On the heterogenous consequences of civil war*

Vincenzo Bove†
Department of Politics and International Studies
University of Warwick

Leandro Elia‡
European Commission
DG Joint Research Centre

Ron P Smith§
Department of Economics Mathematics and Statistics
Birkbeck, University of London

Abstract

We show how the occurrence of a civil war has heterogeneous effects on the level of GDP, using case-study, synthetic control and large-N panel-data approaches. We first discuss the relation between these methods and then provide lower and upper estimates of the economic effect of civil war. Although, on average, the incidence of internal conflicts has a negative effect on the GDP level, it is very often insignificant. More importantly, however, both methods display a wide variety of individual separate effects, and in a large number of countries civil war has either no effect or a positive and significant impact on the prospect for economic growth.

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

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†Email address: v.bove@warwick.ac.uk
‡Email address: leandro.elia@jrc.ec.europa.eu
§Email address: r.smith@bbk.ac.uk

1 Introduction

Civil wars are 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), De Groot *et al.* (2012) and Smith (2014).

We contribute to a very active area of academic debate in recent years by showing how civil wars have heterogenous, country-specific effects on economic performances. Most of the economic studies on civil war are all-country all-year estimations, which conceal the high degree of heterogeneity in countries' response to conflict shocks. In fact, on the one hand, civil wars can cause economic catastrophes, as in Uganda during the military dictatorship of Idi Amin from 1971-79, when up to half a million people were killed and the per capita GDP declined by 40% within one decade. On the other hand, however, civil wars are not identical, and the category encompasses different circumstances and realities; in fact the number of battle deaths in many civil war countries is comparable to the number of homicides in stable and prosperous economies, like Russia or South Africa (Cramer, 2006). Social welfare can even improve in the absence of a central state when the government is exploitative and oppressive (see Powell *et al.* , 2008), thus challenging the very notion of a negative impact.

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 economies. We use a counterfactual approach - the synthetic control method - and compare the post-conflict GDP trajectories of conflict-ridden countries with the trajectories of combinations of otherwise similar but unexposed countries. A common critique of the cross-country literature is the presence of unmeasurable time varying omitted variables, such as the quality of the institutions, that affect both economic growth and the likelihood of war. This method mitigates the bias by accommodating for unobservable confounders. We also examine the relationship between the case-study, synthetic control and large-N panel-data approaches and provide a range of estimates of the effect of civil war. In particular, we show that both models estimated from panel data and models where treatment effects are estimated by comparison of a treated case with a synthetic control can reveal a great degree of heterogeneity in the economic effect of civil war. In a number of cases, countries actually perform better in the presence of conflict, relative to previous periods of peace.

Our case-study analysis shows that, on average, civil war reduces the GDP level by 9.1%. Yet this approach also reveals a great degree of heterogeneity in the way economies react to conflicts: we find that only 12 of the 27 cases show a significant negative effect of war on the GDP level. When we turn to the panel data analysis, we find that estimated impact of conflict on the GDP level is overall insignificant. However, the point estimates obscure the wide range of possible responses to conflict; in fact, by relaxing the homogeneity restrictions in the panel analysis, we find that individual separate effects of civil war for each country range from -33% to +32% of the GDP.[1]

The remainder of our paper is organized as follows. Section 2 provides a short review of the theoretical arguments and empirical studies on the economic costs of war, including the methodological issues involved in the calculation. Section 3 discusses the relationship between panel and synthetic control estimators. Section 4 describes the synthetic control method and presents the implemented experiments by region. Section 5 presents the results of the panel data analyses. Section 6 provides concluding remarks.

[1] Our results are very sensitive to the choice of the dependent variable, level or growth of GDP, as shown in Bove *et al.* (2014).

2 The economic costs of war

War devastates lives, health, and living standards both directly in the form of battle deaths, and indirectly through increased rates of diseases. At the same time, war could destroy obsolete physical infrastructure and some of the social and political institutions that inhibited development in the first place (Van Raemdonck & Diehi, 1989; Blattman & Miguel, 2010). In fact, a number of theoretical studies suggest that war can have both positive and negative impacts on subsequent economic growth, through a variety of channels. Theories on the positive effect of war hinge crucially on the existence of improvements resulting from war participation, in particular institutional changes and technological innovations. Tilly (1992) argues that, starting from 990 AD, major mobilizations for war stimulated states' expansion and consolidation, and created new forms of political organization. Likewise, Cramer (2006) recalls how changing technological demands for warfare in Europe in the 19th century forced states to find new funding sources. In a shift from small mercenary forces to larger domestic military forces, European states had to create taxation institutions to mobilize war finances. Wars were followed by a successful transformation of failed states, and the most successful states had a growing tax base, such as England and Prussia. In fact, "much of the institutional apparatus of modern government and economic management has its origin in the compulsion to finance wars" (Cramer, 2006, p.178).

Seminal empirical studies by Organski & Kugler (1977) and Organski (1981) analyze the economic effects of WWI and WWII on European Countries. The authors suggest that winners and neutrals are only affected marginally by the conflict and that developed societies devastated by war recovered in one generation the levels of performance they would have had in the absence of conflict. This phenomenon is called the 'Phoenix Factor' and underpins two key factors: obsolescent plants and industrial equipment are replaced by more advanced and efficient infrastructures; at the same time, attitudinal factors, in particular the motivation to rebuild and the greater effort exerted by a defeated population, increase the pace of recovery. Taken together, these mechanisms can lead to greater post-war productivity.

Another popular argument for the existence of a positive post-war economic trajectory is offered by Olson (1982). He argues that rent-seeking activities by special interest groups hamper economic growth. These so-called distributional coalitions resist the adoption of new technologies and a more efficient allocation of production factors, thus undermining capital formation and slowing economic development. Civil wars destroy the existing social order and weaken or uproot special interests that block socio-economic changes, and thus contribute to liberating a country's productive resources and improving the level of welfare provision. Chan (1987), among others, explores the experience of the Asian Pacific-rim countries and find support for this mechanism.

