The Impact of the Abolition of the Army on Costa Rica's Educational Development

Amir Grunhaus

December 16th, 2022

Abstract

This research paper investigates the impact of the abolition of the army in Costa Rica on long-term educational development. Using a pre-post analysis, I find that the abolition is associated with an average increase of 6.3% in primary school enrollment as a percentage of the total population. Additionally, I find that primary school enrollment in the 20 years following demilitarization was on average 1.9% higher relative to a synthetic Costa Rica without abolishment. I suggest that the abolition of the army had a significant and positive contribution to the country's long-term educational outcomes.

1 Introduction

Following the Civil War of 1948, José Figueres Ferrer, the President of the Founding Junta of the Second Republic of Costa Rica, made the landmark decision of abolishing the national army as part of his efforts to establish a more peaceful and democratic society. The country has since relied on its police force and other non-military means of defense. Since the abolishment of the army, Costa Rica has not experienced a major armed conflict. It has also allowed the government to redirect funds that would have been used for the military towards education, health care, and other social programs.

The decision to disband the army and invest in social welfare raised questions about whether this would have any impact on the country's long-term development. This research paper seeks to answer these questions by examining the impacts of the abolition of the army on Costa Rica's educational development. By examining the specific case of Costa Rica, I hope to gain insight into the relationship between demilitarization and education in developing countries.

There is very limited literature on the developmental effects of Costa Rica's demilitarization. The most notable work, made by Abarca and Ramírez (2018), suggests that the abolition of the army yielded long term economic benefits for Costa Rica. By using synthetic control methods, they found that after the abolishment of the army, Costa Rica's per capita GDP grew, on average, more than twice as fast as before the abolishment. My research contributes to Abarca and Ramírez's work by expanding the scope of their research to include long-term effects on education, a relevant area that lacks exploration.

To estimate the effect of the abolition of the army on long-run educational development, I first perform a pre-post Analysis of primary school enrollment as a percentage of the total population in Costa Rica before and after the army was abolished. By using data from the Montevideo-Oxford Latin American economic history database (Bértola and Rey, 2018) on primary enrollment rates in Costa Rica, I use simple linear regression to model the relationship between primary enrollment and time. I estimate the magnitude of the change in primary enrollment over time to determine whether there was a significant increase in primary enrollment after the army was abolished.

I then complement this analysis by following the approach of Abadie and Gardeazabal (2003) and Abarca and Ramírez (2018) and using synthetic control methods to estimate the effect of Costa Rica's abolition of the army on primary school enrollment. In the absence of a counterfactual, I compare Costa Rica to a synthetic unit of Latin American countries that resembles key economic and social characteristics of Costa Rica.

My estimates from the pre-post Analysis show that the abolition of the army is associated with an average 6.3% increase in primary school enrollment until 1970. Moreover, the synthetic control shows that primary school enrollment after the abolishment grew, on average, 1.9% more than the synthetic unit, which represents Costa Rica without abolition. Thus, my research suggests that demilitarization had positive consequences on Costa Rica's long-run educational development.

In the next section I will present a brief history of the abolition of the army, followed by an overview of research on the topic. In the third section, I will discuss the methods and techniques I used to address my research question. Then, I will describe the data that I used for my analysis. In the fifth section I will summarize and interpret my experiment results, followed by the last section where I will set forth my conclusions.

2 The Abolition of the Costa Rican Army

2.1 History

The abolition of the army in Costa Rica occurred in 1949, when President José Figueres Ferrer declared the country's official demilitarization through article 12 of the political constitution. This decision was made as part of a broader effort to create a more peaceful and democratic society in Costa Rica (Muñoz, 2014).

Before the abolition of the army, Costa Rica had a long history of political instability and civil conflict. In the 19th and early 20th centuries, the country was ruled by a series of authoritarian leaders who used the military to maintain their power (Rojas-Fonseca, 2020).

In 1948, however, Costa Rica experienced a major political upheaval. The 1948 elections in Costa Rica were held amid political instability and civil unrest. The main candidates were Rafael Ángel Calderón Guardia, a former president, and Otilio Ulate Blanco, a progressive candidate. The elections were marked by fraud and corruption, and both Calderón and Ulate claimed victory. Calderón ultimately declared the elections void and seized power. This led to a period of political uncertainty and a rise in civil unrest. In April 1948, a group of progressive politicians led by José Figueres Ferrer declared war on the Calderón government, leading to a brief civil war. Calderón was forced to resign, and Figueres became the new president of Costa Rica (Muñoz, 2014; Rojas-Fonseca, 2020).

Figueres was determined to create a more peaceful society in Costa Rica. One of his first actions as president was to abolish the country's armed forces and declare Costa Rica a demilitarized zone. Figueres' decision to abolish the army was met with both praise and criticism. Many Costa Ricans saw the move as a bold and necessary step towards creating a more civil society. Others, however, were concerned that the country would be vulnerable to attack without a standing army. Despite these concerns, Figueres remained committed to his decision and the army was officially dissolved on December 1, 1949 (Rojas Aravena, 2018).

Today, Costa Rica remains one of the few countries in the world without a standing army. Since the abolition of the army, Costa Rica has continued to be a leader in promoting peace and democracy in Central America. The country has not experienced any major conflicts or military coups, and has instead focused on building strong institutions and investing in education and health care. Today, Costa Rica is widely regarded as one of the most stable and prosperous countries in the region.

2.2 Research

There are plenty of studies on the negative impact of wars and military expenditure on economic and social growth and development. For instance, Deger and Sen (1995) present through endogenous growth models, how military expenditure in developing countries has a negative impact on the development of human capital. Collier (2006) contributes to these findings by showing how military expenditure and war slow down development. These are just two of many studies that show the negative relationship between militarism and economic growth (Abadie and Gardeazabal, 2003; Bove, Elia, and Smith, 2014; Dunne and Tian, 2016; Lai and Thyne, 2007).

The question of whether demilitarization contributes to economic and social development is an important one, and the case of Costa Rica provides a valuable example. Despite the widely studied effects of military expenditure on growth and the historical significance of Costa Rica's army abolition in 1949, there is very limited research on the long-term economic and developmental consequences of this event.

