), Swaziland (0.03), China (0.15), Rep of Korea (0.164), Singapore (0.12), Brunei Darussalam (0.047), Vanuatu (0.072), Tonga (0.051).

El Salvador: Iceland (0.062), Equatorial Guinea (0.127), Ivory Coast (0.132), Guinea (0.052), Central African Republic (0.158), Zambia (0.025), Malawi (0.142), Lesotho (0.135), Nepal (0.166).

Guinea: Barbados (0.05), Poland (0.104), Hungary (0.285), Sao Tome and Principe (0.021), Equatorial Guinea (0.018), Gabon (0.05), Zimbabwe (0.018), Malawi (0.042), Swaziland (0.014), Madagascar (0.177), Seychelles (0.048), Syria (0.04), Bahrain (0.055), Solomon Islands (0.078).

Guinea Bissau: Cuba (0.051), St. Kitties and Nevis (0.003), Iceland (0.018), Rep of Korea (0.239), Malaysia (0.113), Brunei Darussalam (0.29), Fiji (0.125), Tonga (0.063), Palau (0.099).

Ivory Coast: Cuba (0.119), Albania (0.025), Sao Tome and Principe (0.238), Equatorial Guinea (0.045), Togo (0.071), Malawi (0.007), Swaziland (0.026), Madagascar (0.258), Solomon Islands (0.184), Palau (0.027).

Liberia: The Bahamas (0.058), Jamaica (0.101), Dominica (0.116), Iceland (0.193), Equatorial Guinea (0.061), Zambia (0.024), Malawi (0.117), Namibia (0.117), Bahrain (0.214).

Mauritania: Mexico (0.486), Zambia (0.141), China (0.326), Japan (0.047).

Morocco: Niger (0.029), Lesotho (0.106), Seychelles (0.145), Japan (0.372), Papua New Guinea (0.349).

Mozambique: Luxembourg (0.07), Denmark (0.285), Equatorial Guinea (0.034), Guinea (0.254), Rwanda (0.051), Zambia (0.073), Comoros (0.072), Seychelles (0.081), Papua New Guinea (0.08).

Nepal: Cuba (0.117), St. Kitties and Nevis (0.26), Uruguay (0.129), Luxembourg (0.068), Iceland (0.023), Benin (0.026), gabon (0.144), Jordan (0.059), Kiribati (0.111), Tonga (0.062).

Nicaragua: USA (0.027), Puerto rico (0.045), Sweden (0.323), Iceland (0.062), Equatorial Guinea (0.09), Zambia (0.085), Namibia (0.264), Mauritius (0.104).

Niger: Guyana (0.009), Albania (0.008), Sao Tome and Principe (0.049), Brunei Darussalam (0.31), Micronesia Fed States (0.624).

Papua New Guinea: Jamaica (0.045), Barbados (0.177), Cape Verde (0.142), Zambia (0.171), Malawi (0.115), Vanuatu (0.034), Kiribati (0.086), Marshall Islands (0.004), Micronesia Fed States (0.025), Samoa (0.201).

Peru: Barbados (0.001), Finland (0.035), Equatorial Guinea (0.089), Benin (0.045), Gabon (0.063), Rep of Congo (0.053), Zambia (0.224), Namibia (0.198), China (0.174), New Zealand (0.119).

Rep of Congo: The Bahamas (0.011), Cuba (0.095), Cyprus (0.114), Jordan (0.1002), Mongolia (0.268), Singapore (0.017), Brunei Darussalam (0.087), Vanuatu (0.011), Tonga (0.295).

Rwanda: Cuba (0.023), Guyana (0.625), Mauritius (0.093), Mongolia (0.131), Bhutan (0.012), Marshall Islands (0.116).

Senegal: Equatorial Guinea (0.144), Benin (0.331), Gabon (0.07), Swaziland (0.014), Mauritius (0.069), Brunei Darussalam (0.211), Marshall Islands (0.161).

Sierra Leone: Cuba (0.302), Albania (0.13), Equatorial Guinea (0.038), Benin (0.01), Gabon (0.004), Swaziland (0.233), Mongolia (0.249), Vanuatu (0.009), Kiribati (0.24).

Spain: Greece (0.024), Iceland (0.014), Equatorial Guinea (0.082), Benin (0.038), Zambia (0.015), Malawi (0.018), Lesotho (0.006), Algeria (0.091), Rep of Korea (0.046), Japan (0.206), Singapore (0.11), New Zealand (0.35).

Sri Lanka: Cape Verde (0.104), Gabon (0.029), Malawi (0.162), Namibia (0.084), Lesotho (0.134), Jordan (0.237), China (0.115), Singapore (0.136).

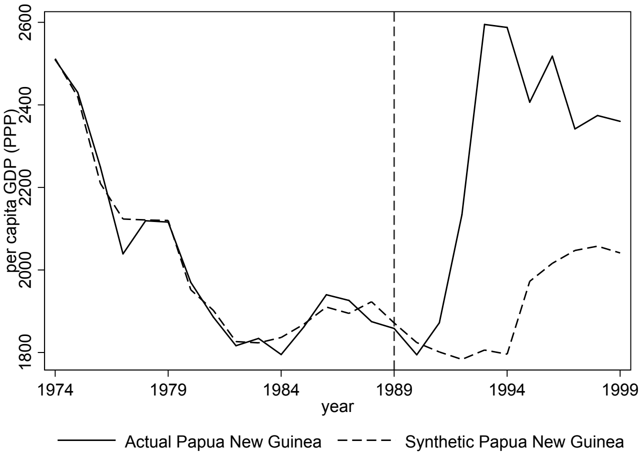
Syria: Trinidad and Tobago (0.629), Guinea (0.132), Mauritius (0.152), Algeria (0.087).

Thailand: Barbados (0.067), Panama (0.284), Iceland (0.066), Equatorial Guinea (0.01), Niger (0.02), Malawi (0.02), Comoros (0.113), China (0.09), Rep of Korea (0.271), Singapore (0.059).

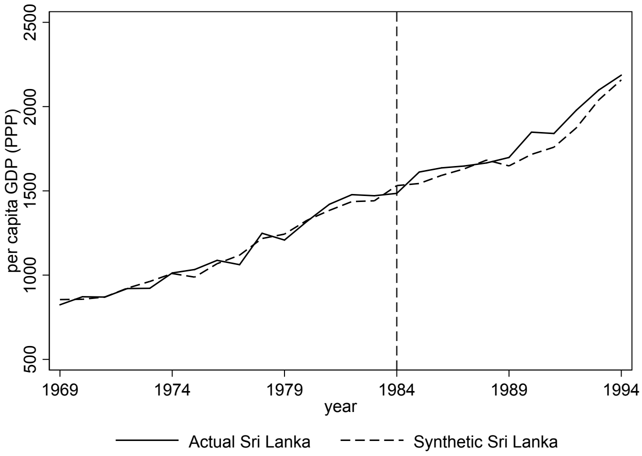
Turkey: USA (0.107), Puerto Rico (0.363), Equatorial Guinea (0.146), Benin (0.034), Ivory Coast (0.079), Guinea (0.002), Zambia (0.066), Botswana (0.036), Mauritius (0.065), Jordan (0.041), China (0.062).

Uganda: Guinea (0.006), Burkina Faso (0.178), Togo (0.02), Lesotho (0.065), Mauritius (0.037), Turkey (0.086), Australia (0.386), New Zealand (0.222).

