Caught in a Trap: Simulating the Economic Consequences of Internal Armed Conflict*

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Abstract

This study presents a statistical model that quantifies the macroeconomic impact of the "conflict trap"—the tendency for countries experiencing conflict to relapse into it. The framework employs a Markov process to represent both conflict and post-conflict growth dynamics and conflict risk. We estimate the model and simulate the macroeconomic effects of falling into the conflict trap for different severity levels to analyze their impact on the overall economic burden. The conflict trap has a substantial negative impact on long-term economic development, with an average GDP per capita decline of 20%, and up to 50% in the most affected countries.

Keywords: Internal armed conflict, Economic development, Conflict trap, Economic growth

JEL Classification: D74, O11, O40

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1 Introduction

TASKS

HANNES: rewrite introudction and also do the ML bits, like ”why” GDP is a strong predictor of the trap.

Internal armed conflict is a major and growing concern for macroeconomic development.[1] It has proven bla bla bla . Furhtermore, by degrading material conditions and social cohesion, its sets the stage for more conflict, leadingto vicious cycles of open violence. Conflict leads to future conflict. This phenomenon is known as the *conflict trap*. Scholars have recognized the significant influence of the conflict trap on macroeconomic development. bla bla bla(Collier et al. 2003; Rohner, Thoenig, and Zilibotti 2013).[2] Yet, it reamins challeignig to quantify the effects of conflicti n the long ther because of thisdynamics since the attributie is hard the conflict trap is hard to define as it persists from the conflict into the post-conflict period.

This article proposes a model to quantify the cost of hte conflict trap.

We follow the conflict literature and assume that conflict dynamics can be captured by a Markov process (Besley and Mueller 2012; Hegre et al. 2013; Besley, Fetzer, and Mueller 2024) but extend the process to the post-conflict period to model the conflict trap. Figure 1 shows the conflict dynamics we incorporate into the model. The y-axis shows the likelihood of internal armed conflict in the next year during and after conflict.[3] The likelihood of remaining in conflict is very high, nearly 80 percent. In the first year of peace after conflict, the likelihood of a renewed outbreak is over 20 percent. It then falls monotonically to 3 percent after 4 years and stabilizes around that level. After 10 consecutive years of peace, the likelihood of resurgence is close to 2 percent. This means not only that conflict is self-perpetuating, but also that the post-conflict period is extremely risky - around half of the countries that escape from conflict will experience a resurgence before reaching 8 years of peace. This pattern of falling risk is extremely robust across time, sets of countries, and conflict definitions.

Our model of the conflict trap is a discrete-time Markov process where there is a state of conflict, multiple states of post-conflict peace which capture the pattern in Figure 1, and a state of stable peace. Modeling the post-conflict period as a sequence of different stages allows us to model the conflict trap in a tractable manner without sacrificing the Markov assumption. We

1. Over half of the world’s extreme poor is predicted to reside in countries marked by fragility, conflict, and violence (World Bank 2020). For an analysis, refer to Corral et al. (2020).

2. and its utility for predicting conflict (Hegre, Nygård, and Ræder 2017; Rohner and Thoenig 2021; Mueller and Rauh 2022).

3. Our conflict definition is discussed below. Mueller and Rauh (2022) exploit this same pattern to forecast conflict risk.

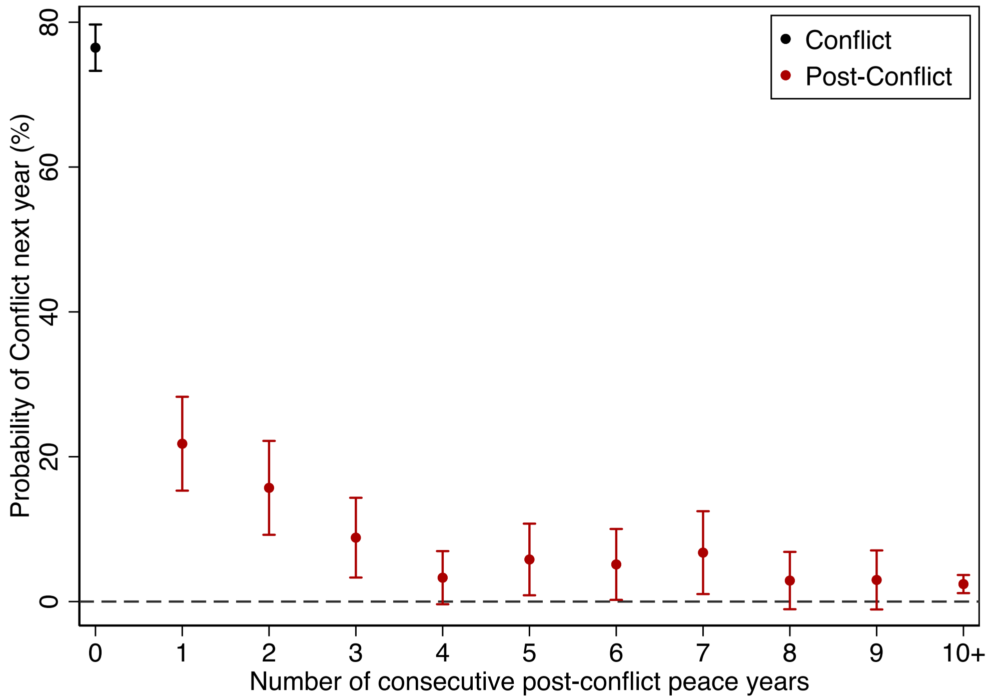

Figure 1: The Conflict Trap: high risk of conflict during conflict and post-conflict peace

Notes: Figure 1 shows the risk of renewed outbreak for the different number of consecutive years of peace after conflict. The risk is estimated using the proportion of transitions observed in the data. Point estimates are displayed as circles where bars indicate significance at 5% using the Wald method. Conflict is defined as surpassing the threshold of violence intensity that significantly harms the economy, which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year.
Source: Authors' calculations based on population data from the World Bank's World Development Indicators, and number of battle-related fatalities from Uppsala Conflict Data Program's Georeferenced Event Dataset.

estimate the transition matrix from the history of armed violence and the GDP per capita growth distribution of each state through a country fixed effects regression. We simulate dynamics between conflict and peace by drawing transition paths from the estimated transition matrix and draw growth rates from the corresponding distribution of the realized states. This allows us to estimate the distribution of developmental effects of the conflict trap holding fixed the severity of the trap. We find that entering a conflict results in an average GDP per capita loss of about 20% over 30 years using the full data set. This loss escalates to 30% at the 75th percentile and nearly 45% at the 90th percentile.

We then explore the role of the severity of conflict trap dynamics which we treat as a country characteristic. We use a Machine Learning (ML) model with cross-validation to predict the extent of the trap for each country using fixed characteristics. We use this prediction to partition our dataset into samples that are more and less prone to trap dynamics. We find that within the conflict-prone sample, the average GDP per capita loss approximates 30%, and losses for the 90th percentile exceed 50%. Even in the less conflict-prone sample, the economic impact remains substantial, with an average loss of about 15% and losses exceeding 35% at the 90th percentile. This underscores the importance of aiding countries in both exiting the conflict trap and, more importantly, preventing them from falling into it, as key strategies for development. We also show that, while the extent of the trap cannot be predicted perfectly, there is a predictable element to the dynamics of the trap. This makes our findings actionable in the sense that macroeconomic development in the most risky countries can be promoted through interventions designed to counter challenges posed by conflict.

Our statistical model provides a way to integrate post-war growth dynamics into the empirical discussion of the long-term effects of internal conflict. Long-run macroeconomic growth and the extent of violent conflict have often been linked theoretically (Rodrik 1999; Collier 2007; North, Wallis, and Weingast 2009; Besley and Persson 2011a). However, causal identification of the link running from conflict to long-run outcomes has been plagued by concerns of reverse causality and omitted variable bias. Empirical macro studies therefore tend to focus on the contemporaneous growth effects of war episodes (Collier 1999; Cerra and Saxena 2008; Mueller 2016; De Groot et al. 2022). Moreover, standard macroeconomic theory suggests that growth is particularly strong after civil wars as capital stocks re-adjust to higher productivity (Collier 1999). This would suggest that the long-term economic costs of conflict are relatively low. Although there is some empirical support for this hypothesis for external wars (Organski and Kugler 1977, Davis and Weinstein 2002, Steven Brakman and Schramm 2004, Miguel and Roland 2011), in the macro data there are no visible growth spurts at the end of internal conflicts (Cerra and Saxena 2008, Mueller 2012). In their review of the latest literature, Rohner and Thoenig (2021) emphasize the presence of macro-level complementarities that perpetuate "war traps" with devastating effects on long-term development.[4] We quantify the long-term effects of averse trap dynamics to demonstrate that a crucial aspect is the post-war risk of re-emerging conflict. Importantly, we use fixed effects growth estimates in our simulations and find relatively minor differences in the contemporaneous growth damages of conflict. Fixed country characteristics therefore drive long-term economic outcomes through the conflict trap dynamics they are associated with.

Our conflict trap model generates averse cycles of growth. These growth dynamics can be linked to macroeconomic studies on growth and volatility (Easterly et al. 1993; Ramey and

4. An additional rationale for the absence of readjustments after internal wars is that human capital is heavily affected and cannot readjust easily (Barro and Sala-i-Martin 2004). There is growing evidence that the costs of internal wars for health and human capital formation are severe (Ichino and Winter-Ebmer 2004; Blattman and Annan 2010; Leon 2012; Akresh et al. 2012; Tapsoba 2023).