Abarca and Ramírez (2018) provide a unique and unprecedented look at Costa Rica's army abolishment. It is the first study to quantitatively investigate the effect of the abolition on Costa Rica's long-run economic growth with respect to other countries in the region. Abarca and Ramírez use long time series data and synthetic control estimates to determine whether the abolition of Costa Rica's army had a positive effect on GDP per capita growth. They find that after demilitarization and until 2010, Costa Rica had an annual GDP per capita growth rate of 2.49%, compared to a pre-demilitarization rate of 0.97% - a 1.52% difference that made Costa Rica go from penultimate in the region to second best. Abarca and Ramírez's research provides evidence that for Costa Rica, the abolishment of the military yielded positive long-term effects on its economic activity. They show that the effects are robustly explained by a phenomenon that started in 1951, right after the abolition.

A concern that arises from Abarca and Ramírez study, is that their estimated results might arise from other shocks besides the abolition of the army, most notably, the set of social reforms implemented in Costa Rica in the 1940s, which include - the creation of the Costa Rican Social Security Fund (CCSS), the National University (UCR), and the enactment of a Workers Code (Rosenberg, 1981). To address these concerns, they perform the synthetic control method with 1944 as the treatment year to show that the divergence in real GDP growth between Costa Rica and the synthetic unit does not materialize until 1951.

My research contributes to Abarca and Ramírez's work by expanding into an almost unexplored but highly relevant area - education. As Rojas-Fonseca (2020) presents, the abolishment of the army translated into higher investments in education, however, the actual impact on educational outcomes is poorly documented. My research investigates the quantitative impact of Costa Rica's demilitarization on primary school enrollment, a key indicator of educational outcomes.

3 Experimental Design

3.1 Pre-Post Analysis

Pre-post analysis is a statistical method that is used to evaluate the impact of a treatment or intervention on a particular outcome variable. This method is based on the principles of ordinary least squares (OLS) regression, which is a statistical technique that is used to model the relationship between a dependent variable and one or more independent variables.

To perform OLS pre-post analysis, data on the dependent and independent variables before and after the intervention must be collected. Then, the data is used to estimate the coefficients for the regression model using OLS regression.

The basic idea behind pre-post analysis is to compare the values of the outcome variable before and after the intervention, and to use regression analysis to determine whether the difference in values is statistically significant. Essentially, outcomes before ($t = 0$) and after ($t = 1$) the treatment event are compared:

$$Y_{it} = \alpha + \beta T_{it} + \delta X_{it} + \varepsilon_{it}$$

Where Y_{it} is the outcome variable, α is the intercept (i.e. the expected value of Y_{it} when all independent variables are zero), β is the coefficient (the effect on Y_{it}) of the independent variable T_{it}, which represents the treatment period (0 when $t = 0$ and 1 when $t = 1$), δ is the coefficient of the omitted variables X_{it}, and ε_{it} represents the error term.

To estimate the causal effect of the treatment T_{it} on the outcome variable Y_{it}, expectations are taken:

$$E[Y_{i1} - Y_{i0}] = \beta E[T_{i1} - T_{i0}] + \delta E[X_{i1} - X_{i0}]$$

$$= \beta + E[X_{i1} - X_{i0}]$$

The causal effect β is captured when the omitted variable term $\delta E[X_{i1} - X_{i0}]$ is 0, that is, when the omitted variables X_{it} are constant over time ($X_{i0} = X_{i1}$). Unlike a difference-in-difference (DID) analysis, in a pre-post analysis there are no control units, and hence, the unobserved variables for the treated unit must be constant over time.

In the case of my research, the abolition of the army is unlikely to be the only dependent variable impacting primary school enrollment (the outcome variable), before and after 1949. Hence, the assumption that the unobserved variables for Costa Rica are constant over time is improbable. To add robustness to my experiment, I complement the pre-post analysis with synthetic control methods.

3.2 Synthetic Control Methods

The synthetic control method was originally proposed by Abadie and Gardeazabal (2003). In classic comparative studies, a unit affected by an event or intervention (also called treated unit), is compared to non-affected units (control units). An issue with such studies is that a treated unit might not always be comparable to control units due to underlying differences between them. If that is the case, a simple comparison of outcomes may not only reflect the impact of the treatment but also of other pre-treatment differences between treated and control units. Synthetic control methods address this issue. The method works on the premise that the treated unit can be more accurately approximated by a combination of similar untreated units than by any single untreated unit.

Synthetic control methods address the shortcomings of a regular DID analysis. A DID analysis requires the existence of a control group that is similar to the treatment group in all respects except for the fact that it does not receive the intervention. This is often difficult to find in practice, especially when the intervention is being implemented on a large scale. To tackle this, the synthetic control method creates a synthetic unit - a weighted combination of the control units. The weights are chosen such that the synthetic unit best resembles key characteristics of the treated unit before the intervention. Then, the estimated post-intervention outcomes for the synthetic unit are used to approximate the outcome that would have been observed in the treatment unit in the absence of treatment, to then obtain more accurate estimates of the impact of the intervention (Abadie, Diamond, and Hainmueller, 2011; Firpo and Possebom, 2018).

As Abadie (2021) reports, a credible application of synthetic control methods has relevant data requirements. First, sufficient data on outcomes and outcome predictors for the treated and untreated units is needed. Second, a synthetic control depends greatly on the availability of pre-intervention information. In order to create a reliable synthetic unit, the synthetic control needs to effectively track the path of the outcome variable for all the units in question before the intervention, thus, increased pre-treatment data leads to enhanced model performance. Finally, extensive post-intervention data is needed to allow for a broader and more comprehensive picture of the effects of the intervention across outcomes of interest.

Here is an overview of the synthetic control method application in Abadie and Gardeazabal (2003). Let J be the number of control units , and $W = (w_1, \ldots, w_j)$ a $(J{*}1)$ vector of weights which sum to one. The scalar $wj(j = 1, \ldots, J)$ represents the weight of region j in the synthetic unit. The weights W are chosen so that the synthetic unit most closely resembles the actual one before treatment. Let X_1 be a $(K * 1)$ vector of pre-treatment values of K predictor variables for the treated unit and X_0 be a $(K * J)$ matrix containing the values of the variables for the J control units. Let V be a diagonal matrix and its diagonal elements' values reflect the relative importance of the different predictor variables. The vector of weights $W*$ is chosen to minimize $(X_1 - X_0W)'V(X_1 - X_0W)$ for w_j greater than or equal to 0 and their sum $(w1 + \ldots + wj)$ equal to 1. Thus, the vector $W*$ defines the combination of control units which best resemble the treated unit in predictor variables before the treatment. The vector of interest is $W*$, the optimal weights, as they tell the 'similarity' of each control region to the treated unit (how much of it was used to create the synthetic unit). The synthetic unit predictor variables provide an indication of how well the weighted combination of control units reproduce the values of predictor variables for the treated unit before treatment.

