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The economic consequences of durable left-populist regimes in Latin America

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ABSTRACT

We study the economic effects of durable left-populist leaders in Latin America. Using synthetic control to create a credible counterfactual for four such regimes, we find that they have, on average, a negative, significant, and sizeable average effect on income. Specifically, these countries at the end of their treatment periods end up over 20% poorer on average than what the average of their synthetic counterfactuals predict. We find negative and significant single country effects on real per-capita GDP in Venezuela, Nicaragua, and Bolivia. Only in Ecuador does GDP keep up with its synthetic counterfactual. We investigate whether there is a trade-off, where national income was sacrificed to improve inequality or health. We find no significant average counter-veiling trade-off in decreased levels of income inequality or infant mortality relative to what the average synthetic predicts.

1. Introduction

We study the economic effects of durable left-populist leaders in Latin America. This is a contentious topic, as populist politicians often use polarizing rhetoric about "us versus them" that can color judgements about their policies according to the ideological predisposition of the observer. Indeed, different people can observe the same outcomes but come away with different ideas of how well a particular president has done. For instance, Shifter (2006), talking about then President of Venezuela Hugo Chávez, points out that to pundits on the left, Chávez was "a hero driven by humanitarian impulses to redress social injustice and inequality – problems long neglected by a traditional political class intent on protecting its own position while denying the masses their rightful share of wealth and meaningful political participation." To Chavez's opponents, however, he was "on a catastrophic course of extending state control over the economy, militarizing politics, eliminating dissent, cozying up to rogue regimes, and carrying out wrong-headed social programs that will set Venezuela

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back." Separating fact and fiction can be extremely challenging when the ideological stakes are high, which means a good counterfactual is more important than ever.[1]

Neither economic decline in Venezuela nor economic resurgence in Bolivia, for example, on their own tells us much about what would have happened in these countries if Hugo Chávez and Evo Morales had not been president. In short, we need a credible counterfactual to make any causal claims. In this paper, we use the synthetic control method to generate such counterfactuals and estimate the average causal effect of these leaders on their economies.

To study the effect of durable left-populist regimes in Latin America, we must first define what we mean by the term and select the relevant cases. We argue that left-populists have three defining characteristics: (i) they concentrate power in the executive branch and greatly reduce checks and balances, (ii) they change the constitution to extend their term in office, and (iii) they enact market-unfriendly economic policies. We find the first Daniel Ortega regime in Nicaragua (1979–1990), Evo Morales in Bolivia (2006–2019), Rafael Correa in Ecuador (2007–2017), and Hugo Chavez in Venezuela to be clear-cut cases of durable left-populism.[2]

We use a multiple-treatment synthetic control model along the lines of Cavallo et al. (2013) and find a negative, significant, and sizeable average effect of these leaders on real per-capita GDP.[3] By the end of their treatment periods, these countries are more than 20% poorer on average than what their synthetic counterfactuals predict. Thus, these regimes created a large wealth penalty for their countries.

Beyond our finding of a negative average effect on real incomes, we also find negative and significant single country effects of Evo Morales and the first Daniel Ortega regime on real per-capita GDP.[4] Only in Ecuador does GDP keep up with its synthetic counterfactual.[5] Our results show the importance of a good counterfactual. For instance, some observers have praised Bolivia's economic performance under Evo Morales.[6] The problem with this is that the raw numbers do not tell us how well the Bolivian economy would have evolved without Morales as President. Our results show that Bolivia actually significantly underperforms synthetic Bolivia. Our paper is valuable in that it helps us accurately evaluate the economic effect of these regimes.

Since the rhetoric of these regimes sometimes stress health and inequality more than economic performance, we also investigate whether there is a trade-off, where increasing GDP was sacrificed to improve inequality or health. We do this by using the same procedures but replacing per capita GDP with infant mortality and the Gini coefficient. We find no significant average effect of these regimes on either variable.

In what follows below, we next describe in more detail how we chose our sample. Section 2 presents our case selection, while Section 3 discusses our data and estimation/identification strategy. Section 4 presents the results of the average effect of this type of leader on real GDP per capita and infant mortality and Section 5 presents the results of left-populism in our individual countries to look for heterogeneous treatment effects.[7]

2. Case selection

As we discussed in the introduction, we identified three characteristics that constitute left- populism in Latin America, namely leaders that (i) concentrate power in the executive branch and greatly reduce checks and balances, (ii) enact constitutional changes to extend their term in office, and (iii) enact market-unfriendly economic policies. We believe these characteristics match well with what political scientists call populism. For instance, Seligson (2007) describes populism as the following:

> Populism properly defined must include a core belief that the institutions of classical liberal democracy, especially legislatures and courts, are anachronistic, inefficient, and inconsistent with the true expression of 'the people's will' (or at least the populist officials' interpretation of it). Populist leaders typically propose instead to listen to the people' with the aim of personally carrying out their will while isolating 'rejectionists' who would deny it. In practice,

[1] The heated rhetoric is not limited to within-country analysis. Here is a quote from U.S. Senator Bernie Sanders on his website: "These days, the American dream is more apt to be realized in South America, in places such as Ecuador, Venezuela and Argentina, where incomes are actually more equal today than they are in the land of Horatio Alger. Who's the banana republic now?"

[2] The Castro Regime in Cuba, the Manuel Zelaya regime in Honduras (2006-9), and the Fernández de Kirchner regime in Argentina (2007-2015) also qualify, but we cannot get comparable data for Cuba, while attempts by Zelaya and Kirchner to change their constitutions to allow re-election backfired (Zelaya was overthrown in a coup and Kirchner backed down after mass protests). Jales et al. (2018) use a unique dataset and find that the Castro regime had significant negative effects on per capita GDP. This result is consistent with what we find here. There are also cases of right-wing populists such as Alberto Fujimori in Peru and Carlos Menem in Argentina.

[3] For other recent applications of the synthetic control method, see Billmeier and Nannicini (2013), Cunningham and Shah (2018), Lynham et al. (2017) and Buettner and Madzharova (2018).

[4] Daniel Ortega's second stint as Nicaraguan president (2007-present) has been characterized by "Chávez-type" rhetoric; however, having lost three consecutive presidential elections before finally winning in 2007 seems to have caused Ortega to significantly moderate his policies.

[5] We also confirm Grier and Maynard's (2016) finding of a negative income effect for Chávez using a different dataset, donor pool, and slightly longer treatment period. We use macro data from the latest version of the Penn World Tables and a slightly different set of donor countries than Grier & Maynard and will report how our results match up to theirs when we discuss our country specific results.

[6] Weisbrot and Johnston (2009) note that "Bolivia's economic growth in the last four years has been higher than at any time in the last 30 years, averaging 5.2% annually since the current administration took office in 2006." They attribute this performance, at least in part, to "a large-scale and well-timed increase in public spending."

[7] The results on inequality are discussed in Appendix A for reasons of space and concerns about data quality.

Table 1
Left populist policy mix.

Policies	Nicaragua	Venezuela	Bolivia	Ecuador
New constitution[a]	Yes	Yes	Yes	Yes
Attacks on judicial independence[b]	Yes	Yes	Yes	Yes
Allowed for re-election[c]	Yes	Yes	Yes	Yes
Expropriation/Nationalization	Yes	Yes	Yes	No
Dissolved Congress/Changed legislative structure[d]	Yes	Yes	No	Yes
Ruled by decree	Yes	Yes	No	Yes

[a] Nicaragua (1987), Venezuela (1999), Bolivia (2009), and Ecuador (2008).
[b] This is based on Coppedge et al. (2017), who measure government attacks on the judiciary with a variable called jupoatck. It asks "How often did the government attack the judiciary's integrity in public?"
[c] Venezuela (1999), Bolivia (2009), Ecuador (2008), and Nicaragua (2011).
[d] Venezuela changed from a bicameral to a unicameral body in 1999. The Nicaraguan legislature was changed from a bicameral institution to a unicameral one under the 1987 Constitution.

> populism often can mean running roughshod over fundamental democratic guarantees of civil liberties, especially free expression and the right to due process.

Here we discuss each characteristic in more detail, although we leave the specifics of each of our treated countries and how they share these characteristics to the second half of the paper. We start by identifying which Latin American leaders were of the left. To do so, we use the Database of Political Institutions, which has a variable called *"execrlc"* that classifies chief executives by ideology.[8] We are interested in presidents that are further to the left than what most center-leftists would be. For that reason, we then identify which left-wing presidents were associated with a higher risk of expropriation. Specifically, we use a variable from the International Country Risk Guide (ICRG) called *"investment profile,"* which is partly determined by the risk of expropriation.[9]

Next, we examine each case on the list to identify which of the remaining presidents also concentrated executive power and changed the constitution to be able to stay in power longer than was previously allowed. With respect to executive power, we look for presidents that significantly changed the composition of the legislature, ruled by decree, or reduced judicial independence during their terms. For instance, as we will discuss below, Hugo Chavez in Venezuela was able to change the legislature from a bicameral structure to a unicameral one, increased the term of the presidency from 5 years to 6, and regularly ruled by decree.

We end up with four presidents that clearly match these characteristics: Hugo Chávez (Venezuela), Evo Morales (Bolivia), Rafael Correa (Ecuador), and Daniel Ortega (Nicaragua). Table 1 presents some salient features of these regimes. All four leaders were able to change the constitution during their tenure, as well as the rules that allowed for re-election. They all regularly attacked judicial independence and all but Morales dissolved congress, changed the legislative structure, or ruled by decree.

We argue that this combination of characteristics has a unique potential to cause economic problems. A leader may run on an anti-market platform, but if there are checks and balances, then he or she may not be able to implement them. And in the cases where a president can implement these types of policies, if there are constitutional term limits, the damage might not be so bad or long lasting. What makes the left-populism we study so potentially damaging is precisely that there are no checks or balances or term limit constraints on the leader espousing these policies. In short, we do not try to isolate the effect of each part of the policy mix and but instead argue that it is the combination that matters.

3. Method, inference, and data

3.1. Method

Our goal is to estimate the average effect of these four regimes on GDP and infant mortality. As noted above, evaluating the impact of these leaders and their policies requires the researcher to estimate what would have happened in these countries in the absence of these four leaders and their policy changes. While randomization is arguably the cleanest approach to causal inference, we will never get a good RCT on political systems. We are thus left with our toolkit of quasi-experimental methods, of which, given the long pre-treatment period and the few treated cases we have, synthetic control seems the best choice.

As developed and expanded in Abadie and Gardeazabal (2003), and Abadie et al. (2010, 2015), synthetic control is a data driven method to produce credible counterfactuals in case studies. The researcher specifies a group of potential donor units that can be used to construct the control along with a set of indicator variables that are important in the determination of the outcome being studied. The control will be a weighted average of the donor units. The weights are chosen to both

[8] We ignored military regimes, which are a different phenomenon from what we are studying.
[9] Since the dataset begins in 1984, we examine presidencies by hand from 1970 to 1983 to identify cases of expropriation or nationalization.

minimize the deviations of the control and the treated unit in the pre-treatment period and to balance the control and the treated unit on the indicator variables. Indicator variables that are more important for predicting the outcome receive more weight in the algorithm.[10] Abadie et al. (2015) emphasize several points in creating the control:

> To avoid interpolation biases, it is important to restrict the donor pool to units with characteristics similar to the treated unit. Another reason to restrict the size of the donor pool and consider only units similar to the treated unit is to avoid overfitting.
>
> In addition, the applicability of the method requires a sizable number of pre-intervention periods. The reason is that the credibility of a synthetic control depends upon how well it tracks the treated unit's characteristics and outcomes over an extended period of time prior to the treatment. We do not recommend using this method when the pretreatment fit is poor or the number of pretreatment periods is small.

In the light of this advice, we choose a focused, 24-country donor pool described in the data section below, and make sure to have a substantial pre-treatment period.[11]

To estimate the average treatment effect in the four cases we study, we use a modified version of the multiple-treatment effect model developed by Cavallo et al. (2013). The method works by estimating individual effects for each unit by synthetic control and then averaging the actual outcomes and the synthetic predictions. The difference between those two averages is the average treatment effect. We differ from Cavallo et al. (2013) in that instead of using a single common set of indicator variables for all the treated units, we customize the models for each country, choosing the variables that produce the best pre-sample fit on a case-by-case basis.

3.2. Inference

Beyond reporting the size of the treatment effect, we also want to give some information about its statistical significance. Here, we also follow Cavallo et al. (2013) in using permutation tests for each period of the treatment interval. For a single country, we take each period's treatment effect (the deviation from the observed value and the synthetic's predicted value), find its absolute value, and rank that effect among the absolute values of the period's placebo effects. The p-value is merely the number of placebos with a larger estimated effect than the treated case, divided by the total number of placebos. This process is repeated for each post-treatment period, allowing the researcher to observe how the effect and statistical significance evolve over time. Note that countries (either treated or donor) that have a poor fit in the pre-treatment period are more likely to witness larger deviations in any post-treatment period. To address this concern, each effect is divided by the pre-treatment root mean squared prediction error (RMSPE).

Determining the statistical significance of our average treatment results across multiple regimes in the synthetic control framework requires certain alterations to the inferential methodology used in the single event analysis. As noted above, to measure the average effect of the multiple treatments, we simply average the treatment effect across all the treated observations. However, when determining the statistical significance of the average effect, we must take into account that averaging smooths the distribution. It is no longer appropriate to estimate the p-value using a pool of single event placebos. Instead, we create a distribution of average placebo effects, by calculating all possible averages across the four treatment cases. For example, in our income analysis, we observe four treated countries. Each placebo average is a combination of randomly selected placebo effects from each of the four cases. Since there are 24 donors and four events in our income analysis, the average treatment effect is ranked among 331,776 placebo averages.[12]

3.3. Identification

All methods of causal inference require some identifying assumptions and synthetic control is no exception. There are two requirements for our results to be causal. The first is that the treatment does not affect any of the control countries. This is known as the stable unit treatment value assumption (SUTVA). While this is an assumption and not testable, we have shown in the direct sense that it likely holds true: none of the countries in our donor pool experienced anything like the same policy mix that our left-wing populists employed during this time period. However, we would need to also rule out indirect effects (spillovers). It is worth noting that in our case, to the extent SUTVA may be violated, it would tend to cause us to underestimate the effect of these left-wing populists. That is, if an economic slowdown (boom) in our treated countries spilled over and created slowdowns (booms) in our control countries, then the gap between the treated and the control would be artificially narrowed compared to the true causal effect.

