The Economic Cost of Armed Conflict: The Case of Colombia

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Abstract

This research analyzes the economic impact of the armed conflict in Colombia during the period 1950-1994, a time characterized by an increase and intensification of violence, primarily driven by links to drug cartels such as the one led by Pablo Escobar. Using the synthetic control methodology, the economic cost of the armed conflict is estimated to be 31.78% of per cápita GDP. The findings suggest that, in the absence of the wave of violence associated with drug trafficking and cartels, economic growth in a Colombia without terorrism would have been significantly higher. This is evidenced by comparing the per cápita GDP trajectory of a ”synthetic Colombia” with its real counterpart. The research addresses the counterfactual question: what would have happened to Colombia´s economic development if this intensified wave of violence had not ocurred?

1. Introduction

A prolonged internal conflict has devastating consequences for any economy, negatively impacting a wide range of economic and social variables. But what is the real economic cost of an event of such magnitude? Answering this question is essential, especially for countries with a historical context marked by conflict, as it reveals the material and intangible losses that affect not only economic growth but also the overall well-being of society. This type of analysis not only quantifies the direct effects of conflict but also highlights its long-term implications for economic development and stability.

The Colombian armed conflict is one of the most prolonged in modern history, with impacts that go beyond direct violence, deeply affecting the country's economic, social, and political development. Understanding the relationship between armed conflict and economic growth underscores the importance of promoting peaceful, stable institutional contexts conducive to sustainable economic growth. Studies such as those by Pinotti (2015), Horiuchi and Mayerson (2015), and Bilgel and Karahasan (2017) examine the negative consequences of a terrorism-driven environment on economic growth using the synthetic control method. This methodology allows for a comparison of the behavior of a variable of interest between a treated unit and an untreated synthetic counterfactual, constructed from a weighted average of multiple untreated units. Through this approach, the artificial unit provides a more accurate representation of the behavior than any individual comparison unit, offering a robust tool for assessing the impacts of conflict on economic development.

Studying the economic costs of violence provides a quantitative perspective on how conflict has constrained economic growth and social welfare, offering a solid foundation for designing public policies aimed at recovery and development. A clear quantification of these costs not only highlights the conflict's impact but also justifies and strengthens the implementation of policies oriented toward peace, victim reparations, and resource redistribution to the most affected and vulnerable communities.

Analyzing the Colombian case within a global framework can offer valuable lessons for other countries experiencing or having experienced armed conflicts. Following the peace agreement with the FARC[1], Colombia stands as an emblematic case of post-peace agreement recovery, and quantifying the economic costs serves as a reference for international communities interested in reconciliation and development processes. In the current context, where remnants of armed groups and signs of their reconfiguration persist, such studies highlight the urgency of prioritizing the management and resolution of these issues. The impact on the productive apparatus and the overall welfare of the population makes it essential to address these dynamics comprehensively and strategically to ensure sustainable development.

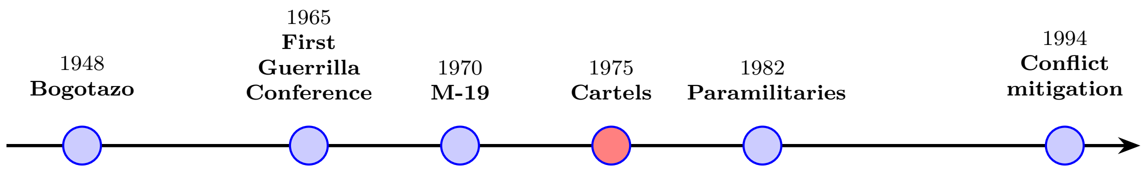
Our findings show that, had Colombia not experienced a period of intensified violence largely related to drug trafficking and cartels like Medellín, the country's per capita GDP would have been 31.78% higher in 1994, as estimated using the synthetic control method applied to an "artificial Colombia."

Subsequently, we subjected our design to various robustness checks to validate our findings, confirming that the observed effect is causal, following a rigorous application of the methodology. This result makes a significant contribution to the literature on the economic costs of conflict, demonstrating a far greater impact than that estimated by traditional methodologies, which calculate direct and indirect costs and have been employed by other authors addressing this topic.

The document is structured as follows: Section 2 provides a contextual overview of the Colombian armed conflict; Section 3 reviews the literature on the use of synthetic control to analyze economic growth; Section 4 outlines the research design and data used; Section 5 presents the results; and finally, Section 6 discusses the conclusions and implications of the study.

2. Armed conflict in Colombia

Figure 1. *Relevant events in Colombia's armed conflict*



[1]Fuerzas Armadas Revolucionarias de Colombia

The armed conflict in Colombia was an extended period of violence involving various illegal armed groups. As shown in Figure 1, one of the triggering events was the assassination of Jorge Eliécer Gaitán, a presidential candidate from the left-wing party, known as the "Bogotazo." This event marked the beginning of an armed and illegal mobilization by different actors. Among them were the Revolutionary Armed Forces of Colombia (FARC), the National Liberation Army (ELN), and the April 19 Movement (M-19), which sought political power and representation based on ideological motivations. On the other hand, counterinsurgency paramilitary groups, such as Death to Kidnappers (MAS) and the United Self-Defense Forces of Colombia (AUC), emerged. According to Romero (2003), these groups were primarily created by landowners in response to the national government's limited effectiveness in controlling guerrilla criminal activities, and they operated in practice as private armies or mercenaries, further exacerbating the conflict.

