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Analysing the impact of climate change on economic growth in the SADC region: a synthetic control approach

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Analysing the impact of climate change on economic growth in the SADC region: a synthetic control approach

Tendai Gwatidzo*

Abstract

Despite its limited role in causing climate change, Africa has been significantly affected by it, particularly in the form of droughts and flooding. Most research on the economic impact of climate change has largely focused on its short-term effects. This study uses panel data covering the period 1980–2018 and the synthetic control method to investigate both short-term and long-term effects of droughts in the Southern African Development Community (SADC) region. The synthetic control method enables us to credibly identify the causal effect of droughts, as it creates a credible counterfactual. Our results show that droughts in the SADC region can be quite devastating. On average, droughts reduced each affected country's gross domestic product per capita by about 18%, apart from South Africa, where the effect was about 5%. The study results also suggest that the effects of the droughts are long-lasting. Policymakers should therefore consider long-term, rather than short-term, policy responses to droughts.

JEL classification

Q01, Q23, Q54, Q56, Q58, O44

Keywords

Climate change, droughts, economic growth, synthetic control method, SADC, panel data

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1. Introduction

African countries cannot afford to ignore the devasting effects of climate change. Climate change affects African economies through droughts, floods, extreme temperatures, storms and earthquakes. In recent years, catastrophic events such as droughts and floods have become more frequent and severe (FAO 2021). These events hinder economic growth and progress towards attaining key Sustainable Development Goals (SDGs), particularly SDG 1 (no poverty), SDG 2 (zero hunger), SDG 6 (clean water and sanitation) and SDG 13 (climate action).[1] The global effects of climate change were clearly stated in the Stern Review on the Economics of Climate Change (Nordhaus 2007: 687):

> The Review estimates that if we don't act, the overall costs and risks of climate change will be equivalent to losing at least 5% of global GDP each year, now and forever. If a wider range of risks and impacts is taken into account, the estimates of damage could rise to 20% of GDP or more…

The agricultural sector in Africa is highly vulnerable to climate change, especially droughts and floods (see Figure 1 for the most important physical hazards). The sector is the backbone of the economy of most African countries as it provides employment, generates export revenues and provides inputs for the manufacturing sector. More than 70% of the population in most African countries stays in rural areas, with most of them depending on the agricultural sector for their livelihood (World Bank 2007). The sector itself contributes more than 30% to the gross domestic product (GDP) of most African countries (World Bank 2007). As a result, any drought or flooding that affects the agricultural sector will be felt by the entire economy. It is therefore unsurprising that most poverty reduction strategies by governments and development partners tend to focus on the agricultural sector.

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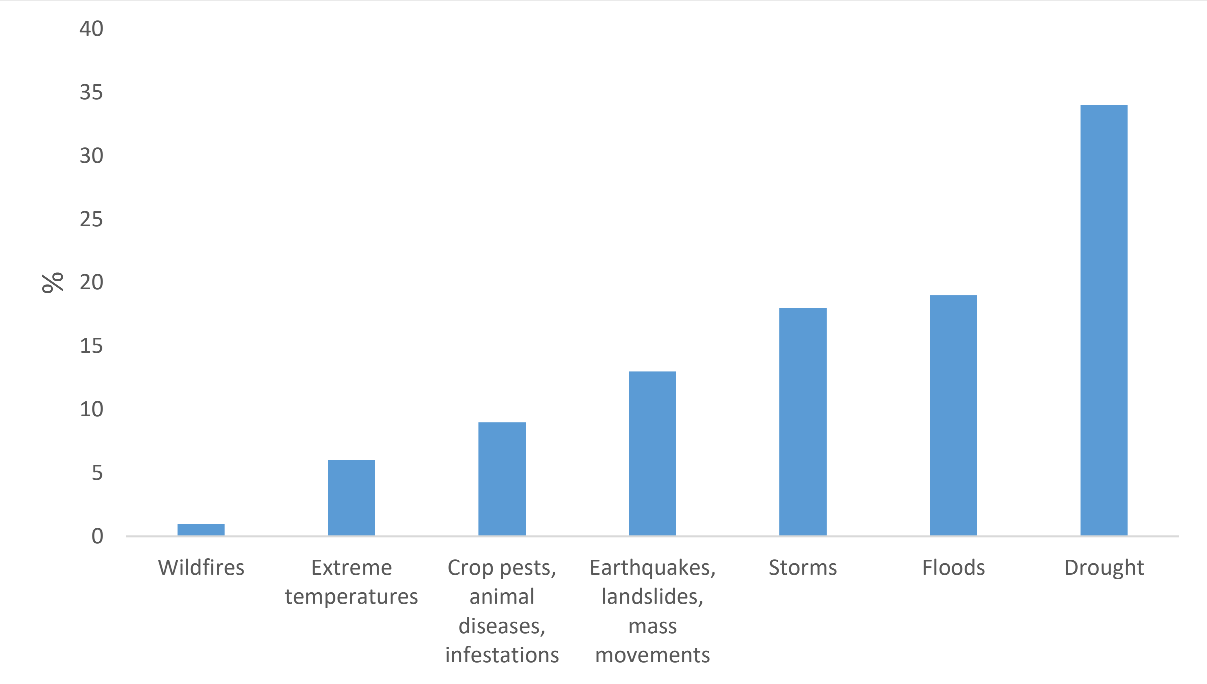
1 For more information on the SDGs, see https://sdgs.un.org/goals

Figure 1: Crop production loss per type of physical hazard in least developed countries and lower-middle-income countries (%) (2008–2018)



Source: FAO (2021)

The aim of the study is to investigate the impact of droughts on economic performance for seven countries in Southern Africa.[2] A drought is considered to be an extended period during which a country receives below average rainfall (Fleming-Muñoz, Whitten and Bonnett 2023). Given the increased frequency and severity of droughts, as well as the importance of agriculture in most African countries, a better understanding of the effects of droughts in Southern Africa is important. It is also important given that most farmers in Southern Africa do not have adequate financial resources to invest in irrigation, which can help mitigate climate change risk. Table 1 shows that on average about 2% of agricultural land in Africa is irrigated. As most farmers rely on rainfall, they are extremely vulnerable to climate change, especially droughts. This study is important not only for governments but for the banking sector and central banks. Ignoring the impact of climate change on important sectors such as the agricultural sector may result in commercial banks, which extend credit to the farming community, being exposed to high levels of risks. If climate change impacts are ignored, numerous physical risks may affect the ability of farmers to honour their

2 We focus on Southern African Development Community (SADC) member states in particular. See Table A1 in Annex A for a list of the member countries. The seven countries studied are the SADC member states that experienced a severe drought during the sample period.

debt obligations. If a larger number of banks experience such problems, this may ultimately affect the stability of the entire banking sector.

Table 1: Agricultural irrigated land (% of total agricultural land)

Country name	Agricultural irrigated land (% of total agricultural land)	Most recent year
Lesotho	0.1	2013
Mauritania	0.1	2004
Tunisia	0.1	2013
Uganda	0.1	2013
Mozambique	0.1	2001
Ghana	0.3	2014
Nigeria	0.3	2017
Rwanda	0.4	2005
Ethiopia	0.5	2020
Malawi	0.5	2008
Niger	0.6	2020
Senegal	0.7	2006
Benin	1.3	2019
Sudan	1.4	2020
South Africa	1.7	2011
Madagascar	2.2	2007
Algeria	3.3	2019
Eswatini	3.7	2002
Seychelles	5.0	2003
Morocco	6.0	2019
Mauritius	17.8	2021
Mean	**2.2**	

Source: World Bank's World Development Indicators (WDI) database

2. Brief literature review

Several approaches have been used in the literature to estimate the economic effects of droughts. Some have used direct approaches, which include direct assessments of costs to companies or sectors, estimating damage functions, market valuation and integrated assessment analysis (see e.g. Benson and Clay 1998; Corti et al. 2009; Corti et al. 2011; Jenkins 2013; Booker, Michelsen and Ward 2005; Ward, Booker and Michelsen 2006). Others have used computable general equilibrium (CGE) and input-output indirect approaches to estimate the indirect cost of droughts. Table 2 lists the different estimation approaches used to estimate the economic costs of droughts.

While these approaches have aided economists in understanding the effects of droughts on economies, their weaknesses cast doubt on whether the estimated effects are accurately measuring the causal effect of droughts. For example, the CGE approach is based on a number of assumptions, and if these assumptions fail to hold, one may fail to estimate credible causal effects of droughts. According to Sheng and Xu (2019), the regression methods also tend to underestimate the effects of droughts.

This study seeks to contribute to this strand of literature by using an approach that better estimates the causal effect of droughts. Most of the studies listed in Table 2 focused on developed economies and covered a small number of developing countries. Most countries in Southern Africa did not receive adequate attention when it comes to the effects of droughts. Given the frequency and severity of droughts and floods in most Southern African countries, it is important to investigate the impact of droughts on relevant economic outcomes. The study approach also helps us investigate the mechanism through which droughts affect important economic outcomes.

Studies that use the synthetic control method (SCM) to investigate the effect of droughts include Sheng and Xu (2019), Truong and Tri (2021), Coffman and Noy (2012), and Goin, Rudolph and Ahern (2017). Using a panel dataset covering 46 countries over the period 1961–2011, Sheng and Xu (2019) investigate the impact of droughts in Australia. The droughts occurred between 2002 and 2010. The study uses the SCM to construct a counterfactual for Australia using a convex combination of six countries (New Zealand, Argentina, the United States, Canada, Israel and Denmark). It then compares Australia's observed total factor productivity to that of its counterfactual and finds that the droughts had a devastating effect on the country's productivity. They resulted in the country's total factor productivity dropping by about 20%, an impact much larger than that estimated using conventional regression methods. Sheng and Xu (2019) conclude that the conventional regression methods may underestimate the negative effects of droughts or other climate shocks.

Truong and Tri (2021) use the SCM to investigate the impact of a 2013 drought in Central Vietnam. The study, which covers 30 provinces in Vietnam, uses the country's other provinces as control units. It uses annual panel data covering the period 2000–2019. The study finds that the drought resulted in both income per capita and income per capita from the agricultural sector dropping by about 10%. It also finds that the drought had both short-term and long-term effects. This is corroborated by Goin, Rudolph and Ahern (2017), who also find evidence of the adverse effect of droughts. They take a different approach, using the SCM to investigate the impact of droughts on crime. They use state-level panel data covering the period 2000–2015 to investigate the impact of the 2011 California drought on property and violent crime rates. They find that the drought resulted in property crime increasing by 10%. Coffman and Noy (2012) use the SCM to investigate the long-term effect of a 1992 natural disaster (Hurricane Iniki). The damages caused by the hurricane were estimated to be more than US$7 billion. The study, which uses other Hawaiian islands as a control group, finds that the hurricane resulted in a 12% decrease in the population and a 15% reduction in employment.

The studies discussed above focus on countries outside Africa. There are not many studies that use the SCM to estimate the effect of droughts on African countries. Those that look at the effects of droughts in Africa use regression methods. They include Danso-Abbeam et al. (2024); Lombe, Carvalho and Rosa-Santos (2024); Van der Geest and Warner (2014); Mariussen (2021); Azzarri and Signorelli (2020); Alagidede, Adu and Frimpong (2016); Barrios, Bertinelli and Strobl (2010); Abidoye and Odusola (2015); and Lanzafame (2014). They all find evidence of the adverse effect of droughts. For example, Barrios, Bertinelli and Strobl (2010) examine the effect of changing rainfall patterns on economic performance in sub-Saharan Africa. They find that rainfall in Africa has been decreasing since the 1960s, which has had a negative effect on the economic performance of African countries. Their simulations show that if the decline in rainfall did not occur, the gap in GDP per capita between African countries and other developing countries would have been 15% to 40% narrower. Lanzafame (2014) notes that African countries experience significant damages from weather shocks. As a result, important resources meant for development (e.g. to address infrastructure deficits) are being diverted to develop coping mechanisms to adapt to climate change (Ayugi et al. 2022).

Most studies tend to focus on developed economies, especially Australia. More importantly, most studies do not use the synthetic control approach that we use for this study. This approach creates a counterfactual – a synthetic unit – for each drought-affected country in the sample. Such a counterfactual tells us how each country would have performed if it was not affected by the drought. With such information one can then compare, after the drought, the observed outcome for a given drought-affected country with the outcome for the synthetic unit. The difference is then considered to be the effect of the drought. This approach has been used to estimate the effect of 'big' events such as droughts, floods, civil wars and terrorism. See, for example, Sheng and Xu (2019); Matta, Appleton and Bleaney (2019); Billmeier and Nannicini (2013); Cunningham and Shah (2018); and Acemoglu et al. (2016).

Table 2: Empirical studies on the impact of droughts

Cost category	Method/estimation approach	Reference
Direct	Direct assessment of cost to companies/sectors	Benson and Clay (1998); Corti et al. (2009); Christian-Smith, Levy and Gleick (2011)
	Damage functions	Corti et al. (2009, 2011); Jenkins (2013)
	Market valuation (willingness to pay market prices, production function, avoided costs, replacement or repair costs, etc.)	Easterling and Mendelsohn (2000); Grafton and Ward (2008)
	Integrated assessment analysis, biophysical-agroeconomic models	Kulshreshtha and Klein (1989); Rosenberg (1993); Holden and Shiferaw (2004); Fischer et al. (2005)
	Integrated assessment analysis, hydrological-economic models	Booker, Michelsen and Ward (2005); Ward, Booker and Michelsen (2006),
Indirect and economy-wide	CGE	Grossmann et al. (2011); Islam (2003); Horridge, Madden and Wittwer (2005); Rose and Liao (2005); Berrittella et al. (2007); Boyd and Ibarrarán (2009); Pauw et al. (2011); Wittwer and Griffith (2010)
	Supply input-output	Davis and Salkin (1984); Freire-González (2011); Pérez y Pérez and Barreiro-Hurlé (2009); Howitt et al. (2014)
	Adaptive regional input-output Inoperability input-output	Jenkins (2013); Santos et al. (2014); Pagsuyoin and Santos (2015)
Intangible	Macroeconometric contingent valuation	Salami, Shahnooshi and Thomson (2009); Pattanayak and Kramer (2001b)
	Choice modelling	Hensher et al. (2006)
	Cost-based methods	Banerjee et al. (2013)
	Life satisfaction analysis	Carroll et al. (2009)
Risk mitigation	Cost of implementation	Michelsen and Young (1993); Woo (1994); Pattanayak and Kramer (2001a, 2001b); Morton et al. (2005); Grafton and Ward (2008)

Note: Adapted from Freire-González, Decker and Hall (2017: 198)

3. Data and methodology

3.1 Methodology: the synthetic control method

To assess whether droughts in the Southern African Development Community (SADC) region affected economic outcomes (such as GDP and agricultural value added), we use the SCM. The SCM, which was introduced by Abadie and Gardeazabal (2003) in 2003 and further demonstrated in Abadie, Diamond and Hainmueller (2010, 2015), has been used extensively in the literature to investigate the impact of 'big' events.[3] See, for example, Matta, Appleton and Bleaney (2019); Billmeier and Nannicini (2013); Cunningham and Shah (2018); and Acemoglu et al. (2016). The method seeks to compare the outcomes of an affected unit and its synthetic counterpart (Cunningham 2021). In fact, like the propensity score matching, difference-in-difference and regression discontinuity estimators, the SCM estimator helps solve the missing data problem created by the fact that, at any one point in time, one cannot simultaneously observe an outcome for a country with and without exposure to the 'big' event or intervention (e.g. a drought).

The SCM approach provides several other important advantages besides bridging the gap between qualitative and quantitative research approaches (Cunningham 2021). First, the weights generated by the SCM estimator make it explicit what each unit is contributing to the counterfactual[4] (Cunningham 2021; Abadie and Gardeazabal 2003; Abadie, Diamond and Hainmueller 2010; Mawejje and McSharry 2021). This implies that the SCM provides a transparent means of selecting countries to be used to generate a synthetic unit (Mawejje and McSharry 2021). Second, the method precludes extrapolation and uses interpolation (Cunningham 2021). Third, the SCM estimator accounts for time-changing unobservable factors, unlike the difference-in-differences approach, which only accounts for time-invariant factors (Mawejje and McSharry 2021).