Ramey 1995; Berg, Ostry, and Zettelmeyer 2012), particularly those identifying the cyclical growth patterns of emerging countries (Aguiar and Gopinath 2007; Garcia-Cicco, Pancrazi, and Uribe 2010). Aguiar and Gopinath (2007) note that emerging market growth is characterized by shocks to trend growth rather than transitory fluctuations around a stable trend. In other words, growth histories in emerging markets are characterized by long-lasting episodes in which economic growth is consistently low which are then followed by sudden growth spurts with a different trend growth. This is the kind of growth behavior that conflict traps generate but the two have not been linked in the Macro literature.

Finally, our methodology for endogenizing trap dynamics is based on the literature that analyzes the causes of conflict. We show issues like geographic features (Nunn and Puga 2012), political institutions (North, Wallis, and Weingast 2009; Besley and Persson 2011b; Robinson and Acemoglu 2012), natural resources (Dube and Vargas 2013; Bazzi and Blattman 2014; Berman et al. 2017) and ethnic and religious composition (Esteban and Ray 1994; Montalvo and Reynal-Querol 2005; Michalopoulos and Papaioannou 2016) can predict some of the variation in the extent of conflict and the conflict trap. We build on this literature by predicting both the extent of violence and time spent in the conflict trap in the period 1989-2021 using these factors and other factors like GDP per capita. We find that predictable conflict risk is associated with substantial long-term economic costs through a worsening of conflict trap dynamics. The crucial role played by GDP per capita levels in our prediction lends support to the view that conflict traps have a strong economic aspect.

The following section outlines the conceptual model of the conflict trap. Section 3 is dedicated to the model's estimation. In Section 4, we present and discuss the results, followed by our conclusions in the final section. Additional details on ML techniques and various robustness checks are available in the appendices.

2 A model of the conflict trap

This section presents our empirical model of the conflict trap. Our central assumption is that a country's transition between conflict and peace can be described by a discrete-time Markov process.

Let s_t represent the state at period t. It can take values from the state space defined as $S = \{0, 1, \ldots, i, \ldots, \tau, \tau + 1\}$. When $s_t = 0$, the country is in the state of *conflict*. When $s_t = k$ s.t. $k \in [1, \tau]$, the country is in the kth consecutive year of post-conflict peace. States 0 to τ form the conflict trap shown in Figure 1. States 1 to τ capture the post-conflict period in a strict chronological order. We refer to this post-conflict peace phase as *unstable peace*. Finally, when $s_t = \tau + 1$, the country is in *stable peace*, i.e. it is outside of the conflict trap. Stable peace represents a state that is not conditioned by the conflict history of a country - once a country escapes the conflict trap, transitions to conflict are as likely as in a country that never had a conflict.

When a country is in conflict ($s_t = 0$), it can either stay in conflict or transition to the first year of post-conflict peace ($s_t = 1$). When a country is in its first year of peace, it can either return to conflict or transition to the second year of post-conflict peace ($s_t = 2$). This pattern repeats until the country reaches τ consecutive years of post-conflict peace ($s_t = \tau$). At this point, the country can either go back to conflict or transition to stable peace ($s_t = \tau + 1$). The parameter τ determines the threshold of consecutive years of peace needed to escape from the conflict trap. Finally, a country in stable peace can either return to conflict or stay in stable peace.

By the structure of the Markov process we assume, a country can only transition in two directions, to conflict or to one more year of peace. This allows us to simplify the notation of the transition probabilities, making π_i to be the probability of transition to conflict from state i. Thus, $1 - \pi_i$ is the probability of adding a year of peace from state i. The transition matrix is

$$\mathbf{\Pi} = \begin{pmatrix} \pi_0 & 1-\pi_0 & 0 & \dots & 0 & 0 \\ \pi_1 & 0 & 1-\pi_1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \pi_\tau & 0 & 0 & \dots & 0 & 1-\pi_\tau \\ \pi_{\tau+1} & 0 & 0 & \dots & 0 & 1-\pi_{\tau+1} \end{pmatrix}$$

Note, the assumption of a Markov process implies that the dynamics in all countries can be described by a single transition matrix. Importantly, this also means that the likelihood of re-entering the conflict during the stabilization process or from stable peace is not a function of the longer history of the country. This is a stark simplification as much of the conflict literature links armed conflict outcomes to fixed characteristics like the colonial history of a country or its geographic features. Some countries will therefore have a higher baseline likelihood of conflict. However, we show in Section 3.2 that predicting which countries will get stuck in the trap based on pre-determined features is surprisingly difficult.

To capture the impact of conflict on development we focus on real GDP per capita. Denote GDP_t as the real GDP per capita when the Markov process is at period t. The realization of the state affects GDP_{t+1} by determining the distribution from which growth, u_{t+1}, is drawn, i.e., $u_{t+1}|s_{t+1} \sim f_{i=s_{t+1}}$. Then, at each period, GDP_{t+1} updates according to

$$GDP_{t+1} = GDP_t(1 + u_{t+1}) \tag{1}$$

For example, if a country is in conflict at period 2 ($s_2 = 0$), u_2 is drawn from f_0. Then, if $u_2 = -0.01$, it implies that GDP per capita is reduced by 1% from period 1 to 2 in the state of conflict.

We consolidate all the growth distributions into a single vector $\boldsymbol{f} = \begin{pmatrix} f_0 & f_1 & \dots & f_{\tau+1} \end{pmatrix}$ which we refer to as *growth vector*. We expect to draw lower growth from f_0 compared to the other elements of the growth vector. This kind of model will therefore lead to dynamics in which countries cycle back and forth between high and low growth episodes.

3 Estimation

3.1 Defining Conflict and Conflict Trap's length

Our definition of conflict is based on surpassing the threshold of violence intensity that significantly harms the economy. We measure violence intensity by calculating the number of battle-related deaths per capita using the Uppsala Conflict Data Program's Georeferenced Event Dataset (UCDP/GED) [5] together with population data from the World Bank's World Development Indicators (WB/WDI).[6] To find this threshold, we identify country-years with violence, arrange them in order of violence intensity, and bin them into deciles. We then run a country fixed effects regression of growth on these deciles, controlling for time fixed effects. We find that an appropriate threshold to define conflict is having as much violence as our seventh decile (top 40% most violent years), which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year.[7] According to this definition, there are 700 conflict country-years which makes our definition relatively inclusive when compared to the standard

5. UCDP defines an event as: "An incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date". We are using the "best" estimate of fatalities summing all types of violence and aggregating all fatalities for each country-year.

6. See Mueller (2016) for a more detailed analysis along these lines using subnational data.

7. The results are displayed in Figure B1 in Appendix B. A clear pattern emerges in which the most intense conflicts are also associated with the largest contraction of growth. The coefficients at the 7th, 8th, 9th, and 10th decile are significantly negative at the 10% level, and among these deciles, only the coefficient at the 8th decile is not significant at the 5% level.

1000 fatalities threshold with 400 conflict country-years. We also show robustness checks for more restrictive thresholds to define conflict.[8]

From Figure 1 we know that the risk of a renewed outbreak next year stabilizes for higher states. We choose $\tau = 7$ so be sure to have enough observations to have meaningful transition likelihoods.[9] This leads to a total of 9 states. We also conducted a robustness check with a shorter conflict trap.[10]

3.2 Predicting the Extent of the Conflict Trap

To study the role of the conflict trap at the intensive margin, we employ a ML model with cross-validation to predict its extent for each country. This prediction enables us to partition our dataset into a more and less conflict-prone sample. By re-running our analysis separately on these subsets, we quantify the effects of more and less pervasive types of conflict traps. This approach also enables us to identify which countries are at higher risk of being trapped.

A comprehensive dataset of country characteristics is constructed from various sources: Nunn and Puga (2012) (legal origin France, Africa dummy, ruggedness, % fertile soil, % desert, distance to coast, longitude and latitude), Montalvo and Reynal-Querol (2005) (ethnic polarization/fractionalization and religious polarization/fractionalization), Polity5 dataset (polity2 score, executive constraints, executive openness, and executive competitiveness) and the WB/WDI (natural resource dependence of GDP, GDP, and population). This represents a broad range of the factors typically considered important by the conflict literature. We use only the values of these variables that are pre-determined in our sample period. For a more detailed explanation of how missing data was addressed, see Appendix A.

We employ two ML models: a linear Lasso regression and a Random Forest. The predicted score is the share of years that the country is in the conflict trap in the period 1989-2021. We then use cross-validation to tune hyperparameters[11] and to calculate the R-squared statistics. For the Random Forest, the cross-validated R-squared score is 0.128, for the Lasso regression this is 0.149, and when we combine both through an average we get 0.173. We therefore always stick to the average of the two models (ensemble). Predicting the extent of the conflict trap in this way is relatively hard ex-ante with an R-squared of less than 20 percent. The out-of-sample

8. They lead to even larger estimates of the impact of internal armed conflict. See Figure B6 in Appendix B.

9. Mueller and Rauh (2022) show that conflict history loses its predictive power for renewed outbreaks between 4 and 10 years.

10. We tested $\tau = 4$ and the results are similar. See Figure B4 in Appendix B.

11. Everything is implemented in Python using the `sklearn` package. We find $Lasso - alpha$: $0.0001, RandomForest - max\_depth : 4, min\_samples\_leaf : 20, n\_estimators : 500$.

prediction ensures that we only use predictable variation of which countries are more conflict-affected in our analysis. We find that GDP per capita levels are a main predictor of trap risk.[12] This highlights the problem of reverse causality when studying the relationship between GDP conflict history in the cross-section.

Using the fitted value from this exercise we generate two samples. We split the sample such that each sub-sample contains a similar total number of years of conflict. The larger and less conflict-prone sample contains 80% of the sample. We refer to the specification of the whole data set as *aggregate sample*, to the less conflict-prone sample as *peaceful sample*, and to the more conflict-prone as *conflict sample*.