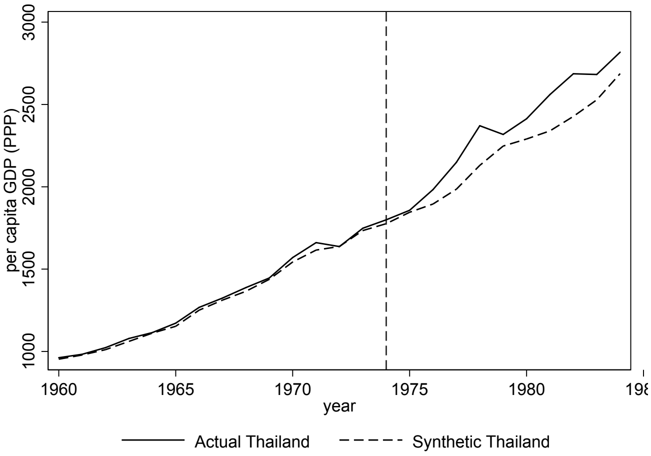
The UK: USA (0.006), Puerto Rico (0.003), Canada (0.006), Haiti (0.059), Jamaica (0.008), Trinidad and Tobago (0.01), Barbados (0.003), Mexico (0.32), Costa Rica (0.006), Panama (0.004), Ecuador (0.095), Brazil (0.008), Paraguay (0.066), Ireland (0.015), Netherlands (0.009), Belgium (0.006), Luxembourg (0.063), Switzerland (0.006), Portugal (0.007), Austria (0.005), Italy (0.003), Greece (0.005), Finland (0.005), Sweden (0.01), Norway (0.006), Denmark (0.008), Iceland (0.005), Cape Verde (0.002), Equatorial Guinea (0.006), Mali (0.003), Senegal (0.031), Benin (0.017), Niger (0.01), Guinea (0.069), Burkina Faso (0.012), Togo (0.005), Central African Republic (0.006), Rep of Congo (0.005), Kenya (0.004), Rwanda (0.002), Zambia (0.002), Malawi (0.003), Namibia (0.005), Lesotho (0.002), Botswana (0.002), Comoros (0.003), Mauritius (0.007), Seychelles (0.007), Turkey (0.003), China (0.003), Rep of Korea (0.003), Japan (0.003), Singapore (0.003), Australia (0.005), Papua New Guinea (0.007), New Zealand (0.006), Fiji (0.013).



(a) Papua New Guinea

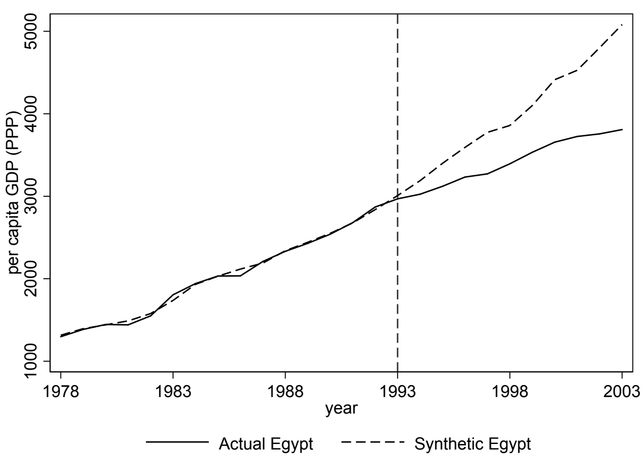


(b) Sri Lanka

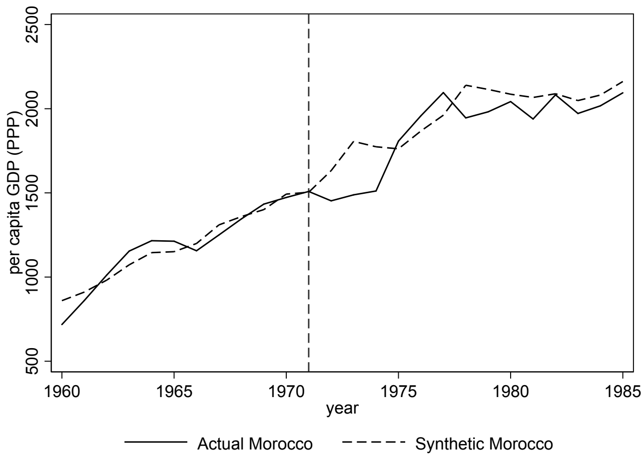


(c) Thailand

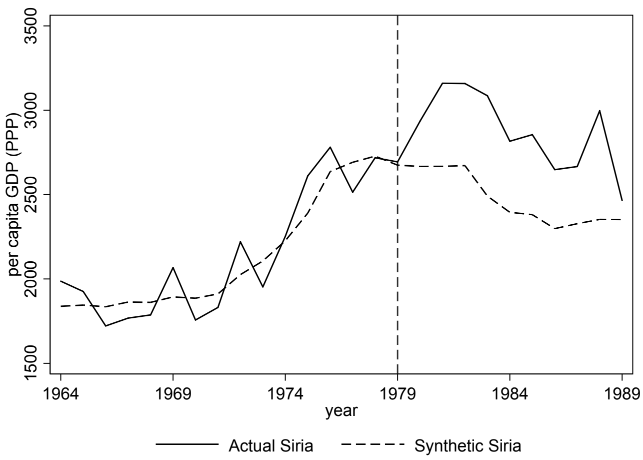
Figure A1: Per capita GDP trends, Treated Country vs. Synthetic Control - Asia



(a) Egypt

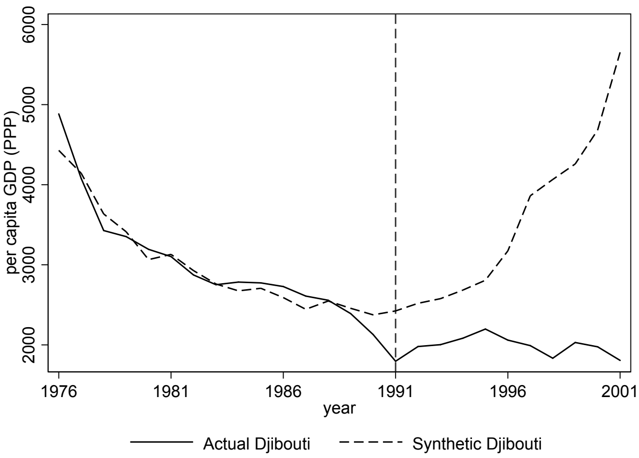


(b) Morocco

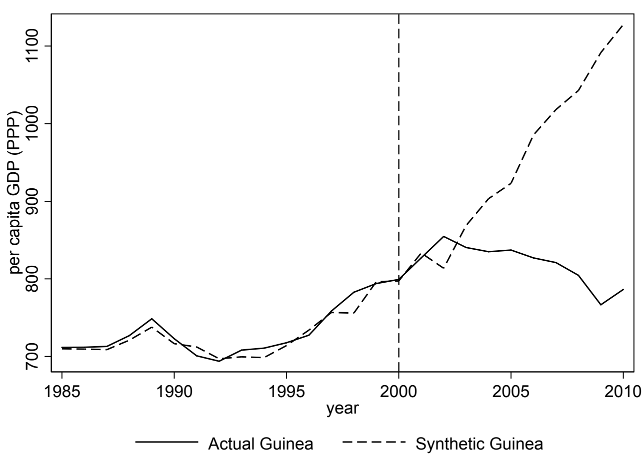


(c) Syria

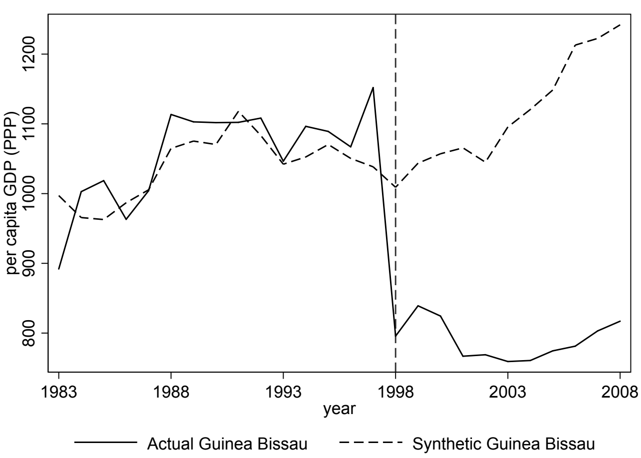
Figure A2: Per capita GDP trends, Treated Country vs. Synthetic Control - Middle East and North Africa