In this section we briefly discuss the SCM approach in the context of a single SADC member state affected by a drought (Mozambique). A similar approach will then be applied to each SADC country affected by a severe drought. For example, the 1991/92

3 See a clear and concise exposition of the approach in Abadie (2021) and Cunningham (2021).

4 Unlike the ordinary least squares method, which does so implicitly (Cunningham 2021).

drought affected a number of countries in the SADC region. We use data covering the period 1980 to 2018.[5] Let t stand for time (years in this case) and assume that the period of interest ranges from period 1 to T. That is, t = 1, 2, …….T_0, …………T. T_0 is the time when the major drought occurred. In this case, we assume 1991 for the drought which took place in Mozambique. So t ranges from 1980 to 2018, with T_0 being 1991 (the year when the drought occurred). The period 1980–1990 is therefore the pre-intervention period and the period 1992–2018 is the post-intervention period. Let the outcome variable for country j at time t be Y_{jt} (in our case, for the country affected by the drought and its counterparts in the donor pool, this could be GDP, agricultural valued added, etc.). Let the sample of the countries being looked at be equal to J+1. We also let j=1 be the treated country (Mozambique), with J being the number of countries in the donor pool (to be used to generate the synthetic unit). The question the SCM approach seeks to answer is: what values would a drought-affected country's outcomes have taken if the country did not experience the drought in 1991? In other words, the SCM estimator attempts to estimate Mozambique's counterfactual. It does that by creating a synthetic Mozambique using data from the J countries in the donor pool. The impact of the drought will then be the difference between Mozambique's actual outcome (observed) and its synthetic outcome (counterfactual). The impact (Δ) of the event based on the SCM estimator is given by:

$$\Delta = Y_{1t} - \sum_{j=2}^{J+1} Y_{jt} W_j^* \qquad (1)$$

where W^* is a vector of optimally chosen weights. In our case, synthetic Mozambique is constructed using the pre-treatment data (1980–1990). The effect of the drought is then estimated by comparing the GDP for actual Mozambique and synthetic Mozambique in the period 1992–2018. The weights are chosen to minimise the norm: $||\boldsymbol{X_1} - \boldsymbol{X_0 W}||$ subject to the following two constraints: (1) the sum of the weights should sum to 1, and (2) no unit in the donor pool receives a negative weight. $\mathbf{X_1}$ is a vector of outcome predictors for the treated units, $\mathbf{X_0}$ is a vector of outcome predictors for the control units and **W** is a vector of weights to be estimated.

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5 The exact period used for each country may differ depending on when it experienced the major drought during the period 1980–2018. It also depends on whether there were subsequent severe droughts in the post-treatment period.

Equation (1) indicates that at any post-treatment point *t* we are looking at the difference between the treated unit's outcome and a weighted average of the outcomes for countries in the donor pool. The unit that generates the weighted average is essentially the synthetic unit. This implies that this approach gives the effect, on an annual basis, over some post-treatment period (indicating whether the effect dissipates or explodes). In our case, when focusing on the post-intervention period, we will then be comparing the outcome for actual Mozambique and synthetic Mozambique on an annual basis.[6] If there are significant adverse effects emanating from the drought we expect the effect (Δ) to be negative.[7]

The SCM, however, has several weaknesses. First, the SCM can fail to take into account the effect of some idiosyncratic shocks that may affect the treated country differently compared to countries in the donor pool (Matta, Appleton and Bleaney 2019). Second, to reduce omitted variable bias the pre-treatment period must be long enough. In most cases, the pre-treatment period may not be long enough for all sample countries, as a balanced panel is ideal for the SCM to work optimally. Third, some country features required for generating a good match between the actual and the synthetic may be difficult to measure. For example, it may be difficult to quantify or measure the relationship between the government and the private sector (Matta, Appleton and Bleaney 2019).

3.2 Data and sources

We use mostly macro data to conduct the study. We use data from the World Bank and the EM-DAT database[8] to identify countries affected by a severe drought. For the purposes of this study, we consider a country to have experienced a severe drought if the drought affected more than 1 million people or if the drought was nationwide. Subsequent droughts were also taken into account by restricting the post-treatment period. We therefore start by including all SADC member states as the potential set of

6 Actual Mozambique yields the observed outcomes while synthetic Mozambique yields the counterfactual.

7 The effect is calculated as GDP from the actual country (observed outcome) less the outcome from the synthetic.

8 For more information on droughts and other natural disasters from the online EM-DAT database, see https://www.emdat.be

treated countries. Countries not affected by a severe drought during the period 1980–2018 were then excluded from the group of treated countries, leaving us with the following countries in the set of treated countries: Zimbabwe (1991), Zambia (1991), South Africa (2004), Mozambique (1991), Malawi (2002), Angola (1989) and Botswana (2015).[9]

It is important to identify a good donor pool for the countries affected by droughts. For the six countries excluding South Africa (Angola, Botswana, Malawi, Mozambique, Zambia and Zimbabwe) we started with all 54 African countries as a potential set for the donor pool. We then eliminated countries with missing data, especially those that had a lot of missing data on outcome variables. Countries that also experienced severe droughts during the sample period were dropped from the sample. Each country's neighbouring countries were also eliminated from its donor pool. After taking all of the above into account, each country ended up with a donor pool of between 33 and 38 countries.

Given South Africa's marked difference from other African economies (in terms of structure and size) we use a slightly different set of countries for its donor pool. We started by including all countries from the following organisations: BRICS (Brazil, Russia, India, China and South Africa), G20, G20 permanent and temporary invitees (e.g. Bangladesh, Egypt, Spain and Nigeria), the Organisation for Economic Co-operation and Development (OECD) and OECD partners (Brazil, China, India, Indonesia and South Africa). We believe South Africa's economy is more comparable to these countries. Most countries are found in several of the listed organisations, so we ensured that a country was only included once in the donor pool. After excluding South Africa's neighbouring countries and those with missing data we ended up with a donor pool of 44 countries for South Africa. Ultimately, the study uses a panel of more than 50 countries, covering the period 1980–2018, to construct each drought-affected country's synthetic control unit.

9 The year in brackets indicates the year when the country experienced a severe drought.

4. Analysis of results

We start by looking at the countries that received a positive weight when creating each country's synthetic. Table 3 shows the countries used to create each country's counterfactual and the weights used. For example, it shows that the synthetic for Angola was created using a convex combination of four countries: Mauritania (0.443), the Seychelles (0.276), Algeria (0.148) and São Tomé and Príncipe (0.133). South Africa's synthetic was created using many countries – perhaps an indication that South Africa is quite different to the rest of the countries on the continent.

Table 3: Weights for countries used to create each country's synthetic control unit

Country affected by the drought	Countries used to create the synthetic (weights are in brackets)
Angola	Mauritania (0.443), Seychelles (0.276), Algeria (0.148), São Tomé and Príncipe (0.133)
Botswana	Mauritius (0.460), Seychelles (0.311), Mali (0.229)
Malawi	Ethiopia (0.556), Rwanda (0.136), Chad (0.131), Djibouti (0.08), Mali (0.061), Togo (0.036)
Mozambique	Mali (0.944), Djibouti (0.024), Liberia (0.018), Côte d'Ivoire (0.014)
South Africa	Brazil (0.368), Morocco (0.262), Thailand (0.177), Bangladesh (0.100), Mexico (0.034), Switzerland (0.022), Greece (0.017), New Zealand (0.016), Republic of Korea (0.004)
Zambia	Djibouti (0.441), Ghana (0.146), Liberia (0.107), Eswatini (0.105), Ethiopia (0.095), Senegal (0.059), Chad (0.047)
Zimbabwe	Rwanda (0.441), Ethiopia (0.238), Eswatini (0.142), Equatorial Guinea (0.097), Congo (0.074), Benin (0.006), Djibouti (0.002)

Source: Own calculations using data from the World Bank's WDI database and Penn World Tables

In this section we briefly discuss the main results of the study for each country. We conclude the section by summarising the main findings. Figure 2 shows actual South Africa and synthetic South Africa's GDP per capita trajectories. The actual GDP per capita trajectory shows the observed GDP for the country over the sample period. The synthetic trajectory shows South Africa's counterfactual – that is, what would have been observed in terms of economic performance if the country did not experience the drought in 2004. During the pre-treatment period, a good synthetic for South Africa should closely follow (or be almost equal to) the actual observed outcomes, only diverging after treatment (when the drought started). For South Africa, we notice that during the pre-treatment period the two outcomes (actual GDP and synthetic) closely followed each other and diverged just after the start of the drought. This implies that if the drought did not take place, the country's economic performance would have followed the dotted line. However, due to the drought it followed the solid line. The gap between the two gives us the impact of the drought.

The first result to note is that, on average over the post-treatment period, the drought was indeed bad for the economy, as it reduced the country's GDP per capita. For South Africa, the effect of the drought was noticed in 2004, even though it became significant after 2008. A similar picture can be discerned from Figure 3, which shows the gap between actual and synthetic GDP per capita. Figure 3 also shows that during the pre-treatment period the actual GDP and its synthetic were almost equal, implying that the gap between the two was almost zero. After the 2004 drought the gap between the two widened.[10]

Figure 2: The impact of the 2004 drought on South Africa's GDP per capita

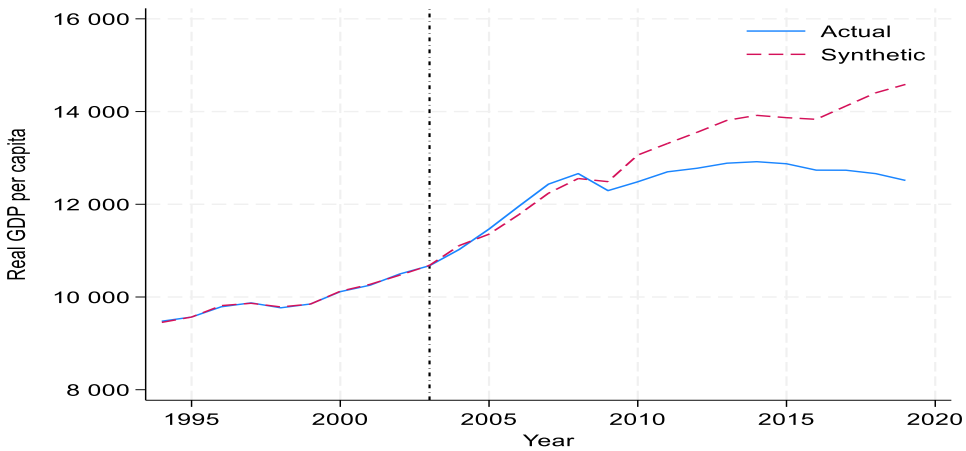
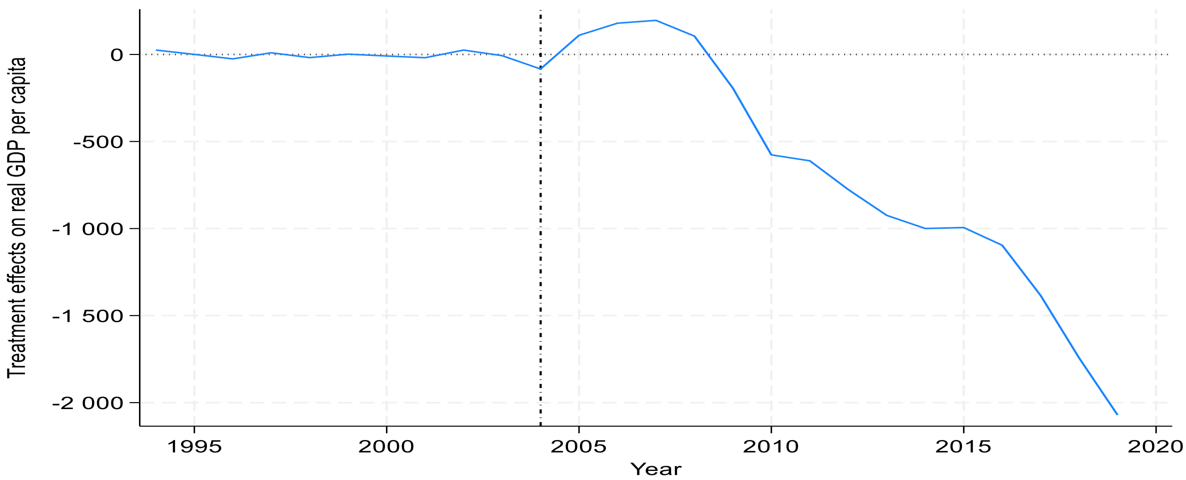


Figure 3: The gap between actual South Africa's GDP per capita and its synthetic counterpart



10 The gap is calculated as actual GDP less synthetic GDP. A negative gap implies that the drought damaged the economy.

The magnitude of the gap or impact of the drought is presented in Table 4. It shows that the country's GDP per capita in 2004 was US$11 026, but if the country did not experience a drought in 2004 the GDP per capita would have been US$83 higher (US$11 109). The 2004 drought thus reduced the country's 2004 GDP per capita by almost 1%. This gap became quite significant after 2008. For example, by 2010 it had increased to negative US$577, implying that had the drought not occurred the country's GDP per capita would have been US$577 higher. Therefore, compared to its counterfactual, the actual GDP per capita in 2004 was about 4% lower. In fact, the average annual treatment effect over the post-treatment period for South Africa was negative US$678.94, implying that compared to its counterfactual the average annual GDP per capita was more than 5% lower than what it would have been if the drought did not occur.

Table 4: Estimated treatment effects of the drought for South Africa

Time	Actual outcome	Synthetic outcome	Treatment effect
2004	11 026.17	11 109.67	-83.50
2005	11 465.24	11 355.10	110.14
2006	11 955.70	11 775.96	179.74
2007	12 434.94	12 239.08	195.86
2008	12 661.69	12 556.15	105.54
2009	12 294.66	12 488.36	-193.70
2010	12 485.36	13 062.13	-576.77
2011	12 700.30	13 311.28	-610.98
2012	12 777.73	13 554.04	-776.31
2013	12 886.86	13 811.23	-924.37
2014	12 918.65	13 918.31	-999.66
2015	12 874.09	13 868.42	-994.33
2016	12 736.61	13 832.41	-1 095.80
2017	12 735.03	14 119.64	-1 384.61
2018	12 661.42	14 404.63	-1 743.21
2019	12 514.91	14 585.99	-2 071.08
Mean	**12 445.59**	**13 124.53**	**-678.94**

A similar analysis shows that the effect of the 2002 drought in Malawi was also quite significant. It lowered the country's post-treatment period GDP per capita by an annual average of US$319. That is, if Malawi did not experience the 2002 drought, its average annual GDP per capita would have been 25% higher. The results of the impact of the drought on Malawi are presented in Figure 4, Figure 5 and Table 5. Malawi's real GDP paths for the actual and synthetic counterparts closely followed each other during the pre-treatment period (before the drought) but then diverged around the drought year.

Table 5 shows that the effect was negative through the entire post-treatment period. Given the frequency of droughts in Malawi, we shortened the post-treatment period to take into account other severe droughts that also affected the country. Malawi's post-treatment period thus ended in 2012 as the country also experienced a drought sometime that year.

Figure 4: The impact of the 2002 drought on Malawi's GDP per capita

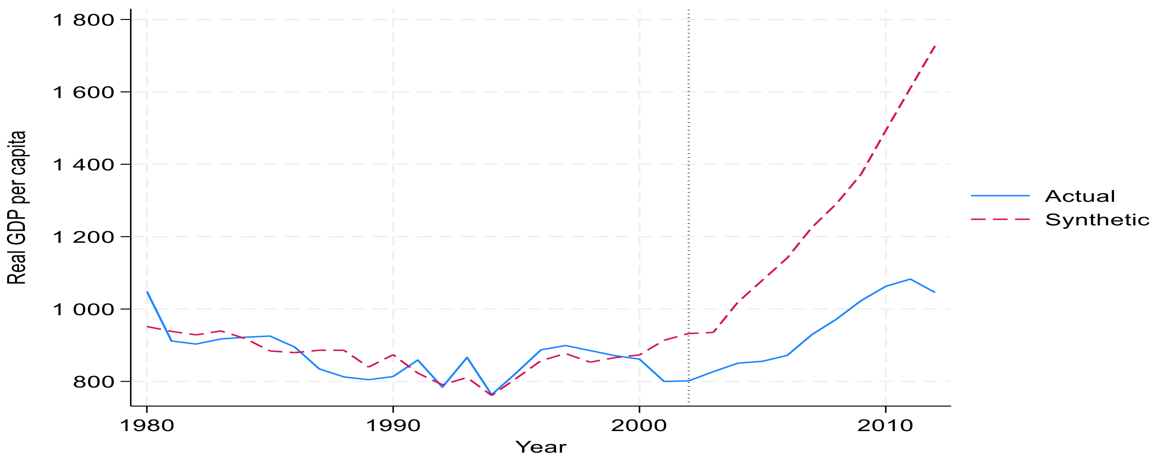


Figure 5: The gap between actual Malawi's GDP per capita and its synthetic counterpart

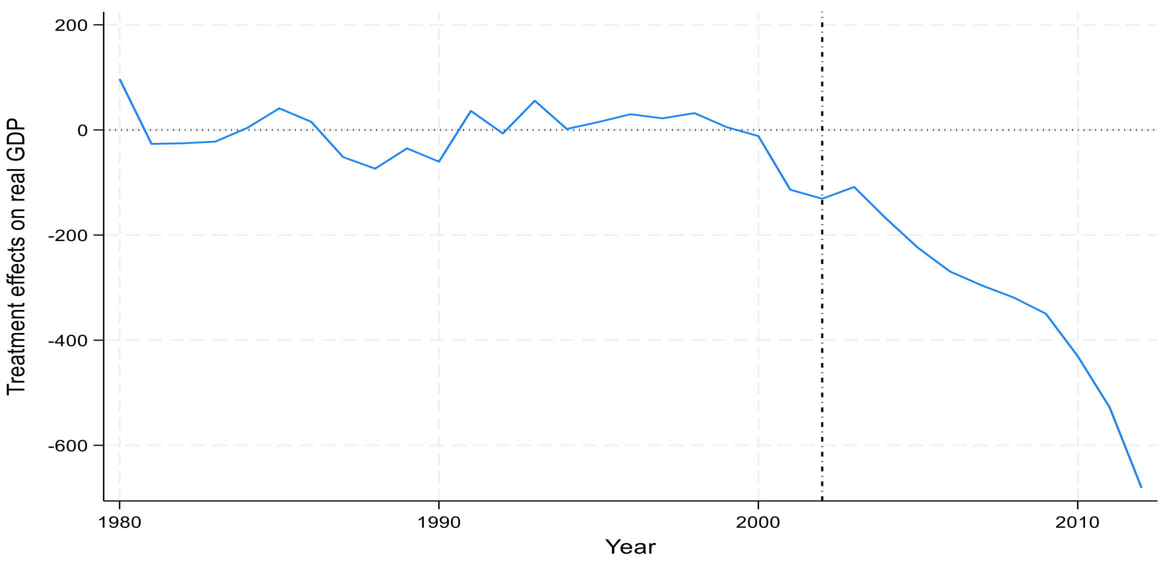


Table 5: Estimated treatment effects of the drought for Malawi

Time	Actual outcome	Synthetic outcome	Treatment effect
2002	801.49	932.38	-130.89
2003	826.99	935.49	-108.50
2004	850.44	1 019.07	-168.63
2005	855.69	1 079.99	-224.30
2006	871.89	1 141.18	-269.29
2007	929.23	1 225.13	-295.90
2008	972.09	1 291.09	-319.00
2009	1 023.21	1 372.72	-349.51
2010	1 062.60	1 492.90	-430.30
2011	1 082.72	1 610.60	-527.88
2012	1 045.86	1 726.98	-681.12
Mean	**938.38**	**1 257.05**	**-318.67**

Angola experienced a severe drought in 1989 and again in 2012. Its post-treatment period was therefore from 1990 to 2011. The results for Angola are shown in Figure 6, Figure 7 and Table 6. The real GDP per capita paths for actual Angola and its synthetic closely followed each other in the pre-treatment period and significantly diverged just after the 1989 drought, with the dotted line showing the country's counterfactual. Table 6 shows that the drought effect was negative throughout the entire post-treatment period. It also shows that the average annual treatment effect for Angola was negative US$1 901, implying that the drought resulted in an output loss of 24%.