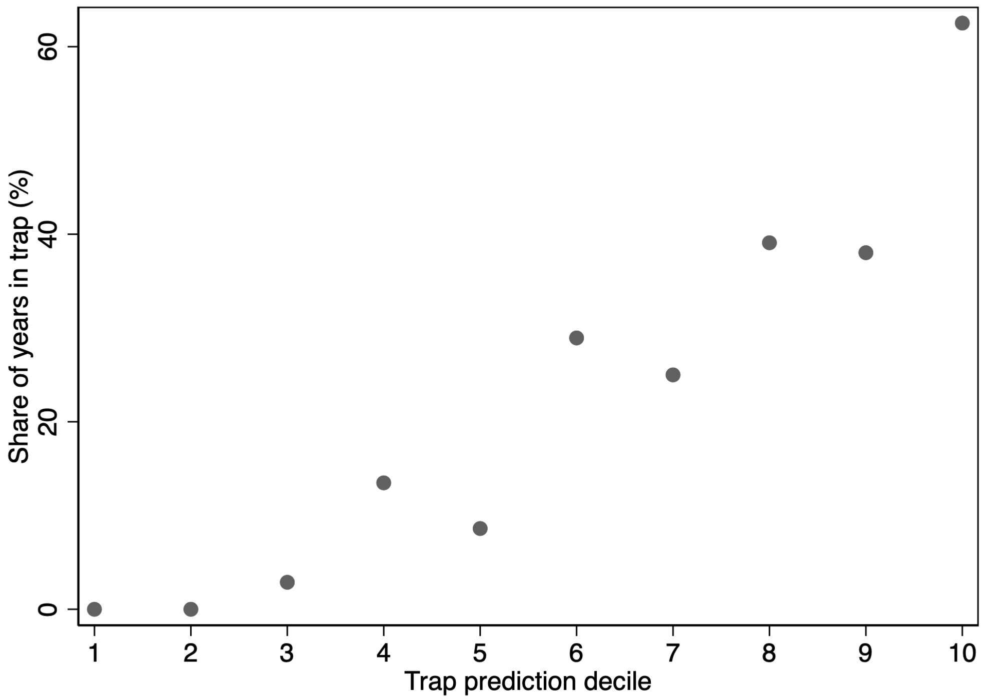

Figure 2: Risk Deciles and Extent of Conflict Trap

Notes: Figure 2 shows the ensemble prediction value binned by decile together with the average extent of the conflict trap in each of the bins. The 20 countries in the top trap risk decile spent more than 60% in the conflict trap in the period 1989-2021.

Source: Authors' calculations based on replication dataset from Nunn and Puga (2012) (legal origin France, Africa dummy, ruggedness, % fertile soil, % desert, distance to coast, longitude and latitude), Montalvo and Reynal-Querol (2005) (ethnic polarization/fractionalization and religious polarization/fractionalization), Polity5 dataset (polity2 score, executive constraints, executive openness, and executive competitiveness) and the WB/WDI (natural resource dependence of GDP, GDP, and population).

In Figure 2 we show the fit of the model. We binned countries into deciles according to the prediction score they obtained. We show these cross-fitted values on the x-axis an actual

12. See features' importances in Figure B2 in Appendix B.

variation in conflict trap exposure on the y-axis. The conflict-affected group defined as the countries in the 9th and 10th deciles would go on to spend half their years in the conflict trap. We will return to this point after presenting our main results in Section 4.

3.3 Transition Matrix and Growth Vector

The transition matrix is estimated using the proportion of transitions observed in the data. The corresponding estimates for each specification are shown in Table 1. When using the whole dataset, the likelihood of staying in an additional year of conflict is 76%. This leads to an expected duration of uninterrupted conflict of 4.17 years.[13] Once conflict ends, the likelihood of going back to conflict falls dramatically to 22% in the first year after conflict, 16% in the second year, and 7% after seven years in peace. Finally, the baseline likelihood of conflict is just 2% in stable peace. On average, it takes 18.46 years, i.e. almost two decades, to escape from the trap.[14]

Table 1: Estimated transition probabilities

	Stay in Conflict	Unstable Peace to Conflict							Stable Peace to Conflict
	$\hat{\pi}_0$	$\hat{\pi}_1$	$\hat{\pi}_2$	$\hat{\pi}_3$	$\hat{\pi}_4$	$\hat{\pi}_5$	$\hat{\pi}_6$	$\hat{\pi}_7$	$\hat{\pi}_8$
AS	0.76	0.22	0.16	0.09	0.03	0.06	0.05	0.07	0.02
PS	0.71	0.20	0.12	0.07	0.03	0.07	0.04	0.06	0.01
CS	0.82	0.24	0.23	0.12	0.03	0.03	0.08	0.08	0.05

Notes: Table 1 shows the estimated transition probabilities for each specification: the aggregate sample (AS), the peaceful sample (PS), and the conflict sample (CS). They are estimated using the proportion of transitions observed in the data. $\hat{\pi}_i$ denotes the probability of transitioning to conflict from state i, where $i = 0$ is conflict, $i = k$ s.t. $k \in [1, 7]$ is the kth number of consecutive years in post-conflict peace, and $i = 8$ is stable peace. Conflict is defined as surpassing the threshold of violence intensity that significantly harms the economy, which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year.
Source: Authors' calculations based on population data from WB/WDI, and number of battle-related fatalities from UCDP/GED. The methodology for sample partitioning is described in Section 3.2

Comparing the other two specifications, the transition probabilities show that the likelihood of transitioning to conflict is significantly higher in the conflict sample for most of the states, indicating a higher tendency to remain in the conflict trap. Specifically, the expected duration of uninterrupted conflict is 3.45 years for the peaceful sample and 5.56 years for the conflict one. Meanwhile, the expected number of periods in the conflict trap is 15.72 for the peaceful sample and 24.49 for the conflict one. Note that the pattern of high persistence in conflict

13. We calculate it using the geometric distribution formula: $1/(1 - \hat{\pi}_0)$.
14. To obtain this statistic one can use the fundamental matrix of $\hat{\mathbf{\Pi}}$ when stable peace is set to be an absorbing state.

and falling risks in post-conflict is robust across samples. However, the conflict sample suffers a significantly higher baseline risk of conflict outbreaks from stable peace. This is the only element we will not include in our simulations.

To estimate the growth vector, we regress GDP per capita growth on a set of dummy variables d_{ijt} that correspond to the state of country j at year t. We use GDP (in constant 2015 US$) covering the period from 1989 to 2021 across over 190 countries. The regression equation is

$$Growth_{jt} = \sum_{i=0}^{\tau} \beta_i d_{ijt} + \mu_j + \gamma_t + \varepsilon_{jt}, \tag{2}$$

where μ_j and γ_t represent country and time fixed effects respectively. The omitted category is stable peace. The results for each specification are shown in Table 2. In all specifications, a year in conflict lowers growth by more than 3 percentage points, which lies inside the bounds of the literature. Importantly, the different conflict samples produce very similar findings regarding the growth effects of conflict. The coefficients of the rest of the states are small and insignificant in all specifications.

Both concerns of omitted variable bias and reverse causality apply to cross-country regressions. There is now, however, a large literature that shows that conflict has large economic causal effects at the micro level,[15] and Rohner and Thoenig (2021) concludes that these probably still constitute a lower bound. The causal interpretation is in line with the finding that more intense violence is associated with more dramatic declines in growth.[16] In any case, we are using reliable estimates with a reasonable claim to identification and outside validity. These results are also robust to a more demanding specification with country time trends.[17] Lastly, considering recent debates on the problems of two-way fixed effects in cases of potentially heterogeneous treatment (De Chaisemartin and d'Haultfoeuille 2020; Callaway and Sant'Anna 2021; Sun and Abraham 2021),[18] we can show that these are not an issue in our case.[19]

Since stable peace is the omitted category, we normalize growth for this state to 0, i.e. $\hat{f}_{\tau+1} = 0$. For the rest of the states, the growth distribution follows a normal distribution

15. Guiso, Sapienza, and Zingales (2009), Cassar, Grosjean, and Whitt (2011), and Rohner (2011) provide evidence that conflict diminishes economic activity by eroding trust, cooperation, and trade. Conversely, findings on the reverse channel at the country level have given contradictory or weak results Bazzi and Blattman (2014) and Berman and Couttenier (2015).

16. In our robustness analysis with stricter conflict definitions, we observe that higher violence intensity results in greater economic losses. See Figure B1 in Appendix B.

17. See Table C10 in Appendix C.

18. See De Chaisemartin and d'Haultfoeuille (2023) for a related survey.

19. Using the command `twowayfeweights` we find that the proportion of negative weights is less than 5% and their sum is -0.0018.

