Sebastian Martinez

# Effects of promoting management of the social, political, and institutional environment on conflict in the Polochic Valley

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Sebastian Martinez
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This study uses data from the Presidential Commission for Peace and Human Rights early warning system for social conflict and the Armed Conflict Location & Event Data Project (www.acleddata.com).

## Executive summary

Disputes over land tenure are a major source of conflict globally, causing significant human suffering and economic and environmental costs. While a large body of academic literature studies the causes and consequences of agrarian conflict, relatively little is known about the effectiveness of interventions aimed at preventing conflict. This report presents the impact evaluation of a set of interventions supported by the UN Peacebuilding Fund between 2022 and 2023 aimed at managing the social, political, and institutional environment in the Polochic Valley of Guatemala.

The project aimed to address key constraints in conflict management, with the ultimate objective of reducing agrarian and land-based conflict in the area. Project activities included the promotion of multi-stakeholder participation in conflict prevention and management, training for community leaders on mediation and conflict resolution, the development of community land and people registries, and food security support in select communities.

This impact evaluation uses data from national and international conflict monitoring systems to analyze aggregate impacts of the project on conflict levels. We assemble a unique municipal-level panel dataset with more than 9,700 conflicts reported throughout the country in the nine-year period between 2015 and 2023. The analysis applies a synthetic control method using lasso (least absolute shrinkage and selection operator) regression: a data-driven method that uses pre-intervention time-series data to generate a weighted average of untreated units that approximates the treated unit. This weighted average of untreated units is called the “synthetic unit” and serves to approximate the counterfactual scenario after the program is implemented.

In the present context, the analysis compares the number of conflicts in the project’s four intervention municipalities with the number of conflicts in a “synthetic” comparison composed of weighted non-intervention donor municipalities. Results suggest that by its second year of operation, the project had large effects on conflict reduction.

Specifically, in 2023 the project contributed to an average reduction of 16.2 conflicts in intervention municipalities in the Polochic Valley, an 80 percent reduction relative to the estimated counterfactual number of conflicts. Impacts are largest in municipalities with the highest baseline conflict levels, and the effect is robust to dropping the baseline period of 2021, a period of high conflict in one particular municipality in the valley.

This study has several important limitations. First, data sources do not uniquely identify land-based conflicts. Thus, we analyzed all conflict types reported in the available data sources—though existing data suggest that agrarian disputes are a major source of conflict in Guatemala, particularly in rural areas such as the Polochic Valley. Secondly, we were only able to analyze short-term effects of the project during its two years of implementation.

Finally, we lacked additional national-level data on intermediate outcomes and covariates that would allow us to explore causal mechanisms, conduct placebo tests, and carry out other complementary analyses that would lend additional credibility to the primary analysis. Analyses of additional post-intervention years and indicators remain potential future extensions of this research project.

## Resumen ejecutivo

Las disputas por la tenencia de la tierra son una fuente importante de conflicto a nivel mundial, generando sufrimiento humano y costos económicos y ambientales. Si bien existe una amplia literatura académica que estudia las causas y consecuencias de los conflictos agrarios, se sabe relativamente poco sobre la efectividad de las intervenciones dirigidas a prevenirlos. Este informe presenta la evaluación de impacto de un conjunto de intervenciones apoyadas por el Fondo de las Naciones Unidas para la Consolidación de la Paz entre 2022 y 2023, destinadas a gestionar el entorno social, político e institucional en el Valle del Polochic de Guatemala.

El proyecto buscó abordar las principales limitaciones en la gestión de conflictos, con el objetivo final de reducir los conflictos agrarios. Las actividades del proyecto incluyeron la promoción de la participación de múltiples actores en la prevención y gestión de conflictos, la capacitación de líderes comunitarios en mediación y resolución de conflictos, el desarrollo de registros comunitarios de tierras y pueblos, y el apoyo a la seguridad alimentaria en comunidades seleccionadas.

Esta evaluación de impacto utiliza datos de sistemas nacionales e internacionales de monitoreo de conflictos para analizar los impactos agregados del proyecto sobre el numero de conflictos. Recopilamos un conjunto único de datos de panel a nivel municipal con más de 9700 conflictos reportados en todo el país durante el período de nueve años comprendido entre 2015 y 2023. El análisis implementa un modelo de control sintético con regresión lasso, un método basado en datos que utiliza series temporales previas a la intervención para generar un promedio ponderado de unidades no tratadas que se aproxima a la unidad tratada. Este promedio ponderado de unidades no tratadas se denomina "unidad sintética" y sirve para aproximar el escenario contrafactico tras la implementación del programa.

En el presente contexto, el análisis compara el número de conflictos en los cuatro municipios de intervención del proyecto con el número de conflictos en una comparación "sintética" compuesta por municipios donantes no intervenidos. Los resultados sugieren que, para su segundo año de funcionamiento, el proyecto tuvo un impacto en la reducción de conflictos.

Específicamente, en 2023, el proyecto contribuyó a una reducción promedio de 16,2 conflictos en los municipios de intervención del Valle del Polochic, una reducción del 80 por ciento con respecto al número contrafactico estimado de conflictos. Los impactos son mayores en los municipios con los niveles de conflicto iniciales más altos, y el efecto es robusto al descartar el período de referencia de 2021, un período de alta conflictividad en un municipio particular del Valle del Polochic.

Este estudio presenta varias limitaciones importantes. En primer lugar, las fuentes de datos no identifican de forma única los conflictos relacionados con la tenencia de la tierra. Por lo tanto, analizamos todos los tipos de conflicto reportados en las fuentes de datos disponibles, aunque los datos existentes sugieren que las disputas agrarias son una fuente importante de conflicto en Guatemala, particularmente en zonas rurales como el Valle del Polochic. En segundo lugar, solo podemos analizar los efectos a corto plazo del proyecto durante los dos años de implementación.

Finalmente, carecíamos de datos adicionales a nivel nacional sobre resultados intermedios y covariables que nos permitieran explorar los mecanismos causales, realizar pruebas placebo y otros análisis complementarios que aportaran mayor credibilidad al análisis principal. El análisis de años e indicadores adicionales posteriores a la intervención se mantiene como una posible extensión futura de este proyecto de investigación.

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## Acronyms

| | |
|---|---|
| **ACLED** | Armed Conflict Location & Event Data Project |
| **COPADEH** | Presidential Commission for Peace and Human Rights |
| **PBF** | UN Secretary-General's Peacebuilding Fund |
| **SCM** | Synthetic control method |

# 1. Introduction

Longstanding inequities in landholding and the more recent proliferation of agro-industrial production are drivers of decades-long agrarian-based conflict in the Polochic Valley of Guatemala. Conflict over land tenure dates back to the colonial era, when colonizers established large estates (*haciendas*) on lands used by indigenous communities for agricultural production. The region was also an epicenter of displacement and violence during Guatemala's civil war (1960–1996). More recently, the expansion of large-scale palm oil production and sugarcane plantations has resulted in further tension over land tenure, thereby exacerbating agrarian-based conflicts.

Between 2022 and 2023, the UN Peacebuilding Fund (PBF) supported efforts to manage the social, political, and institutional environment in the Polochic Valley, with the ultimate goal of reducing conflict. Amongst its major activities, the project focused on promoting multi-stakeholder participation in conflict prevention and management, conducted training for community leaders on conflict mediation and resolution, invested in food security interventions for a select group of communities, and supported the development of community land and people registries.

This report presents the impact evaluation of this peacebuilding effort, with the goal of identifying its short-term effects on conflict levels in the Polochic Valley. The analysis employs secondary data on conflict events from the Presidential Commission for Peace and Human Rights (COPADEH) National Early Conflict Detection System and the Armed Conflict Location and Event Data Project (ACLED), as well as select covariate data from Guatemala's National Statistics Institute.

The study employs a synthetic control model with lasso regression to identify the project's causal impacts on conflict. This approach compares the actual number of conflicts in the Polochic Valley to the estimated counterfactual number of conflicts in a "synthetic" Polochic Valley, where the synthetic control is composed of a weighted combination of donor (non-intervention) municipalities that mimic pre-intervention conflict levels in the Polochic Valley.

Results suggest that by the second year of operation, the project contributed to large reductions in conflict. Specifically, in 2023 we estimate an average reduction of 16.2 conflicts in the Polochic Valley. This represents an 82 percent reduction relative to the almost 20 annual conflicts predicted by the model to have occurred in the absence of the project (i.e., the estimated counterfactual number of conflicts).

A municipality-by-municipality analysis shows that impacts are largest in areas with the highest levels of baseline conflict. Given a spike in conflict in 2021 (the year prior to the program's launch), we implement a validity check that drops 2021 from the analysis, and find that the estimated reduction in conflicts remains statistically significant, though of a smaller size.

It is important to recognize several limitations of this study. First, available data sources do not uniquely identify land conflict, although existing evidence suggests that agrarian conflicts comprise more than half of all conflicts in years where we can disaggregate these data according to type (agrarian or non-agrarian). Even when this classification is not possible, we expect that agrarian-related disputes are highly relevant in rural areas such as the

Polochic Valley. Second, data were available only through 2023, thereby limiting the analysis to short-term impacts within the two project implementation years. Moreover, implementation activities with communities were limited to one year (2023), allowing us to focus only on very short-term effects.

Finally, we lacked additional national-level data on intermediate outcomes and covariates (e.g., access and participation in conflict mediation) that would allow us to explore causal mechanisms, and to conduct placebo tests and other complementary analysis that would lend additional credibility to the primary analysis.

Nevertheless, results from this initial analysis suggest that the investments in peacebuilding activities in the Polochic Valley contributed to significant reductions in conflict in the intervention areas. A behavioral field experiment implemented as part of PeaceFIELD in the same study areas revealed that providing local residents with project-related information reduced the population's perception of direct confrontation as an adequate and effective approach to conflict resolution (see Ferguson et al. 2024, 2025).

Taken together, these studies provide encouraging initial evidence that the project's approach alleviated key drivers of conflict in the Polochic Valley, resulting in a reduction in conflict. However, only additional years of post-intervention data will reveal whether these effects are sustained beyond the life of the project.

This report is structured as follows: Section 2 summarizes existing literature on the application of synthetic control methods to the study of conflict. Section 3 describes the project objectives and main activities. Section 4 discusses the synthetic control identification strategy, and Section 5 describes the data used for this impact evaluation. Section 6 presents the main results, and Section 7 concludes.

## 2. Literature review

This section presents a brief overview of related literature, with a focus on applications of the synthetic control mehtod (SCM) to study the impacts of peacebuilding efforts. We identified only two studies that used the SCM to measure peace outcomes specifically, and only one used it as the primary identification strategy.

The first of these studies examined factors that contribute to states falling into or exiting from fragility. Using the SCM, Akanbi et al. (2021) used covariates from nationally representative datasets to construct a synthetic counterfactual for a group of events that led a country into fragility and events that led a country out of fragility.[1] The synthetic comparison was comprised of countries and events that could have led a country into fragility (or out of it) but did not.

A second study by Bloem (2018) analyzed the impact of the American Dodd-Frank Act (which imposed reporting requirements on US companies using "conflict materials" in their supply chains) on the prevalence of conflict events in the Democratic Republic of the Congo. This study used the SCM as a robustness check to supplement core results from a difference-in-differences identification strategy.

[1] See Appendix II of Akanbi et al. (2021) for a full list of covariates used to construct the synthetic control.

While application of the SCM to measure impacts of interventions on peacebuilding outcomes is limited, it has numerous uses in the peacebuilding field more generally. In fact, one of the original applications of the SCM by Abadie and Gardeazabal (2003) measured the economic cost of conflict (taken as per capita GDP) in the Basque Country.