Figure 6: The impact of drought on Angola's GDP per capita

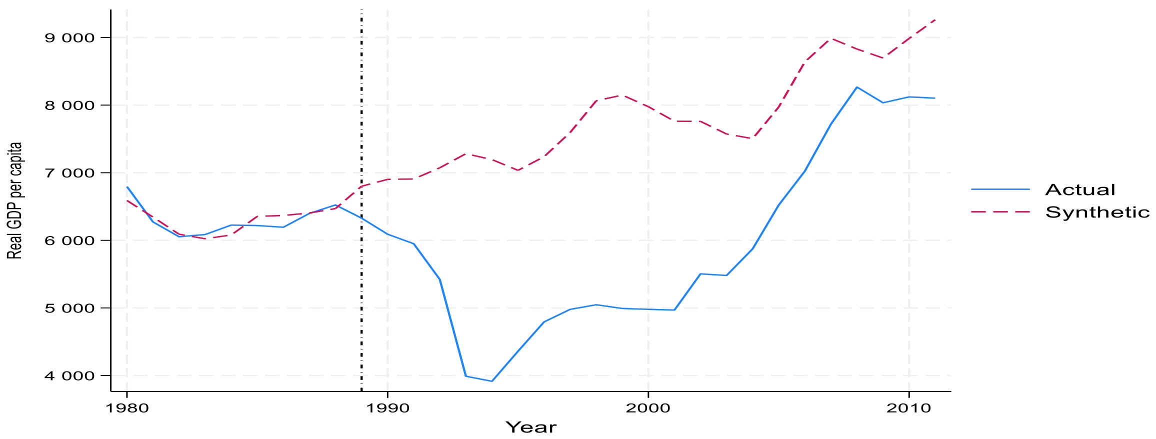


Figure 7: The gap between actual Angola's GDP per capita and its synthetic counterpart

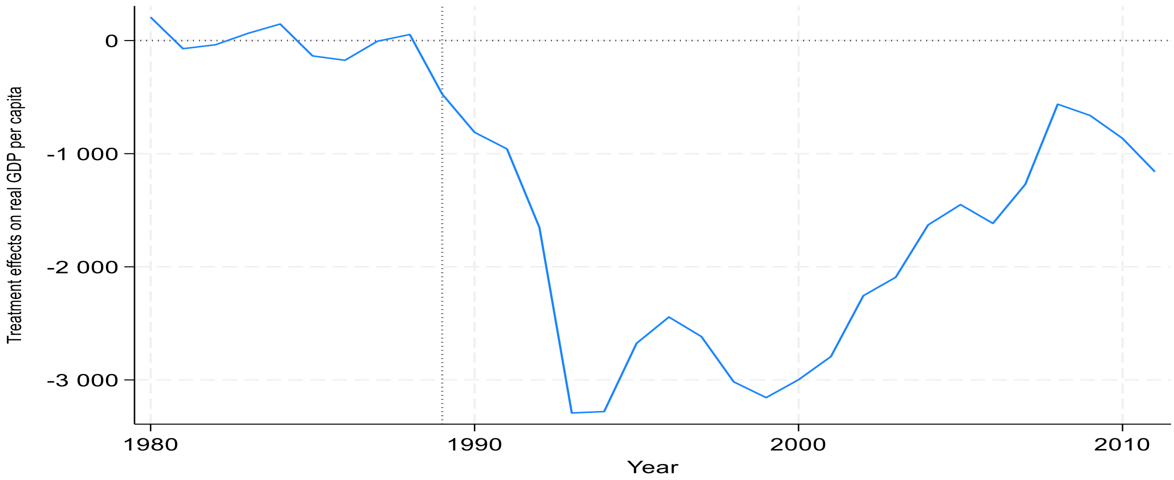


Table 6: Estimated treatment effects of the drought for Angola

Time	Actual outcome	Synthetic outcome	Treatment effect
1989	6 328.18	6 800.76	-472.58
1990	6 090.76	6 902.41	-811.65
1991	5 950.01	6 907.92	-957.91
1992	5 421.83	7 073.27	-1 651.44
1993	3 989.83	7 281.89	-3 292.06
1994	3 914.91	7 194.71	-3 279.80
1995	4 359.62	7 035.80	-2 676.18
1996	4 793.52	7 237.61	-2 444.09
1997	4 979.41	7 596.27	-2 616.86
1998	5 047.36	8 064.70	-3 017.34
1999	4 992.59	8 148.96	-3 156.37
2000	4 979.21	7 977.67	-2 998.46
2001	4 968.79	7 762.15	-2 793.36
2002	5 504.41	7 759.93	-2 255.52
2003	5 480.64	7 573.09	-2 092.45
2004	5 874.55	7 504.47	-1 629.92
2005	6 522.58	7 972.94	-1 450.36
2006	7 023.45	8 639.60	-1 616.15
2007	7 718.02	8 988.60	-1 270.58
2008	8 267.18	8 829.96	-562.78
2009	8 034.97	8 697.36	-662.39
2010	8 121.68	8 986.42	-864.74
2011	8 103.74	9 263.48	-1 159.74
Mean	**5 933.36**	**7 834.78**	**-1 901.42**

We find more or less similar results for Botswana, which experienced a severe drought in 2015 (see Figure 8, Figure 9 and Table 7). Table 7 shows that the effects were negative throughout the post-treatment period. Its average annual effect of negative US$1 746 implies an output loss of 10% (in per capita terms).

Figure 8: The impact of drought on Botswana's GDP per capita

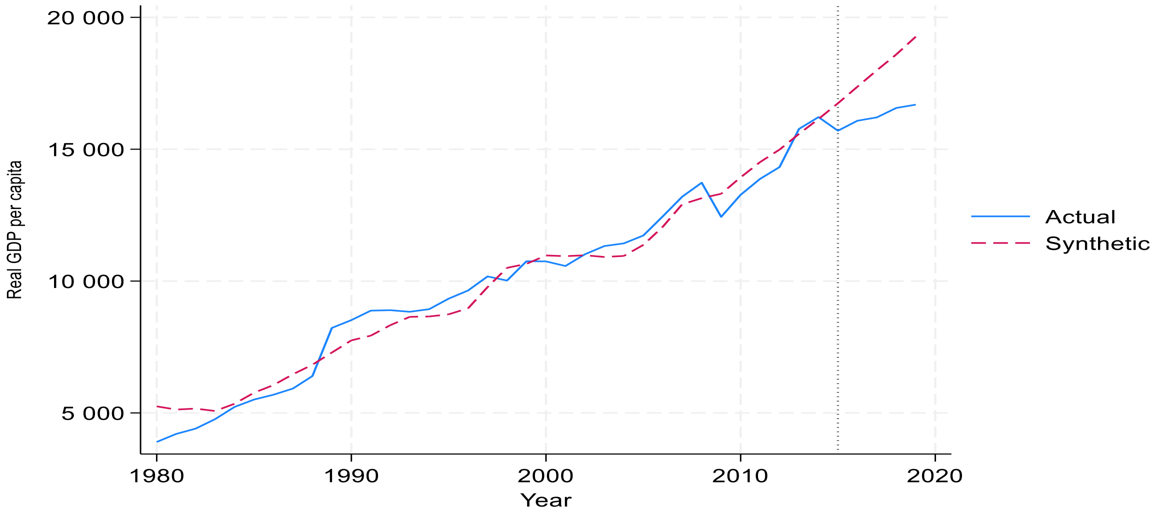


Figure 9: The gap between actual Botswana's GDP per capita and its synthetic counterpart

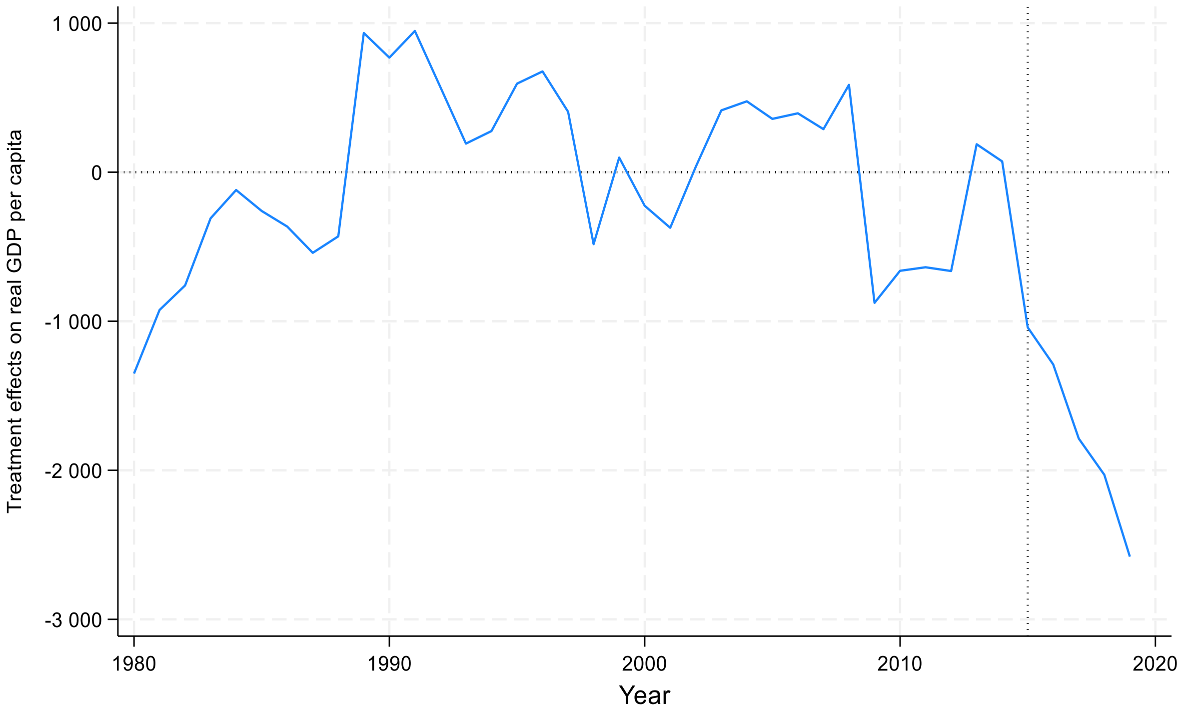


Table 7: Estimated treatment effects of the drought for Botswana

Time	Actual outcome	Synthetic outcome	Treatment effect
2015	15 701.67	16 742.43	-1 040.76
2016	16 080.12	17 369.82	-1 289.70
2017	16 208.26	17 995.45	-1 787.19
2018	16 566.16	18 595.86	-2 029.70
2019	16 690.06	19 269.35	-2 579.29
Mean	**16 249.25**	**17 994.58**	**-1 745.33**

The results for Mozambique show that it was one of the SADC countries significantly affected by the 1991 drought (see Figure 10, Figure 11 and Table 8). Its average annual real GDP per capita decreased by 37% due to the drought. The drought had a negative effect for each of the post-treatment years. Mozambique's drought had the largest adverse effect on real GDP per capita. Zambia was also significantly affected by the 1991 drought. Its main results are shown in Figures 12 and 13 and Table 9. Figures 12 and 13 show that during the post-treatment period the counterfactual was consistently larger than the actual outcome, a clear indication that the drought had an adverse effect on economic growth. These results are supported by the evidence from Table 9. In fact, the average annual output loss for the country was 13%. Figures 14 and 15 and Table 10 show the effect of the 1991 drought on Zimbabwe. The evidence suggests that the country experienced an average annual output loss of 11%. Given that Zimbabwe went through a land reform programme from around 2000, we restricted the post-treatment period to 1999.

Figure 10: The impact of drought on Mozambique's GDP per capita

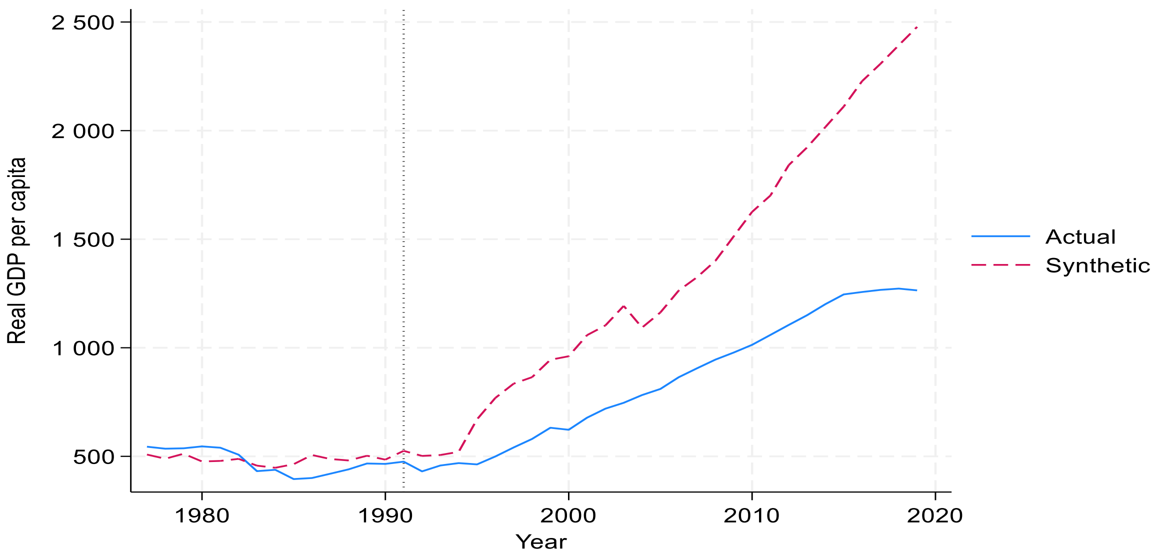


Figure 11: The gap between actual Mozambique's GDP per capita and its synthetic counterpart