Finally, let Y_1 be a $(T * 1)$ vector whose elements are the values of the outcome of interest for the treated unit during T time periods. Let Y_0 be a $(T * J)$ matrix which contains the values of the same variables for the control units. The goal is to approximate the path of the outcome of interest that the treatment unit would have experienced in the absence of treatment. This counterfactual outcome path is calculated as the outcome of the synthetic unit $Y*_1 = Y_0W*$. Here, the relevant number is the difference or divergence (if any) between the actual outcome of interest Y_1 and the estimated outcome of interest for the synthetic unit $Y*_1$, namely:

$$Y_1 - Y*_1$$

The synthetic control method helps address the issues of lacking an appropriate counterfactual; first, by creating a weighted combination of similar untreated units that better approximate the treated unit (vector $W*$), and second, by assigning different weights, and thus different importance, to different predictor variables (matrix $V*$). By assigning different weights to different predictor variables, it also tackles the issue of missing data.

4 Data

I used panel data from the Montevideo-Oxford Latin American economic history database (MOxLAD) to perform my analysis. MOxLAD is a collaboration between the Universidad de la República in Montevideo, Uruguay and Oxford University. The database contains a wide range of economic and social data for 20 countries in the region, covering the 20th century up until 2010. It is intended to provide economic and social historians with a comprehensive, single online source of statistical information. The data in MOxLAD has been collected with the aim of providing comprehensive coverage while also ensuring consistency and comparability between countries. The original goal was to cover the 20th century, but it is now being extended both backwards and forwards.

I selected 15 country-specific variables and indicators that I found useful for a pre-post analysis and a synthetic control study. I selected the variables based on consistency, comparability and uniformity for every country across the available years, with special emphasis on the country of interest, Costa Rica.

I scraped the data from the online database and created my own panel dataframe made up of 20 units (countries): 1 treated unit (*1 – Costa Rica*) and 19 control units (*2 – Uruguay, 3 – Argentina, 4 – Bolivia, 5 – Brasil, 6 – Chile, 7 – Colombia, 8 – Cuba, 9 – Dominican Republic, 10 – Ecuador, 11 – Guatemala, 12 – Haiti, 13 – Honduras, 14 – Mexico, 15 – Nicaragua, 16 – Panama, 17 – Paraguay, 18 – Peru, 19 – El Salvador, 20 – Venezuela*). In my sample there are 18 variables (15 country-specific variables, country code, country name, and year) and 100 time periods (1900-2000), for a total of 2020 data entries. Due to lack of data and consistency in the pre-treatment period, I left out Dominican Republic, Haiti, and Paraguay from the experiment sample.

The selected variable of interest is primary school enrollment as a percentage of the total population, which is a key indicator of educational development. A high value indicates that a country is making progress in providing access to education for all children. Figure 1 illustrates primary school enrollment in Costa Rica from 1920 to 1970.

The selected predictor variables are: population (in thousands), land area (in square kilometers), population density, GDP per capita (in 1990 purchasing power parity USD), secondary school enrollment as a percentage of the total population, illiteracy rates as a percentage of the total population, life expectancy at birth, a fixed weight index of value for both exports and imports (where 1970 = 100), foreign direct investment (in million current USD), energy consumption per capita (in Mtoe), railway and road density, and passenger and commercial vehicles per capita. These variables represent fundamental economic, social, educational, and health characteristics for each of the countries in the panel. Table 1 displays summary statistics for these variables.

As the table shows, most of the variables have high variation, which suggests that the units have very different characteristics and thus, a simple comparison might not capture the true effect of an intervention. This supports the synthetic control method premise that a weighted average of the units can more accurately approximate the treated unit than any single untreated unit. I will expand on this in the next section.

Figure 1: Primary School Enrollment in Costa Rica (1920-1970)