Table 2: Estimation of the growth vector

	Aggregate Sample	Peaceful Sample	Conflict Sample
	GDP per capita Growth		
Conflict	-0.0320	-0.0335	-0.0320
	(0.00823)	(0.0112)	(0.0111)
1st Year Post-conflict Peace	0.00481	0.00419	0.00568
	(0.00761)	(0.0108)	(0.00894)
2nd Year Post-conflict Peace	0.00176	0.00494	-0.00276
	(0.00713)	(0.0102)	(0.00710)
3rd Year Post-conflict Peace	0.000921	0.000639	-0.00111
	(0.00633)	(0.00790)	(0.0106)
4th Year Post-conflict Peace	0.00608	0.00495	0.00355
	(0.00562)	(0.00700)	(0.00998)
5th Year Post-conflict Peace	0.000295	0.000306	-0.000776
	(0.00503)	(0.00570)	(0.00977)
6th Year Post-conflict Peace	0.00217	0.000923	0.00112
	(0.00461)	(0.00541)	(0.00950)
7th Year Post-conflict Peace	0.00155	-0.00387	0.0122
	(0.00417)	(0.00455)	(0.00840)
Observations	5730	4676	1054
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
(Within country) R^2	0.122	0.175	0.0815

Notes: Table 2 shows the regression results from equation 2 used to estimate the growth vector for each specification: the aggregate sample, the peaceful sample, and the conflict sample. A country fixed effects model is employed where GDP per capita growth is regressed on a set of dummies representing the states of the model. The base category is stable peace, defined as having more than 7 consecutive years of post-conflict peace. Year fixed effects were also included as control variables. Conflict is defined as surpassing the threshold of violence intensity that significantly harms the economy, which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year. Robust standard errors are in parentheses.
Source: Authors' calculations based on GDP (constant 2015 US$) and population data from WB/WDI, and number of battle-related fatalities from UCDP/GED. The methodology for sample partitioning is described in Section 3.2.

with the estimated coefficient as the mean and the standard error as the standard deviation. Formally, for $h \in S$ s.t. $h \leq \tau$, $\hat{f}_h = \mathcal{N}(\hat{\beta}_h, \hat{\sigma}_h^{SE})$ with $\hat{\sigma}_h^{SE}$ being the standard error of β_h. Therefore, the estimated growth vector is given by the growth estimates from Table 2 with a 0 added, i.e., $\hat{\boldsymbol{f}} = \left(\mathcal{N}(\hat{\beta}_0, \hat{\sigma}_0^{SE}) \quad \mathcal{N}(\hat{\beta}_1, \hat{\sigma}_1^{SE}) \quad \dots \quad 0\right)$. This means that GDP per capita growth is stochastic for all states but not for stable peace due to the 0 growth normalization that we impose. Assumptions regarding the baseline growth do not affect the relative GDP losses we show in the results.

Note that the different specifications have very similar growth vectors. This suggests that any variation between them in the simulation results can be mainly attributed to differences in conflict dynamics, rather than to variations in the impact of conflict itself. Furthermore, a reduction of 3 percentage points is significant, but it is unclear whether such a number can explain large cross-country differences.

3.4 Simulation

Given our estimated Markov model composed by the estimated transition matrix ($\hat{\mathbf{\Pi}}$) and growth vector ($\hat{\boldsymbol{f}}$), we can simulate growth paths that countries experience as they move through the state space.

We make a thought experiment in which a control group of countries is always in stable peace which always generates 0 growth. The treated group of countries suffers an outbreak of conflict. Treated countries start with $GDP_0 = 100$ and in the state of conflict.[20] Importantly, we make stable peace absorbing ($\hat{\pi}_8 = 0$) to capture the net aggregate effect of falling into the conflict trap once. We draw transition paths from the estimated transition matrix and the growth from the corresponding distribution in the growth vector. The simulation has $T = 30$ periods and it is repeated $N = 100000$ times to get a good sense of the distribution of the GDP loss (compared to $GDP_t = 100$) over time.

Note that we only impose a starting year in conflict, along with its associated immediate economic impact. The long-term losses stem from the repeated outbreaks of violence a typical country will suffer after this initial onset. In this way, we are able to study the effect of the conflict trap in isolation. This provides a nuanced interpretation of the results, which differs from the conflict literature where aggregate losses are typically reported conditional on the specific duration of one conflict episode.

4 Results

The results of the simulations for each specification are shown in Figure 3. The x-axis of the figures counts the years after an outbreak of conflict in the treated sample. Since all treated countries start in conflict, the loss increases sharply. Then, as time goes by, more countries first

20. The distribution of states in period 0 is $\boldsymbol{p_0} = \begin{pmatrix} 1 & 0 & \dots & 0 \end{pmatrix}'$.

leave ongoing conflict and escape the conflict trap. When a large part of the treated samples reaches absorbing stable peace growth converges back to the benchmark's growth rate.

In the aggregate sample (shown on the left), the average loss in GDP per capita after 30 years is almost 20%. This is a large effect. For comparison, the median growth of GDP per capita in the 30 years between 1990 to 2020 was about 50 percent. Importantly, there is a large heterogeneity across simulations with the 75th percentile experiencing a decline of 30% while the 90th percentile declines by almost 45%. In other words, doing better or worse inside the conflict trap can explain substantial changes in the long-run.[21]

When comparing the two other samples, the higher conflict tendency of the conflict sample leads to significantly greater losses, the average loss in the conflict sample is almost twice as high than in the peaceful sample. More strikingly, the 90th percentile of the conflict sample reaches losses above 50%. Losses in the 90th percentile in the peaceful sample are 35% which makes the conflict trap important even here. Overall, we get a good understanding that both the extensive and intensive margins matter.

As discussed in the previous section the larger losses in the conflict sample are the result of a more severe conflict trap dynamics with more persistent conflict and a higher likelihood of re-surging conflict in the years after conflict. Keep in mind that our classification was based on cross-validated predictions which suggest that the conflict sample would spend around half of its time in the conflict trap. Our results suggest that if such a sample can be identified today—perhaps through existing conflict histories or other structural factors—we can expect severe macroeconomic effects of the conflict trap for this sample.

5 Conclusion

This study aims to enhance our comprehension of the long-term developmental consequences of the conflict trap. To achieve this, we propose a simple framework that combines a probabilistic model of conflict dynamics with within-country estimates of economic costs. Together, we can simulate the growth trajectories that countries follow as they navigate through periods of conflict and peace. We use ML techniques to predict conflict trap's extent for each country, allowing us to classify our dataset into more and less conflict-prone samples and conduct separate analyses on these groups.

21. We checked whether the random growth element coming from the growth regression alone can explain some of this variation. We find that the long-run level changes that could be explained by this part are small. For more information, see Figure B5 in Appendix B.

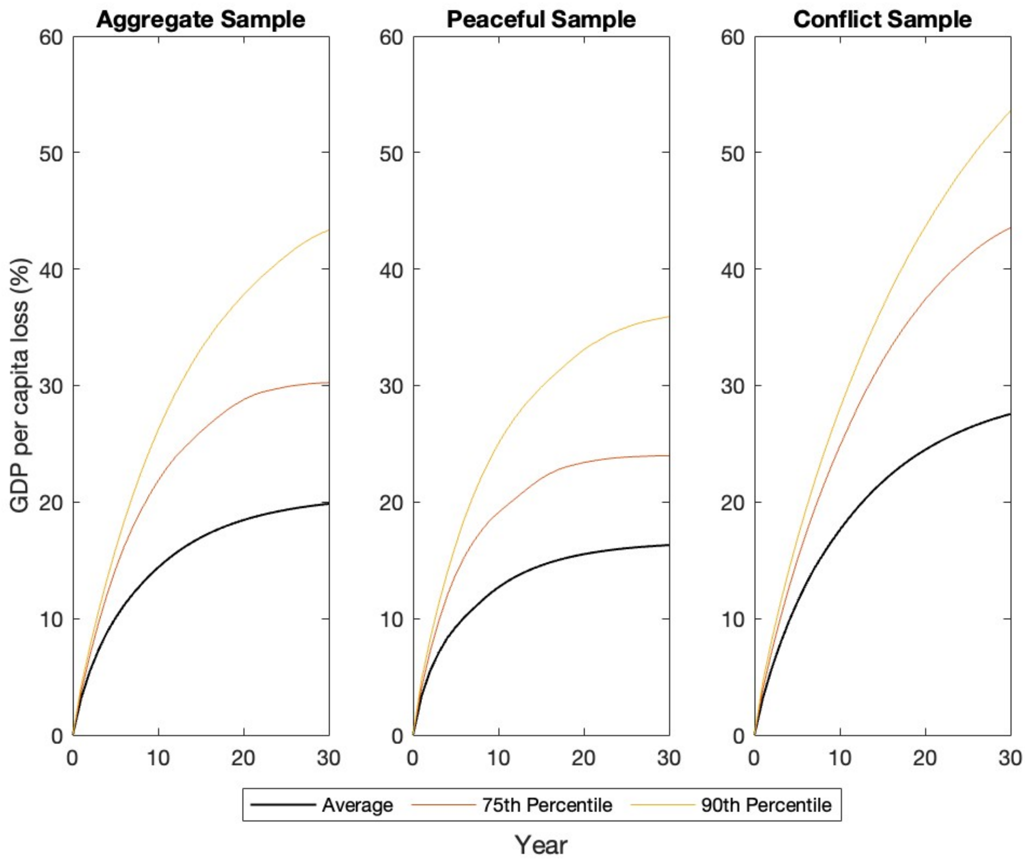

Figure 3: Evolution of GDP per capita loss

Notes: Figure 3 describes the evolution of GDP per capita loss due to entering into conflict for each specification: the aggregate sample, the peaceful sample, and the conflict sample. Growth paths are simulated for countries as they transition through the state space, utilizing the respective estimated transition matrix from Table 1 and growth vector from Table 2. Countries start in conflict and stable peace is absorbing. Conflict is defined as surpassing the threshold of violence intensity that significantly harms the economy, which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year. The distribution at each period is described by the average, 75th percentile, and 90th percentile. The horizon for simulation is $T = 30$, and the number of simulations conducted is $N = 100000$. The methodology for sample partitioning is described in Section 3.2

The simulation results show that entering conflict will induce an average loss in GDP per capita after 30 years by close to 20%, a loss of 30% in the 75th percentile, and a decline of nearly 45% in the 90th percentile. The loss in the 90th percentile for the conflict sample is more than 50% and for the peaceful one is still 35%. We only impose one outbreak of conflict, and the remainder of the losses are due to the effect of the estimated conflict dynamics. This underscores that aiding countries in exiting the conflict trap, and more importantly, preventing them from falling into it in the first place, are key to development.

Another takeaway from our method is that predicting the extent of the conflict trap both in the long-run and in the short run should help target preventative policies. The model we estimate using a simple ML ensemble produces a highly imperfect forecast which could nonetheless help flag countries that would be affected by the conflict trap much more severely. If such a sample can be identified today, for example through forecasting or simple conflict histories, thinking about policies for escaping the conflict trap becomes a prerogative from a Macroeconomic perspective.