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[10] For further details on the mechanics of this process see the articles by Abadie and his co-authors cited above or Grier and Maynard (2016).

[11] Getting a good fit over a long pre-treatment period means that it is unlikely that there are unobserved confounders spuriously creating the measured treatment effect. This is especially important for us as several of our cases are oil producers and not all oil shocks are alike and not all oil country economies respond to shocks in the same way. However, if our estimated synthetic can track the treated country accurately for 30 years before the treatment, these kinds of concerns are minimized. If the two respond significantly differently to shocks, it should show up in that long pre-treatment period. For more on the complications of oil shocks, see Kilian (2009). For another empirical approach to the issue, see Jarrett et al. (2019).

[12] $24^4 = 331{,}776$

Table 2
Donor countries by case.

	Dependent variable	
Donor	Income	Infant mortality
Algeria	✓	✓
Argentina	✓	×
Brazil	✓	✓
Canada	✓	✓
Chile	✓	✓
Colombia	✓	✓
Costa Rica	✓	✓
El Salvador	✓	✓
Guatemala	✓	✓
Honduras	✓	✓
Indonesia	✓	✓
Iran	✓	✓
Iraq	✓	✓
Kuwait	✓	✓
Mexico	✓	✓
Nigeria	✓	✓
Norway	✓	✓
Panama	✓	✓
Paraguay	✓	✓
Peru	✓	✓
Saudi Arabia	✓	✓
United Arab Emirates	✓	✓
United States	✓	✓
Uruguay	✓	✓

Note. A check indicates that the donor is included in all cases, while an "X" indicates the donor has insufficient data and was omitted. Although attempts are made to estimate missing data, some cases simply have too few observations to reliably interpolate.

The second identifying assumption is that the effects we find are due only to the treatment that we claim. In other words, the assumption is that there are no other simultaneous or subsequent treatments that may be causing the results we see. Events that affect both the donors and the treated units do not violate this identifying assumption.

3.4. Data

Since our cases are from Latin America, and three-fourths of them are energy producers, we start with the 20-country donor pool used in Grier and Maynard (2016) for Venezuela, which focuses on the Americas and OPEC members. To their list we add three additional OPEC members and the USA (which is the only non-island country in the Americas missing from the Grier and Maynard donor pool).[13]

We end up with a set of 24 potential donor countries as shown in Table 2. As noted above, we are studying three outcome variables: real per capita GDP, which comes from the Penn World Tables (Feenstra et al 2015); infant mortality, from the World Bank (World Bank Group 2019); and national Gini coefficients, which are taken from the SWIID (Solt 2009).[14] Our potential indicator variables are mainly from the Penn World Tables. They consist of the human capital index, capital stock per capita, merchandise exports as a share of GDP, investment as a share of GDP, government consumption as a share of GDP, and labor compensation as a share of GDP. Table 3 gives summary statistics and a brief description of each of these variables.

As noted above, we actually employ a different subset of these variables (and their lags) for each country and each outcome variable, looking for a synthetic control that closely matches the outcome under study pre-treatment and whose values on the chosen indicator variables 5 match up with those for the country under study as well. We discuss the exact specifications for each country and outcome in Section 5 below, but we begin by presenting and discussing the average treatment effects of this policy mix in Latin America.

[13] Note that in Abadie and Gardeazabal (2003) the donor pool is the 16 non-Basque regions of Spain. In Abadie et al. (2010), the donor pool is restricted to US states that did not greatly raise their cigarette taxes during California's treatment period. Abadie et al. (2015) uses 16 OECD countries as potential donors to construct a synthetic West Germany. The Campos et al. (2019) study of EU expansion uses between 14 and 23 donors depending on the accession date of the country being studied.

[14] We use the variable RGDPE which is real PPP adjusted GDP. It is standard in the literature to use PPP adjusted real GDP. For example, Cavallo et al. (2013), Abadie et al. (2015), and Campos et al. (2019) all use such a variable. In the PWT documentation, it says that RGDPE is proper variable to use, "to compare relative living standards across countries and over time," which is exactly what our models are doing.

Table 3
Summary statistics.

Variable	Mean	Standard deviation	*n*	Description	Source
GDP per capita	16429.82	27419.96	1260	Measured in 2011 US$.	Penn World Table
Human capital index	2.14	0.59	1260	Index based on years of schooling and returns to education.	Penn World Table
Capital stock per capita	46502.69	82252.51	1260	Measured in 2011 US$.	Penn World Table
Government consumption (% GDP)	0.16	0.09	1260	Share of current government consumption at current PPP.	Penn World Table
Export (% GDP)	0.20	0.16	1260	Share of merchandise exports at current PPP.	Penn World Table
Gross capital formation (%GDP)	0.22	0.09	1260	Share of gross capital formation at current PPP.	Penn World Table
Labor compensation (% GDP)	0.47	0.13	1125	Share of labor compensation in GDP at current national prices.	Penn World Table
Infant mortality	40.37	32.34	1257	Infant mortality rate per 1000 live births.	World Bank
Gini	42.98	8.26	811	Estimate of Gini index of inequality in equivalized household income.	SWIID
Polity score	2.46	7.39	1207	Measures the quality of political institutions. Ranges from −10 to 10.	Polity IV Project

Note. The summary statistics are calculated for all countries from 1970 to 2014.

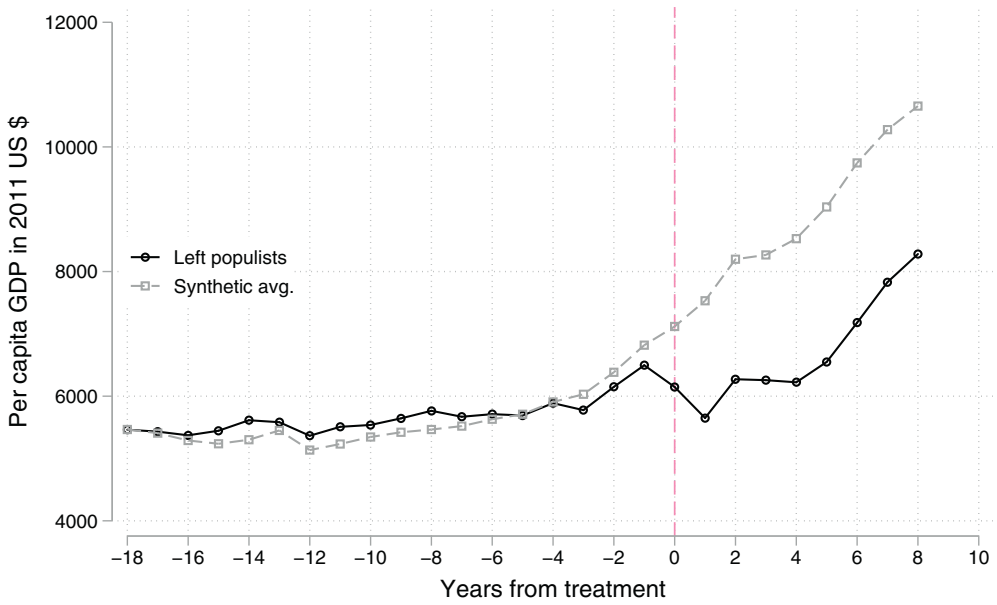

Fig. 1. Trends in income - left populists and synthetic avg.

4. Average treatment effect results

To calculate these average effects, we estimate single country synthetic control models for each country. These individual models are presented in the following section. All the averaging here is done post-estimation of the individual models. We line up each country and synthetic with the others on the year the regime under study took power in each. For example, the first treatment year in Nicaragua is 1979, in Venezuela, it is 1999, in Bolivia, 2006 and in Ecuador, 2007. The GDP values for each of those years are averaged together and plotted as the point labeled 1 on the horizontal axis of Fig. 1, with the rest of the years filled out in the same manner. We do exactly the same thing with the synthetic control for each country and plot its average on the same graph. On the right-hand side of the vertical line, the difference between the two plots gives the average treatment effect.

Fig. 1 shows that the average synthetic for real per-capita GDP closely tracks the average outcome in the pre-treatment years. Table 4 reports that the pre-treatment RMPSE when using the average of the synthetic controls to predict the average of the treated units is $416.55, which is notably lower than the average RMPSE obtained using the average of all Latin

Table 4
Average income predictor means.

Variables	Left populists	Synthetic LP
GDP per capita	$5695.61	$5935.75
Human capital index	2.02	1.97
Capital stock per capita	$14245.54	$15829.83
Government consumption	0.19	0.16
Merchandise exports	0.14	0.19
Gross capital formation share	0.18	0.17
Avg. RMSPE	–	416.55

Note. In this table, we compare the left populists to their synthetic counterfactual in the 19 years prior to the left populist treatment. This is the minimum number of pre-treatment periods among the four cases. Nicaragua is the binding constraint with data ranging from 1960 to 1979. Variables are averaged across the pre-treatment period.

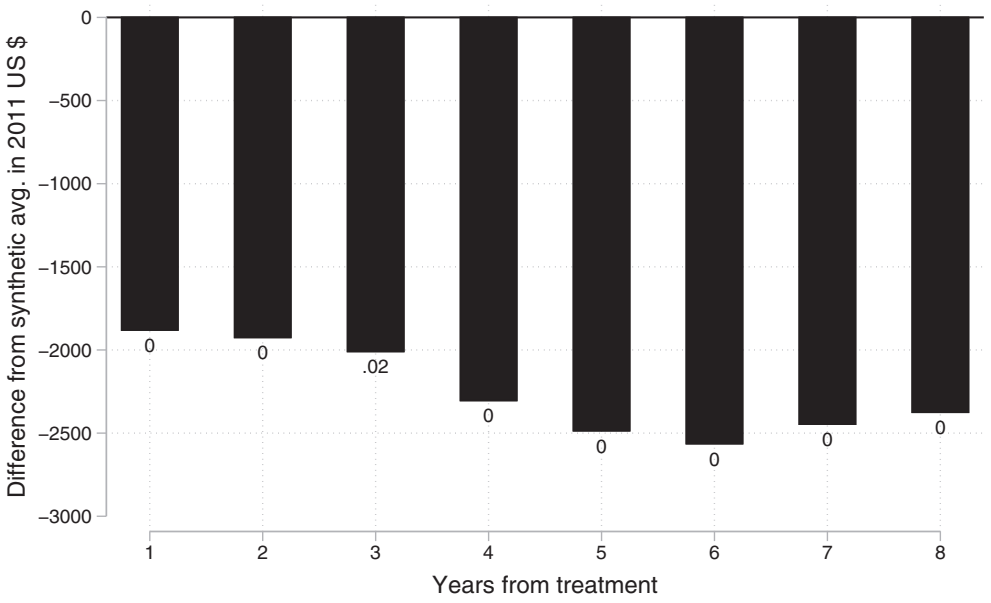

Fig. 2. The avg. effect of left populists on income.

American countries in our pool to predict the average of the treated units ($2608.91).[15] Fig. 1 also shows that the average treatment effect is immediate, large, negative, and persistent. At the end of our experiment, there is roughly a $2000 shortfall of average real GDP per capita relative to the prediction of the averaged synthetic. Comparing this to the final value of average GDP shows that the average effect of the regimes we study was to reduce real per-capita GDP by over 20%, which is a very large effect.

Fig. 2 presents the period-by-period p-values for the average effects shown in Fig. 1. The height of the bar gives the size of the treatment effect and the associated p-value is written at the end of each bar. Each year's effect is significant at the 0.05 level or better. In sum, we find very strong evidence of a large GDP penalty from these regimes.

Of course, the rhetoric of these regimes was rarely exclusively about economic performance. They tended to stress health and poverty. There is a real dearth of internationally comparable poverty data, but we are able to study health.[16] We take infant mortality as our health measure and perform exactly the same analysis for these outcomes that we did for real per-capita GDP.

Fig. 3 shows the average results for infant mortality. The average of this outcome variable is monotonically declining during the treatment period, a fact that is often used to praise these regimes. However, it was also monotonically declining before the treatment period, and its fall is matched very closely by the average of the synthetic controls. Table 5 shows that the average pre-treatment fit is quite good with an average RMSPE of 2.68. In the treatment period, Fig. 3 shows

[15] Table 4 also shows that the average of the four synthetic controls matches the average of the four treated units fairly well on indicator variables like human capital, capital stock, government consumption, and investment. We do not list Latin America as a counterfactual in Table 4, but Latin America can be found in individual country results. The RMSPE listed is the average RMPSE across all four cases.

[16] These leaders also emphasize inequality, but the data on it is also sparse. We present results on inequality in Appendix A and it shows that average inequality was lower than what was predicted by the average synthetic control. However, the effect is small and not statistically significant.

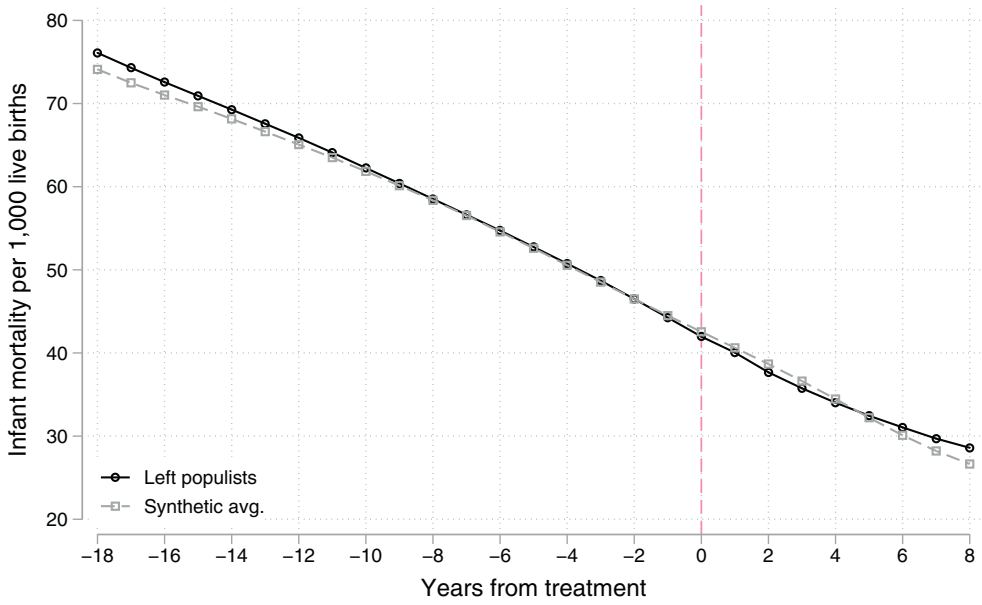

Fig. 3. Trends in infant mortality - left populists and synthetic avg.

