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The Impact of Ethnic Conflict on Economic Complexity: a synthetic difference-in-differences study

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Abstract

This study examines how ethnic conflict affects economic complexity, the latter a measure which captures an economy's capacity to produce and export sophisticated goods. While prior research has focused on macroeconomic indicators like GDP, little attention has been paid to how conflict shapes the underlying industrial structure of economies. Using the synthetic difference-in-differences (SDiD) method on panel data from 85 countries (1995-2021), we analyse episodes of conflicts with more than 100 annual fatalities. The results show that ethnic conflict reduces economic complexity by 0.206 standard deviations, with effects persisting beyond the actual conflict period. Further analysis reveals that exports of the most complex products are disproportionately affected, indicating that conflict undermines the diversification and sophistication of export structures. Hypothesized mechanisms linking ethnic conflict to economic complexity include the destruction of productive capital, fragmentation of inter-ethnic business networks, and declining quality of foreign investment.

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1 Introduction

"Suddenly, it was Kenya that was on fire. The ethnic cleansing was so utterly ruthless that a shocked world drew its breath. Women and children from one ethnic group were burnt to death in a church."

Leif Norman, Axess magasin, 2008

After the incumbent President Mwai Kibaki was declared the victor of Kenya's controversial elections in December 2007, violent demonstrations erupted in the streets of Nairobi. Members of the Kikuyu ethnic group, which supported the incumbent President, were targeted by incensed members of the Luo ethnic group that backed the opposition leader Raila Odinga, fomenting widespread ethnic conflict. As tensions escalated, the political crisis spiraled into economic chaos. Key economic sectors were ground to a halt: factories shuttered, tourism collapsed, and public finances strained under the growing weight of economic uncertainty. By April 2008, when the signing of the National Accord and Reconciliation Act restored order to the country, the damage was already done - 1,500 lives vanished, 350,000 individuals displaced [Elekwa and Eme, 2011] and Kenya's economy GDP growth slid from 6.9 % in 2007 to 0.2 % in 2008, falling short of the 8 % growth forecast [Porhel, 2008, World Bank, 2025b]. The macroeconomic collapse was most acutely felt in key export sectors. Floriculture, a key export industry, had exports plunge by 38 % [Ksoll et al., 2021, Muhammad et al., 2013] as production and logistics networks were disrupted. In Naivasha, a flower-farming hub town 93 kilometres north-west of Nairobi, the crisis displaced 10,000 workers or approximately one-fifth of the total workforce [Bobb, 2009]. Those who remained were unable to report to work due to road closures and genuine concerns for their own safety. Even after the signing of the accords, heightened inter-ethnic rivalry between the Kikuyus and Luos reduced productivity as workers discriminated against one another [Hjort, 2014]. The erosion of trust extended beyond labour markets - it affected relationships with crucial export partners. Floriculture firms that sought to rebuild from the chaos feared the permanent loss of customers to foreign competitors Mexico and India, as customers questioned the Kenya's reliability. Kenya's experience underscores a broader pattern. Electoral violence, terrorist attacks and armed conflict, often stemming from underlying inter-ethnic animosities, can alter a country's intrinsic economic structure through undermining its pursuit of export-oriented growth and long-term export diversification.

Although many researchers have examined the impact of ethnic conflict on common macroeconomic indicators, including the declines in gross domestic product (GDP) [Alesina and La Ferrara, 2005, Azariadis and Drazen, 1990, Bove et al., 2017, Cerra and Saxena, 2008] and foreign direct investment (FDI) outflows [Doctor and Bagwell, 2020], few have examined the impact on the industrial structure of economies, especially economic complexity. Economic complexity captures an economy's ability to produce and export sophisticated goods, and has been linked to sustainable economic growth and strengthening the resilience of economies to macroeconomic fluctuations [Hidalgo et al., 2009].

This paper seeks to examine how episodes of ethnic conflict harms economic complexity using a synthetic difference-in-differences (SDiD) approach [Arkhangelsky et al., 2021]. The analysis draws on data from the Ethnic One-Sided Violence (EOSV) dataset by the Uppsala Conflict Data Program (UCDP) to identify episodes of ethnic conflict [Fjelde et al., 2019] as well as the Economic Complexity Index (ECI) from The Growth Lab at Harvard University [2025]. It finds that severe ethnic conflict is followed by a 0.206 standard deviation decline in the ECI of countries, equivalent to a drop of approximately 8 to 10 positions in global ECI rankings for an average country. These findings are robust across various placebo tests and sensitivity checks. The effect is particularly pronounced in cases of ethnic conflict characterized by electoral violence. Using disaggregated product-level trade data from the United Nations Comtrade Database [Gaulier and Zignago, 2010] and the Product Complexity Index [The Observatory of Economic Complexity, 2023], we find that ethnic conflict disproportionately affects the most complex exports, suggesting that conflict undermines the sectors most crucial for long-term economic development and structural transformation.

We hypothesize that ethnic conflict, characterized by outbursts of violence along ethnic lines, damage economic complexity through the following channels: it destroys physical capital and human capital, deters quality FDI directed at developing capabilities in new industries, fragments economic networks and erodes state institutions. These channels hinder the production of complex products that depend on dense networks of economic cooperation and knowledge diffusion, which in turn require a stable political and social environment. Ethnic conflict risks locking these countries into the continued extraction of commodities and simple manufacturing, creating path dependencies that raise concerns of the resource curse taking hold.

The paper begins by introducing the concept of economic complexity and proposes the channels connecting ethnic conflict to economic complexity in Section 2. We then present the literature review in Section 3, our approach to the data in section 4 and outline the SDiD methodology in section 5. We proceed with the results and robustness checks in the following section, before concluding with the discussion and our assessment of the different mechanisms.

2 Background

2.1 On Economic Complexity

Long-term economic growth models gained prominence with the Cobb-Douglas production function, which attributes output growth to a combination of labour, capital and land [Solow, 1957]. The Solow residual or Total Factor Productivity (TFP) as it is more commonly understood, refers to the unexplained portion of economic growth unexplained by the factors considered in the production function [Baumol, 1968]. Subsequent efforts to improve the explanatory power of the Solow model have included additional variables, including human capital [Mankiw et al., 1992], institutions [Acemoglu et al., 2005], social capital [Knack and Keefer, 1997] and technological growth [Romer, 1990]. While these additions further narrowed the Solow residual, but the true determinants of long-term economic growth remain elusive.

Economic complexity probes the determinants of long-term growth through an alternative angle by utilizing insights from the structure of international trade networks. At its core, it is a multi-disciplinary approach using network science and machine learning techniques to scrutinize underlying economic structures [Hidalgo et al., 2009]. Instead of relying on sophisticated models or assumptions about production factors, inherent to the Cobb-Douglas framework, economic complexity interprets the spatial and product-based distribution of trade as a reflection of a society's latent capabilities and economic development [Hidalgo et al., 2007]. This approach emphasizes that modern societies thrive by constructing networks that aggregate and mobilize the knowledge of individuals [Freeman, 1995, Sepehrdoust et al., 2019], thereby enabling the creation of increasingly sophisticated goods and services. Central to this process are entrepreneurs, who engage in a cost discovery process by applying localized knowledge to determine if their country possesses a comparative advantage in specific exports [Hausmann et al., 2007, Hausmann and Rodrik, 2003].

Critically, economic complexity diverges from endogenous growth theories. While the latter emphasizes the non-rivalrous nature of knowledge [Jones, 2019], the former emphasizes the non-fungibility of knowledge [Hidalgo, 2023]. Non-fungibility refers to knowledge being domain-specific - tied to particular industries, technologies and institutional contexts - rather than universally applicable. This means an economy's innovative potential rests upon its ability to both generate new knowledge and combine existing knowledge across disparate domains. For example, the race to design and manufacture advanced semiconductors require technical breakthroughs in lithography, transistor design and manufacturing precision. These technical domains demand highly specialised expertise such that no country dominates all areas: ASML (Netherlands) leads in extreme ultraviolet lithography equipment, SK Hynix (South Korea) leads in memory chips, while others excel in their respective niches. Such fragmented specialization underscores how non-fungible, context-bound knowledge shapes global innovation hierarchies. It further reveals how the ability to generate and combine knowledge becomes a source of comparative advantage [Bahar and Rapoport, 2018], increasingly so as products get more complex over time.

These dynamics are captured by an economy's extensive and intensive production margins. The extensive margin (*what* an economy produces) reflects diversification into complex products such as semiconductors, while the intensive margin (*how much* it produces) reflects the ability to scale production efficiently [Mini et al., 2025]. Sustainable economic development often requires progress on both fronts: diversification insulates countries from sector-specific shocks, while scaling ensures success in export-oriented growth. The Prebisch-Singer hypothesis warns undiversified developing economies [Harvey et al., 2010] the future possibility of a decline in the terms-of-trade and the unsustainability of relying solely on commodity exports. Economic complexity quantifies these margins by measuring how effectively societies mobilize their collective knowledge pool through entrepreneurs and institutions to innovate and compete in export markets.

We proceed by introducing the most popular measures of economic complexity: the Economic Complexity Index (ECI) and the Product Complexity Index (PCI) [Hidalgo et al., 2009]. The ECI ranks countries based on the diversity and exclusivity of their export baskets, while the PCI ranks products by the breadth of capabilities required to produce them. Japan, a country with a high ECI value, manufactures complex products such as cars and semiconductors while Nigeria, a country with a low ECI value mainly exports crude petroleum. Semiconductors are a lot more complicated to produce than coffee beans and hence would have a higher PCI value. The overall thrust behind the computation for ECI and PCI is to jointly solve for the complexity of the locations and the activities: each location reveals information on the complexity of the activity and each activity reveals information on the complexity of the location. We provide a brief explanation on the derivation of ECI and PCI. [1]

[1] For the astute reader, a thorough explanation on the derivation of ECI and PCI is provided in Appendix A.1.

The ECI and PCI begins by looking at disaggregated export data that is based on the Harmonized System (HS) or Standard International Trade Classification (SITC) product classification systems. We begin by compiling the Revealed Comparative Advantages (RCA) of countries in each product. A country is determined to have a revealed comparative advantage in a product if it exports more of the product than the global average. Altogether, a binary matrix is obtained that reveals two things: how many exports a country has (*diversity*) and how many countries currently export the product (*ubiquity*). Hidalgo et al. [2009] uses an iterative process of Method of Reflections on this binary matrix to converge on a transformed matrix, one for ECI and another for PCI. The ECI and PCI are the standardized form of the second eigenvectors of their respective transformed matrices.

The informational value of the economic complexity framework, using measures such as ECI, on long-term economic growth and other economic outcomes should not be understated. Economic complexity predicts the economic efficiency of economies [Du and O'Connor, 2021], future economic growth, income inequality [Stojkoski and Kocarev, 2017] and other developmental indicators. A drop in ECI can be indicative of damage to a country's underlying economic potential, signaling changes to the underlying economic potential that may not be immediately obvious from GDP figures alone. With economic complexity as the outcome of interest, we turn our attention towards examining ethnic conflicts as the variable shock that can afflict a country's economic complexity.

2.2 On Ethnic Conflict and Potential Links to Economic Complexity

Before analyzing how ethnic conflict undermines economic complexity, we must first understand its origins. At the heart of ethnic conflict lies the fundamental economic problem - competition for scarce resources. As economic resources are unequally distributed across society [Cederman et al., 2011], tensions flare up - particularly when ethnicity is a convenient means of defining coalitions and mobilizing collective action [Caselli, 2013, Esteban et al., 2015]. Inter-ethnic competition is intensified if there are several ethnic groups sufficiently large enough to rival each other and compete for political influence, often turning competition into outright conflict [Esteban et al., 2012]. Three interconnected factors drive this escalation. First, security dilemmas emerge: fearing marginalization or violence, groups may strike preemptively due to mistrust in rivals' true intentions [Posen, 1993]. Second, informational asymmetries distort perceptions which amplify negative stereotypes and hate [Acemoglu and Wolitzky, 2014]. Third, elite manipulation leverages on these fears as self-interested politicians weaponize narratives to consolidate power [Glaeser, 2005]. A controversial policy or inflammatory rhetoric often serves as the spark, igniting widespread conflict.

Once ignited, ethnic conflict erodes economic complexity through multiple channels. Physical infrastructure and human capital are destroyed. Foreign investors flee and knowledge diffusion stalls. Inter-ethnic economic networks fracture. Institutions decay as politics itself becomes ethnicized, prioritizing ethnic affiliations over competence.

2.2.1 Destruction of physical and human capital

Ethnic conflict undermines economic complexity by damaging physical and human capital, disrupting production networks, and reducing export capacity. The most direct channel is the destruction of infrastructure, loss of life, and displacement of workers, which collectively degrade a country's productive base. For example, the 1994 Rwandan genocide—instigated by Hutu extremists—resulted in 800,000 deaths, displaced 2 million refugees, and caused a 58% GDP decline. These losses not only crippled short-term economic performance but also hindered Rwanda's ability to diversify exports, thereby reducing its economic complexity [Hodler, 2019].

However, the significance of this channel depends on conflict intensity and context. Lower-intensity ethnic conflicts or those concentrated in rural areas may spare physical infrastructure but still disrupt economic activity. During Kenya's 2008 post-election violence, for instance, ethnic clashes reduced floriculture exports not through targeted attacks on firms but by deterring employees from working and destabilizing transport systems [Ksoll et al., 2021]. Even in such cases, the cumulative effect—reduced capital efficiency and labour participation—lowers output and export volumes. Since economic complexity is tied to the diversity and sophistication of exports, diminished export capacity directly weakens it. Thus, both high-intensity and low-intensity ethnic conflicts limit productive efficiency , hindering economic complexity.

2.2.2 Deters foreign investment and reduces foreign technology transfer

Uncertainty induced by the escalation of ethnic violence would not only harm capital and disrupt value chains, but also deter future foreign investment. Foreign investment is integral in helping connect local business networks to global networks that possess the expertise to develop new industries of higher knowledge intensities. Moreover, international business travel has been found to be most significant bilateral relationship in influencing the industrial structure of national economies [Coscia et al., 2020]. Ethnic conflict would dissuade both foreign investment and international business travel into destabilized areas, curbing foreign technology transfer.

Complex knowledge required to create more sophisticated products are more difficult to diffuse, thereby requiring more robust knowledge networks and improved inter-firm interactions [Sorenson et al., 2006]. The difficulty of diffusing knowledge for more sophisticated products and the sensitivity of production networks to disruption leaves economically complex products the most vulnerable to ethnic conflict. Korn and Stemmler [2025] found that trade relocation away from conflict zones is more persistent in the manufacturing sector than the fuels and minerals sector. The fuels and minerals sectors are partly insulated from ethnic conflict due to their particular relevance in financing the government and ethnic insurgents, which incentives the side exercising control over these resources to ensure continuity in these commodity exports. Lee and Chung [2022] find that multi-national enterprises are less likely to exit areas with violent conflict if the foreign subsidiary is engaged in the extraction of natural resources. For most other products, the converse happens. New value chains that emerged from the trade relocation post-conflict may endure even after the conflict ends, since countries that initially imported from the conflict zone are incentivized to form Preferential Trade Agreements with other potential trade partners. The minimal trade relocation in non-agricultural commodities contrasted by the trade relocation in manufacturing and agricultural goods could explain the enduring inability of conflict-prone countries to diversify their industrial base. Crucially, we expect ECI levels for countries whereby ethnic conflict has occurred to remain low due to indelible damage to export relationships. [2]

2.2.3 Fragmentation of economic networks

Another first order channel is the damage to social capital through the fragmentation of society. Ethnicity becomes more salient [Sestito, 2025] from ethnic conflict, leading individuals within economic networks to conclude that individuals from opposing ethnic groups are less likely to cooperate. Compared to economic networks in highly complex economies that are organised through formal and professional ties, much of the economic networks in less complex economies are arranged along ethnic lines based on kinship [Bahrami-Rad and Schulz, 2022], especially seen in certain African economies [Fisman, 2003]. The bifurcation of society is often the consequence

[2] Geopolitical considerations may be relevant. Since ethnicities often extend beyond sovereign borders, the sympathies and antipathies of the country's trading partners may affect external trade. The breakdown of inter-ethnic trust following the Russian-Ukrainian conflict of 2014 resulted in trade diversion and lowered the economic performance of affected Ukrainian firms [Korovkin and Makarin, 2023]. Developmental aid flows [Bluhm et al., 2021] and sanctions may further influence ethnic conflict outcomes and the impact on the economic structure. The impact of geopolitics on trade relationships, conditional on the occurrence and intensity of ethnic conflict are beyond the scope of this paper.

of unresolved hostilities from ethnic violence, owing to the overlapping nature of economic and social networks. Since informational exchange between individuals are facilitated by shrinking the physical and social proximity between them [Agrawal et al., 2008], ethnic conflict which increases the social distance between individuals of different ethnicities would in turn limit knowledge diffusion. Thus, innovation [Nathan, 2015] and trade across the relevant ethnic fault lines are impeded, at least in the short run. Inter-ethnic economic cooperation is stifled within these countries [Hjort, 2014, Rohner et al., 2013]. An important caveat is that the extent of damage from ethnic conflict on economic complexity increases in magnitude if the current production of existing products and the future development of more complex products depends on strengthening inter-ethnic ties. Fundamentally, ethnic conflict impacts the growth of new industries if economic cooperation between the affected ethnicities is essential, either in the form of inter-firm or intra-firm relations. The most vulnerable economies tend to be ethnically diverse and highly fractionalized [Costalli et al., 2017].

As ethnic conflict persists, smaller firms especially struggle to survive and exit the market. Surviving firms have to contend with impaired technological capabilities and reduced productivity as supply chains adapt to post-conflict conditions [Brück et al., 2013]. In the worst case scenario, as the conditions for nurturing new industries disappear following the ethnic conflict, entrepreneurs are now incentivized to resort to rent-seeking behaviour [Baumol, 1990] that sustains ethnic coalitions and the conflict in general [Mehlum et al., 2003]. This scenario is more likely to occur in state-based conflict [Naudé et al., 2023], which leads us to consider another channel of institutional decay that occurs alongside the ethnicization of politics.

2.2.4 Ethnicization of politics and corruption driving underinvestment

Concurrently, ethnic conflict cements the ethnicization of politics which drives an underinvestment in public goods [Alesina et al., 2016] vital for the growth and success of new industries. The fracturing of local networks along ethnic fault lines will extend to the ethnicization of politics and alter the policies pursued by local and, potentially, national governments. Competing preferences over the form and beneficiaries of public goods provided by governments [Habyarimana et al., 2007] are hardened through ethnic conflict [Easterly et al., 1999]. As ethnic conflict and an overall history of hostile inter-ethnic relations drives up the saliency of ethnicity, non-pecuniary incentives will dominate the ethnic-based political movement [Laurent-Lucchetti et al., 2024]. The dominance of one's ethnic identity over one's national identity [Akerlof and Kranton, 2000] would result in an individual deriving less utility from welfare of members of other ethnic groups relative to the welfare of members from their own ethnic group [Easterly and Levine, 1997]. Moreover, ethnic conflict often concludes with the dominant ethnic coalition gaining further dominance over the economy and strengthening their political representation. The result is the consolidation of patronage networks within the dominant ethnic coalition [Kemp, 2004], whereby through the relevant political apparatus, the dominant ethnic coalition either prioritizes ethnic public goods favouring their own ethnicities [Ghosh and Mitra, 2022] or discriminate against rival ethnic coalitions through denying them access to club goods and private goods essential for economic empowerment.

Furthermore, the strategic complementarity between political uncertainty created by ethnic conflict and corruption [Berdiev et al., 2020] means that if ethnic conflict raises the risk of local government officials losing power, they are more likely to engage in rent-seeking behaviour instead of focusing on future-oriented policies conducive for economic development [Mauro, 1995]. Underinvestment in economic infrastructure, education and healthcare are likely to persist which limit substantial improvements to human and physical capital [Seidel, 2023]. Therefore, through these institutional channels, ethnic conflict dampens a country's prospects of diversifying its export capabilities.