These armed groups funded their operations primarily through illicit activities such as kidnapping, land expropriation, and predominantly drug trafficking, which became their main source of income. Studies like those by Angrist and Kugler (2008) and Mejia and Restrepo (2013) establish a strong causal relationship between drug trafficking and violence indicators in Colombia, showing how this activity fueled and intensified the armed conflict. This link between drug trafficking and conflict was marked by a growing wave of victims and terrorist attacks. According to data from de la Verdad (2023), the armed conflict had a devastating toll: 450,664 people killed, 121,768 forcibly disappeared, 50,770 kidnapped, 16,238 children recruited, and 752,964 forcibly displaced. Of these victims, 81.5% were civilians, while only 18.5% were combatants, highlighting the disproportionate impact of the conflict on the civilian population.

In the context of the link between drug trafficking and armed conflict, cartels were mostly founded in the 1970s[2] and became consolidated drug-trafficking organizations in Colombian history. Research by Sanchez Torres and Nunez Mendez (2001) and Gaviria (2000) highlights several key factors that contributed to the intensification of this spiral of violence: the normalization of criminal culture among youth, the collapse of the judicial system, reduced costs associated with criminal operations, and the transfer of technical knowledge from cartels to vulnerable sectors of the civilian population. These elements not only strengthened the cartels but also deepened the dynamics of violence and criminality in the country.

What, then, is the economic cost of this conflict? Pioneering works by Rubio (1997) and Badel and Trujillo (1998) addressed this question using a methodology that considers both direct and indirect costs, estimating an annual GDP loss of between 2% and 4.5%. Subsequent studies, such as those by Echeverry et al. (2001), Vargas Duque (2003), Querubin Borrero (2003), and Cardenas-Santamaria (2007), calculated annual reductions in economic growth of between 0.3 and 0.5 percentage points. More recently, Salamanca et al. (2013) identified GDP losses equivalent to 1.7 percentage points annually.

The conflict's impact also extends to human capital. Gaviria (2004) and Rodriguez and Sanchez (2012) estimated that, in the absence of conflict, Colombian students would have achieved between 0.6 and 1.2 additional years of schooling, while

[2] The Medellín Cartel was founded in 1976, and the Cali Cartel in 1977

Colombian emigrants show higher educational levels than their peers who remained in the country. Meanwhile, Ibanez Londono (2008) analyzed the losses in agricultural production caused by forced displacement, calculating an impact equivalent to 3.4% of the agricultural sector's GDP. These studies highlight the magnitude of the economic consequences of the armed conflict, demonstrating the numerous ways in which it has hindered the country's development.

In recent years, Rettberg (2008) revealed that, in the absence of conflict, the private sector would significantly increase its investment in productivity, innovation, and job creation. Supporting this conclusion, Pshisva and Suarez (2010) identified a negative causal relationship between kidnapping rates and business investment levels in various Colombian departments, showing how violence disincentivizes economic activity. Additionally, Camacho and Rodriguez (2013) demonstrated that the armed conflict has substantially impacted the market exit of competitive firms, limiting economic dynamism and reducing growth opportunities in the business sector. These findings emphasize the profound effect of the armed conflict on the structure and performance of Colombia's private sector.

Nevertheless, Ibanez et al. (2024) presents a controversial finding: Colombian territories where armed groups maintained consistent control and established local institutions, such as the provision of public goods and security, show greater economic resilience in terms of consumption and income following consumption shocks, such as the "La Niña" and "El Niño" weather events in 2012 and 2013. According to the authors, this result does not imply that armed conflict has positive effects but highlights the complexity of the phenomenon, with multiple dimensions interacting in unexpected ways. This approach invites deeper analysis to better understand the economic and social dynamics in prolonged conflict contexts.

In summary, the literature on the economic cost of armed conflict has yielded significant quantitative results. However, much of these findings rely on methodologies with a significant limitation: they are based on techniques of direct and indirect cost accounting, raising a crucial question: Is it truly possible to quantify all direct and indirect costs using only national account data? Given the existence of the informal economy, which remains a "black box," the immediate answer is that this approach has important limitations. This underscores the need to explore and develop complementary methodologies to better capture the full complexity and scope of the economic impact of armed conflict.

A crucial aspect of the evolution of the armed conflict in Colombia was the relationship between drug cartels and illegal armed groups, which marked a radical shift in the paradigm and rules of the game. Conflict actors found in drug traffickers not only significant economic resources but also methods and technologies to enhance their military capabilities. This connection enabled armed groups to finance their territorial expansion, acquire sophisticated weaponry, and strengthen their operational structure, challenging state authority and worsening violence in the country. As a result, the armed conflict experienced a notable intensification, reflected in increased confrontations, attacks, and victims, marking one of the most critical stages in the history of the Colombian conflict.