Table 5
Average infant mortality predictor means.

Variables	Left populists	Synthetic LP
Infant mortality	58.91	58.39
Human capital index	2.02	2.04
Government consumption share	0.19	0.17
Gross capital formation share	0.18	0.24
Avg. RMSPE	–	2.68

Note. In this table, we compare the left populists to their synthetic counterfactual in the 19 years prior to the left populist treatment. This is the minimum number of pre-treatment periods among the four cases. Nicaragua is the binding constraint with data ranging from 1960 to 1979. Variables are averaged across the pre-treatment period.

the averaged synthetic control continues to match the average outcome in the treated units until close to the end of the treatment period where the treated units underperform compared the control.

Fig. 4 presents the p-values for the average treatment effect each period and shows that the average effect is both relatively small and insignificant, except for the last three treatment periods where the p-values are 0.09, 0.06, and 0.06 respectively. The implication of these results is that there is no improvement in infant mortality that can be causally attributed to the advent of the four regimes we are studying, but rather a small but significant underperformance at the end of the treatment period.

5. Individual country results

We now go country-by-country, describing the political and economic changes introduced by each regime and presenting single country treatment effect results.[17] We show results for both real GDP per capita and infant mortality. The reader will note that for a given country, the composition of the synthetic for income will differ from the composition of the synthetic for infant mortality. We believe this makes sense. For example, Venezuela is an extremely oil dependent country with income volatility similar to Nigeria. However, Venezuela, at the beginning of the sample was wealthier than Nigeria. Thus, it is not surprising that Nigeria is relevant for explaining the evolution of Venezuelan income, but not its infant mortality.

5.1. Nicaragua

In 1979, the Sandinistas forced then-dictator Anastasio Somoza to resign and flee the country. The new junta ruled by decree and abolished the constitution, the office of the president, the legislature, and the national courts. They also nation-

[17] See also Acemoglu et al. (2013) for a discussion of the history / politics in Venezuela, Bolivia, and Ecuador. We believe it is important to document in detail why these cases fit the left-populist profile in order to strengthen the plausibility of our empirical results (Sekhon 2009).

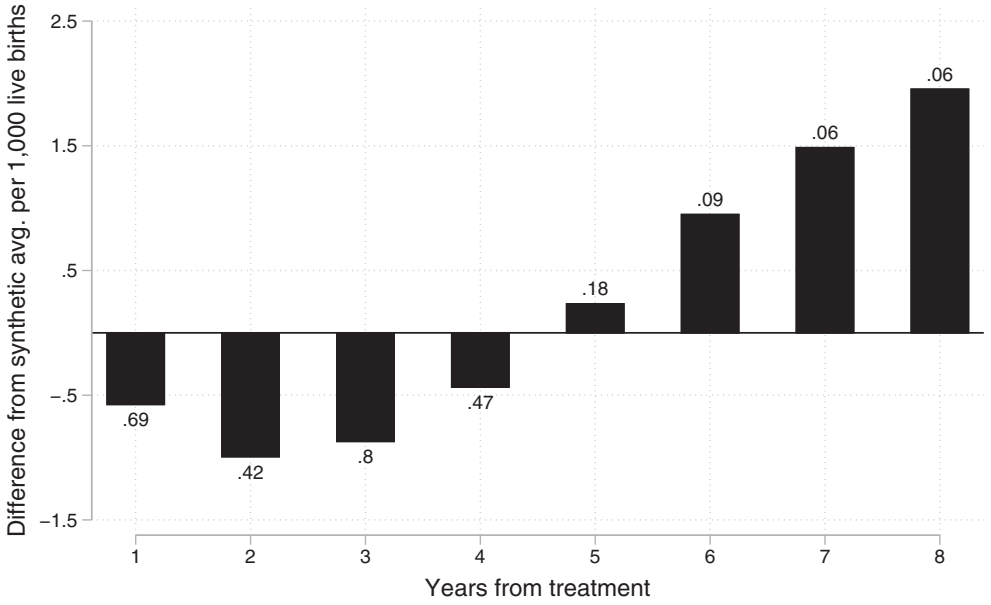

Fig. 4. The avg. effect of left populists on infant mortality.

alized the banking system, the mining and fishing sectors, and over 20% of the arable land in the country (which had been held by the Somoza family or its supporters). The Sandinistas also "fixed land rents below market rates" and had an "unfavorable attitude towards private landowners, not enforcing property rights nor preventing illegal occupations of land."[18]

Elections were held in 1984 and a new constitution was approved three years later. Daniel Ortega won the 1984 elections and stayed in power until 1990. While he returned to the presidency in 2007, we limit our treatment period to 1979 – 1990 because of the reasons we discussed above.[19]

Panel A of Fig. 5 shows the evolution of real per-capita GDP in Nicaragua, along with that of its synthetic control. As shown in Table B1 of Appendix B, the control is composed of 23% Chile, 54% Honduras, 9% Mexico, 8% Norway, and 7% the US. The synthetic tracks actual GDP quite well until the Sandinistas take over. As shown in Panel A of Table 6, our predictor variables are six lags of per-capita GDP, human capital, and the gross capital formation share. The RMSPE is $387 (about 5% of final pre-treatment income), which compares very favorably with the fit achieved using either the average of all Latin American countries in our donor pool or the single best fitting country, Costa Rica.

However, when the treatment period begins, Nicaraguan income takes an immediate, large, and sustained drop relative to the control. By 1990, Nicaragua is only half as rich as the control predicted. Panel B of Fig. 5 plots the period-by-period treatment effects and associated p-values, showing that the effects are large, but not precisely measured, except at the beginning and end of the treatment period.

Panel A of Fig. 6 presents the results for infant mortality. Our predictor variables are four lags of infant mortality, human capital, and gross capital formation share. Here the synthetic control (70% Algeria, 10% Peru, 9% Nigeria, and 9% Chile) very closely tracks the actual Nicaraguan outcomes in the pre-treatment period with a RMSPE of 0.42 (Panel B of Table 6). The control continues to track well in the first few years of the treatment period, after which Nicaragua notably underperforms its control. Panel B of Fig. 6 plots the treatment effects and p-values. Over the second half of the treatment period the effect is large and significant, with around 15 additional infant deaths per 1000 live births.[20]

In sum, the effect of Ortega and the Sandinistas on the country's real GDP and infant mortality was devastating.

[18] Food was rationed by state and the regime convicted "14 major companies of 'economic sabotage'—inadequate output—and their assets taken into state control." All quotes in this paragraph are from Elliott (1987, 27-28).

[19] Under Ortega's second time around as president, Nicaragua's ICRG investment profile variable and Polity 2 score both improved from what they were under his predecessor. Coppedge et al. (2017) also do not report any judicial tampering.

[20] It is possible to create one synthetic control for multiple outcomes in the treated unit. If you take each of the (say) two outcomes, subtract the mean and divide by the standard deviation (so that each outcome would get the same weight in constructing the synthetic), you can stack the outcomes and use existing software to estimate a single control for both of them. For example, Eliason and Lutz (2018) do this. Their two outcomes are tax revenues and expenditures in the state of Colorado and they report little difference between estimating two separate controls and the "standardized and stacked" procedure. Since states are constrained in borrowing, it's not surprising that revenues and expenditures can be well explained with a single control since their time series are so similar. However, in most of our 4 countries, this is not the case. Real incomes are quite volatile, while infant mortality is pretty smoothly declining. When we use the "standardized and stacked" approach (via the MSCMT R package of Becker and Klossner (2016)), we end up with very poor pre-treatment fits for at least one of the two outcome variables. Since a good pre-treatment fit is the very foundation of a valid synthetic control exercise, we stick with the one outcome at a time approach.

Fig. 5. (A) Trends in income - Nicaragua & synthetic. (B) Daniel Ortega's effect on Nicaraguan income.

5.2. Venezuela

Hugo Chávez, president of Venezuela from 1999 until his death in 2013, was a hugely polarizing figure in Venezuelan politics. He came to power in 1998 on a left-leaning platform promising to eradicate poverty and inequality, combat US imperialism, and revolutionizing elite-driven politics. He was a political outsider at the time. Having helped engineer a failed military coup in 1992, he was jailed for two years afterwards, and was not associated with either of the two established political parties.[21]

In his initial campaign for president, Chávez called for a constitutional convention and the abolishment of the existing legislature. The Supreme Court ruled this unconstitutional and argued that any institutional changes must wait until after the convention. Chávez may have lost that battle but he won the war by going on to greatly expand the Court and pack it with party supporters.[22] The constitution transformed the bicameral structure of the legislature into a unicameral one, increased the presidential term from 5 years to 6, and allowed for presidential re-election. In 2000, Chávez's party won such a commanding advantage in the legislature (101 of 165 total seats), that the latter ended up granting him the power to

[21] He created his own political movement, calling his party the Fifth Republic Movement (MVR – Movimiento Quinta República).
[22] Rohter (1999) and Nelson (2009).

Table 6
Nicaragua's predictor means.

Panel A: Income				
Variables	Nicaragua	Synthetic Nicaragua	Latin America	Costa Rica
GDP per capita (1960)	$4476.47	$4880.63	$3372.98	$4683.93
GDP per capita (1964)	$5877.65	$5594.35	$3710.58	$4834.54
GDP per capita (1968)	$6422.17	$6385.35	$4079.24	$5430.18
GDP per capita (1972)	$6439.35	$6856.90	$4689.11	$6211.56
GDP per capita (1975)	$6527.42	$6569.55	$4808.16	$6424.32
GDP per capita (1977)	$7999.42	$7328.55	$5171.72	$7818.54
Human capital index	1.40	1.83	1.68	1.71
Gross capital formation share	0.18	0.17	0.16	0.11
RMSPE	–	387.49	2058.14	780.15
Panel B: Infant mortality				
Variables	Nicaragua	Synthetic Nicaragua	Latin America	Guatemala
Infant mortality (1964)	127.10	127.24	96.61	134.80
Infant mortality (1968)	121.70	121.47	84.03	122.50
Infant mortality (1973)	109.50	109.18	71.91	107.10
Infant mortality (1977)	91.70	92.46	61.48	94.80
Human capital index	1.40	1.44	1.68	1.21
Capital stock per capita	8243.76	71888.45	6332.58	3023.31
Gross capital formation share	0.04	0.16	0.14	0.11
RMSPE	–	0.42	33.78	6.82

Note. This table shows the values of indicator variables for Nicaragua and synthetic Nicaragua in the pre-treatment period (1970–1998). Unless otherwise indicates, variables are averaged across the pre-treatment period. We compare Nicaragua to counterfactuals: synthetic Nicaragua, the average of Latin American countries, and the best single-country counterfactual as measured by RMSPE (Costa Rica and Guatemala).

rule by decree. Chávez would go on to change the constitution again in 2009 to allow for a fourth consecutive presidential term.

Business uncertainty rose during Chávez's tenure as he nationalized large industries (like energy, iron, steel, cement, and mining), food production (rice, grocery chains, farms, and food distribution), as well as services (including banking, telecommunications, and hotels). The investment profile, calculated by the ICRG, fell from an average of 5.84 in the pre-Chávez period to an average of 3.77 during his time as president, or about 35%.[23]

Panel A of Fig. 7 plots the evolution of real per-capita GDP in Venezuela, along with that of its synthetic control. Our predictor variables are three lags of the human capital index, average physical capital per capita, average government consumption and average exports, all from the Penn World Tables. The control is composed of 17% El Salvador, 44% Nigeria, 21% Norway, 15% Peru, and 2% Saudi Arabia (Table B2 of Appendix B).

We find that the control matches pre-treatment Venezuela reasonably well (the RMSPE is $937) and that during the treatment period, Venezuela notably underperforms relative to what the synthetic would have predicted. By the end of our data, Venezuela is about 30% poorer than what it should have been according to the control. Panel A of Table 7 shows that the values for the predictor variables for this synthetic match very well to the values for actual Venezuela. Panel B of Fig. 7 shows the annual deviations during the treatment period along with their p-values. The effects are most significant at the beginning and end of the period.[24]

We now consider infant mortality. Our predictor variables are three lags of the outcome variable along with average investment share of GDP, average share of government consumption in GDP and the average value of the human capital index. Panel B of Table 7 reports the values of these variables for both the actual and synthetic Venezuela. The table also shows how much better the synthetic control fits pre- Chávez Venezuela than does the Latin American average, or the values for Panama, which would be the single best predictor country to use. The control in this case is composed of 27% Kuwait, 2% Nigeria, 22% Norway, 13% Panama, 35% Paraguay, and 1% Peru. Panel A of Fig. 8 shows that the control tracks Venezuelan infant mortality almost perfectly from 1975 to 1999. During the Chávez regime, Venezuela slightly outperforms its control. Panel B of Fig. 8 shows that from 2000 to 2009, these small improvements are often statistically significant. From 2010 onward the results reverse. We thus see a significant, but temporary, decrease in infant mortality that can be attributed to the Chávez regime, followed by a statistically significant increase in the latter portion of the post-treatment window.

In sum, Venezuela's suffered a large and significant decline in real GDP compared to its synthetic, and mixed results in infant mortality.

[23] Note that the ICRG data does not extend far enough back in time to show the effect the Sandinistas had on the investment climate in Nicaragua.

[24] It is worthwhile to compare these results to those in Grier and Maynard (2016), which used an older version of the Penn World Tables database. Their conclusion is the same as ours. Venezuela is almost one-third poorer than what the control indicates. However, Grier & Maynard were able to produce a better fitting control in the pre-treatment period and to achieve greater statistical significance. The countries chosen for the control also vary in the two studies (our algorithm selects Norway instead of Canada and Nigeria instead of Iran). If we adopt Grier & Maynard's specification using our data, we get a worse pre-treatment fit than what we have reported above, but roughly the same estimated underperformance in the treatment period.