The aforementioned channels do not establish clear unidirectional causality; institutional development, inter-ethnic relations and economic development co-evolve through path dependencies that may be decided by ethnic conflicts and subsequent responses to it. The progression towards robust institutions designed to realize inclusive economic growth and defuse ethnic tensions limits the incidence of ethnic conflict [Easterly, 2001] and strengthens a country's ability to recover from bouts of ethnic violence. Economic development, beyond looking at the growth and export figures, is about rebuilding trust in institutions and a shared future. The endogeneity of institutional development and inter-ethnic relations necessitates care in our econometric approach, to be addressed later in our methodology. As ethnic conflict and economic malaise are often attributed to ethnic identities dominating an individual's national identity, the blame is squarely pinned on both the lack or failed implementation of nation-building policies. The lack of trust between different ethnicities at the early stages of development or following collapses in ethnic relations in heterogeneous societies remains a challenge for realizing more robust economic networks.

3 Literature Review

Following the surge of ethnic conflict in the 1990s in Rwanda and former Yugoslavian states, much attention has been paid to the causes of ethnic conflict [Horowitz, 2001]. These include the economic roots in underdevelopment [Easterly et al., 2006, Ray and Esteban, 2017], exogenous economic shocks [Miguel et al., 2004], failed institutions [Bardhan, 1997], as well as the opportunity cost of initiating ethnic violence [Esteban et al., 2015]. Caselli [2013] explained the ethnic character of conflict often observed relative to class conflicts. A portion of the literature on economic development have examined the connection between ethnic diversity [Easterly and Levine, 1997] and ethnic polarization to economic performance [Karnane and Quinn, 2019, Novta, 2016]. More specifically, the empirical literature on the long-term adverse economic consequences of civil war [Chen et al., 2007, Kang and Meernik, 2005] emerged from the cross-country studies of Collier [1999], identifying the negative impact on the GDP growth path [Azariadis and Drazen, 1990] in the immediate aftermath and over longer term horizons [Cerra and Saxena, 2008, Mueller, 2012]. While some papers found that, in some cases, civil conflict has no impact or a positive impact on GDP [Bove et al., 2017], we confirm the findings that ethnic conflict results in a negative impact on GDP.

Prior country-level studies detected the heterogeneous effects of civil conflict on individual economies [Hodler, 2019], their labour markets [Kondylis, 2010], the rate of firm exit [Camacho and Rodriguez, 2013] and the impact across various economic sectors [Vothkneckt and Sumarto, 2011]. Transmission channels linking civil conflict to delayed economic development involve the destruction of capital, the portfolio substitution from private investors [Imai and Weinstein, 2000] and the breakdown of eroding inter-ethnic business networks [Costalli et al., 2017, Paz, 2023]. We attempt to relate to these transmission channels within the economic complexity framework. Within the economic complexity literature specifically, drivers of economic complexity recently explored include FDI [Antonietti and Franco, 2021], natural resource endowments [Ben Saad et al., 2023], investment in research and development [Zhu and Fu, 2013], institutional quality and human capital [Vu, 2022] among others.

Closest to our research is Emeka et al. [2024] who explore the link between the terrorism and economic complexity in African economies, testing for military expenditure as a possible transmission mechanism. To the best of our knowledge, we are the first to examine the impact of ethnic conflict on economic complexity and find that ethnic conflict results in a significant decline in economic complexity. Instead of the commonly used generalized method of moments (GMM) approach (ibid.), impulse response function [Cerra and Saxena, 2008] or synthetic control methods [Costalli et al., 2017], we differ by applying the synthetic difference-in-differences approach [Arkhangelsky et al., 2021].

4 Data

Data on the two key variables, economic complexity and ethnic conflict, are processed alongside additional data on real income per capita, population, Human Capital Index (HCI) and foreign direct investment (FDI) to construct a balanced panel dataset encompassing 85 countries. Firstly, the Economic Complexity Index (ECI), initially covering 133 countries during the years 1995-2021, is accessed from The Growth Lab at Harvard University [2025]. ECI is measured as a z-score which represents the number of standard deviations an observation is away from the mean. The ECI is constructed using different product classifications, the Harmonized System (HS) and the Standard International Trade Classification (SITC). HS provides more granular data compared to SITC, since the former system was created for the purposes of tariff collection and not economic analysis [Cadot et al., 2011]. As our goal is to evaluate the impact on the overall economy and not highly specific sectors, we maintain the view that SITC is more appropriate for our purposes.

For ethnic conflict, the Ethnic One-Sided Violence (EOSV) dataset from the Uppsala Conflict Data Program (UCDP) is utilized [Fjelde et al., 2019]. The EOSV dataset tracks the number of fatalities and the ethnic identity of the victims from one-sided violence during the period 1989-2014 by country. One-sided violence is defined by UDCP as "the use of armed force by the government of a state or by a formally organised group against civilians which results in at least 25 deaths during a calendar year". Instances of cross-border ethnic violence are included in the dataset as single observations spanning multiple countries. However, the data does not clearly denote the distribution of fatalities across the countries involved. We manually allocated the fatalities on a case-by-case basis when the relevant information is available. Otherwise, we uniformly split the fatalities between each country. Furthermore, when multiple instances of violence are reported within the same country in a given year, the fatalities from each conflict are aggregated to produce a single observation per country-year.

We utilize two different quasi-experimental approaches, a two-way fixed effects difference-in-differences model and synthetic difference-in-differences. Constructing a pre-treatment period with no conflict for both the treated countries and the donor pool used to form the synthetic control, countries with fatalities above a particular threshold during the pre-treatment period are excluded.[3] With the ECI data being available from 1995-2021 and the ethnic conflict data being available from 1989-2014, each country with ethnic violence occurring between 1989-2000 is dropped from the sample. This ensures that the control pool should not contain any countries suffering a treatment effect, and that there are at least 5 pre-treatment periods of ECI data among the treated countries. Furthermore, to extend the post-treatment period beyond 2014 the EOSV conflict data is complemented with the One-Sided Violence (OSV) dataset by the UCDP [Davies et al., 2024, Eck and Hultman, 2007]. The OSV reports one-sided violence against civilians during 1989-2023 using a similar overall structure as the ESOV, but without reporting the ethnic identity of victims. To the best of our knowledge, the EOSV is a subset of the OSV. Since we cannot be sure that a conflict reported in the OSV is an ethnic conflict, no countries are assigned treatment post 2014. Instead, the OSV is used to verify that no one-sided violence is occurring in any control countries after 2014, i.e. any countries that become treated after 2014 are dropped from the sample. This enables us to extend our period of interest to 2021, and leaves us with a sample of 9 treated countries, and 76 control countries.

However, the construction of this sample is not without shortcomings, as many instances of ethnic violence that are relevant to our narrative have been excluded. The 1990s saw several regions experience intense ethnic conflict, such as the Rwandan Genocide, the Bosnian War, the Kurdish conflicts, and the Chechen Wars. Furthermore, countries like the Democratic Republic of Congo, Sudan, and India, which experience regular cycles of ethnic violence, had to be excluded since conflict occurred in those countries before 1995. As such, the most characteristic ethnic conflicts portrayed by our narrative connecting ethnic violence on economic complexity may be excluded.[4]

The final sample consists of countries experiencing ethnic violence of varying intensity, typically arising from either electoral violence or terrorism. Figure 1 illustrates the normalized ECI trends for the final sample of treated countries which have varying directions and volatilities. More developed countries with higher ECI scores like Mexico and Spain are observed to have very stable trends with lower volatility than their less developed counterparts such as Cameroon and Libya. Most countries appear to have relatively flat trends over time with normalized ECI scores ranging between 80 and 120. However, this is in fact quite a large span and the relative visual flatness is partially a result of the y-axis scaling caused by the periodic sharp declines of Libya and Guinea. Furthermore, Zimbabwe is observed to have a relatively

[3] For a more detailed explanation of which conflicts are excluded, see the methodology section.

[4] See Appendix A.3 for an illustration of the final sample of treated countries.

large decline, as is Cameroon from 2010.

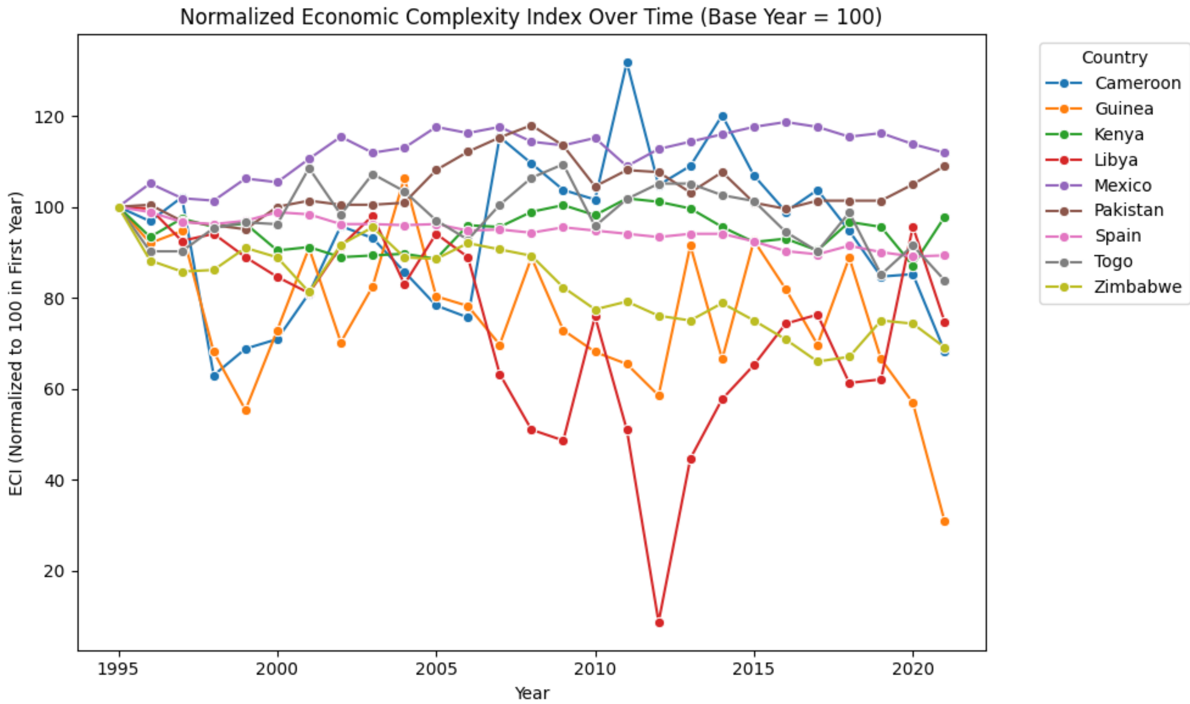

Figure 1: ECI Trends of Treated Countries Over Time

Note: For visualization purposes, the ECI has been normalized such that the first observed year for each country is scaled to 100. A constant of 3 is added to each value to avoid negatives, and then each value is divided by the value of the first observed year for each country, and multiplied by 100.

Moreover, data on additional country indicators have been collected to be used as control variables and investigate potential mechanisms. The real GDP per capita (constant 2015 US$) has been retrieved from the World Development Indicators [World Bank, 2025b] and is used as a control variable to proxy for trends in the general level of development in a country. GDP per capita is particularly useful as a covariate in our SDiD model to be used in an effort to avoid overfitting the synthetic controls purely on the ECI. While ECI and GDP per capita are correlated, it has previously argued that they do not measure the same underlying economic phenomenon [Balland et al., 2022, Destek et al., 2023]. GDP per capita does not account for the structure or complexity of an economy in terms of how diversified and sophisticated a country's production base is, and thus fails to fully account for a country's capacity to produce and export a range of complex products requiring diverse capabilities. However, controlling for GDP per capita allows us to disentangle the effect of conflict on economic complexity from broader income or developmental trends, ensuring that the estimates of the impact on ECI are not merely capturing changes in general economic performance. Another control used is population, retrieved from the World Development Indicators [World Bank, 2025c]. Population is included as a control variable to account for broader demographic transitions that may reflect different stages of economic development, such as urbanization or shifts in labour force composition, both of which could serve as sources of internal tensions and independently affect economic complexity. More intuitively, there may be fundamental differences between the economies of countries with small and large populations. Since economic complexity has been characterized to be the product of aggregating the knowledge and expertise among its people, a country with a larger population would be expected to have an advantage, ceteris paribus. While conflict could itself influence population dynamics through mass killings or emigration, the conflicts included in the sample involve relatively few fatalities, and such effects are therefore expected to be highly limited.

In addition to estimating the effect of ethnic conflict on economic complexity, SDiD models are also estimated using foreign direct investment (FDI) net inflows and the Human Capital Index (HCI) as outcome variables. FDI net inflows have been retrieved from the World Development Indicators World Bank [2025a] and the HCI was retrieved from the Penn World Table 10.01 [Feenstra et al., 2025].[5] We divide FDI by population, obtaining FDI per capita, in an effort to normalize the values such that it does not simply measure the size of the country. The HCI is constructed using data on educational attainment [Barro and Lee, 2013] as well as Mincer equation estimates on the rate of returns of schooling [Psacharopoulos and Patrinos, 2018]. FDI inflows capture investors' perceptions of political and economic stability, which are likely to be influenced by the occurrence of ethnic conflict. Since FDI can provide not only capital but also access to international markets, knowledge, and technology, it constitutes an important mechanism through which conflict could affect a country's economic complexity. Similarly, the HCI reflects the education and health status of a population, both of which are fundamental inputs into the development of complex economic activities. Ethnic conflict could undermine human capital accumulation either directly, by disrupting education and health services, or indirectly, by reallocating resources away from public goods provision.

[5] Note that data for the HCI is only available until 2019.

5 Methodology

This section outlines the empirical strategy to estimate the effect of ethnic conflict on economic complexity. We first employ a conventional two-way fixed effects difference-in-differences (TWFE-DiD) model to establish a baseline estimate. Building on this, we use the synthetic difference-in-differences (SDiD) model that relaxes the parallel trends assumption inherent to the TWFE-DiD framework.

5.1 TWFE Difference-in-Differences

To estimate the average treatment effect of ethnic conflict using a TWFE-DiD approach, we estimate the following panel regression model:

$$ECI_{it} = \beta_0 + \beta_1 Conflict_{it} + \beta_2 GDPpc_{it-1} + \beta_3 Population_{it} + \gamma_i + \delta_t + \epsilon_{it} \qquad (1)$$

ECI_{it} represents the economic complexity index of country i at time t. $GDPpc_{it-1}$ is the GDP per capita of country i in the year $t-1$. The lag is introduced to mitigate issues of endogeneity, enabling the use of GDP per capita as a control to proxy for different developmental trajectories between countries.[6] γ_i and δ_t denote the country fixed effects and yearly fixed effects respectively, and ϵ_{it} is the error term. We use clustered standard errors at the country level. The main variable of interest, $Conflict_{it}$, is a binary indicator taking the value 1 for all treated countries during all years post treatment, which is defined as suffering at least 100 fatalities of ethnic conflict during a calendar year. Although the EOSV data used has a fatality threshold of 25 for a conflict to be included, we refer to the approach taken by others [Fearon and Laitin, 2003, Neudorfer et al., 2025, Ray and Esteban, 2017] which establish the threshold of an ethnic civil war at a yearly average of 100 deaths and a cumulative total of 1,000 deaths across the entirety of the conflict.

To mitigate the risk that countries in the control group are themselves affected by ethnic conflict, we exclude any country experiencing fatalities exceeding 50% of the treatment threshold (i.e., more than 50 deaths) in a given calendar year. Relying solely on a sharp cutoff risks including countries with fatality counts just below the threshold, which may still exhibit treatment effects, thereby biasing the estimates. Conversely, excluding all countries with any fatalities would overly restrict the control pool, which could be particularly problematic for the synthetic difference-in-differences (SDiD) specification that relies on a sufficient number of

[6]Note that while lagging GDP per capita helps address reverse causality, it may still constitute a "bad control" if GDP is itself affected by the treatment (conflict), violating the assumption of exogeneity.

untreated units. We examine the robustness of our results to alternative fatality thresholds in Section 7.2.

The validity of the TWFE-DiD estimator hinges on the parallel trends assumption, which requires that, in the absence of treatment, treated and control countries would have followed similar trajectories in economic complexity. In a staggered treatment setting, this assumption must hold for each treated country relative to the control group. However, this is unlikely in our context. Differences in economic structure, institutional structures, business cultures make it difficult to argue that any country is similar to another, let alone identical in their developmental paths. Furthermore, DiD applies equal unit weights across all control units and thus compares the ECI trajectories of treated countries to the average ECI trajectory of all control countries. Since the ECI is standardized as a z score, averaging across a broad set of control countries is likely to produce an artificially flat counterfactual trend, further weakening the credibility of parallel trends assumption in this context. Additionally, due to the multidimensional nature of ethnic conflict, we expect treatment effects to be heterogeneous. In such cases, staggered DiD is likely to yield biased estimates [Baker et al., 2022]. Therefore, alternative methods to TWFE-DiD are required.

5.2 Synthetic Difference-in-Differences (SDiD)

Hence, we consider the use of synthetic difference-in-differences (SDiD) [Arkhangelsky et al., 2021] to address the above issues. SDiD is conceptualized as a means to combine the attractive features of DiD and synthetic control methods (SCM). SCM uses a weighted average of untreated units from a donor pool to construct a synthetic control. A common criticism of SCM approaches is that the synthetic control is unable to achieve the parallel trends assumption in some applied contexts, such as when traditional SCM methods require that unit weights are non-negative and sum to 1 [Doudchenko and Imbens, 2016]. Moreover, SCM is often carried out on a single treated unit, as when Abadie and Gardeazabal [2003] studied the economic impact of terrorism on the Basque Country. Meanwhile, DiD applies to a different empirical setting by allowing for inference with many treated units in large panel settings. DiD operates on the identifying assumption that once unit and time fixed effects are allowed for, the parallel trends assumption holds. SDiD overcomes the aforementioned problem by using a mixture of both unit weights and time weights, while allowing for a level difference between the treated units and their respective synthetic controls. Consequently, the additional flexibility from having more weights would ostensibly reduce the bias from violations of the parallel trends assumption through achieving a better fit on the pre-treatment trends.

$$(\hat{\tau}^{sc}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\tau,\mu,\alpha,\beta}{argmin}\left\{\sum_{i=1}^{N}\sum_{t=1}^{T}(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \hat{w}_i^{sdid} \hat{\lambda}_t^{sdid}\right\} \tag{2}$$

For a balanced panel with N units and T time periods, Y_{it} denotes the observed outcome for unit i at time t upon exposure to binary treatment W_{it} [Arkhangelsky et al., 2021]. A notable limitation in the SDiD approach that would be later discussed is the inability for the method to consider the intensity of treatment, especially if the number of units treated at similar intensities are insufficiently large for meaningful comparisons. We proceed by forming the donor pool with never-treated units $ControlPool = \{N_k : k \in \{1, 2, ...donorsize\}\}$ and have the remaining treated units form the treatment pool $TreatedPool = \{N_j : j \in \{donorsize + 1, ..., N\}\}$. Compared to the DiD equation, the SDiD equation includes the aforementioned unit weights $\hat{w}_i^{sdid}$ and the time weights $\hat{\lambda}_t^{sdid}$. The unit weights match the pre-treatment trends of the synthetic control with the treated pool, subject to $\sum_{i=1}^{donorsize} \hat{w}_i^{sdid} = 1$ and $\hat{w}_i^{sdid} \in \mathbb{R}$, similar to the SCM approach. A new addition in the SDiD approach, the time weights ensures that for each control unit, the average post-treatment outcome has a level difference with the weighted average of the pre-treatment outcome. This ensures that after accounting for the time weights, the control units move in parallel with a constant difference to obey a relaxed form of the parallel trends assumption. As in any other two-way fixed effects equation, α_i denotes the unit fixed effect for unit i and β_t represents the time fixed effect for period t.