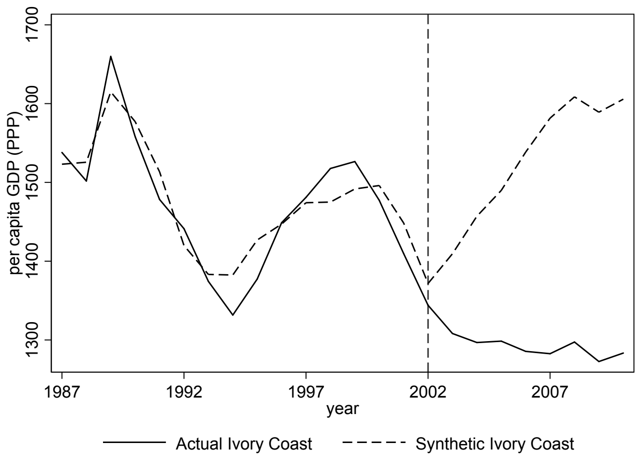
(a) Djibouti



(b) Guinea

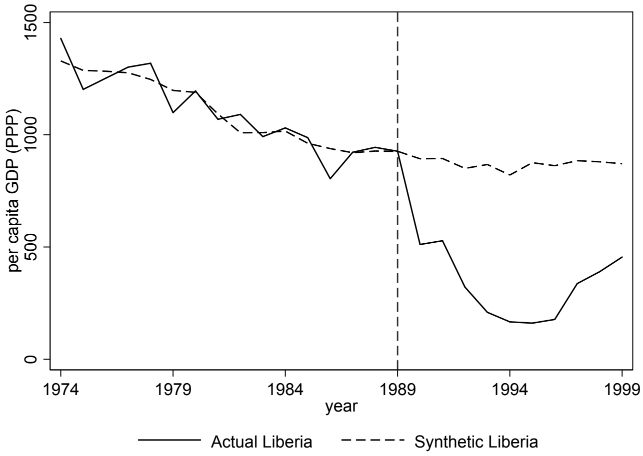


(c) Guinea Bissau

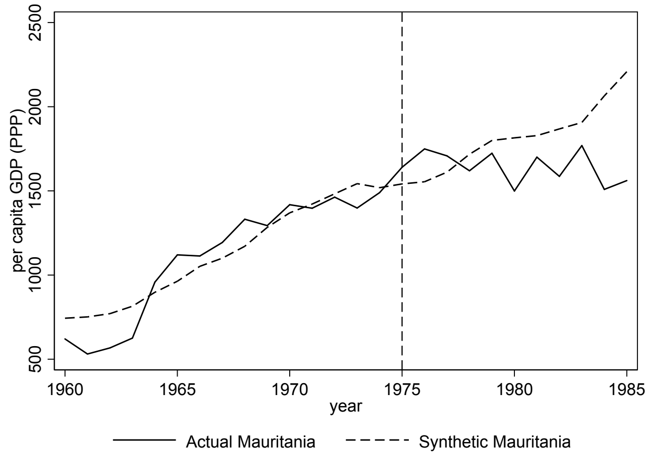


(d) Ivory Coast

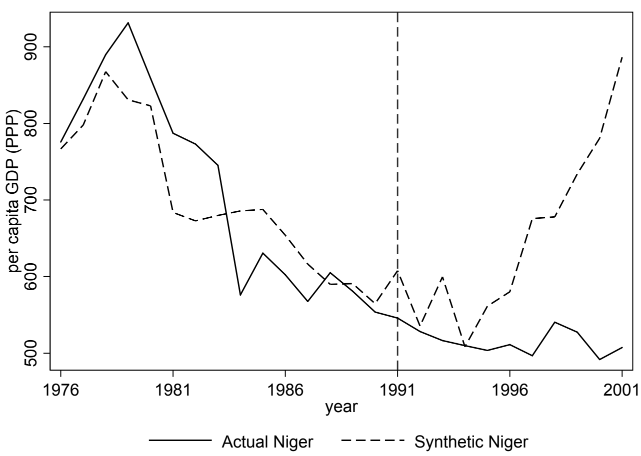
Figure A3: Per capita GDP trends, Treated Country vs. Synthetic Control - Sub-saharan Africa (I)



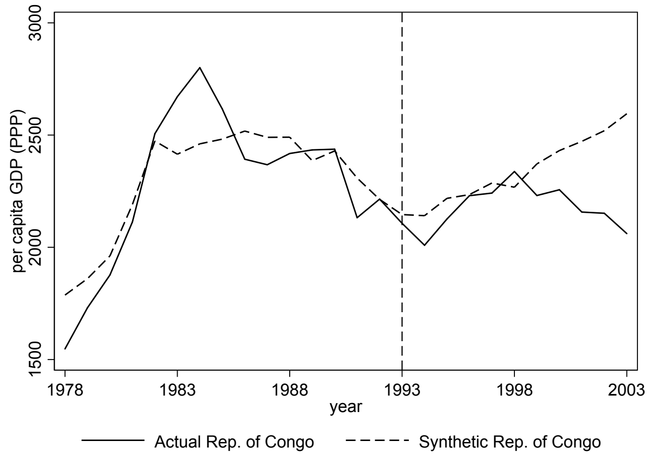
(a) Liberia



(b) Mauritania

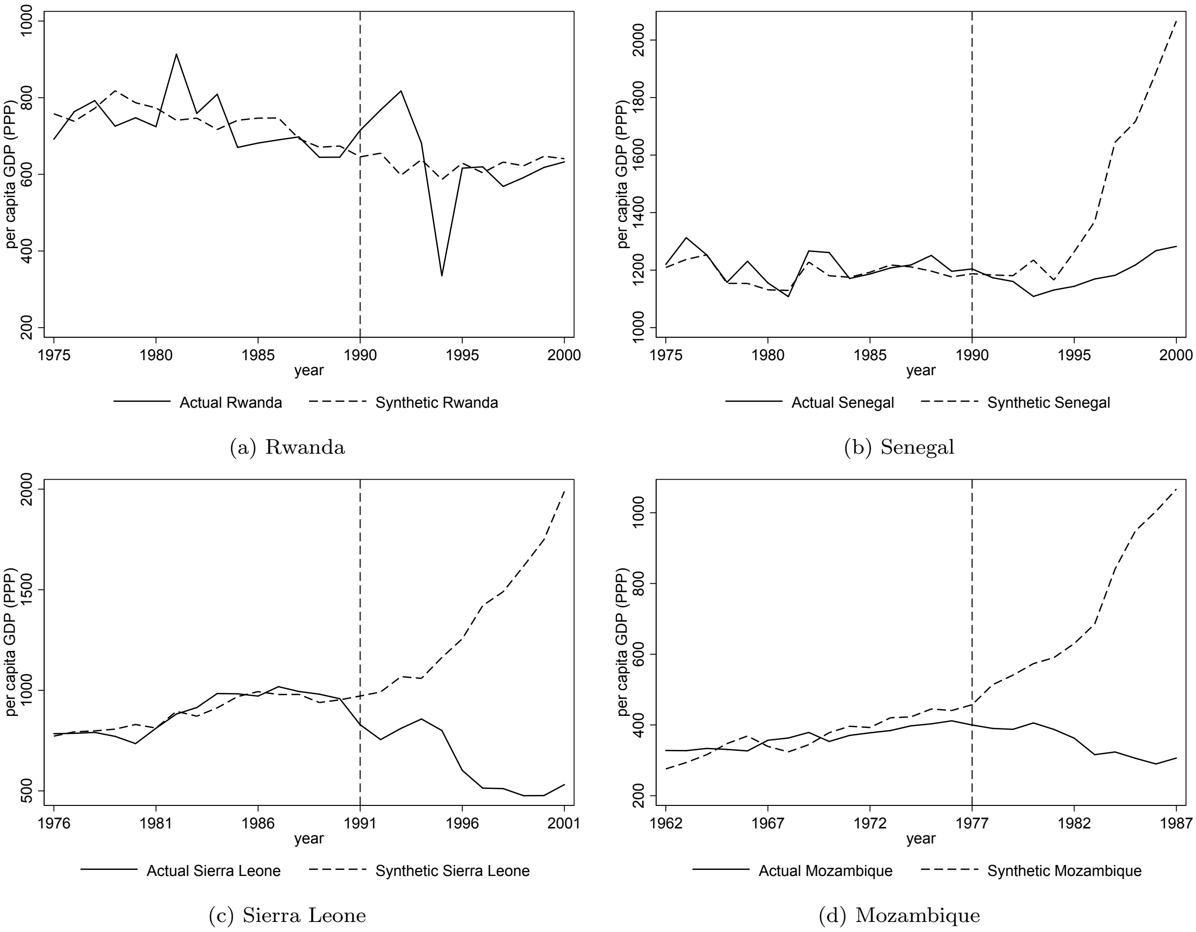


(c) Niger



(d) Republic of Congo

Figure A4: Per capita GDP trends, Treated Country vs. Synthetic Control - Sub-saharan Africa (II)