Numerous other studies examined the effect of peace or conflict on economic outcomes such as GDP or inflation, or development outcomes such as child mortality. One of the most common applications of the SCM has been to measure the impacts or costs of conflict on economic indicators such as GDP or poverty rates (Rao and Vidyattama 2017; Mawejje and McSharry 2021; Neuenkirch and Neumier 2016; Singhal and Nilakantan 2016; Costalli, Moretti, and Pischedda 2017; Bilgel and Karahasan 2019). It has also been used to investigate the impact of conflict or momentous political events on nation- and region-wide socioeconomic indicators such as child mortality, education, and health (see Hönig 2017; Alnafrah and Mouselli 2019; Grier and Maynard 2016; Pieters et al. 2016; Geloso and Pavlik 2021).

## 3. Intervention

This study evaluates the Promoting Management of the Social, Political and Institutional Environment to Reduce Agrarian Conflict in the Polochic Valley project (henceforward "the project"). The project was implemented by three UN agencies: the Food and Agriculture Organization, the Office of the United Nations High Commissioner for Human Rights, and the World Food Programme, with a USD 1.5 million grant from the PBF.

The project additionally included the participation of partners from several public institutions and local civil society.[2] Implementation spanned a 24-month period between 2022 and 2023; the first year focused on institutional strengthening and preparation activities, while local community activities took place between January and December 2023.

The Polochic Valley is a region comprising four municipalities in the departments of Alta Verapaz and Izabal in northeastern Guatemala. Its population is predominantly indigenous, with approximately 89 percent belonging to the Maya-Q'eqchi' and Poqomchi' groups. Competition over land and resources in the Valley dates to the colonial period, and the area was an epicenter of violence during the country's two-and-a-half decade civil war spanning the 1960s through the mid-1990s. Land-based conflict has been exacerbated there in recent decades due to the proliferation of agro-industrial production of sugar cane and palm oil.

The project had three primary objectives, all of which aimed to reduce agrarian-related conflict in the Polochic Valley using a gender-sensitive and human rights-based approach:

1. **Strengthen capacities** of public institutions to manage and prevent agrarian conflicts.
2. **Improve participation of indigenous and peasant communities** in conflict management, improve community governance for land tenure and use, and improve nutritional security.
3. **Strengthen existing spaces for multisectoral dialogue** to resolve agrarian conflicts at the local level.

[2] Government: COPADEH. Local civil society organisations: Comite Campesino del Altiplano, Comité Unidad Campesina, Fundación Guillermo Toriello, Asociación Utz Che, and Fundación Propaz.

To accomplish these objectives, the project implemented three related components. The first entailed the promotion of multi-stakeholder participation in conflict prevention and management. The second focused on mediation and conflict-resolution training for community leaders, emphasizing women and indigenous groups, and invested in food security for a select set of ten communities. The third focused on development of community land and people registries. The following sections summarize the project's main activities.

## 3.1 Strengthening institutional capacity

To address the first objective, the project worked with COPADEH, whose objective was to ensure the protection of human rights and compliance with government commitments under the Peace Agreement. In mid-2020, the Guatemalan government reconfigured its institutional structure through the creation of COPADEH,[3] the role of which was to coordinate the management of agrarian conflict with other government institutions[4] and to assemble spaces for dialogue between stakeholders (e.g., indigenous and peasant communities, civil society, public institutions, private initiatives). The project provided support to COPADEH and assisted in its coordination role with government institutions.

The intervention provided public institutions with knowledge and skills to improve the prevention and management of agrarian conflicts through training of public officials.[5] Activities included a diagnosis of training needs, the elaboration of a plan and methodology, and the development of training processes. Additionally, public institutions incorporated the use of standard human rights-, gender-, and nutrition-sensitive tools and methodologies to address agrarian conflict.

## 3.2 Improving participation of indigenous and peasant communities

To achieve the second objective, the project worked closely with indigenous and peasant communities to increase their capacity for conflict management, improve community governance for land tenure and use, and develop efficient livelihood management. Activities included developing a training plan and a local governance diagnosis with a food security and nutrition approach, and promoting leadership among women and youth.

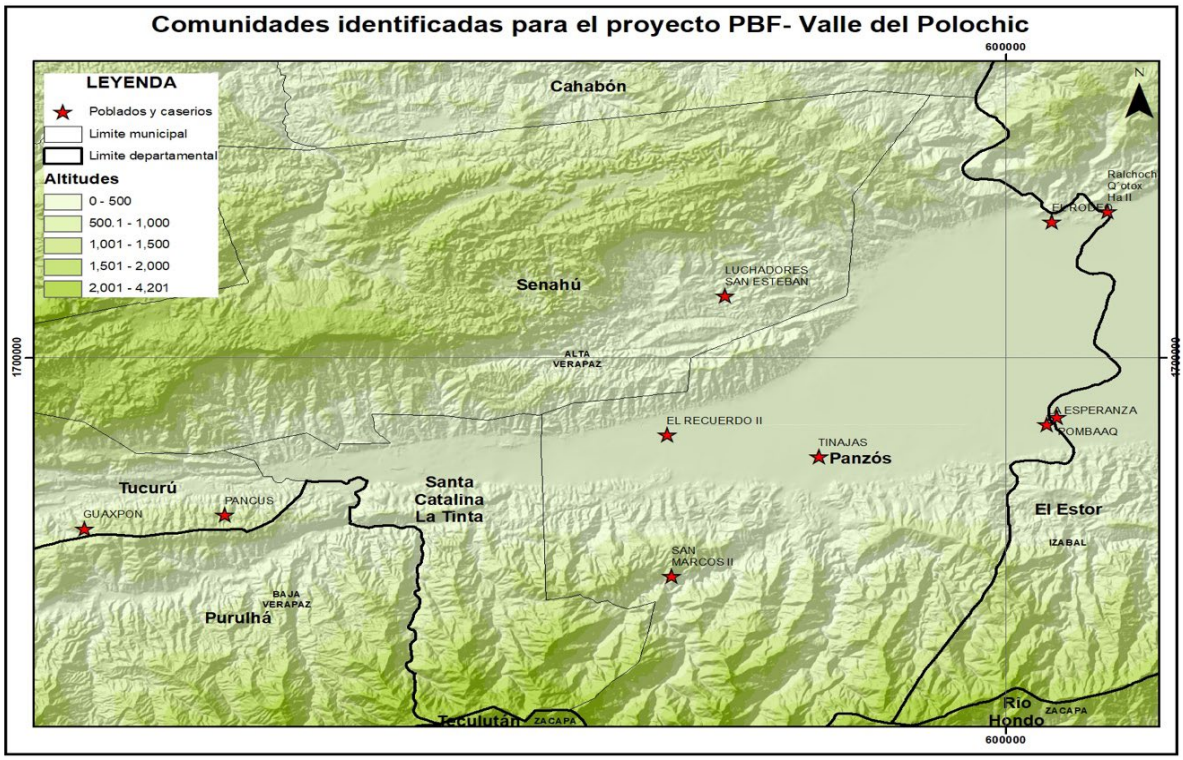
Additionally, to improve land administration and the efficient use of livelihoods, the program developed a community registry, community regulations, and a land-use plan. These actions were expected to improve community participation in the management of agrarian conflicts and enhance the quality of requests presented in dialogue spaces.

Activities under the second component targeted ten indigenous and farmer communities, comprising 840 families in the Polochic Valley. These communities were prioritized based on: the presence of precautionary protection measures granted by the Inter-American Commission on Human Rights, or judicial resolutions from the competent national court in favor of the community; conditions of vulnerability; forced eviction (experienced by seven

[3] In July 2020, the Secretariat for Agrarian Affairs of the Presidency, the Secretariat for Peace, and the Presidential Coordinating Commission for the Executive's Policy on Human Rights were dissolved, and COPADEH was created, unifying the functions of all three agencies.
[4] Such as the Land Fund, the Registry of Cadastral Information, the Secretariat of Food Security, the Ministry of Agriculture, the Judiciary, the Public Prosecutor's Office, and the Ombudsman's Office.
[5] The goal is to train 60 public officials at the municipal, departmental and national levels.

communities); and previous work with the implementing agencies and participation in consultation workshops.

**Figure 1: Map of intervention area**




## 3.3 Strengthening existing multisectoral dialogue spaces at the local level

The third objective of the program was to strengthen multisectoral dialogue spaces that address agrarian conflicts in a more inclusive manner, improving stakeholder participation and trust. The intervention generated action plans, methodologies, trainings, and tools to improve evidence-based analysis, discussion, and conciliation for the resolution of agrarian conflicts.

The project also built the capacities of community leaders, community organizations, and civil society organizations that assist communities in generating technical proposals and interacting with public institutions. It also provided technical assistance to public institutions at the national, departmental, and municipal levels to develop action plans, define agendas, and use tools to ensure evidence-based conflict resolution.

Activities focused on the dialogue spaces generated by departmental governments in Alta Verapaz and Izabal and municipal authorities to address agrarian conflicts. Additionally, the intervention worked with these spaces for dialogue, which were established to implement the precautionary measures dictated by the Inter-American Commission on Human Rights.

## 4. Identification strategy

The objective of this study is to identify the impacts of the project activities described in Section 3 on the number of conflicts in the Polochic Valley. To accomplish this objective, we implemented an SCM, which compares the number of conflicts in the Polochic Valley to those of a "synthetic Polochic Valley" that models the predicted number of conflicts that would have occurred in the absence of the project.

The SCM can be applied to study impacts of regional-, subnational-, or even national-level programs that treat a small number of aggregate intervention units. Peace and conflict research can often fall into this category since drivers of conflict and political conditions are confined to specific geographies, which complicates the identification of control areas required to conduct causal analyses.

Impact evaluations must overcome the challenge of estimating the counterfactual outcome—in this case, the level of conflict that would have prevailed in the project's absence. In the present context of an intervention focused on a small number of aggregate units (four municipalities of the Polochic Valley), this challenge translates into identifying a comparable set of untreated municipalities that replicate the counterfactual outcome.

To overcome this challenge, the SCM—first used in Abadie and Gardeazabal (2003), further conceptualized in Abadie, Diamond, and Hainmueller (2010, 2015) and summarized in Abadie (2021)—solves the problem of causal inference when only few units are treated. Using pre-intervention time-series data on treated and untreated units, the method builds a weighted average of untreated units that would resemble the counterfactual of the treated units. This weighted average of untreated units is called the "synthetic unit" and serves to represent the scenario of how the treated unit would behave had it not been affected by the intervention.

Classic examples of the application of the synthetic control method include an evaluation of a tobacco control policy on tobacco consumption in California (Abadie, Diamond, and Hainmueller 2010), and a study of the effect of German reunification on GDP per capita (Abadie, Diamond, and Hainmueller 2015)..

To evaluate the combined effect of a set of interventions focused on reducing agrarian conflict in the Polochic Valley, we applied the SCM using a data-driven approach that automates model selection using lasso regression (Greathouse 2022).[6] Results of the SCM with predictor variables do not perform as well, and we attribute the difference at least in part to the sparseness of the outcome data and the limited availability of covariates for the current application.