Arkhangelsky et al. [2021] explained that SDiD's advantage over the traditional DiD estimator relies upon the existence of "systematic heterogeneity in outcomes by either units or time periods". In this context, the extra sampling variability is an appropriate sacrifice since there is substantial heterogeneity between countries. The time weights are relevant when we consider how the ECI may vary due to exogenous sectoral shocks and fluctuations in the business cycle. Referring to the results from the TWFE-DiD approach (Figure 2), the relatively flat ECI curve in the control group means the parallel trends assumption definitely would not hold. Strong heterogeneity between countries and across time makes SDiD the prime candidate for analyzing the impact of ethnic conflict on economic complexity. Although post-treatment shocks should still be accounted for, SDiD mitigates the bias it causes through the optimization of time weights.

In this context, staggered SDiD is implemented since ethnic conflicts occur at different times. Staggered SDiD repeatedly applies the SDiD estimator at each time period that any units are treated and constructs a weighted average that accounts for the number of units treated in each time period (ibid.). The results from a staggered SDiD include the tau estimators representing the treatment effect estimated for each treatment year. Similar to how Pickett et al. [2022] argued that covariates are relevant in empirical settings for SCM with finite pre-treatment periods, we adopt a similar stance in using covariates to construct a valid counterfactual for SDiD. The pre-treatment matching of the dependent variable will then be carried out on the residuals, after accounting for the covariates. Our model includes real GDP per capita as a covariate using the "*projected*" option in the *sdid* package on STATA [Kranz, 2022]. Standard errors are measured using the clustered bootstrap variance estimation algorithm with 50 repetitions,[7] following the recommendations of Clarke et al. [2023].

[7]We experimented with a higher number of repetitions for the main SDiD specification and obtained nearly identical results, albeit with significantly increased computation time.

6 Results

	Dependent variable:
	Economic Complexity Index (ECI)
Conflict	-0.180^{*}
	(0.093)
Population	0.000
	(0.000)
GDP_pc_lag1	-0.00000
	(0.00000)
Observations	2,295
R^2	0.953
Note:	*p<0.1; **p<0.05; ***p<0.01
	Clustered standard errors at the country level

Table 1: Estimated Effect of Ethnic Conflict on ECI (TWFE-DiD)

The results of the TWFE-DiD model are illustrated in Table 1 and suggest that ethnic conflict has a negative effect on economic complexity, statistically significant at the 10% level. While this result aligns with our hypothesis, the estimated effect is likely biased due to the aforementioned limitations of the TWFE-DiD model. This concern is further illustrated in Figure 2. As predicted, the ECI trajectory for the control countries is flat by the construction of the ECI as a standardized z-score. In contrast, this is not necessarily the case for individual countries. Figure 2 shows that the first treated country, Spain, has a negative trend over time, which is not matched by the relatively flat DiD counterfactual in the pre-treatment period, casting further doubt on the validity of the parallel trends assumption in this setting.[8]

[8]The trend-lines for all remaining treated countries is available in Appendix A.2, but compared to their respective SDiD counterfactual rather than the TWFE-DiD counterfactual.

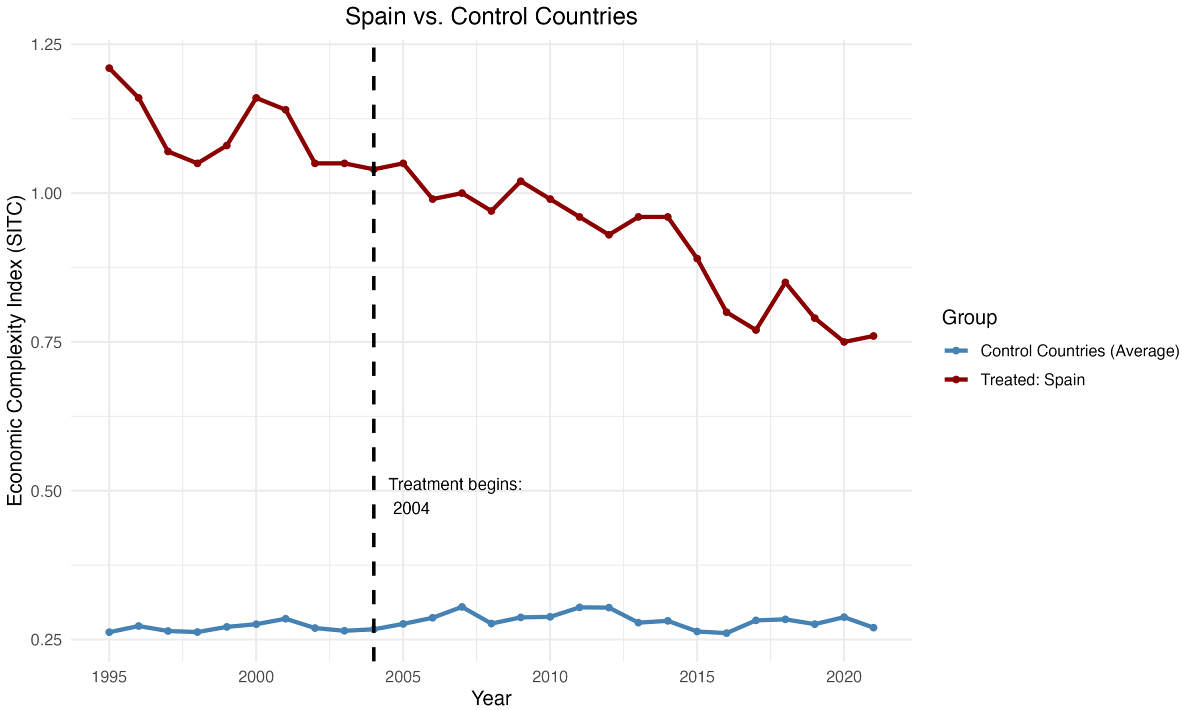

Figure 2: Trends in the ECI of Spain and the control group average

Moving on to the SDiD estimation found in Table 2, the results suggest a statistically significant negative effect at the 1% level, indicating that the incidence of ethnic conflict is associated with approximately a 0.206 standard deviation drop in the ECI (SITC) on average in the affected countries. In terms of country rankings, moving from an ECI score of 0 to -0.206 is equivalent to dropping by roughly 8-10 spots, depending on the year. This result holds when using the ECI calculated with the HS product classification as seen in Appendix A.3. To validate the credibility of this result, the tau estimators (i.e. the individual treatment effects by treatment year), graphical results, and unit and time weights are examined to establish whether or not the model appears to be able to create reasonable synthetic controls. The tau estimators for the nine treatment years are shown in Table 3 where each year except for 2007 has a negative estimate, six of which are significant. This is an important result as it indicates that the SDiD average treatment on the treated (ATT) estimate is not driven by a few outliers, but rather seems to be a fairly consistent phenomenon, albeit with a varying effect size even among significant treatment years.

	ATT	Std. Err.	t-stat	p-value	95% CI
Ethnic Conflict	-0.206^{***}	0.060	-3.42	0.001	$[-0.324, -0.088]$

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2: Estimated Effect of Ethnic Conflict on ECI (SDiD)

	τ	Std. Err.	Time
r1	-0.143^{***}	0.0345	2004
r2	-0.180^{***}	0.0551	2005
r3	0.030	0.0279	2007
r4	-0.308^{***}	0.0902	2008
r5	-0.271^{***}	0.0624	2009
r6	-0.135^{***}	0.0401	2010
r7	-0.517^{***}	0.1027	2011
r8	-0.068	0.0554	2014

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3: Tau estimators: The treatment effect on the ECI by treatment year

The tau estimators indicate the adoption-period specific SDiD "treatment effect on the treated" estimates for each individual treatment year. The weighted average of these estimates are then used to construct the SDiD average treatment effect on the treated (ATT) estimate as seen in Table 2.

As for the graphical results, an example is provided in Figure 3 indicating the ECI trends for Spain and its synthetic control. The graphical output for all other treatment years can be found in Appendix A.2.[9] While an apparent level difference is still present in Figure 3, the trend of the control unit is no longer completely flat as was the case with TWFE-DiD, and instead appears to mimic the observed pre-treatment trajectory of Spain quite well. Considering the graphical output for all treatment years found in Appendix A.2, the pre-treatment trends look parallel for most treatment years, with the main exceptions being 2014, 2009 and 2005 which all show signs of rather volatile ECI trends among the treated countries where the SDiD algorithm seems

[9]Reviewing the full set of graphical outputs is important to assess whether the SDiD method has generated credible synthetic controls. Due to space constraints, only one example is shown in the main text, but readers are encouraged to consult the appendix for the complete set of graphs.

to struggle to replicate. Indeed, a general pattern when observing the graphical results is that any larger short-term shocks or spikes in the trend-lines of treated countries appear difficult for the algorithm to mimic, indicating that there may be no perfect matches in the pool of control countries. While this may hurt the feasibility that the synthetic controls sufficiently match the trends of treated countries which would cause bias, another key issue of fitting the synthetic controls is to avoid overfitting, in which case it is likely undesirable for the counterfactual to mimic each short term shock. Overall, the algorithm seems to mimic the overall pre-treatment trends of treated countries reasonably well after accounting for level differences.

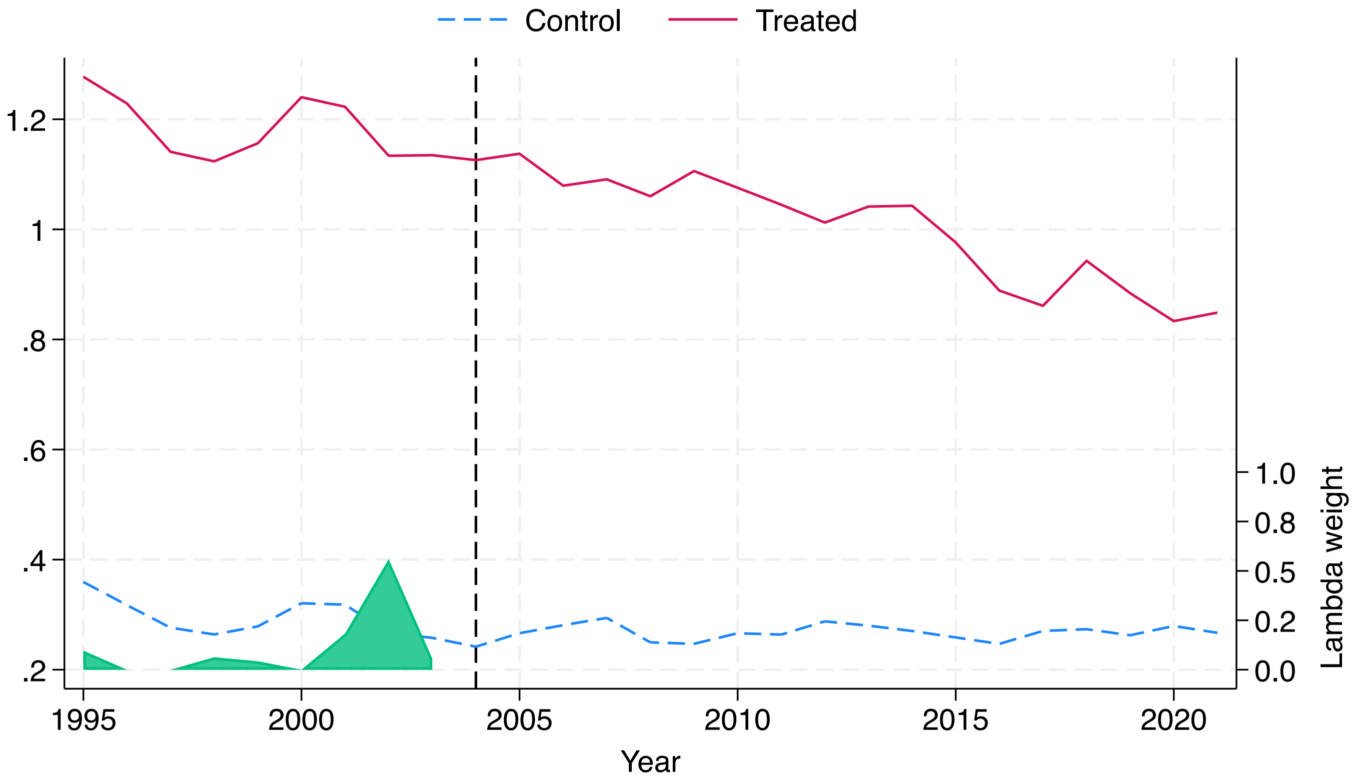

Figure 3: Trends in the ECI for Spain and synthetic Spain, and time weights.

Note: The solid line shows Spain's actual ECI trend, while the dashed line represents the counterfactual trend estimated by SDiD. The green shaded area represents the time weights used by the SDiD algorithm to emphasize periods with the highest predictability of future outcomes.

To further assess the risk of overfitting, the estimated unit and time weights, shown in Appendix A.2, are briefly examined. A common pattern among units with fewer pre-treatment periods is that they tend to assign positive weights to a larger number of control countries, often with very small weights on each. While relying heavily on a few specific matches may increase the risk of fitting to idiosyncratic shocks rather than capturing broader trends, spreading weights too thinly across many dissimilar countries can result in a synthetic control that fails to adequately track the treated unit's trajectory. This risk is exacerbated when the pre-treatment period is short, as the limited data makes it more difficult to identify a robust counterfactual. With regard to the time weights, it is crucial to examine whether too large emphasis is being placed on a particular year, especially the year before treatment. This can be an indication that the algorithm is overfitting the synthetic controls to statistical noise or that the fit of the counterfactual is poor, both of which would introduce bias to our estimate. The graphical output in the appendix suggest that this is not a strong concern as most treatment years do not show signs of this with weights either being balanced out across at least a few pre-treatment periods without having the bulk of the time weights being placed on the year before treatment. The treatment year 2007 is the main exception to this with a very large time weight on the year before treatment, and the treatment year 2005 further shows a similar pattern, but not equally extreme. While it is difficult to state the direction of bias, Table 3 suggests that the estimated average treatment effect is not driven by these two treatment years.

Furthermore in this context, a SDiD approach is supported by the fact that the EOSV dataset has a lot more control countries (76) that can form the donor pool relative to the number of treated countries (9). Moreover, the unit weight graphs show no single control country in the donor pool possessing a dominant unit weighting which implies that it is not a corner solution. The L_2 regularization regression embedded within the computation of unit weights for SDiD helps address overfitting concerns relative to traditional SCM approaches. Thus, relatively balanced unit weighting and satisfactory matching of pre-treatment outcomes mitigates concerns that SDiD within this context results in the extrapolation of data through constructing an unrealistic counterfactual.

7 Robustness Checks

In this section, we conduct a series of placebo tests and sensitivity analyses to assess the robustness of our main findings and the credibility of our causal interpretation. To the best of our knowledge, the SDiD literature does not yet offer well-established guidelines for robustness checks. An example is provided in the working paper by Sileci [2023] who used SDiD to estimate the effects of British Columbia's carbon tax on air quality and environmental equity. For robustness checks, this paper used a different data source for the air quality data, restricted the geographical scope of treated areas within British Columbia and restricted the temporal scope of the analysis through using a narrower timeline. In contrast, the SCM literature routinely applies "in-time" and "in-space" placebo tests to strengthen their causal claims [Abadie, 2021]. The in-time placebo test is ran by shifting the treatment year forward, and the in-space placebo test is performed by letting each control unit act as a fake treated unit and estimating a distribution of placebo effects where no true treatment actually occurs.

Building on these approaches, we implement two similar tests: a time placebo test and a unit placebo test. For the time placebo test, the treatment years of each treated unit will be shifted forward and backwards one year at a time up to four years in each direction (± 4 years), re-estimating the SDiD model at each shift. This allows us to assess whether similarly strong effects are observed during years surrounding the actual treatment—when no real intervention has occurred. The unit placebo test is conducted by randomly assigning treatment to countries from the pool of control units in order to assess whether the SDiD estimator detects spurious effects in the absence of actual treatment. Specifically, we exclude all originally treated units and randomly assign placebo treatment to ten of the remaining control countries. These placebo treatments are randomly drawn from the set of possible treatment years in the original design (2000–2014). For each random allocation, we estimate an SDiD model and record the resulting treatment effect estimates. This process is repeated 50 times, constructing a distribution of placebo effects that serves as a benchmark for evaluating the credibility of our main results. Following the placebo tests, sensitivity analyses are conducted to examine the robustness of our findings to alternative empirical design choices. First, we vary the fatality threshold used to define treatment and the minimum fatality "gap" required for a country to be included in the control pool and analyzing how it impacts the findings. Second, SDiD models are estimated on subsets of treated units, focusing on specific types of ethnic conflicts, which we define as terrorism or electoral violence, to explore potential heterogeneous effects.

7.1 Placebo Testing

The findings of the time placebo tests are illustrated in Table 4. The results suggest that when treatment is moved backward in time, the magnitude of the effect drops, but remains statistically significant at a 5% level for the first three years and then loses significance in the fourth year due to a less precise estimate. While the drop in magnitude is reassuring as it indicates that the escalation of violence coincides with the largest reduction of economic complexity, the high significance level indicates that the SDiD model is picking up a treatment effect before the treatment actually occurs by our definition. A precise interpretation of the results would recall that treatment occurs when fatalities from an ethnic conflict crosses a particular threshold, which indicates an escalation of conflict but not necessarily its inception. The worsening of inter-ethnic relations, the destruction of capital and the ethnicization of politics may precede the fatalities, returning to the notion that ethnic conflict is an ongoing process. This is likely particularly true in the case of electoral violence, but less so in conflicts characterized by terrorist attacks. Furthermore, a caveat with shifting treatment timing backwards is that the pre-treatment period may be too short for countries treated early which may result in variability in the results. Additionally, post-treatment effects are tested through shifting the treatment timing forwards. The results for shifting the treated placebo one year forward are similar, indicating that ethnic conflict could either occur near the end of the year or that there is a delay from the escalation of violence towards noticeable impact on the country's export structure. However, moving the treatment timing beyond that yields results of smaller magnitude with the 2 and 3 year shifts being significant at 10% and the 4 year shift being significant at 5%. This suggests that the impact of ethnic conflict on ECI is persistent and last for multiple years.

Model	ATT	Std. Err.	t	P>|t|	[95% Conf. Interval]
Placebo +4	-0.08520**	0.04196	-2.03	0.042	(-0.16744, -0.00296)
Placebo +3	-0.07606*	0.04610	-1.65	0.099	(-0.16641, 0.01429)
Placebo +2	-0.12471*	0.07137	-1.75	0.081	(-0.26460, 0.01517)
Placebo +1	-0.18663**	0.07252	-2.57	0.010	(-0.32877, -0.04449)
Original (0)	-0.20629***	0.06030	-3.42	0.001	(-0.32448, -0.08810)
Placebo -1	-0.13785**	0.06545	-2.11	0.035	(-0.26613, -0.00956)
Placebo -2	-0.13970**	0.06298	-2.22	0.027	(-0.26313, -0.01627)
Placebo -3	-0.14299**	0.07074	-2.02	0.043	(-0.28164, -0.00434)
Placebo -4	-0.15719	0.11696	-1.34	0.179	(-0.38642, 0.07205)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: Time Placebo Tests for SDID Estimation

Each row reports the result of an SDiD estimation where the treatment year is shifted relative to the original specification. A value of +1 indicates the treatment year is moved one year later, while -1 indicates it is moved one year earlier.