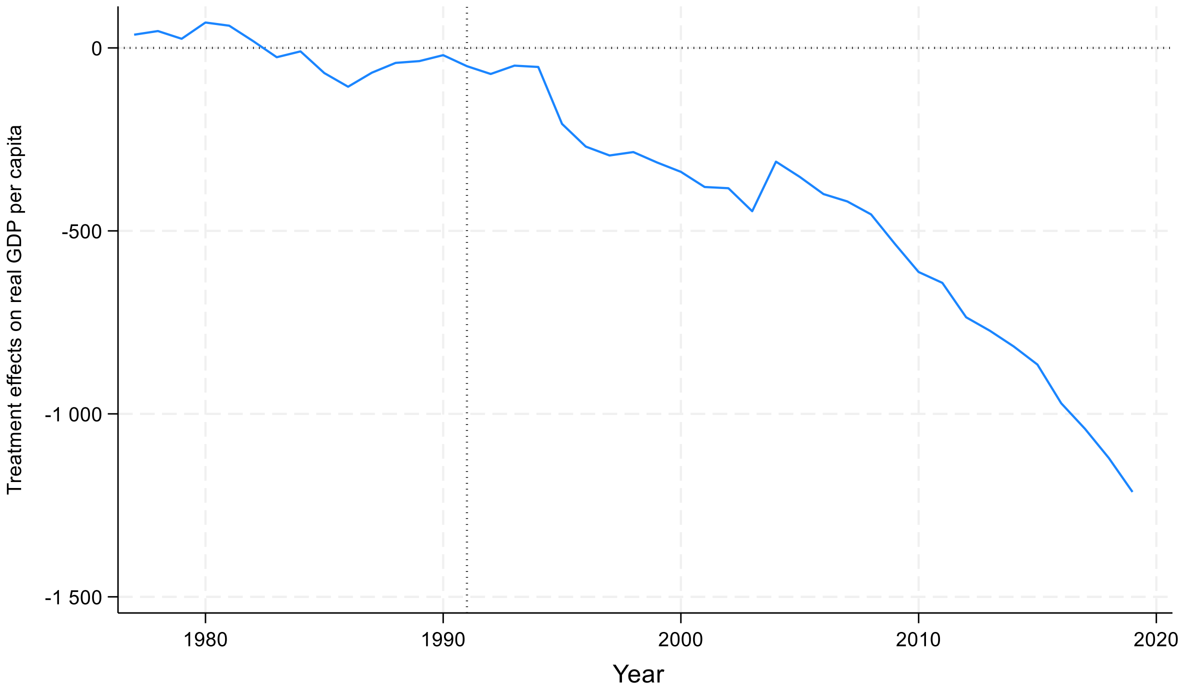


Table 8: Estimated treatment effects of the drought for Mozambique

Time	Actual outcome	Synthetic outcome	Treatment effect
1991	475.49	525.29	-49.80
1992	430.92	502.02	-71.10
1993	457.85	506.22	-48.37
1994	468.94	520.88	-51.94
1995	462.96	670.51	-207.55
1996	499.43	769.04	-269.61
1997	541.06	834.84	-293.78
1998	580.05	864.60	-284.55
1999	631.75	944.84	-313.09
2000	622.32	960.86	-338.54
2001	678.02	1 058.04	-380.02
2002	719.60	1 102.94	-383.34
2003	746.54	1 192.70	-446.16
2004	782.20	1 092.88	-310.68
2005	810.43	1 162.73	-352.30
2006	864.28	1 263.56	-399.28
2007	905.60	1 324.99	-419.39
2008	945.55	1 400.42	-454.87
2009	978.15	1 513.43	-535.28
2010	1 013.56	1 625.72	-612.16
2011	1 059.22	1 701.17	-641.95
2012	1 105.25	1 841.20	-735.95
2013	1 149.92	1 922.80	-772.88
2014	1 200.92	2 016.59	-815.67

2015	1 245.84	2 111.03	-865.19
2016	1 256.86	2 227.92	-971.06
2017	1 266.61	2 307.48	-1 040.87
2018	1 272.60	2 393.18	-1 120.58
2019	1 264.37	2 477.74	-1 213.37
Mean	**842.63**	**1 339.16**	**-496.53**

Figure 12: The impact of drought on Zambia's GDP per capita

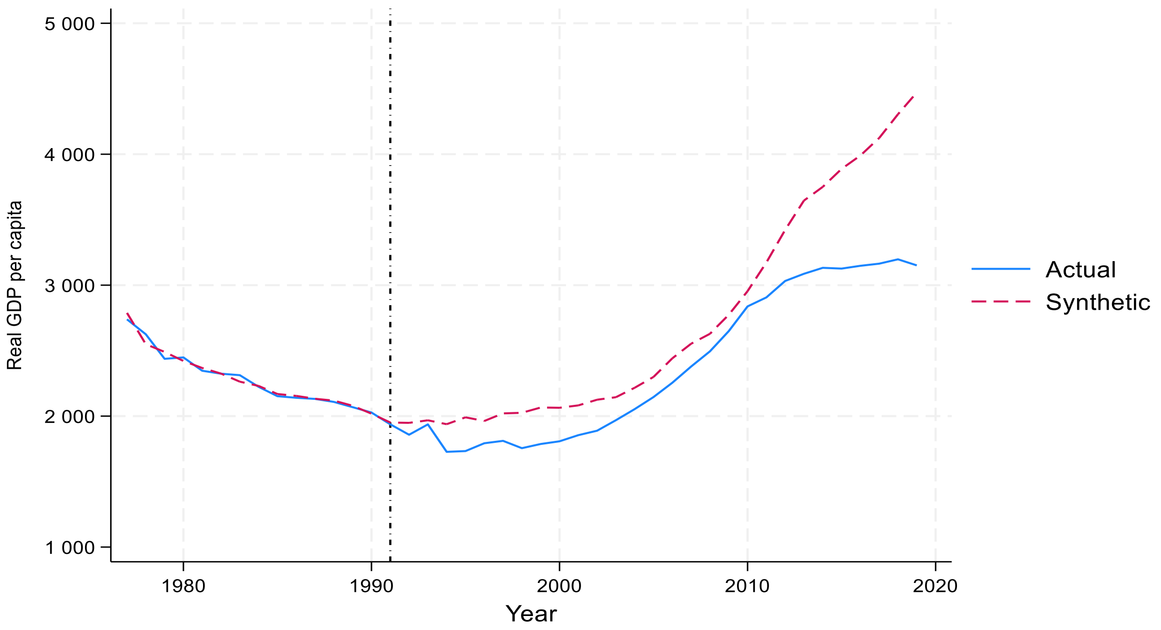


Figure 13: The gap between actual Zambia's GDP per capita and its synthetic counterpart

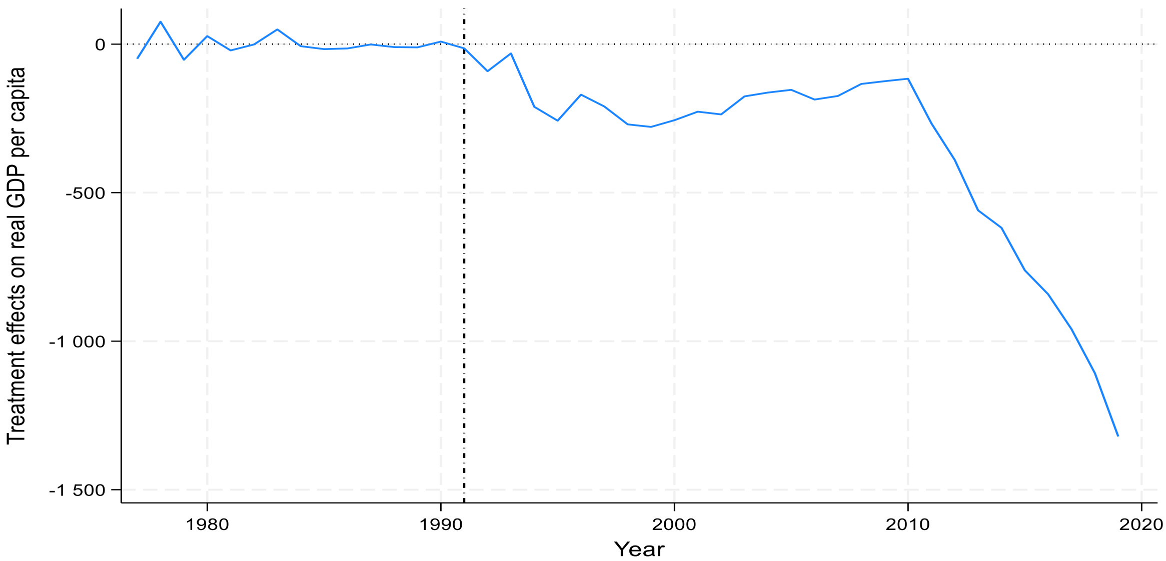


Table 9: Estimated treatment effects of the drought for Zambia

Time	Actual outcome	Synthetic outcome	Treatment effect
1991	1 937.38	1 951.47	-14.09
1992	1 857.73	1 948.82	-91.09
1993	1 936.99	1 968.12	-31.13
1994	1 727.36	1 938.19	-210.83
1995	1 733.09	1 990.71	-257.62
1996	1 792.94	1 962.85	-169.91
1997	1 811.31	2 021.20	-209.89
1998	1 755.15	2 025.24	-270.09
1999	1 787.12	2 065.66	-278.54
2000	1 807.69	2 063.69	-256.00
2001	1 854.61	2 081.98	-227.37
2002	1 888.80	2 125.28	-236.48
2003	1 968.83	2 144.64	-175.81
2004	2 053.67	2 216.69	-163.02
2005	2 145.50	2 299.24	-153.74
2006	2 254.74	2 441.28	-186.54
2007	2 378.69	2 553.12	-174.43
2008	2 494.66	2 628.59	-133.93
2009	2 649.08	2 773.81	-124.73
2010	2 837.96	2 954.32	-116.36
2011	2 906.76	3 173.35	-266.59
2012	3 032.04	3 421.80	-389.76
2013	3 086.96	3 646.46	-559.50
2014	3 132.48	3 750.73	-618.25
2015	3 126.72	3 888.11	-761.39
2016	3 148.11	3 990.24	-842.13
2017	3 164.38	4 123.92	-959.54
2018	3 197.54	4 305.47	-1 107.93
2019	3 151.12	4 471.83	-1 320.71
Mean	**2 366.19**	**2 721.61**	**-355.43**

Figure 14: The impact of drought on Zimbabwe's GDP per capita

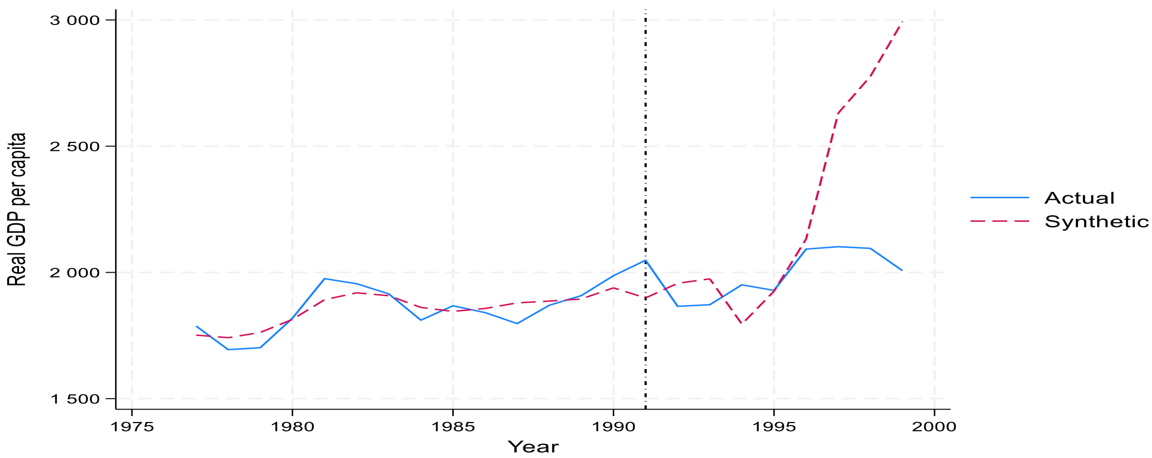


Figure 15: The gap between actual Zimbabwe's GDP per capita and its synthetic counterpart

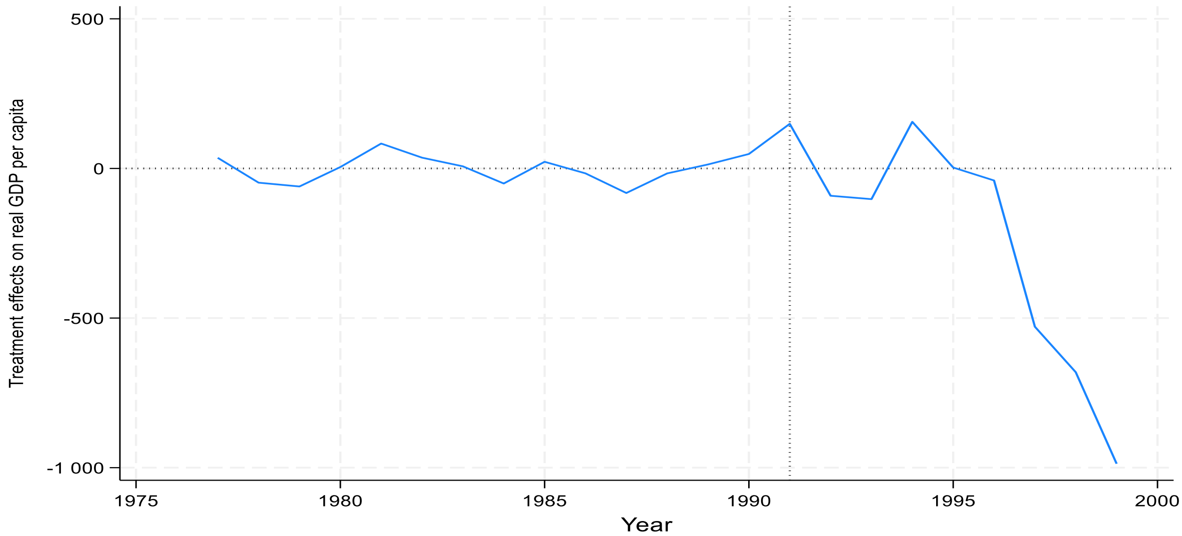


Table 10: Estimated treatment effects of the drought for Zimbabwe

Time	Actual outcome	Synthetic outcome	Treatment effect
1991	2 048.14	1 899.05	149.09
1992	1 865.76	1 957.04	-91.28
1993	1 872.12	1 974.67	-102.55
1994	1 951.00	1 795.17	155.83
1995	1 928.66	1 925.55	3.11
1996	2 092.46	2 132.68	-40.22
1997	2 101.89	2 630.79	-528.90
1998	2 095.37	2 776.24	-680.87
1999	2 007.07	2 993.94	-986.87
Mean	**1 995.83**	**2 231.68**	**-235.85**

Source: Own calculations using data from the World Bank's WDI database and Penn World Tables

Table 11 shows the average annual treatment effect of the drought across the seven countries. It shows that Mozambique experienced the largest output loss (37%), followed by Malawi (25%). South Africa experienced the lowest output loss of 5%. This indicates that South Africa is more diversified than other African countries and is therefore in a better position to absorb and withstand shocks. Our results corroborate findings from elsewhere that also use the SCM. For example, Sheng and Xu (2019) found that a 2002 drought in Australia resulted in a productivity decrease of 18%. Truong and Tri (2021) found evidence of a per capita loss of 11% due to a 2013 drought in Vietnam. Coffman and Noy (2012) found that a natural disaster in Hawaii reduced employment by 15% and population by 12%.

Table 11: Average annual treatment effect over the post-treatment period for SADC countries affected by severe droughts

Country	Actual outcome	Synthetic outcome	Treatment effect	% of synthetic outcome (output loss)	Rank
Mozambique	843	1 339	-496	-37	1
Malawi	938	1 257	-319	-25	2
Angola	5 933	7 835	-1 902	-24	3
Zambia	2 366	2 722	-356	-13	4
Zimbabwe	1 996	2 232	-236	-11	5
Botswana	16 249	17 995	-1 746	-10	6
South Africa	12 446	13 125	-679	-5	7

Source: Own calculations using data from the World Bank's WDI database and Penn World Tables

5. Inference and robustness checks

To be sure that our results are really due to the drought and not an anomaly (and also given that we do not have the traditional post-estimation outcomes like the p-values, R-squared and F-statistics), we conduct two placebo tests (in-space and in-time placebo tests) for each country as well as leave-one-out (LOO) robustness tests, as suggested in Yan and Chen (2023). We explain the tests conducted using the example of South Africa, which experienced a drought in 2004. South Africa had a donor pool of 44 countries and 9 of them were used to construct its synthetic, as these were the only countries with positive weights.[11]

To conduct the in-space placebo test we use a fake treatment test, moving South Africa into the donor pool and iteratively estimating the treatment effect (impact of the 2004 drought) for each of the countries in the donor pool. For example, we assume that India (which is part of the donor pool and therefore not affected by the drought in South Africa) is the treated unit. In other words, we assume that it was exposed to the treatment of experiencing the 2004 drought that affected South Africa. We expect the untreated countries not to be significantly affected by the event. With regards to the fake treatment period test, we pick a different year (during the pre-treatment period) and assume that the country was affected by the drought during that period. For example, South Africa experienced the drought in 2004, so we conduct a fake treatment in, say, 2000. We do not expect the effect of that treatment to be significant.

11 This is normally the case when constructing the synthetic control units.

This exercise was done across all the treated countries, taking into account their drought years.

We conducted the in-space placebo test for South Africa. Figure B6 shows the treatment and placebo effects for South Africa. It shows that for a majority of donor countries, the effect on South Africa is larger than the placebo effects, as expected. Figure B5 also shows the post- to pre-treatment mean squared prediction error (MSPE) ratios from the above exercise. It shows that the ratio for the treated unit is larger than those for a majority of the donor pool countries, as expected.

The estimated treatment effects reported in section 4 may well be disproportionately driven by a single country with a non-zero weight. We therefore conducted the LOO robustness test. It estimates the treatment effects while omitting one unit with a non-zero weight (Yan and Chen 2023). The expectation is that the estimated treatment effects under the LOO scenario should not be significantly different to those estimated using all control units (Yan and Chen 2023). That is, the results should be qualitatively similar regardless of the non-zero weight control unit excluded. Figure B3 compares the LOO and predicted outcomes for South Africa, and Figure B4 shows the treatment effects under the LOO scenario for South Africa. The two figures show that the results were qualitatively similar in the pre-treatment period and part of the post-treatment period (before 2010), but beyond 2010 the results are qualitatively dissimilar. This suggests that perhaps one or two countries have some disproportionate influence on the results.

The LOO scenario results for the following countries indicate some qualitatively similar results: Malawi (Figures B9 and B10), Angola (Figures B13 and B14) and Zambia (Figures B21 and B22). The results for Botswana (see Figures B15 and B16) and Zimbabwe (see Figures B25 and B26) seem to suggest that some countries have a disproportionate influence on the results. For a quantitative comparison of the synthetic outcomes and those under the LOO scenario, see the following tables: Tables B1 and B2 (South Africa), Tables B3 and B4 (Malawi), Tables B5 and B6 (Angola), Tables B7 and B8 (Botswana), Tables B9 and B10 (Zambia), and Tables B11 and B12 (Zimbabwe).