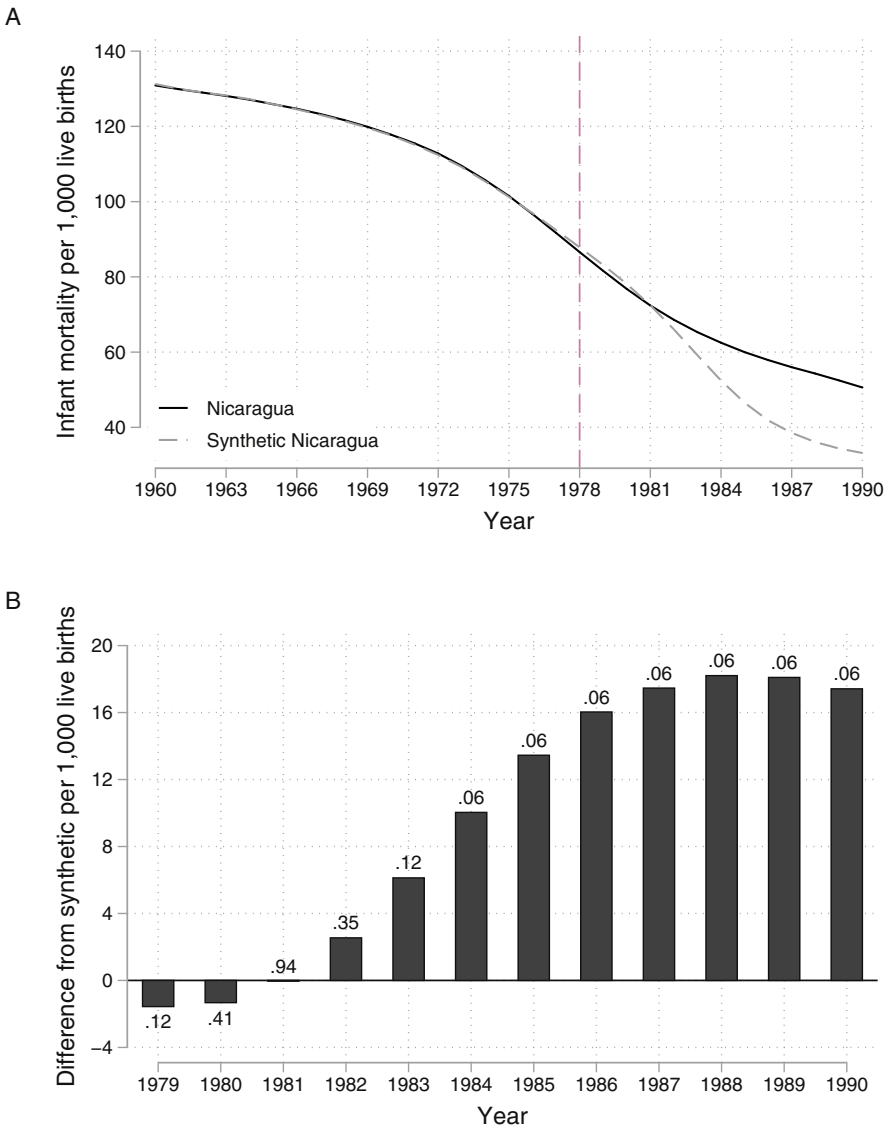

Fig. 6. (A) Trends in infant mortality - Nicaragua & synthetic. (B) Daniel Ortega's effect on Nicaraguan infant mortality.

5.3. Bolivia

Evo Morales, president of Bolivia from 2006 until 2019, was also a political outsider. A coca grower and head of the cocalero trade union for much of his life, he was the first indigenous president of Bolivia. The policies he promised were also a break from the past. He campaigned on a platform of "21st century socialism," an end to the US war on drugs, and the nationalization of the oil and gas industry (Kennemore and Weeks, 2011).

Like Chávez, Morales also called for constitutional change. He succeeded in 2009, and the new constitution allowed the president to be re-elected to consecutive terms. Morales argued that his first term did not count since the new constitution made Bolivia a "plurinational state instead of a republic."[25] The constitutional tribunal agreed and granted him the ability to run for office for a third time. After that, Morales questioned his inability to run for a fourth term, despite what his constitution stated. He called for a referendum on the issue in 2016 and lost. Subsequently however, Bolivia's "highest court overruled the constitution, scrapping term limits altogether for every office (Blair 2017)."[26]

[25] The *Guardian*, December 17th, 2016.

[26] Morales won 47% of the vote in his fourth electoral bid in October 2019. There was a large outcry about electoral fraud and he was forced from office one month later.

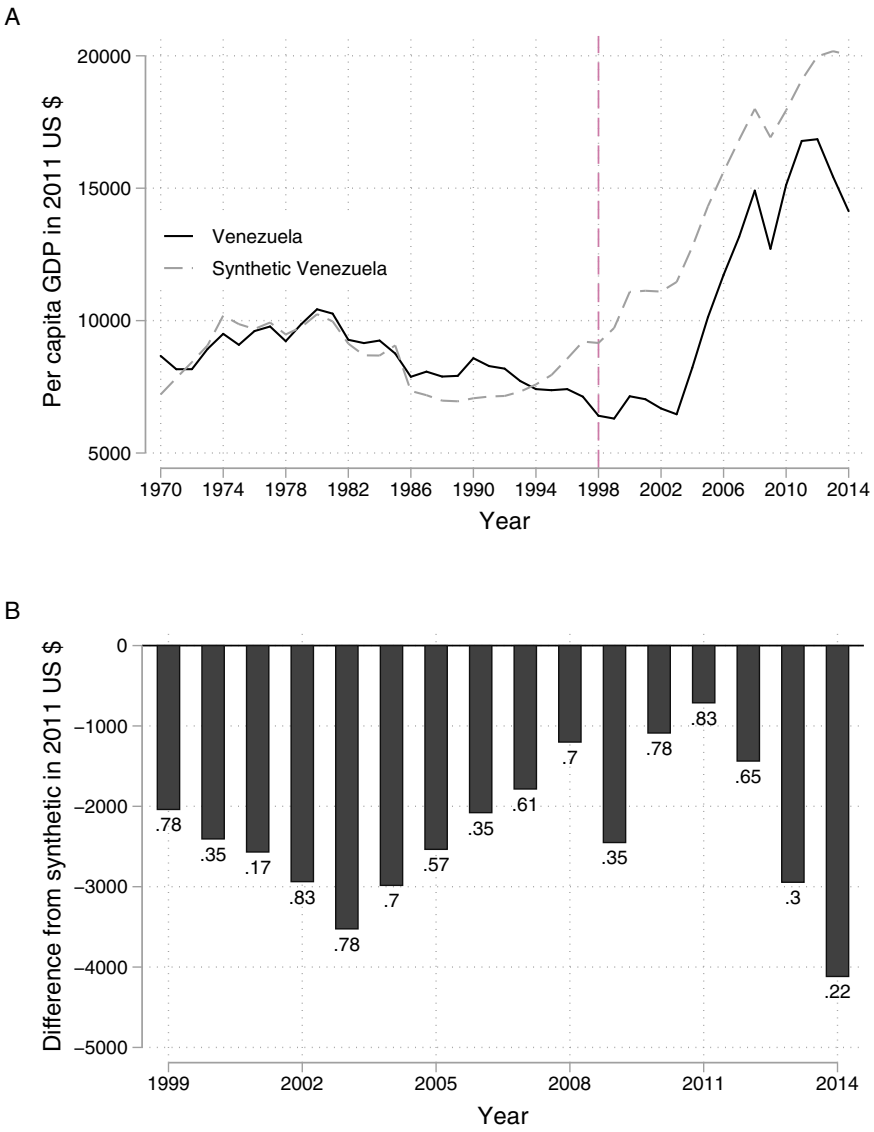

Fig. 7. (A) Trends in income - Venezuela & synthetic. (B) Hugo Chavez's effect on Venezuelan income.

Morales did not change the structure of the legislature or rule by decree, although he threatened to do the latter if legislators did not start cooperating with his agenda."[27] The Morales government also repeatedly attacked the separation of power in Bolivia, suggesting at one point "that the judicial branch of government for the country should not be independent."[28] Indeed, Coppedge et al. (2017) documents how government attacks on the judiciary went from being rare occurrences in the decade before Morales to happening on a weekly or monthly basis during his presidency.

Bolivia's investment profile score fell from 8.67 in the 10 years before Morales to 3.45 afterwards, representing a 60% decrease. This large decrease is not surprising as Morales followed through on his campaign promise to nationalize the oil and gas industry. He went beyond that and nationalized telecommunications and mining, as well as placing price controls on a variety of products including food and gas.[29]

[27] A Wikileaks cable from January 13th, 2009 documents how Morales addressed a conference of his MAS party: "Morales then warned congress of the results if implementing legislation is not passed: 'If some congressmen oppose and do not approve the laws, which are based on the people's vote, I will implement the constitution through decrees.' The cable goes on to note that "this is not the first time Morales has declared that he will circumvent the congress by use of decrees.

[28] Martín (2017).

[29] Flores-Macías (2010). Kennemore and Weeks (2011, p. 271) argue that the Bolivian government has been rather pragmatic about the nationalizations, renegotiating how much foreign firms must pay to the government. The issue, they argue, is that the government's regulatory policies are causing chaos:

Table 7
Venezuela's predictor means.

Panel A: Income				
Variables	Venezuela	Synthetic Venezuela	Latin America	Algeria
GDP per capita (1970)	$8667.92	$7210.71	$4421.06	$5363.25
GDP per capita (1988)	$7887.75	$6977.63	$5632.53	$7972.87
GDP per capita (1995)	$7371.88	$7948.74	$7260.93	$6973.38
GDP per capita (1998)	$6408.24	$9155.72	$8001.86	$7255.25
Human capital index (1970)	1.38	1.60	1.68	1.17
Human capital index (1988)	1.82	1.85	2.04	1.46
Human capital index (1995)	1.99	1.99	2.19	1.71
Capital stock per capita	$27485.51	$22824.72	$9553.36	$26541.15
Government consumption	0.27	0.27	0.15	0.20
Merchandise exports	0.26	0.25	0.11	0.14
RMSPE	–	937.63	3412.73	1615.14
Panel B: Infant mortality				
Variables	Venezuela	Synthetic Venezuela	Latin America	Panama
Infant mortality (1973)	44.20	44.41	71.91	44.00
Infant mortality (1985)	29.50	29.30	43.27	29.70
Infant mortality (1998)	19.90	19.94	25.81	22.60
Gross capital formation	0.27	0.24	0.16	0.20
Government consumption	0.26	0.19	0.15	0.22
Human capital index	1.80	2.19	1.87	2.25
RMSPE	–	0.26	26.00	1.12

Note. This table shows the values of indicator variables for Venezuela and synthetic Venezuela in the pre-treatment period (1970–1998). Variables are averaged across the pre-treatment period, unless otherwise indicated. We compare Venezuela to counterfactuals: Synthetic Venezuela the average of Latin American countries, and the best single-country counterfactual as measured by RMSPE (Algeria and Panama).

We have income data for Bolivia from 1970 to 2014, giving us a 35-year pre-treatment period and a 9-year treatment period. For our indicator variables, we use four lags of the outcome variable, three lags of the human capital index, average physical capital per capita, average government consumption and average exports. Table B3 of Appendix B shows that the control consists of 43% El Salvador, 36% Indonesia, 9% Nigeria, 1% Paraguay, and 12% Peru, and Panel A of Table 8 shows that our synthetic Bolivia matches actual Bolivia fairly well on our indicators.

Panel A of Fig. 9 displays our estimate of the treatment effect of Morales on Bolivia's real per-capita GDP. As can be seen, the deviation of Bolivia from its synthetic control is large, negative, and persistent. This is a stark contrast to how well the control matched Bolivian performance during the 35-year pre-treatment period, when the RMSE was only $100.

By the end of the treatment period, Bolivian per-capita income is almost $2500 less than what the synthetic would predict. In other words, in 2014 Bolivia is almost 40% poorer than what the control, (which predicted very accurately for 35 years pre-Morales) says it should be. Panel B of Fig. 9 graphs the deviations of Bolivian per-capita GDP from the control by year and provides a p-value for each period. All deviations are significant at the 0.01 level. While Bolivian income did rise under Morales, it rose nowhere near as much as the control predicts.

This result underscores the importance of a valid counterfactual. While Bolivia performs quite well in the treatment period, it is actually a very poor performer relative to its counterfactual potential.

We now turn to infant mortality, where data availability issues mean that our analysis begin in 1973, giving us 32 years of pre-treatment and 9 years of treatment. Our indicator variables are 5 lags of the outcome variable, average investment share, average share of government consumption and the average value of the human capital index. Panel B of Table 8 shows that the synthetic Bolivia does a good job of matching the values of these variables in actual Bolivia, and that the control tracks Bolivia well in the pre-treatment period with a RMSPE of around 10 (deaths per 1000 live births). Panel A of Fig. 10 displays the time series of actual infant mortality in Bolivia and the predictions from our control, which is composed of 32% Nigeria and 68% Peru. While infant mortality fell under Morales, it had been steadily falling in Bolivia over our entire period. Bolivia does out-perform the synthetic control during the treatment period, but as Panel B of Fig. 10 shows, the deviations are not statistically significant.

In Bolivia's case, we find a significant GDP penalty with no statistically significant offsetting improvements in health outcomes.

"internal polarization and unpredictable regulation have damaged its investment climate." They go on to note that "annual FDI averaged $452 million between 1990 and 2000, but by 2007 was $204 million."