A related argument posits that after war less predatory political regime could emerge. Most of the civil wars usually 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 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. Therefore, when a good government is not an option in a country's institutional opportunity set, anarchy could be more desirable for its economic development (Leeson, 2007).[2]

Yet, as Van Raemdonck & Diehi (1989) point out, the theoretical arguments for why

[2] Finally, Van Raemdonck & Diehi (1989) review additional theoretical arguments on the positive effects of war on economic growth. They suggest that war can i) enhance government research and development efforts that spawn spinoffs for the economy; ii) encourage the exploration of new resources or raw material; iii) prompt better transportation and communication facilities that yield benefits after the war is over; iv) improve managerial and organizational skills; and v) redirect resources to peacetime industries that were ignored during the war.

wars have negative economic effects are inverted versions of the previous mechanisms. War destroys transportation facilities and productive human capital, including economic skills, while large-scale killings create demographic distortions and military demobilization leads to labor surplus. Other economic distortion stems from the servicing of debts, the lack of investments, higher levels of military spending for deterrence, and the disruption of international economic linkages, such as trade (see Smith, 2014, for an overview).

Collier (1999), possibly the most popular article on the cost of civil wars, 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 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. 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. A number of 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).

There are several methodological difficulties involved in quantifying the economic costs of conflict, reviewed in Smith (2014). 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.[3] 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

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

to a theoretical one-time shock (see also Skaperdas, 2011). Another methodological issue hinges on the coding procedure: Cerra & Saxena (2008) use a dummy variable that takes on the value 1 in all civil war-years (as opposed to the start years when they analyze other shocks such as banking crisis). Mueller (2012) shows how this leads to an underestimation of the output response to civil war, which ends up being the most devastating type of crisis.

Country experiences in terms of growth of course vary widely and aggregate studies conceal a deal of heterogeneity in countries' response to conflict. 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). Yet these works are case studies and 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 social 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 the study of the economic effect of war a central issue is the definition of the counterfactual, what would have happened in the absence of the conflict, something which can never be observed.

The synthetic control method is a well established technique used in Abadie & Gardeazabal (2003) to estimate the economic cost of the Basque conflict, and has gained increased popularity recently through the availability of the package Synth available on MATLAB, R and Stata. This 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. Others have used it to examine a diversity of cases, such as Abadie *et al.* (2010) who examine the effect of California's smoking control program, Billmeier & Nannicini (2013) who look at the impact of economic liberalization, or the study of Costalli *et al.* (2014), developed independently from ours, which examine the economic effects of civil war on 20 countries, the case we are concerned with.[4] 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 the following section 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.

3 Synthetic control method and panel model

The synthetic control approach arises from the microeconometric literature where it is natural to try and measure the treatment effect by comparing the treated cases with untreated controls who are similar in all respect but treatment. 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

[4] Another study is from Gardeazabal & Vega-Bayo (2015), on the effect of conflicts on real GDP per capita and investments, which appeared after the working paper version of this paper was circulated.

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.

Gobillon & Magnac (2016) also compare panel models (the closely related interactive fixed effects model), difference-in-differences and synthetic control. They show that difference-in-differences is generically biased when different units respond differently to the factors and derive the support conditions that are required for the application of synthetic controls. This literature which considers the difference between the treatment group and a control to measure the effect of the treatment uses static models. If a lagged dependent variable were included it would embody the effect of conflict in the previous year treatment, reducing the effect of conflict. The conflict itself is likely to change the degree of persistence of GDP further complicating the analysis. For comparability with the other literature and to aid interpretation we also use static models. The appropriate way to handle dynamics and parameter change in this context are discussed in Pesaran & Smith (2016).

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 affected 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.[5] Then the $N-1 \times 1$ vector of weights $W = (w_2, w_3, ..., w_N)'$ are chosen to minimize

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

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) prove (subject to condition) 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

[5]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. The choice of predictor variables is not uncontroversial and Kaul *et al.* (2015) argue against the use of pre-intervention outcomes.

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. Note that the fact that regression methods can give negative weights comes as no surprise 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 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

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

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

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

This brings out the similarities to the synthetic control and Hsiao *et al.* (2012) approaches, where the cross-section averages 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).[6]

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

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

[6]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.

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 the log 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.[7] 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 'over-control' and under-estimate the total effect of civil war. Pesaran & Smith (2012) discuss this issue. We do not include other covariates although the argument can be extended to allow for them.

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 3, the synthetic control method is based on the premise that in the 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

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

of pre-conflict characteristics for the country at war and the treated units include only pre-treatment levels of per capita GDP.

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 contemporary 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 is 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;[8] (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.[9] For the sake of brevity and to show the heterogenous effect

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

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

of civil war, this section will only briefly cover four case studies, one in the MENA region (i.e., Algeria), one in Oceania (i.e., Papua New Guinea), one in Asia (i.e, Sri Lank), and one in Sub-Saharan Africa (i.e., Uganda). We refer the reader to the online appendix for the remaining countries.[10]

Figure 1 shows the real GDP per capita trends in levels 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. A visual inspection of the discrepancies between solid and dotted lines in the four cases suggests that civil war has no homogenous effects. Algeria shows the case of a level shift, and a one-off temporary effect on the GDP. Uganda displays a situation in which conflict causes the growth rate to deteriorate, and thus a steady divergence from their artificial counterfactual following the onset of the civil war. In Papua New Guinea the divergence between the solid and the dotted lines after the outbreak of the conflict indicates that the country at war outperformed its synthetic counterpart and that civil war had a positive impact on its subsequent GDP levels. In Sri Lanka the treated countries and the synthetic control behave similarly in both the pre-treatment period and the post-treatment period, showing virtually no divergence and therefore no clear effect of civil war on economic growth (see Figure 1).

——————— [Figures 1 in here] ———————

The appendix contains the remaining cases. In particular, Figure A1 includes Nepal and Thailand. The Middle East and North Africa sample in Figures A2 includes Egypt,

[10]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).

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). Latin America countries, El Salvador, Nicaragua and Peru, are in Figure A6, while Europe (Figure A7) includes Spain, Turkey and the United Kingdom.[11] Overall, the divergence between the solid and the dotted lines after the outbreak of the conflict indicates that civil war produces very heterogeneous effects on the GDP, and these vary across countries and over time.

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

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

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

[11] 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.

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. Table 1 displays 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. For example we detect significant negative effects of the civil war on real per capita GDP in Algeria and Uganda. These effects start materializing one year after the onset of the conflict in Algeria and eight years after in Uganda. The positive effect on Papua New Guinea's economy is significant at convention level during the whole post-1992 period, whereas the difference between Sri Lanka GDP and its synthetic counterpart is insignificant in most of the conflict years.