The basic SCM model is defined as follows. Suppose that $J + 1$ units are observed, where units in this application are municipalities in Guatemala. Without loss of generality, it is assumed that only the first unit is treated, so we have $J$ units belonging to the control group.[7] Let $Y_{jt}^{N}$ be the outcome, in this case the number of conflicts, for any unit $j$ in period $t$ if that unit was not treated during this period. Let $T$ be the total number of available periods and $T_0$

[6] The procedure is implemented in Stata© version 17 using the "SCUL" command (Greathouse 2022).
[7] This group is also known as the donor pool, referring to the matching literature.

the period in which the treatment is applied. Let $Y_{jt}^{I}$ be the result that we would observe if unit $j$ in period $t$ is treated. It is assumed that the intervention has no effect in the periods prior to the intervention, so $Y_{jt}^{I} = Y_{jt}^{N}$ for $t = \{1, \dots, T_0\}$. In addition, we assume that the intervention does not have any effect on outcomes of the control group.

Let $\alpha_{jt} = Y_{jt}^{I} - Y_{jt}^{N}$ be the effect of the treatment for unit $j$ in period $t$ and $D_{jt}$ be a binary indicator that takes the value 1 when $j$ in period $t$ is exposed to the intervention and 0 in any other case. Since only the first unit is exposed to the treatment, and that treatment is not interrupted for $t > T_0$ the variable $D_{jt}$ is defined as:

$$D_{jt} = \begin{cases} 1 \; if \; = 1 \; and \; t > T_0 \\ 0 \; any \; other \; case \end{cases}$$

Then, the objective of the synthetic control will be to estimate $\alpha_{1t}$ for $t = T_0 + 1, \dots, T$. Since $Y_{1t}^{I}$ is observed for $t > T_0$, it is necessary to estimate $Y_{1t}^{N}$, the counterfactual that is not observed.

Suppose that $Y_{it}^{N}$ can be defined as:

$$Y_{it}^{N} = \delta_t + \theta_t \boldsymbol{Z_i} + \lambda_t \mu_i + \varepsilon_{it} \qquad (1)$$

where $\delta_t$ are fixed effects by period in the data; $\theta_t$ are unknown parameters common to all units; $\boldsymbol{Z_i}$ is a vector of observed variables; $\lambda_t$ are unobserved common factors; $\mu_i$ is a vector of unknown factor loadings or unit specific fixed effects; and $\varepsilon_{it}$ is a mean zero error term of transitory shocks at the unit level.

Consider a vector of weights $\boldsymbol{W} = (w_2, \dots, w_{J+1})'$, where $w_j \geq 0$ for $j = 2, \dots, J+1$ and $\sum_{j=2}^{J+1} w_j = 1$. Estimation of these weights is needed to replicate the counterfactual. That is, each value in $\boldsymbol{W}$ corresponds to a particular value of the weights that will create a potential synthetic unit. The SCM chooses the optimal value of $\boldsymbol{W}$ that best replicates the counterfactual scenario. By multiplying (1) by any vector $\boldsymbol{W}$, the equation can be transformed to:

$$\sum_{j=2}^{J+1} w_j Y_{jt} = \delta_t + \theta_t \sum_{j=2}^{J+1} w_j \boldsymbol{Z_j} + \lambda_t \sum_{j=2}^{J+1} w_j \, \mu_j + \sum_{j=2}^{J+1} w_j \, \varepsilon_{it} \qquad (2)$$

Suppose that there is a value of $\boldsymbol{W}$, $(w_2^*, \dots, w_{J+1}^*)$, such that the following equalities hold:

$$\sum_{j=2}^{J+1} w_j^* Y_{j1} = Y_{11}, \dots, \sum_{j=2}^{J+1} w_j^* Y_{jT_0} = Y_{1T_0} \quad \text{and} \quad \sum_{j=2}^{J+1} w_j^* Z_i = Z_1 \qquad (3)$$

That is, the set of weights, $(w_2^*, \dots, w_{J+1}^*)$, are such that for every period before the intervention the weighted average of units used as control groups replicate the value of the unit that is intervened in these same periods. Under certain plausible assumptions, these weights can be used to replicate what would have happened to the intervened unit had it not been intervened in the post-intervention periods $(T_0 + 1, \dots, T)$ using information from the control units. If these weights are optimal, then we can estimate the effect at each period after the intervention has started as:

$\widehat{\alpha_{1t}} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$ for every $t \in \{T_o, \dots, T\}$

where $\widehat{\alpha_{1t}}$ denotes the estimator of the estimand $\alpha_{1t} = Y_{1t}^{I} - Y_{1t}^{N}$.

For the equalities shown in (3) to hold, it is necessary that both outcomes treated units and their observed characteristics belong to a strictly convex union of the control group units. If this does not hold, then we will not be able to replicate the counterfactual scenario with the control units, as the assumptions will not be met. Of course, there is no set of weights that will ensure equality, but there can be weights that ensure a close-enough approximation that could be used to approximate the counterfactual.

Let $K = (k_1, \dots k_{T_0})'$ be a $(T_0 \times 1)$ vector that for each unit in the sample will define a value for each unit that is a linear combination that considers all periods preceding the intervention. We represent this linear combination by $\bar{Y}_i^{\boldsymbol{K}} = \sum_{s=1}^{T_0} k_s^* Y_{is}$. For instance, if $(k_1 = 0, k_2 = 0, \dots, k_{T_0-1} = 0, k_{T_0} = 1)$, then $\bar{Y}_i^{\boldsymbol{K}} = Y_{iT_0}$, so that the linear combination results in a value for that unit in the preceding periods that is equal to the period just before the intervention.

If $k_s = 1/T_0$, then $\bar{Y}_i^{\boldsymbol{K}}$ will be the simple average over all periods for that unit and outcome. Of course, there are many possible values for $K$. Let the number of possible combinations be $M$, so that we have $K_1, K_2, \dots K_M$ possible values for each unit in the sample in pre-intervention periods. Then, we can define a vector of possible outcomes and characteristics for the treated unit as $\boldsymbol{X_1} = (\boldsymbol{Z}_1', \bar{Y}_1^{\boldsymbol{K_1}}, \bar{Y}_1^{\boldsymbol{K_2}}, \dots, \bar{Y}_1^{\boldsymbol{K_M}})'$. For no treated units, we define a $(k \times J)$ that contains the same variables for untreated units, where the $jth$ column of this matrix is $(\boldsymbol{Z}_j', \bar{Y}_j^{\boldsymbol{K_1}}, \bar{Y}_j^{\boldsymbol{K_2}}, \dots, \bar{Y}_j^{\boldsymbol{K_M}})'$. Then the vector $\boldsymbol{W}^*$ gives the optimal weights that minimize the following distance $|| \boldsymbol{X}_1 - \boldsymbol{X}_0 \boldsymbol{W} ||$.

The recommended function to minimize the distance above is such that:

$$|| \boldsymbol{X}_1 - \boldsymbol{X}_0 \boldsymbol{W} ||_V = \sqrt{(\boldsymbol{X}_1 - \boldsymbol{X}_0 \boldsymbol{W})' \boldsymbol{V} (\boldsymbol{X}_1 - \boldsymbol{X}_0 \boldsymbol{W})}$$

where $\boldsymbol{V}$ is some $(k \times k)$ symmetric and positive semidefinite matrix. An optimal choice of V is one that assigns weights to linear combinations that minimize the mean square error of the synthetic control estimator.

The estimated counterfactual for the treated unit is compared with a distribution of placebo estimates and so the method is able to include the uncertainty derived from estimating a counterfactual. To do this, the estimation method is applied to all control units, generating their respective counterfactual while the treated unit acts as a donor. Then the magnitude of the effect estimated above, denoted by $\widehat{\alpha_{1t}}$, is compared with the value of all the placebo estimates, denoted by $\widehat{\alpha_{it}}$ with $i \neq 1$. Then we can infer about the significance of the estimate with the following test:

$$p = \frac{\sum_{i \neq 1} 1\{|\widehat{\alpha_{1t}}| \leq |\widehat{\alpha_{it}}|\}}{N}$$

where $N$ corresponds to the estimated number of placebos, that is, the number of control units. As such, the $p$ statistic measures the proportion of the average effect of the placebos that are greater in magnitude than the average effect of the treated unit. Thus, if all the placebos and the treated unit are plotted, we would expect a null effect of the treatment in the permutations.

We can extend the above framework to accommodate the presence of multiple treated units, as in the case of the Polochic Valley, where four municipalities are intervened by the project. We estimate synthetic units for each treated unit and estimate an effect for each of the municipalities separately. The next step is to decide, under a transparent criterion, how to aggregate them to obtain a summary measure. In this analysis, we estimate effects for the average level of conflicts in Polochic Valley and impacts separately for each of the four intervention municipalities, while excluding other treated municipalities from the donor pool.

## 5. Data

Following Abadie (2021), for an estimate using synthetic control to be credible, the following data requirements must be met. First, the model requires sufficient aggregate data on predictors and outcomes for the treated and donor units. In the current application, we construct a unique dataset with the count of conflicts at the municipal-year level for all municipalities in Guatemala. Second, sufficient pre-intervention information must be available for all units. This is especially relevant, since the credibility of this method depends largely on the ability to generate a pre-treatment trajectory for the variables of interest. In the current application, we have baseline data for seven years (2015–2021).

Finally, sufficient post-treatment information must be available for all units to be able to assess short- and long-term effects. This requirement is a limitation in the current application given the presence of only two post-intervention years—2022 and 2023—noting that that program's first year of operation was in 2022 and the intervention was still under implementation in 2023. Extensions of this analysis may consider additional post-treatment periods, once additional data for future periods become available.

To construct the data set used in this analysis, we rely on two independent sources of information that capture conflicts in Guatemala: the social conflict database by COPADEH[8] and ACLED (Raleigh et al. 2010; Raleigh, Kishi, and Linke 2023).

The COPADEH database on social conflict was collected through an early warning system financed by the United Nations Development Program. Data were collected between 2015 and 2018, and again between 2021 and 2023 (the system experienced an interruption in 2019 and 2020, and no data were reported for these years). The dataset reports a total of 1,389 conflict events. Variables include the date, municipality, conflict category, type of demand involved, and number of people involved and affected by the conflict.

Conflict categories in the 2021–2023 period include public policies, agrarian conflict, natural resources, electrical energy, democratic security, civil and political rights, and cultural rights. The type of demand includes land, infrastructure, labor, resource protection, use rights, public services, education, cost of services, wages, provision of services, and occupations of private areas, among others. Between 2021 and 2023, 58 percent of conflicts were classified as agrarian conflicts.

The ACLED dataset contains georeferenced conflict information on political violence and protest events between 2018 and 2023. The dataset contains 8,389 conflict events in Guatemala over this period. The variables include dates, involved actors, GPS locations,

[8] COPREDEH was dissolved in 2020, and its functions were taken over by COPADEH.

fatalities, and types of violence enacted. The involved actors include state forces, rebel groups, political militias, identity militias, rioters, and protesters. The types of violence outlined in the dataset are explosions/remote violence, violence against civilians, protests, riots, and strategic developments.

Importantly, we are unable to uniquely identify agrarian conflicts, leading us to consider all types of conflict regardless of the conflict type. Nevertheless, given that 58 percent of conflicts reported between 2021 and 2023 in the COPADEH database were agrarian, we assume that a significant proportion of conflicts, particularly in rural areas, are likely to have roots in the type of land-based or agrarian conflict targeted by the project.

Our primary outcome variable of interest is the number of conflicts as reported by COPADEH or ACLED in a given municipality and year. We tally the reported number of conflict events per municipality and per year in each database, creating municipal-year panel data. These data sets are then merged by municipal ID, and the total conflict variable is constructed as the sum of the number of conflicts reported by the two data sources in each municipality and year.