In this context, my research aims to contribute to the analysis of the armed conflict by employing a relevant methodology that has proven effective for such studies. By constructing a transparent counterfactual based on per capita GDP, it is possible to capture the economic cost of the armed conflict more precisely and comprehensively. Furthermore, by identifying a significant economic impact, the findings of this research not only complement but also strengthen the results of previous studies, offering a robust quantitative perspective on the economic consequences of the conflict.

3. Synthetic control and economic growth

An increasing number of studies employ the synthetic control method to evaluate the impact of interventions in various fields such as health, education, the environment, nutrition, and markets, among others Abadie et al. (2010), Billmeier and Nannicini (2013), Andersson (2019), Bauhoff (2014). However, a significant portion of the literature has utilized this methodology specifically to analyze the consequences of events such as political regime changes, the development of armed conflicts, and terrorist attacks on economic growth, demonstrating its versatility and usefulness in addressing complex phenomena in both historical and contemporary contexts.

For instance, Abadie et al. (2015) employs the synthetic control method to assess the economic impact of German reunification on West Germany's per capita GDP. By constructing a synthetic West Germany that reflected pre-reunification economic predictors, the study found that, had reunification not occurred, West Germany's per capita GDP would have grown 8% more, highlighting a notable economic impact.

Similarly, Grier and Maynard (2016) analyzes the economic impact of Hugo Chávez's leadership in Venezuela, contrasting the country's actual economic outcomes with a counterfactual "no-change" scenario. The study reveals a significant decline in per capita income during his tenure, emphasizing the severe economic consequences and a substantial divergence from the synthetic control trajectory, illustrating the so-called "Chávez effect."

In addition, many studies have applied this methodology to isolate the effects of conflicts and terrorism. For example, Abadie and Gardeazabal (2003) examines the economic impact of terrorism in the Basque Country, finding an average gap of 10% in per capita GDP between this region and its synthetic counterpart, free from terrorism, over two decades.

Similarly, Pinotti (2015) uses synthetic control to evaluate the economic effects of organized crime in the Italian regions of Apulia and Basilicata, comparing them to a counterfactual constructed from other Italian regions. The results show a significant drop in per capita GDP and a rise in homicide rates, underscoring the profound impact of organized crime on economic development and social stability.

Likewise, Horiuchi and Mayerson (2015) analyzes the economic impact of the Second Intifada in Israel, using synthetic control to compare the country's actual and counterfactual economic trajectories after 2000. The findings reveal a substantial reduction in per capita GDP, highlighting the economic relevance of a peace agreement in the Israeli-Palestinian conflict.

Finally, Bilgel and Karahasan (2017) investigates the economic consequences of terrorism in Turkey, particularly in regions affected by PKK attacks and armed conflicts. Through synthetic control analysis, the study identifies a significant negative impact on economic growth and development in Eastern and Southeastern Anatolia, reinforcing the need for policies to mitigate the economic toll of terrorism and promote regional stability.

Based on the above, there is a clear opportunity to employ a design justified by the literature for this type of research, where the expected treatment effect of the armed conflict in Colombia is both significant and negative for its economic growth. Furthermore, this study capitalizes on the fact that few studies have focused on Latin American countries using synthetic control, and even fewer have specifically examined Colombia.

4. Research design

4.1 Synthetic control

The synthetic control method aims to estimate the treatment effect on a variable of interest when a specific event, referred to as the treatment, has occurred by creating an artificial counterfactual. Mathematically, it is defined as:

$$ATE \equiv Y_{i,t}^{T} - Y_{i,t}^{C}$$

where $Y_{i,t}^{T}$ represents the actual and observable behavior of the variable of interest, and $Y_{i,t}^{C}$ represents the unobservable counterfactual behavior in the absence of the treatment. This method is typically applied to aggregated geographic units, such as countries, and the variables analyzed are also often aggregated, such as gross domestic product (GDP), investment rate, consumption rate, among others.

The sample consists of $J+1$ units, where $j=1$ is the treated unit, which has been exposed to the event or intervention of interest, and $j=2,...,J+1$ form the "donor pool," representing the untreated units that serve as potential candidates for constructing the synthetic control.

The data spans T periods, divided into: T_0, the pre-intervention periods, and T_1, the post-intervention periods. The objective is to measure the effect of the intervention on an outcome by estimating what would have occurred with the treated unit ($j=1$) in the absence of the treatment.

A synthetic control is a weighted combination of units from the "donor pool." The combination is represented by a weight vector $w=(w_2,...,w_{j+1})$ such that:

$$0 \leq w_j \leq 1 \quad \wedge \quad \sum_{j=2}^{J+1} w_j = 1$$

To select w, the discrepancy between the pre-treatment characteristics of the treated unit (X_1) and its synthetic control (X_0W) is minimized using a weighted metric:

$$||X_1 - X_0W|| = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)}$$

Where:

- X_1: Vector ($kx1$) of characteristics of the treated unit.

- X_0: Matrix (kxJ) of unit characteristics in the "Donor pool".

- V: Diagonal matrix of weights reflecting the relative importance of each characteristic.

Thus, the treatment effect estimator at time t is the difference between the observed outcome of the treated unit and the estimated outcome of the synthetic control:

$$\tilde{\tau}_t = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$$

Where w_j^* are the optimal weights obtained in the previous stage.