Our model is modular in the sense that it allows using estimates derived from different methodologies regarding the economic costs of conflict. We use cross-country regressions with fixed effects to derive the cost of ongoing conflict and our results are consistent with comparable subnational studies (Abadie and Gardeazabal 2003; Mueller 2016). However, our framework is not restricted to using these results. If comparable evidence from, say, natural experiments on the cost of conflict become available, these can easily be used to simulate growth effects. Thus, the flexible structure of our model allows research to rely on the best available estimates.

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Online Appendices

A Filling Missing Data in the Cross-Country Sample

Several variables are not available for the entire sample like the share of GDP produced in the natural resource sector in the previous years, the earlier average over the polity2 score, executive constraints, executive openness and executive competitiveness from the Polity5 dataset, and ethnic and religious fractionalization and polarization scores from Montalvo and Reynal-Querol (2005).

We impute the average values for all variables with missing values. We impute missing values through a clustering method that uses continent, longitude, and latitude to match countries. Note, this imputation imposes some measurement error but experiments with the smaller sample suggest performance is not affected substantially.

B Appendix Figures

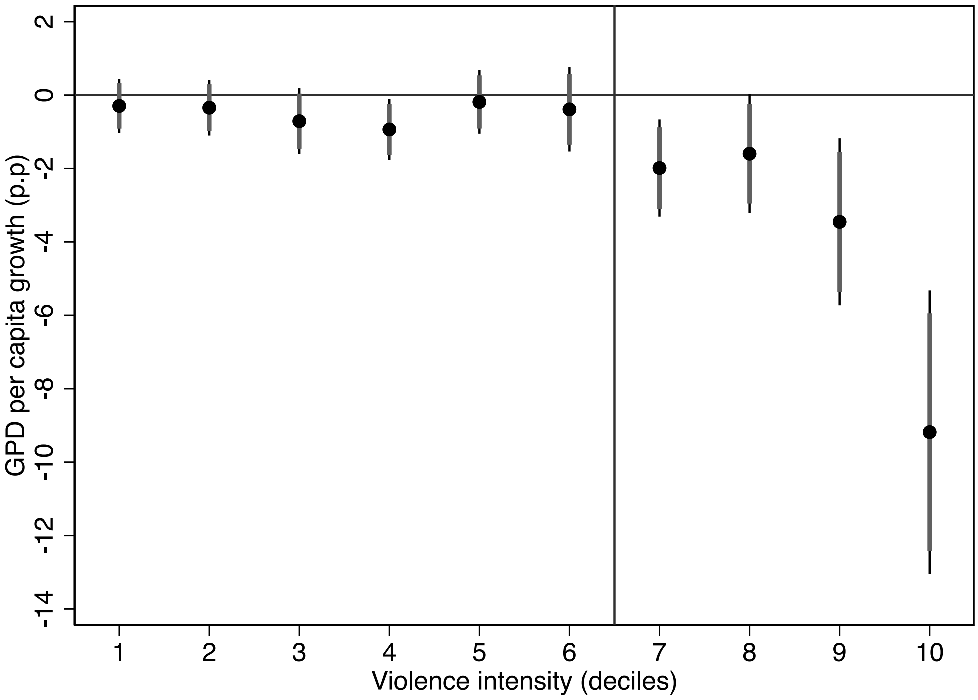

Figure B1: Violence intensity and economic growth

Notes: Figure B1 depicts the impact on GDP per capita growth for different levels of violence intensity, categorized by deciles. A country fixed effects model is used, where GDP per capita growth is regressed on a set of dummies representing each decile while controlling for year fixed effects. Violence intensity is quantified by the number of battle-related deaths per capita. Point estimates are displayed as circles where grey bars and black bars indicate significance at 5% and 10% respectively using robust standard errors.
Source: Authors' calculations based on GDP (constant 2015 US$) and population data from WB/WDI, and number of battle-related fatalities from UCDP/GED.

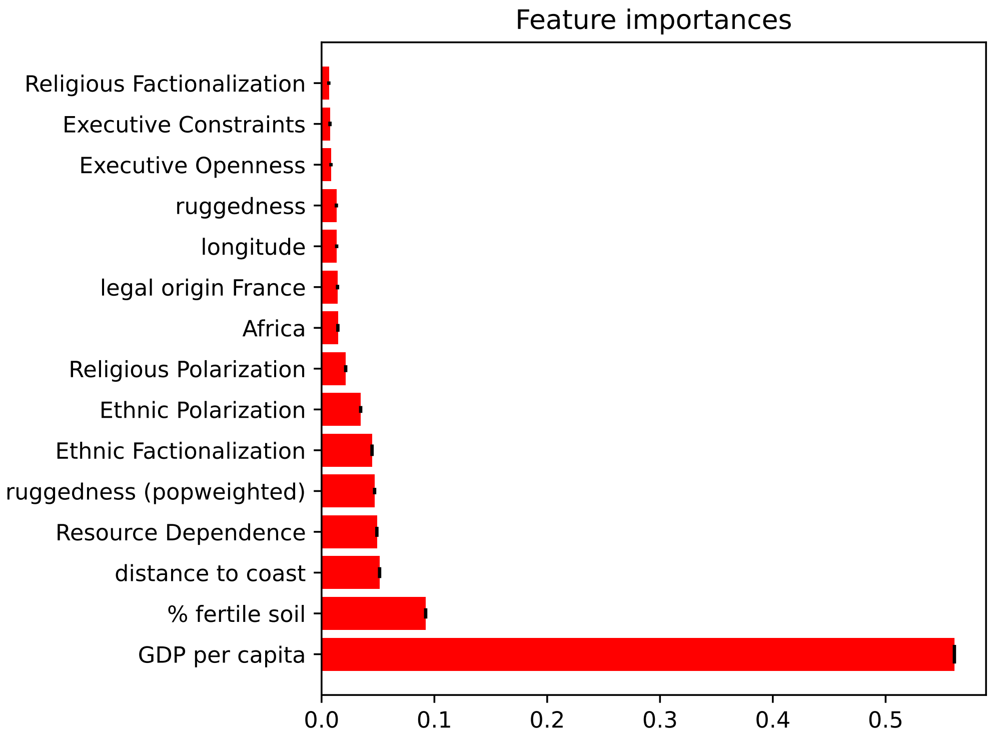

Figure B2: Importances of Random Forest when Predicting Conflict Trap

Notes: Figure B2 shows the variables' importances in the random forest model for the 15 most important variables according to the random forest. A variable is deemed important if it appears often and tends to be chosen towards the top of the decision trees in the forest. In sklearn, feature importances are provided by the fitted attribute feature importances.

Source: Authors' calculations based on replication dataset from Nunn and Puga (2012) (legal origin France, Africa dummy, ruggedness, % fertile soil, % desert, distance to coast, longitude and latitude), Montalvo and Reynal-Querol (2005) (ethnic polarization/fractionalization and religious polarization/fractionalization), Polity5 dataset (polity2 score, executive constraints, executive openness, and executive competitiveness) and the WB/WDI (natural resource dependence of GDP, GDP, and population).

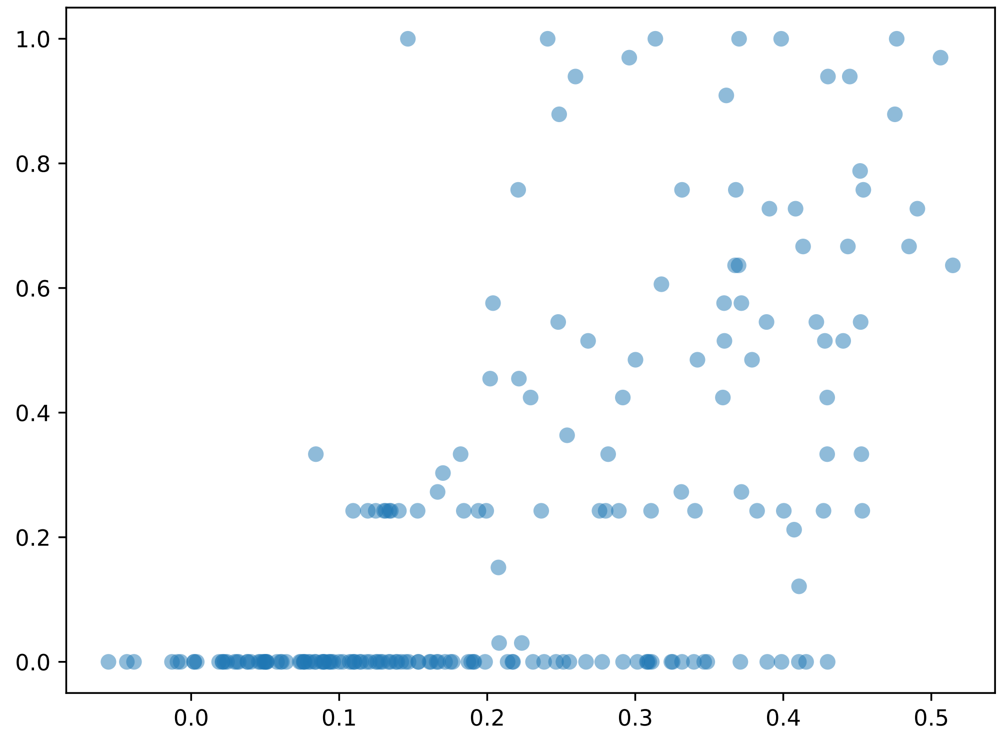

Figure B3: Fitted Values of Ensemble Model and Actual Values

Notes: Figure B3 shows the within-fitted values (x-axis) when compared to the actual variation (y-axis). Note that the dependent variable here is the share spent inside the conflict trap and is therefore a value between 0 and 1. The ensemble is the mean of two prediction scores one of which is a linear regression model and is therefore not guaranteed to lie between 0 and 1. Note, this does not affect our classification into two classes.