——————— [Table 1 in here] ———————

Table 2 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 2 in here] ———————

We find that 17 of the 27 cases show a negative effect of war on the GDP level, of which 12, according to the Chow test, are statistically significant at conventional levels. On the other hand, 4 out of 10 cases exhibit a positive and significant impact. In terms of magnitude, Table 2 indicates that the average impact of conflict on the GDP level is around -9.1%, even though this is imprecisely estimated (the standard deviation of all βs is 0.19).[12] 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).[13]

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 in a country i at time t.

Table 3 displays our estimates of equation (5). We use two balanced samples, one over the full period 1960-2010 (models i to iii), in which however we need to drop three countries, Liberia, Sierra Leone and Djibouti, as we do not have data for the first decade, and the other over the period 1970-2010 (models iv to vi), which includes the full set of countries. In order to compare the output gaps obtained from the synthetic control method with a balanced panel data estimation, we use the same pool of control units selected in the synthetic control method procedure (models i and iv). We also use a restricted sample, with models (ii) and (v) estimating equation (5) only for the 27 case-

[12]Note that the countries at war omitted from the analysis show on average a larger per capita GDP than the economies included in our study. Therefore, if we had also included these countries, the heterogeneity in the estimated effects of conflict would have possibly been even more pronounced.

[13]Gardeazabal & Vega-Bayo (2015) use only pre-treatment values of the outcome variable and given the similarity of the specification, they reach a finding similar to ours, i.e., the size of the effect of war is very heterogeneous, although they do not report individual estimates, and only look at the GDP level, thus making a direct comparison unfeasible.

studies who experienced civil wars. Finally, in models (iii) and (vi) we run a mean group (MG) estimator *a la* Pesaran & Smith (1995), which produces consistent estimates of the average of the individual country-specific parameters β_i.

The models of Table 3 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 is never significant at conventional levels, with the exception of model (iv), where it is around -6.4%. Although most of the coefficients are not significantly different from zero, this should come as no surprise given the extreme heterogeneity in countries' reaction to conflict shocks. Recall that table 2, reporting the country-specific effects estimated by means of the synthetic control, suggests that 10 of out 27 countries exhibit a positive, rather than negative, average response to civil war.

——————— [Table 3 in 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 summarize the results of this exercise in columns (iii) and (vi) of Table 3 by means of the Mean Group estimator. As is made clear, the effect of war on the per capita GDP is insignificant at conventional levelsl. Note that, although closely related, the panel data analysis and the synthetic control methods are not expected to produce exactly the same estimates. Firstly, we are allowing for $\bar{c}_t$, the correlated common effect estimator, in the panel data analysis, to capture unobserved factors, which is however excluded in the synthetic. Secondly, in the panel data analysis the comparator groups income is $\bar{y}_t$, while this is $\bar{y}_{it}^S$ in the synthetic control method. In other words, the synthetic control method will only use a restricted number of countries to construct the counterfactual for each treated unit.

Finally, in Figure 2 we present the distribution of the estimated coefficients of civil war, $\hat{\beta}_i^c$, in the per capita GDP equation over the balanced sample 1 and 2 (Figure 2(a) and 2(b) respectively). As we can see, again, there is a wide range of possible responses to conflict shocks, ranging from -33% (Sierra-Leone) to +32% (Nicaragua and Egypt) in the GDP level. This further reinforces the presence of a highly heterogeneous impact of conflict on economic performances, which is variegated and it is often positive rather than negative.

——————— [Figure 2 in here] ———————

6 Conclusions

The economic impact of conflict has been a very active area of academic debate in recent years. Despite an extensive literature on this topic, the very direction of the effect - whether it is negative, positive or null - and its size are still contentious. Wars have heterogenous, country-specific effects on economic outcomes and there has been considerable controversy in 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.

This paper attempts to provide lower and upper estimates of the effect of civil war on the level of economic activity by linking panel data analyses, case studies and synthetic control methods, and by proposing a host of inferential methods. 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 development of exposed countries every year. On average, however, we find that civil war reduces the GDP level by 9.1%, even though this is imprecisely estimated. We then compare these results with a panel data analysis and find that the incidence of internal conflicts has mostly insignificant effects on the GDP level. Yet, by relaxing the homogeneity restrictions, panel data also reveals a surprising wide array of positive and negative effects of conflict on the economy of afflicted countries. Overall, both methods display a variety of individual separate effects, and in a number of countries civil war has either no effect or a positive and significant impact on the prospect for economic growth. Substantial uncertainty on the effect of war on the economy remains, ensuring that the subject will be a fertile area of study for the foreseeable future.

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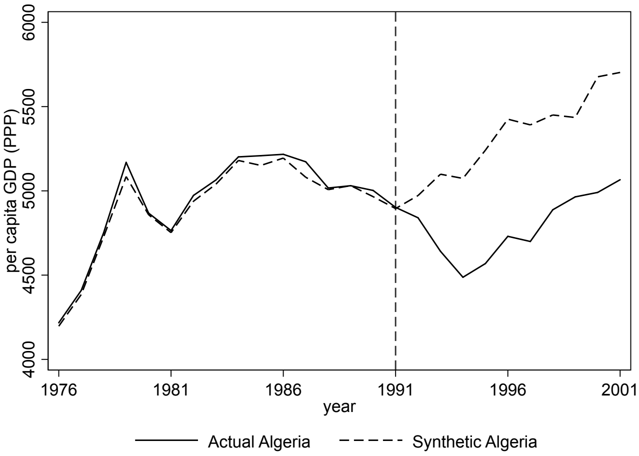
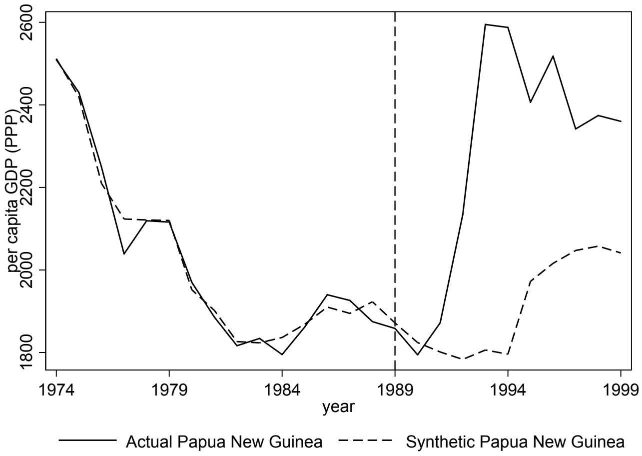
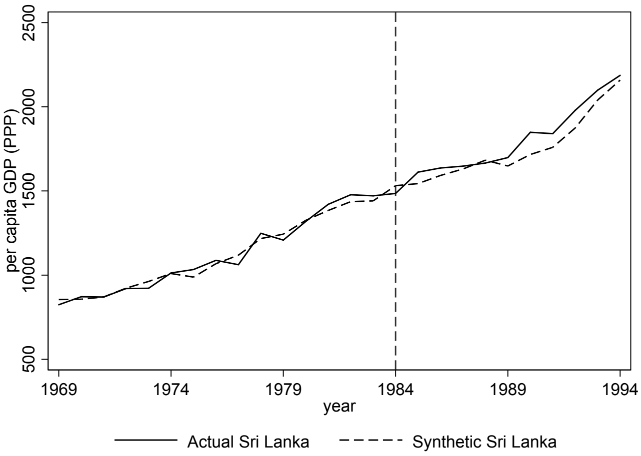