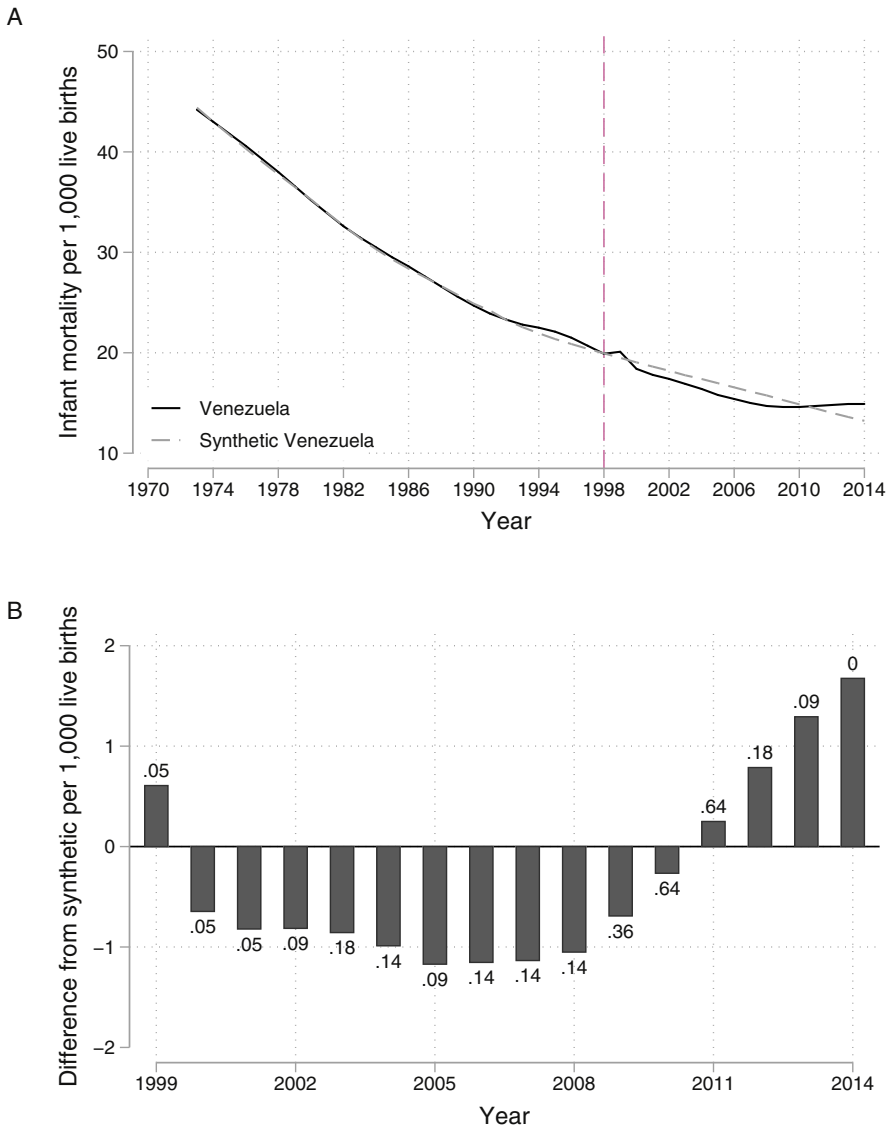

Fig. 8. (A) Trends in infant mortality - Venezuela & synthetic. (B) Hugo Chavez's effect on Venezuelan infant mortality.

5.4. Ecuador

Rafael Correa, president of Ecuador from 2007 to 2017, had a more technocratic background than the other three presidents we study. He was, however, largely a political unknown when he ran for president in 2006 and had never been affiliated with a political party. Correa rejected "the neoliberal market policies advocated by the US (including a bilateral free trade agreement with the US) and the privatization of industry (vowing to return Ecuador's oil wealth to the Ecuadorian people)."[30]

In addition, he argued that the country needed a constitutional assembly to get rid of the existing legislature. Correa succeeded in getting a new constitution passed in 2008.[31] Like the Venezuelan case, Ecuador's new constitution greatly strengthened the chief executive relative to other branches of government.[32] For instance, the president could now "call national referenda, partially veto or amend laws passed by the National Assembly, which in such cases can restore the original legislation only by the vote of a two-thirds majority." The constitution also allowed the president to be re-elected,

[30] Hemphill (2008, p. 290). The parentheses are in the original quote.

[31] Correa would also become dissatisfied with his constitution, going so far as to question its constitutionality as it prohibited him from running for a consecutive third term. He argued that the 2008 constitution was a violation of his human rights!

[32] Conaghan (2016, p. 111-2) notes that the previous constitution of 1998 had already awarded the president strong powers and the 2008 constitution goes beyond those.

Table 8
Bolivia's predictor means.

Panel A: Income				
Variables	Bolivia	Synthetic Bolivia	Latin America	Honduras
GDP per capita (1970)	$1708.65	$1571.92	$4421.06	$2277.12
GDP per capita (1988)	$2002.19	$2027.95	$5632.53	$2887.96
GDP per capita (1995)	$2848.57	$2891.06	$7260.93	$3125.74
GDP per capita (1998)	$3098.80	$3067.73	$8001.86	$3247.30
Human capital index (1970)	1.65	1.35	1.68	1.47
Human capital index (1988)	2.10	1.71	2.04	1.74
Human capital index (1995)	2.32	1.90	2.19	1.82
Capital stock per capita	$3752.51	$3731.65	$11,187.99	$5501.84
Government consumption	0.22	0.19	0.14	0.12
Merchandise exports	0.17	0.24	0.12	0.15
RMSPE	–	100.81	3513.07	513.27
Panel B: Infant mortality				
Variables	Bolivia	Synthetic Bolivia	Latin America	Indonesia
Infant mortality (1999)	42.80	44.44	24.44	42.80
Infant mortality (2001)	45.20	46.35	22.37	39.50
Infant mortality (2003)	47.70	48.39	20.58	36.50
Infant mortality (2004)	52.90	52.89	19.77	36.30
Infant mortality (2005)	58.50	57.90	18.98	33.80
Gross capital formation	3831.82	6568.24	13381.25	5208.72
Government consumption	0.23	0.22	0.15	0.15
Human capital index	2.14	1.92	2.06	1.84
RMSPE	–	9.75	47.91	21.81

Note. This table shows the values of indicator variables for Bolivia and synthetic Bolivia in the pre-treatment period (1970–2005). Unless otherwise indicated, variables are averaged across the pre-treatment period. We compare Bolivia to counterfactuals: Synthetic Bolivia, Latin American countries, and the best single-country counterfactual as measured by RMSPE (Honduras and Indonesia).

to dissolve the National Assembly and call new elections, a power that Correa did not exercise but rather used as a threat to keep legislators in line.[33] Similar to Chavez, Correa had campaigned on a promise to "depoliticize the courts" and instead did the opposite. De la Torre (2013, p. 35) writes: "All branches of government are under his (Correa's) control, so there will be no institutional mechanisms for holding him accountable."

Correa departed from Chavez and Morales in one important way though; while he threatened to nationalize the oil industry, he never actually did.[34] This greater pragmatism is reflected in Ecuador's investment profile. In the 10 years before Correa, the investment profile index averaged 5.64. During his presidency, it fell to an average of 4.82. While this decrease (15%) is not negligible, it is much smaller than the declines in Venezuela and Bolivia.[35]

Correa took office in 2007, giving us a 36-year pre-treatment period and an 8-year treatment period. We begin our analysis with real per-capita GDP. Panel A of Fig. 11 presents the time series of actual real GDP per capita in Ecuador along with our estimated synthetic control. The control is composed of 22% Algeria, 2% Canada, 15% El Salvador, 50% Paraguay, 11% Peru, and 1% Saudi Arabia. Estimated weights for all outcome variables in Ecuador's analysis can be found in Table B4 of Appendix B. The predictor variables used in the estimation are four lags of the outcome variable, three lags of the human capital index, average physical capital per capita, average share of government consumption in GDP and average share of exports in GDP. Panel A of Table 9 lists the predictor variables and covariate balance of Ecuador and Synthetic Ecuador.

The control matches Ecuadorian performance very well in the pre-treatment period (the RMSE is $240) and, unlike the previous cases we studied, continues to match in the treatment period. This indicates that the policy mix of the Correa administration had no influence on the evolution of real per capita GDP in Ecuador.

We show this in Panel B of Fig. 11, which graphs the deviation of Ecuadorian GDP from the control in each of the eight treatment years. The deviations are small and statistically insignificant, indicating that Correa was no improvement over what would have happened to Ecuadorean income if his policies had not been enacted. On the other hand, Ecuador avoided the huge shortfall of GDP that the other three cases experienced.[36]

[33] Conaghan (2016, p. 111-2). Conaghan (2016, p. 110) describes the legislature under Correa's presidency a "rubber stamp." See Conaghan (2016) as well for an interesting description of how Correa has strengthened the executive even more by adding a fifth branch of government in the area of "transparency and social control," which essentially answers to the executive branch.

[34] He did use the threat of expropriation though to get foreign oil companies to restructure their contracts with the government. In 2010, Correa stated: "My patience with this is up. We're sending a bill to the National Assembly that would give me the power to expropriate oil fields in the event these oil companies don't want to sign the new service contracts." Latin American Herald Tribune (2010).

[35] As we mentioned above, the threat of expropriation only makes up a part of this index and we do not have access to data for the sub-components.

[36] It is worth noting though that Correa had made big promises about Ecuador's economic performance under his leadership. Conaghan (2018) writes that "Correa had spent a decade vowing to turn Ecuador into a South American "jaguar" with an economy akin to Asian 'tiger' economies like Hong Kong, Singapore, and South Korea." However, "the promised transformation never got off the ground. Even as Correa directed planners to jumpstart import-

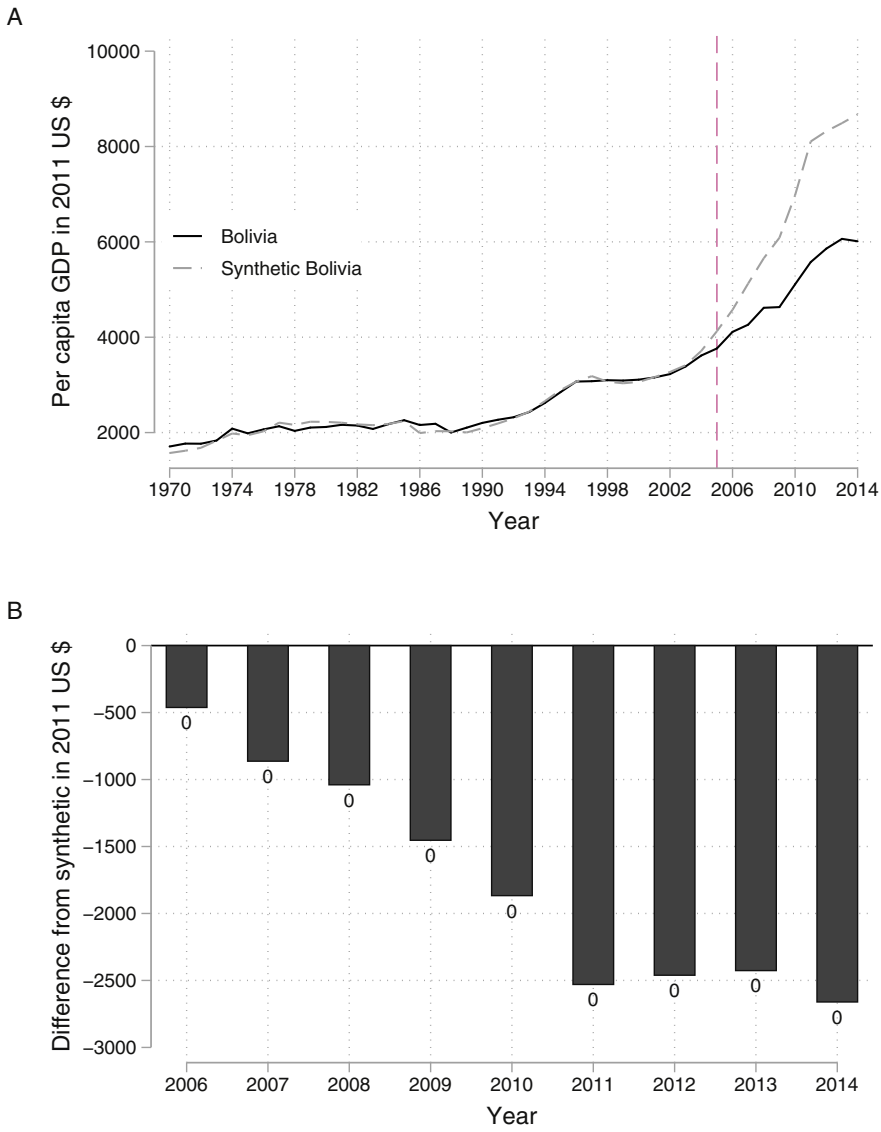

Fig. 9. (A) Trends in income - Bolivia & synthetic. (B) Evo Morales' effect on Bolivian income.

Next, we consider infant mortality in Ecuador. Due to data limitations, our sample period begins in 1973. Our control is 11% Algeria, 22% Chile, 13% Kuwait, 2% Nigeria, 51% Peru, and 1% Saudi Arabia (Table B4 of Appendix B). Panel B of Table 9 presents the indicator variables and their values for both Ecuador and its synthetic control. We use three lags of the outcome variable, which comes from the World Bank, along with the average share of government consumption in GDP, the average share of investment in GDP, and the average value of the human capital index from the Penn World Tables. Panel A of Fig. 12 plots infant mortality and its synthetic control before and after Correa. Infant mortality falls monotonically over the sample and the control fits almost perfectly before Correa comes to power. In the treatment period, however, Ecuador underperforms its control. Panel B of Fig. 12 shows that although those deviations are small, they are statistically significant. Infant mortality fell more slowly under Correa by a small but statistically significant amount.

To summarize, we find that starting around 2000, per-capita GDP rose rapidly. However, the Correa administration which began in 2007, had no measurable impact on these pre-existing trends. The one area where we find a significant impact is in infant mortality, though there we find that the Correa regime underperformed its control by a small amount.

substitution industries and seed high-tech ventures, the economy remained stubbornly traditional, dependent primarily on revenues from petroleum and mining along with traditional agricultural exports like bananas and shrimp."