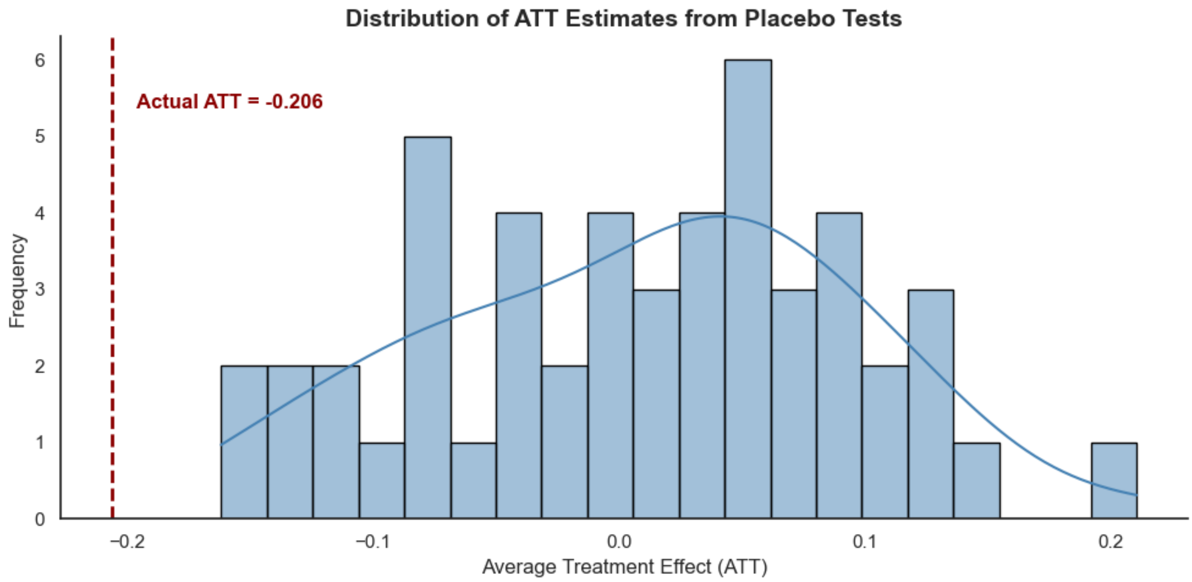

Figure 4: Distribution of ATT estimates from the unit placebo test. The dashed red line shows the actual ATT from the main SDID regression.

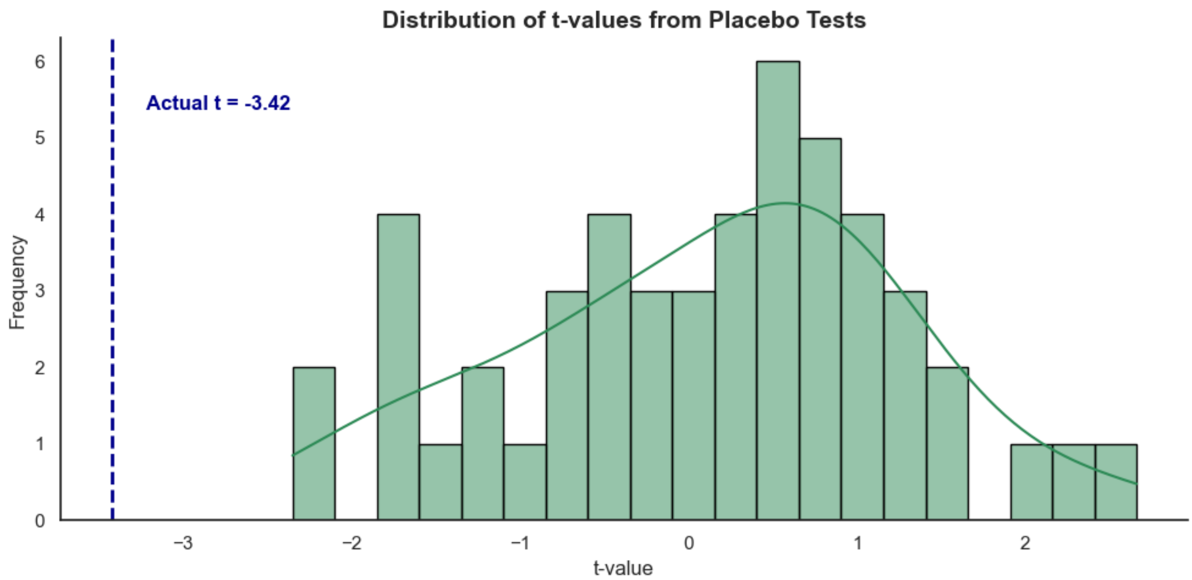

Figure 5: Distribution of t-values from the unit placebo test. The dashed blue line shows the actual t-value from the main SDID regression.

Proceeding to the unit placebo test, we plot the distributions of the ATT estimates and t-values in Figures 4 and 5 respectively. The histograms compare the results of the 50 unit placebo SDiD models to the actual estimate, both in terms of magnitude and statistical significance. Among the 50 unit placebo iterations, four yield statistically significant at 5%, two negative and two positive, and there one is significantly positive at a 1% level. While the number of significant results is slightly above what is expected by chance, it is not overly concerning. Importantly, none of the 50 unit placebo iterations reproduce the magnitude of our actual results. The most negative placebo ATT is approximately -0.162 compared to the actual ATT of -0.206. This suggests that the observed effect is unlikely to be replicated by placebo, reinforcing the credibility of our findings.

7.2 Sensitivity Analysis

Threshold	ATT	Std. Err.	t	P>|t|	[95% Conf. Interval]
25	-0.02788	0.06392	-0.44	0.663	(-0.15316, 0.09740)
50	-0.16519	0.10746	-1.54	0.124	(-0.37581, 0.04544)
100 (Baseline)	-0.20629***	0.06030	-3.42	0.001	(-0.32448, -0.08810)
150	-0.23024***	0.06032	-3.82	0.000	(-0.34845, -0.11202)
200	-0.20753***	0.06271	-3.31	0.001	(-0.33044, -0.08462)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Sensitivity Check: Results for Different Fatality Thresholds

Each row reports the result of an SDiD estimation where the fatality threshold for being considered treated has been adjusted from the baseline value of 100.

Sensitivity analysis is carried out firstly through varying the fatality threshold required to be assigned treatment, and secondly through changing the minimum fatality gap a country must have from the threshold to be included in the control group. Varying the fatality threshold can impact the sample in two ways. The less obvious way is that a decreased threshold can cause both treated and control countries to be dropped from the sample if they have conflict in the pre-treatment period which cross the new threshold. The more obvious difference is the inclusion of new treated countries including, but not limited to, Bahrain (25 fatalities), Saudi Arabia (26), and Madagascar (31). The results are reported in Tables 5 and 6 respectively. In the former table, result for any used threshold above 100 is statistically significant at a 1% level, whereas the two lower threshold are not statistically significant, with the ATT dropping to nearly zero when the threshold is 25. While fatalities are an imperfect proxy for conflict intensity, the result suggest that a certain level of conflict intensity is required to be able to identify a visible effect on economic complexity. Thus, more intense conflicts appear to result in greater declines in economic complexity. However, moving beyond 100 fatalities as a threshold does not appear to have any significant impacts on the results in our setting. Additionally, the main drivers of any differences in the results will be stemming from either including new treated countries, or excluding previous treated countries following a threshold change. Thus it follows that deeper case studies on the pool of treated countries would be required to fully understand potential differing results for different threshold, which is beyond the scope of this paper.

In contrast, the result shown of the second sensitivity check in Table 6 is purely driven by changes in the pool of control countries, all of which are statistically significant at the 5% level at the lowest. Removing all countries which suffer any ethnic conflict from the control pool yields the largest ATT estimate, whereas our baseline estimate, which only removes countries suffering between 50 and 100 fatalities, is the only specification that is significant at a 1% level. These findings suggest that varying the fatality gap between treated and control units does not appear to have a large impact on the results. If anything, removing countries that risk suffering a treatment effect on ECI through a sub-threshold fatality count appears to yield larger estimates.

Threshold	ATT	Std. Err.	t	P> $\|t\|$	[95% Conf. Interval]
0%	-0.23832^{**}	0.11785	-2.02	0.043	$(-0.46930, -0.00735)$
50% (Baseline)	-0.20629^{***}	0.06030	-3.42	0.001	$(-0.32448, -0.08810)$
100%	-0.16521^{**}	0.06697	-2.47	0.014	$(-0.29647, -0.03396)$

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Sensitivity Check: Varying Control Pool Based on Fatality Thresholds

Each row reports an SDiD estimation that excludes control countries that exceed varying shares of the 100 fatality threshold. Thus, the first model excludes control countries with any fatalities in any year, the second one excludes control countries with over 50 fatalities in a year, and the third one simply has a sharp treatment threshold of 100 fatalities.

7.3 Subset of conflicts

In broad terms, the ethnic conflicts included in the treated sample can be categorized as either terrorist attacks or electoral violence. In order to categorize the events, each conflict was researched on a case by case basis since the EOSV data does not provide explicit classifications. Countries classified as experiencing electoral violence have typically sustained civil unrest over an extended period of time which further escalates around the time of elections, with state actors, often government forces, being identified as the perpetrators of the fatalities which are directed towards specific ethnic groups. Meanwhile, countries classified as experiencing terrorist attacks typically faced mass killings carried out by internationally recognized terrorist organisations.[10] These events are generally isolated incidents rather than prolonged conflicts which is the key difference between the two subsets of ethnic conflict. Another potential distinction is that electoral violence would cause greater damage to economic complexity than terrorist attacks. First, terrorist attacks are likely to result in less damage in physical capital and human capital. Secondly, terrorist attacks are unlikely to damage inter-ethnic relations if society deems these fringe elements as a collective threat instead of being a divisive entity. Electoral violence raises the potential of severely damaging inter-ethnic relations and drives the ethnicization of politics. Moreover, the persistence of electoral violence after its outbreak relative to the sporadic nature of terrorist attacks may contribute to their different impacts.

Conflict Type	ATT	Std. Err.	t	P>|t|	[95% Conf. Interval]
Terrorist Attacks	-0.14329***	0.04021	-3.56	0.000	(-0.22211, -0.06448)
Electoral Violence	-0.25580**	0.11153	-2.29	0.022	(-0.47439, -0.03721)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Effect of Different Types of Conflict on Economic Complexity

Each row reports an SDiD estimation for the respective subset of conflict type. The terrorist attacks include Spain, Pakistan, Mexico and Cameroon, and the electoral violence include Togo, Kenya, Zimbabwe, Guinea, and Libya.

After dividing the treated countries into terrorist attacks and electoral violence, the largest estimated negative impacts emerged from bouts of post-election violence as observed in Table 7. While the p-value is, to our surprise, smaller for terrorist attacks, both results are statistically significant at 5% and the ATT estimate is considerably larger for electoral violence. Comparing the tau estimators in Table 8 and Table 9, it is evident that the negative effect for terrorist attacks is typically of a lower magnitude than electoral violence, confirming our hypothesis. With the exception of Cameroon, which experienced the highest number of fatalities in our treated

[10]The exception is Mexico, where the perpetrator was a drug cartel. We still recognize this as an instance of narcoterrorism. [Cordero, 2013]

	τ	Std. Err.	Time
r1	-0.143^{***}	0.0411	2004
r2	-0.193^{***}	0.0283	2008
r3	-0.135^{***}	0.0376	2010
r4	-0.068	0.0687	2014

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: Tau estimators: The treatment effect on the ECI by treatment year – Terrorist Attacks

The tau estimators indicate the treatment effect estimates by treatment year.

	τ	Std. Err.	Time
r1	-0.180^{***}	0.0495	2005
r2	0.030	0.0284	2007
r3	-0.436^{***}	0.0288	2008
r4	-0.271^{***}	0.0566	2009
r5	-0.517^{***}	0.1407	2011

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9: Tau estimators: The treatment effect on the ECI by treatment year – Electoral Violence

The tau estimators indicate the treatment effect estimates by treatment year.

sample and falls into the terrorist attack group, there is no clear difference in fatality levels between the two groups. This suggests that the larger estimated effect observed among cases of electoral violence is not driven by higher fatality counts, but rather by the distinct nature of the conflicts themselves. In summary, these findings suggest that while the magnitude of the main results is primarily driven by conflicts categorized as electoral violence, the high level of statistical significance is not solely attributable to one category.

8 Mechanisms

This section seeks to understand the results deeper by exploring the channels through which ethnic conflict may influence economic complexity. A series of SDiD models are estimated with the same treatment assignment, but different outcome variables. Specifically, models are estimated using GDP per capita (level and growth rate), FDI per capita, and HCI as outcome variables, the results of which are summarized in Table 10. The findings are that ethnic conflict has a positive effect on per capita GDP growth while the effect on per capita GDP is negative, albeit only weakly significant at a 10% level. The estimates on FDI and HCI are insignificant.

Outcome Variable	ATT	Std. Err.	t	P>|t|	[95% Conf. Interval]
GDP per capita	$-1{,}230^{*}$	637.26	-1.93	0.054	($-2{,}480$, 21.94)
GDPpc growth (%)	2.001^{**}	0.942	2.12	0.034	(0.155, 3.848)
FDI per Capita	-148	295.41	-0.50	0.615	(-727, 430.63)
HCI	-0.038	0.039	-0.99	0.324	(-0.114, 0.038)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 10: Effect of Ethnic Conflict on Mechanisms: GDP, FDI, and Human Capital

Each row reports an SDiD estimation on the respective outcome variables.

A caveat, however, is that by examining the Tau estimates for GDP in Table 11, the economic significance is driven predominantly by Spain (2004) and Libya (2011). The outbreak of the Libyan civil war in 2011 did not just include protests against then-Prime Minister Muammar Gaddafi that emerged against the backdrop of the Arab Spring, but eventually involved military intervention in the country by members of the North Atlantic Treaty Organization (NATO) [Daalder and Stavridis, 2012]. Hence, the course of the conflict after the initial outbreak of violence seen in the example of Libya is not necessarily representative of the other treated countries. Meanwhile, the conflict in Spain mainly refers to the Madrid bombings in 2004 with responsibility attributed to the Moroccan Islamic Combatant Group (GICM) that opposed Spanish involvement in Iraq. However, the decline in GDP per capita may be attributed to the confluence of a factors: collapse of the Spanish housing market following the 2008 financial crisis and the subsequent Euro-zone crisis. These concerns cast doubt on the identification assumptions of SDiD, based upon a modified version of the parallel trends assumption from the DiD paradigm, which we address later on. Furthermore, there may be criticism that ethnic

	τ	Std. Err.	Time
r1	-3395^{***}	413.8420	2004
r2	-784^{***}	187.4929	2005
r3	-180	202.7186	2007
r4	24	274.7559	2008
r5	-47	184.9802	2009
r6	-400	264.1533	2010
r7	-6118^{***}	326.8702	2011
r8	-68	73.4658	2014

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11: Tau estimators: The treatment effect on GDP per capita by treatment year

The tau estimators indicate the treatment effect estimates by treatment year.

	τ	Std. Err.	Time
r1	-1.657***	0.2310	2004
r2	2.849**	1.4330	2005
r3	2.231***	0.4217	2007
r4	4.321*	2.8771	2008
r5	2.720***	0.4481	2009
r6	2.378***	0.7951	2010
r7	0.300	1.2444	2011
r8	0.483	0.4467	2014

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: Tau estimators: The treatment effect on GDP per capita growth by treatment year

The tau estimators indicate the treatment effect estimates by treatment year.

terrorism does not fit into the concept of *conventional* ethnic conflict. Yet, there are no universally accepted definition on terrorism due to its politicized nature. We maintain the view that terrorism, perpetrated either by the state or by non-state actors, does not change the underlying ethnic character of the conflict.

Meanwhile, the observed increase in GDP growth appears to be driven by a broader set of countries according to the Tau estimates of Table 12. All except Spain (2004), Libya (2011) and Cameroon (2014) boast a positive coefficient, all statistically significant at various levels. While the combination of negative effects on both ECI and GDP alongside a positive effect on GDP growth is somewhat counterintuitive, it may reflect a phase of post-conflict economic recovery.[11] Furthermore, this pattern suggests that the recovery is likely driven by forms economic activity that do not necessarily enhance economic complexity. Overall, ethnic conflict is likely to disrupt production chains and harm the development of underlying capabilities in the economy as seen in the decline in GDP and ECI.

Regarding the insignificant results on FDI, a plausible explanation is that the recipients of FDI are unaffected by the ethnic conflict. If ethnic conflict occurs in urban centres and FDI is directed towards oil fields or mines that are geographically distant, the impact may be mitigated. We further suggest that while the quantity of FDI may not decrease, the *quality* of FDI would decrease instead. This is based on the understanding that not all FDI is equal, a belief that policymakers subscribe to when constructing their sophisticated FDI regimes [Alfaro and Charlton, 2007]. Using evidence from Colombia [Maher, 2015], civil war violence may create the conditions favourable for FDI inflows. This occurs when the violence is propagated by parties forwarding the interests of foreign investors, referring especially to the oil industry. This would be relevant to Libya in a post-Gaddafi era, as oil firms including British Petroleum and Royal Dutch Shell moved in to secure drilling rights and contribute to the country's reconstruction efforts [Ali and Harvie, 2013]. When put into context with the eclectic paradigm [Dunning, 1988] used to rationalize the international production of multi-national enterprises, this emphasizes the distinction between resource-seeking FDI and other forms of FDI. Their distinction, in this context, refers to their contribution to a country's economic complexity and holistic economic development.

There are different definitions on what constitutes quality FDI [Alfaro and Charlton, 2007],

[11] Note further that the countries driving the effect of the GDP results differ from the ones driving the effect of the GDP growth result, with Libya being insignificant in the latter and Spain having a significant result in the opposite direction.

but all share the characteristics of helping a country achieve sustainable growth. In our context, quality FDI refers to FDI that is concentrated on introducing new industries that produce more sophisticated products and move countries up the value chain, compared to FDI that is focused on expanding low value-added activities. However, the quality of FDI with respect to increasing economic complexity depends on the interaction of the characteristics of the specific investment inflow and the country involved; FDI that brings about knowledge transfer in industries that require professional expertise depend on the existence of an educated workforce. With ethnic conflict FDI quality would decline in most cases. A decrease in quality FDI inflows would be substituted by an inflows of lower quality FDI, obscuring the overall impact on FDI flows. A reason is that production of more complex products are more sensitive to changes in socio-economic conditions relative to commodities.. Path dependencies that constrain countries to focus on development based on low-value extractive processes [Ben Saad et al., 2023] may result from ethnic conflict, conditioning both the domestic political institutions and foreign investors to seek lower quality FDI.

No significant impact of ethnic conflict on human capital was found, as measured by the Human Capital Index (HCI) of the Penn World Table 10.01 [Feenstra et al., 2025]. This measure is calculated using data on educational attainment and returns to schooling. However, the HCI index is likely to be lagged in its response, should ethnic conflict adversely affect the quality of education systems through driving underinvestment in public goods. Unless severe ethnic civil wars are considered, we expect the impact on HCI to be minimal, as confirmed by the Table 10 results. The HCI index is likely to be too insensitive to detect the impacts of disruptions from ethnic conflicts that lack the intensity of full-blown civil wars or conflicts that threaten state failure. Our findings are in agreement with Ben Saad et al. [2023]. Hence, we require investigations on more dimensions of human capital, and especially entrepreneurial capital.

While the findings so far in this section suggest that ethnic conflict conflict has an effect on per capita GDP and GDP growth, the mechanisms behind its impact on the ECI remain unclear. Since the ECI is constructed using export data, a natural follow-up involves returning to the disaggregated trade data to make sense of what contributes to the decline in ECI. We combine disaggregated trade data on product level from the United Nations Comtrade Database [Gaulier and Zignago, 2010] with data on the product complexity index (PCI) from The Observatory of Economic Complexity [2023] using the HS92 product classification for both data sources.[12] Like

[12]Since the Comtrade Data contained more product classifications than the PCI data, many products were left without a PCI score after the initial matching. In these cases, the hierarchical structure of the 6-digit HS92 codes was used to assign an average PCI score based on the most similar available products.

the ECI, the PCI is measured as a z-score and the trade data is measured in terms of value in US$. Using the average PCI score of each product, products are ranked by complexity within each country's export basket. This ranking is then used to compute the weighted average PCI among the top and bottom 20% of the export value within each country and year, allowing us to analyse if ethnic conflict has an impact on the overall composition of trade with SDiD. The process is repeated for the top and bottom 5%, 10% and 15% and the findings are summarized in Table 13.