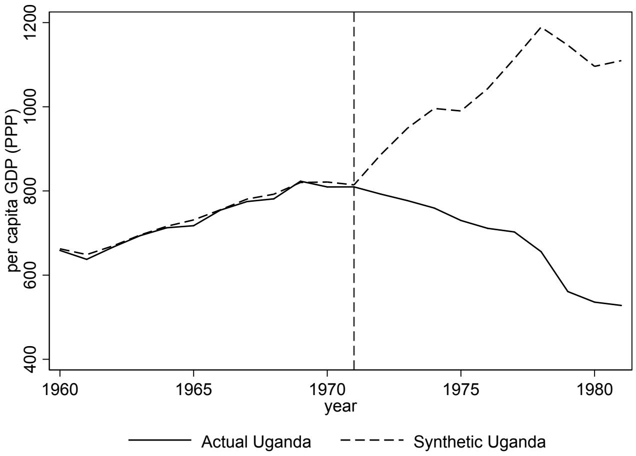
(a) Algeria



(b) Papua New Guinea



(c) Sri Lanka



(d) Uganda

Figure 1: Per capita GDP 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
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
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

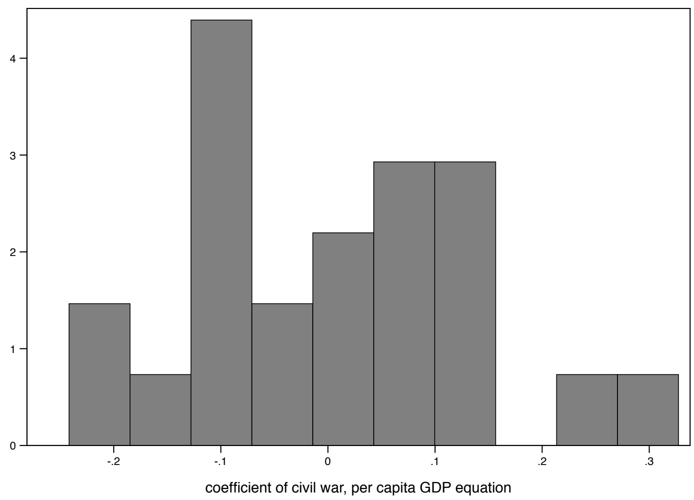
Table 2: Summary of results from case study analysis

Country	Mean effect	Mean effect (p-value)	years	Chow test (p-value)	SER
Nepal	-0.125	0.000	96-06	0.000	12.6
PapuaNewGuinea	0.164	0.000	89-90;92-96	0.000	121.1
Sri Lanka	0.025	0.043	84-94	0.017	32.2
Thailand	0.042	0.001	74-82	0.001	45
Algeria	-0.106	0.000	91-01	0.000	26.6
Egypt	-0.032	0.451	93-98	0.979	413.3
Morocco	0.024	0.421	71; 75-85	0.840	124.4
Syria	0.057	0.284	79-82	0.400	244.8
Djibouti	-0.163	0.346	91-94; 99	0.836	1134.15
Guinea	0.058	0.514	00-01	0.807	111.1
Guinea-Bissau	-0.100	0.500	98-99	0.820	190.7
Ivory Coast	-0.011	0.844	02-04	0.914	133.5
Liberia	0.151	0.741	89-90	0.651	290.5
Mauritania	0.133	0.112	75-78	0.449	206.4
Mozambique	-0.670	0.000	77-87	0.000	33
Niger	0.027	0.767	91-92;94-95;97	0.921	125.5
Rep of Congo	-0.010	0.800	93; 97-99; 02	0.662	186.5
Rwanda	0.007	0.900	90-94; 96-00	0.046	67.5
Senegal	-0.180	0.005	90; 92-93; 95; 97-98; 00	0.002	155.5
Sierra leone	-0.583	0.001	91-00	0.053	367.3
Uganda	-0.300	0.017	71-72; 74; 79-81	0.033	176.3
El Salvador	-0.260	0.000	79-89	0.000	78.6
Nicaragua	-0.210	0.000	77-79; 82-87	0.000	284.8
Peru	-0.194	0.000	82-92	0.000	51
Spain	-0.108	0.002	78-82; 85-87	0.100	1350.6
Turkey	-0.083	0.000	84-94	0.000	50
the UK	-0.013	0.015	71-81	0.177	155
Mean of means	-0.091				

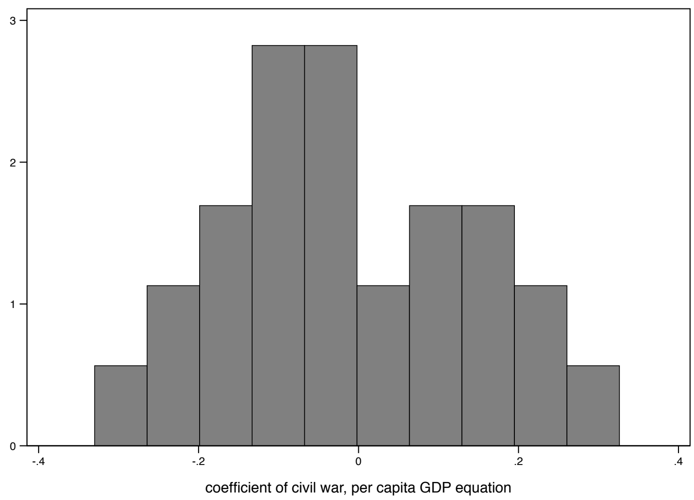
Table 3: The impact of civil war (c_{it}) on log per capita GDP (y_{it})