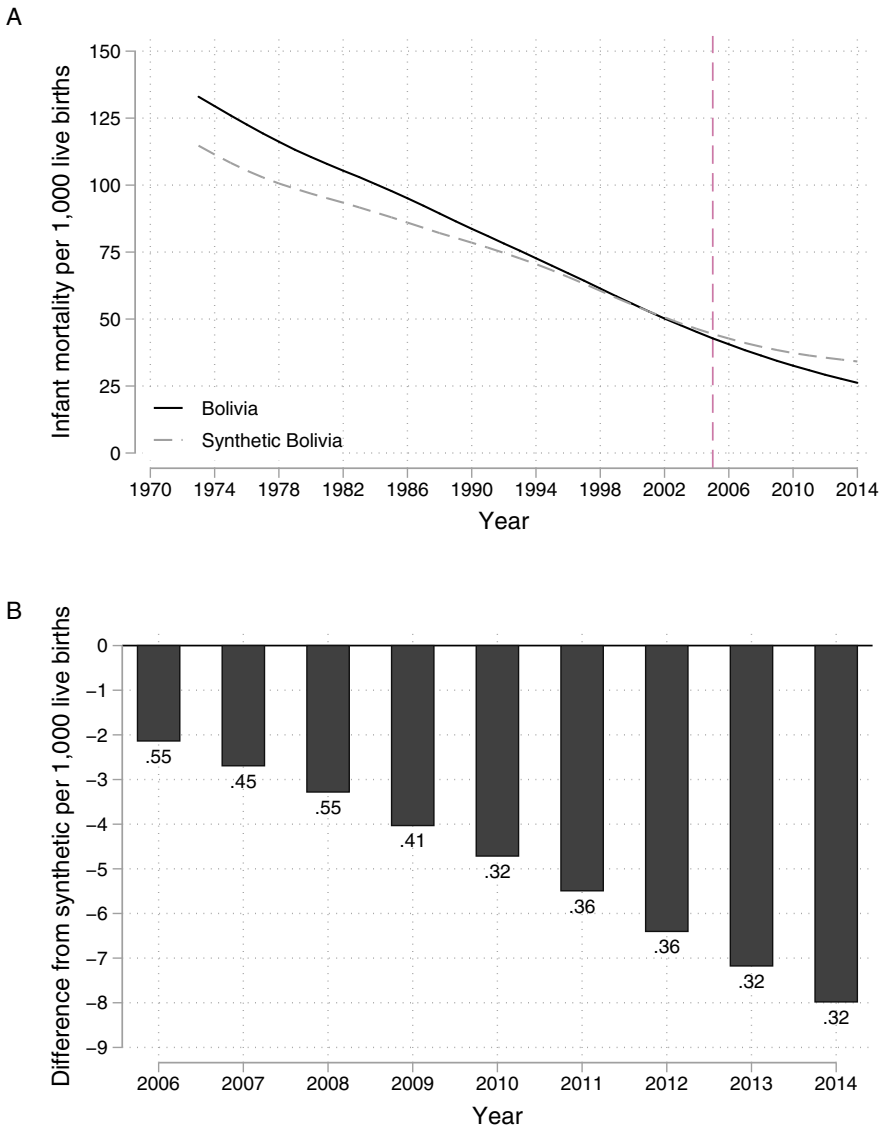

Fig. 10. (A) Trends in infant mortality - Bolivia & synthetic. (B) Evo Morales' effect on Bolivian infant mortality.

In sum, we show that Ortega and the Sandinistas greatly reduced real incomes and significantly raised infant mortality relative to the synthetic. The Chávez regime is associated with a large and significant decline in real GDP and a small but significant improvement in infant mortality over a 7-year period. This benefit slowly evaporates and ultimately reverses in the latter half of the analysis window. Our results for Bolivia reveal a large GDP penalty with no statistically offsetting improvements in health outcomes. Lastly, we find that starting around 2000, per-capita GDP in Ecuador rose rapidly, but the Correa administration, which began in 2007, had no measurable impact on these pre-existing trends. The one area where we find a significant impact is in infant mortality, though there we find that the Correa regime significantly underperformed its control by a small amount.[37]

[37] The single country results show that inequality is lower in Venezuela, Bolivia and Ecuador that what is predicted by their synthetic controls. However, the estimates do not reach statistical significance. It is worth remembering that the SCM method inference method uses a ranking of the ratio of post- to pre-treatment fits. Thus, a small treatment effect likely will only achieve significance if the pre-treatment matching is excellent, which is not the case for us here. The effects of these left-populist leaders on inequality are a topic deserving further study.

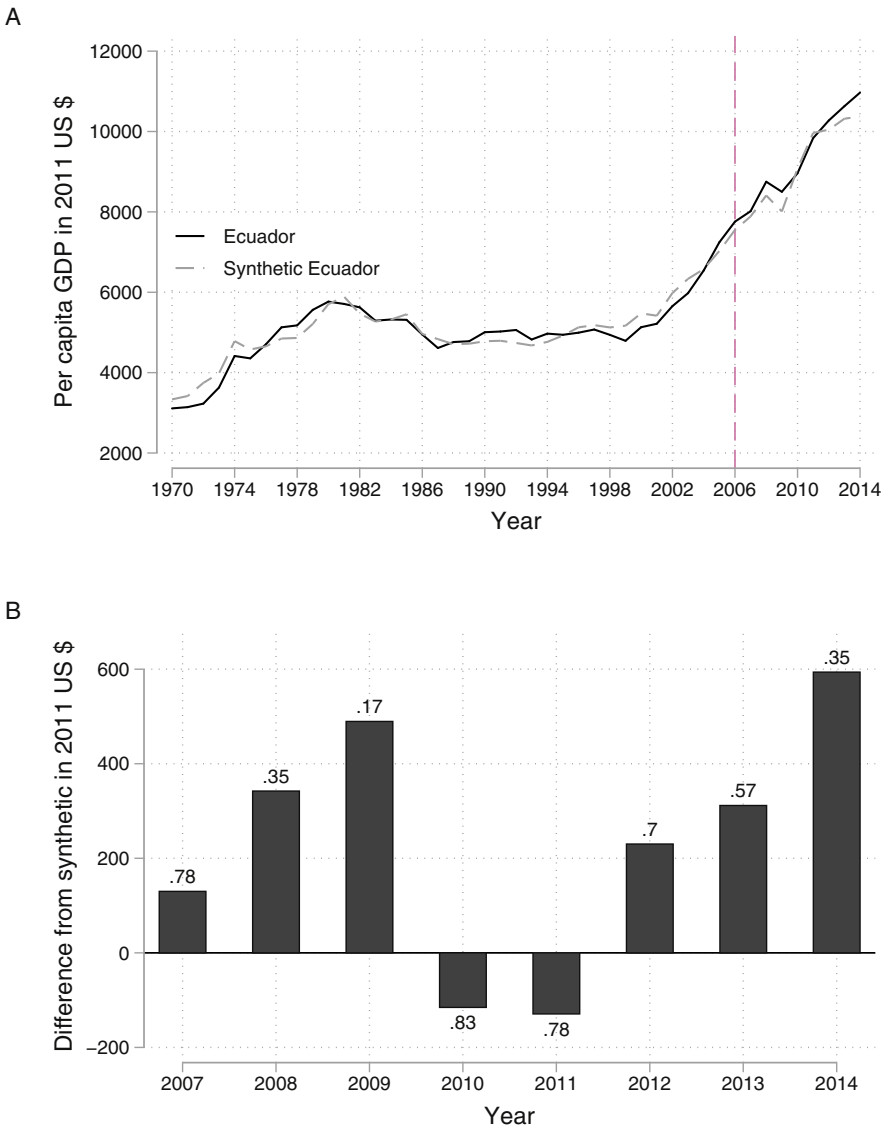

Fig. 11. (A) Trends in income - Ecuador & synthetic. (B) Rafael Correa's effect on Ecuadorian income.

6. Conclusion

It is common for the media to credit or blame national leaders for whatever might be going on with the domestic economy. It is much less clear whether this is a fair judgment; that is, how much of any observed correlation is truly causal. In this paper, we have used a multiple-treatment synthetic control model to estimate the average effect of durable left-populists in Latin America on income, infant mortality, and inequality. These regimes are defined by (1) a concentration of power in the executive branch, (2) an attempt to stay in power indefinitely, and (3) the enactment of anti-market economic policies.

This combination of characteristics has a unique potential to cause economic problems. As we discussed above, a leader may be elected on an anti-market platform, but if there are institutional checks and balances, then that platform might be greatly modified by the time it is enacted. When the leader can implement these types of policies, the damage may be mitigated if there are constitutional term limits on the executive. We argue that what makes durable left-populism so potentially damaging is the combination of: (i) a concentration of executive power which limits the checks and balances from other political institutions; and (ii) a dismantling of term limits through constitutional changes. This concern about these characteristics is borne out in our results.

We show that, on average, these regimes reduced real per capita incomes by over 20% relative to their synthetic control. This result is both large and strongly significant. However, these leaders often stressed equity and redistribution over higher

Table 9
Ecuador's predictor means.

Panel B: Income				
Variables	Ecuador	Synthetic Ecuador	Latin America	Peru
GDP per capita (1970)	$3109.85	$3334.63	$4421.06	$3560.34
GDP per capita (1988)	$4761.13	$4708.54	$5632.53	$4174.50
GDP per capita (1995)	$4941.47	$4921.53	$7260.93	$4651.55
GDP per capita (1998)	$4940.43	$5124.37	$8001.86	$4916.79
Human capital index (1970)	1.78	1.51	1.68	1.64
Human capital index (1988)	2.17	1.85	2.04	2.14
Human capital index (1995)	2.33	2.02	2.19	2.37
Capital stock per capita	$11644.12	$12654.21	$11484.75	$8243.65
Government consumption	0.23	0.16	0.14	0.20
Export share	0.16	0.16	0.12	0.10
RMSPE	–	240.26	1451.71	1022.35
Panel B: Infant mortality				
Variables	Ecuador	Synthetic Ecuador	Latin America	Honduras
Infant mortality (1973)	88.20	88.19	71.91	90.70
Infant mortality (1985)	52.70	52.71	43.27	55.50
Infant mortality (1998)	27.30	27.77	25.81	36.50
Gross capital formation share	0.21	0.21	0.18	0.18
Government consumption	0.24	0.21	0.15	0.12
Human capital index	2.21	2.17	2.07	1.75
RMSPE	–	0.28	8.98	4.07

Note. This table shows the values of indicator variables for Ecuador and synthetic Ecuador in the pre-treatment period (1970–2006). Unless otherwise indicated, variables are averaged across the pre-treatment period. We compare Ecuador to counterfactuals: synthetic Ecuador, average of Latin American countries, and the best single-country counterfactual as measured by RMSPE (Peru and Honduras).

average incomes, so voters may have been willing to trade off GDP for progress on these goals. However, we find no evidence of such a trade-off on average, as the average performance of these regimes on infant mortality and inequality did not significantly differ from the predictions of the average synthetic control counterfactual.[38]

The SCM is a reduced form causal method and as such does not tell us the how or why of this documented relative economic underperformance. A full investigation is beyond the scope of this paper, but in Appendix B we show that in the three countries that underperform their income synthetic, there is on average a corresponding underperformance in investment and total factor productivity. While these results are not causal, they are intuitive and may provide a starting point for further work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2020.07.001.

Appendix A. Inequality

We show in the main text that these four durable-left-populist regimes suffered a significant income penalty relative to their controls. We then checked whether there was a trade off in terms of improved public health, as measured by infant mortality. We found no evidence that the income penalty was offset by a reduction in infant mortality.

Here we check for another possible trade-off, namely in inequality. It is possible that even though income fell (relative to the controls), that inequality may have also fallen by more than predicted and under some sets of preferences, the gain from the second could outweigh the loss from the first. For the three countries where we have sufficient inequality data (Venezuela, Bolivia, and Ecuador), we find that the average fall in inequality was greater than that in the average control. However, the result is not statistically significant.

There are several reasons why this might be the case. First, the inference procedure used here relies on the ranking of the ratios between post- and pre-treatment fit for the treated unit and the control units. If the treatment effect is moderate

[38] This is true for the average treatment effect. When we consider the country-specific effects, Venezuela outperforms its control in infant mortality at the beginning of the treatment period, while Ecuador and Nicaragua significantly underperform their controls in the case of infant mortality.

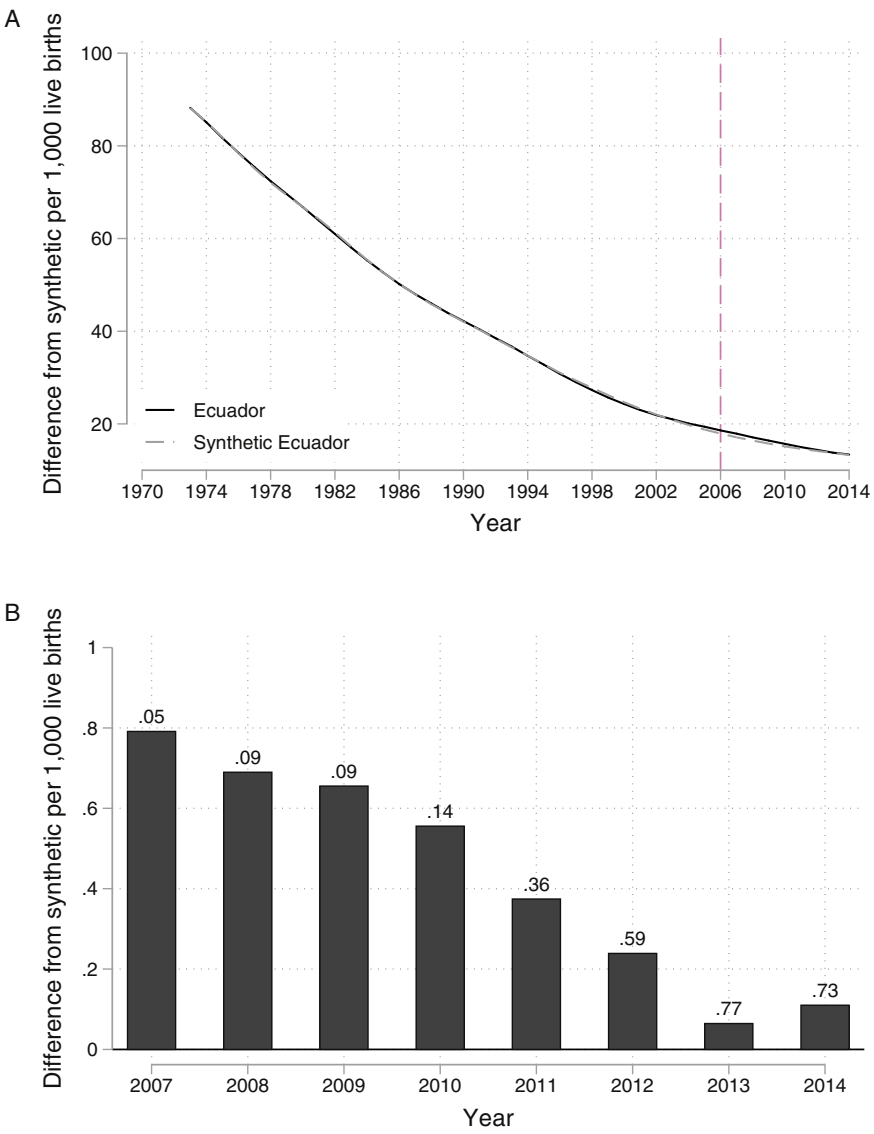

Fig. 12. (A) Trends in infant mortality - Ecuador & synthetic. (B) Rafael Correa's effect on Ecuadorian infant mortality.

in size, the pre-treatment matching likely needs to be quite good for the effect to achieve significance. And we are not able to produce an excellent pre-treatment fit for our treated cases. Second, the low quality of the inequality data and the frequent interpolations and combining of mis-matched surveys required to make an annual dataset cause us not to be able to see an effect. Third, it is possible that the relative decline in incomes fell harder on the poor and this sufficiently muted the governments' redistributive efforts enough for them to not be significant.