In my design, the impact variable of interest is GDP per capita adjusted for purchasing power parity (PPP) in 2011 terms. The predictor variables include the investment ratio, inflation rate, human capital index, educational attainment rates for primary, secondary, and tertiary levels, and the average years of education for the working-age population. The treatment is defined as the creation of cartels in 1975, which marked an intensification of terrorist acts within the context of the armed conflict. The pre- and post-treatment time horizons are 1950–1975 and 1976–1994, respectively.

4.2 Implementation requirements

As Abadie (2021) explains, this method has two specific types of requirements: data requirements and contextual requirements. If these requirements are met as thoroughly as possible and various robustness tests are applied, the method allows for the estimation of a causal treatment effect. In the following subsections, I will detail the contextual requirements of this design and how I have addressed them in my study.

4.2.1 Context

First, the impact variable of interest must exhibit low volatility in both the treated unit and the untreated units in the "donor pool." Second, there must be independence of the treatment in the donor countries; that is, these countries should not have experienced a treatment similar to that of the treated unit, yet they must still possess comparable characteristics. Third, there should be no anticipation effects of the treatment. Fourth, the "Convex Hull" condition must be satisfied, meaning that no combination of donor countries should replicate or closely approximate the characteristics of the treated unit during the pre-treatment period. Lastly, there must be an adequate temporal horizon for early activation of the treatment, ensuring that sufficient data is available to capture the treatment effect, especially for interventions with delayed effects.

In relation to these requirements, the first requirement is met by using countries that did not experience high volatility in their GDP per capita during the study period. The second requirement is satisfied by considering that the armed conflict in Colombia and the creation of the Medellín Cartel is a unique and idiosyncratic event, and by excluding from the donor pool countries that may have had a strong connection to the subject of study, such as Peru, Bolivia, Honduras, Guatemala, and El Salvador, among others. For the third requirement, a backdating test will be conducted to verify that there are no anticipation effects of the treatment. Finally, the last two requirements are met by having an extensive post-treatment time window and by confirming that no combination of donor countries approximates Colombia's behavior during the pre-treatment period.

4.2.2 Data

First, aggregated data must be available for both the impact variable and the predictor variables. Second, there must be a sufficient amount of data in the pre-treatment period, as the credibility of the synthetic control method relies on how well the artificial unit replicates the behavior of the treated unit before the intervention. Finally, there must be enough post-treatment data to observe the estimated treatment effect.

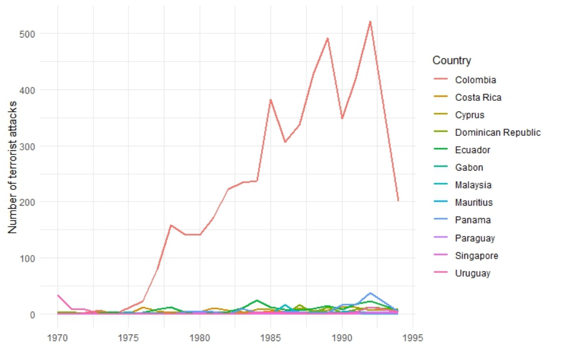
In my design, both the predictor and impact variables are aggregated: GDP per capita, investment ratio, educational attainment rates, human capital indices, among others. Additionally, the pre-treatment period spans 25 years, while the post-treatment period covers 19 years. This window is not extended further, despite the availability of data, to avoid capturing the positive effects of Colombia's economic growth in the 2000s, which resulted from national security policies that significantly reduced terrorist activity in the country.

4.3 Donor Pool

For this design, I use panel data from various sources, such as the historical GDP per capita database by Bolt and van Zanden—Maddison Project Database 2023—which provides information for different countries. I also employ the Barro and Lee (1994) database, widely used in the economic development literature, along with its 2000 update, which includes educational attainment rates for multiple countries starting in 1950. Additionally, I use the Penn World Tables database by Feenstra, Inklaar, and Timmer (2015), which compiles economic development variables for many countries from 1950 onward. Lastly, the Global Terrorism Database (2023) serves as an initial filter for selecting potential donor pool countries.

My donor pool includes Costa Rica, Cyprus, the Dominican Republic, Gabon, Mauritius, Paraguay, Singapore, Uruguay, Ecuador, Malaysia, and Panama. The selection of these countries was conducted through an initial review of the number of terrorist attacks in the Global Terrorism Database as the first filter. Subsequently, countries that exhibited similar characteristics to Colombia during the pre-treatment period were chosen.

Figure 2. *Donor pool*



The purpose of this initial filter is to select countries that have not experienced intensified terrorist activity, measured by the annual number of terrorist attacks. Analyzing the data shows that the donor countries exhibit a stable trend with low numbers of terrorist attacks compared to Colombia.

It is important to note that some countries, despite meeting both filters mentioned, such as Nicaragua, Honduras, Mexico, and Guatemala, were excluded due to their strong connection—both in economic performance and idiosyncratic factors—to the focus of my study: armed conflict and drug trafficking.