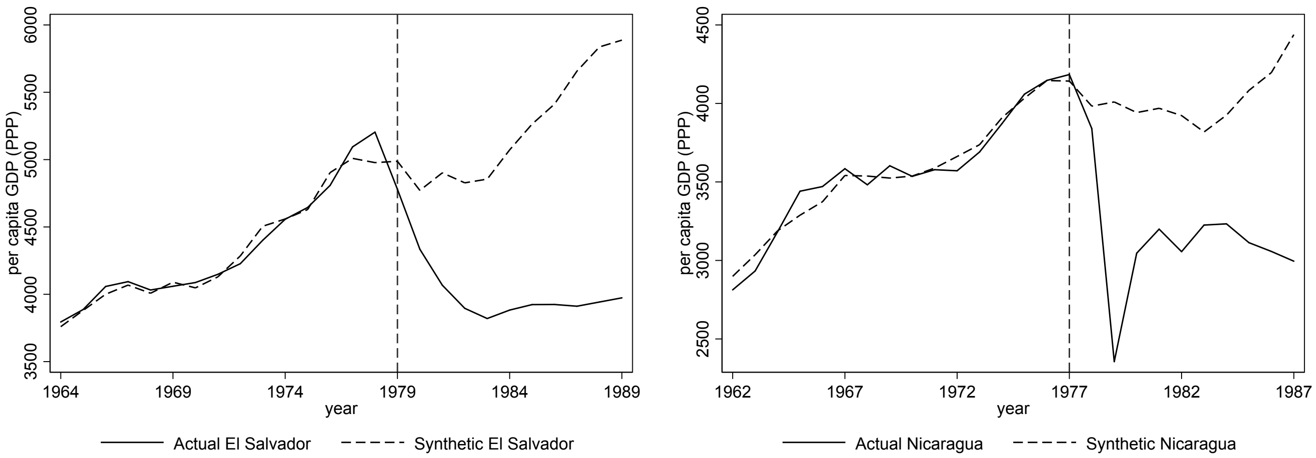
(a) Rwanda

(b) Senegal

(c) Sierra Leone

(d) Mozambique

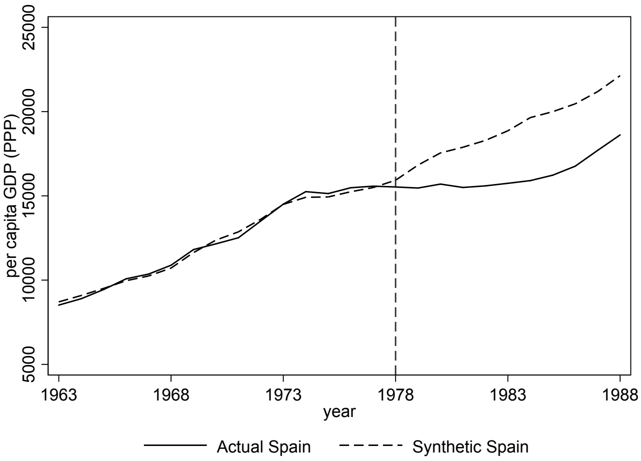
Figure A5: Per capita GDP trends, Treated Country vs. Synthetic Control - Sub-saharan Africa (III)



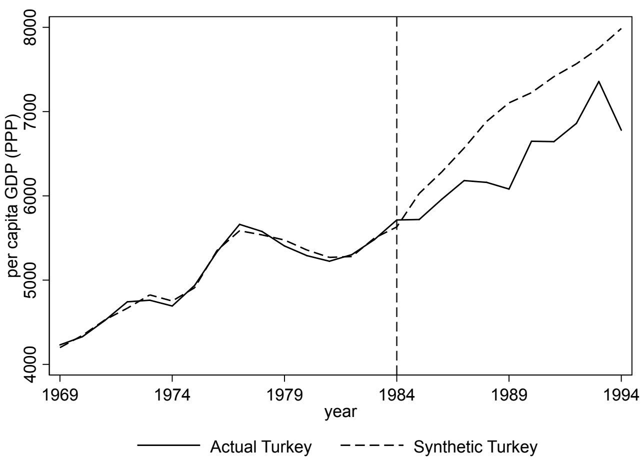
(a) El Salvador

(b) Nicaragua

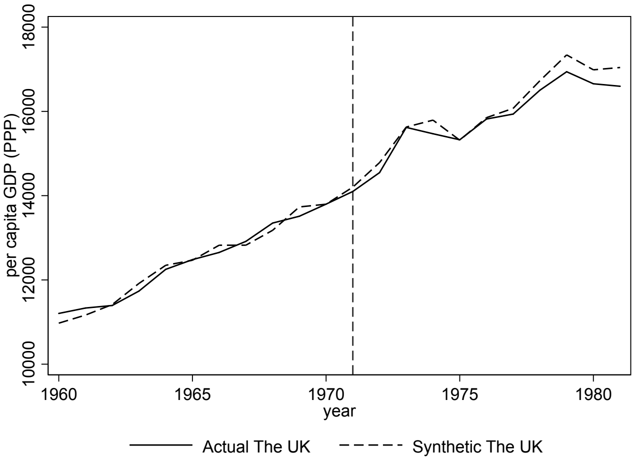
Figure A6: Per capita GDP trends, Treated Country vs. Synthetic Control - Latin America



(a) Spain



(b) Turkey



(c) UK

Figure A7: Per capita GDP trends, Treated Country vs. Synthetic Control - Europe

Table A1: Chow test for case studies: Asia. Dependent variable is per capita GDP.

	stat	p-value
Papua New Guinea		
1989	-0.499	0.624
1990	-0.630	0.537
1992	2.430	0.026
1993	5.955	0.000
1994	5.977	0.000
1995	3.100	0.006
1996	3.647	0.002
F-test	12.826	0.000
Sri Lanka		
1984	-1.490	0.158
1985	1.951	0.071
1986	1.238	0.236
1987	0.407	0.690
1988	-0.609	0.552
1989	1.407	0.181
1990	3.871	0.002
1991	2.346	0.034
1992	3.050	0.009
1993	1.662	0.119
1994	0.751	0.465
F-test	3.395	0.017
Thailand		
1974	-0.157	0.877
1975	-0.411	0.687
1976	1.222	0.241
1977	2.850	0.012
1978	4.529	0.000
1979	0.856	0.405
1980	1.984	0.066
1981	4.095	0.001
1982	4.917	0.000
F-test	7.097	0.001

Table A2: Chow test for case studies: MENA. Dependent variable is per capita GDP.

	stat	p-value
EGYPT		
1993	0.440	0.665
1994	0.147	0.885
1995	-0.123	0.903
1996	-0.315	0.756
1997	-0.654	0.521
1998	-0.563	0.580
F-test	0.180	0.979
MOROCCO		
1971	0.486	0.635
1975	0.804	0.436
1976	1.151	0.271
1977	1.493	0.159
1978	-1.057	0.310
1979	-0.584	0.569
1980	0.109	0.915
1981	-0.545	0.595
1982	0.400	0.695
1983	-0.146	0.886
1984	-0.049	0.962
1985	-0.072	0.944
F-test	0.557	0.840
SYRIA		
1979	-0.484	0.633
1980	0.510	0.615
1981	1.406	0.174
1982	1.382	0.182
F-test	1.066	0.398

Table A3: Chow test for case studies: Sub-saharan Africa (I). Dependent variable is per capita GDP.

	stat	p-value
Djibouti		
1991	-0.047	0.963
1992	0.029	0.977
1993	-0.001	0.999
1994	-0.023	0.982
1999	-1.426	0.169
F-test	0.410	0.836
Guinea		
2000	0.510	0.615
2001	0.437	0.666
F-test	0.217	0.807
Guinea-Bissau		
1998	-0.481	0.635
1999	-0.434	0.668
F-test	0.202	0.819
Ivory Coast		
2002	0.415	0.683
2003	-0.124	0.903
2004	-0.556	0.585
F-test	0.172	0.914

Table A4: Chow test for case studies: Sub-saharan Africa (II). Dependent variable is per capita GDP.

	stat	p-value
LIBERIA		
1989	0.719	0.480
1990	-0.570	0.574
F-test	0.438	0.651
MAURITANIA		
11975	1.008	0.325
1976	1.464	0.158
1977	0.998	0.330
1978	0.075	0.941
F-test	0.961	0.449
NIGER		
1991	-0.123	0.903
1992	0.303	0.765
1994	0.370	0.715
1995	-0.091	0.928
1997	-1.036	0.313
F-test	0.275	0.921
REPUBLIC OF CONGO		
1993	0.160	0.874
1997	0.130	0.898
1998	0.730	0.474
1999	-0.374	0.713
2002	-1.562	0.134
F-test	0.654	0.662

Table A5: Chow test for case studies: Sub-saharan Africa (III). Dependent variable is per capita GDP.