We take the Gini coefficient from the SWIID as our inequality measure and perform exactly the same analysis for these outcomes that we did for real per-capita GDP and health. Fig. A1 presents the average results.[39] The average Gini for the treated units rises through most of the pre-treatment period and then declines for the last four pretreatment periods and all of the treatment period. The averaged control picks up the part of the rise and is late to track the decline. Table A1 shows the countries in the donor pool for this experiment, while table A2 shows the RMPSE in the pre-treatment period is 0.33, which is lower than that obtained using the Latin American or OPEC averages. Fig. A2 presents size of the treatment effect

[39] The dearth of inequality data from the 1960s and early 1970s means that we cannot include the Ortega / Sandinista regime in this experiment. It is based on the averages for Venezuela, Bolivia and Ecuador.

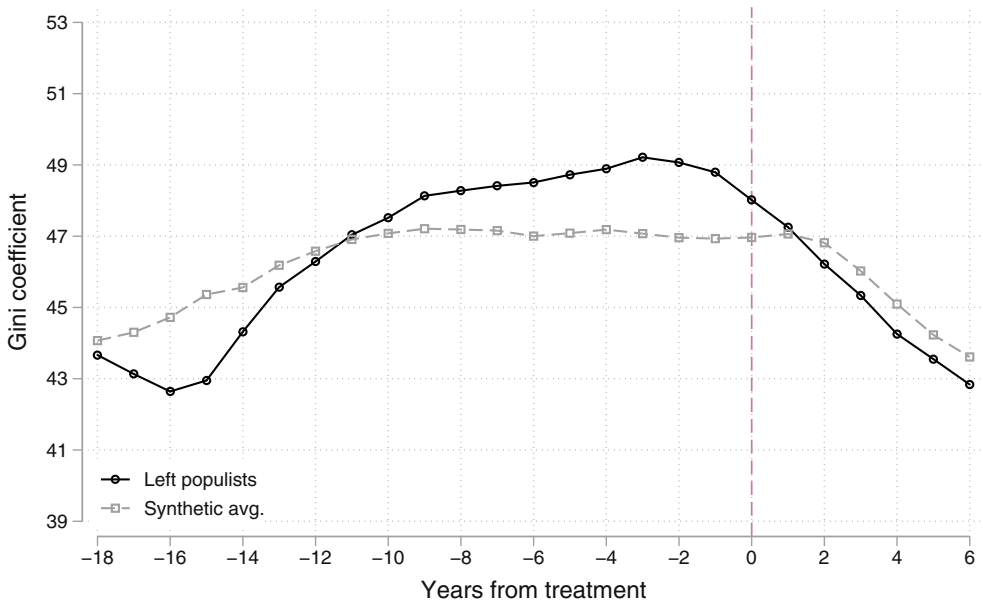

Fig. A1. Trends in inequality - left populists and synthetic avg.

Table A1
Donor countries for inequality.

Donor	Dependent variable Inequality
Algeria	×
Argentina	✓
Brazil	✓
Canada	✓
Chile	✓
Colombia	✓
Costa Rica	✓
El Salvador	×
Guatemala	✓
Honduras	×
Indonesia	✓
Iran	✓
Iraq	×
Kuwait	×
Mexico	✓
Nigeria	✓
Norway	✓
Panama	✓
Paraguay	×
Peru	✓
Saudi Arabia	×
United Arab Emirates	×
United States	✓
Uruguay	✓

Note. A check indicates that the donor is included in all cases, while an "X" indicates the donor has insufficient data and was omitted. Although attempts are made to estimate missing data, in some cases there are too few observations to interpolate.

and its p-value for each period. The largest reduction in inequality relative to the control is in the 3rd treatment period and is about 1.25 points, which is small relative to the average Gini value of around 35 for that period. All the effects are completely insignificant. In sum, we find no average decline in inequality that can be causally attributed to the regimes we study. We now turn to examining inequality in the individual countries, starting with Venezuela.

For the Venezuelan case, our predictor variables are four lags of Gini, labor compensation share, gross capital formation, and three lags of income, all from the Penn World Tables. The control is composed of 32% Canada, 15% Indonesia, 27% Nigeria, and 26% Peru (Table A3). Table A4 displays the predictor variables and their respective values. Panel A of Fig. A3 graphs Venezuela's Gini along with the Gini predicted by our control. We can see that starting in 2006, Venezuela starts to outper-

Table A2
Average inequality predictor means.

Variables	Left populists	Synthetic LP
Gini coefficient	44.76	45.39
Labor compensation share	0.49	0.51
Human capital index	2.08	1.95
Gross capital formation share	0.20	0.19
GDP per capita	$5510.04	$7683.96
Polity	7.55	4.30
Export share	0.18	0.15
RMSPE	–	0.33

Note. This table shows the values of indicator variables for the left populist and their synthetic counterfactuals in their respective pre-treatment periods. Variables are averaged across the pre-treatment period.

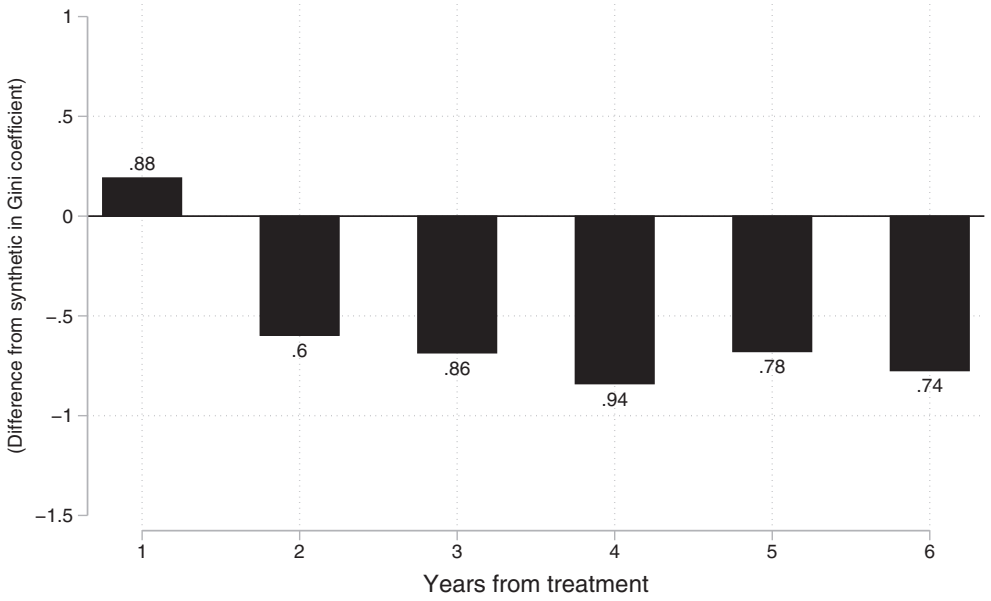

Fig. A2. The avg. effects of left populists on inequality.

Table A3
Venezuela's estimated synthetic weights for inequality.

Donor	Outcome variable Inequality
Argentina	0
Brazil	0
Canada	0.318
Chile	0
Colombia	0
Costa Rica	0
Guatemala	0
Indonesia	0.154
Iran	0
Mexico	0
Nigeria	0.269
Norway	0
Panama	0
Peru	0.260
United States	0
Uruguay	0

Note. Columns show the weights that compose the synthetic counterfactual. Values are in percentage points and are rounded, so the columns may not sum to one.

Table A4
Venezuela's inequality predictor means.

Variables	Venezuela	Synthetic Venezuela	Latin America	Argentina
Gini coefficient (1981)	37.84	37.90	48.44	37.82
Gini coefficient (1985)	39.48	39.13	47.08	38.76
Gini coefficient (1990)	38.50	39.46	47.75	41.56
Gini coefficient (1998)	42.99	42.68	48.61	44.46
Labor compensation share	0.43	0.48	0.52	0.51
Gross capital formation share	0.23	0.18	0.18	0.15
GDP per capita (1981)	10264.77	11024.70	6766.08	4470.22
GDP per capita (1990)	8580.86	11319.18	6598.31	5945.50
GDP per capita (1998)	6408.24	13028.35	9465.36	15587.75
RMSPE	–	0.72	8.17	1.64

Note. This table shows the values of indicator variables for Venezuela and synthetic Venezuela in the pre-treatment period (1970–1998). Unless otherwise indicated, variables are averaged across the pre-treatment period. We compare Venezuela to counterfactuals: synthetic Venezuela, the average of Latin American countries, and Panama (the most similar single-country, measured by RMSPE).

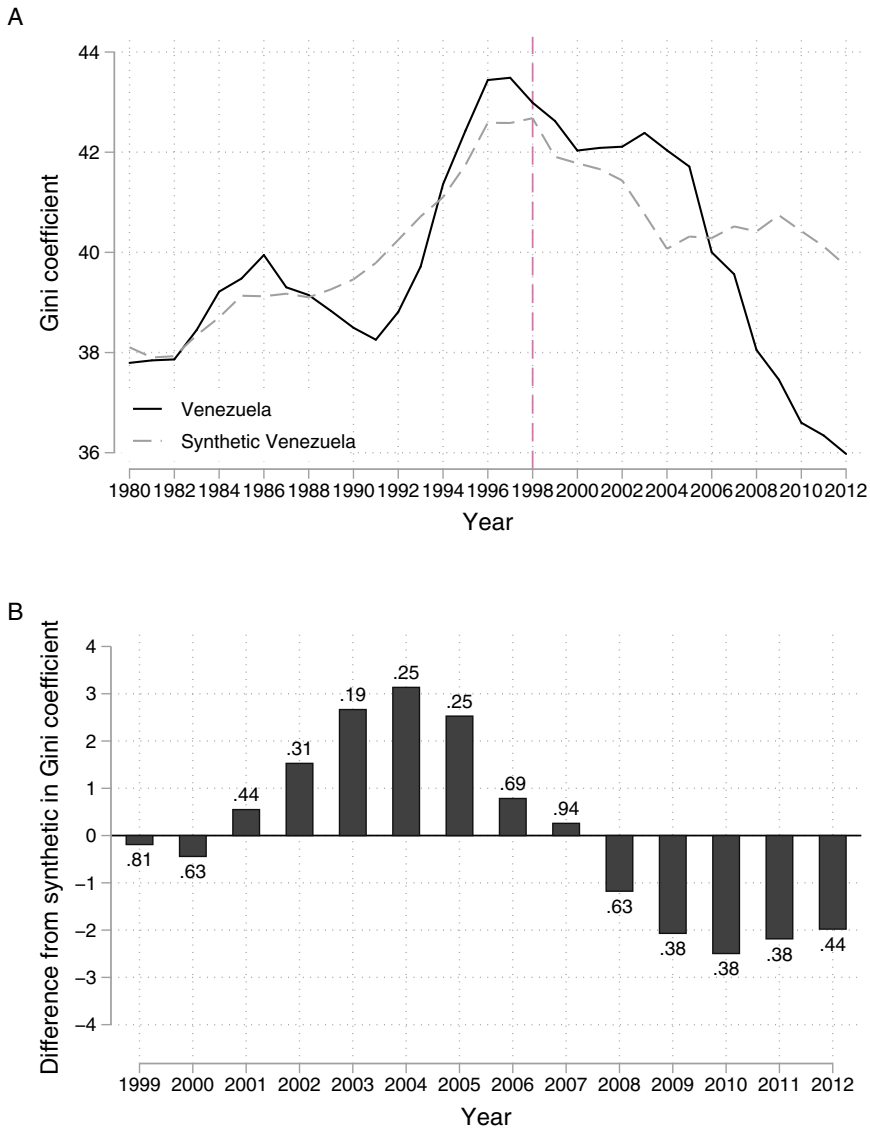

Fig. A3. (A) Trends in inequality - Venezuela and synthetic. (B) Hugo Chavez's effect on Venezuelan inequality.

Table A5
Bolivia's estimated synthetic weights for inequality.

Donor	Outcome variable Inequality
Argentina	0.101
Brazil	0
Canada	0
Chile	0
Colombia	0.397
Costa Rica	0
Guatemala	0
Indonesia	0
Iran	0
Mexico	0
Nigeria	0.021
Norway	0
Panama	0.145
Peru	0.336
United States	0
Uruguay	0

Note. Columns show the estimated weights for synthetic Bolivia. Values are in percentage points and are rounded, so the columns may not sum to one.

Table A6
Bolivia's inequality predictor means.