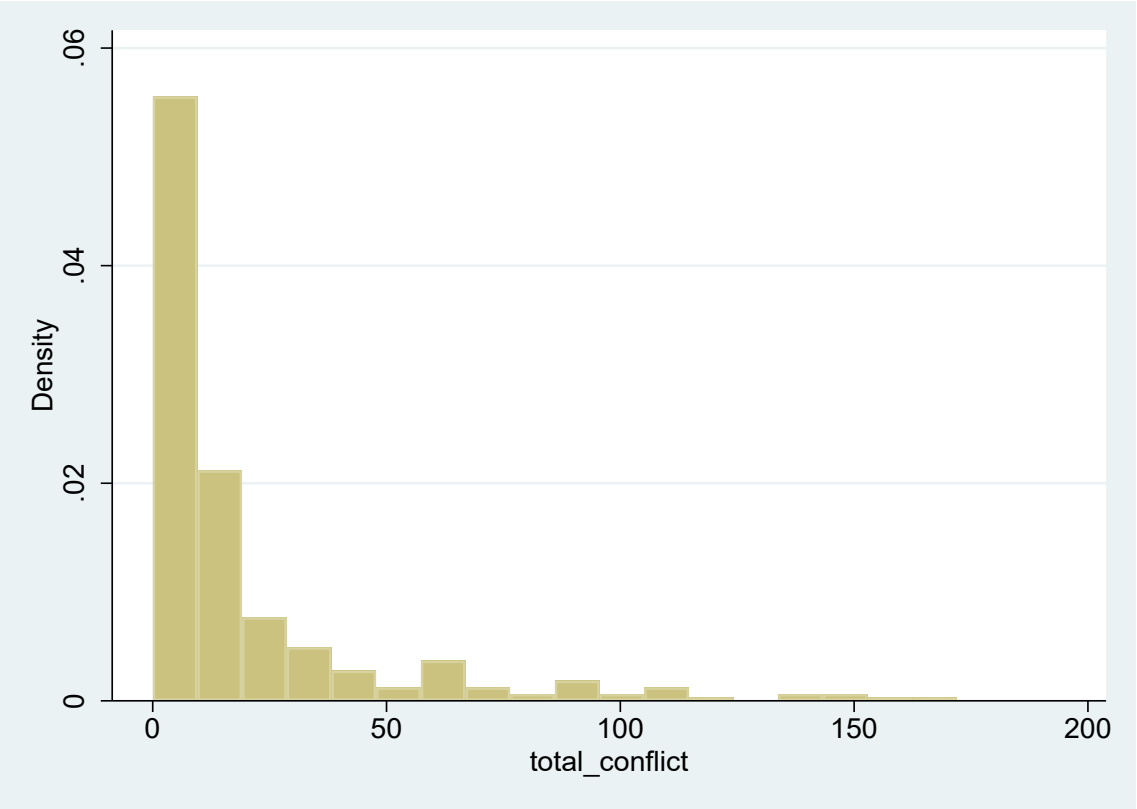
This procedure generates a dataset with a total of 9,778 conflicts, assuming that conflicts in the two data sets are unique. If the same conflict was reported in both datasets, this procedure would double count some conflicts. Since we are unable to determine which conflicts may be repeated in the datasets, we create an alternative version of the variable that keeps only the maximum number of conflicts reported in either data set in a given municipality-year. This procedure produces a variable with 9,405 conflicts. This analysis suggests that at most there are 373 repeated conflicts in the two data sets, and confirms that the COPADEH and ACLED data are collecting mostly independent conflict events.

Of the 9,778 conflict events in the data set, approximately 30% are concentrated in just three municipalities: Guatemala (22.2%), Mixco (4.9%) and Villa Nueva (4.6%). These are largely urban and densely populated municipalities that comprise the Guatemala City metropolitan area. Since these municipalities are urban and present very different socioeconomic and contextual conditions, they are dropped from the donor pool. On the other extreme, an important number of municipalities experienced very few reported conflicts in the nine-year observation period and are not good candidates for the donor pool. We discuss further adjustments of the donor pool for individual analysis in the results section.

The distribution of municipalities by total number of conflicts over the nine-year period (2015–2023) is presented in Figure 2 (dropping the three outlier urban municipalities in the Guatemala City metro area mentioned previously). As anticipated, the distribution of conflicts is skewed left, with most municipalities having few conflicts.

The intervention areas comprise four geographically adjacent municipalities of the Polochic Valley: Tucurú, Panzós, and Senahú (located in the department of Alta Verapaz), and El Estor (located in the department of Izabal). When we look at total conflicts for each individual municipality, there is substantial heterogeneity, with Senahú at the lower end of the distribution (with 17 total conflicts) and El Estor at the upper end (with 138 conflicts) during the observation period (Tucurú and Panzós are in the middle, with 25 and 55 conflicts, respectively).

**Figure 2: Distribution of total conflicts (all municipalities excluding Guatemala City metropolitan area)**




*Data Source: COPADEH and ACLED.*

In addition to the main outcome variable of interest, we also accessed several data sets produced by the National Institute of Statistics of Guatemala as covariates in alternative versions of the SCM with predictor variables. Specifically, we have taken datasets for vital statistics from 2015 to 2020, and education statistics from 2017 to 2023.[9] Both datasets are representative at the municipality level and collected annually. These covariates are used to run SCMs with predictors (as in Abadie, Diamond, and Hainmueller [2010] and Abadie [2021]), with graphical analysis presented in the appendix (Figures A1–A5).

From the vital statistics dataset, we constructed variables for the total number of deaths and total number of births recorded in every municipality.[10] Other variables include an indicator for low birth weight, taking the value 1 if the newborn's birth weight was recorded as lower than 5 pounds and 8 ounces, and 0 otherwise.[11] An indicator for institutional birth took the value 1 if the birth was recorded as having occurred in a private or public hospital, health center, or social security/insurance center (*seguro social*), and 0 otherwise.

[9] National Institute of Statistics of Guatemala datasets for vital statistics are available at https://www.ine.gob.gt/ine/vitales/ (Accessed August 23, 2022). National Institute of Statistics of Guatemala datasets for education are available at https://www.ine.gob.gt/ine/estadisticas/bases-de-datos/educacion/ (Accessed August 23, 2022).

[10] We imputed the number of births with the municipal average for municipalities with missing data.

[11] The classification of low birth weight is based on the following by Stanford Medicine: https://www.stanfordchildrens.org/en/topic/default?id=low-birthweight-90-P02382 (Accessed August 23, 2022).

Datasets for death records were collapsed at the municipality level where the death was registered. Datasets for birth records were collapsed at the municipality level where the mother was a resident. The collapsed datasets recorded the means of all variables at the above-mentioned municipality level.

From the education dataset, we constructed an indicator variable that took the value 1 if the person was in their "age-appropriate" grade, and 0 if they were not. This classification was as follows:[12]

- Level pre-primary (*preprimaria*): ages 3–6
- Level primary (*primaria*): ages 7–12
- Level middle (*básico*): ages 13–15
- Level diversified secondary (*diversificado*): ages 16–18

Children below the age of 3 were dropped from the analysis.

Indicator variables for different ethnicities were also constructed. Indicators for European and Asian ethnicities took the value 1 for all students from German, French, English, Italian, Japanese, Chinese, Portuguese, Russian, Thai, and Turkish ethnic communities, and 0 otherwise. Similarly, indicators for students of Spanish (Castellano) ethnicity, and for students of all Indigenous ethnicities, were constructed. Students recorded as being from "other" ethnic groups were dropped from the analysis. The education datasets were collapsed at the municipality level where the school was located, and recorded the means of all variables at the said municipality level.

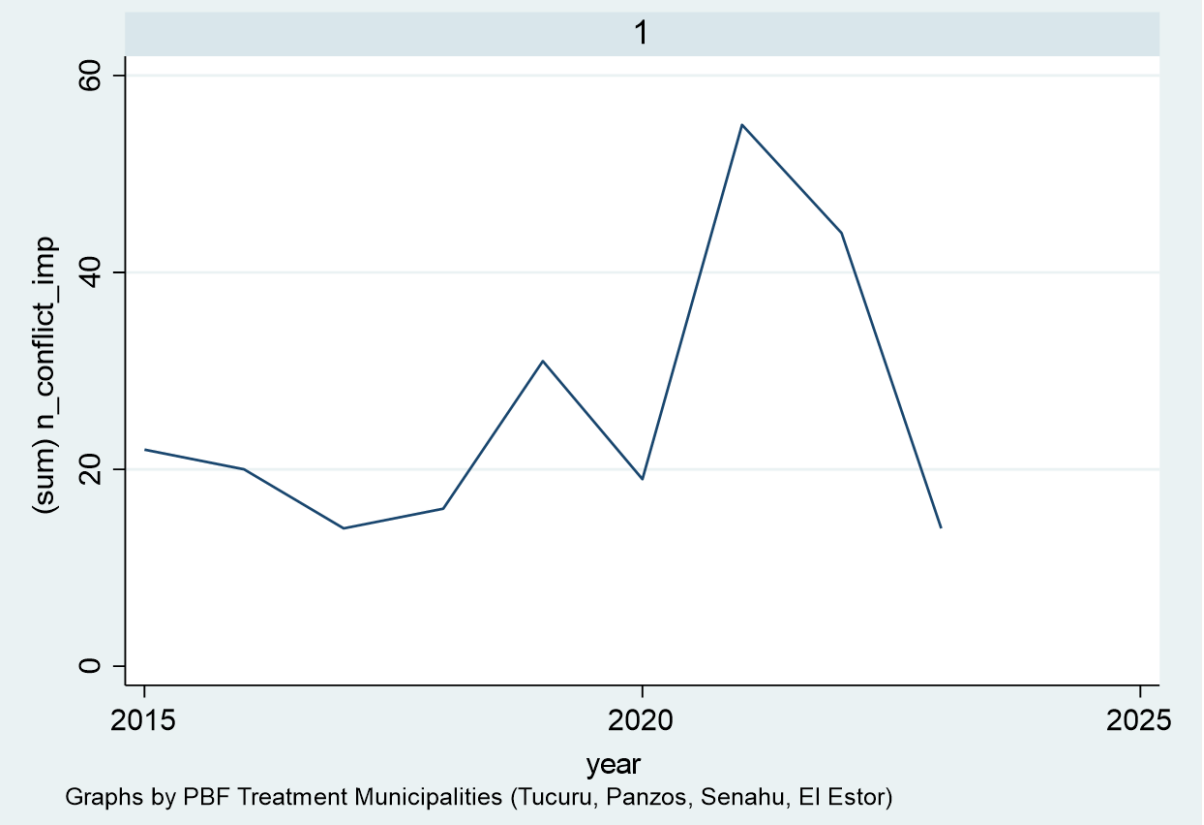
# 6. Results

## 6.1 Descriptive analysis

Figure 3 presents the time series of total conflicts in the Polochic Valley between 2015 and 2023. We observe that the number of yearly conflicts hovers around 20 in the years prior to the program's launch. Conflicts increased substantially in the year preceding the program, reaching more than 50 conflicts in 2021, and declining thereafter. This significant increase is attributed largely to a localized struggle over natural resource management (mining) in the El Estor municipality, and represents an atypical shock relative to historical trends. Section 6.4 presents a robustness test, dropping 2021 from the analysis to help rule out the influence of this single data point as the sole driver of the main results.

[12] The classification of grades and their corresponding ages is based on the Scholaro Database: https://www.scholaro.com/db/Countries/Guatemala/Education-System (Accessed August 23, 2022).