	Balanced sample 1			Balanced sample 2		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
LOG PER CAPITA GDP:						
c_{it}	-0.065	-0.004	0.004	-0.064*	-0.026	-0.012
	(0.046)	(0.047)	(0.028)	(0.037)	(0.047)	(0.030)
$\bar{y}_t$	1.000***	1.000***	1.021***	1.000***	1.000***	0.974***
	(0.129)	(0.198)	(0.195)	(0.142)	(0.329)	(0.326)
$\bar{c}_t$	0.065	0.004	-0.031	0.064	0.026	-0.012
	(0.287)	(0.137)	(0.137)	(0.323)	(0.224)	(0.202)
RMSE	0.305	0.252	0.108	0.278	0.262	0.140
Countries	68	24	68	92	27	92
Observations (N×T)	3468	1224	1224	3772	1107	1107

NOTE. - Ordinary least squares estimates given. A constant is included in every model but not shown. Standard errors in models (i)-(ii) and (v)-(vi) are clustered by country. Balanced sample 1 excludes Liberia, Sierra Leone and Djibouti from the treated group and considers period 1960-2010. Balanced sample 2 considers period 1970-2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



(a)



(b)

Figure 2: Distribution of the estimated coefficient of civil war (c_{it}) of the per capita GDP equation. Balanced sample 1 in (a), balanced sample 2 in (b).

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).

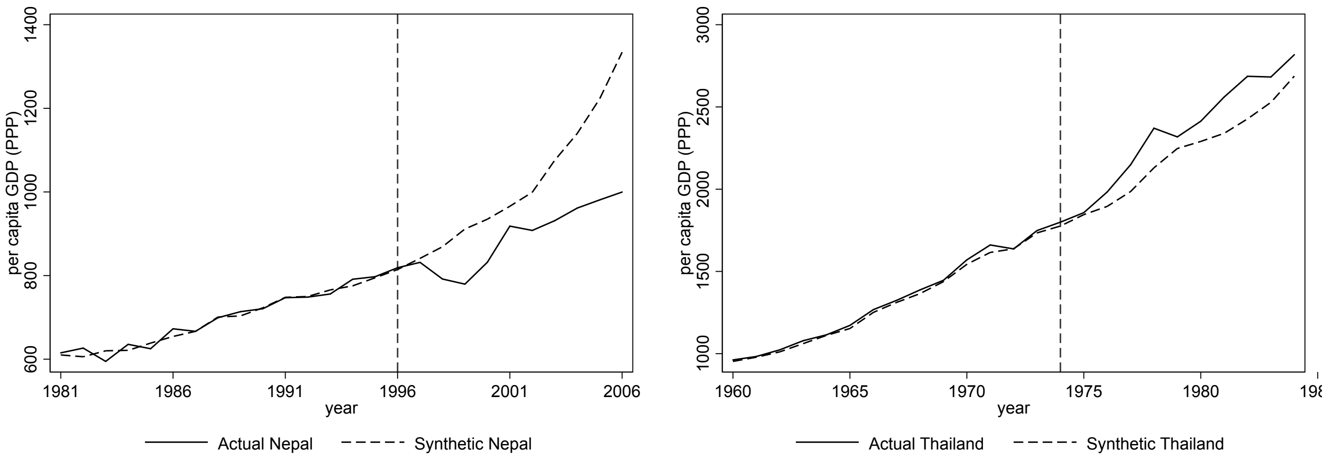
Syria: Jamaica (0.018), Trinidad and Tobago (0.068), Brazil (0.003), Sweden (0.005), Equatorial Guinea (0.305), Guinea (0.439), Mauritius (0.161).

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).

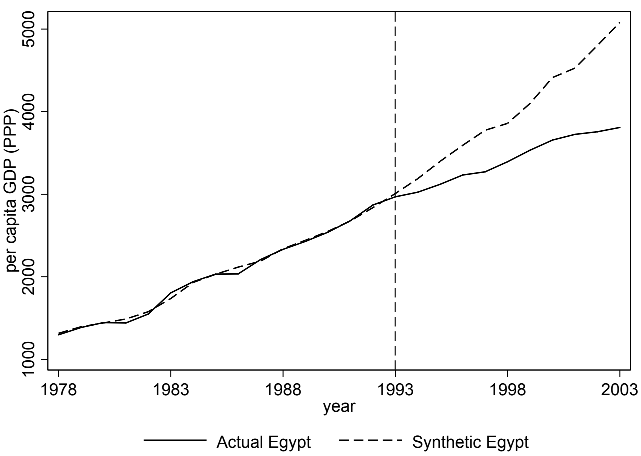
Uganda: Equatorial Guinea (0.056), Guinea (0.041), Burkina Faso (0.318), Togo (0.068), Lesotho (0.396), Turkey (0.006), China (0.059), Rep of Korea (0.049), New Zealand (0.007).

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

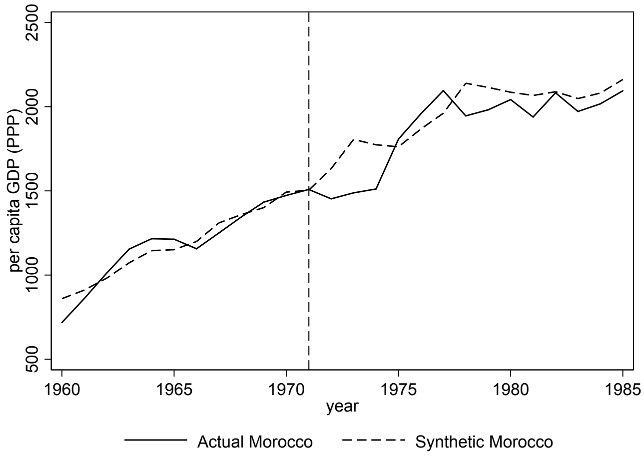


(a) Nepal (b) Thailand

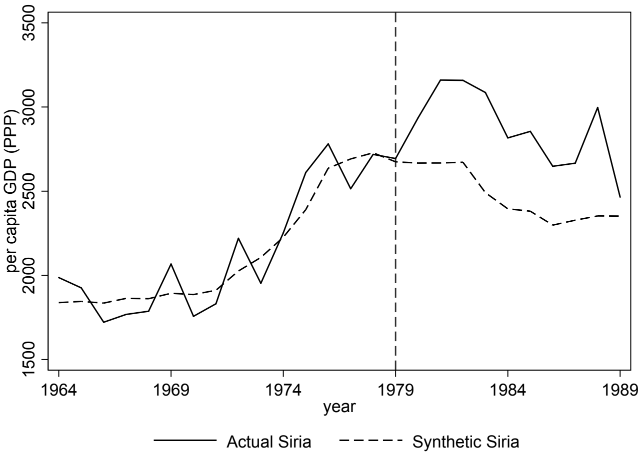
Figure A1: Per capita GDP trends, Treated Country vs. Synthetic Control - Asia