Export Share (X%)	ATT	Std. Err.	t	P>|t|	[95% Conf. Interval]
Top 5%	-0.21316^{**}	0.10454	-2.04	0.041	$(-0.41806, -0.00826)$
Top 10%	-0.23674^{*}	0.12558	-1.89	0.059	$(-0.48287, 0.00939)$
Top 15%	-0.24921^{*}	0.14289	-1.74	0.081	$(-0.52928, 0.03085)$
Top 20%	-0.20191^{**}	0.10322	-1.96	0.050	$(-0.40421, -0.00039)$
Bottom 5%	-0.00565	0.06747	-0.08	0.933	$(-0.13789, 0.12660)$
Bottom 10%	-0.02782	0.08824	-0.32	0.752	$(-0.20076, 0.14511)$
Bottom 15%	-0.07091	0.08196	-0.87	0.387	$(-0.23155, 0.08974)$
Bottom 20%	-0.06501	0.08502	-0.76	0.444	$(-0.23164, 0.10161)$

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13: Effect of Treatment on Product Complexity of Export Share Tails

Each row reports the ATT from an SDiD estimation of the treatment effect on the weighted average PCI of the top or bottom X% most export-dominant goods in each country-year.

The results suggest that the weighted average PCI of the most complex exports within countries significantly decreases following an ethnic conflict, whereas the no significant results are found for the least complex goods. In terms of magnitude, there is little variation among the estimates of the most complex goods, but the precision is slightly lower for the estimates on the top 10% and 15% causing the significance level to drop from 5% to 10%. Overall, the fact that the average PCI of the top export segment declines significantly, while the bottom segment remains unaffected, suggests that ethnic conflict disproportionately disrupts a country's ability to sustain its most sophisticated exports. Whether this effect stems from disruptions in domestic production or from the loss of trade partners due to increased political risk, the inability to sustain exports of more sophisticated products may undermine a country's long-term development and growth prospects. In contrast, the exports of less complex goods appear more resilient, likely because these products depend less on the capability-intensive systems most vulnerable to conflict-related disruptions.

9 Discussion

The key finding of this study is that ethnic conflict leads to a significant and persistent decline in economic complexity, affirming our narrative on the destructive impacts of ethnic violence. While GDP growth increases following the conflict, the simultaneous decline in GDP level and economic complexity indicates that this growth may reflect a shift toward less sophisticated economic activity rather than a full recovery—highlighting the lasting negative impact of ethnic conflict. The further inspection of the exports and PCI data found that, following an ethnic conflict, the most complex goods within an economy tend to be the most negatively affected. This indicates that complex goods are more vulnerable to negative shocks, raising concerns about an increased reliance on commodities as conflict-affected countries struggle to diversify their exports. Such a shift could undermine long-term economic competitiveness, as rival countries take advantage of the gaps created in the market, illustrating the true long-term costs of the instability created by ethnic conflict [Arunatilake et al., 2001].

We proceed by revisiting the first proposed mechanism: the loss of human and physical capital. This effect is not clearly supported by the data. The Human Capital Index (HCI) shows no discernible change, possibly due to its insensitivity to conflicts that do not escalate into full-scale civil wars. Moreover, we lacked access to sufficiently disaggregated data on physical capital to draw additional conclusions. Country-level capital-stock data is too aggregated to capture the localized economic disruptions caused by ethnic conflict, which frequently harms specific regions or communities more severely than others. The second mechanism on limited foreign technology transfer and a decline in foreign direct investment is not clearly observed in the data either. FDI flows had no significant change, which requires us to reconsider the link of FDI to developing new export capabilities needed to increase economic complexity. This differs from Frantz [2018] who found that capital flight is more likely to occur during election years, which is relevant to our examination of electoral violence. Unfortunately, we lack concrete data to draw appropriate conclusions on the last two mechanisms on the fragmentation of economic networks and the erosion of local institutions by the ethnicization of politics. Yet, the fragility of the most complex products seen in our findings provides circumstantial evidence for the above. This findng is new; the only similar paper to our knowledge [Bricongne et al., 2022] examined the response of export performance to shocks across firms of different sizes.

9.1 Limitations and Future Research

Next, we examine the limitations of the paper and how they affect the overall study. We begin by considering potential violations of the identification assumption for the SDiD approach, which refers to the modified version of the parallel trends assumption inherited from the DiD framework. A key challenge of using country-level data arises from post-treatment shocks with heterogeneous effects on each country. Notable examples include the global financial crises of 2008 and the Eurozone debt crisis, which in turn affect countries depending on their trade relationships and financial institutions. The issues of post-treatment shocks are mitigated by SDiD's approach in the construction of time weights. Future research could formally evaluate how robust the SDiD approach is to different kinds of post-treatment shocks, further strengthening the internal validity of studies using this empirical method.

Another potential threat to internal validity comes from concerns about general equilibrium effects. As ethnic conflict alters export patterns, new winners and losers will inevitably be created, a reality of the highly inter-connected global economy. A collapse in output of a particular product in a country may result in foreign investors directing their attention to other candidate areas for production. We believe that SDiD sufficiently addresses these concerns by using many countries to comprise the donor pool, such that if any particular country were to benefit from ethnic conflict, their limited unit weight used to construct the synthetic control would sufficiently dilute any benefit. Moreover, the treatment pool contains no large countries that are sufficiently centralized nodes of global trade and knowledge networks for general equilibrium effects to be a major issue.

An additional limitation of the current SDiD approach is the restrictiveness of the binary treatment variable based on a fatality threshold. Although binary treatment is appropriate for examining straightforward one-off policy changes, it means that we are unable to account for the intensity of ethnic conflict and its recurrence to reflect its possibly heterogeneous and episodic nature. Recalling that the results were insignificant when the fatality threshold was lowered from 100 to a baseline of 50, we return to the problem of approximating the true intensity of ethnic conflict [Ray and Esteban, 2017]. Further work can involve distinguishing between the bulk of the countries whose ECI suffer following the conflict outbreak from countries whose ECI remained resilient through the process. This may require further case studies examining the character of individual ethnic conflicts and the economic institutions of the relevant country. We expect that the true effect after accounting for intensity and recurrence to be more negative, and that our current figures are conservative. Another important consideration is the nature of the conflicts classified as ethnic in this study. Specifically, ethnic mass killings commonly occur as parts of larger events such as during the 2011 conflict in Libya which also involved foreign military intervention. While our approach identifies the conflict's effect as a whole, it cannot differentiate the effect purely caused by the ethnic dimension of the conflict [Gilley, 2004]. This limitation highlights the need for more granular conflict data and contextual analysis. Furthermore, an avenue for future research would be to explore whether the observed effects hold more generally across different types of conflict, or whether they are unique to those with a primarily ethnic character.

Data limitations are further abound. As natural in a conflict zone, our attempts to understand the impact on entrepreneurial and social capital are frustrated by the lack of firm-level data on economic activities and local data on inter-ethnic business ties. Since firms are less likely than households to provide potentially sensitive information [Brück et al., 2013], we are left with more consumption data than micro-level production data. Additional bottom-up initiatives to investigate multiplexed relationships, such as the study on an Indian village by [Chandrasekhar et al., 2024], would complement our understanding of the mechanisms linking ethnic conflict to economic complexity.

Future research on the robustness checks within the SDiD framework can help make it a more popular tool to examine more intricate phenomenons such as ethnic conflict. Examining economic complexity on a sub-national level is another emerging sub-literature within the broader economic complexity literature [Gomez-Lievano and Patterson-Lomba, 2021, Magalhães et al., 2023], which would help one understand the impact of ethnic conflict on a more granular level. Additionally, we believe the potentially heterogeneous impact of FDI on economic complexity can be a promising area for future research.

Moving forward, governments and the inter-governmental organisations should seek to create trust and promote ethnic cooperation across ethnic boundaries as part of their strategy for conflict prevention and post-conflict recovery. Inter-ethnic cooperation occurs when individuals believe that others who flout the law are held accountable by state institutions and informal social institutions [Fearon and Laitin, 1996]. Hence, local governments should be strongly encouraged to hold all ethnic groups equal in the eyes of the law for there to be trust in these institutions. Failing which, unresolved disputes would likely cause countries to spiral into further ethnic conflict. Special attention should be accorded to ensuring the recovery of the most complex products, given their vulnerability. These efforts overall contribute to improving the economic complexity of countries over time and make developing economies especially more resilient to inter-ethnic tensions. Our paper contributes to two distinct strands of literature: the growing literature on the drivers of economic complexity and literature on the economic outcomes from ethnic conflict. First, it extends the literature on economic complexity since [Hidalgo and Hausmann, 2009] through theorizing how the capabilities of economies are affected by bouts of sociopolitical instability. Second, it furthers research on ethnic conflict by shifting the focus from common economic indicators towards understanding the underlying structural transformation of economies.

10 Conclusion

This paper has scrutinized the impact of ethnic conflict on economic complexity, providing new evidence on how the escalation of ethnic violence affects an economy's export structure. Economic complexity was selected as the main outcome variable due to its reflection of the underlying resilience of the economy, and its role in predicting the success of sustainable development. We posit the existence of several channels through which ethnic conflict undermines economic complexity: disruption of export activities through the destruction of physical capital and the displacement of human capital, the fragmentation of knowledge networks and the ethnicization of politics that drives an underinvestment in public goods necessary for industrial upgrading.

Through a synthetic difference-in-differences approach, we find evidence that the outburst of violent ethnic conflict leads to a statistically significant decline in the economic complexity index by 0.206 standard deviations—a decline equivalent to losing 8–10 ranking positions globally. The effect persists beyond the immediate conflict period and is disproportionately driven by collapses in the most complex export categories, revealing how ethnic violence erodes the sophisticated production networks that underpin long-term development. Notably, while GDP growth rebounds post-conflict, the simultaneous decline in GDP levels and ECI suggests this recovery masks a shift toward less complex, commodity-like activities, heightening risks of a resource curse trap. The study contributes to development literature by highlighting the vulnerability of economic complexity to conflict-related disruptions and underlining the broader importance of inter-ethnic cohesion and institutional stability for sustaining economic sophistication.

11 References

Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature*, 59(2):391–425.

Abadie, A. and Gardeazabal, J. (2003). The economic costs of conflict: A case study of the basque country. *The American Economic Review*, 93(1):113–132.

Acemoglu, D., Johnson, S., and Robinson, J. A. (2005). Chapter 6 institutions as a fundamental cause of long-run growth. volume 1 of *Handbook of Economic Growth*, pages 385–472. Elsevier.

Acemoglu, D. and Wolitzky, A. (2014). Cycles of conflict: An economic model. *American Economic Review*, 104(4):1350–67.

Agrawal, A., Kapur, D., and McHale, J. (2008). How do spatial and social proximity influence knowledge flows? evidence from patent data. *Journal of Urban Economics*, 64(2):258–269.

Akerlof, G. A. and Kranton, R. E. (2000). Economics and identity. *The Quarterly Journal of Economics*, 115(3):715–753.

Alesina, A. and La Ferrara, E. (2005). Ethnic diversity and economic performance. *Journal of Economic Literature*, 43(3):762–800.

Alesina, A., Michalopoulos, S., and Papaioannou, E. (2016). Ethnic inequality. *Journal of Political Economy*, 124(2):428–488.

Alfaro, L. and Charlton, A. (2007). Growth and the Quality of Foreign Direct Investment: Is All FDI Equal? CEP Discussion Papers dp0830, Centre for Economic Performance, LSE.

Ali, I. and Harvie, C. (2013). Oil and economic development: Libya in the post-gaddafi era. *Economic Modelling*, 32:273–285.

Antonietti, R. and Franco, C. (2021). From fdi to economic complexity: a panel granger causality analysis. *Structural Change and Economic Dynamics*, 56:225–239.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., and Wager, S. (2021). Synthetic difference-in-differences. *The American Economic Review*, 111(12):pp. 4088–4118.

Arunatilake, N., Jayasuriya, S., and Kelegama, S. (2001). The economic cost of the war in sri lanka. *World Development*, 29(9):1483–1500.

Azariadis, C. and Drazen, A. (1990). Threshold externalities in economic development. *The Quarterly Journal of Economics*, 105(2):501–526.

Bahar, D. and Rapoport, H. (2018). Migration, knowledge diffusion and the comparative advantage of nations. *The Economic Journal*, 128(612):F273–F305.

Bahrami-Rad, Jonathan Beauchamp, J. H. and Schulz, J. (2022). Kin-based institutions and economic development. Ssrn working paper.

Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2):370–395.

Balassa, B. and Noland, M. (1989). "revealed" comparative advantage in japan and the united states. *Journal of International Economic Integration*, 4:8–22.

Balland, P.-A., Broekel, T., Diodato, D., Giuliani, E., Hausmann, R., O'Clery, N., and Rigby, D. (2022). The new paradigm of economic complexity. *Research Policy*, 51(3):104450.

Bardhan, P. (1997). Method in the madness? a political-economy analysis of the ethnic conflicts in less developed countries. *World Development*, 25(9):1381–1398.

Barro, R. J. and Lee, J.-W. (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of Development Economics*, 104:184–198.

Baumol, W. J. (1968). Entrepreneurship in economic theory. *The American Economic Review*, 58(2):64–71.

Baumol, W. J. (1990). Entrepreneurship: Productive, unproductive, and destructive. *Journal of Political Economy*, 98(5):893–921.

Ben Saad, M., Brahim, M., Schaffar, A., Guesmi, K., and Ben Saad, R. (2023). Economic complexity, diversification and economic development: The strategic factors. *Research in International Business and Finance*, 64:101840.

Berdiev, A. N., Goel, R. K., and Saunoris, J. W. (2020). The path from ethnic inequality to development: The intermediary role of institutional quality. *World Development*, 130:104925.

Bluhm, R., Gassebner, M., Langlotz, S., and Schaudt, P. (2021). Fueling conflict? (de)escalation and bilateral aid. *Journal of Applied Econometrics*, 36(2):244–261.

Bobb, S. (2009). Kenya violence hurts flower exports for valentine's day. https://www.voanews.com/a/a-13-2008-02-14-voa47/404891.html. Voice of America, Accessed April 2025.

Bove, V., Elia, L., and Smith, R. (2017). On the heterogeneous consequences of civil war. *Oxford Economic Papers*, 69:550–568.

Bricongne, J.-C., Carluccio, J., Fontagné, L., Gaulier, G., and Stumpner, S. (2022). From macro to micro: Large exporters coping with common shocks. Technical Report 881, Banque de France.

Brück, T., Naudé, W., and Verwimp, P. (2013). Business under fire: Entrepreneurship and violent conflict in developing countries. *The Journal of Conflict Resolution*, 57(1):3–19.

Cadot, O., Carrère, C., and Strauss-Kahn, V. (2011). Export diversification: What's behind the hump? *The Review of Economics and Statistics*, 93(2):590–605.

Camacho, A. and Rodriguez, C. (2013). Firm exit and armed conflict in colombia. *The Journal of Conflict Resolution*, 52:89–116.

Caselli, F. (2013). On the theory of ethnic conflict. *Journal of the European Economic Association*, 11(s1):161–192.

Cederman, L.-E., Weidmann, N. B., and Gleditsch, K. S. (2011). Horizontal inequalities and ethnonationalist civil war: A global comparison. *The American Political Science Review*, 105(3):478–495.

Cerra, V. and Saxena, S. (2008). Growth dynamics: The myth of economic recovery. *American Economic Review*, 98:439–457.

Chandrasekhar, A., Chaudhary, V., Golub, B., and Jackson, M. (2024). Multiplexing in networks and diffusion. Technical report, Stanford University.

Chen, S., Loayza, N. V., and Reynal-Querol, M. (2007). The aftermath of Civil War. Economics Working Papers 1043, Department of Economics and Business, Universitat Pompeu Fabra.

Clarke, D., Pailañir, D., Athey, S., and Imbens, G. W. (2023). Synthetic Difference-in-Differences Estimation. IZA Discussion Papers 15907, Institute of Labor Economics (IZA).

Collier, P. (1999). On the economic consequences of civil war. *Oxford Economic Papers*, 51:168–183.

Cordero, C. F. (2013). Breaking the mexican cartels: A key homeland security challenge for the next four years. Technical Report 13-028, Georgetown University Law Center.

Coscia, M., Neffke, F. M., and Hausmann, R. (2020). Knowledge diffusion in the network of international business travel. *Nature Human Behaviour*, 4:1011–1020.

Costalli, S., Moretti, L., and Pischedda, C. (2017). The economic costs of civil war: Synthetic counterfactual evidence and the effects of ethnic fractionalization. *Journal of Peace Research*, 54(1):80–98.

Daalder, I. H. and Stavridis, J. G. (2012). Nato's victory in libya: The right way to run an intervention. *Foreign Affairs*, 91(2):2–7.

Davies, S., Engström, G., Pettersson, T., and Öberg, M. (2024). Organized violence 1989-2023, and the prevalence of organized crime groups. *Journal of Peace Research*, 61(4).

DeepSeek-AI (2025). Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *Large Language Model*.

Destek, M. A., Hossain, M. R., Aydın, S., Shakib, M., and Destek, G. (2023). Investigating the role of economic complexity in evading the resource curse. *Resources Policy*, 86:104131.

Doctor, A. and Bagwell, S. (2020). Risky business: Foreign direct investment and the economic consequences of electoral violence. *Global Security Studies*, 5:339–360.

Doudchenko, N. and Imbens, G. W. (2016). Balancing, Regression, Difference-In-Differences and Synthetic Control Methods: A Synthesis. NBER Working Papers 22791, National Bureau of Economic Research, Inc.

Du, K. and O'Connor, A. (2021). Examining economic complexity as a holistic innovation system effect. *Small Business Economics*, 56(1):pp. 237–257.

Dunning, J. H. (1988). The eclectic paradigm of international production: A restatement and some possible extensions. *Journal of International Business Studies*, 19(1):1–31.

Easterly, W. (2001). Can institutions resolve ethnic conflict? *Economic Development and Cultural Change*, 49(4):687–706.

Easterly, W., Alesina, A., and Baqir, R. (1999). Public goods and ethnic divisions. *The Quarterly Journal of Economics*, 114:1243–1284.

Easterly, W., Gatti, R., and Kurlat, S. (2006). Development, democracy, and mass killings. *Journal of Economic Growth*, 11(2):129–156.

Easterly, W. and Levine, R. (1997). Africa's growth tragedy: Policies and ethnic divisions. *The Quarterly Journal of Economics*, 112(4):1203–1250.

Eck, K. and Hultman, L. (2007). Violence against civilians in war. *Journal of Peace Research*, 44(2).

Elekwa, N. N. and Eme, O. I. (2011). Post-election violence in africa : A comparative case of kenya and zimbabwe. *The Indian Journal of Political Science*, 72(3):833–844.

Emeka, E. T., Ogbuabor, J. E., and Ekeocha, D. O. (2024). Terrorism and economic complexity in africa: The unconditional impact of military expenditure. *African Development Review*, 36(1):139–152.

Esteban, J., Mayoral, L., and Ray, D. (2012). Ethnicity and conflict: An empirical study. *American Economic Review*, 102(4):1310–42.

Esteban, J., Morelli, M., and Rohner, D. (2015). Strategic mass killings. *Journal of Political Economy*, 123(5):1087–1132.

Fearon, J. and Laitin, D. (2003). Ethnicity, insurgency, and civil war. *American Political Science Review*, 97(1):75–90.

Fearon, J. D. and Laitin, D. D. (1996). Explaining Interethnic Cooperation. *American Political Science Review*, 90(4):715–735.

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2025). Penn world table version 10.01. https://www.rug.nl/ggdc/productivity/pwt/. Groningen Growth and Development Centre, University of Groningen. Accessed March 2025.

Fisman, R. (2003). Ethnic Ties and the Provision of Credit: Relationship-Level Evidence from African Firms. *The B.E. Journal of Economic Analysis & Policy*, 3(1):1–21.

Fjelde, H., Hultman, L., Schubiger, L., Cederman, L.-E., Hug, S., and Sollenberg, M. (2019). Introducing the ethnic one-sided violence dataset. *Conflict Management and Peace Science*.

Frantz, E. (2018). Elections and capital flight: Evidence from africa. *International Studies Quarterly*, 62(1):pp. 160–170.

Freeman, C. (1995). The 'National System of Innovation' in Historical Perspective. *Cambridge Journal of Economics*, 19(1):5–24.