**Figure 3: Total conflicts in the Polochic Valley**

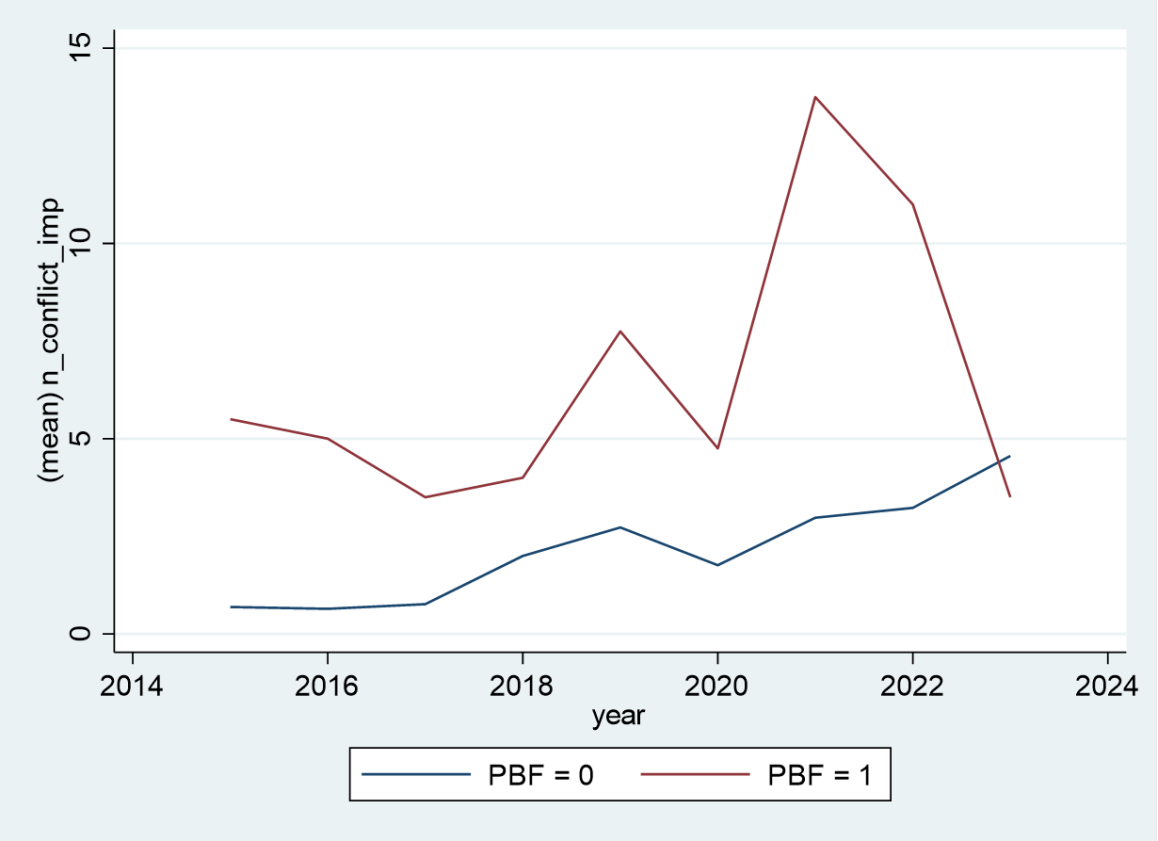



*Data Source: COPADEH and ACLED.*

Figure 4 plots the average number of conflicts in the Polochic Valley (red line) and in all other donor municipalities (blue line) between 2015 and 2023. It is clear that municipalities in the Polochic Valley have substantially more conflicts on average than others, with a difference 2–5 times the national average in most pre-intervention years. Over the period 2015–2021, municipalities in the Polochic Valley experienced an average of 4.78 conflicts per year, while the complete donor pool of all other municipalities experienced an average of 1.46 conflicts.

We also observe that while conflicts declined in Polochic Valley in 2022 and 2023, the average number of conflicts nationally continued in a positive trend and surpassed Polochic Valley in 2023. As previously discussed, to improve the donor pool we will restrict the set of donor municipalities to those with a minimum threshold, thus eliminating municipalities with no or very few conflicts reported in the pre-intervention period.

**Figure 4: Average number of conflicts in Polochic Valley and pool of donor municipalities**




*Data Source: COPADEH and ACLED.*

## 6.2 SCM

In this section we present the main results of the SCM with lasso regression. The donor pool of municipalities is restricted to municipalities outside of the Polochic Valley with more than three conflicts over the observation period, and dropping three urban municipalities from the Guatemala City metropolitan area (Guatemala, Mixco and Villanueva), leaving a total of 66 potential donor municipalities. Table 1 presents the annual number of conflicts in the Polochic Valley and the number estimated with the synthetic control. A graphical representation is provided in Figure 5, wherein the synthetic control (dotted line) mimics the number of conflicts in Polochic Valley very closely in the pre-intervention period.

In the first year of project implementation (2022), there is a small divergence in the number of conflicts (a reduction of 1.7 conflicts in the Polochic Valley), although this difference is not statistically significant. The absence of an observable effect in 2022 is consistent with the project roll out, which did not begin implementation activities on the ground until 2023. In the final year of the project (2023), the number of conflicts in Polochic Valley declined significantly relative to the synthetic control, with 16.2 fewer conflicts: an 82 percent decline relative to the counterfactual of almost 20 conflicts in the absence of the project.

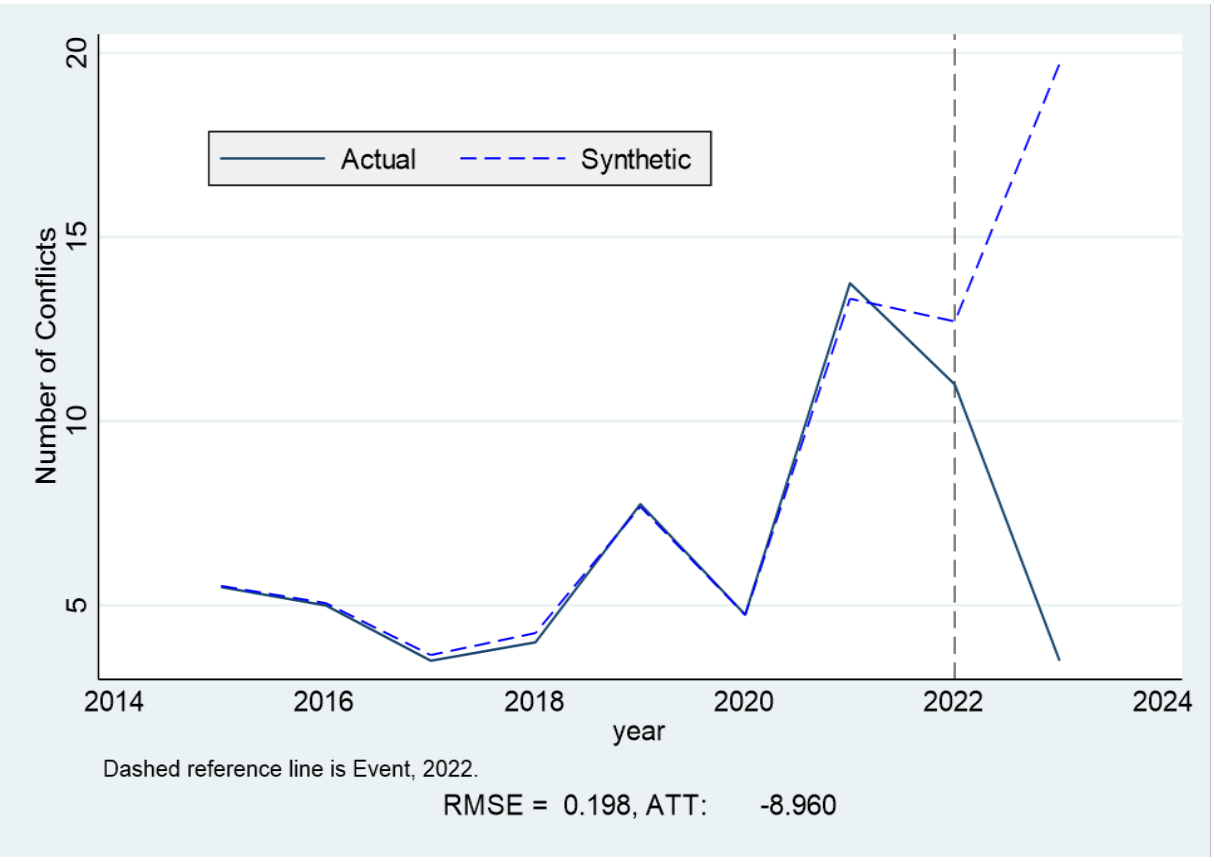
Figure 6 provides an additional representation of the synthetic control, including the confidence interval (shaded) around the estimated counterfactual number of conflicts.

**Table 1: Synthetic control results**

| Year | Polochic valley | Synthetic control | Difference |
|---|---|---|---|
| 2015 | 5.5 | 5.53 | -0.03 |
| 2016 | 5 | 5.06 | -0.06 |
| 2017 | 3.5 | 3.65 | -0.15 |
| 2018 | 4 | 4.25 | -0.25 |
| 2019 | 7.75 | 7.68 | 0.07 |
| 2020 | 4.75 | 4.74 | 0.01 |
| 2021 | 13.75 | 13.33 | 0.42 |
| 2022 | 11 | 12.71 | -1.71 |
| 2023 | 3.5 | 19.71 | **-16.21**** |

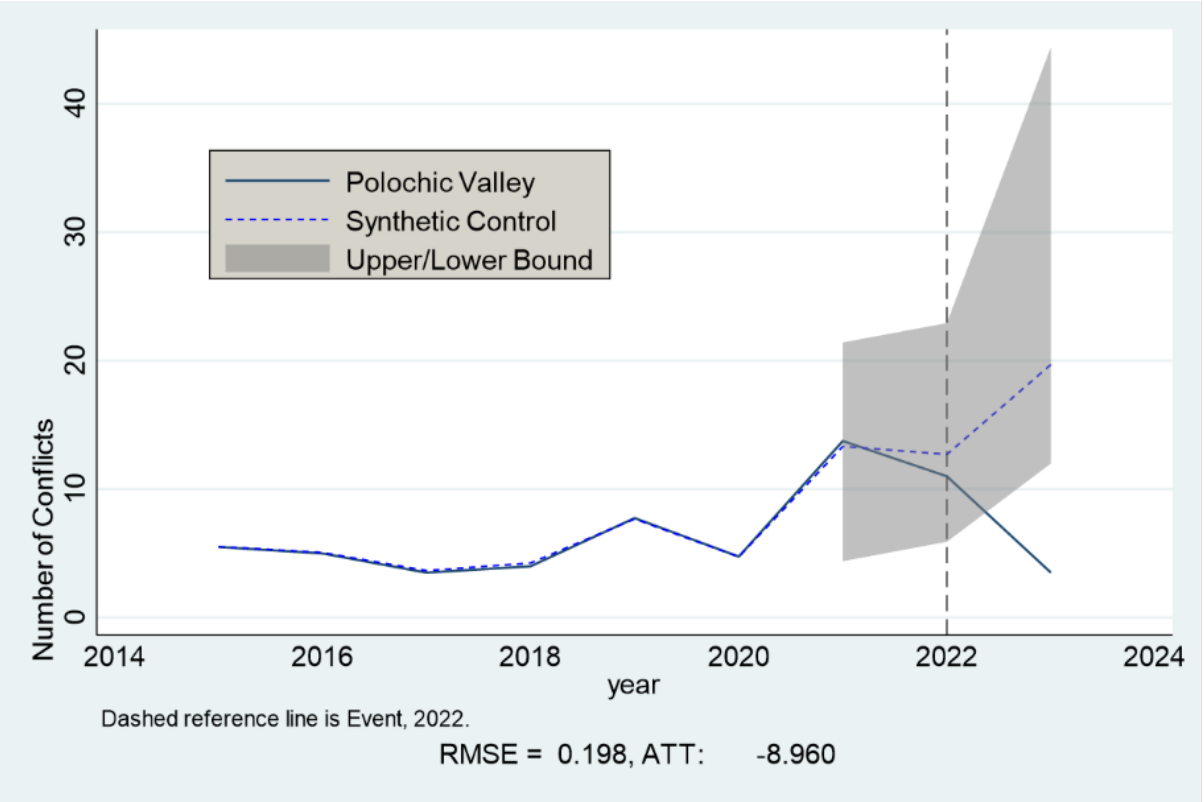
*Data Source: COPADEH and ACLED.*

**Figure 5: SCM impact on number of conflicts**




*Data Source: COPADEH and ACLED.*

**Figure 6: SCM with confidence interval**




*Data Source: COPADEH and ACLED.*

## 6.3 Municipal-level effects

In this section, we present the individual, municipal-level treatment effects for each municipality in the Polochic Valley. The analysis tailors the minimum number of conflicts in the donor pool, and excludes other treated municipalities.