Source: Authors' calculations based on replication dataset from Nunn and Puga (2012) (legal origin France, Africa dummy, ruggedness, % fertile soil, % desert, distance to coast, longitude and latitude), Montalvo and Reynal-Querol (2005) (ethnic polarization/fractionalization and religious polarization/fractionalization), Polity5 dataset (polity2 score, executive constraints, executive openness, and executive competitiveness) and the WB/WDI (natural resource dependence of GDP, GDP, and population).

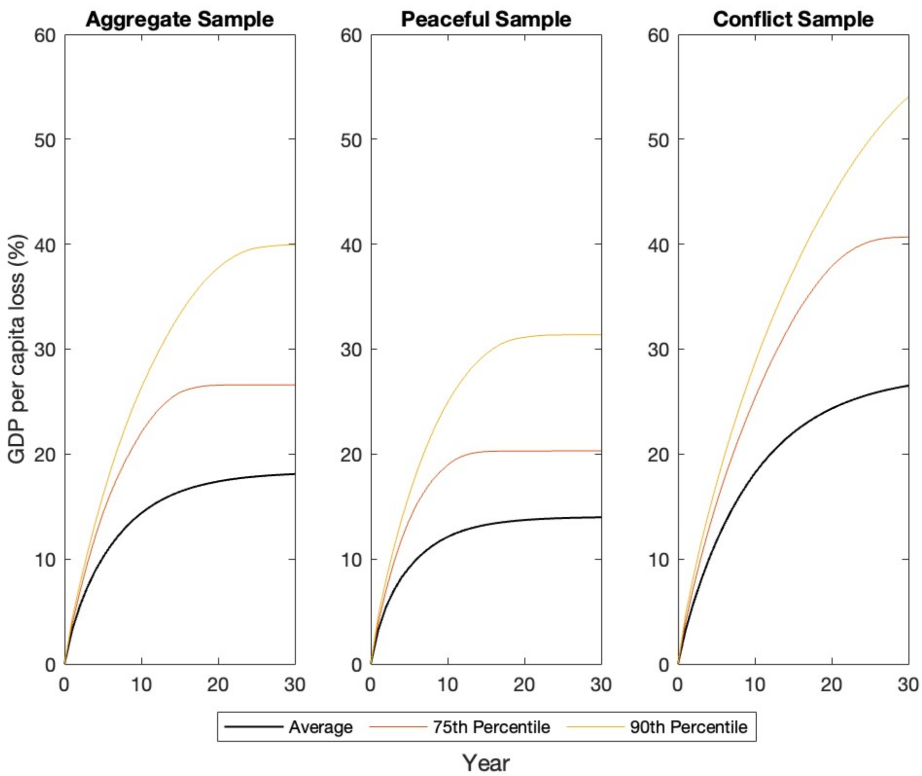

Figure B4: Evolution of GDP per capita loss with $\tau = 4$

Notes: Figure B4 describes the evolution of GDP per capita loss due to entering into conflict when $\tau = 4$ for each specification: the aggregate sample, the peaceful sample, and the conflict sample. Growth paths are simulated for countries as they transition through the state space, utilizing a re-estimated transition matrix (see Table C8) and a re-estimated growth vector (see Table C9). Countries start in conflict and stable peace is absorbing. Conflict is defined as surpassing the threshold of violence intensity that significantly harms the economy, which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year. The distribution at each period is described by the average, 75th percentile, and 90th percentile. The horizon for simulation is $T = 30$, and the number of simulations conducted is $N = 100000$. The methodology for sample partitioning is described in Section 3.2

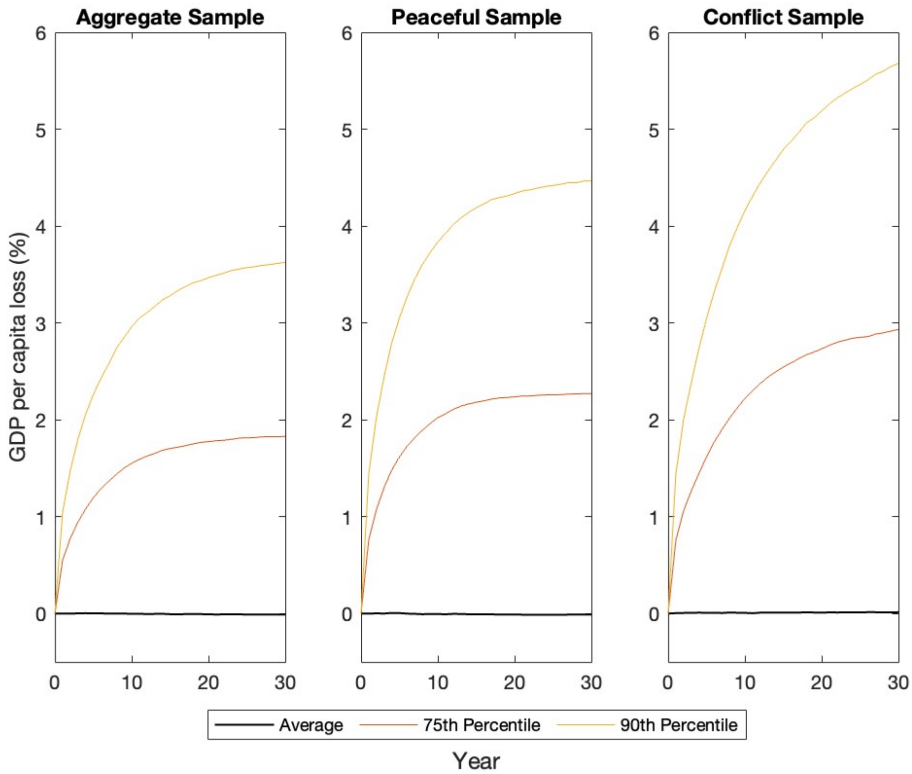

Figure B5: Evolution of GDP per capita loss due to the variation component of the estimation

Notes: Figure B5 describes the evolution of GDP per capita loss due to entering into conflict caused solely by the variation component of the estimation for each specification: the aggregate sample, the peaceful sample, and the conflict sample. To achieve this, the effect coming from the coefficients is eliminated, which represents the means in the growth vector. Formally, for $h < \tau + 1$, $\hat{f}_h = \mathcal{N}(0, \hat{\sigma}_h^{SE})$. The transition matrix for each specification is the same as in the main setting (Table 1) and the standard errors come from Table 2. Countries start in conflict and stable peace is absorbing. Conflict is defined as surpassing the threshold of violence intensity that significantly harms the economy, which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year. The distribution at each period is described by the average, 75th percentile, and 90th percentile. The horizon for simulation is $T = 30$, and the number of simulations conducted is $N = 100000$. The methodology for sample partitioning is described in Section 3.2

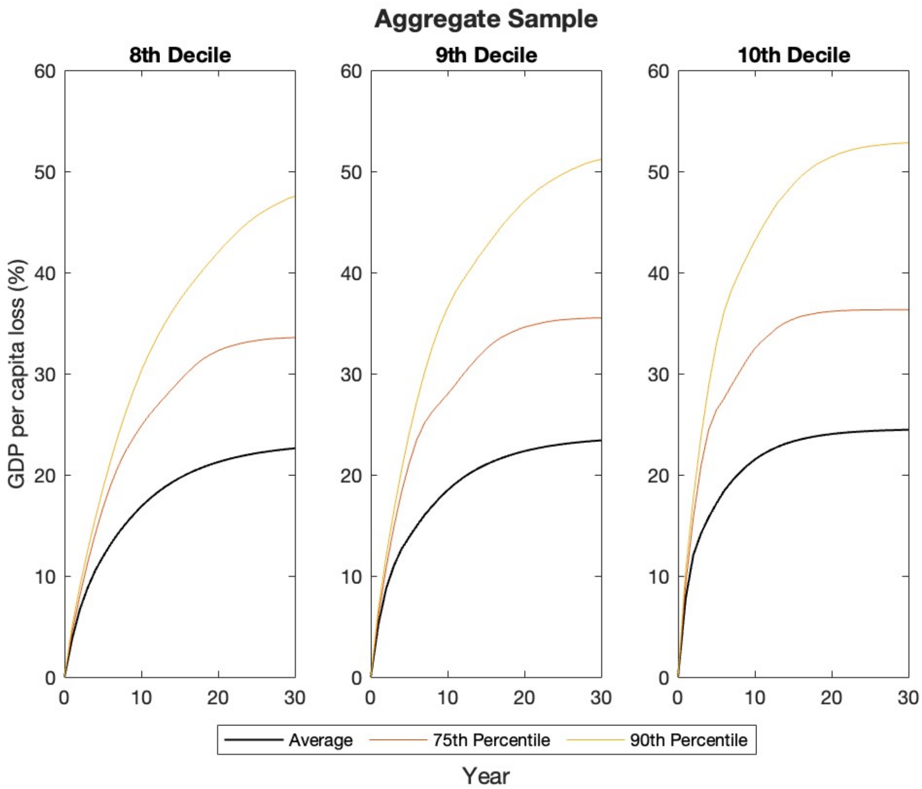

Figure B6: Evolution of GDP per capita loss for more restrictive definitions of conflict

Notes: Figure B6 describes the evolution of GDP per capita loss due to entering into conflict for different conflict definitions, each associated with surpassing different deciles of violence. Growth paths are simulated for countries as they transition through the state space, utilizing a re-estimated transition matrix (see Table C6) and a re-estimated growth vector (see Table C7) based on the aggregate sample. Countries start in conflict and stable peace is absorbing. Conflict is defined as having more than 21.71 (8th decile), 51.77 (9th decile), and 155.56 (10th decile) battle-related deaths per million inhabitants during a year. The distribution at each period is described by the average, 75th percentile, and 90th percentile. The horizon for simulation is $T = 30$, and the number of simulations conducted is $N = 100000$.