5. Estimation results

5.1 Main estimation

To begin, it is important to highlight the relative significance of each predictor variable in descending order: GDP per capita (0.431), human capital index (0.264), primary education attainment rate (0.114), secondary education attainment rate (0.089), tertiary education attainment rate (0.014), investment rate and average years of schooling (0.007), and inflation rate (0.075). These predictor variables are a combination of those used by Abadie et al. (2015) and Abadie and Gardeazabal (2003) in similar studies, and the weights obtained for each predictor are consistent. The main difference is that, in Abadie's study, the second most important variable is secondary education attainment. This variation is reasonable, as Abadie's studies use developed countries as donors, while this design employs developing countries.

Table 1: Synthetic and regression weightings for Colombia Synthetic

Country	Synthetic weight	Regression weight	Country	Synthetic weight	Regression weight
Costa Rica	0.04	0.53	Singapur	0.05	1.14
Chipre	0.12	-0.65	Uruguay	0.12	0.03
República Dominicana	0	0.52	Ecuador	0	0.67
Gabón	0.03	-0.61	Malasia	0	-0.93
Mauricio	0.27	0.22	Panamá	0.03	-0.65
Paraguay	0.27	0.74			

Table 1 shows the weights assigned to each country in the donor pool, revealing that synthetic Colombia is constructed through a weighted average of Mauritius (0.27), Paraguay (0.27), Cyprus (0.12), Uruguay (0.12), Singapore (0.05), Costa Rica (0.04), Gabon (0.03), and Panama (0.03). The table also displays the weights assigned by the traditional regression method, which assigns negative weights to some countries[3].

Table 2 shows that while the use of a sample average approximates the characteristics of Colombia's variables, it is not the most suitable method, as several variables are either under- or overestimated, such as the inflation rate (0.12) and GDP per capita (5744.4). In contrast, the synthetic control method achieves an almost perfect reproduction of these characteristics during the pre-treatment period. As previously mentioned, it is essential for synthetic Colombia to closely replicate these pre-treatment characteristics to accurately capture the treatment effect.

Table 2: Predictors of economic growth before the escalation of the armed conflict

	Colombia	Synthetic Colombia	Sample mean
Inflation rate	14.1	14.0	12.0
GDP per capita	5414.5	5413.8	5744.4
Investment rate	0.2	0.2	0.2
% Secondary	14.4	14.3	13.7
% Primary	83.2	83.1	83.4
% Tertiary	2.4	2.3	2.6
Human capital index	1.7	1.7	1.7
Average years of schooling	3.6	3.6	3.7

Notas: % Secondary, % Primary, % tertiary are percentages of educational attainment in the working-age population.

We can observe in Figure 3 that the selected combination of countries almost perfectly reproduces the trajectory of Colombia's GDP per capita during the pre-treatment period. However, start-

[3] Extrapolation issues

ing from the year of treatment, synthetic Colombia's trajectory shows an upward trend during the first few years until 1980; then, after a slight decline over 2–3 years, it begins to rise again. Notably, synthetic Colombia's GDP per capita consistently remains above Colombia's observed real GDP. This difference between Colombia's observed GDP and the potential GDP of its synthetic counterpart can be interpreted as the economic cost of the armed conflict.

Figure 3. *Evolution of GDP per capita: Colombia vs. synthetic Colombia*

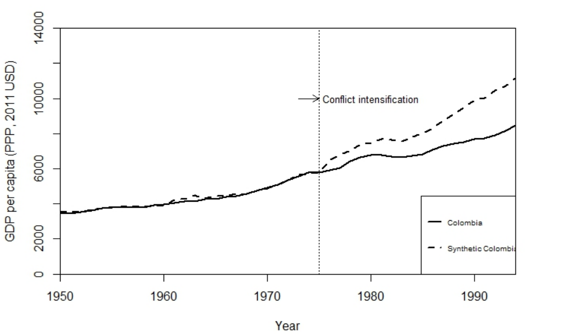
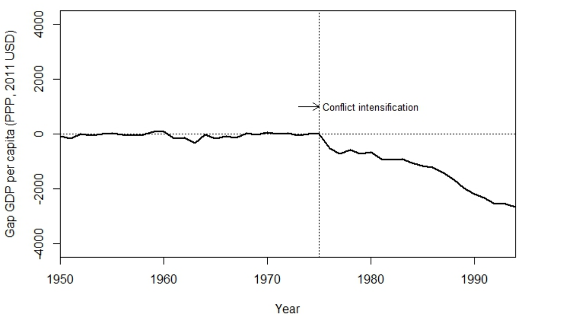


Figure 4 illustrates the difference between Colombia and its synthetic counterpart over the study period. It can be observed that this gap becomes more pronounced as the years progress. Using this difference, the annual loss in GDP per capita is calculated.

Figure 4. *Difference in GDP per capita between Colombia and synthetic Colombia*



Between 1975 and 1994, the average annual loss in GDP per capita for Colombia was estimated at 627.29 USD, representing approximately 10.86% of the 1975 baseline level. Specifically, Colombia's GDP per capita in 1994 was 8,447.85 USD, while its synthetic counterpart reached 11,133.06 USD, marking a significant gap and highlighting the economic impact of the armed conflict.