French, S. (2017). Revealed comparative advantage: What is it good for? *Journal of International Economics*, 106:83–103.

Gaulier, G. and Zignago, S. (2010). BACI: International Trade Database at the Product-Level. The 1994–2007 Version. Working Paper 2010-23, CEPII.

Ghosh, S. and Mitra, A. (2022). Ethnic identities, public spending and political regimes. *Journal of Comparative Economics*, 50(1):256–279.

Gilley, B. (2004). Against the concept of ethnic conflict. *Third World Quarterly*, 25(6):1155–1166.

Glaeser, E. L. (2005). The Political Economy of Hatred. *The Quarterly Journal of Economics*, 120(1):45–86.

Gomez-Lievano, A. and Patterson-Lomba, O. (2021). Estimating the drivers of urban economic complexity and their connection to economic performance. *Royal Society Open Science*, 8.

Habyarimana, J., Humphreys, M., Posner, D. N., and Weinstein, J. M. (2007). Why does ethnic diversity undermine public goods provision? *The American Political Science Review*, 101(4):709–725.

Harvey, D. I., Kellard, N. M., Madsen, J. B., and Wohar, M. E. (2010). The prebisch-singer hypothesis: Four centuries of evidence. *The Review of Economics and Statistics*, 92(2):367–377.

Hausmann, R., Hwang, J., and Rodrik, D. (2007). What you export matters. *Journal of Economic Growth*, 12(1):1–25.

Hausmann, R. and Rodrik, D. (2003). Economic development as self-discovery. *Journal of Development Economics*, 72(2):603–633.

Hidalgo, C. and Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, 106(26):10570–10575.

Hidalgo, C. A. (2023). The policy implications of economic complexity. *Research Policy*, 52(9):104863.

Hidalgo, C. A., Hausmann, R., and Dasgupta, P. S. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences of the United States of America*, 106(26):10570–10575.

Hidalgo, C. A., Klinger, B., Barabasi, A. L., and Hausmann, R. (2007). The Product Space Conditions the Development of Nations. *Science*, 317:482–487.

Hill, M. O. (1973). Reciprocal averaging: An eigenvector method of ordination. *Journal of Ecology*, 61(1):237–249.

Hjort, J. (2014). Ethnic divisions and production in firms. *The Quarterly Journal of Economics*, 129(4):1899–1946.

Hodler, R. (2019). The economic effects of genocide: Evidence from rwanda. *Journal of African Economies*, 28:1–17.

Horowitz, D. (2001). *Ethnic Groups in Conflict*. University of California Press.

Imai, K. and Weinstein, J. (2000). Measuring the Economic Impact of Civil War. CID Working Papers 51A, Center for International Development at Harvard University.

Jones, C. I. (2019). Paul Romer: Ideas, Nonrivalry, and Endogenous Growth. *Scandinavian Journal of Economics*, 121(3):859–883.

Kang, S. and Meernik, J. (2005). Civil war destruction and the prospects for economic growth. *The Journal of Politics*, 67(1):88–109.

Karnane, P. and Quinn, M. A. (2019). Political instability, ethnic fractionalization and economic growth. *International Economics and Economic Policy*, 16(2):435–461.

Kemp, W. (2004). The business of ethnic conflict. *Security Dialogue*, 35(1):43–59.

Kemp-Benedict, E. (2014). An interpretation and critique of the Method of Reflections. MPRA Paper 60705, University Library of Munich, Germany.

Knack, S. and Keefer, P. (1997). Does social capital have an economic payoff? a cross-country investigation. *The Quarterly Journal of Economics*, 112(4):1251–1288.

Kondylis, F. (2010). Conflict displacement and labor market outcomes in post-war Bosnia and Herzegovina. *Journal of Development Economics*, 93(2):235–248.

Korn, T. and Stemmler, H. (2025). The persistence of trade relocation from civil conflict. *Journal of Development Economics*, 172:103376.

Korovkin, V. and Makarin, A. (2023). Conflict and intergroup trade: Evidence from the 2014 russia-ukraine crisis. *American Economic Review*, 113(1):34–70.

Kranz, S. (2022). Synthetic difference-in-differences with time-varying covariates. Technical report. arXiv:2202.02903.

Ksoll, C., Macchiavello, R., and Morjaria, A. (2021). Guns and roses: Flower exports and electoral violence in Kenya. Global Poverty Research Lab Working Paper 17-102.

Laurent-Lucchetti, J., Rohner, D., and Thoenig, M. (2024). Ethnic conflict and the informational dividend of democracy. *Journal of the European Economic Associaion*, 22(1):73–116.

Lee, H. and Chung, C. C. (2022). Go small or go home: Operational exposure to violent conflicts and foreign subsidiary exit. *Journal of World Business*, 57(6):101361.

Magalhães, L., Kuffer, M., Schwarz, N., and Haddad, M. (2023). Bringing economic complexity to the intra-urban scale: The role of services in the urban economy of belo horizonte, brazil. *Applied Geography*, 150:102837.

Maher, D. (2015). The fatal attraction of civil war economies: Foreign direct investment and political violence, a case study of colombia. *International Studies Review*, 17(2):217–248.

Mankiw, N. G., Romer, D., and Weil, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, 107(2):407–437.

Mauro, P. (1995). Corruption and growth. *The Quarterly Journal of Economics*, 110(3):681–712.

Mealy, P., Farmer, J. D., and Teytelboym, A. (2019). Interpreting Economic Complexity. *Science Advances*, (1711.08245).

Mehlum, H., Moene, K., and Torvik, R. (2003). Predator or prey?: Parasitic enterprises in economic development. *European Economic Review*, 47(2):275–294.

Miguel, E., Satyanath, S., and Sergenti, E. (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy*, 112(4):725–753.

Mini, L., Moyo, C., and Phiri, A. (2025). Governance, institutional quality and economic complexity in selected african countries. *International Journal of Economic Policy Studies*, 19(723):159–181.

Mueller, H. (2012). Growth dynamics: The myth of economic recovery: Comment. *American Economic Review*, 102.

Muhammad, A., D'Souza, A., and Amponsah, W. (2013). Violence, instability, and trade: Evidence from kenya's cut flower sector. *World Development*, 51:20–31.

Nathan, M. (2015). Same difference? minority ethnic inventors, diversity and innovation in the uk. *Journal of Economic Geography*, 15.

Naudé, W., Amorós, E., and Brück, T. (2023). State-based conflict and entrepreneurship: Empirical evidence. Technical report, IZA - Institute of Labor Economics.

Neudorfer, N. S., Theuerkauf, U. G., and Wolff, S. (2025). Territorial arrangements and ethnic conflict management: The paradox that isn't. *World Development*, 185:106812.

Novta, N. (2016). Ethnic diversity and the spread of civil war. *Journal of the European Economic Association*, 14(5):1074–1100.

OpenAI (2025). Chatgpt. *Large Language Model*.

Paz, S. (2023). Long Run Consequences of Ethnic Conflict On Social Capital: Evidence from South Africa. Documentos CEDE 20923, Universidad de los Andes, Facultad de Economía, CEDE.

Pickett, R., Hill, J., and Cowan, S. (2022). The myths of synthetic control: Recommendations for practice. Working Paper 041122, New York University.

Porhel, R. (2008). The economic consequences of the political crisis. *The East African Review*, pages 231–258.

Posen, B. R. (1993). The security dilemma and ethnic conflict. *Survival*, 35(1):27–47.

Psacharopoulos, G. and Patrinos, H. A. (2018). Returns to investment in education: A decennial review of the global literature. Policy Research Working Paper 8402, World Bank. License: CC BY 3.0 IGO.

Ray, D. and Esteban, J. (2017). Conflict and Development. *Annual Review of Economics*, 9(1):263–293.

Rohner, D., Thoenig, M., and Zilibotti, F. (2013). War signals: A theory of trade, trust, and conflict. *The Review of Economic Studies*, 80(3):1114–1147.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5):S71–S102.

Seidel, A. (2023). A global map of amenities: Public goods, ethnic divisions and decentralization. *Journal of Development Economics*, 164:103113.

Sepehrdoust, H., Davarikish, R., and Setarehie, M. (2019). The knowledge-based products and economic complexity in developing countries. *Heliyon*, 5(12):e02979.

Sestito, M. (2025). Identity conflict, ethnocentrism and social cohesion. *Journal of Development Economics*, 174:103426.

Sileci, L. (2023). Carbon pricing with regressive co-benefits: Evidence from british columbia's carbon tax. Working Paper 121047, Grantham Research Institute on Climate Change and the Environment, London School of Economics.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 39(3):312–320.

Sorenson, O., Rivkin, J. W., and Fleming, L. (2006). Complexity, networks and knowledge flow. *Research Policy*, 35(7):994–1017.

Stojkoski, V. and Kocarev, L. (2017). The Relationship Between Growth and Economic Complexity: Evidence from Southeastern and Central Europe. MPRA Paper 77837, University Library of Munich, Germany.

The Growth Lab at Harvard University (2025). Growth projections and complexity rankings. https://doi.org/10.7910/DVN/XTAQMC. Accessed March, 2025.

The Observatory of Economic Complexity (2023). Product Complexity Index (PCI) HS6 REV. 1992 (1995–2023). `https://oec.world/en/resources/bulk-download/international?category=PCI&topic=Complexity`. Accessed April 2025.

Vothkneckt, M. and Sumarto, S. (2011). Beyond the overall economic downturn: Evidence on sector-specific effects of violent conflict in indonesia. Diw discussion paper, DIW Berlin.

Vu, T. (2022). Does institutional quality foster economic complexity? the fundamental drivers of productive capabilities. *Empirical Economics*, 63:1571–1604.

World Bank (2025a). Foreign direct investment, net inflows (bop, current US$). https://data.worldbank.org/indicator/BX.KLT.DINV.CD.WD. Accessed March 2025.

World Bank (2025b). Gdp per capita (constant 2015 US$). https://data.worldbank.org/indicator/NY.GDP.PCAP.KD. Accessed March 2025.

World Bank (2025c). Population, total. https://data.worldbank.org/indicator/SP.POP.TOTL. Accessed March 2025.

Zhu, S. and Fu, X. (2013). Drivers of Export Upgrading. *World Development*, 51(C):221–233.

A Appendix

A.1 Mathematical Explanation of the Economic Complexity Index (ECI) and Product Complexity Index (PCI)

In this appendix, we provide a brief explanation of the derivation of the complexity indexes, ECI and PCI.

$$RCA_{cp} = \frac{x_{cp} / \sum\limits_{p} x_{cp}}{\sum\limits_{c} x_{cp} / \sum\limits_{c}\sum\limits_{p} x_{cp}} \tag{3}$$

The above equation provides the Balassa index, a measure classically used to denote Relative Comparative Advantage (RCA). The index is the ratio of country c's exports in product p to its share in total product exports [Balassa and Noland, 1989]. A binary country-product matrix M is then constructed with elements M_{cp}, whereby c denotes country and p denotes product, satisfying the following condition:

$$M_{cp} = \begin{cases} 1 & \text{if } RCA_{cp} > 1 \\ 0 & \text{otherwise} \end{cases}$$

When aggregated across products and countries, the matrix M reveal the underlying patterns of comparative advantage and identifies countries that compete in similar product markets [French, 2017]. The objective is to derive the complexity K of a particular country, denoted by K_c, and a particular product, denoted by K_p. Recalling that the complexity of locations (ECI) are informed by the products present and that the complexity of products (PCI) are informed by the locations whereby they are produced, the following relationship is represented by functions f and g:

$$K_c = f(M_{cp}, K_p)$$

$$K_p = g(M_{cp}, K_c)$$

By substitution, we can see that $K_c = f(M_c p, g(M_{cp}, K_c))$ and that $K_p = g(M_{cp}, f(M_{cp}, K_p))$. For notational ease, the location *diversity* (i.e., the number of activities in a location whereby the location has a revealed comparative advantage $RCA_{cp} > 1$) and the product *ubiquity* (i.e., the number of locations whereby the activity is produced with a revealed comparative advantage) is given by $k_{c,0} = \sum_p M_{cp}$ and $k_{p,0} = \sum_c M_{cp}$ respectively. Using reciprocal averaging [Hill, 1973], higher order elements are iteratively obtained [Kemp-Benedict, 2014], such that ECI and PCI are respectively defined by the following system of equations:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_p M_{cp} k_{p,N-1} \tag{4}$$

$$k_{p,N} = \frac{1}{k_{p,0}} \sum_c M_{cp} k_{c,N-1} \tag{5}$$

The above approach of reciprocal averaging is used by Hidalgo and Hausmann [2009] in their original approach. To see this in action in a linear algebra context [Kemp-Benedict, 2014], we substitute in $k_{p,N-1}$ to only include even terms in the sequence: [13]

$$k_{c,N} = \sum_{c'} \left(\frac{1}{k_{c,0}} \sum_p M_{cp} \frac{1}{k_{p,0}} M_{c'p}\right) k_{c',N-2} \tag{6}$$

Intuitively, the Method of Reflections is an iterative approach that alternates between country characteristic $k_{c,j}$ and product characteristic $k_{p,j}$ for $j \in \{0, N\}$. Through iteration, it converges to a stable equilibrium characterized by the matrix equations below. The matrix equation is then derived, whereby the following matrix connecting related countries is obtained and by a symmetrical argument, the matrix connecting related products is derived:

$$\vec{k_N} = \tilde{M}_{cc'} \cdot \vec{k_{N-2}} \tag{7}$$

$$\tilde{M}_{cc'} = \sum_p \frac{M_{cp} M_{c'p}}{k_{c,0} k_{p,0}}$$

$$\tilde{M}_{pp'} = \sum_c \frac{M_{cp} M_{cp'}}{k_{c,0} k_{p,0}}$$

As $\lim_{N\to\infty} N$, a linear algebra interpretation arises as $K_c \equiv \lim_{N\to\infty} k_{c,N}$ and similarly, $K_p \equiv \lim_{N\to\infty} k_{p,N}$. Since both matrices are row-stochastic, their first eigenvector is a row of 1s.[14] The solution to this system are the eigenvectors of $\tilde{M}_{cc'}$ and $\tilde{M}_{pp'}$. Mealy et al. [2019] demonstrate that the Method of Reflection converges to a singular value decomposition (SVD) of the matrix M_{cp}, which means that the aforementioned eigenvectors converge to the principal components of M_{cp}. Existing research rely upon the SVD approach for the improved stability of results and ease of interpretation. Ignoring the largest eigenvector 1, K_c and K_p are then the second-largest eigenvector of $\tilde{M}_{cc'}$ and $\tilde{M}_{pp'}$. The second-largest eigenvectors partition the locations and products exactly where ECI and PCI equal to 0 respectively [Mealy et al., 2019].

ECI and PCI are then obtained through a Z-transform on K_c and K_p respectively, ensuring that the indexes are normalized and thus comparable across time.

[13] Note the inclusion of c' to denote different terms in the sequence.

[14] Utilizing the property of a 'steady state' in Markov chains.

$$ECI = \frac{K_c - \bar{K_c}}{\sigma(K_c)} \tag{8}$$

$$PCI = \frac{K_p - \bar{K_p}}{\sigma(K_p)} \tag{9}$$

A.2 Pre-Treatment Trends, Time Weights and Unit Weights by Year

In this subsection, the graphical output from the main SDiD specification estimated in Table 2 is presented. The graphical output includes two figures for each treatment year, one comparing the ECI trends of the treated unit(s) to the counterfactual constructed by SDiD as well as displaying the time weights, and one figure plotting the unit weights used to construct the counterfactual. The axis of the time weights is shown in the right hand side of the plots, and they indicate which pre-treatment periods are most predictive of the post-treatment outcomes. For the unit weight graphs, the size of the dots determine the relative importance of the weighting on this country, meaning that large dots have larger unit weights. The y-axis measures the difference in the pre-treatment trend of the treated country relative to the country labeled on the x-axis. For example, in the unit weight plot for Cameroon, Vietnam's large dot situated below 0 indicates that Vietnam holds a relatively large unit weight in the counterfactual of Cameroon, and that the pre-treatment trend of Cameroon was negative relative to Vietnam. To examine the goodness of fit of the unit weight plots, it is ideal with large dots clustered near zero. If there are few large dots which are all far away from zero, this would indicate that the counterfactual is relying on few countries with mismatching trends causing a poor fit.