Variables	Bolivia	Synthetic Bolivia	Latin America	Chile
Gini coefficient (1982)	51.58	52.63	48.06	50.62
Gini coefficient (1986)	52.54	49.72	46.98	51.09
Gini coefficient (1988)	47.42	48.80	47.33	51.32
Gini coefficient (1990)	42.84	49.99	47.75	51.28
Gini coefficient (1992)	47.13	49.87	47.63	50.25
Gini coefficient (1994)	51.12	50.56	47.91	50.07
Gini coefficient (1998)	54.03	52.02	48.61	51.52
Gini coefficient (2002)	55.44	51.39	48.83	50.89
Gini coefficient (2005)	52.44	49.81	47.66	49.13
Labor compensation share	0.55	0.54	0.51	0.45
Human capital index	2.24	2.21	2.22	2.66
Polity	7.54	5.94	5.32	3.46
Export share	0.12	0.09	0.11	0.17
RMSPE	–	3.11	4.63	3.45

Note. This table shows the values of indicator variables for Bolivia and synthetic Bolivia in the pre-treatment period (1980–2005). Variables are averaged across the pre-treatment period, unless otherwise indicated. We compare Bolivia to counterfactuals: synthetic Bolivia, the average of Latin American countries, and Chile (the most similar single-country, measured by RMSPE).

form the control with a lower Gini. However, Panel B of Fig. A3 shows that these differences are not statistically significant. The Chávez regime did not significantly lower inequality below the predictions of the "business as usual" synthetic control.

For Bolivia, our predictor variables include nine lags of the Gini coefficient, the average value of labor compensation as a fraction of output, the average value of the human capital index, the average polity score and the average export share. The control is composed of 10% Argentina, 40% Colombia, 2% Nigeria, 15% Panama, and 34% Peru (Table A5). Panel A of Fig. A4 shows that Bolivia's Gini is quite volatile and the control does not match it extremely well, although Table A6 show that the synthetic control does fit better than three other plausible counterfactuals. Inequality rises sharply throughout the 1990s and begins falling around 2000. After Morales is elected, inequality continues to fall and falls more rapidly than predicted by the control. However, Panel B of Fig. A4 shows that the improvement is statistically insignificant.

Finally, we consider inequality in Ecuador. In this case our sample begins in 1980 and the control is 49% Colombia, 39% Nigeria, and 12% Panama (Table A7). We use six lags of the Gini coefficient, labor compensation share, and the human capital index. Table A8 show the predictor variables match closely between actual Ecuador and the synthetic, suggesting the synthetic not only tracks inequality in the pre-treatment period, but resembles actual Ecuador along other pertinent dimensions as well. As Panel A in Fig. A5 shows, Ecuador's Gini is also volatile, rising by 10 points in a little over 10 years and then falling by 10 points. During the Correa era, we see that inequality in Ecuador fell by more than the prediction of the control, but Panel B in Fig. A5 shows that these sized deviations are common in the data and thus not statistically significant.

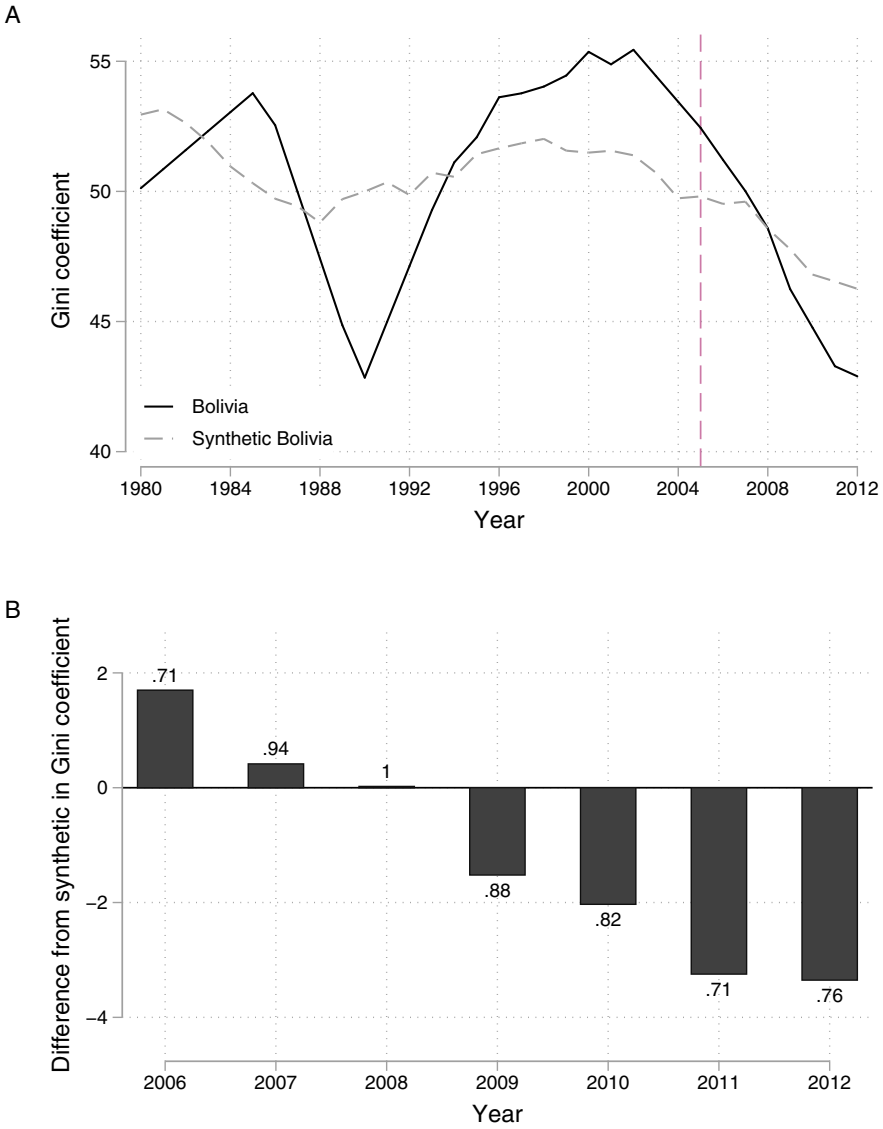

Fig. A4. (A) Trends in inequality - Bolivia and synthetic. (B) Evo Morales' effect on Bolivian inequality.

Table A7
Ecuador's estimated synthetic weights for inequality.

Donor	Outcome variable Inequality
Argentina	0
Brazil	0
Canada	0
Chile	0
Colombia	0.485
Costa Rica	0
Egypt	0
Guatemala	0
India	0
Indonesia	0
Iran	0
Mexico	0
Nigeria	0.392
Norway	0
Panama	0.124
Peru	0
United States	0
Uruguay	0

Note. Columns show the estimated weight for the synthetic Ecuador. Each column represents an outcome variable, labeled at the top of the column. Values are in percentage points and are rounded, so the columns may not sum to one.

Table A8
Ecuador's inequality predictor means.

Variables	Ecuador	Synthetic Ecuador	Latin America	Mexico
Gini coefficient (1981)	46.17	46.75	48.44	48.25
Gini coefficient (1985)	44.42	45.09	47.08	45.29
Gini coefficient (1988)	43.22	44.62	47.33	45.40
Gini coefficient (1992)	48.75	47.73	47.63	47.41
Gini coefficient (1998)	52.57	50.68	48.61	48.59
Gini coefficient (2007)	47.93	48.86	47.28	45.55
Labor compensation share	0.48	0.52	0.51	0.48
Human capital index	2.29	1.80	2.23	2.24
RMSPE	–	1.36	2.65	2.68

Note. This table shows the values of indicator variables for Ecuador and synthetic Ecuador in the pre-treatment period (1980–2006). Variables are averaged across the pre-treatment period, unless otherwise indicated. We compare Ecuador to counterfactuals: synthetic Ecuador, the average of Latin American countries, and Peru (the most similar single-country, measured by RMSPE).

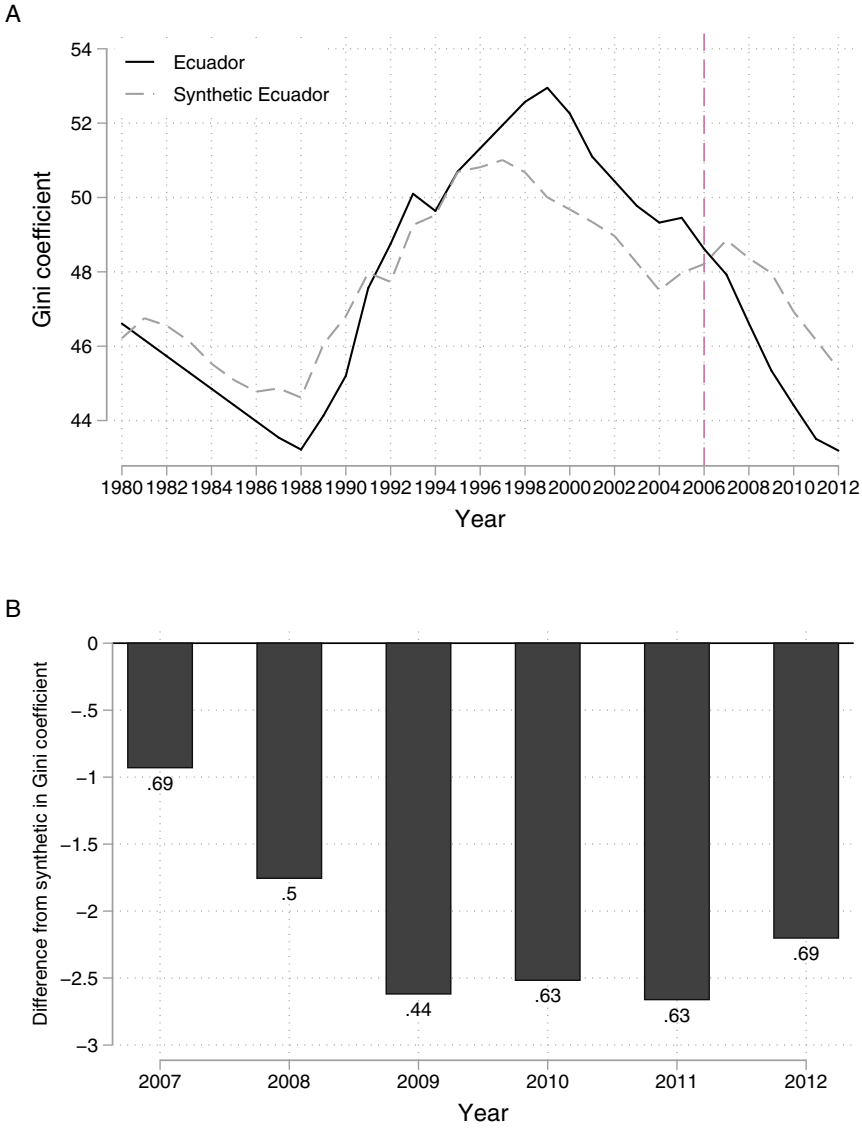

Fig. A5. (A) Trends in inequality - Ecuador and synthetic. (B) Rafael Correa's effect on Ecuadorian inequality.

Appendix B. Synthetic weights

Table B1, B2, B3, B4

Table B1
Nicaragua's estimated synthetic control weights by outcome variable.

	Outcome variable	
Donor	Income	Infant mortality
Algeria	0	0.707
Argentina	0	–
Brazil	0	0
Canada	0	0
Chile	0.226	0.086
Colombia	0	0
Costa Rica	0	0
El Salvador	0	0
Guatemala	0	0
Honduras	0.537	0
Indonesia	0	0
Iran	0	0
Mexico	0.088	0
Nigeria	0	0.098
Norway	0.084	0
Panama	0	0
Paraguay	0	0
Peru	0	0.109
United States	0.065	0
Uruguay	0	0

Note. Columns show the estimated weight for the synthetic Nicaragua. Each column represents an outcome variable, labelled at the top of the column. Values are in percentage points and are rounded, so the columns may not sum to one.

Table B2
Venezuela's estimated synthetic control weights by outcome variable.

	Outcome variable	
Donor	Income	Infant mortality
Algeria	0	0
Argentina	0	0
Brazil	0	0
Canada	0	0
Chile	0	0
Colombia	0	0
Costa Rica	0	0
El Salvador	0.172	0
Guatemala	0	0
Honduras	0	0
Indonesia	0	0
Iran	0	0
Iraq	0	0
Kuwait	0	0.27
Mexico	0	0
Nigeria	0.444	0.022
Norway	0.209	0.217
Panama	0	0.129
Paraguay	0	0.353
Peru	0.151	0.008
Saudi Arabia	0.024	0
United Arab Emirates	0	0
United States	0	0
Uruguay	0	0

Note. Columns show the estimated weight for the synthetic Venezuela. Each column represents an outcome variable, labeled at the top of the column. Values are in percentage points and are rounded, so the columns may not sum to one.

Table B3
Bolivia's estimated synthetic weights by outcome variable.

	Outcome variable	
Donor	Income	Infant mortality
Algeria	0	0
Argentina	0	0
Brazil	0	0
Canada	0	0
Chile	0	0
Colombia	0	0
Costa Rica	0	0
El Salvador	0.432	0
Guatemala	0	0
Honduras	0	0
Indonesia	0.359	0
Iran	0	0
Iraq	0	0
Kuwait	0	0
Mexico	0	0
Nigeria	0.087	0.317
Norway	0	0
Panama	0	0
Paraguay	0.007	0
Peru	0.115	0.683
Saudi Arabia	0	0
United Arab Emirates	0	0
United States	0	0
Uruguay	0	0

Note. Columns show the estimated weight for the synthetic Bolivia. Each column represents an outcome variable, labeled at the top of the column. Values are in percentage points and rounded so columns may not sum to one.

Table B4
Ecuador's estimated synthetic weights by outcome variable.

	Outcome variable	
Donor	Income	Infant mortality
Algeria	0.216	0.111
Argentina	0	0
Brazil	0	0
Canada	0.016	0
Chile	0	0.221
Colombia	0	0
Costa Rica	0	0
El Salvador	0.151	0
Guatemala	0	0
Honduras	0	0
Indonesia	0	0
Iran	0	0
Iraq	0	0
Kuwait	0	0.129
Mexico	0	0
Nigeria	0	0.020
Norway	0	0
Panama	0	0
Paraguay	0.502	0
Peru	0.105	0.514
Saudi Arabia	0.009	0.005
United Arab Emirates	0	0
United States	0	0
Uruguay	0	0

Note. Columns show the estimated weight for the synthetic Ecuador. Each column represents an outcome variable labeled at the top of the column. Values are in percentage points and rounded so the columns may not sum to one.

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