Although these figures may seem striking, they must be contextualized. In 2002, Colombia's GDP per capita was 8,631 USD, rising to 13,604 USD by 2019. This period was characterized by the implementation of new national defense policies that significantly reduced the impact of the armed conflict and boosted economic growth. Consequently, there was a 57.61% increase in GDP per capita between 2002 and 2019, reflecting substantial economic progress alongside improved national stability.

The study by Fanta and Larramona (2023) uses synthetic control referencing the start of Colombia's peace treaty consolidation period in 2012. Their findings suggest that, without the onset of these negotiations—which culminated in 2016 with the cessation of most hostilities—Colombia's GDP per capita would have been 12% lower, with the peak impact observed in 2021, showing a gap of 18.74%. This study provides evidence that the armed conflict significantly constrained Colombia's economy over an extended period.

However, compared to our findings, Fanta and Larramona (2023) present more conservative estimates. This discrepancy can be attributed to the analysis period, as their study examines a time when various defense policies had already been implemented, mitigating the conflict's effects. By then, the conflict's negative impacts on Colombian society were less intense. Moreover, their analysis excludes the period of greatest cartel influence, such as that of the Medellín Cartel. Therefore, the 31.78% difference in Colombia's GDP per capita, isolating the period of heightened conflict intensity, is a coherent estimate by comparison.

5.2 Robust

In the following subsections, we will conduct various robustness tests that allow for inferential conclusions when using this method, specifically through placebo studies.

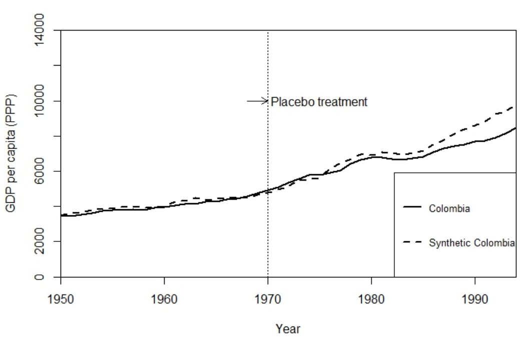
In placebos in time, the intervention of interest is reassigned to a period prior to its actual occurrence. If the estimated effects during this fictitious period are similar to or greater than the estimated real effect, it would indicate that the model lacks predictive power, and the real results could be questionable. This test helps verify whether the synthetic control estimates generate significant gaps only when the intervention actually occurs, ruling out effects attributable to the historical adjustment of the variables used to construct the control.

On the other hand, in placebos in space, the intervention is reassigned to units in the "donor pool" that were not directly exposed to the intervention. This creates a distribution of placebo effects that can be compared to the estimated effect for the treated unit. If the real effect falls within the distribution of the placebos, its significance is questioned. Conversely, if the real effect is unusually large compared to the placebos, confidence in the results is strengthened. Moreover, this approach allows for the calculation of p-values, interpreted as the probability of obtaining an effect as large as the estimated one by randomly assigning the intervention within the dataset.

5.2.1 Time

This test involves reassigning the treatment date to a point in time prior to the actual intervention. If the observed effect is genuinely linked to the treatment of interest, shifting the treatment date should not result in a significant difference between the trajectory of Colombia's GDP per capita and that of its synthetic counterpart.

Figure 5. *Placebo over time 1970-Trends in GDP per capita: Colombia v.s synthetic Colombia*



In Figure 5, we observe that when the treatment date is shifted to 1970[4], the trajectory of GDP per capita does not show a significant difference during the studied period, which serves as a validation signal for the test. However, the model's fit in this case is less precise, which we attribute to the quality of the available data for that period. Nevertheless, the fit is sufficiently adequate to be considered valid.

5.2.2 Space

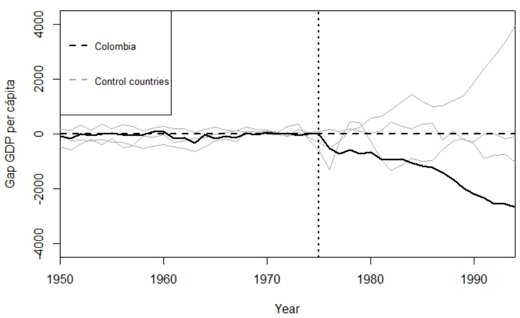
Instead of altering the treatment date, we will apply the same treatment (using the synthetic control) to each of the donor countries. This strategy will allow us to

[4]The same test was conducted for 1965 and 1960, with no significant changes observed compared to this case

obtain a distribution of results, where the test will be considered valid if the most pronounced treatment effect is associated with Colombia within this distribution.

For this test, it is common to exclude the results of countries that do not exhibit an adequate RMSPE[5], as this value reflects the quality of the synthetic control's fit. Therefore, we will exclude countries with an RMSPE greater than 10, as their inclusion in the graph would not provide relevant information.

Figure 6. *Placebo in space -Differences in GDP per capita: Colombia vs. donors*



Observing the results in Figure 6, we can see that Colombia (represented by the gray lines) exhibits the largest effect compared to the control countries (represented by the blue lines). Based on this criterion, we can conclude that the test validates our findings.