C Appendix Tables

Table C1: Country Data Overview

ISO	Years	CS	ISO	Years	CS	ISO	Years	CS	ISO	Years	CS
AFG	2003 - 2020	0	AGO	1990 - 2020	0	ALB	1990 - 2020	0	AND	1990 - 2020	0
ARE	1990 - 2020	0	ARG	1990 - 2020	0	ARM	1991 - 2020	0	ATG	1990 - 2020	0
AUS	1990 - 2020	0	AUT	1990 - 2020	0	AZE	1991 - 2020	0	BDI	1990 - 2020	1
BEL	1990 - 2020	0	BEN	1990 - 2020	0	BFA	1990 - 2020	1	BGD	1990 - 2020	0
BGR	1990 - 2020	0	BHR	1990 - 2020	0	BHS	1990 - 2020	0	BIH	1995 - 2020	0
BLR	1991 - 2020	0	BLZ	1990 - 2020	0	BMU	1990 - 2020	0	BOL	1990 - 2020	0
BRA	1990 - 2020	0	BRB	1990 - 2020	0	BRN	1990 - 2020	0	BTN	1990 - 2020	0
BWA	1990 - 2020	0	CAF	1990 - 2020	1	CAN	1998 - 2020	0	CHE	1990 - 2020	0
CHL	1990 - 2020	0	CHN	1990 - 2020	1	CIV	1990 - 2020	1	CMR	1990 - 2020	1
COD	1990 - 2020	1	COG	1990 - 2020	1	COL	1990 - 2020	0	COM	1990 - 2020	0
CPV	1990 - 2020	1	CRI	1990 - 2020	0	CUB	1990 - 2020	0	CYP	1990 - 2020	0
CZE	1991 - 2020	0	DEU	1990 - 2020	0	DJI	2014 - 2020	1	DMA	1990 - 2020	0
DNK	1990 - 2020	0	DOM	1990 - 2020	0	DZA	1990 - 2020	0	ECU	1990 - 2020	0
EGY	1990 - 2020	1	ERI	1993 - 2011	1	ESP	1990 - 2020	0	EST	1996 - 2020	0
ETH	1990 - 2020	1	FIN	1990 - 2020	0	FJI	1990 - 2020	0	FRA	1990 - 2020	0
FSM	1990 - 2020	0	GAB	1990 - 2020	0	GBR	1990 - 2020	0	GEO	1990 - 2020	0
GHA	1990 - 2020	0	GIN	1990 - 2020	1	GMB	1990 - 2020	0	GNB	1990 - 2020	1
GNQ	1990 - 2020	1	GRC	1990 - 2020	0	GRD	1990 - 2020	0	GTM	1990 - 2020	0
GUY	1990 - 2020	0	HKG	1990 - 2020	0	HND	1990 - 2020	0	HRV	1996 - 2020	0
HTI	1990 - 2020	0	HUN	1992 - 2020	0	IDN	1990 - 2020	0	IND	1990 - 2020	0
IRL	1990 - 2020	0	IRN	1990 - 2020	0	IRQ	1990 - 2020	1	ISL	1996 - 2020	0
ISR	1996 - 2020	0	ITA	1990 - 2020	0	JAM	1990 - 2020	0	JOR	1990 - 2020	0
JPN	1990 - 2020	0	KAZ	1991 - 2020	0	KEN	1990 - 2020	0	KGZ	1990 - 2020	1
KHM	1994 - 2020	0	KIR	1990 - 2020	0	KNA	1990 - 2020	0	KOR	1990 - 2020	0
KWT	1993 - 2020	0	LAO	1990 - 2020	0	LBN	1990 - 2020	0	LBR	2001 - 2020	1
LBY	2000 - 2020	1	LCA	1990 - 2020	0	LKA	1990 - 2020	0	LSO	1990 - 2020	0
LTU	1996 - 2020	0	LUX	1990 - 2020	0	LVA	1996 - 2020	0	MAC	1990 - 2020	0
MAR	1990 - 2020	1	MCO	1990 - 2019	0	MDA	1996 - 2020	0	MDG	1990 - 2020	0
MDV	1996 - 2020	0	MEX	1990 - 2020	0	MHL	1990 - 2020	0	MKD	1991 - 2020	0
MLI	1990 - 2020	1	MLT	1990 - 2020	0	MMR	1990 - 2020	0	MNE	1998 - 2020	0
MNG	1990 - 2020	0	MOZ	1990 - 2020	0	MRT	1990 - 2020	1	MUS	1990 - 2020	0
MWI	1990 - 2020	0	MYS	1990 - 2020	0	NAM	1990 - 2020	0	NER	1990 - 2020	1
NGA	1990 - 2020	0	NIC	1990 - 2020	0	NLD	1990 - 2020	0	NOR	1990 - 2020	0
NPL	1990 - 2020	1	NRU	2005 - 2020	0	NZL	1990 - 2020	0	OMN	1990 - 2019	0
PAK	1990 - 2020	1	PAN	1990 - 2020	0	PER	1990 - 2020	0	PHL	1990 - 2020	0
PLW	2001 - 2020	0	PNG	1990 - 2020	0	POL	1991 - 2020	0	PRI	1990 - 2020	0
PRT	1990 - 2020	0	PRY	1990 - 2020	0	QAT	2001 - 2020	0	ROU	1991 - 2020	0
RUS	1990 - 2020	0	RWA	1990 - 2020	0	SAU	1990 - 2020	0	SDN	1990 - 2020	1
SEN	1990 - 2020	0	SGP	1990 - 2020	0	SLB	1990 - 2020	0	SLE	1990 - 2020	1
SLV	1990 - 2020	0	SMR	1998 - 2019	0	SOM	2014 - 2020	1	SRB	1996 - 2020	0
SSD	2009 - 2015	1	STP	2002 - 2020	0	SUR	1990 - 2020	0	SVK	1993 - 2020	0
SVN	1996 - 2020	0	SWE	1990 - 2020	0	SWZ	1990 - 2020	0	SYC	1990 - 2020	0
SYR	1990 - 2019	0	TCD	1990 - 2020	1	TGO	1990 - 2020	1	THA	1990 - 2020	0
TJK	1990 - 2020	1	TKM	1990 - 2019	0	TLS	2001 - 2020	0	TON	1990 - 2020	0
TTO	1990 - 2020	0	TUN	1990 - 2020	0	TUR	1990 - 2020	0	TUV	1991 - 2020	0
TZA	1990 - 2020	0	UGA	1990 - 2020	1	UKR	1990 - 2020	0	URY	1990 - 2020	0
USA	1990 - 2020	0	UZB	1990 - 2020	1	VCT	1990 - 2020	0	VNM	1990 - 2020	0
VUT	1990 - 2020	0	WSM	1990 - 2020	0	XKX	2009 - 2020	1	YEM	1991 - 2018	0
ZAF	1990 - 2020	0	ZMB	1990 - 2020	1	ZWE	1990 - 2020	0			

Notes: Table C1 shows the ISO codes of the countries included in the dataset, the years covered, and if it belongs to the Peaceful Sample (CS=0) or the Conflict Sample (CS=1).
Source: GDP (constant 2015 US$) and population data from WB/WDI, and number of battle-related fatalities from UCDP/GED. The methodology for sample partitioning is described in Section 3.2

Table C2: Summmary Statistics for Aggregate Sample (N=5718)

	Mean	Std. Dev.	Min	Max
Population (Mill.)	34.65	131.05	0.01	1402.11
GDP (Cons. 2015 US$, Bill.)	306.07	1326.71	0.02	19974.54
Growth Rate	0.02	0.06	-0.65	1.40
Num. Battle-Related Fatalities	426.44	7506.77	0.00	533436.00
Num. Battle-Related Fatalities per Pop	0.03	1.20	0.00	89.86
Conflict Status Dummy	0.10	0.30	0.00	1.00
ML Predicted Score	0.22	0.14	-0.06	0.51

Notes: Table C2 shows summary statistics for the Aggregate Sample. Conflict is defined as surpassing the threshold of violence intensity that significantly harms the economy, which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year.
Source: Authors' calculations based on GDP (constant 2015 US$) and population data from WB/WDI, and number of battle-related fatalities from UCDP/GED.

Table C3: Summmary Statistics for Peaceful Sample (N=4707)

	Mean	Std. Dev.	Min	Max
Population (Mill.)	28.88	100.63	0.01	1380.00
GDP (Cons. 2015 US$, Bill.)	326.02	1337.23	0.02	19974.54
Growth Rate	0.02	0.05	-0.55	0.92
Num. Battle-Related Fatalities	361.16	8144.52	0.00	533436.00
Num. Battle-Related Fatalities per Pop	0.03	1.32	0.00	89.86
Conflict Status Dummy	0.06	0.24	0.00	1.00
ML Predicted Score	0.17	0.11	-0.06	0.37

Notes: Table C3 shows summary statistics for the A Peaceful sample. Conflict is defined as surpassing the threshold of violence intensity that significantly harms the economy, which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year.
Source: Authors' calculations based on GDP (constant 2015 US$) and population data from WB/WDI, and number of battle-related fatalities from UCDP/GED.

Table C4: Summmary Statistics for Conflict Sample (N=1011)

	Mean	Std. Dev.	Min	Max
Population (Mill.)	61.52	221.70	0.34	1402.11
GDP (Cons. 2015 US$, Bill.)	213.17	1273.09	0.17	14631.84
Growth Rate	0.02	0.10	-0.65	1.40
Num. Battle-Related Fatalities	730.35	3128.39	0.00	49856.00
Num. Battle-Related Fatalities per Pop	0.05	0.29	0.00	7.69
Conflict Status Dummy	0.27	0.45	0.00	1.00
ML Predicted Score	0.43	0.04	0.37	0.51

Notes: Table C4 shows summary statistics for the Conflict Sample. Conflict is defined as surpassing the threshold of violence intensity that significantly harms the economy, which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year.
Source: Authors' calculations based on GDP (constant 2015 US$) and population data from WB/WDI, and number of battle-related fatalities from UCDP/GED.