(a) Egypt

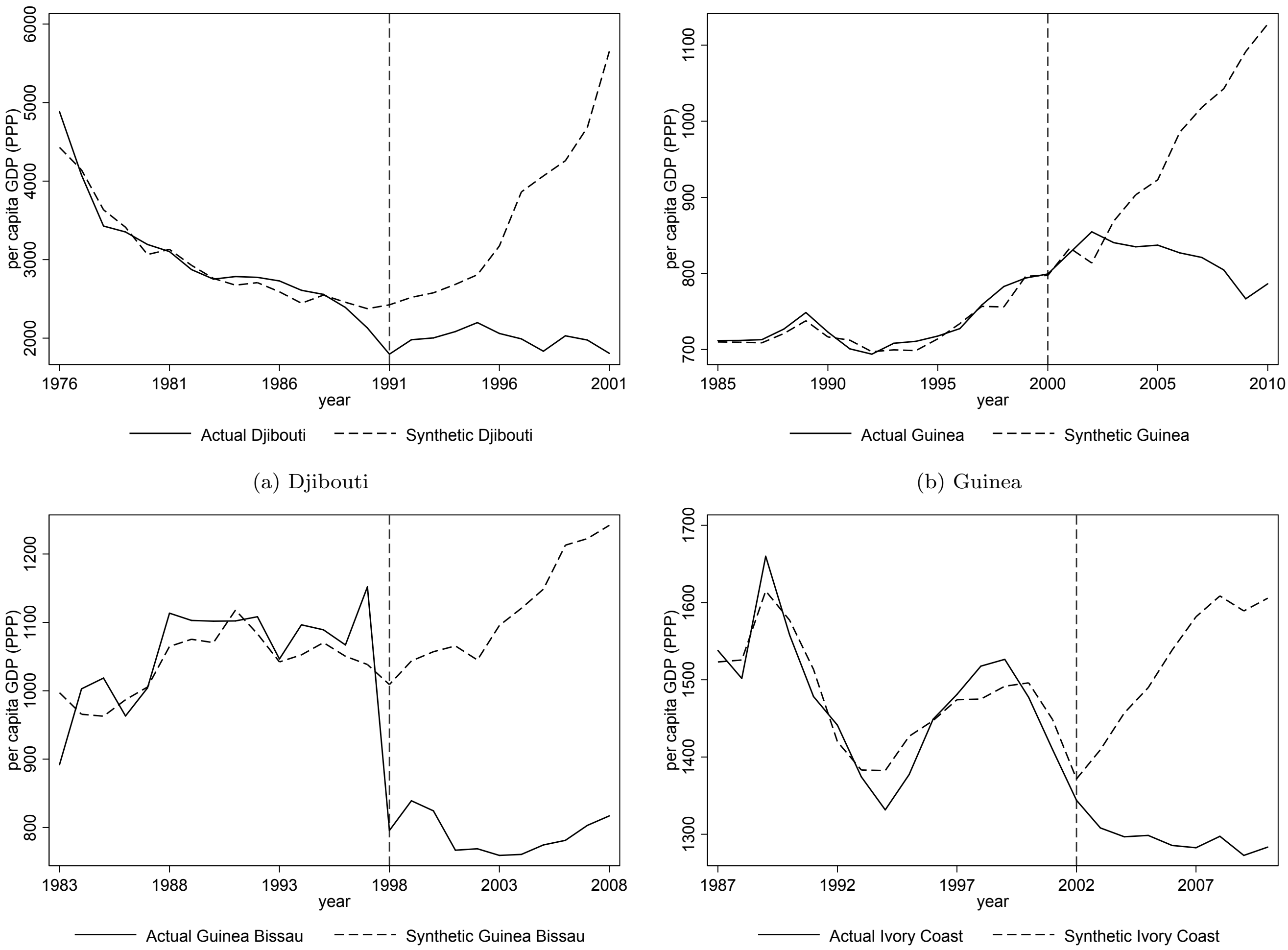


(b) Morocco



(c) Syria

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



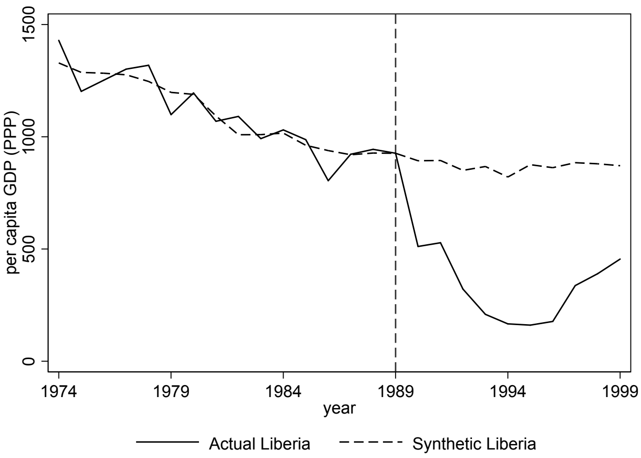
(a) Djibouti

(b) Guinea

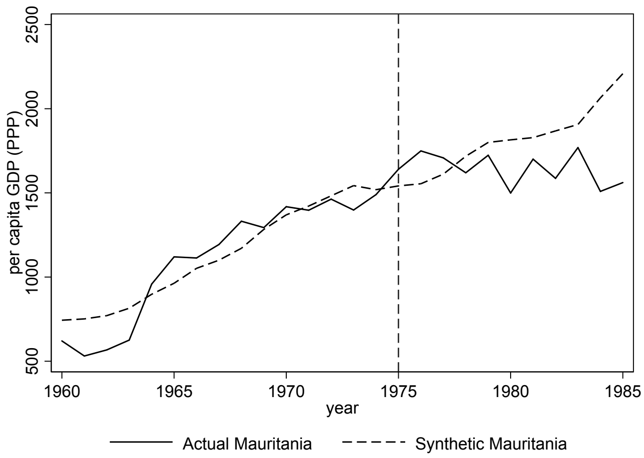
(c) Guinea Bissau

(d) Ivory Coast

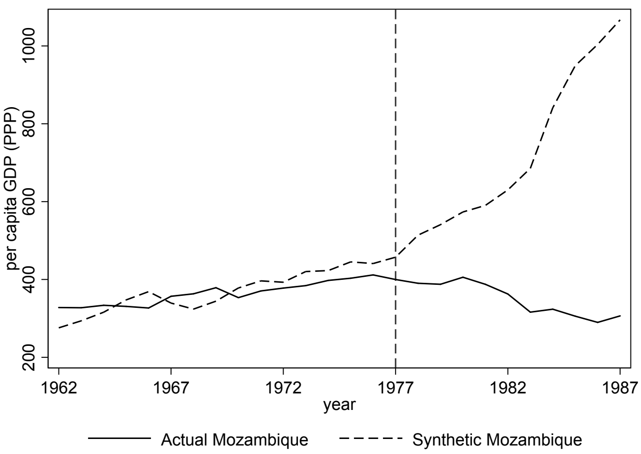
Figure A3: Per capita GDP trends, Treated Country vs. Synthetic Control - Sub-saharan Africa (I)