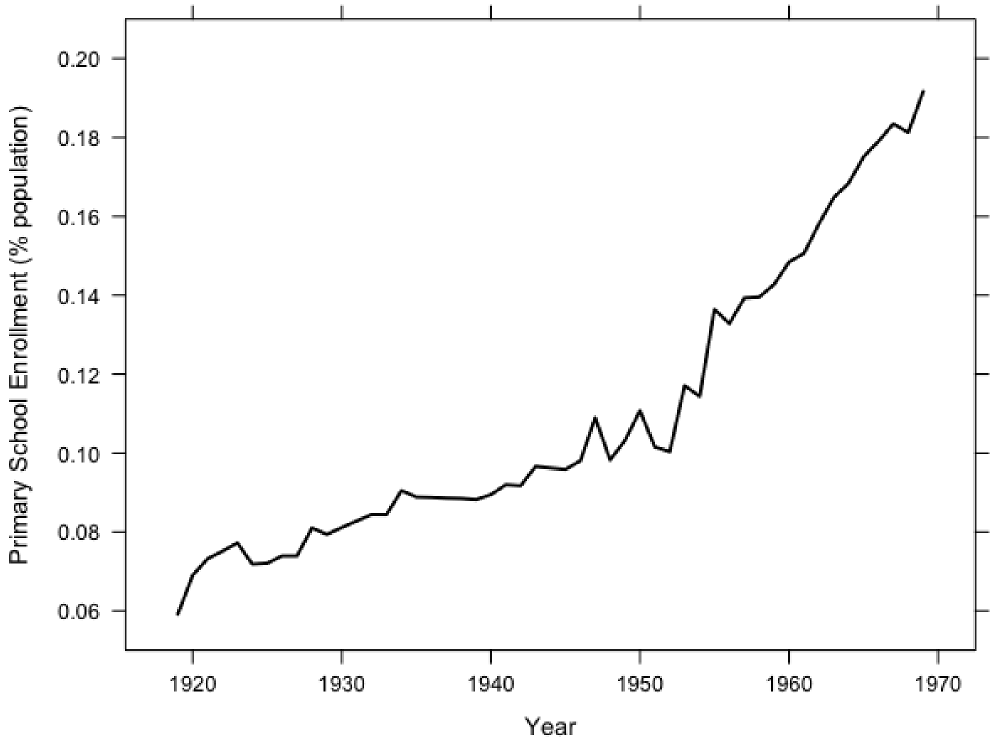


Table 1: Sample Data Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
population	2020	10608.171	21020.9	280	1774	9226.25	174167
land area	2020	999877.8	1871937.156	21040	100521.75	1109372.75	8515767
population density	2020	31.327	48.076	1.268	6.096	32.931	309.117
GDP per capita	1696	2928.883	1959.57	557.413	1543.909	3816.442	11123.585
primary enrollment	1618	0.115	0.044	0	0.077	0.152	0.211
secondary enrollment	1094	0.022	0.025	0	0.004	0.032	0.118
illiteracy	756	26.854	20.989	2.3	10.1	37.9	92
life expectancy	941	60.575	11.461	23.731	55.018	68.961	77.734
unit value of exports	1726	147.736	167.628	10.435	44.259	209.423	1604.275
unit value of imports	1638	161.763	182.232	6.863	51.184	230.79	1929.73
foreign direct investment	720	775.641	2825.904	-889	14	374.75	32779.2
energy consumption per capita	1970	284.453	379.23	0.28	36.505	395.268	2463.36
railway density	1931	0.009	0.01	0	0.002	0.012	0.047
road density	544	0.133	0.137	0.004	0.052	0.146	0.725
vehicles per capita	1215	0.03	0.036	0	0.005	0.035	0.193

Source: MOxLAD database

Most of the variables were already available in the MOxLAD database, and for some others I performed the necessary calculations or adjustments. As seen in the table, data availability is not uniform across the units. Furthermore, more economically developed countries tend to have more data availability and reliability. As I explained before, the missing data points should not be a concerning issue due to the design of the synthetic control method, moreover, whenever necessary, I implemented linear interpolation to account for missing data values.

5 Results

5.1 Pre-Post Analysis

5.1.1 Experiment Design

In my pre-post analysis, I evaluate the impact of the 1949 abolition of the army in Costa Rica on primary school enrollment as a percentage of the total population. I perform an OLS regression to model the relationship between the two variables and try to capture, if any, a causal effect.

In my regression equation, $primary\_enrollment_{it}$ is the outcome of interest, and $treatment_{it}$ is a dummy variable for the treatment period; it takes on the value 1 for observations collected after the intervention was implemented and the value 0 for observations collected before the intervention was applied ($t = 0$ before 1950 and $t = 1$ afterwards). I chose 1950 (the year after the intervention), as the treatment period and narrowed down the available data from 1920 to 1970.

The regression equation is the following:

$$primary\_enrollment_{it} = \alpha + \beta * treatment_{it} + \delta X_{it} + \varepsilon_{it}$$

Here, I made the assumption that the omitted variables, represented by X_{it}, are constant over time ($X_{i0} = X_{i1}$), and hence, β, the coefficient of interest, captures the causal effect of the abolition of the army (treatment) on primary school enrollment. I will address the limitations of this approach later in this section.

5.1.2 Findings

Table 2 presents the results of the regression analysis. The dependent variable in the analysis is primary school enrollment, which is measured as a percentage of the total population. The independent variable is a dummy variable for the treatment period, with the value 1 representing the period after the abolition of the army (1950) and the value 0 representing the period before the abolition of the army.

The table provides estimates of the coefficients for the treatment and constant terms in the regression model, along with measures of the goodness of fit of the model and the statistical significance of the coefficients.

According to the table, the coefficient for the treatment term, β, is 0.063, which is statistically significant (indicated by the three asterisks after the coefficient estimate). This suggests that, on average, primary school enrollment increased by 0.063 percentage points after the abolition of the army, compared to the period before the abolition of the army. The coefficient for the constant term is 0.086, which is also statistically significant. This represents the expected value of primary school enrollment when the treatment term is equal to 0 (i.e., before the abolition of the army).

Overall, the results of this analysis suggest that the abolition of the army had a statistically significant positive effect on primary school enrollment. The model fits the data well, with an R-squared value of 0.708, indicating that the model explains about 70% of the variation in primary school enrollment. The regression results support my initial hypothesis that the abolition of the army had a positive effect on long-run educational outcomes.

5.1.3 Limitations and Robustness Checks

As I explained before, in this case, the abolition of the army (treatment) is unlikely to be the only dependent variable impacting primary school enrollment (the outcome variable). For instance, other policy reforms and structural changes made both before and

Table 2: The Effect of the Abolition of the Army on Primary School Enrollment

	Dependent variable:
	Primary Enrollment
Treatment	0.063^{***}
	(0.006)
Constant	0.086^{***}
	(0.004)
Observations	51
R^2	0.708
Adjusted R^2	0.702
Residual Std. Error	0.020 (df = 49)
F Statistic	118.793^{***} (df = 1; 49)
Note:	*p<0.1; **p<0.05; ***p<0.01

Notes: standard errors are in parentheses. The analysis data covers the years 1920 to 1970. The dependent variable (Primary Enrollment) represents primary school enrollment as a percentage of the total population. The independent variable (Treatment) is a dummy variable for the treatment period ($t = 1$ after the abolition of the army (1950), $t = 0$ otherwise).

after 1950 may also play an important role in influencing primary school enrollment rates. Hence, the assumption that the omitted variables are constant over time ($X_{i0} = X_{i1}$) is unlikely to hold.

As a robustness check, I performed the same regression as before but with 1945 as the treatment year to confirm that the positive estimated effect is less before the intervention of interest was implemented. Table 3 shows the regression results.

The treatment coefficient is 0.057 for the year 1945, a 0.006 difference compared to the original coefficient of 0.063 in Table 2. This suggests that the 1950 intervention did have a significant and potentially larger effect on primary enrollment than any other treatment before the abolishment of the army.