Table C5: Violence intensity and economic growth

	GDP per capita Growth
1st Decile	-0.295
	(0.374)
2nd Decile	-0.342
	(0.385)
3rd Decile	-0.710
	(0.454)
4th Decile	-0.936
	(0.420)
5th Decile	-0.187
	(0.438)
6th Decile	-0.389
	(0.582)
7th Decile	-1.987
	(0.671)
8th Decile	-1.597
	(0.821)
9th Decile	-3.453
	(1.154)
10th Decile	-9.183
	(1.958)
Observations	5730
Country FE	Yes
Time FE	Yes
(Within country) R^2	0.142

Notes: Table C5 shows the impact on GDP per capita growth for different levels of violence intensity, categorized by deciles. A country fixed effects model is used, where GDP per capita growth is regressed on a set of dummies representing each decile while controlling for year fixed effects. Year fixed effects were also included as control variables. Violence intensity is quantified by the number of battle-related deaths per capita. Robust standard errors are in parentheses.
Source: Authors' calculations based on GDP (constant 2015 US$) and population data from WB/WDI, and number of battle-related fatalities from UCDP/GED.

Table C6: Estimated transition probabilities for more restrictive definitions of conflict

		Stay in Conflict	Unstable Peace to Conflict							Stable Peace to Conflict
		$\hat{\pi}_0$	$\hat{\pi}_1$	$\hat{\pi}_2$	$\hat{\pi}_3$	$\hat{\pi}_4$	$\hat{\pi}_5$	$\hat{\pi}_6$	$\hat{\pi}_7$	$\hat{\pi}_8$
	D8	0.76	0.16	0.13	0.09	0.06	0.04	0.07	0.06	0.01
AS	D9	0.69	0.24	0.08	0.08	0.1	0.09	0	0.09	0.01
	D10	0.64	0.1	0.15	0.07	0.1	0.03	0.03	0.03	0.01

Notes: Table C6 shows the estimated transition probabilities for different conflict definitions, each associated with surpassing different deciles of violence. The analysis is performed using the 8th decile (D8), 9th decile (D9), and 10th decile (D10) on the aggregate sample (AS). They are estimated using the proportion of transitions observed in the data. $\hat{\pi}_i$ denotes the probability of transitioning to conflict from state i, where $i = 0$ is conflict, $i = k$ s.t. $k \in [1, 7]$ is the kth number of consecutive years in post-conflict peace, and $i = 8$ is stable peace. Conflict is defined as having more than 21.71 (8th decile), 51.77 (9th decile), and 155.56 (10th decile) battle-related deaths per million inhabitants during a year.
Source: Authors' calculations based on population data from WB/WDI, and number of battle-related fatalities from UCDP/GED.

Table C7: Estimation of the growth vector for more restrictive definitions of conflict

	Aggregate Sample		
	8th Decile	9th Decile	10th Decile
	GDP per capita Growth		
Conflict	-0.0378	-0.0522	-0.0779
	(0.00996)	(0.0123)	(0.0210)
1st Year Post-conflict Peace	-0.00579	-0.00211	0.00887
	(0.00929)	(0.0133)	(0.0248)
2nd Year Post-conflict Peace	0.00755	0.0182	0.0219
	(0.00770)	(0.0101)	(0.0159)
3rd Year Post-conflict Peace	-0.000627	0.00677	0.00569
	(0.00671)	(0.00874)	(0.0149)
4th Year Post-conflict Peace	0.00770	0.0121	0.0000339
	(0.00523)	(0.00773)	(0.00962)
5th Year Post-conflict Peace	-0.00370	-0.00199	-0.00126
	(0.00624)	(0.00700)	(0.00677)
6th Year Post-conflict Peace	-0.000231	-0.000573	0.00384
	(0.00484)	(0.00594)	(0.00878)
7th Year Post-conflict Peace	0.00178	0.00156	0.0000347
	(0.00536)	(0.00665)	(0.0104)
Observations	5730	5730	5730
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
(Within country) R^2	0.123	0.131	0.136

Notes: Table C7 shows the regression results from equation 2 used to estimate the growth vector for different conflict definitions, each associated with surpassing different deciles of violence. The analysis is performed using the 8th decile, 9th decile, and 10th decile on the aggregate sample. A country fixed effects model is employed where GDP per capita growth is regressed on a set of dummies representing the states of the model. The base category is stable peace, defined as having more than 7 consecutive years of post-conflict peace. Year fixed effects were also included as control variables. Conflict is defined as having more than 21.71 (8th decile), 51.77 (9th decile), and 155.56 (10th decile) battle-related deaths per million inhabitants during a year. Robust standard errors are in parentheses.
Source: Authors' calculations based on GDP (constant 2015 US$) and population data from WB/WDI, and number of battle-related fatalities from UCDP/GED.

Table C8: Estimated transition probabilities when $\tau = 4$

	Stay in Conflict	Unstable Peace to Conflict				Stable Peace to Conflict
	$\hat{\pi}_0$	$\hat{\pi}_1$	$\hat{\pi}_2$	$\hat{\pi}_3$	$\hat{\pi}_4$	$\hat{\pi}_5$
AS	0.76	0.22	0.16	0.09	0.03	0.02
PS	0.71	0.20	0.12	0.07	0.03	0.01
CS	0.82	0.25	0.23	0.12	0.03	0.05

Notes: Table C8 shows the estimated transition probabilities when $\tau = 4$ for each specification: the aggregate sample (AS), the peaceful sample (PS), and the conflict sample (CS). They are estimated using the proportion of transitions observed in the data. $\hat{\pi}_i$ denotes the probability of transitioning to conflict from state i, where $i = 0$ is conflict, $i = k$ s.t. $k \in [1, 4]$ is the kth number of consecutive years in post-conflict peace, and $i = 5$ is stable peace. Conflict is defined as surpassing the threshold of violence intensity that significantly harms the economy, which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year.
Source: Authors' calculations based on population data from WB/WDI, and number of battle-related fatalities from UCDP/GED. The methodology for sample partitioning is described in Section 3.2

Table C9: Estimation of the growth vector when $\tau = 4$

	Aggregate Sample	Peaceful Sample	Conflict Sample
	GDP per capita Growth		
Conflict	-0.0323	-0.0333	-0.0327
	(0.00813)	(0.0110)	(0.0112)
1st Year Post-conflict Peace	0.00452	0.00436	0.00484
	(0.00734)	(0.0104)	(0.00900)
2nd Year Post-conflict Peace	0.00147	0.00510	-0.00374
	(0.00677)	(0.00984)	(0.00622)
3rd Year Post-conflict Peace	0.000628	0.000801	-0.00201
	(0.00594)	(0.00752)	(0.00989)
4th Year Post-conflict Peace	0.00579	0.00511	0.00245
	(0.00523)	(0.00656)	(0.00920)
Observations	5730	4676	1054
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
(Within country) R^2	0.122	0.175	0.0811

Notes: Table C9 shows the regression results when $\tau = 4$ from equation 2 used to estimate the growth vector for each specification: the aggregate sample, the peaceful sample, and the conflict sample. A country fixed effects model is employed where GDP per capita growth is regressed on a set of dummies representing the states of the model. The base category is stable peace, defined as having more than 4 consecutive years of post-conflict peace. Year fixed effects were also included as control variables. Conflict is defined as surpassing the threshold of violence intensity that significantly harms the economy, which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year. Robust standard errors are in parentheses.
Source: Authors' calculations based on GDP (constant 2015 US$) and population data from WB/WDI, and number of battle-related fatalities from UCDP/GED. The methodology for sample partitioning is described in Section 3.2

Table C10: Estimation of the growth vector with country-specific time trends

	Aggregate Sample	Peaceful Sample	Conflict Sample
	GDP per capita Growth		
Conflict	-0.0371	-0.0351	-0.0372
	(0.00851)	(0.0119)	(0.0117)
1st Year Post-conflict Peace	0.00542	0.00958	0.00162
	(0.00770)	(0.0108)	(0.0108)
2nd Year Post-conflict Peace	0.00154	0.00667	-0.00497
	(0.00708)	(0.00995)	(0.00963)
3rd Year Post-conflict Peace	0.000591	0.00206	-0.00265
	(0.00677)	(0.00811)	(0.0139)
4th Year Post-conflict Peace	0.00655	0.00779	0.00412
	(0.00587)	(0.00682)	(0.0123)
5th Year Post-conflict Peace	0.000269	0.000837	-0.000189
	(0.00502)	(0.00588)	(0.0104)
6th Year Post-conflict Peace	0.00173	-0.00131	0.00603
	(0.00519)	(0.00575)	(0.0104)
7th Year Post-conflict Peace	0.00103	-0.00477	0.0155
	(0.00464)	(0.00508)	(0.00992)
Observations	5730	4707	1023
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Country Time Trends	Yes	Yes	Yes
(Within country) R^2	0.197	0.249	0.161

Notes: Table C10 shows the regression results from equation 2 is used to estimate the growth vector for each specification: the aggregate sample, the peaceful sample, and the conflict sample. A country fixed effects model is employed where GDP per capita growth is regressed on a set of dummies representing the states of the model where country-specific time trends are included. The base category is stable peace, defined as having more than 7 consecutive years of post-conflict peace. Year fixed effects were also included as control variables. Conflict is defined as surpassing the threshold of violence intensity that significantly harms the economy, which corresponds to having more than 9.35 battle-related deaths per million inhabitants during a year. Robust standard errors are in parentheses.
Source: Authors' calculations based on GDP (constant 2015 US$) and population data from WB/WDI, and number of battle-related fatalities from UCDP/GED. The methodology for sample partitioning is described in Section 3.2