For the municipality of Senahú, given the low number of conflicts, the lasso model does not converge (graphical analysis of the SCM with predictors is presented in the appendix). For the remaining three municipalities, we observe that no impacts are detected in Tucurú, the municipality with the second-lowest number of conflicts following Senahú. In Panzós, there is a statistically significant decline of 4 conflicts in 2023, while in El Estor (the most conflictive of the municipalities in the Polochic Valley), the project is associated with a decline of 24.8 conflicts: a decline of 75 percent relative to the counterfactual estimate of 32.8 conflicts.

Municipality-level graphical analyses are presented in Appendix figures A1–A3. The municipality-level analysis reveals that the greatest effects of the project are concentrated in areas with the highest levels of pre-intervention conflict, while impacts in the two less-conflictive municipalities are negligible.

**Table 2: Municipal-level impacts**

| Year | Tucurú | Synthetic Tucurú (Control) | Difference | Panzós | Synthetic Panzós (Control) | Difference | El Estor | Synthetic El Estor (Control) | Difference |
|---|---|---|---|---|---|---|---|---|---|
| 2015 | 6 | 2.57 | 3.43 | 6 | 6.32 | -0.32 | 5 | 4.98 | 0.02 |
| 2016 | 2 | 2.57 | -0.57 | 11 | 6.96 | 4.04 | 6 | 6.06 | -0.06 |
| 2017 | 3 | 2.57 | 0.43 | 6 | 5.89 | 0.11 | 5 | 5.06 | -0.06 |
| 2018 | 1 | 2.57 | -1.57 | 7 | 6.32 | 0.68 | 8 | 8.11 | -0.11 |
| 2019 | 2 | 2.57 | -0.57 | 4 | 5.89 | -1.89 | 23 | 22.99 | 0.01 |
| 2020 | 0 | 2.57 | -2.57 | 2 | 5.89 | -3.89 | 17 | 16.83 | 0.17 |
| 2021 | 4 | 2.57 | 1.43 | 8 | 6.74 | 1.26 | 37 | 36.97 | 0.03 |
| 2022 | 4 | 2.57 | 1.43 | 8 | 8.03 | -0.03 | 29 | 25.93 | 3.07 |
| 2023 | 3 | 2.57 | 0.43 | 3 | 7.38 | **-4.38**** | 8 | 32.86 | **-24.86**** |

*Data Source: COPADEH and ACLED.*

## 6.4 Robustness checks

The SCM identifies the difference between the actual number of conflicts in Polochic valley and the predicted number of conflicts in the synthetic control. Attribution of this difference to the intervention of interest, in this case the PBF funded project in the Polochic Valley, assumes no other systematic differences between the intervention and synthetic control during the intervention period. Any events or interventions in the Polochic Valley that were confined to this area and occurred concurrently with the project could potentially account for at least part of the difference in outcomes estimated through the SCM.

We are not aware of other localized peacebuilding efforts confined to the Polochic Valley in the 2022–2023 period; however, one particular event that occurred differentially in the pre-intervention year of 2021 in the municipality of El Estor was a peak in conflict over mineral extraction in a local nickel mine. We observe this surge in conflict in Table 2, where El Estor experienced 37 conflict events in a single year, the highest number for any year in our data set in the Polochic Valley.

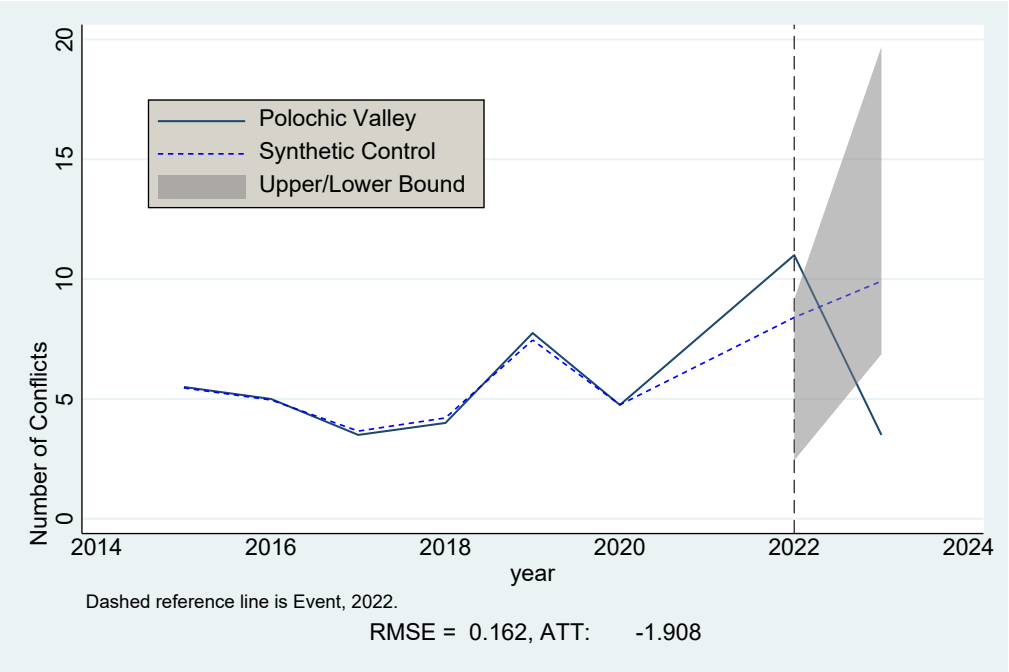
We perform a validity check that estimates the synthetic control while dropping the pre-intervention year 2021 and find that the estimated impact on conflict remains negative and significant, while of a smaller magnitude. Table 3 shows a reduction of 6.41 conflicts: a 65 percent reduction relative to the counterfactual estimate of 9.91 conflicts. A graphical representation of the analysis is presented in Figure 7.

**Table 3: SCM dropping baseline year 2021**

| Event | Polochic Valley | Synthetic control | Difference |
|---|---|---|---|
| 2015 | 5.5 | 5.46 | 0.04 |
| 2016 | 5 | 4.96 | 0.04 |
| 2017 | 3.5 | 3.66 | -0.16 |
| 2018 | 4 | 4.21 | -0.21 |
| 2019 | 7.75 | 7.46 | 0.29 |
| 2020 | 4.75 | 4.76 | -0.01 |
| 2021 | - | - | - |
| 2022 | 11 | 8.40 | 2.60 |
| 2023 | 3.5 | 9.91 | **-6.41**** |

*Data Source: COPADEH and ACLED.*

**Figure 7: SCM dropping baseline year 2021**




*Data Source: COPADEH and ACLED.*

## 7. Conclusion

This impact evaluation analyzes the effects of the PBF-funded interventions in the Polochic Valley of Guatemala. At the level of the PBF Strategic Framework in Guatemala (2020–2025), the study supports the importance of a programmatic approach aimed at reducing territorial conflict through peaceful, inclusive, and collaborative solutions including strengthening institutional and community capacity for conflict management.

Results suggest that by its second year of operation, the program contributed to large reductions in the number of conflicts. Specifically, in 2023 the project contributed to an average reduction of 16.2 conflicts in intervention municipalities: an 80 percent reduction relative to the estimated counterfactual number of conflicts. Impacts are largest in municipalities with the highest baseline conflict levels, and the effect is robust to dropping the baseline period of 2021, a period of high conflict in one particular municipality of the Polochic Valley.

The program's impact is highest in municipalities with high levels of baseline conflict, and we find no detectable effects in municipalities with low baseline levels of conflict. This suggests that further analysis of targeting criteria (taking into consideration initial conditions such as historical levels of conflict as well as the potential for future conflict) may be beneficial when designing and deploying peacebuilding efforts similar to the program studied here.

An important point of context for the interpretation of results is the spike in conflicts in the municipality of El Estor in 2021, driven to a large extent by conflicts surrounding a nickel mining operation. Given that the mine stopped operating in 2022, it is possible that the decline in conflict in El Estor in 2022 and 2023 was caused at least in part by the cessation of mining activities, rather than the effect of the PBF-funded program.

While we cannot fully rule out this potential source of bias, several aspects of the results presented in the report suggest that the relationship between the program and reduced conflict in the Polochic Valley is causal. First, the timing of the reduction in conflicts coincides with the onset of program activities in the Polochic Valley in 2023. If the 2022 closing of the mining operation at Maya Nikel were a major driver of this reduction, we would expect to observe this effect in the data beginning that year.

Second, we present a robustness test dropping the outlier baseline year of 2021. While the estimated effects diminish in magnitude, they remain statistically significant and large as a proportion of baseline conflict. Finally, through the municipal-level analysis, we observe that the program in Panzós—which had relatively high levels of baseline conflict independent of the mining operation—effectively reduced conflict levels.

This study has several limitations worth noting. First, data sources do not uniquely identify land conflict. Thus, we analyze all conflict types reported in the available data sources, though existing data suggest that land is a major source of conflict in Guatemala, particularly in rural areas such as the Polochic Valley. Second, we are only able to analyze the project's short-term effects during its two years of implementation.

Finally, we lacked additional national-level data on intermediate outcomes and covariates that would allow us to explore causal mechanisms, and to conduct placebo tests and other complementary analysis, that would lend additional credibility to the primary analysis.