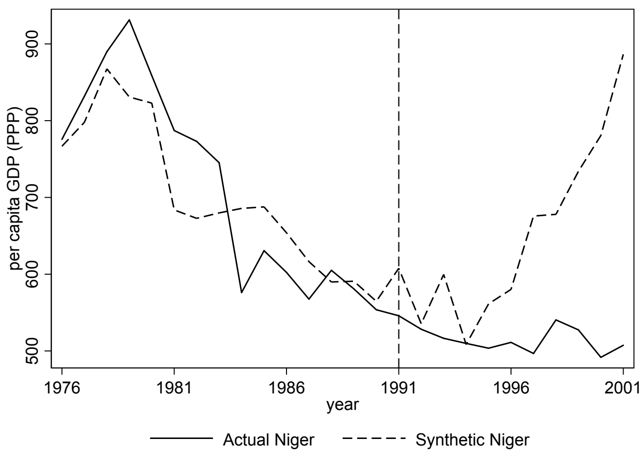
(a) Liberia



(b) Mauritania

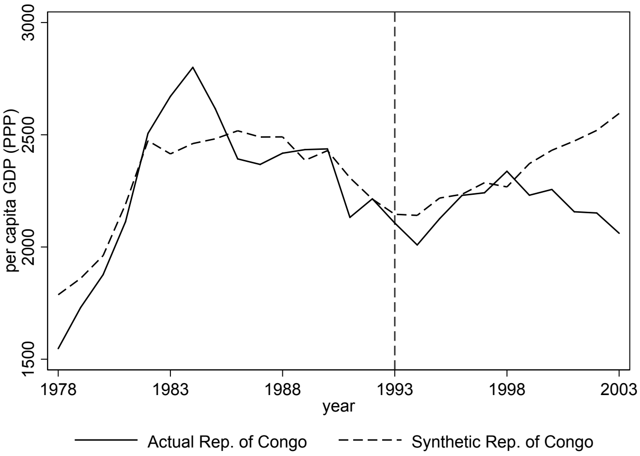


(c) Mozambique

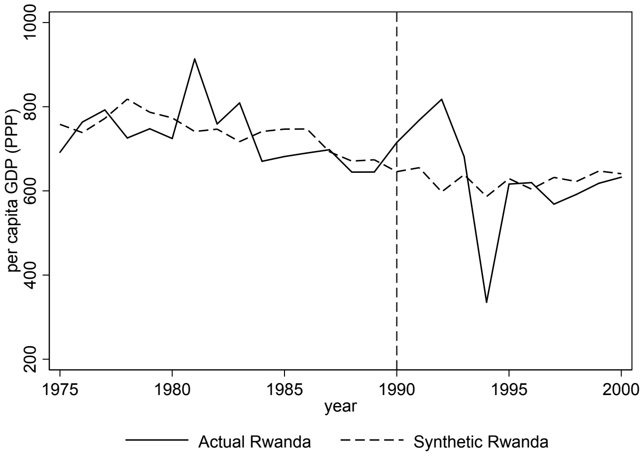


(d) Niger

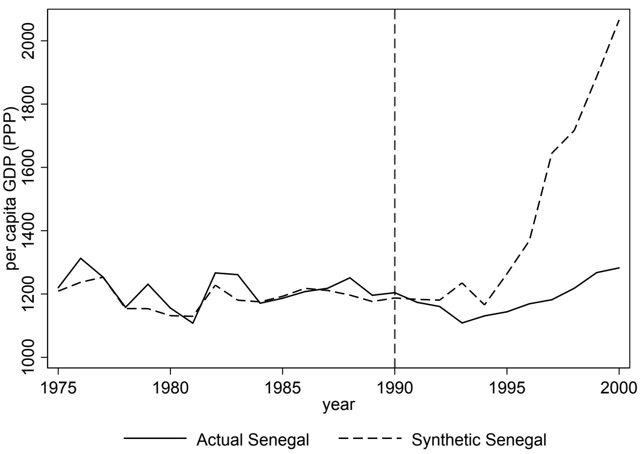
Figure A4: Per capita GDP trends, Treated Country vs. Synthetic Control - Sub-saharan Africa (II)