Figure 7. *Relationship between post-treatment RMSPE and pretreatment RMSPE: Colombia and control countries*

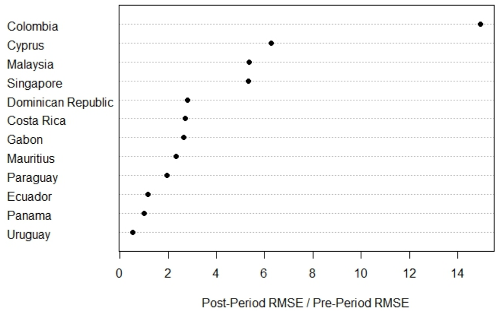


Figure 7 illustrates the relationship between the Root Mean Squared Prediction Error (RMSPE) in the pre-treatment and post-treatment periods for all countries included in this design. This relationship measures the difference between the impact variable for each country and its synthetic counterpart (similar to the placebo test in space). The idea is that a high RMSPE in the post-treatment period does not necessarily indicate a significant effect if the RMSPE in the pre-treatment period is also high. Therefore, calculating the ratio between these two values provides a clearer view of the validity of the treatment effect.

From the graph, we can see that Colombia exhibits the highest ratio of pre- to post-treatment RMSPE. This suggests that the treatment effect captured is strongly associated with Colombia, as its ratio is 15 times greater than that of the other countries. Furthermore, if we randomly select a country from our sample, the probability of obtaining a ratio as high as Colombia's is approximately $\frac{1}{11} \approx 0.090$.

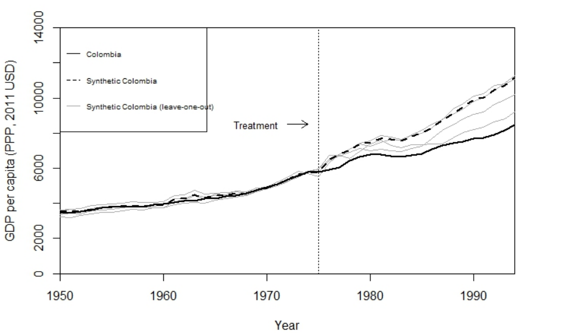
5.3 Control group

It is important to evaluate the sensitivity of our results to the inclusion of control

[5]Root Mean Squared Prediction Error, which essentially indicates whether the synthetic control's fit is sufficiently good to be compared with Colombia's fit

countries. To do this, we will perform a robustness test by iteratively applying the synthetic control method, omitting in each iteration one of the countries that receives a positive weight in Table 1. This sensitivity analysis will sacrifice the fit of our model to assess whether our findings are significantly influenced by any particular country.

Figure 8. *Leave-one-out Synthetic Control Distribution for Colombia*



In Figure 8, we can see that even with the omission of countries with the highest weights, the direction of our findings remains consistent across all scenarios, although the magnitude of the results changes in certain cases. While the magnitude of the effect is slightly reduced, it remains significant. In the worst case, instead of being 10.86%, the effect decreases to 7% with the exclusion of highly weighted control countries.

Next, we will conduct a sensitivity analysis of the model's fit by selecting only six control units, excluding the remaining countries for this analysis. This approach, known in the literature as sparse synthetic control, aims to compare our results by applying the synthetic control method with a reduced number of control units, ranging from a single unit to the aforementioned six.

Table 3: Synthetic weights of the control country mix

Synthetic mix	Countries & weights					
Six control countries	Paraguay 0.36	Mauritius 0.26	Uruguay 0.12	Singapur 0.11	Costa Rica 0.08	Chipre 0.07
Five control countries	Mauritius 0.31	Paraguay 0.31	Chipre 0.20	Uruguay 0.12	Gabon 0.06	
Four control countries	Paraguay 0.55	Singapur 0.27	Uruguay 0.14	Gabon 0.04		
Three control countries	Paraguay 0.56	Singapur 0.30	Uruguay 0.13			
Two control countries	Mauritius 0.69	Panama 0.31				
One control countries	Mauritius 1					