It is important to note that large-scale policy interventions tend to have lagged effects, and hence, it is difficult to pinpoint the exact moment at which the treatment has an effect on the outcome variable. For this reason, any treatment period selection will prompt questions about arbitrariness.

Table 3: Robustness Check

	Dependent variable:
	Primary Enrollment
Treatment	0.057***
	(0.007)
Constant	0.083***
	(0.005)
Observations	51
R^2	0.591
Adjusted R^2	0.583
Residual Std. Error	0.024 (df = 49)
F Statistic	70.940*** (df = 1; 49)
Note:	*p<0.1; **p<0.05; ***p<0.01

Notes: standard errors are in parentheses. This table has the same regression design as the one presented in Table 2. The only difference is that the treatment period begins in 1945 (before the army abolition) instead of 1950.

Despite the limitations of this regression design, which include, the lack of control variables that might influence the dependent variable and the unlikeliness of the omitted variables to stay constant over time, it still gives us a relevant insight into the effect of the abolition of the army on primary school enrollment. To complement these findings and address some of these limitations, I performed a synthetic control analysis, covered in the next subsection.

5.2 Synthetic Control Method

5.2.1 Experiment Design

Following the approach originally proposed by Abadie and Gardeazabal (2003) and replicated by Abarca and Ramírez (2018), I performed a synthetic control method, as described before, to compare primary school enrollment in Costa Rica to a synthetic unit representing Costa Rica without abolishing its army.

Table 4 compares the pre-abolishment (1920-1950) features of Costa Rica, the synthetic unit, and the sample mean. The synthetic control created this synthetic unit by finding the optimal weights for every unit and variable available in the sample data. Table 5 shows the variable weights (diagonal matrix $V*$), and Table 6 shows the country weights (vector $W*$).

Table 4: Synhtetic Control - Pre-Abolishment Characteristics

	Costa Rica	Synthetic Unit	Sample Mean
population	690.61	1903.20	7088.41
land area	51060.00	187397.68	1216477.50
population density	13.53	16.65	14.70
energy consumption per capita	64.84	138.01	141.32
primary enrollment	0.09	0.09	0.08
gdp per capita	1679.38	2243.05	2013.96
illiteracy	30.73	39.79	51.26
life expectancy	45.73	45.69	39.31
unit value of exports	34.32	43.72	47.27
unit value of imports	50.44	58.44	53.31
foreign direct investment	27.00	31.99	190.31
railway density	0.01	0.01	0.01
road density	0.06	0.11	0.05
vehicles per capita	0.01	0.01	0.01

Notes: this table presents the pre-treatment (1920-1950) characteristics of the treated unit (Costa Rica), the synthetic unit created by the synthetic control, and the sample mean.

As Table 4 shows, most of the pre-treatment variables are very similar between Costa Rica and the synthetic unit, with a few exceptions (population, land area, energy consumption per capita). These predictor variables give an indication of how well the weighted combination of control units reproduce the values of predictor variables for the treated unit before treatment.

Every predictor variable also has an associated weight in the synthetic unit, as shown in Table 5. The weights of each variable represent the relative importance of each in the synthetic unit. The two most important variables are life expectancy, with 21.1%, and population, with 20.6%. These are followed by railway density, illiteracy, and foreign direct investment with 10.8%, 9.9%, and 7.8% respectively. The synthetic control left out road density and unit value of imports from the synthetic unit.

Table 6 shows the optimal country weights; the 'similarity' of each control region to the treated unit (how much of it was used to create the synthetic unit). Uruguay and Ecuador are the countries with the highest weights, with 39.3% and 31.6% respectively,

Table 5: Synthetic Control - Variable Weights

Variable	Weights
life expectancy	0.211
population	0.206
railway density	0.108
illiteracy	0.099
foreign direct investment	0.078
primary enrollment	0.068
population density	0.067
unit value of exports	0.052
energy consumption per capita	0.047
land area	0.030
gdp per capita	0.026
vehicles per capita	0.008
road density	0.000
unit value of imports	0.000

Notes: this table represents diagonal matrix $V*$, the weights assigned to each pre-treatment (1920-1950) variable in the synthetic unit. The table is ordered by variable weight.

followed by Panama with 17.1%, and El Salvador with 9.4%. The rest of the countries have zero or almost zero weight in the synthetic unit.

Now that the synthetic unit was created, the synthetic method can estimate the path of the outcome variable (primary enrollment) for the synthetic unit, pre and post treatment period. Just like in the pre-post analysis, the treatment year is 1950 and the path is narrowed down to the years 1920-1970. The relevant estimate is the difference or divergence between the path of the treated unit (Y_1) and the synthetic unit ($Y*_1 = Y_0W*$).

5.2.2 Findings

Figure 2 plots primary school enrollment for Costa Rica and the estimates for the synthetic unit. The dotted line is the treatment year. After 1950, there is a clear difference between the outcome variable of interest for Costa Rica and its synthetic unit. The difference in paths suggests that after the abolishment of the army in 1949, there was a considerable positive change on primary school enrollment. Costa Rica experienced a significant increase in primary enrollment while the synthetic unit seems to experience an

Table 6: Synthetic Control - Country Weights

Country	Weights
Uruguay	0.393
Argentina	0.000
Bolivia	0.000
Brasil	0.000
Chile	0.020
Colombia	0.004
Cuba	0.002
Ecuador	0.316
Guatemala	0.000
Honduras	0.000
Mexico	0.000
Nicaragua	0.000
Panama	0.171
Peru	0.000
El Salvador	0.094
Venezuela	0.000

Notes: this table represents vector $W*$, the weights assigned to each country in the synthetic unit.

almost linear and relatively moderate trend. Figure 3 complements Figure 2 by plotting the observed gaps for the outcome variable. Table 7 shows the numerical values of the gaps per year.

Before the abolition, the average gap is 0.000. This number shows that the synthetic control was successful in creating a synthetic unit that resembles Costa Rica and its primary school enrollment path before treatment. The average gap after treatment is 0.019; in other words, after the abolition, there is an average difference of 1.9% in school enrollment between Costa Rica and its synthetic unit. This suggests that demilitarization is associated with a positive effect on primary school enrollment. As seen in Figure 3 and Table 7, the positive gap in primary enrollment appears after 1955, which might indicate that the effects of the intervention on primary school enrollment were lagged.