We also conducted in-time placebo tests for each country and found no evidence that the effect estimated could have happened at any other pre-treatment period. The results of the in-time placebo tests can be found in the following figures: Figures B1 and B2 (South Africa), Figures B7 and B8 (Malawi), Figures B11 and B12 (Angola), Figures B17 and B18 (Botswana), Figures B19 and B20 (Mozambique), Figures B23 and B24 (Zambia), and Figures B27 and B28 (Zimbabwe).

6. Conclusion

Understanding the effects of drought is important for countries in Africa, given that they are highly vulnerable to climate change. This understanding encourages governments to invest in irrigation and drought-resistant seeds to mitigate the impacts of climate change. It is important to note that despite its limited role in causing climate change, Africa has been significantly affected by climate change, particularly in the form of droughts and flooding.

Most research on the economic impact of climate change has largely focused on its short-term effects (Sheng and Xu 2019). This study uses the SCM to investigate both short-term and long-term effects of droughts in the SADC region. The SCM enables us to credibly identify the effect of droughts, as it creates a credible counterfactual. Our results show that the droughts in the SADC region can be quite devastating. The average annual GDP per capita loss was about 18% across the countries studied, except for South Africa, where it was about 5%. The study results also suggest that the effects of the droughts are long-lasting. Rather than focusing on short-term responses, policymakers should therefore consider both long-term and short-term policy responses to droughts. Commercial banks and central banks may find the study's results important as farmers often rely on bank credit. If they fail to honour their obligations (due to climate change), it could trigger systemic risks for the banking sector and possibly the entire economy.

Annexures: Tables and results

Annex A

Table A1: SADC member states

Angola	Mauritius
Botswana	Mozambique
Comoros	Namibia
Democratic Republic of Congo	Seychelles
Eswatini	South Africa
Lesotho	Tanzania
Madagascar	Zambia
Malawi	Zimbabwe

Table A2: Definitions of the variables

Variable name used	Variable name from the source	Definition	Source[12]
Outcomes			
FDI	FDI	Foreign direct investment net inflows (US$ million)	WDI
Real GDP	rgdpna	Real GDP at constant 2017 national prices (in million 2017 US$)	PWT
Expenditure-side real GDP	rgdpe	Expenditure-side real GDP at chained purchasing power parity (PPP) (in million 2017 US$)	PWT
Cereal production per capita	cereal_pdn_per_capita	Annual total production of cereals in metric tonnes divided by total population. Production data on cereals relate to crops harvested for dry grain only.	WDI
Crop production index	crop_production_index	Crop production index (2014–2016 = 100). Crop production index shows agricultural production for each year relative to the base period 2014–2016. It includes all crops except fodder crops.	WDI
Food production index	food_prod_index	Food production index (2014–2016 = 100). Food production index covers food crops that are considered edible and that contain nutrients. Coffee and tea are excluded because, although edible, they have no nutritive value.	WDI
Agricultural valued added	Value added	Real agricultural value added per capita based on 2015 prices	WDI
Predictors			
Real household consumption	ccon_pwt	Real household consumption at constant 2017 national prices (in million 2017 US$)	PWT
Human capital	Human capital	Human capital index, based on years of schooling and returns to education	PWT
Employment	emp	Number of people engaged (in millions)	PWT
Population	pop	Population (in millions)	PWT
Capital stock	cn	Capital stock at current PPPs (in million 2017 US$)	PWT
Real capital stock	rnna	Capital stock at constant 2017 national prices (in million 2017 US$)	PWT

[12] WDI stands for World Development Indicators; PWT stands for Penn World Tables.

Annex B: Robustness checks results

South Africa

Figure B1: In-time placebo test – actual vs synthetic outcomes (South Africa)

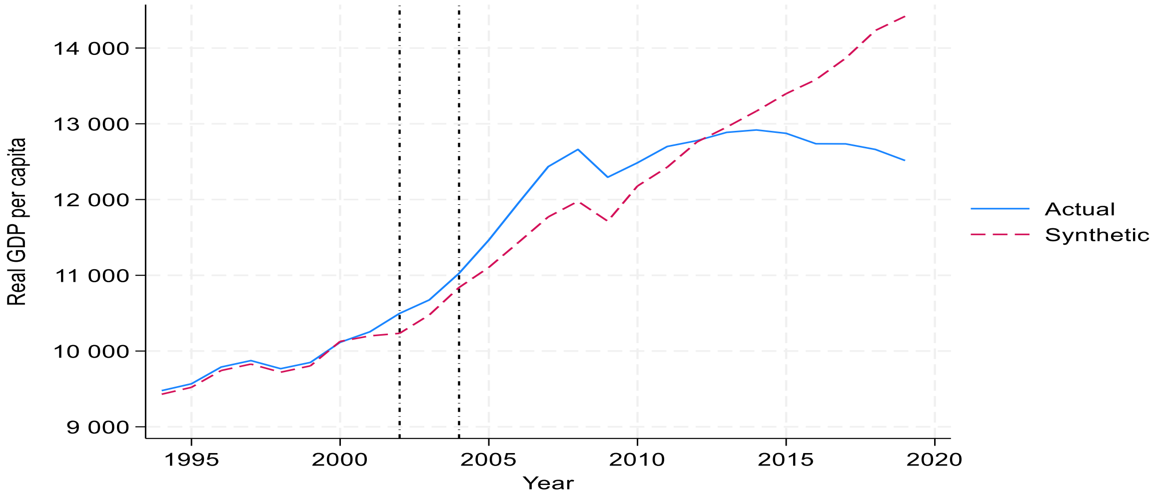


Figure B2: In-time placebo test – treatment effects (South Africa)

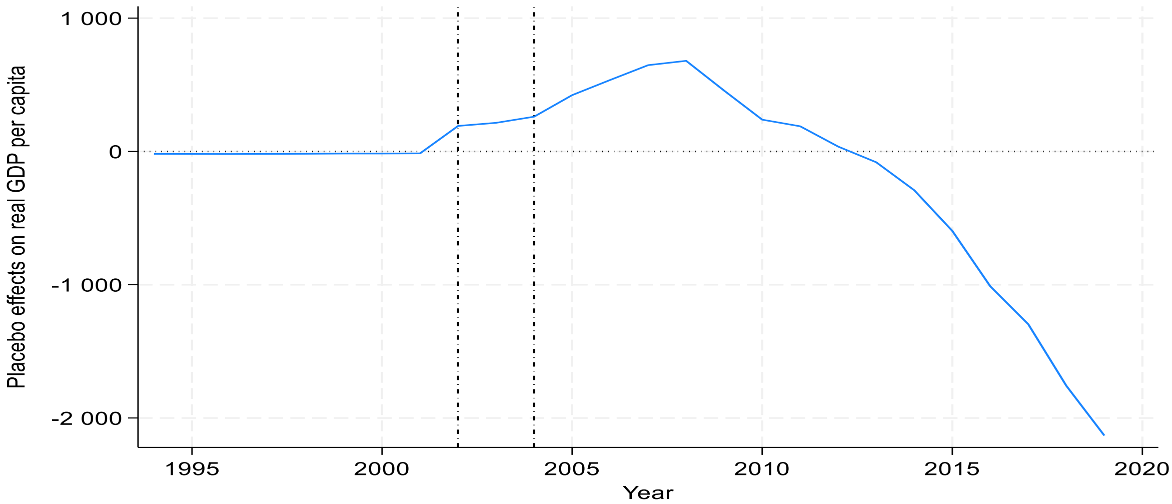


Figure B3: LOO robustness tests – actual vs predicted paths (South Africa)

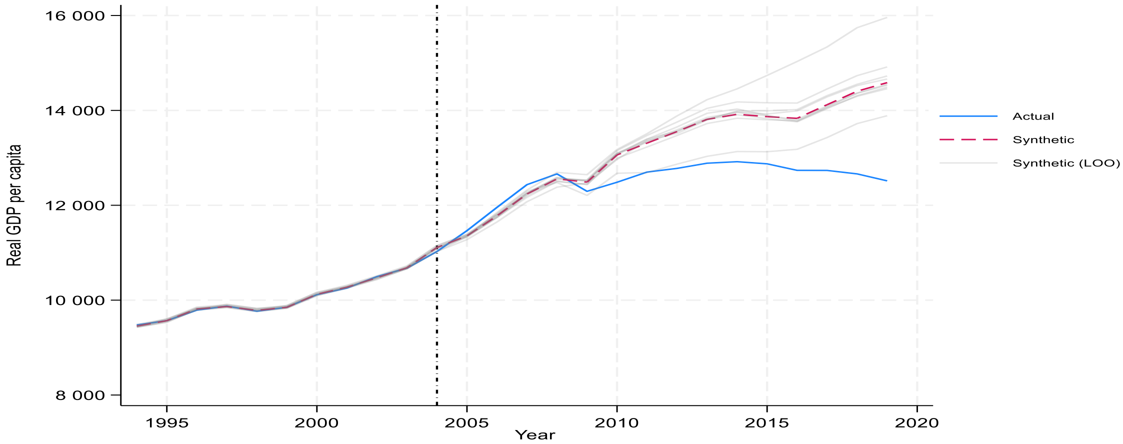


Figure B4: LOO robustness test – predicted vs LOO scenario treatment effects (South Africa)

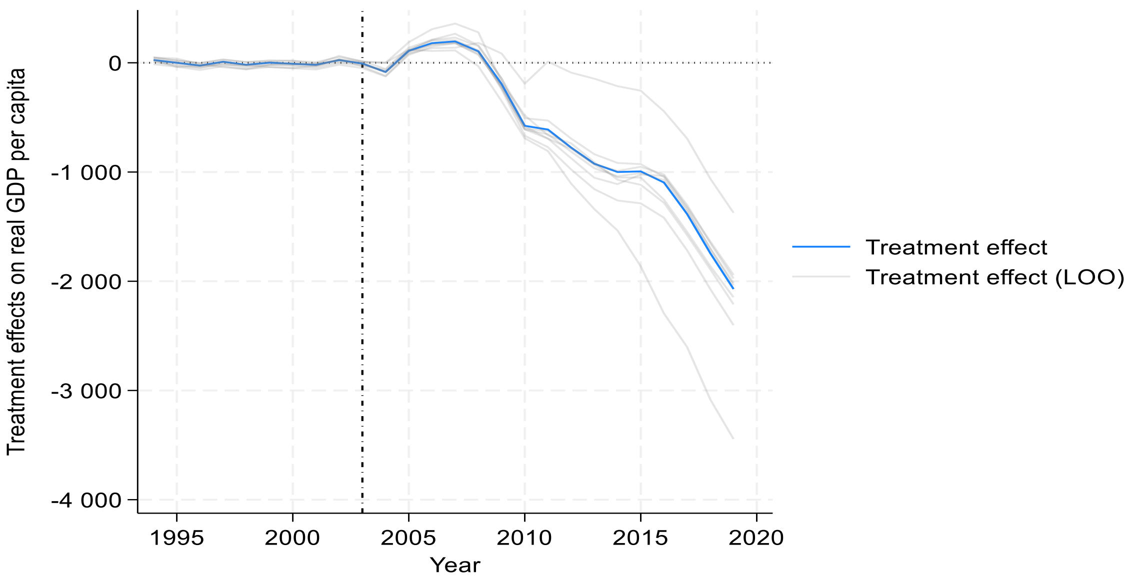


Table B1: LOO robustness test – actual vs synthetic vs synthetic LOO outcomes (South Africa)

	Outcome		Synthetic outcome (LOO)	
Time	Actual	Synthetic	Min	Max
2004	11 026	11 110	11 024	11 151
2005	11 465	11 355	11 277	11 393
2006	11 956	11 776	11 648	11 847
2007	12 434	12 239	12 075	12 322
2008	12 662	12 556	12 382	12 693
2009	12 295	12 488	12 209	12 645
2010	12 485	13 062	12 676	13 176
2011	12 700	13 311	12 690	13 509
2012	12 778	13 554	12 868	13 883
2013	12 887	13 811	13 032	14 226
2014	12 919	13 918	13 132	14 454
2015	12 874	13 868	13 129	14 738
2016	12 737	13 832	13 180	15 031
2017	12 735	14 120	13 429	15 338
2018	12 661	14 404	13 722	15 744
2019	12 515	14 586	13 888	15 960

Note: The last two columns report the minimum and maximum synthetic outcomes when one control unit with a non-zero weight is excluded at a time.

Table B2: LOO robustness test – predicted vs LOO scenario treatment effects (South Africa)

Time	Treatment effect	Treatment effect (LOO)	
		Min	Max
2004	-84	-125	2
2005	110	73	189
2006	180	109	308
2007	195	113	360
2008	106	-32	279
2009	-193	-350	86
2010	-577	-690	-190
2011	-611	-808	11
2012	-776	-1 106	-90
2013	-924	-1 339	-145
2014	-999	-1 536	-213
2015	-994	-1 863	-255
2016	-1 095	-2 295	-444
2017	-1 385	-2 603	-694
2018	-1 743	-3 082	-1 061
2019	-2 071	-3 445	-1 373

Note: The last two columns report the minimum and maximum treatment effects when one control unit with a non-zero weight is excluded at a time.

Figure B5: In-space placebo test: post/pre-treatment MSPE ratios

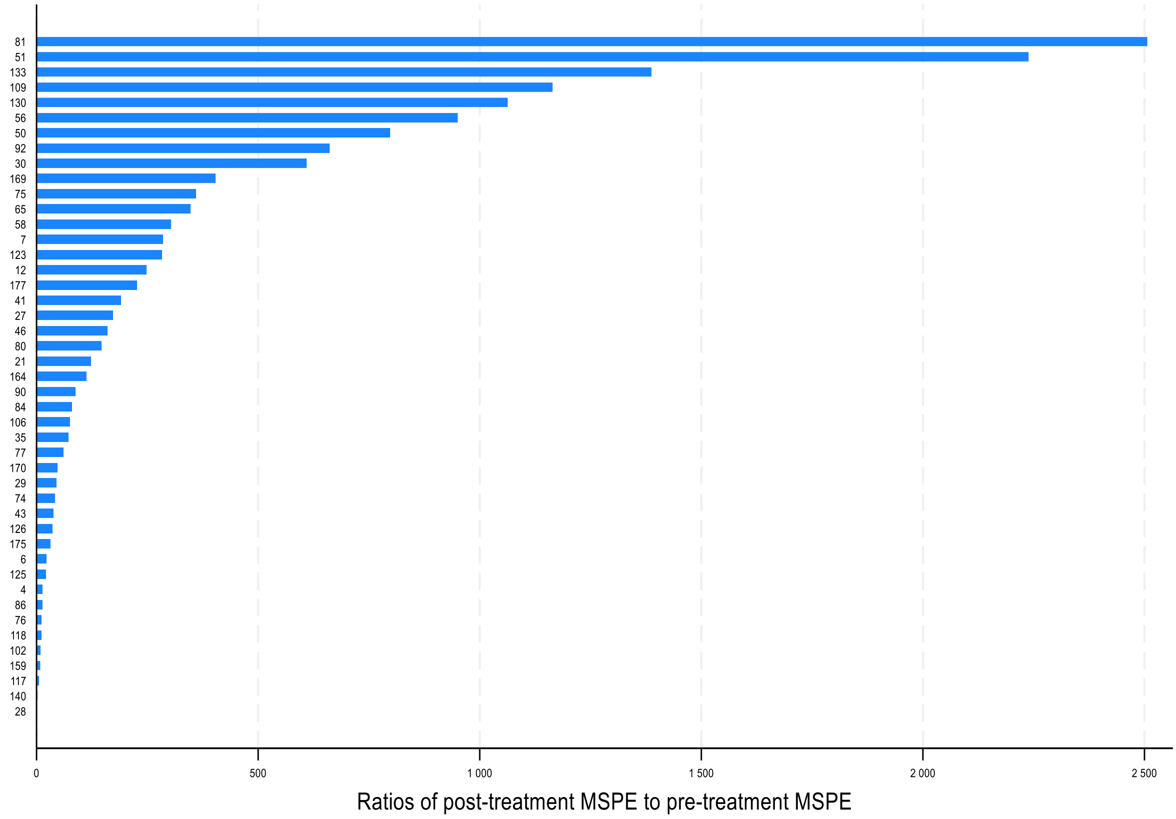
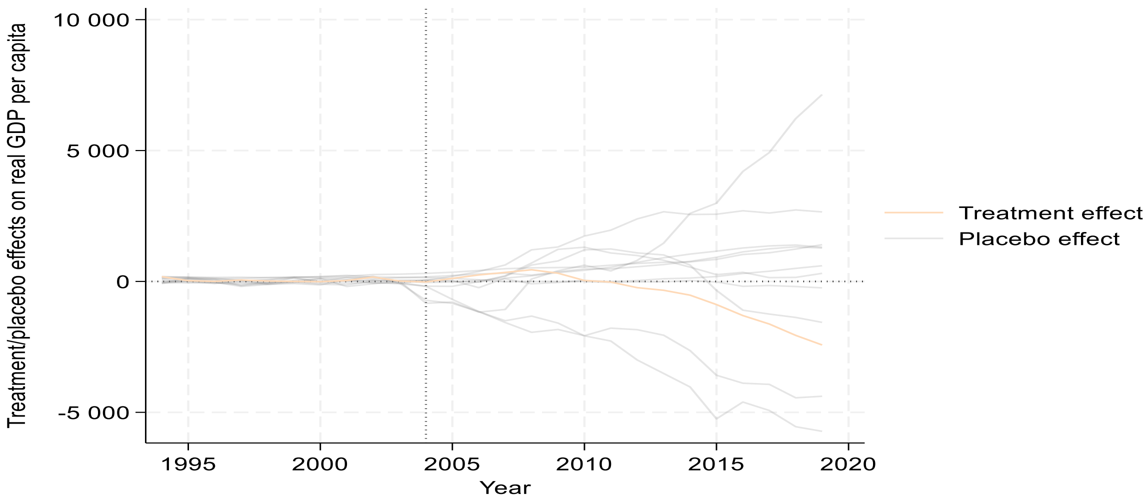