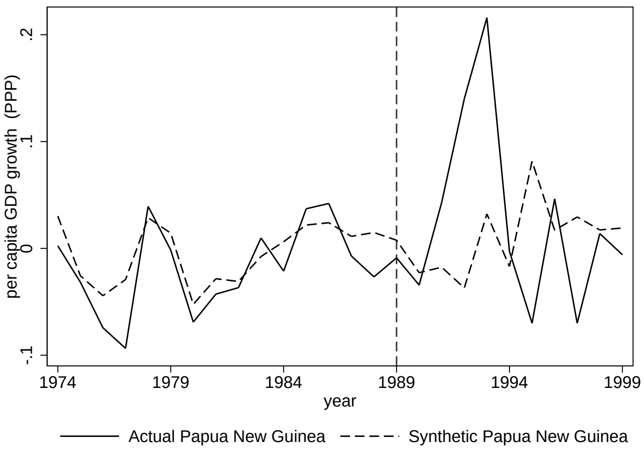
	stat	p-value
RWANDA		
1990	1.158	0.265
1991	1.785	0.094
1992	3.322	0.005
1993	0.780	0.448
1994	-3.446	0.004
1996	0.385	0.706
1997	-0.748	0.466
1998	-0.277	0.786
1999	-0.254	0.803
2000	0.044	0.966
F-test	3.039	0.026
SENEGAL		
1990	0.274	0.787
1992	0.043	0.966
1993	-0.623	0.541
1995	-0.583	0.567
1997	-2.732	0.014
1998	-2.957	0.008
2000	-4.743	0.000
F-test	5.200	0.002
SIERRA LEONE		
1991	-0.146	0.886
1992	-0.394	0.699
1993	-0.448	0.661
1994	-0.302	0.767
1995	-0.727	0.479
1996	-1.497	0.155
1997	-2.165	0.047
1998	-2.352	0.033
1999	-2.781	0.014
2000	-3.128	0.007
F-test	2.497	0.053
MOZAMBIQUE		
1977	-1.570	0.139
1978	-3.525	0.003
1979	-4.398	0.001
1980	-4.827	0.000
1981	-5.860	0.000
1982	-7.770	0.000
1983	-10.777	0.000
1984	-15.147	0.000
1985	-18.865	0.000
1986	-20.952	0.000
1987	-22.319	0.000
F-test	123.461	0.000

Table A6: Chow test for case studies: Latin America. Dependent variable is per capita GDP.

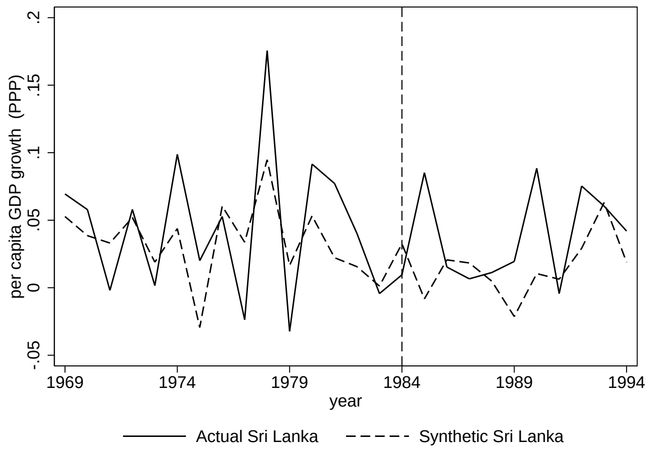
	stat	p-value
El Salvador		
1979	-2.759	0.015
1980	-5.581	0.000
1981	-10.471	0.000
1982	-11.669	0.000
1983	-12.942	0.000
1984	-14.843	0.000
1985	-16.699	0.000
1986	-18.521	0.000
1987	-21.693	0.000
1988	-23.518	0.000
1989	-23.757	0.000
F-test	181.072	0.000
Nicaragua		
1977	0.484	0.635
1978	-0.146	0.886
1979	-5.301	0.000
1982	-2.616	0.019
1983	-1.681	0.112
1984	-2.020	0.060
1985	-2.967	0.009
1986	-3.545	0.003
1987	-4.581	0.000
F-test	7.672	0.000

Table A7: Chow test for case studies: Europe. Dependent variable is per capita GDP.

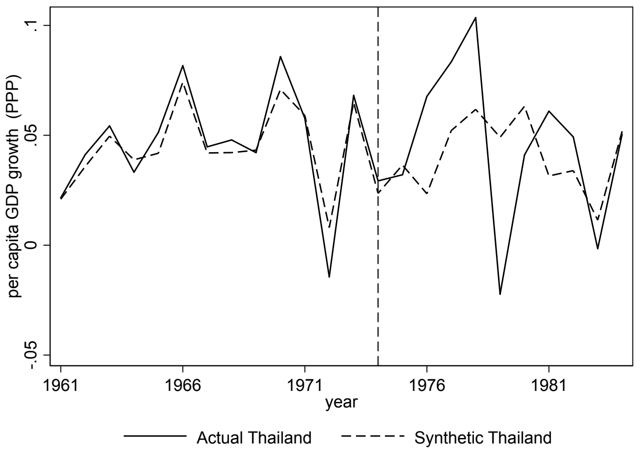
	stat	*p*-value
Spain		
1978	0.115	0.910
1979	-0.579	0.570
1980	-0.931	0.365
1981	-1.318	0.205
1982	-1.540	0.142
1985	-2.312	0.034
1986	-2.265	0.037
1987	-2.110	0.050
F-test	2.065	0.100
Turkey		
1984	1.719	0.108
1985	-5.905	0.000
1986	-6.199	0.000
1987	-7.402	0.000
1988	-13.939	0.000
1989	-19.779	0.000
1990	-11.099	0.000
1991	-14.890	0.000
1992	-13.630	0.000
1993	-7.575	0.000
1994	-23.349	0.000
F-test	123.818	0.000
the UK		
1971	-0.629	0.544
1972	-1.462	0.175
1973	-0.045	0.965
1974	-1.988	0.075
1975	0.063	0.951
1976	-0.193	0.851
1977	-0.834	0.424
1978	-1.386	0.196
1979	-2.463	0.034
1980	-2.043	0.068
1981	-2.745	0.021
F-test	1.820	0.177



(a) Papua New Guinea

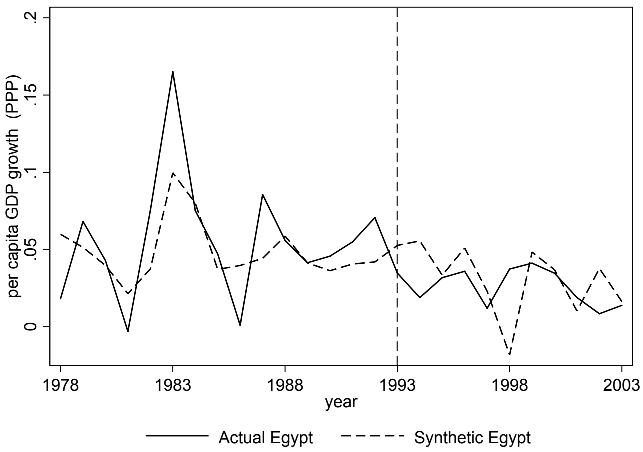


(b) Sri Lanka

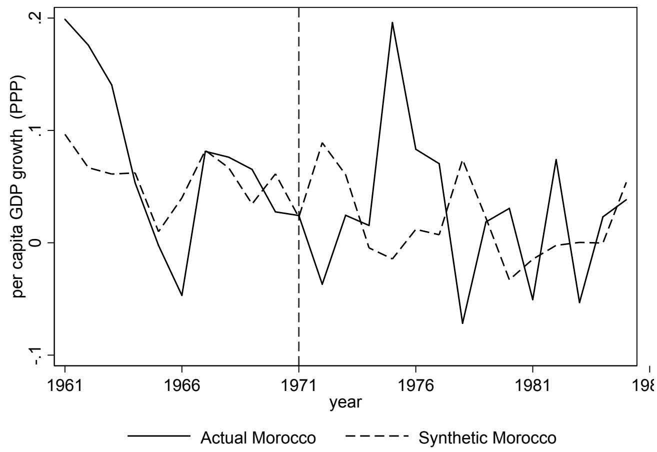


(c) Thailand

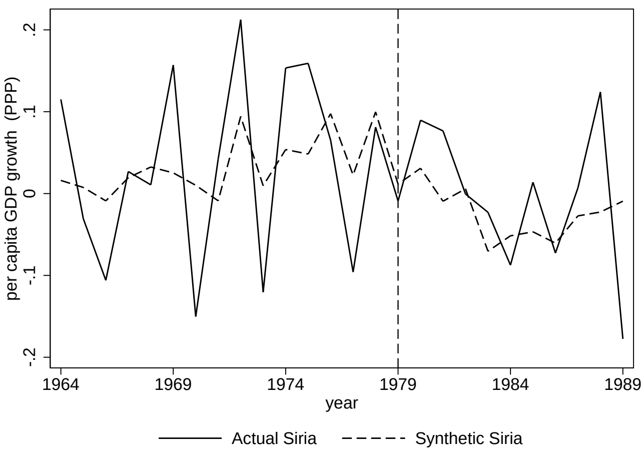
Figure A8: Per capita GDP growth trends, Treated Country vs. Synthetic Control - Asia