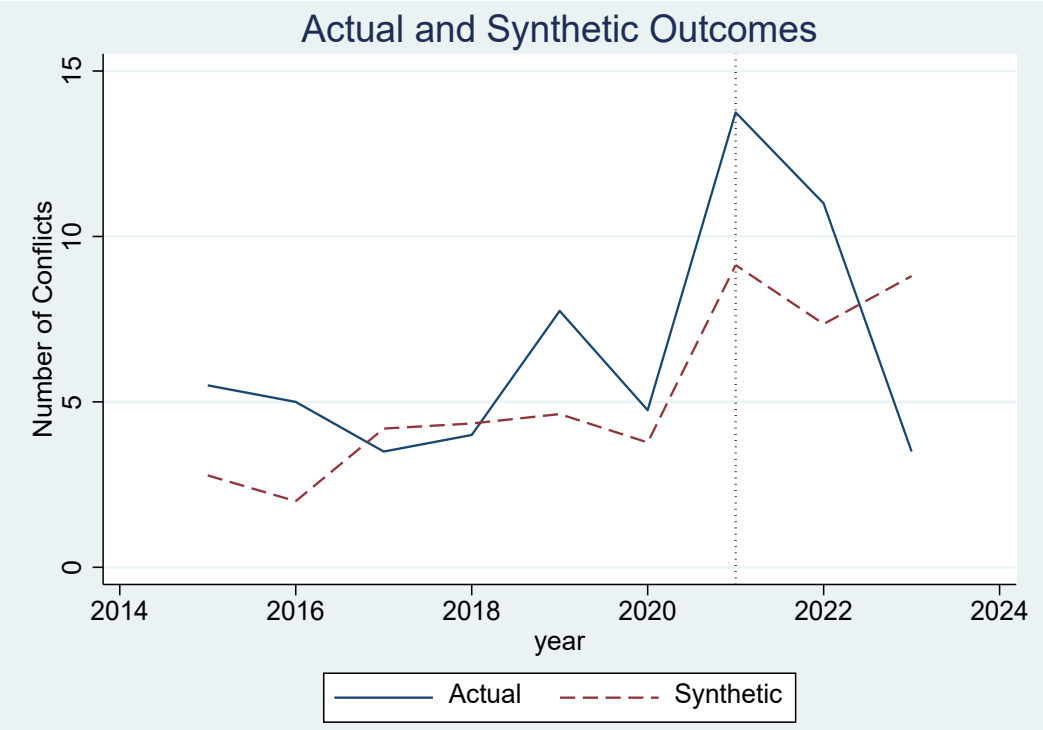
Several extensions of the current analysis may be feasible in its future iterations. First and foremost, additional years of post-intervention data will reveal whether short-term effects are sustained over time. Additional placebo and robustness tests will assess the results' sensitivity to different compositions of the donor pool. If additional intermediate outcomes related to the project (such as use of formal conflict-resolution mechanisms) were available, the SCM could be extended to explore causal mechanisms.

Furthermore, additional extensions could consider implications of reduced conflict on economic proxy indicators measured with remote-sensing data—including radiance (night lights) and the normalized difference vegetation index (a measure of vegetation canopy greenness). Finally, post-intervention interviews could be conducted with local actors to determine whether conflict-resolution mechanisms promoted by the program remain active in the longer term.

# Appendix

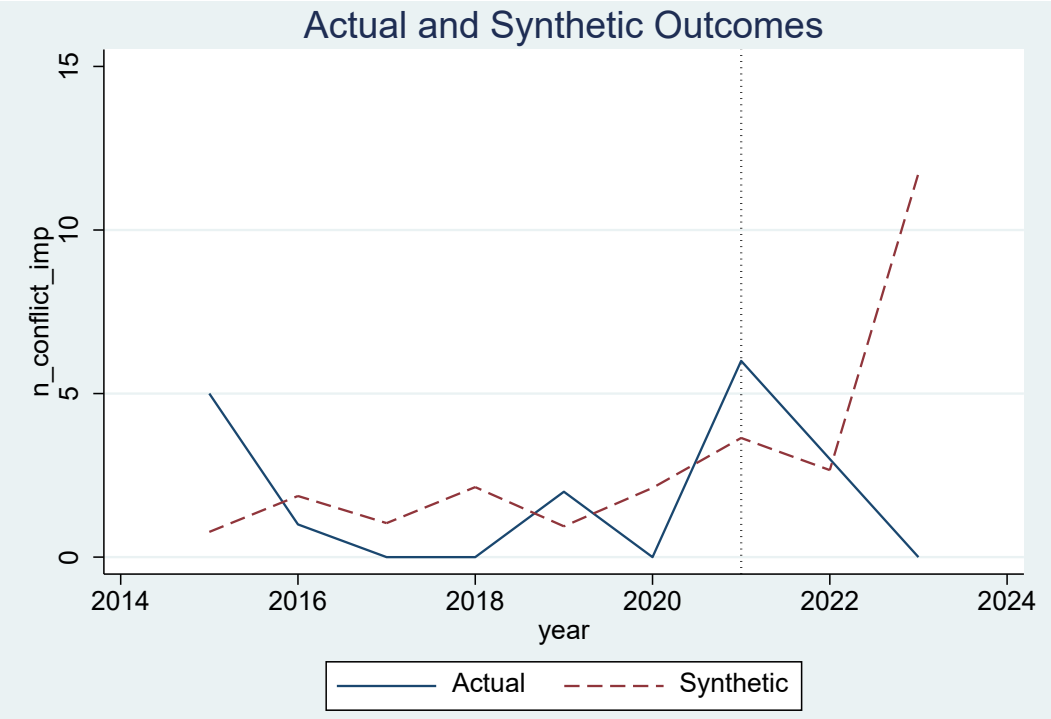
## Graphical analysis of SCM with predictors