Figure B6: In-space placebo tests – treatment and placebo effects



Malawi

Figure B7: In-time placebo test – actual vs synthetic outcomes (Malawi)

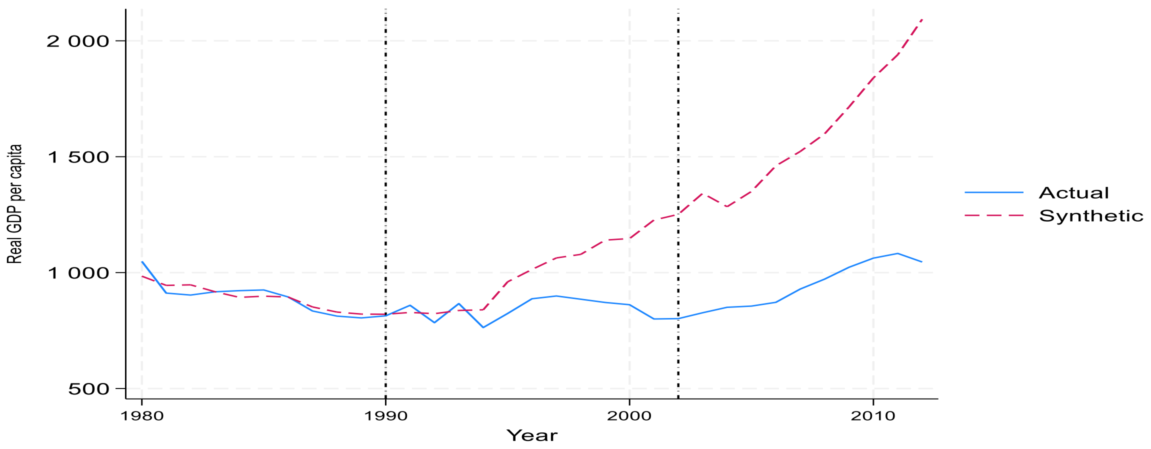


Figure B8: In-time placebo test – treatment effects (Malawi)

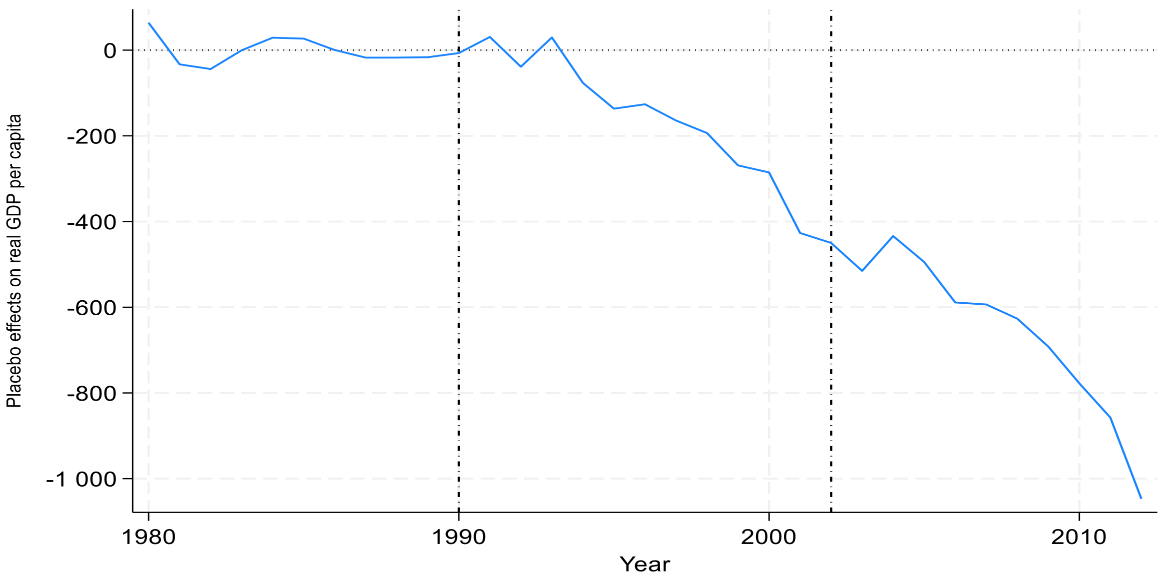


Figure B9: LOO robustness test – actual vs predicted paths (Malawi)

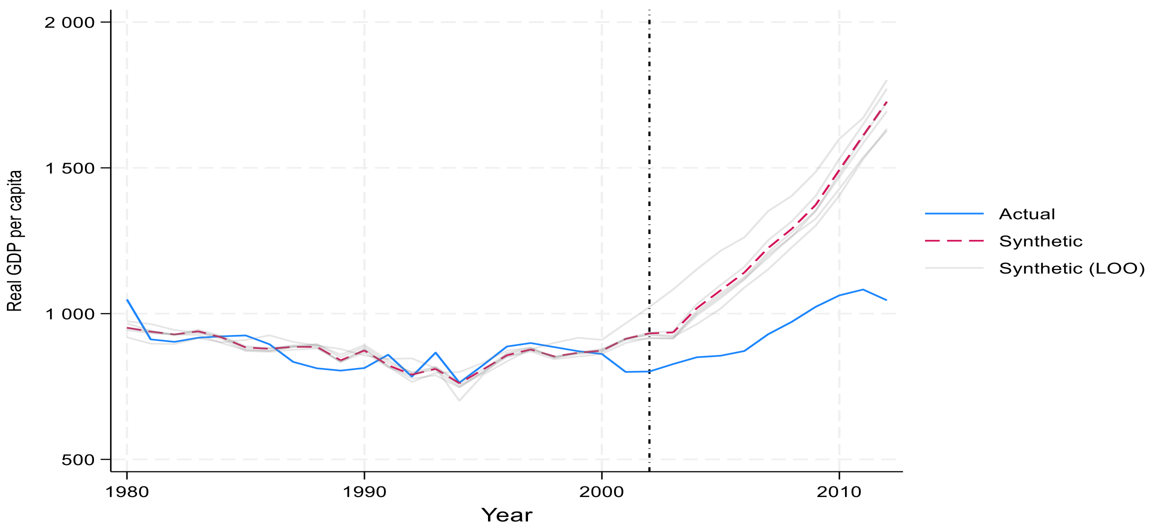


Figure B10: LOO robustness test – predicted vs LOO scenario treatment effects (Malawi)

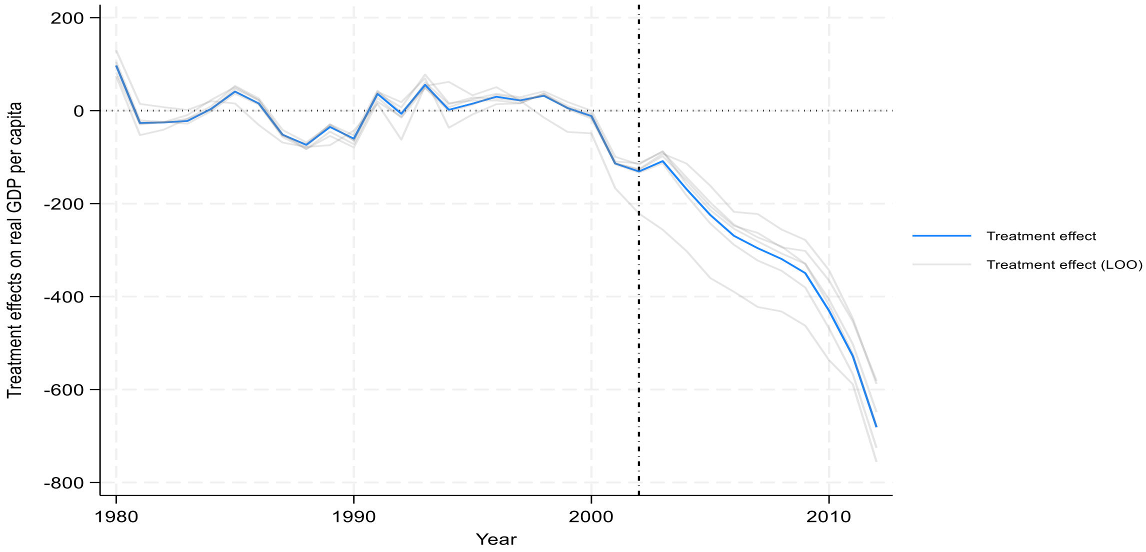


Table B3: LOO robustness test – actual vs synthetic vs synthetic LOO outcomes (Malawi)

	Outcome		Synthetic outcome (LOO)	
Time	Actual	Synthetic	Min	Max
2002	801	932	915	1 023
2003	827	935	914	1 083
2004	850	1 019	964	1 152
2005	856	1 080	1 017	1 216
2006	872	1 141	1 090	1 262
2007	929	1 225	1 152	1 352
2008	972	1 291	1 228	1 404
2009	1 023	1 373	1 301	1 486
2010	1 063	1 493	1 407	1 599
2011	1 083	1 611	1 530	1 671
2012	1 046	1 727	1 627	1 802

Note: The last two columns report the minimum and maximum synthetic outcomes when one control unit with a non-zero weight is excluded at a time.

Table B4: LOO robustness test – predicted vs LOO scenario treatment effects (Malawi)

Time	Treatment effect	Treatment effect (LOO)	
		Min	Max
2002	-131	-221	-113
2003	-108	-256	-87
2004	-169	-302	-114
2005	-224	-360	-161
2006	-269	-390	-218
2007	-296	-422	-222
2008	-319	-432	-256
2009	-350	-463	-278
2010	-430	-537	-343
2011	-528	-589	-447
2012	-681	-756	-581

Note: The last two columns report the minimum and maximum treatment effects when one control unit with a non-zero weight is excluded at a time.

Angola

Figure B11: In-time placebo test – synthetic vs actual outcomes (Angola)

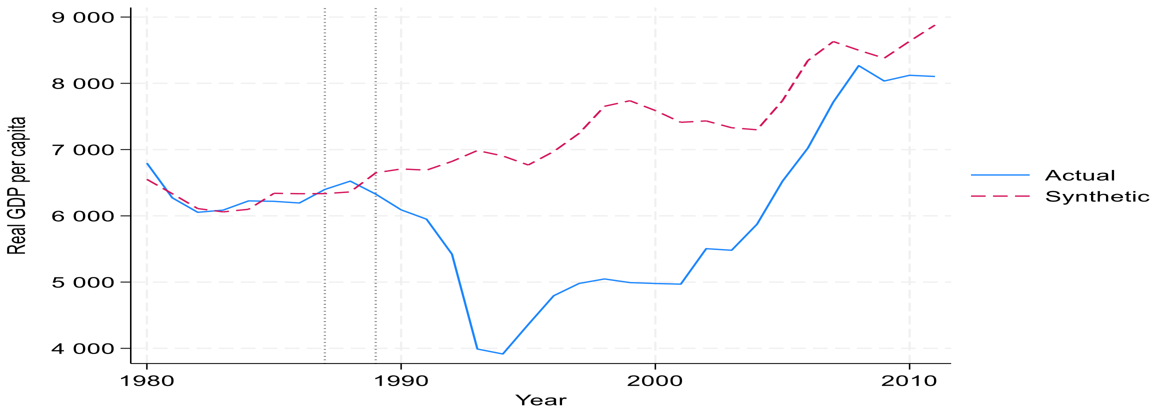


Figure B12: In-time placebo test – treatment effects (Angola)

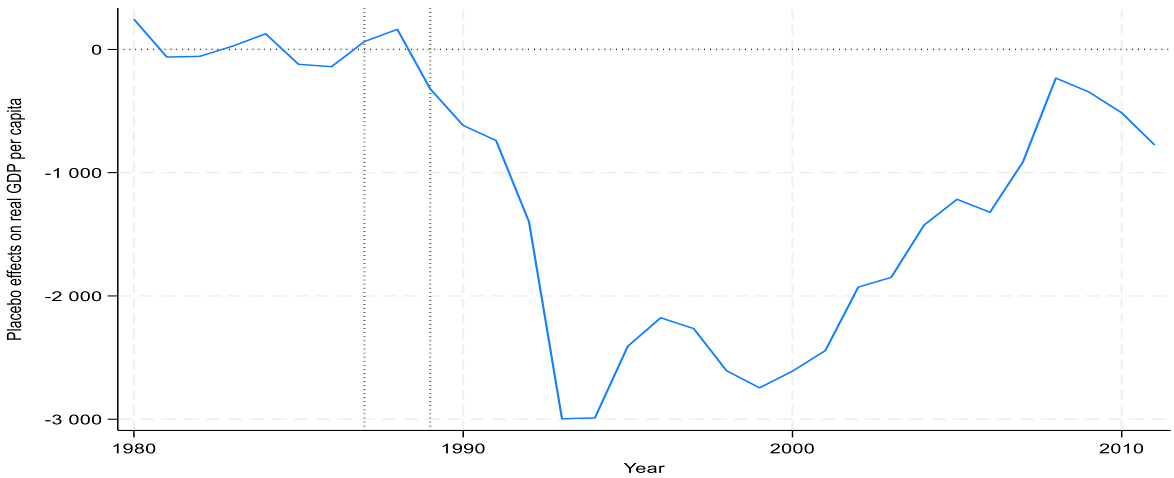


Figure B13: LOO robustness test – predicted vs LOO scenario treatment effects (Angola)

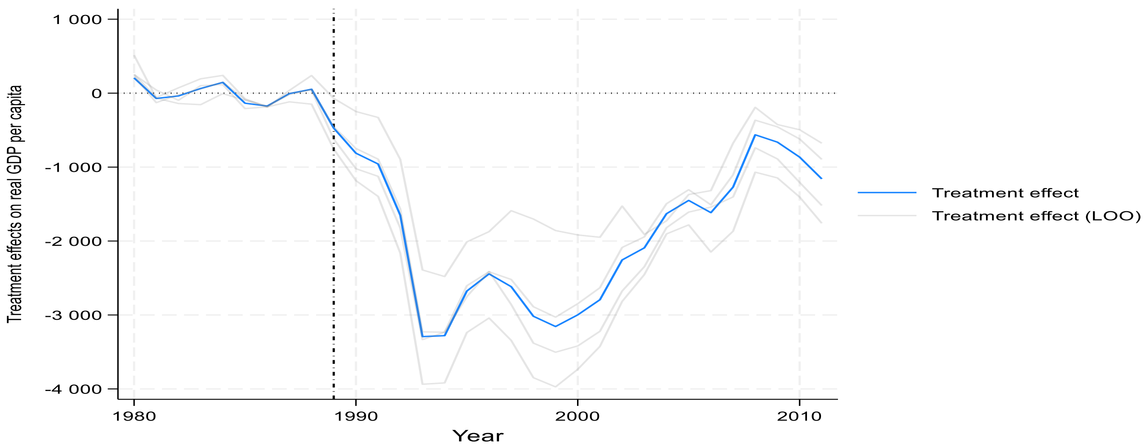


Figure B14: **LOO robustness test – actual vs predicted paths (Angola)**

Table B5: LOO robustness test – actual vs synthetic vs synthetic LOO outcomes (Angola)

	Outcome		Synthetic outcome (LOO)	
Time	**Actual**	**Synthetic**	**Min**	**Max**
1989	6 328	6 801	6 398	7 084
1990	6 091	6 902	6 339	7 273
1991	5 950	6 908	6 279	7 346
1992	5 422	7 073	6 317	7 585
1993	3 990	7 282	6 381	7 926
1994	3 915	7 195	6 395	7 833
1995	4 360	7 036	6 371	7 597
1996	4 794	7 238	6 667	7 835
1997	4 979	7 596	6 569	8 323
1998	5 047	8 065	6 750	8 896
1999	4 993	8 149	6 850	8 965
2000	4 979	7 978	6 897	8 714
2001	4 969	7 762	6 918	8 394
2002	5 504	7 760	7 031	8 321
2003	5 481	7 573	7 391	7 934
2004	5 875	7 504	7 369	7 778
2005	6 523	7 973	7 829	8 304
2006	7 023	8 640	8 341	9 172
2007	7 718	8 989	8 396	9 586
2008	8 267	8 830	8 459	9 336
2009	8 035	8 697	8 459	9 181
2010	8 122	8 986	8 616	9 526
2011	8 104	9 263	8 781	9 863

Note: The last two columns report the minimum and maximum synthetic outcomes when one control unit with a non-zero weight is excluded at a time.