(a) Egypt

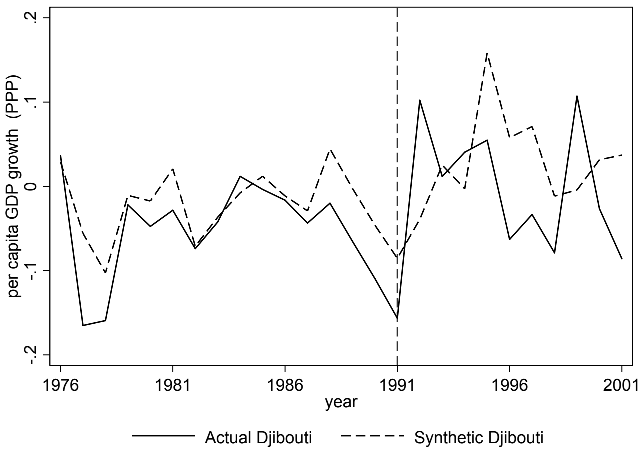


(b) Morocco

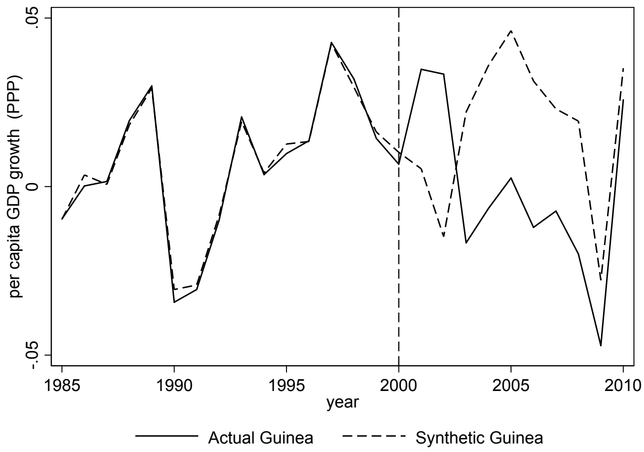


(c) Syria

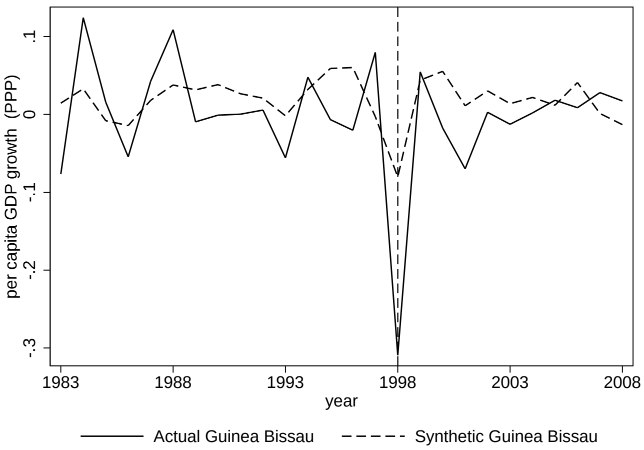
Figure A9: Per capita GDP growth trends, Treated Country vs. Synthetic Control - Middle East and North Africa



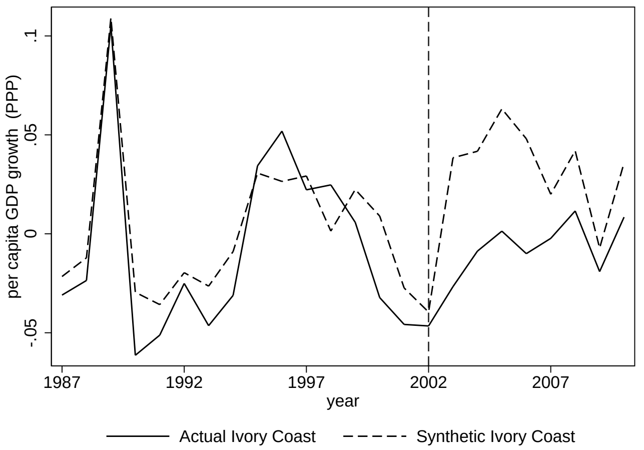
(a) Djibouti



(b) Guinea

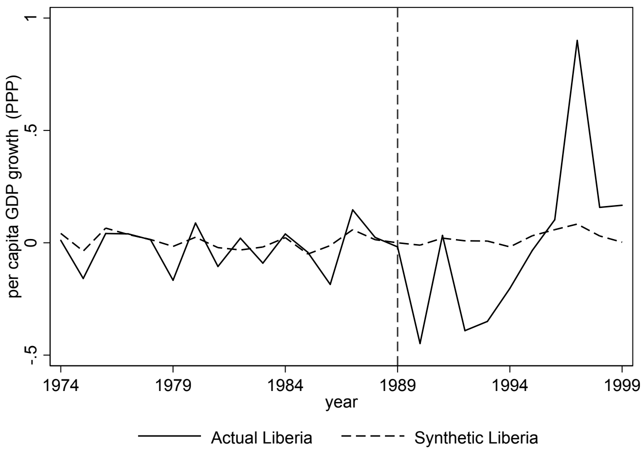


(c) Guinea Bissau

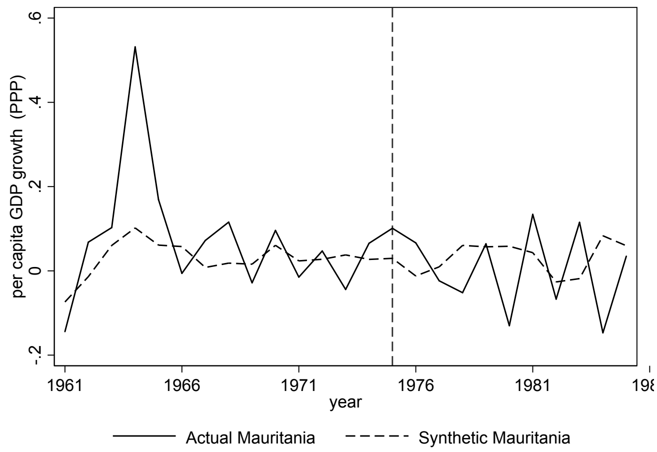


(d) Ivory Coast

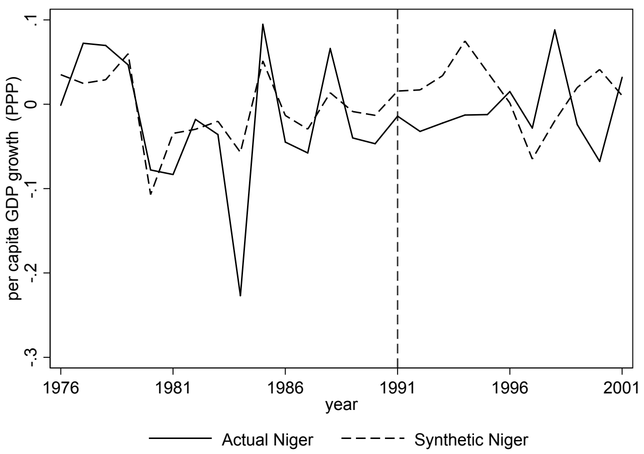
Figure A10: Per capita GDP growth trends, Treated Country vs. Synthetic Control - Sub-saharan Africa (I)