The estimates of the synthetic control provide sufficient evidence to support the hypothesis that, leaving aside other variables, Costa Rica's demilitarization provided long-run benefits to educational development. The positive changes in primary enrollment took place not immediately after abolition, but a few years later, which might be expected

Figure 2: Synthetic Control Estimates: Primary School Enrollment Paths (1920-1970)

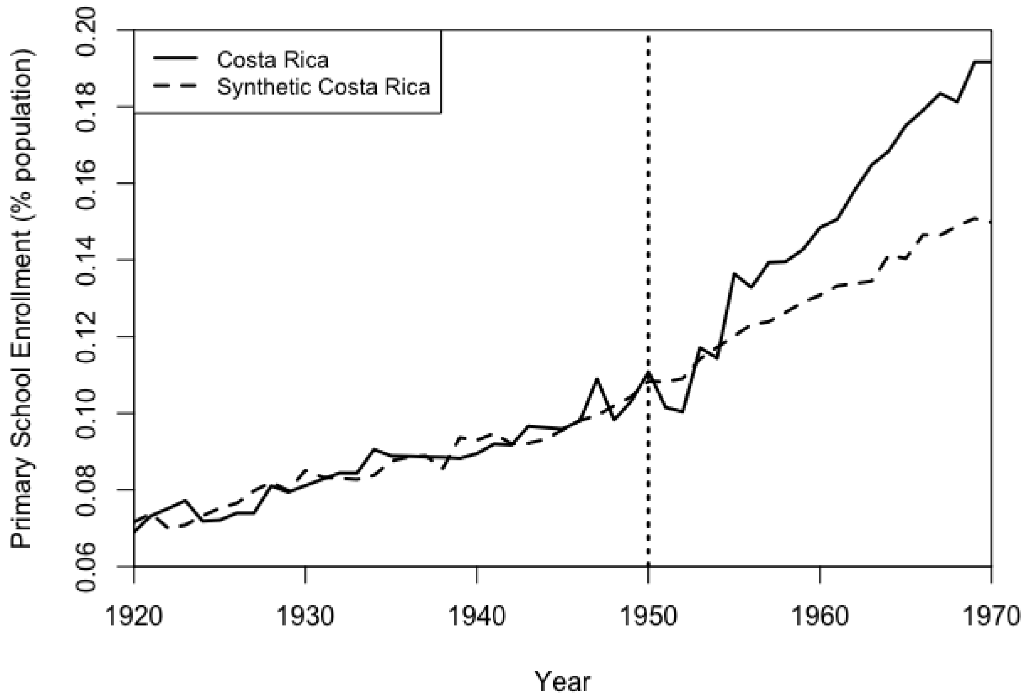


Figure 3: Primary Enrollment Gaps in Costa Rica and Synthetic Unit

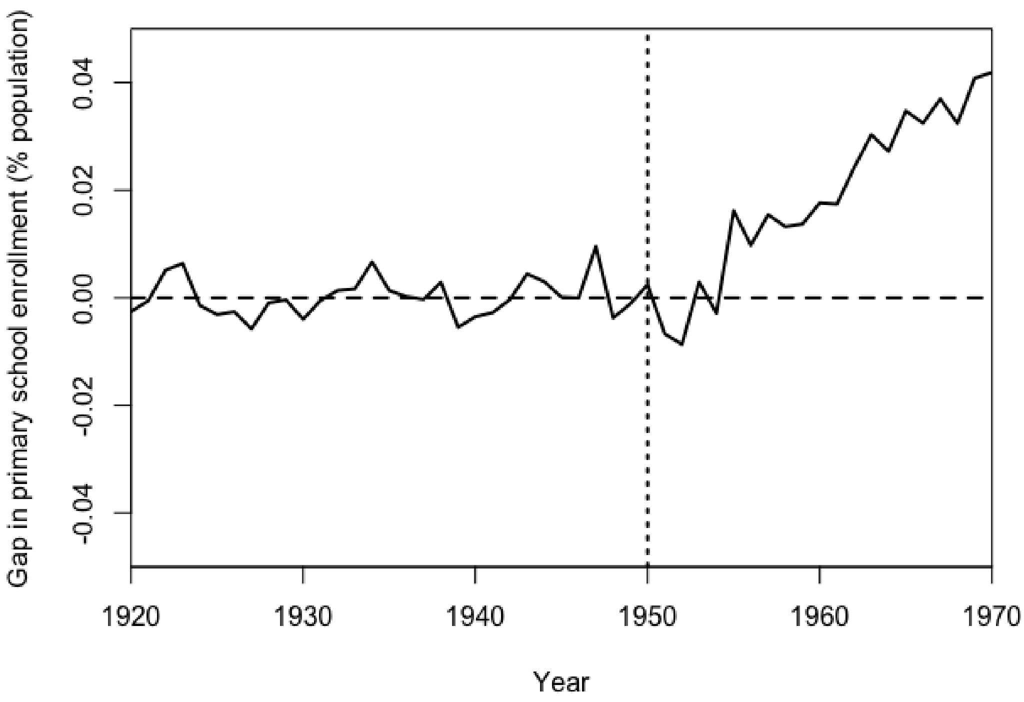


Table 7: Synthetic Control - Primary Enrollment Gaps

Year	Gap	Year	Gap
1920	-0.00	1946	-0.00
1921	-0.00	1947	0.01
1922	0.01	1948	-0.00
1923	0.01	1949	-0.00
1924	-0.00	1950	0.00
1925	-0.00	1951	-0.01
1926	-0.00	1952	-0.01
1927	-0.01	1953	0.00
1928	-0.00	1954	-0.00
1929	-0.00	1955	0.02
1930	-0.00	1956	0.01
1931	-0.00	1957	0.02
1932	0.00	1958	0.01
1933	0.00	1959	0.01
1934	0.01	1960	0.02
1935	0.00	1961	0.02
1936	0.00	1962	0.02
1937	-0.00	1963	0.03
1938	0.00	1964	0.03
1939	-0.01	1965	0.03
1940	-0.00	1966	0.03
1941	-0.00	1967	0.04
1942	-0.00	1968	0.03
1943	0.00	1969	0.04
1944	0.00	1970	0.04
1945	0.00		

Notes: this table shows the gaps in primary school enrollment between Costa Rica and the synthetic unit created by the synthetic control for every year between 1920-1970.

from a large-scale policy intervention such as this. These results are consistent with the results from the pre-post analysis, and both suggest that demilitarization can have positive effects on long-run educational outcomes.