### Figure A1: Polochic Valley SCM with predictors



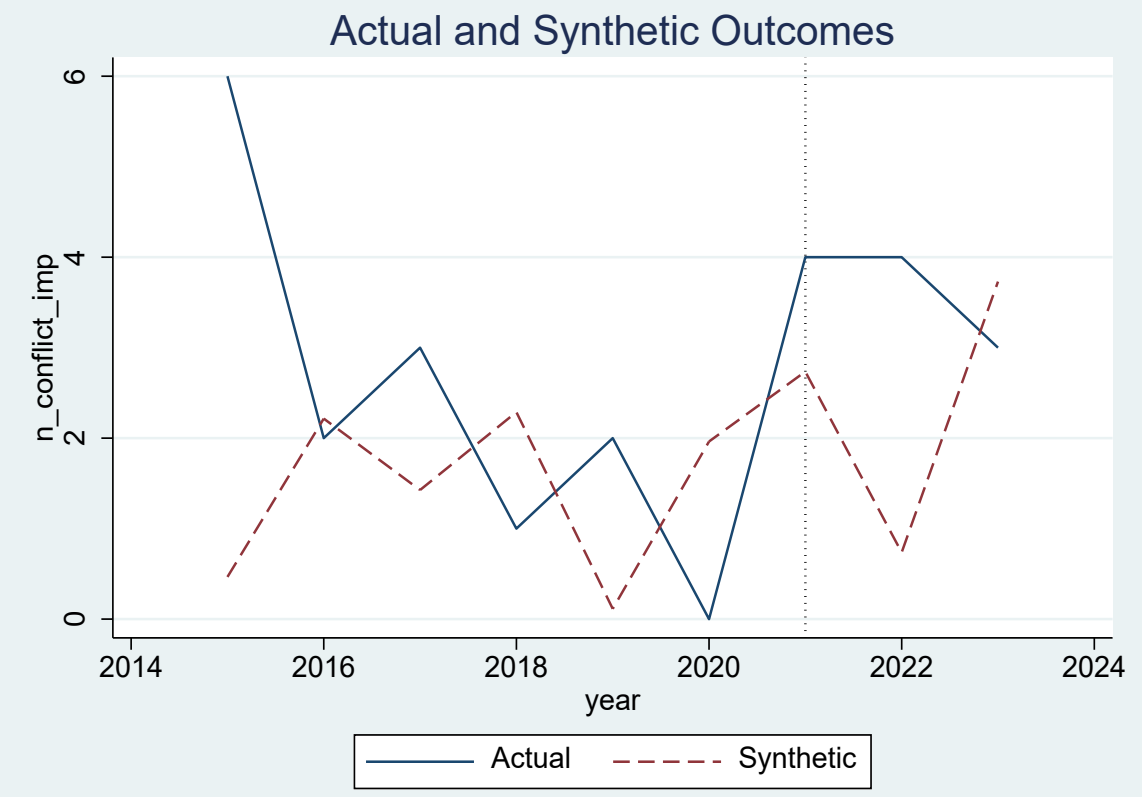

*Data Source: COPADEH and ACLED.*

### Figure A2: Senahú Municipality SCM with predictors



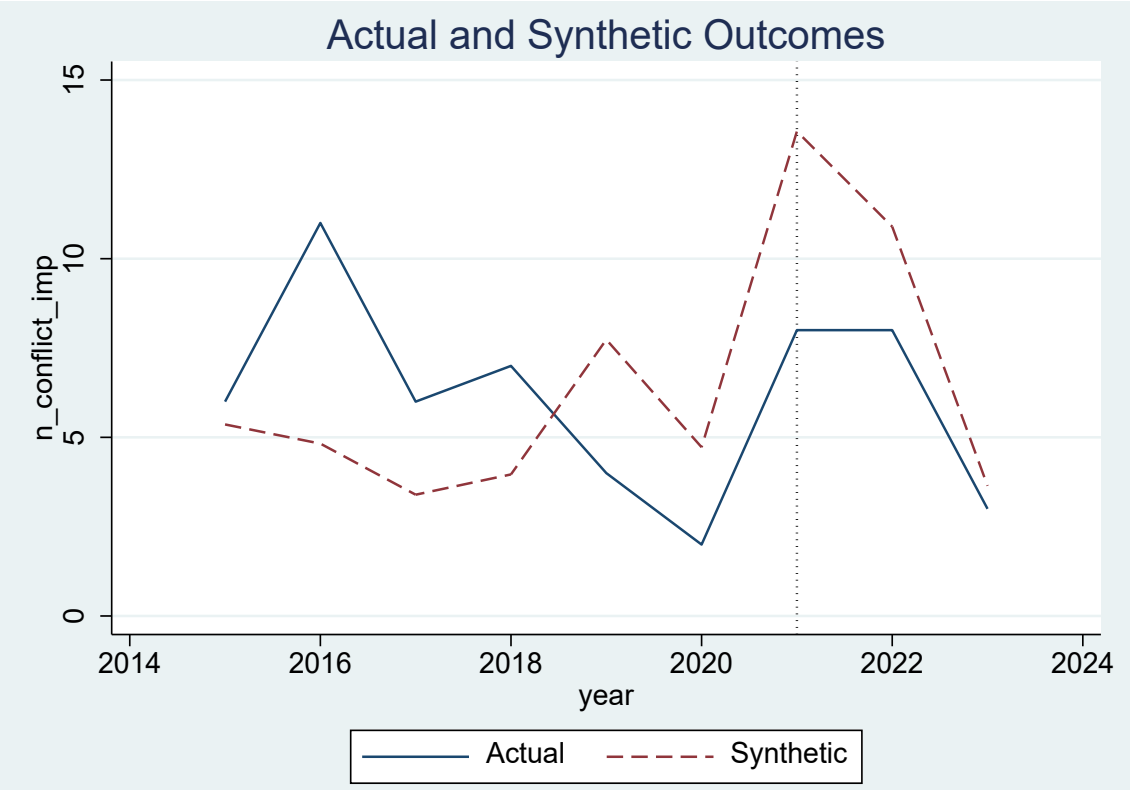

*Data Source: COPADEH and ACLED.*

**Figure A3: Tucurú Municipality SCM with predictors**



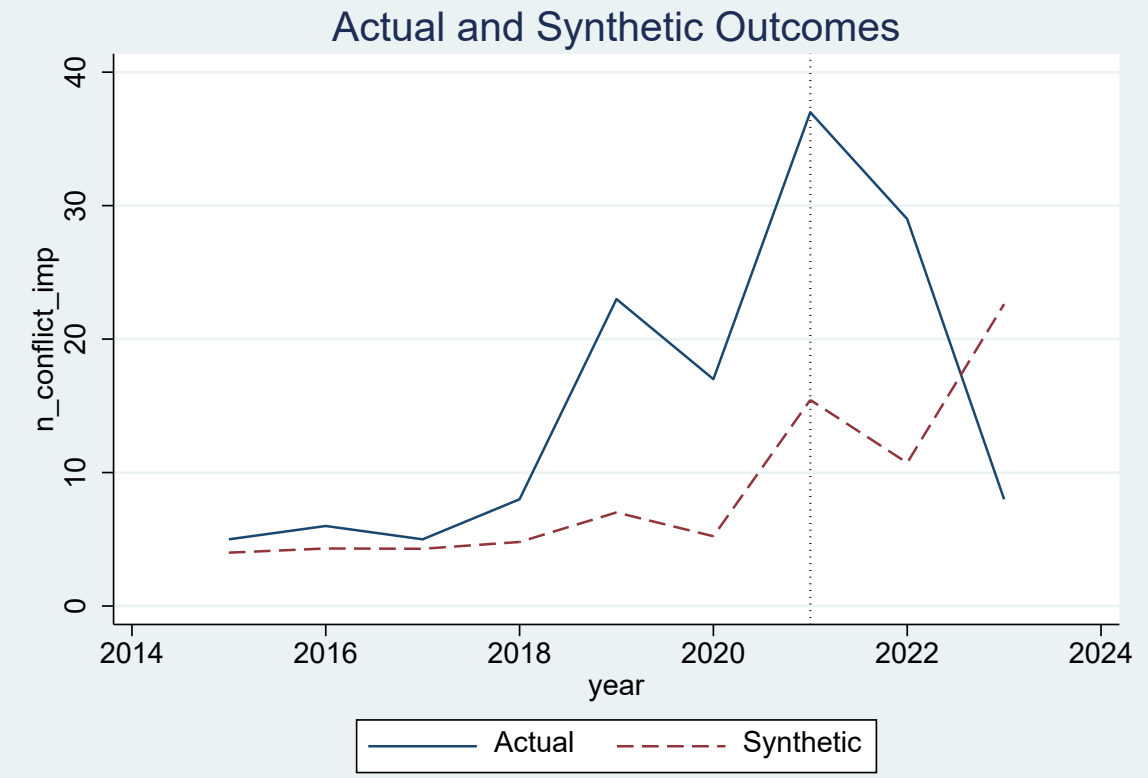

*Data Source: COPADEH and ACLED.*

**Figure A4: Panzós Municipality SCM with predictors**




*Data Source: COPADEH and ACLED.*

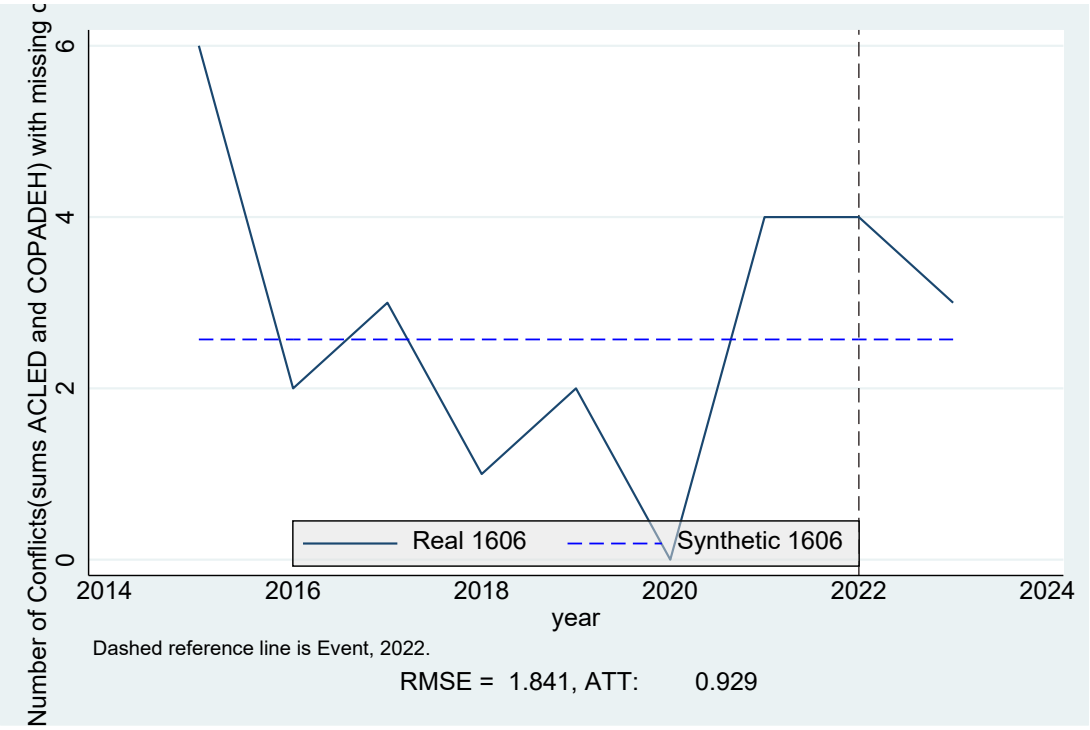
**Figure A5: El Estor Municipality SCM with predictors**




*Data Source: COPADEH and ACLED.*

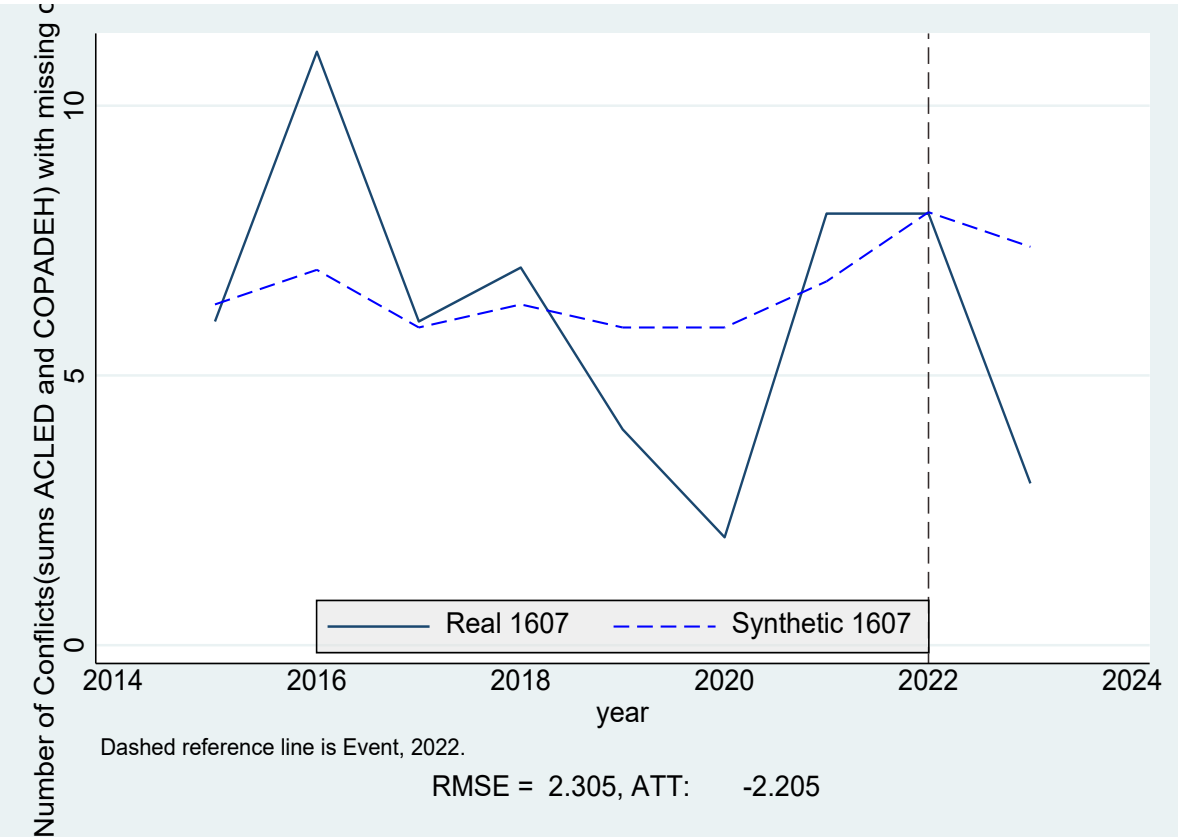
## Graphical analysis of synthetic control with lasso regression: municipal-level analysis

**Figure A6: Tucurú Municipality SCM with lasso regression**



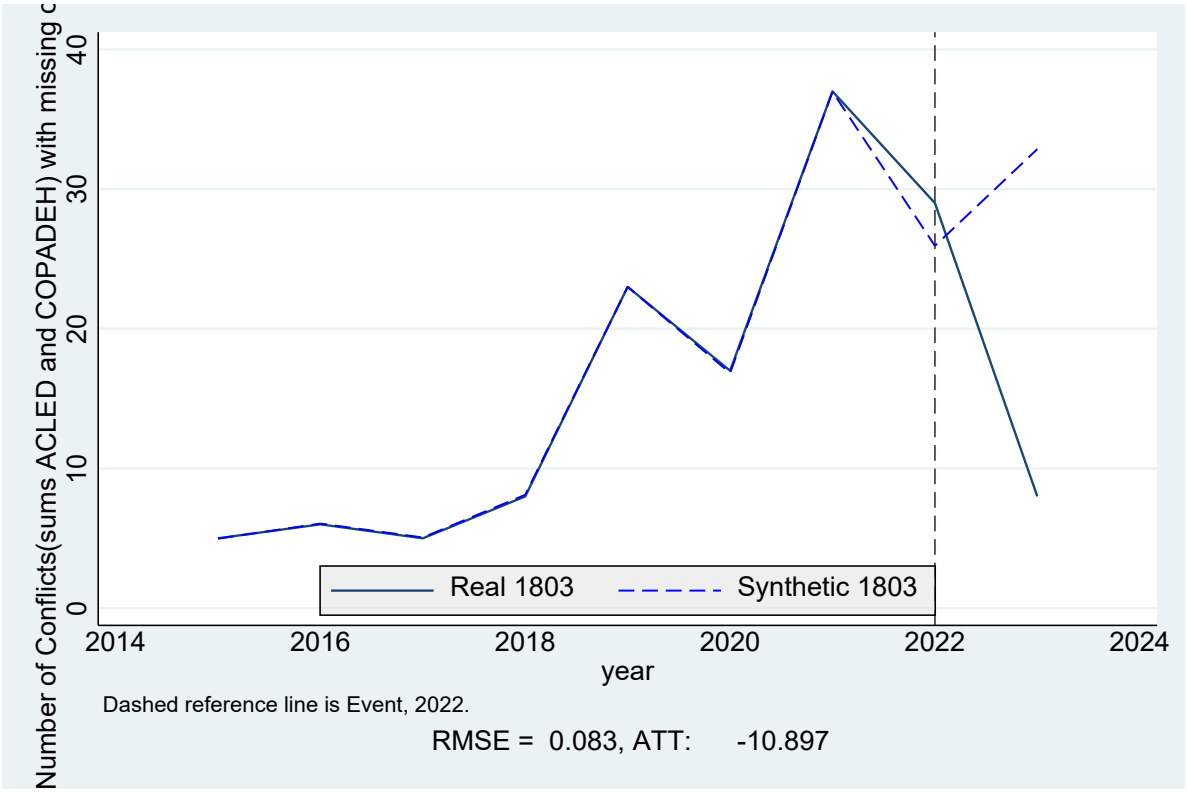

*Data Source: COPADEH and ACLED.*

**Figure A7: Panzós Municipality SCM with lasso regression**




*Data Source: COPADEH and ACLED.*

**Figure A8: El Estor Municipality SCM with lasso regression**




*Data Source: COPADEH and ACLED.*

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