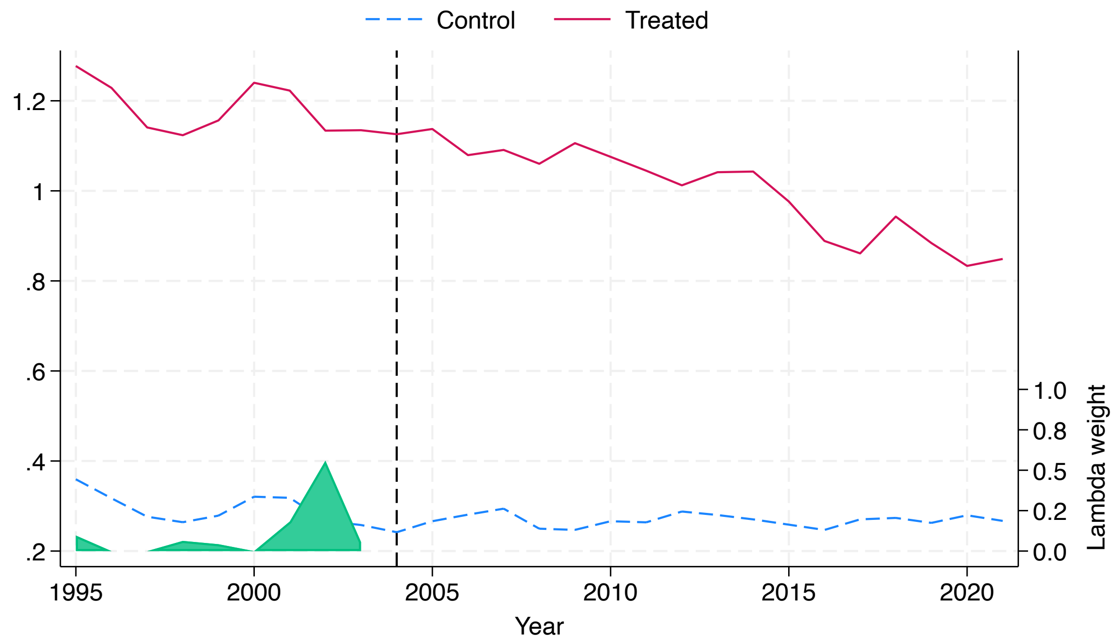

Figure A.2.1: Trends for Spain, 2004

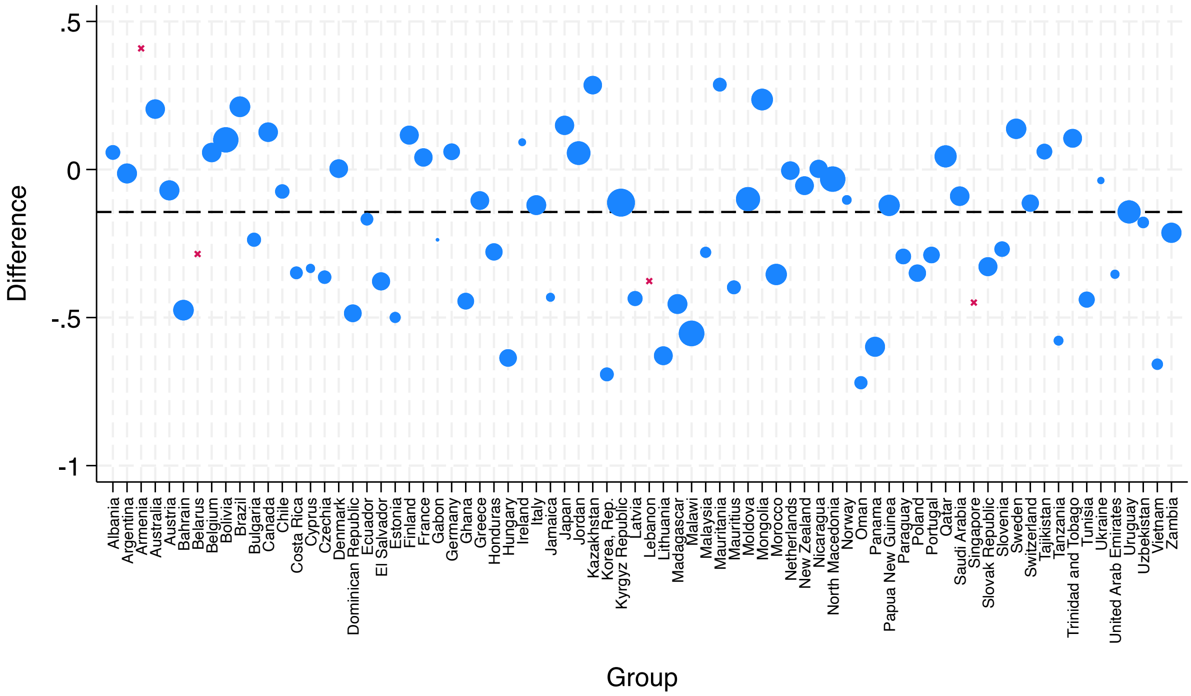

Figure A.2.2: Weights for Spain, 2004

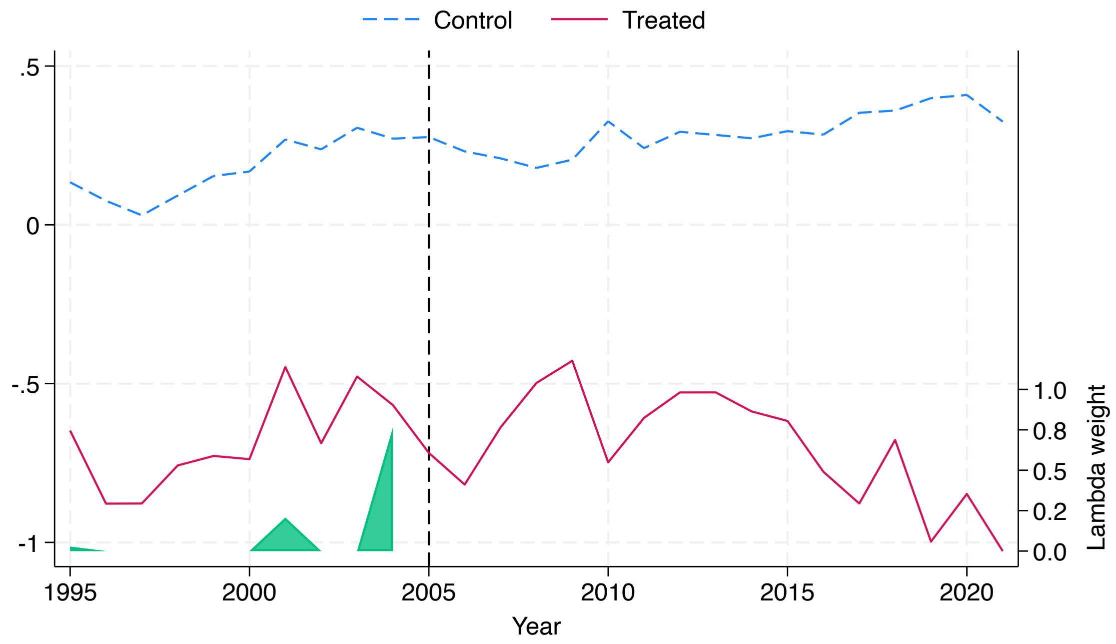

Figure A.2.3: Trends for Togo, 2005

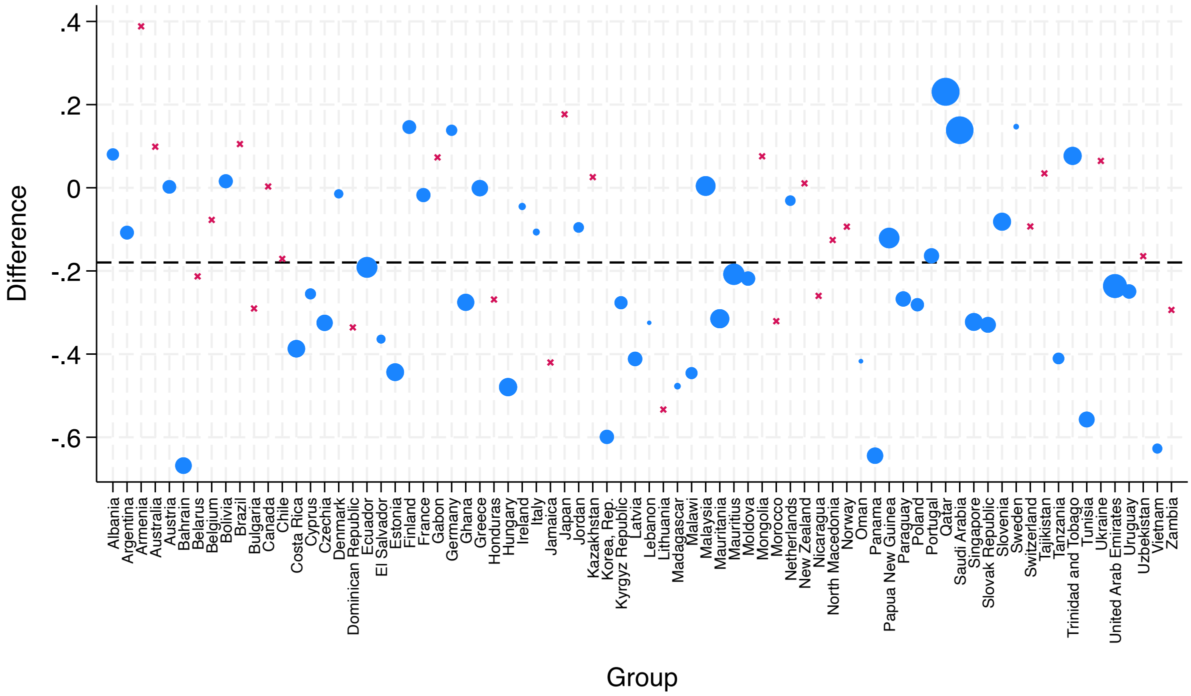

Figure A.2.4: Weights for Togo, 2005

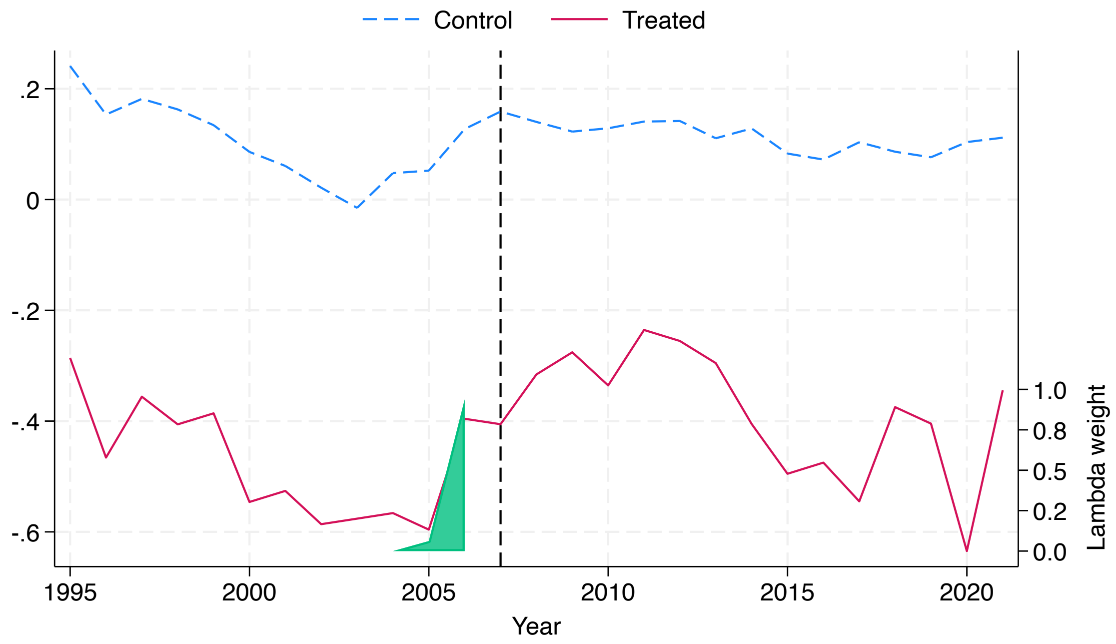

Figure A.2.5: Trends for Kenya, 2007

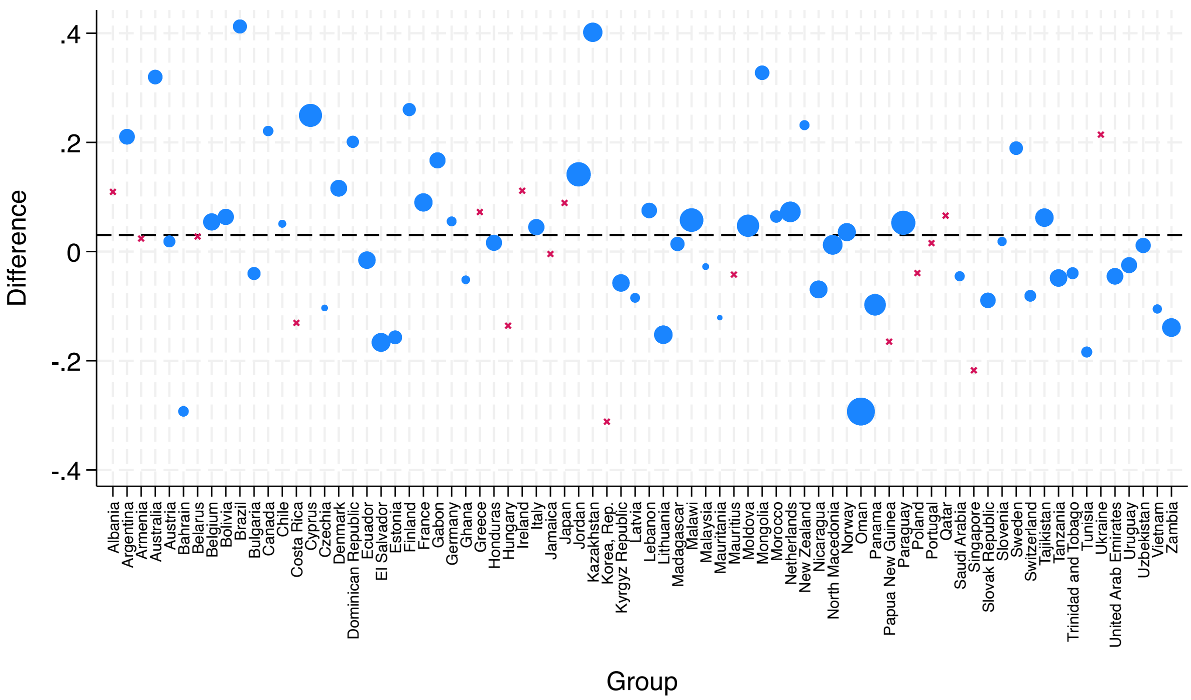

Figure A.2.6: Weights for Kenya, 2007

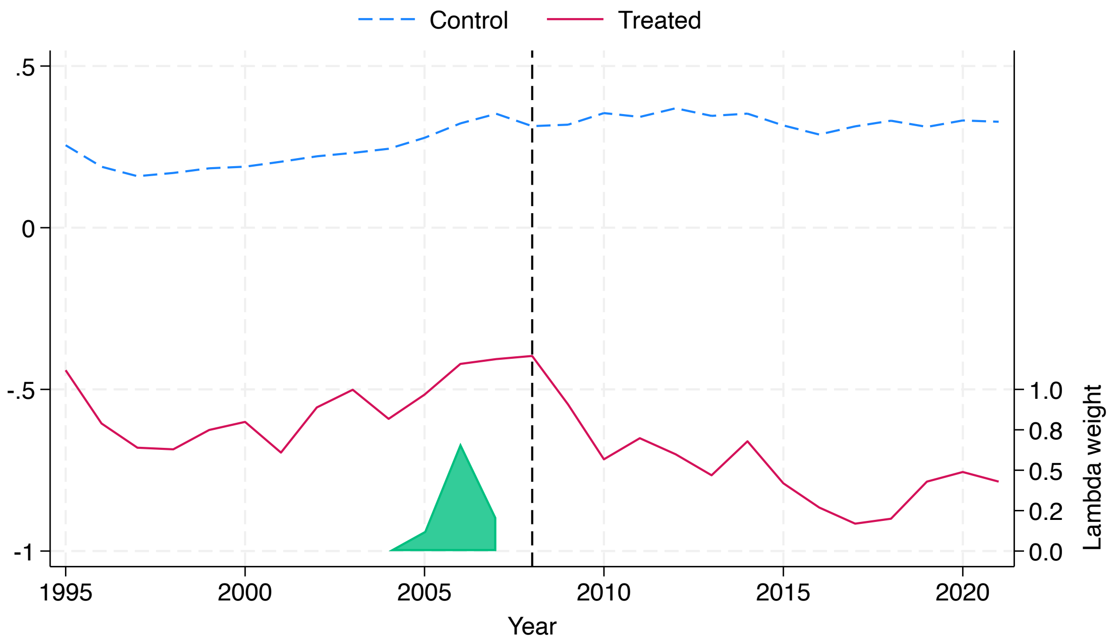

Figure A.2.7: Trends for Pakistan and Zimbabwe, 2008

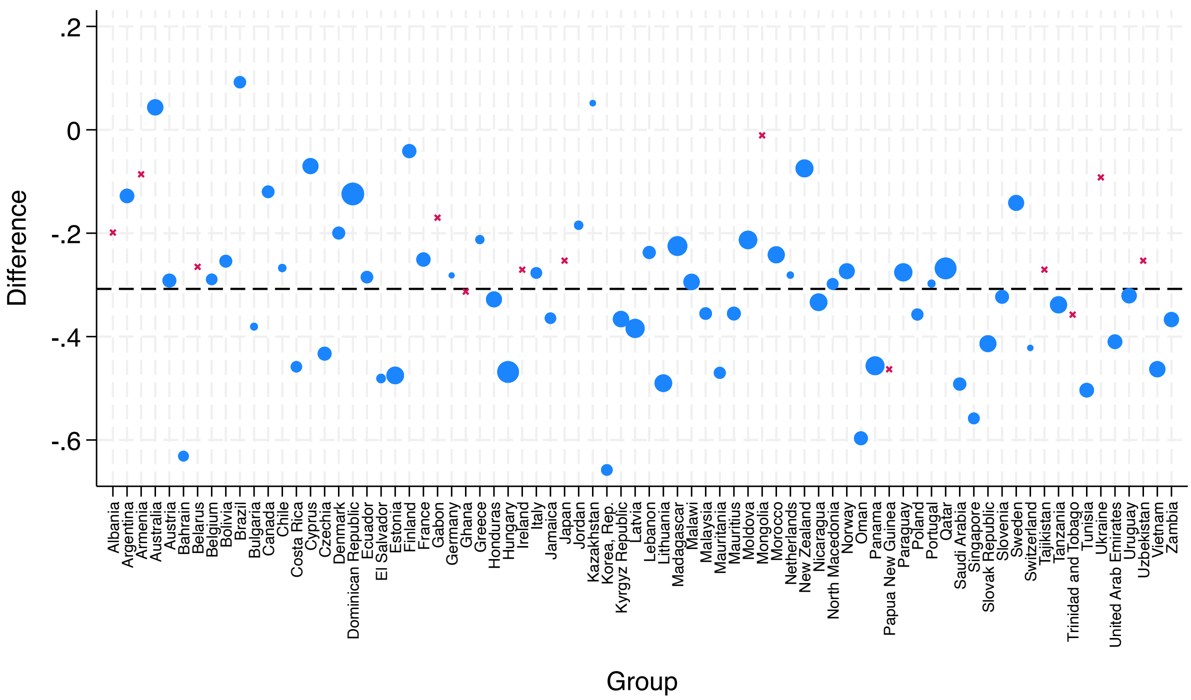

Figure A.2.8: Weights for Pakistan and Zimbabwe, 2008

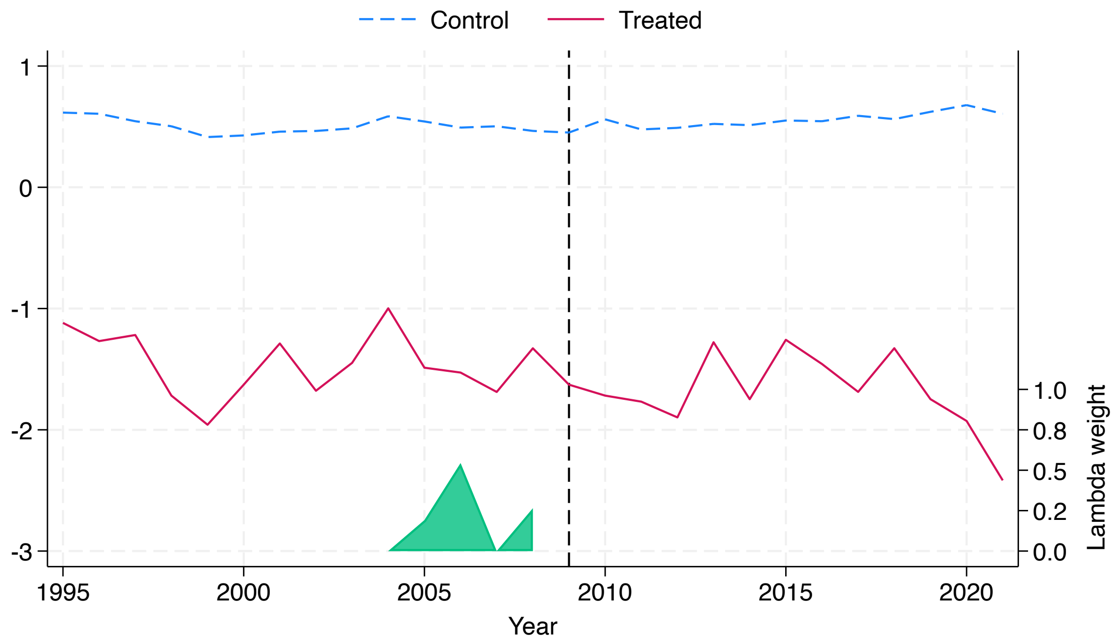

Figure A.2.9: Trends for Guinea, 2009

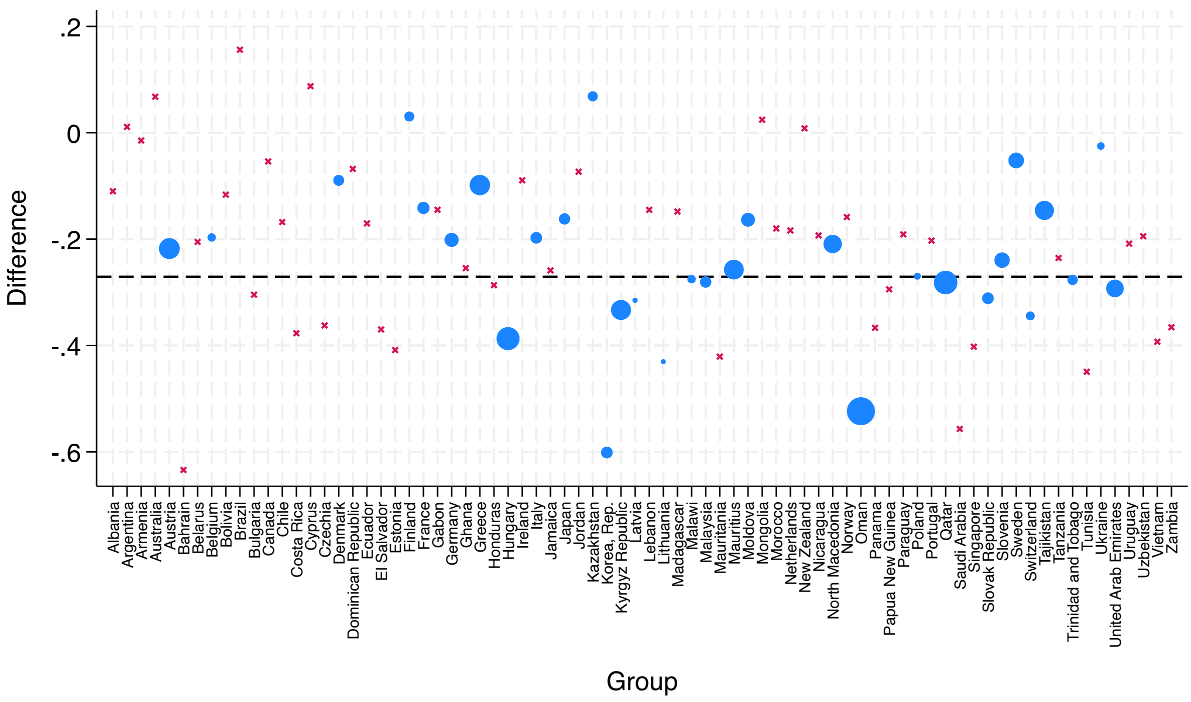

Figure A.2.10: Weights for Guinea, 2009

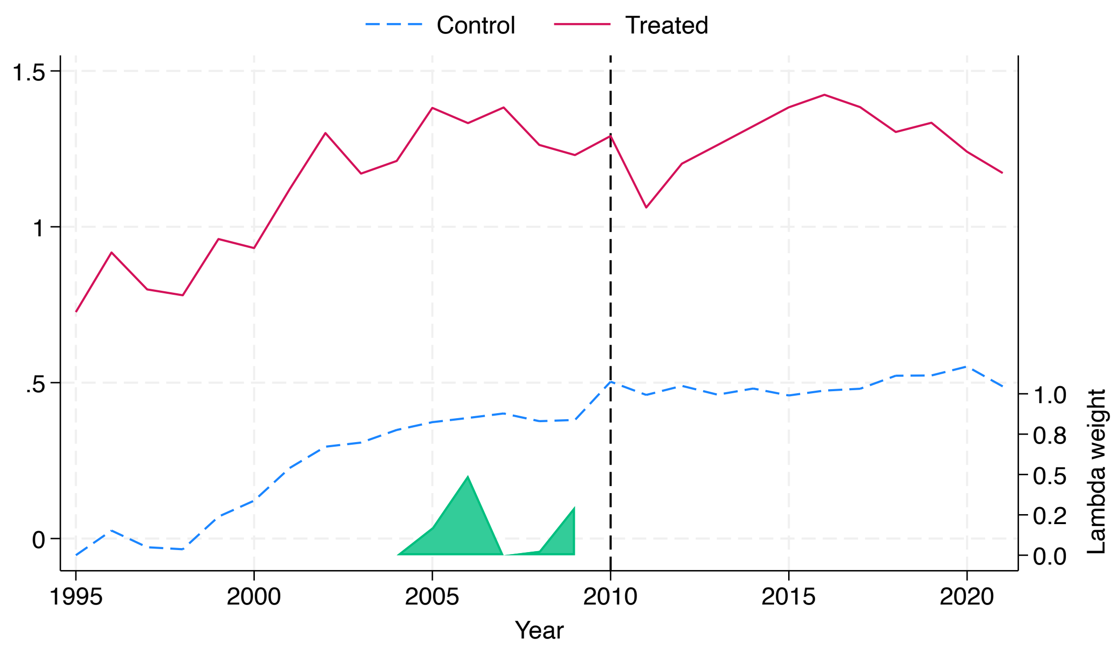

Figure A.2.11: Trends for Mexico, 2010

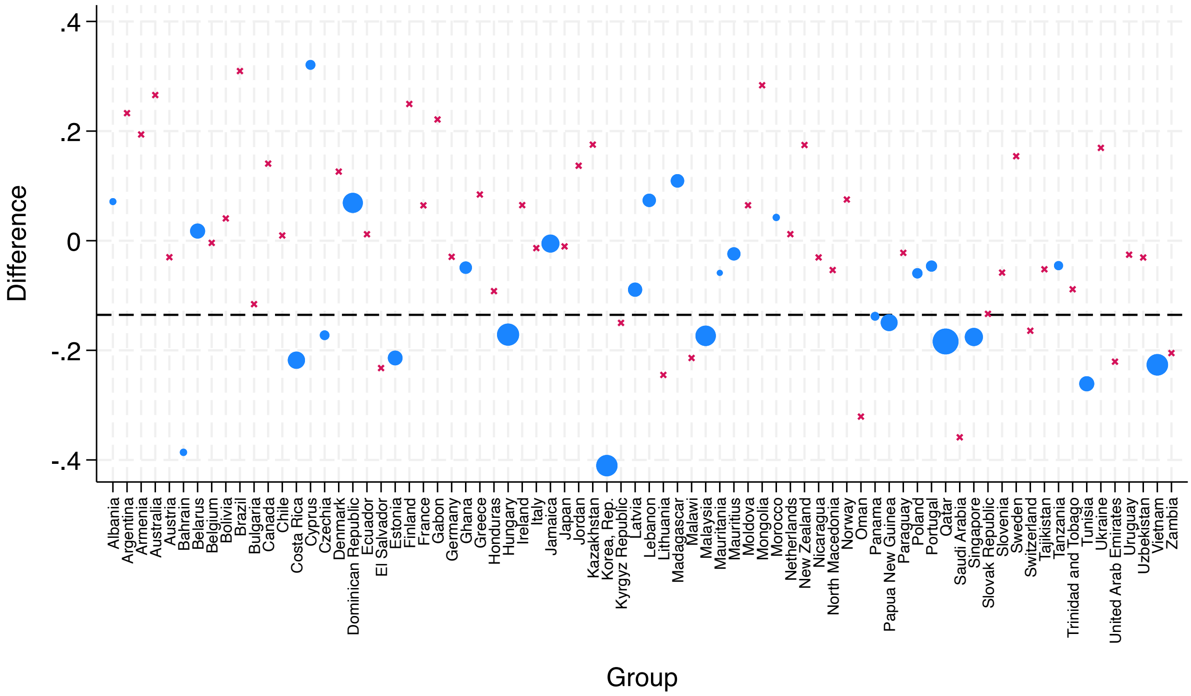

Figure A.2.12: Weights for Mexico, 2010

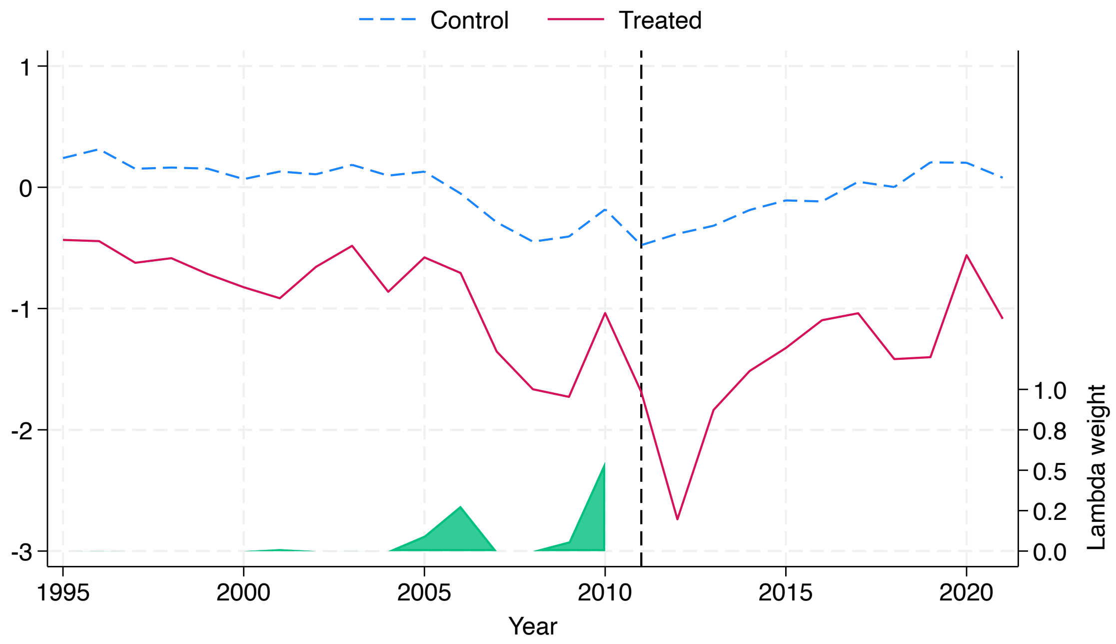

Figure A.2.13: Trends for Libya, 2011

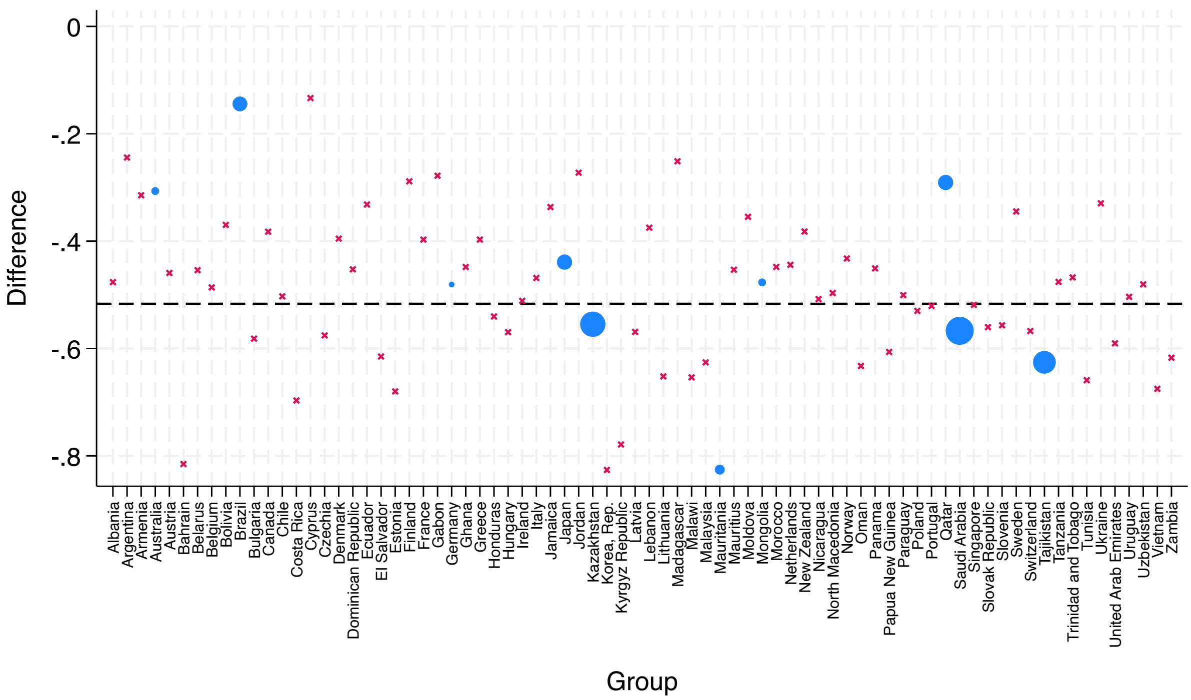

Figure A.2.14: Weights for Libya, 2011

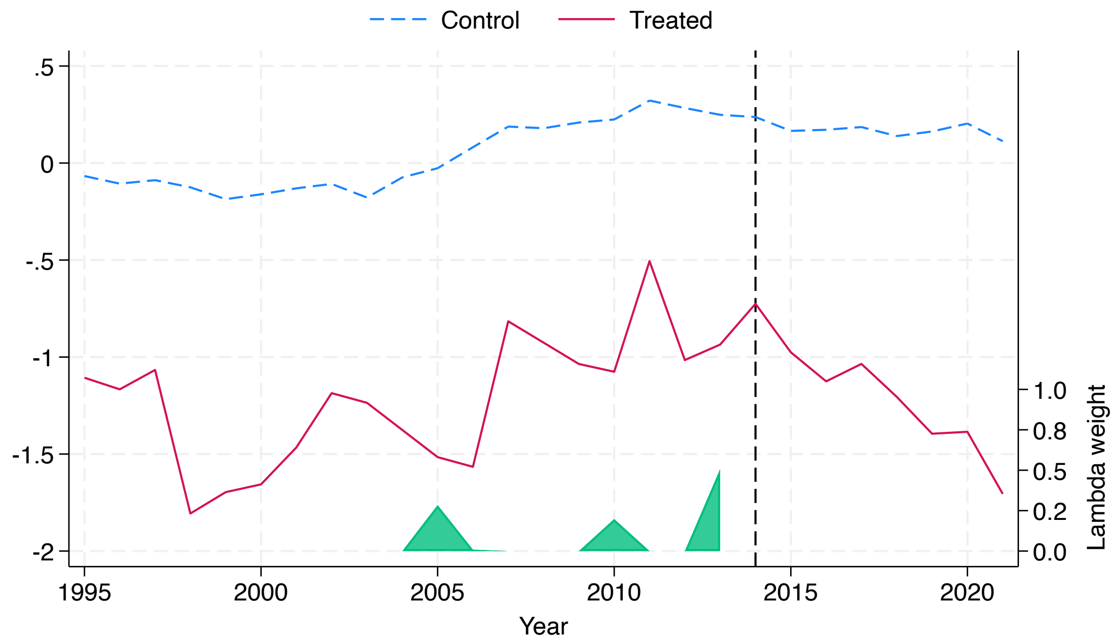

Figure A.2.15: Trends for Cameroon, 2014

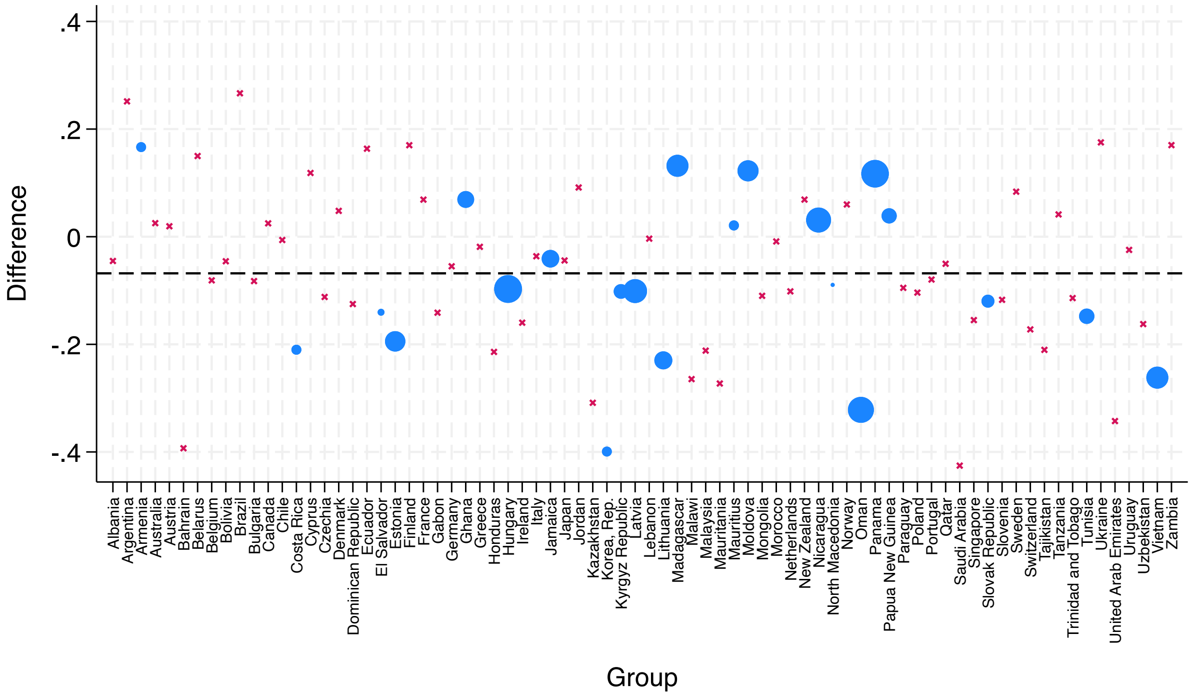

Figure A.2.16: Weights for Cameroon, 2014

A.3 Tables and Figures

Statistic	N	Mean	St. Dev.	Min	Max
Fatalities	2,052	0.197	2.630	0	47
ECI (SITC)	2,052	0.278	0.982	−2.120	2.860
GDPpc	2,052	17,664	19,151	370	94,184
GDPpc Growth (%)	2,052	2.200	4.170	−20.100	24.900
Population	2,052	18,455,688	29,645,022	514,325	209,550,294
FDIpc	2,024	957.	3,968.	−27,957	60,042
HCI	1,700	2.770	0.553	1.400	4.350

Table A.3.1: Summary Statistics for Control Countries

Statistic	N	Mean	St. Dev.	Min	Max
Fatalities	243	32.4	140.0	0	1,680
ECI (SITC)	243	−0.467	0.926	−2.780	1.390
GDPpc	243	5,749	7,850	566	28,292
GDPpc Growth (%)	243	1.090	8.750	−49.100	91.800
Population	243	48,573,632	59,579,858	4,410,832	239,477,801
FDIpc	242	130	272	−69.200	1,612
HCI	175	2.140	0.412	1.450	2.980

Table A.3.2: Summary Statistics for Treated Countries

Country	Conflict Year	Fatalities
Spain	2004	191
Togo	2005	436
Kenya	2007	134
Pakistan	2008	297
Zimbabwe	2008	253
Guinea	2009	160
Mexico	2010	220
Libya	2011	152
Cameroon	2014	1680

Table A.3.3: Treated Countries, First Year of Treatment, and Fatalities

Index Type	ATT	Std. Err.	t	P>|t|	[95% Conf. Interval]