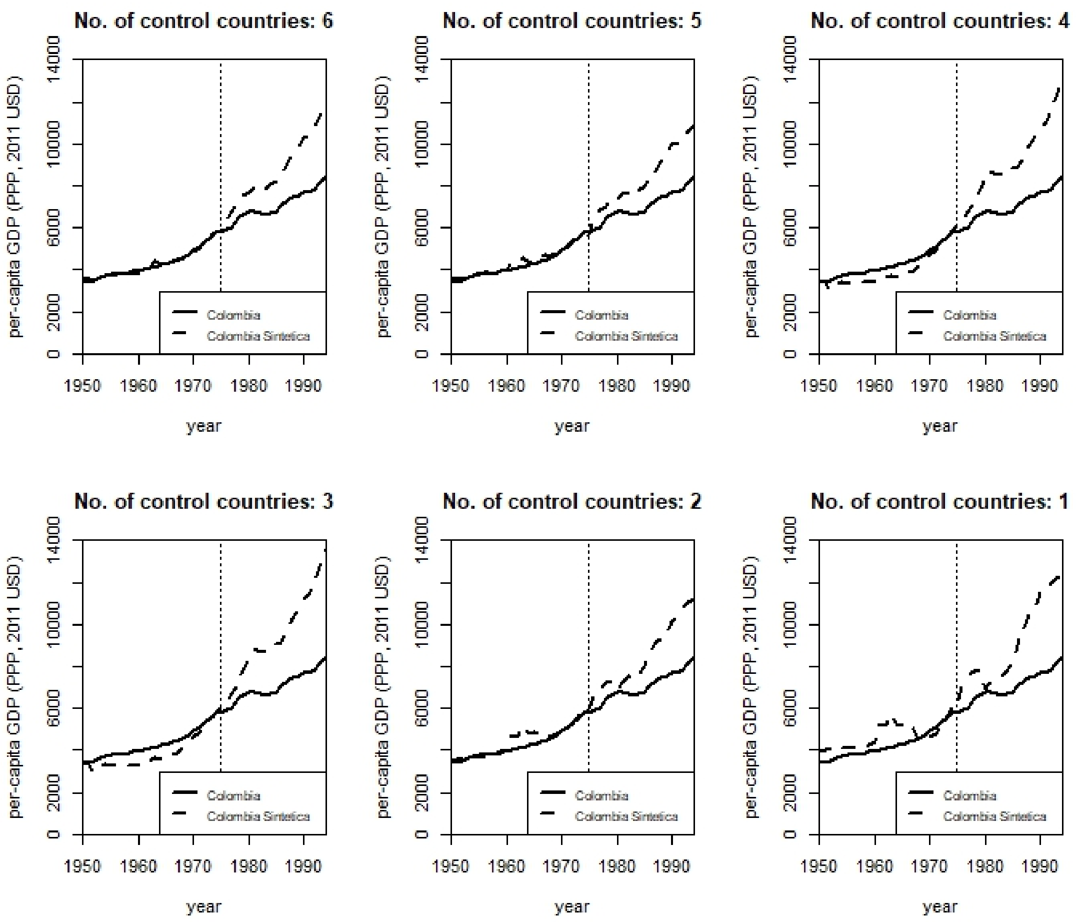
As shown in Table 3, the countries initially selected as controls are retained in nearly all cases. These countries largely overlap with those selected in the design not limited to six control units, maintaining consistency within the donor pool.

Table 4: Mean predictors of economic growth prior to the intensification of the armed conflict in Colombia for control country combinations

		Synthetic Colombia						
		Number of countries in synthetic control						
	Colombia	6	5	4	3	2	1	Sample
Inflation rate	14.1	14.0	14.0	13.8	15.1	14.2	6.8	12.0
GDP per capita	5414.5	5413.8	5413.7	5419.1	5393.6	5342.9	5434.8	5744.4
Investment rate	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
% Secondary	14.4	14.3	14.3	14.3	14.4	14.9	15.5	13.7
% Primary	83.2	83.1	83.1	83.2	83.0	82.4	82.0	83.4
% Tertiary	2.4	2.3	2.4	2.2	2.3	2.3	2.5	2.6
Human capital index	1.7	1.7	1.7	1.7	1.7	1.7	1.7	1.7
Average years of schooling	3.6	3.6	3.6	3.5	4.0	4.1	2.6	3.7

Additionally, in Table 4, we can observe that the fit of our synthetic control is not optimal when only one control country is used (which is expected), but it improves as more countries are added to the control group. However, overall, there are no drastic changes in the fit as more countries are included in the donor pool.

Figure 9. *GDP per capita gap between Colombia and synthetic dispersed controls*



In Figure 9, we can see that the direction of the effect remains unchanged, which is crucial for this type of analysis. Furthermore, as more countries are included in the control group, the model fit gradually improves, reaching the same level of fit as the initial design when 5–6 countries are used. This indicates that our design is robust, and while the sensitivity analyses may not be perfect, they are consistent with each other.

6. Discussion

We have developed an alternative methodology to estimate the economic cost of the armed conflict in Colombia, finding that, in the absence of the conflict's intensification—largely driven by the emergence of cartels—the synthetic counterpart grew 31.78% more than real Colombia. This gap has been defined as the potential loss in GDP per capita or the economic cost of the armed conflict.

The primary advantage of this design over other approaches, including the traditional method of direct and indirect cost accounting, lies in its complete transparency and robustness for quantifying treatment effects associated with events of interest when applied correctly. While other methods rely on cost accounting, which raises questions such as: How are these costs measured? Is it possible to account for all costs associated with a conflict?—these approaches face limitations that our design overcomes.

Our findings align with the existing literature on the economic cost of the armed conflict in Colombia. The results suggest that Colombia's GDP per capita trajectory would have been significantly higher, providing empirical evidence that the nexus between drug trafficking and the armed conflict had substantial consequences on the country's productive apparatus.

We emphasize that this design can be further improved with better predictor variable data or by expanding the donor pool. Regarding potential bias from including Asian countries, it is worth noting that the structural policies implemented in these nations began in the 1980s. Furthermore, the low weighting of these countries in the model minimizes the likelihood of significant bias.

In conclusion, our findings support the argument that events such as an armed conflict or the development of an economy embedded in a criminal culture are detrimental to any economy. Therefore, it is crucial for relevant stakeholders to design and implement public policies that promote institutional development and steer as far away from criminality as possible.

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