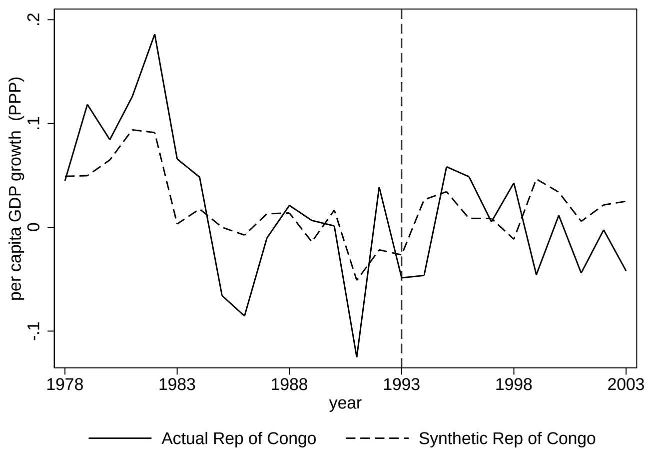
(a) Liberia



(b) Mauritania

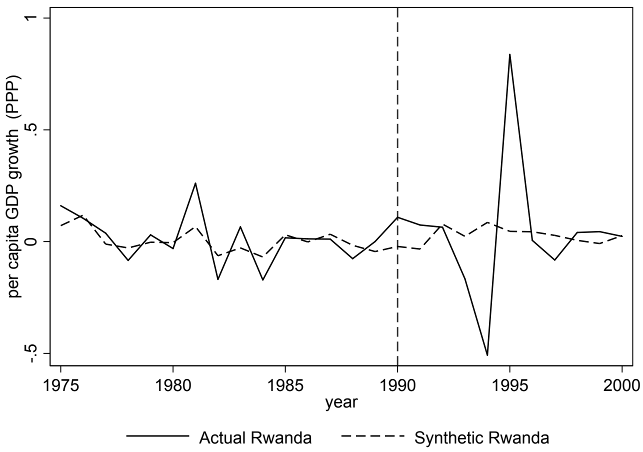


(c) Niger

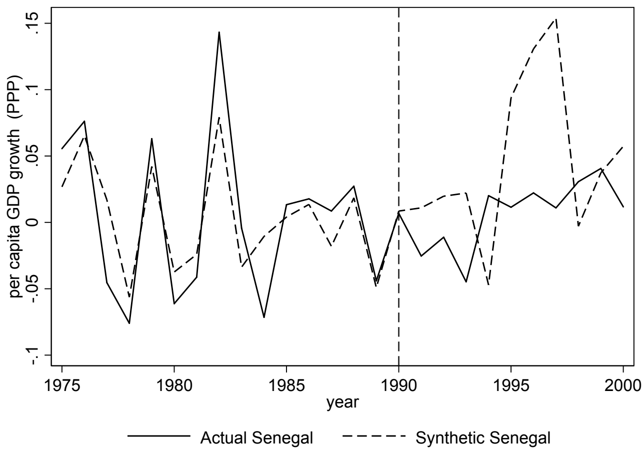


(d) Republic of Congo

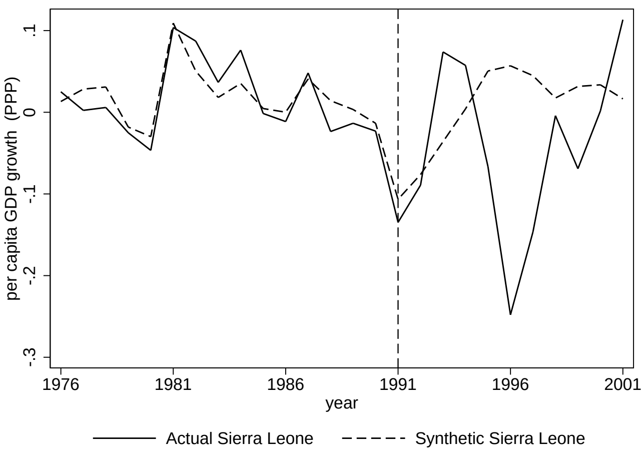
Figure A11: Per capita GDP growth trends, Treated Country vs. Synthetic Control - Sub-saharan Africa (II)



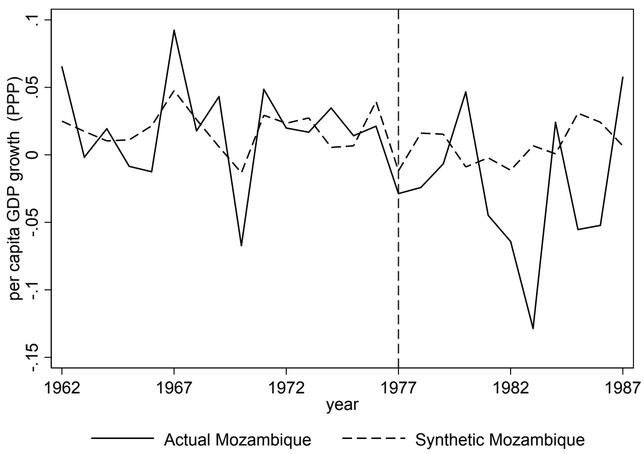
(a) Rwanda



(b) Senegal

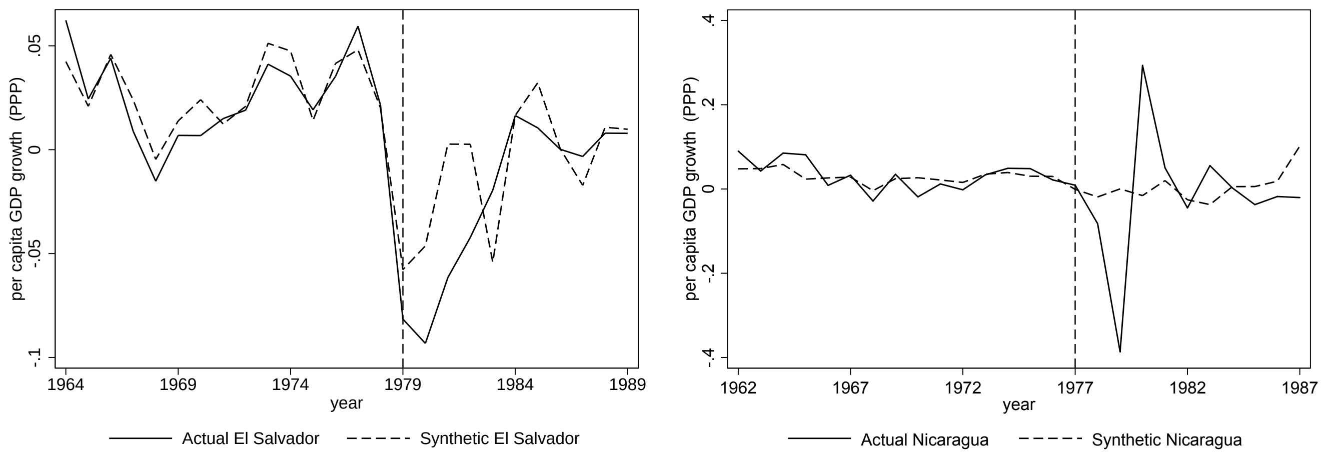


(c) Sierra Leone



(d) Mozambique

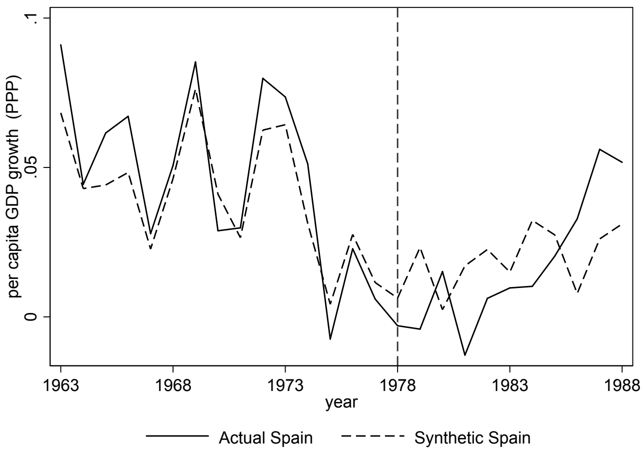
Figure A12: Per capita GDP growth trends, Treated Country vs. Synthetic Control - Sub-saharan Africa (III)