ECI (SITC)	-0.20629***	0.06030	-3.42	0.001	(-0.32448, -0.08810)
ECI (HS)	-0.19654***	0.07368	-2.67	0.008	(-0.34096, -0.05212)

Note: Standard errors are calculated using the bootstrap method with 50 repetitions.
*p<0.1; **p<0.05; ***p<0.01

Table A.3.4: Estimated Treatment Effects on Economic Complexity Index (SITC and HS)

	τ	Std. Err.	Time
r1	-0.175^{***}	0.0525	2004
r2	-0.045	0.0498	2005
r3	-0.044^{**}	0.0208	2007
r4	-0.290^{***}	0.0785	2008
r5	0.043	0.0674	2009
r6	-0.100^{***}	0.0357	2010
r7	-0.808^{***}	0.0804	2011
r8	-0.220^{***}	0.0605	2014

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.3.5: Tau estimators: The treatment effect on the Economic Complexity Index (HS) by treatment year

B Declaration on the use of Generative AI

We cautiously embraced the recent innovations in Generative AI, especially the leading large language models (LLMs) ChatGPT [OpenAI, 2025] and DeepThink R1 [DeepSeek-AI, 2025]. ChatGPT was mainly used as an assistant to help write code in Python during the data cleaning process, as well as to construct more presentable tables and graphs based on our STATA output. DeepThink R1, with its strengths as a reasoning model, was mainly used to improve the logical flow of the paper by identifying lapses in our prose. For example, we used it to evaluate our proposed robustness checks on the SDiD framework. However, given the absence of clear guidelines on robustness checks on SDiD specifically, there was a noticeably high tendency to hallucinate. Yet, these hallucinations helped us to reevaluate the assumptions and feasibility of our own approach. Cognizant of GenAI's potential for confirmation bias, we used it to help critique our paper and understand the flaws before proceeding to manually address relevant concerns. In our case, GenAI is viewed as a sparring opponent used to challenge our line of thinking and the presentability of our research. The main insight on the usage of GenAI is that prompt engineering is important to provide the LLMs direction, which first requires us to have a very sound grasp of the subject matter. Since LLMs are trained upon the existing corpus spanning multiple disciplines, it can generate insights that elude researchers constrained within their individual fields. Hence, we emphasize that GenAI when used effectively can hone our ability for critical thought instead of blunting it.