Table B6: LOO robustness test – predicted vs LOO scenario treatment effects (Angola)

Time	Treatment effect	Treatment effect (LOO)	
		Min	Max
1989	-473	-756	-70
1990	-811	-1 183	-248
1991	-958	-1 396	-329
1992	-1 651	-2 163	-895
1993	-3 292	-3 937	-2 391
1994	-3 280	-3 919	-2 480
1995	-2 676	-3 237	-2 011
1996	-2 444	-3 041	-1 873
1997	-2 617	-3 344	-1 589
1998	-3 018	-3 848	-1 702
1999	-3 156	-3 972	-1 858
2000	-2 999	-3 735	-1 917
2001	-2 793	-3 425	-1 949
2002	-2 256	-2 817	-1 527
2003	-2 092	-2 454	-1 910
2004	-1 629	-1 903	-1 495
2005	-1 450	-1 781	-1 306
2006	-1 617	-2 149	-1 318
2007	-1 271	-1 868	-678
2008	-563	-1 068	-191
2009	-662	-1 146	-424
2010	-864	-1 404	-494
2011	-1 160	-1 760	-677

Note: The last two columns report the minimum and maximum treatment effects when one control unit with a non-zero weight is excluded at a time.

Botswana

Table B7: LOO robustness test – actual vs synthetic vs synthetic LOO outcomes (Botswana)

	Outcome		Synthetic outcome (LOO)	
Time	Actual	Synthetic	Min	Max
2015	15 701	16 742	15 710	16 723
2016	16 080	17 370	16 007	17 344
2017	16 208	17 995	16 316	17 926
2018	16 566	18 596	16 581	18 491
2019	16 690	19 269	17 043	19 138

Note: The last two columns report the minimum and maximum synthetic outcomes when one control unit with a non-zero weight is excluded at a time.

Table B8: LOO robustness test – predicted vs LOO scenario treatment effects (Botswana)

Time	Treatment effect	Treatment effect (LOO)	
		Min	Max
2015	-1 041	-1 021	-9
2016	-1 290	-1 264	73
2017	-1 787	-1 718	-108
2018	-2 030	-1 925	-15
2019	-2 579	-2 448	-353

Note: The last two columns report the minimum and maximum treatment effects when one control unit with a non-zero weight is excluded at a time.

Figure B15: LOO – predicted vs LOO outcomes (Botswana)

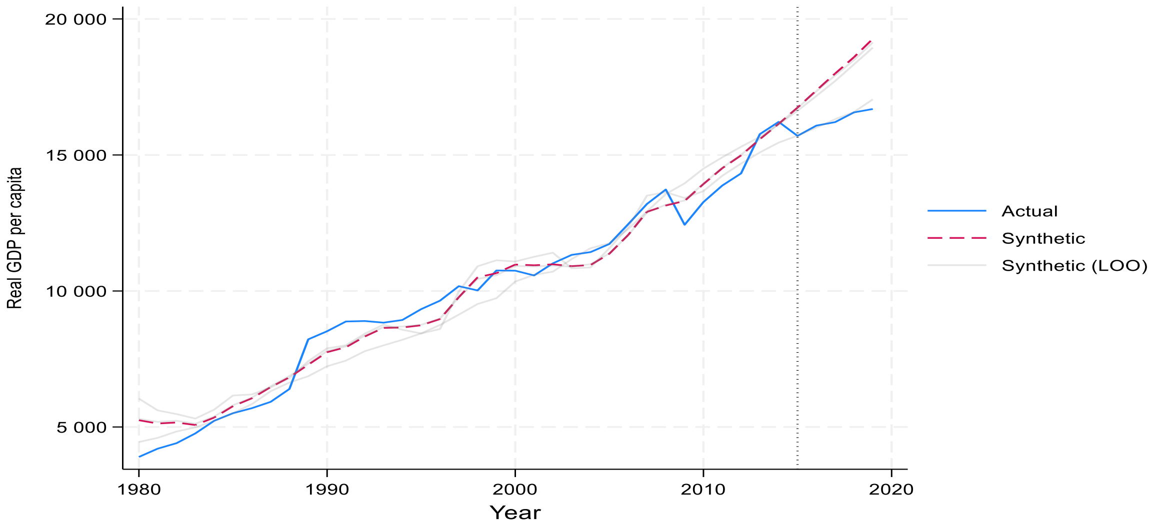


Figure B16: LOO estimated treatment effects vs LOO treatment effects (Botswana)

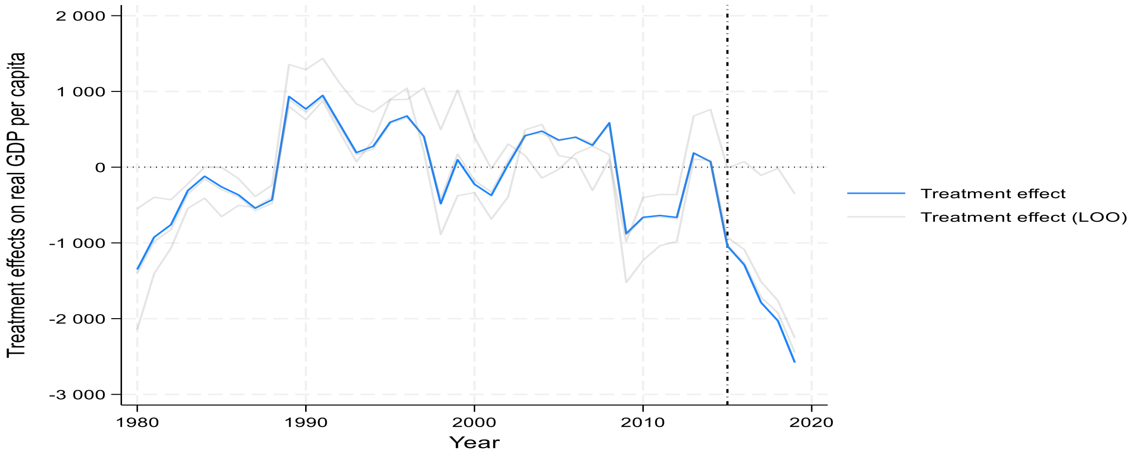


Figure B17: In-time placebo test – treatment effect (Botswana)

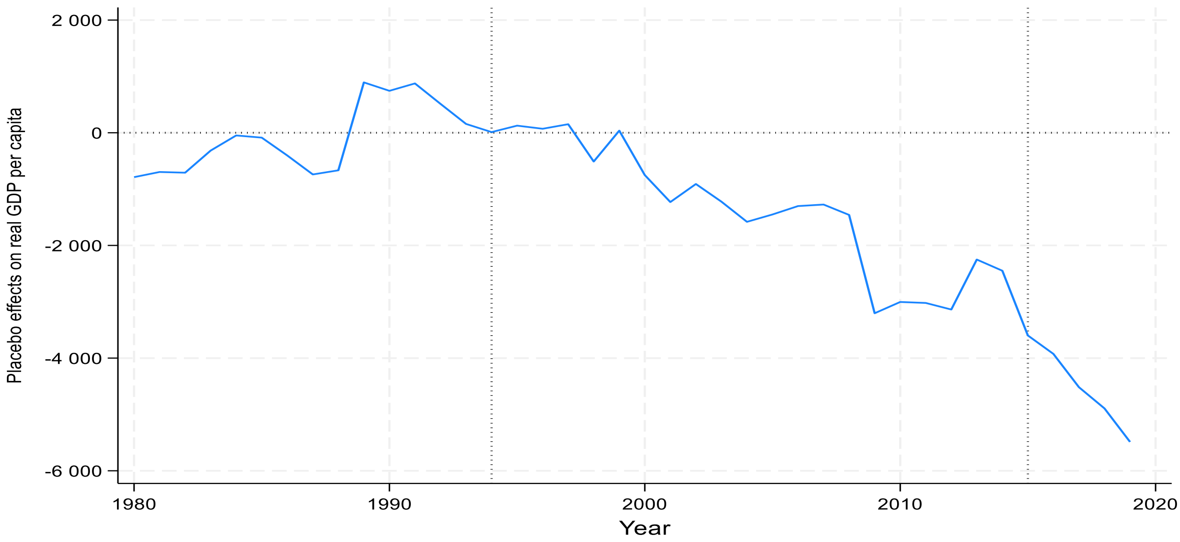
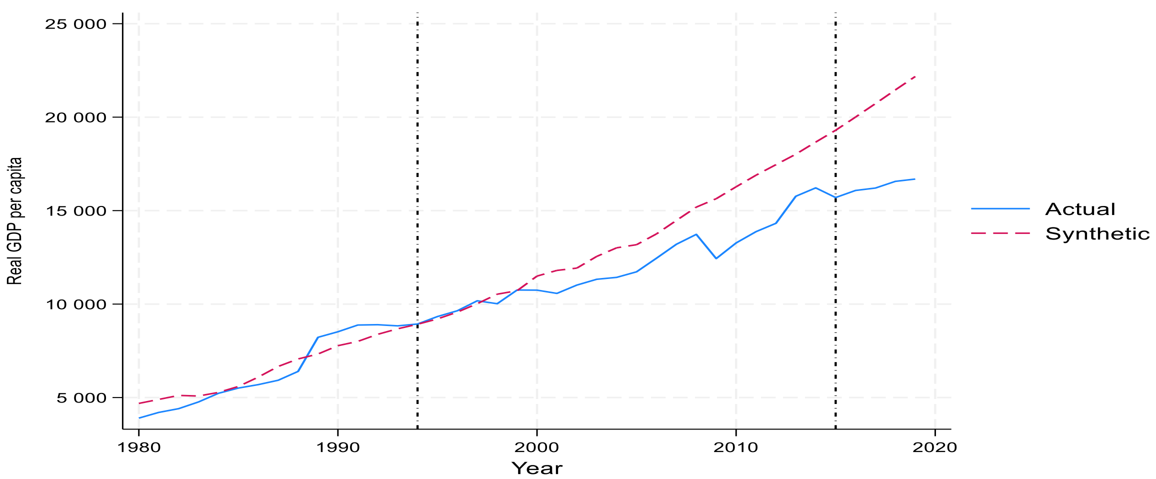


Figure B18: In-time placebo test – actual vs synthetic outcomes (Botswana)



Mozambique

Figure B19: In-time placebo test – actual vs synthetic (Mozambique)

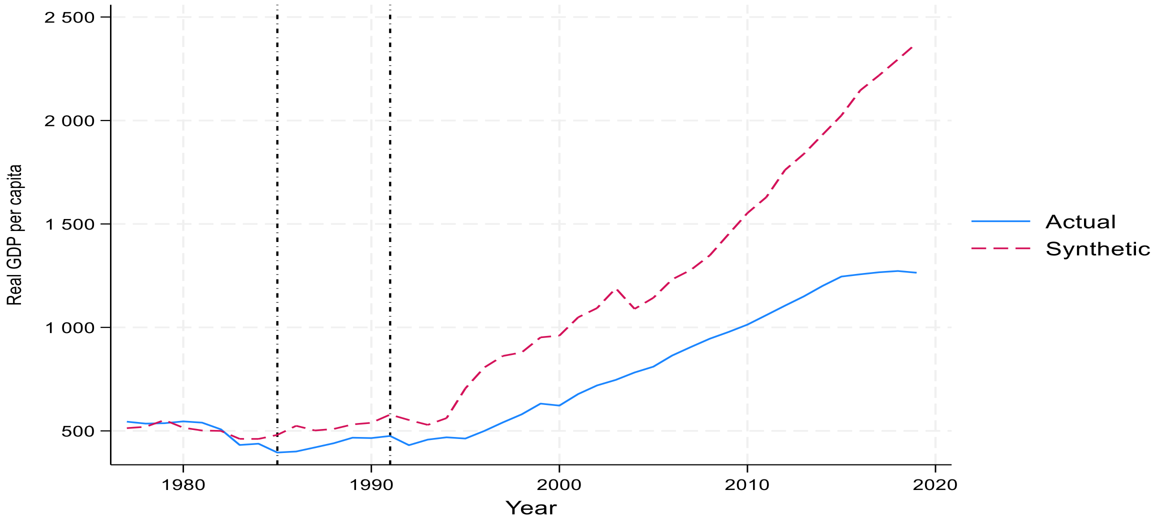
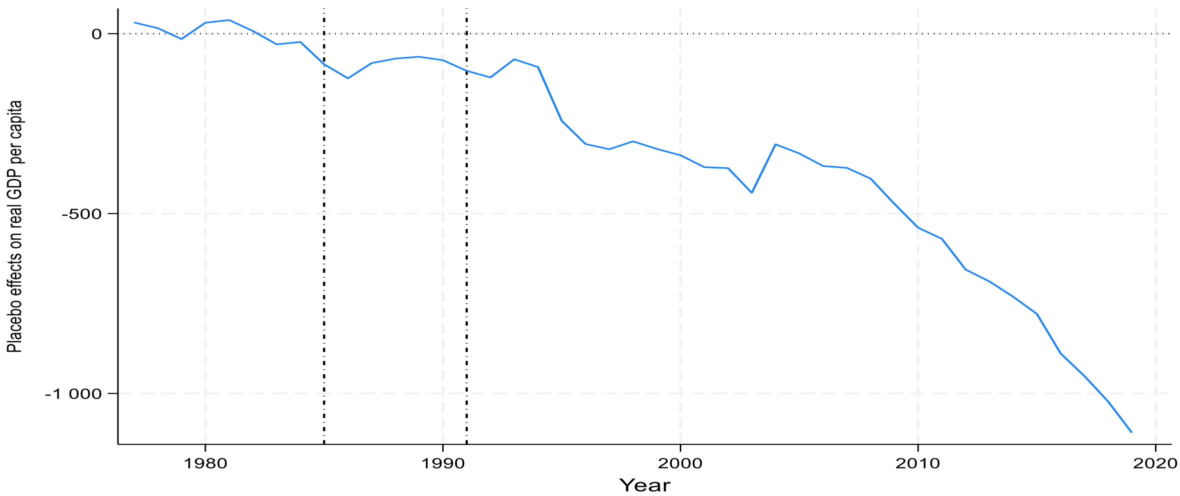


Figure B20: In-time placebo test – treatment effects (Mozambique)



Zambia

Figure B21: LOO – synthetic vs LOO vs actual outcomes (Zambia)

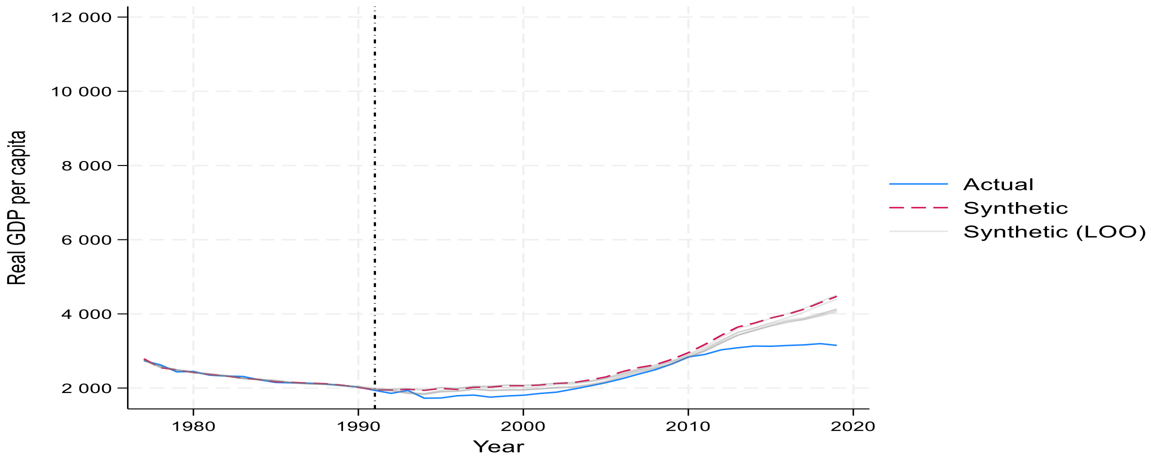


Figure B22: LOO treatment effects (Zambia)

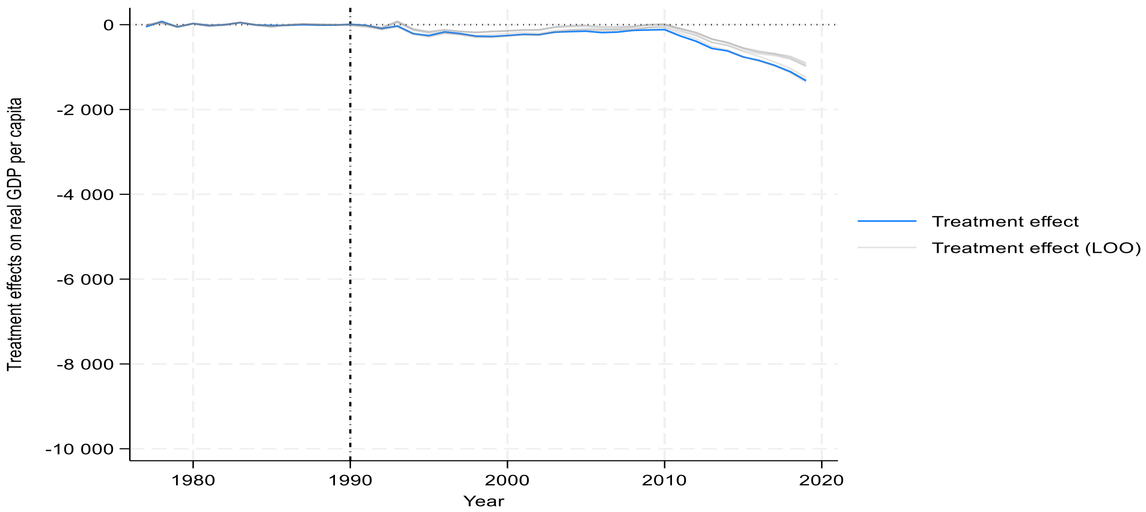


Figure B23: In-time placebo test – treatment effects (Zambia)