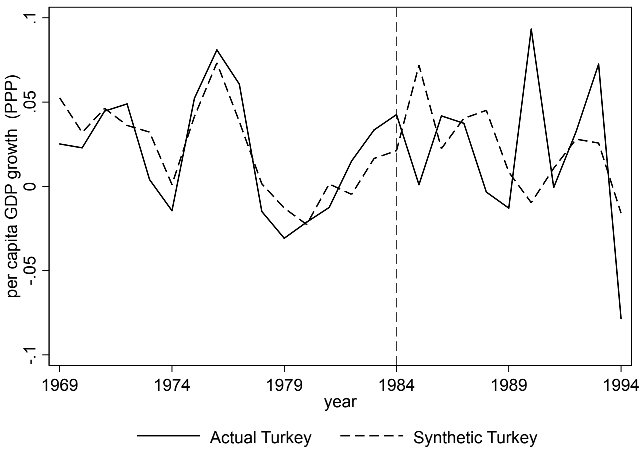
(a) El Salvador

(b) Nicaragua

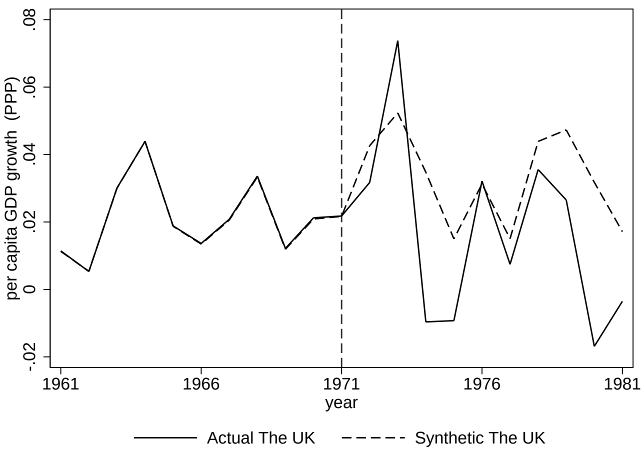
Figure A13: Per capita GDP growth trends, Treated Country vs. Synthetic Control - Latin America



(a) Spain



(b) Turkey



(c) UK

Figure A14: Per capita GDP growth trends, Treated Country vs. Synthetic Control - Europe

Table A8: Chow test for case studies: Asia. Dependent variable is per capita GDP growth.

	stat	p-value
Papua New Guinea		
1989	-0.059	0.953
1990	0.082	0.936
1992	5.504	0.000
1993	5.697	0.000
1994	0.820	0.423
1995	-3.944	0.001
1996	1.261	0.223
F-test	11.610	0.000
Sri Lanka		
1984	-0.824	0.424
1985	1.954	0.071
1986	-0.402	0.694
1987	-0.556	0.587
1988	-0.124	0.903
1989	0.697	0.497
1990	1.584	0.136
1991	-0.529	0.605
1992	0.823	0.424
1993	-0.339	0.740
1994	0.276	0.787
F-test	0.860	0.593
Thailand		
1974	0.529	0.605
1975	-0.536	0.600
1976	4.610	0.000
1977	3.233	0.006
1978	4.339	0.001
1979	-7.607	0.000
1980	-2.406	0.030
1981	3.045	0.009
1982	1.550	0.144
F-test	14.757	0.000

Table A9: Chow test for case studies: MENA. Dependent variable is per capita GDP growth.

	stat	p-value
Egypt		
1993	-0.808	0.429
1994	-1.497	0.151
1995	-0.210	0.836
1996	-0.702	0.491
1997	-0.555	0.585
1998	1.887	0.074
F-test	1.254	0.324
Morocco		
1971	-0.028	0.978
1975	2.917	0.013
1976	0.955	0.358
1977	0.842	0.416
1978	-2.105	0.057
1979	-0.099	0.922
1980	0.846	0.414
1981	-0.557	0.588
1982	1.027	0.325
1983	-0.804	0.437
1984	0.278	0.786
1985	-0.268	0.793
F-test	1.534	0.235
Syria		
1979	-0.244	0.810
1980	0.564	0.579
1981	0.841	0.410
1982	-0.098	0.923
F-test	0.275	0.891

Table A10: Chow test for case studies: Sub-saharan Africa (I). Dependent variable is per capita GDP growth.

	stat	p-value
DJIBOUTI		
1991	-0.473	0.641
1992	4.206	0.000
1993	0.795	0.436
1994	2.048	0.054
1999	3.547	0.002
F-test	6.574	0.001
GUINEA		
2000	0.274	0.786
2001	1.806	0.084
F-test	1.651	0.214
GUINEA-BISSAU		
1998	-4.087	0.000
1999	0.472	0.642
F-test	8.553	0.002
IVORY COAST		
2002	0.464	0.647
2003	-2.177	0.042
2004	-1.511	0.147
F-test	2.375	0.100

Table A11: Chow test for case studies: Sub-saharan Africa (II). Dependent variable is per capita GDP growth.

	stat	p-value
LIBERIA		
1989	-0.033	0.974
1990	-1.885	0.072
F-test	1.778	0.191
MAURITANIA		
1975	0.398	0.695
1976	0.451	0.657
1977	-0.372	0.714
1978	-0.956	0.351
F-test	0.368	0.829
NIGER		
1991	-0.290	0.775
1992	-0.605	0.552
1994	-1.230	0.233
1995	-0.625	0.539
1997	0.787	0.440
F-test	0.592	0.706
REPUBLIC OF CONGO		
1993	-0.398	0.695
1997	-0.050	0.961
1998	1.013	0.323
1999	-1.695	0.106
2002	-0.435	0.668
F-test	0.871	0.518

Table A12: Chow test for case studies: Sub-saharan Africa (III). Dependent variable is per capita GDP growth.

	stat	p-value
RWANDA		
1990	0.340	0.739
1991	0.234	0.818
1992	-0.327	0.748
1993	-1.137	0.273
1994	-2.998	0.009
1996	-0.440	0.666
1997	-0.770	0.453
1998	-0.100	0.922
1999	-0.016	0.988
2000	-0.277	0.785
F-test	1.091	0.426
SENEGAL		
1990	0.021	0.984
1992	-0.637	0.532
1993	-1.449	0.165
1995	-1.798	0.089
1997	-3.166	0.005
1998	0.816	0.425
2000	-0.969	0.345
F-test	2.313	0.072
SIERRA LEONE		
1991	-0.920	0.372
1992	-0.475	0.642
1993	3.132	0.007
1994	1.471	0.162
1995	-3.527	0.003
1996	-9.035	0.000
1997	-5.703	0.000
1998	-0.727	0.478
1999	-3.047	0.008
2000	-1.030	0.320
F-test	14.381	0.000
MOZAMBIQUE		
1977	-0.609	0.552
1978	-1.393	0.185
1979	-0.777	0.450
1980	1.818	0.090
1981	-1.471	0.163
1982	-1.813	0.091
1983	-4.578	0.000
1984	0.737	0.473
1985	-2.933	0.011
1986	-2.604	0.021
1987	1.663	0.119
F-test	4.444	0.005

Table A13: Chow test for case studies: Latin America. Dependent variable is per capita GDP growth.

	stat	p-value
El Salvador		
1979	-2.022	0.063
1980	-4.225	0.001
1981	-5.869	0.000
1982	-4.022	0.001
1983	3.546	0.003
1984	0.235	0.818
1985	-1.825	0.089
1986	0.217	0.831
1987	1.563	0.140
1988	-0.030	0.977
1989	0.054	0.958
F-test	8.254	0.000
Nicaragua		
1977	-0.155	0.879
1978	-1.066	0.302
1979	-5.084	0.000
1982	-0.516	0.613
1983	0.873	0.395
1984	-0.317	0.756
1985	-0.810	0.430
1986	-0.728	0.477
1987	-1.797	0.091
F-test	3.413	0.016

Table A14: Chow test for case studies: Europe. Dependent variable is per capita GDP growth

	stat	p-value
Spain		
1978	-1.044	0.311
1979	-2.380	0.029
1980	0.583	0.568
1981	-2.568	0.020
1982	-1.569	0.135
1985	-0.885	0.389
1986	1.485	0.156
1987	1.855	0.081
F-test	2.875	0.032
Turkey		
1984	1.361	0.195
1985	-3.883	0.002
1986	1.247	0.233
1987	-0.021	0.983
1988	-2.607	0.021
1989	-1.069	0.303
1990	5.996	0.000
1991	-0.502	0.623
1992	0.404	0.692
1993	2.806	0.014
1994	-3.411	0.004
F-test	7.981	0.000
the UK		
1971	-0.206	0.841
1972	-77.575	0.000
1973	149.311	0.000
1974	-312.455	0.000
1975	-171.238	0.000
1976	4.971	0.001
1977	-54.400	0.000
1978	-59.670	0.000
1979	-146.979	0.000
1980	-342.424	0.000
1981	-146.080	0.000
F-test	25828.618	0.000