5.2.3 Limitations and Robustness Checks

There are some relevant limitations in the design of the synthetic control. The first issue is whether the observed gap after treatment is actually due to the abolition of the army or the inability of the synthetic control to reproduce the primary enrollment path in the absence of treatment. To address this, I perform the same method I applied to compute the gap for Costa Rica to another country that did not experience the intervention. This is called a 'placebo study' (Abadie, Diamond, and Hainmueller, 2011), and its goal is to assess the robustness of the original synthetic control by gauging whether the observed gap corresponds to demilitarization or to some other factor. I chose Ecuador as the placebo unit as it is one of the countries with the highest weights in the synthetic unit.

Figure 4 shows the estimated primary enrollment paths for Ecuador and its synthetic unit. It is clear from the figure that after the treatment period, there is no sizeable gap between the two. In fact, the average gap between Ecuador and synthetic Ecuador in the post-treatment period is 0.004. This suggests that while Ecuador contributed to build Costa Rica's synthetic unit, the observed gap in Costa Rica's case is not driven by a similar event in the control group nor by randomness, but rather by a particular shock that happened in Costa Rica around 1950.

The second limitation of this method is similar to the one addressed in the pre-post analysis. The gap in primary enrollment might be driven by another intervention or shock in the years when there was no treatment. To control for this, I want to discard that there is a gap between Costa Rica and its synthetic units in years prior to the treatment. Just like I did with the pre-post analysis, I perform the same experiment but with a new treatment year. I chose 1945 as it is before the intervention of interest and because it should capture lagged effects of the 1940s social reforms.

Figure 5 shows the primary enrollment paths for Costa Rica and its synthetic unit with 1945 as the intervention year. Although there is a small positive gap between the two right after 1945, the gap does not become noticeably large until 1955, just like in Figure 2. In addition to this, the average gap from 1945-1949 is 0.005, which is significantly smaller than the mean gap of 0.019 in Figure 2. All of this suggests that there are no positive effects from other shocks on primary enrollment in the pre-treatment period, which provides credibility and robustness to the implemented synthetic control method.

Despite its potential limitations, most notably, the observed gap being artificially

Figure 4: Synthetic Control Placebo: Ecuador

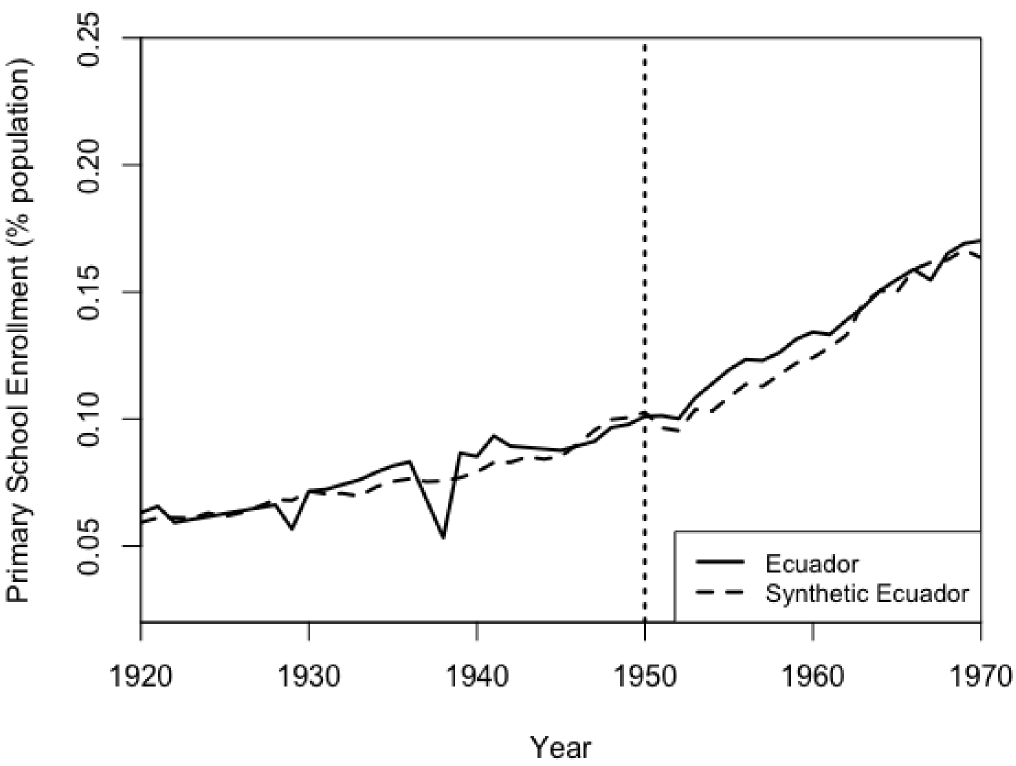
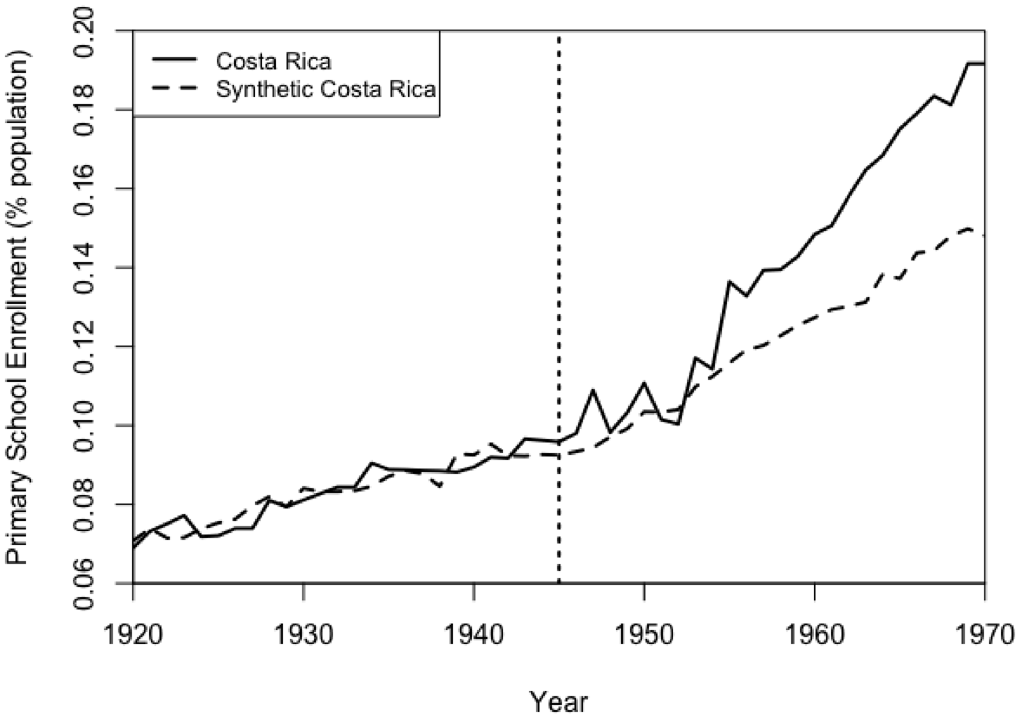