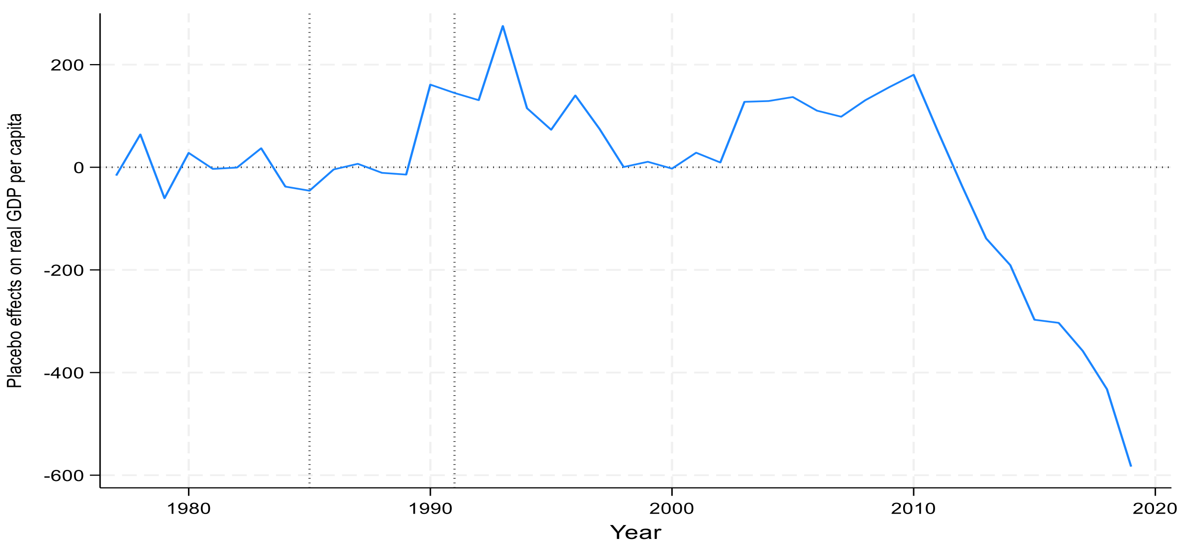


Figure B24: In-time placebo effects – actual vs synthetic outcomes (Zambia)

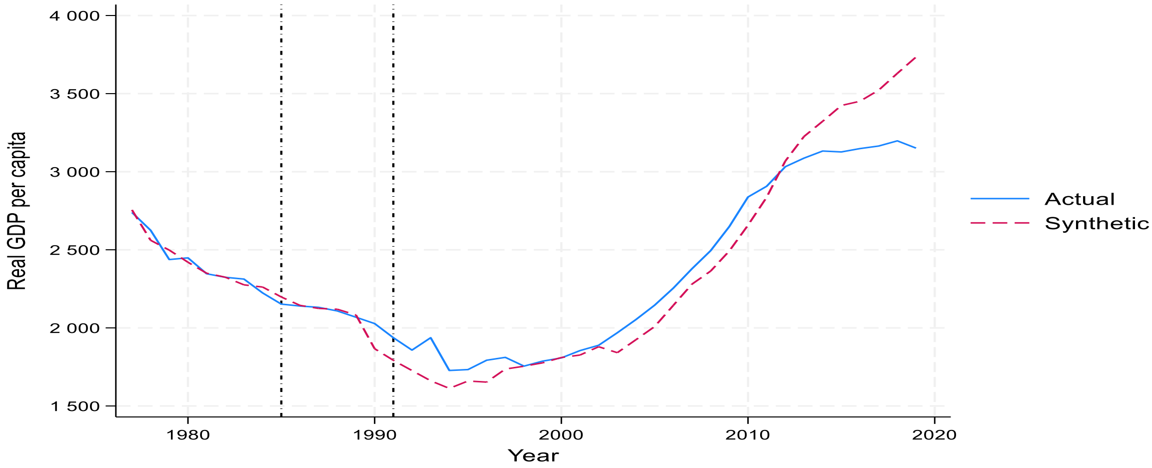


Table B9: LOO robustness test – actual vs synthetic vs synthetic LOO outcomes (Zambia)

	Outcome		Synthetic outcome (LOO)	
Time	Actual	Synthetic	Min	Max
1991	1 937	1 951	1 952	1 998
1992	1 858	1 949	1 924	1 969
1993	1 937	1 968	1 853	1 990
1994	1 727	1 938	1 822	1 963
1995	1 733	1 991	1 894	2 018
1996	1 792	1 963	1 909	2 339
1997	1 811	2 021	1 966	3 426
1998	1 755	2 025	1 933	3 731
1999	1 787	2 066	1 945	4 194
2000	1 807	2 064	1 951	4 440
2001	1 855	2 082	1 975	6 405
2002	1 889	2 125	2 005	7 237
2003	1 969	2 145	2 019	7 735
2004	2 054	2 217	2 079	9 011
2005	2 145	2 299	2 161	9 411
2006	2 255	2 441	2 306	9 530
2007	2 379	2 553	2 426	10 429
2008	2 495	2 629	2 533	11 621
2009	2 649	2 774	2 643	11 318
2010	2 838	2 954	2 820	10 138
2011	2 907	3 173	2 996	10 344
2012	3 032	3 422	3 213	10 788
2013	3 087	3 646	3 421	10 170
2014	3 132	3 751	3 550	9 988
2015	3 127	3 888	3 671	9 115
2016	3 148	3 990	3 766	8 309
2017	3 164	4 124	3 847	7 812
2018	3 198	4 305	3 943	7 342
2019	3 151	4 472	4 053	6 980

Note: The last two columns report the minimum and maximum synthetic outcomes when one control unit with a non-zero weight is excluded at a time.

Table B10: LOO robustness test – predicted vs LOO scenario treatment effects (Zambia)

Time	Treatment effect	Treatment effect (LOO)	
		Min	Max
1991	-14	-61	-15
1992	-91	-112	-66
1993	-31	-53	84
1994	-211	-236	-95
1995	-258	-285	-161
1996	-171	-546	-116
1997	-210	-1 615	-154
1998	-270	-1 976	-177
1999	-279	-2 407	-158
2000	-257	-2 632	-143
2001	-227	-4 550	-120
2002	-236	-5 348	-116
2003	-176	-5 766	-50
2004	-163	-6 957	-25
2005	-154	-7 266	-16
2006	-186	-7 276	-51
2007	-174	-8 050	-48
2008	-134	-9 126	-39
2009	-125	-8 668	6
2010	-116	-7 300	18
2011	-266	-7 437	-89
2012	-390	-7 756	-181
2013	-559	-7 083	-334
2014	-619	-6 855	-418
2015	-761	-5 988	-544
2016	-842	-5 160	-618
2017	-960	-4 648	-683
2018	-1 107	-4 144	-746
2019	-1 321	-3 829	-902

Note: The last two columns report the minimum and maximum treatment effects when one control unit with a non-zero weight is excluded at a time.

Zimbabwe

Figure B25: LOO – treatment effects (Zimbabwe)

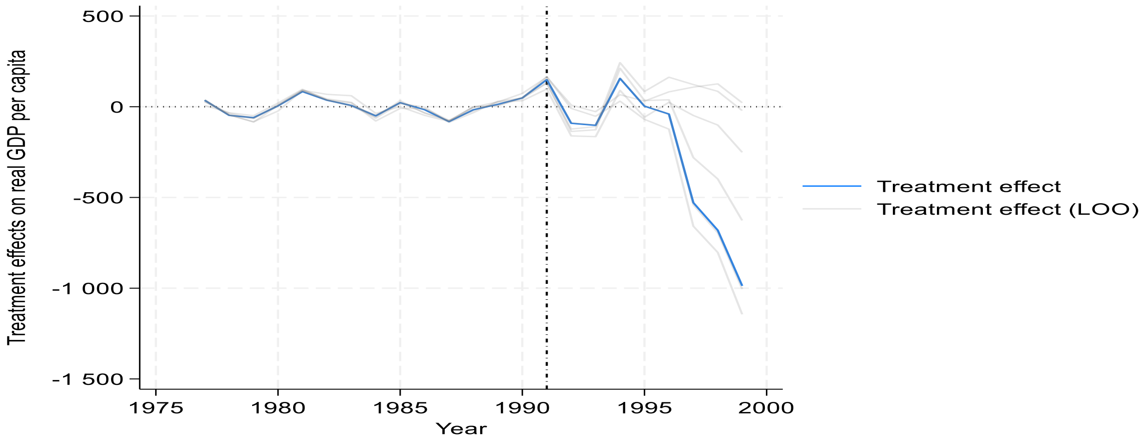


Figure B26: LOO – actual vs synthetic vs LOO outcomes (Zimbabwe)

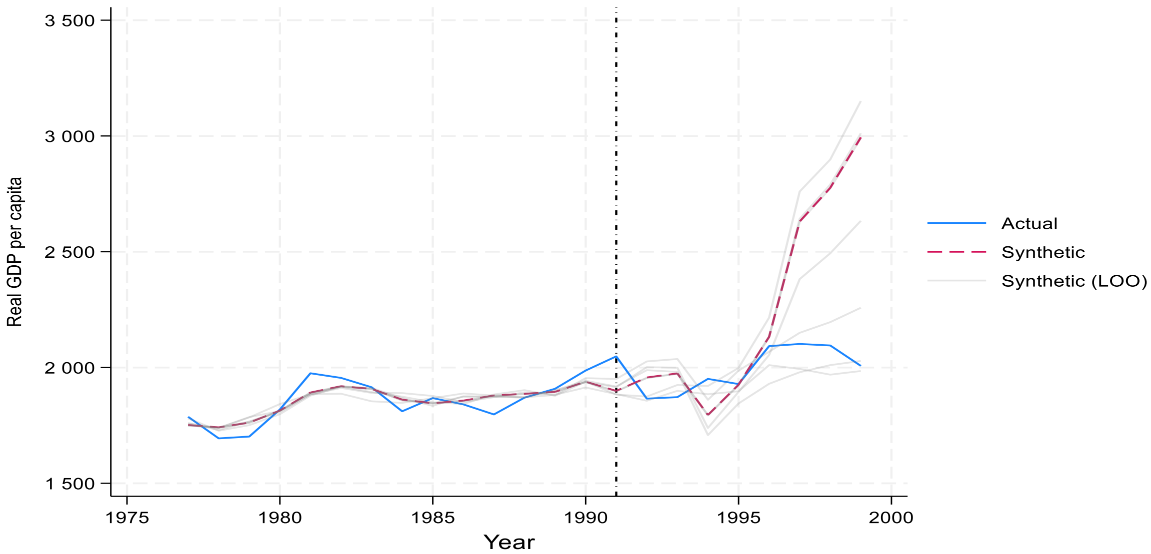


Table B11: LOO robustness test – actual vs synthetic vs synthetic LOO outcomes (Zimbabwe)

	Outcome		Synthetic outcome (LOO)	
Time	**Actual**	**Synthetic**	**Min**	**Max**
1991	2 048	1 899	1 883	1 951
1992	1 866	1 957	1 857	2 026
1993	1 872	1 975	1 899	2 137
1994	1 951	1 795	1 708	1 920
1995	1 929	1 926	1 845	1 998
1996	2 093	2 133	1 930	2 216
1997	2 102	2 631	1 980	2 760
1998	2 095	2 776	1 969	2 898
1999	2 007	2 994	1 985	3 151

Note: The last two columns report the minimum and maximum synthetic outcomes when one control unit with a non-zero weight is excluded at a time.

Table B12: LOO robustness test – predicted vs LOO scenario treatment effects (Zimbabwe)

Time	Treatment effect	Treatment effect (LOO)	
		Min	Max
1991	149	98	165
1992	-91	-160	9
1993	-103	-165	-27
1994	156	31	243
1995	3	-70	84
1996	-40	-123	163
1997	-529	-658	122
1998	-681	-803	126
1999	-987	-1 144	22

Note: The last two columns report the minimum and maximum treatment effects when one control unit with a non-zero weight is excluded at a time.

Figure B27: In-time placebo test – treatment effects (Zimbabwe)

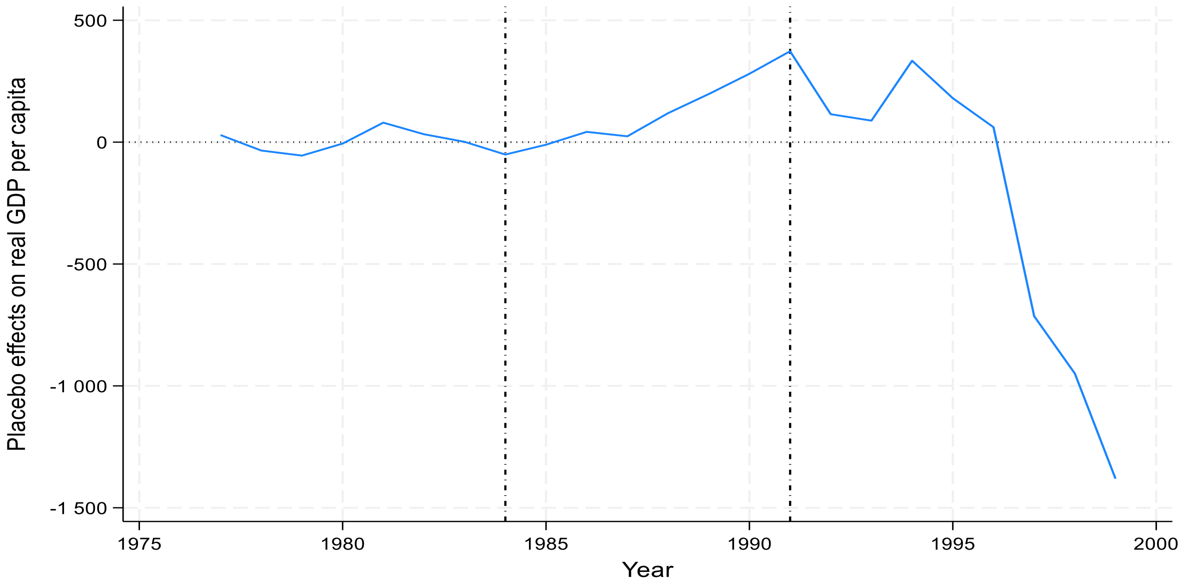
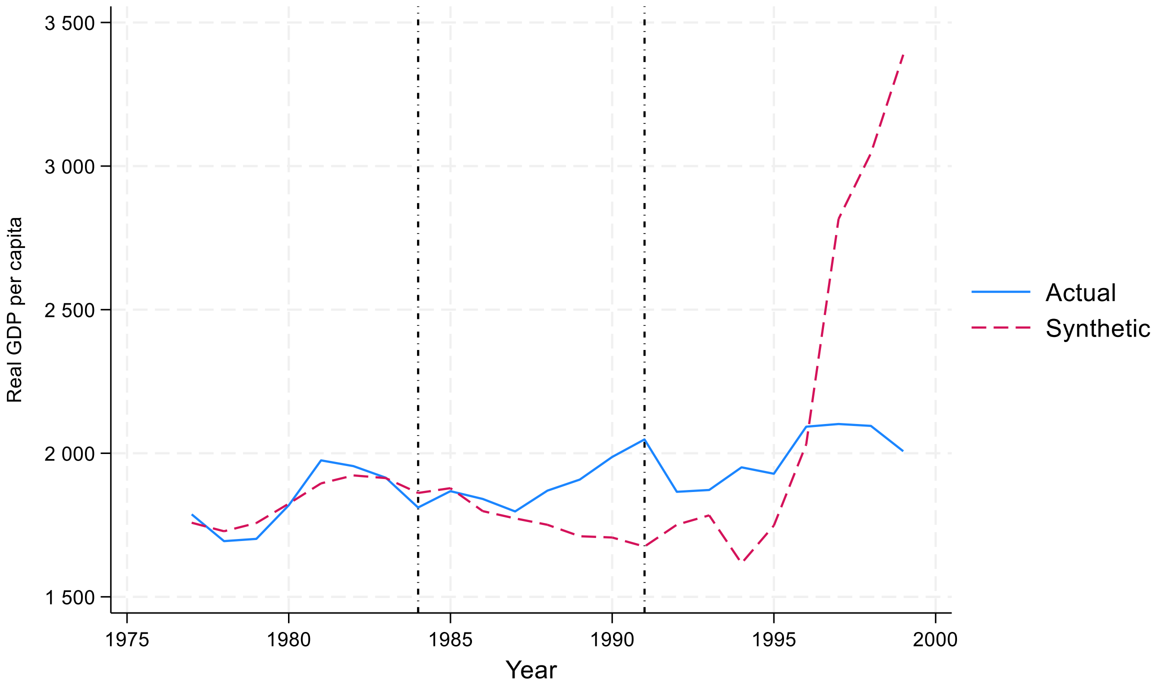


Figure B28: In-time placebo test – actual vs synthetic outcomes (Zimbabwe)



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