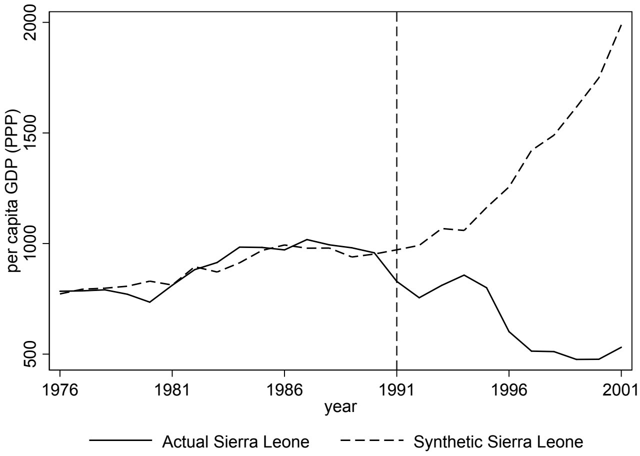
(a) Republic of Congo



(b) Rwanda

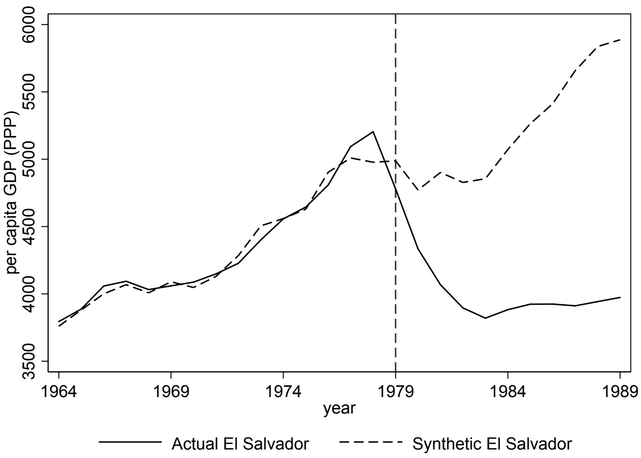


(c) Senegal

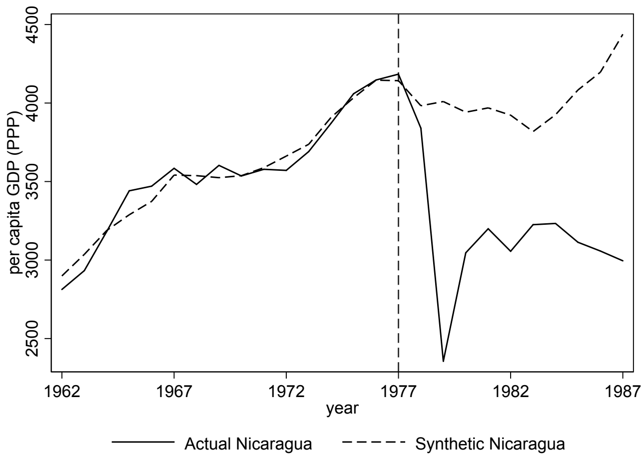


(d) Sierra Leone

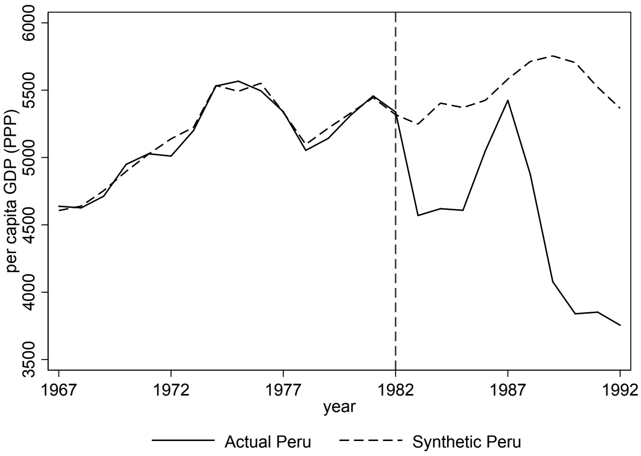
Figure A5: Per capita GDP trends, Treated Country vs. Synthetic Control - Sub-saharan Africa (III)



(a) El Salvador

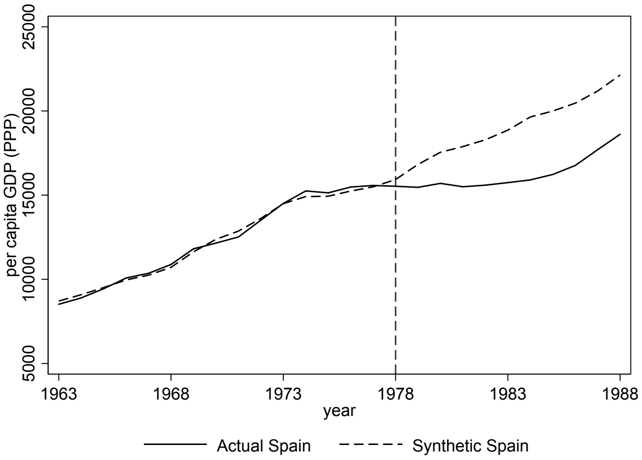


(b) Nicaragua

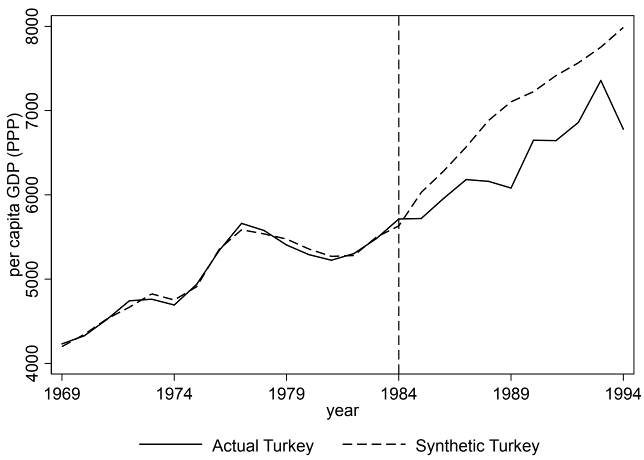


(c) Peru

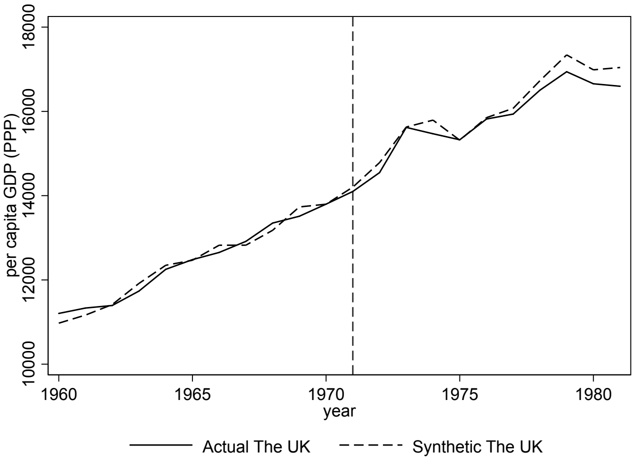
Figure A6: Per capita GDP trends, Treated Country vs. Synthetic Control - Latin America



(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
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
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
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

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