Figure 5: Synthetic Control In-Time Placebo: 1945



influenced by unaccounted shocks, and the inability of the synthetic control to exactly reproduce Costa Rica before demilitarization, this method provides a solid approach to establish causal effects and draw inferential conclusions on large-scale policy interventions.

6 Conclusion

Although the relationship between war and economic development has been widely studied, little research has been made on complete demilitarization, especially the case of Costa Rica. This research paper complements the findings of Abarca and Ramírez (2018) by studying the effects that the abolition of the army in Costa Rica had on primary school enrollment, a key indicator of educational development, two decades after abolishment (1950-1970). The first experiment of the study, the pre-post analysis, shows that the abolishment is associated with an average increase in primary enrollment of 6.3%. The second experiment, the synthetic control, shows that an average gap of 1.9% appears between the primary school enrollment of Costa Rica and that of an analogous synthetic unit made to represent Costa Rica in the absence of abolishment. Both experiments provide robust evidence to suggest that demilitarization in Costa Rica had positive effects on Costa Rica's long-run educational development.

The abolition of the army in Costa Rica translated into higher spending in education, health care, and social programs. Funds that would have been directed to military spending, were redirected to construct a more peaceful, democratic, educated, healthier, and civil society. This increased spending on social welfare, made possible by demilitarization, is possibly the driver of the improved educational outcomes reported in this study.

It is important to note that the methodologies covered by this research are far from perfect and have several limitations. First, any improvement in educational outcomes, might be driven by several variables or interventions that were omitted from my experimental design. For instance, the Costa Rican 1940s social reforms might have had lagged effects that would in turn overstate the captured impact of the abolishment. Second, in the case of the synthetic control, the synthetic unit might not be a perfect representation of the treated unit in the absence of treatment. Despite the limitations that the experimental design of this research might have, this study still provides a valuable insight into the relationship between demilitarization and educational outcomes in developing countries.

I hope that this study will serve as a stepping stone in further research on demilitarization in developing countries. The topic of demilitarization is an important and complex issue that requires in-depth analysis. By conducting this study, I hope to contribute to the body of knowledge on Costa Rica's army abolition and provide a foundation for future research on the topic. In particular, I hope that my findings can be used to inform policy decisions on demilitarization and support efforts to promote peace and stability in the region. I believe that demilitarization is crucial for long-term development and prosperity, and I hope that my work will help to further this important goal.

References

Abadie, Alberto. 2021. "Using synthetic controls: Feasibility, data requirements, and methodological aspects." *Journal of Economic Literature* 59 (2).

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2010. "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program." *Journal of the American statistical Association* 105 (490).

———. 2011. "Synth: An R package for synthetic control methods in comparative case studies." *Journal of Statistical Software* 42 (13).

Abadie, Alberto, and Javier Gardeazabal. 2003. "The economic costs of conflict: A case study of the Basque Country." *American economic review* 93 (1).

Abarca, Alejandro, and Suráyabi Ramírez. 2018. "A farewell to arms: The Long run developmental effects of Costa Rica's army abolishment." *Observatory of Development at the University of Costa Rica.*

Bértola, Luis, and María Rey. 2018. "The Montevideo-Oxford Latin American economic history database (MOxLAD): origins, contents and sources." *Economic History of Developing Regions* 33 (3).

Bove, Vincenzo, Leandro Elia, and Ron P Smith. 2014. "The relationship between panel and synthetic control estimators of the effect of civil war." *Birkbeck Centre for Applied Macroeconomics BCAM Working Papers, Oct.*

Collier, Paul. 2006. "War and military spending in developing countries and their consequences for development." *The Economics of Peace and Security Journal* 1 (1).

Deger, Saadet, and Somnath Sen. 1995. "Military expenditure and developing countries." *Handbook of defense economics* 1.

Dunne, J Paul, and Nan Tian. 2016. "Military expenditure and economic growth, 1960–2014." *The Economics of Peace and Security Journal* 11 (2).

Firpo, Sergio, and Vitor Possebom. 2018. "Synthetic control method: Inference, sensitivity analysis and confidence sets." *Journal of Causal Inference* 6 (2).

Lai, Brian, and Clayton Thyne. 2007. "The effect of civil war on education, 1980—97." *Journal of peace research* 44 (3).

Muñoz, Mercedes. 2014. "Costa Rica: La abolición del ejército y la construcción de la paz regional." *Historia y Comunicación Social* 19.

Rojas Aravena, Francisco. 2018. "Costa Rica: siete décadas sin fuerzas armadas." *Nueva Sociedad,* no. 278.

Rojas-Fonseca, Carolina. 2020. "La abolición del ejército, y su entorno Una revisión de las circunstancias y personajes de la crisis del 48'." *Acta Académica* 67 (Noviembre).

Rosenberg, Mark B. 1981. "Social reform in Costa Rica: social security and the presidency of Rafael Angel Calderon." *Hispanic American Historical Review* 61 (2): 278–296.

Rubin, Donald B. 1974. "Estimating causal effects of treatments in randomized and nonrandomized studies." *Journal of educational Psychology* 66 (5).