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

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Abstract

This study proposes a statistical model to capture the economic impact of the "conflict trap" phenomenon - a period of recurring outbreaks of internal armed conflict. The framework captures conflict dynamics through a discrete-time Markov process. We estimate the transition matrix and link the states to GDP per capita growth distributions through country fixed effects regressions. This allows for simulating the distribution of developmental effects of the conflict trap. We find that the trap has a large detrimental effect on long-term economic development, reaching a relative decline of GDP per capita of over 50% in the most affected countries.

Keywords: Armed Conflict, Economic Development, Conflict Trap, Economic Growth

JEL Classification: D74, O11, O40

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1 Introduction

Internal armed conflict is often regarded as a key inhibitor to economic development.[1] And indeed, if we compare across countries, internal armed conflict appears to be strongly associated with differences in economic development. For example, a country that has suffered almost constant internal armed conflict, the Democratic Republic of Congo, has a GDP per capita that is less than one-tenth the one of South Africa which suffered much less conflict. Most economists agree, however, that these differences in GDP per capita should not be solely attributed to conflicts as there is clearly a potential for reverse causality and other factors that could drive a wedge between the output of the two countries and also make one more prone to internal armed conflict.

The literature has therefore turned toward using within-country differences, both on the time and geographic dimension, to identify the costs of war.[2] But there is a stark difference in results between the *cross-sectional* findings, comparing peaceful and conflict-affected countries, and the *within-country* view as estimates from within-country tend to suggest a much smaller impact of conflict. This matters, if conflict is not a major determinant of cross-country differences in economic development then the recent pivot of developmental agencies towards armed conflict as a causal driver of economic development will not have a transformative effect.

We propose a statistical framework to help bridge part of the gap between the large cross-country differences and the within-country evidence. The event to be studied is not an episode of ongoing conflict and its impact on the economy but the first outbreak into intensive violence after prolonged episodes of peace. These outbreaks are systematically followed by decades with episodes of open violence - a phenomenon known as the *conflict trap*. It has long been argued that the conflict trap exists - but to the best of our knowledge, this is the first attempt to gauge its impact on long-term development quantitatively.[3]

Our definition of internal armed conflict follows the Uppsala Conflict Data Program's Georeferenced Event Dataset (UCDP/GED) which we aggregate to the country-year.[4] To focus on the economic effects of internal armed conflict, we define conflict as a level of per capita violence that significantly harms the macroeconomy of the country. Based on this definition, we propose the definition of the conflict trap as the period between the first onset of conflict and the crossing of a threshold of time without a renewed outbreak.[5] Figure 1 shows the likelihood of resurgence of internal armed conflict in the first seven years after the last conflict year. We show the resurgence likelihood with its 95 percent confidence intervals in the data. In the first year after conflict, the likelihood of a renewed outbreak is over 20 percent. It

1. See, for example, the World Bank report Corral et al. 2020
2. See Abadie and Gardeazabal 2003; Miguel and Roland 2011; Besley and Mueller 2012; Tapsoba 2023.
3. Collier et al. 2003; Rohner and Thoenig 2021 stress the importance of the conflict trap for macro development. Hegre, Nygård, and Ræder 2017 and Mueller and Rauh 2022 conceptualize the conflict trap for conflict prediction purposes.
4. 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".
5. Our analysis here follows the conflict risk analysis in Mueller and Rauh 2022.

then falls relatively monotonically to 4 percent after 4 years and stabilizes around that level. Outside the 7-year period, the likelihood of resurgence is close to 2 percent. This means that the post-conflict period is extremely risky - around half of the overall sample will experience a resurgence of open conflict before reaching 8 years of peace.

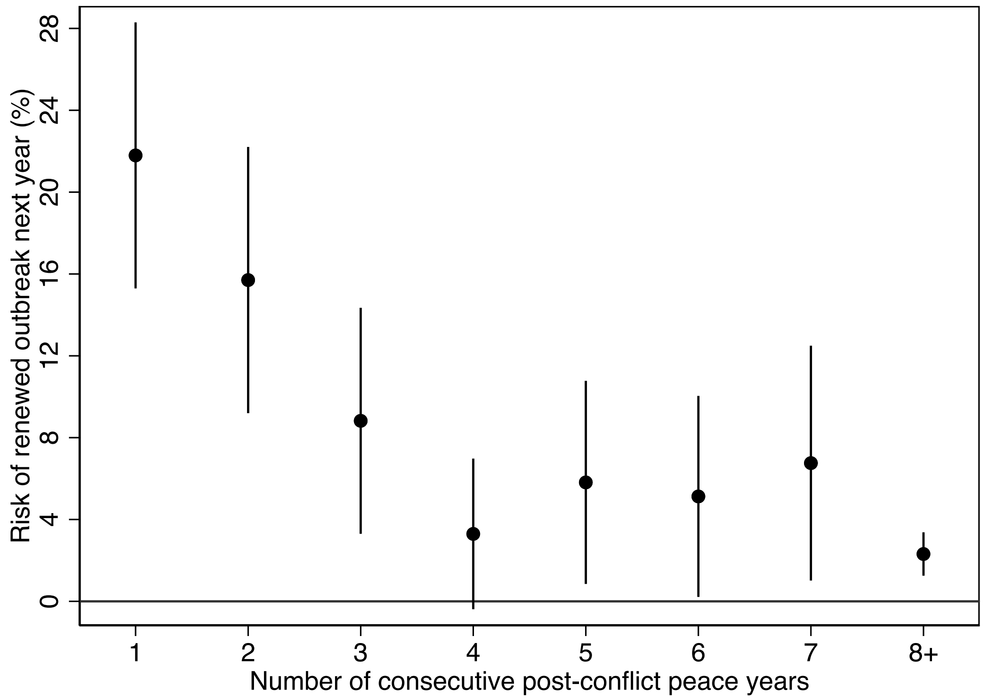

Figure 1: The Conflict Trap: high risk of renewed outbreak during post-conflict peace

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 a linear probability model, with conflict outbreak regressed on a set of dummy variables representing the number of post-conflict peace years. Point estimates are displayed as circles where bars indicate significance at 5% using robust standard errors. 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. For further details about the regression analysis, see Table A1 in the appendix.
Source: Authors' calculations based on population data from the World Bank's World Development Indicators, and number of battle-related fatalities from UCDP/GED.

We model these dynamics through a discrete-time Markov process where, in addition to states of conflict and stable peace, there are multiple states of post-conflict peace with a relatively higher probability of transitioning to conflict. We estimate the transition matrix and link the states to GDP per capita growth distributions through country fixed effects regressions. The combination of the transition matrix and the states' growth distribution allows us to build a bridge from within-country evidence to the long-run developmental effect. We simulate draws on the Markov chain to simulate dynamics between conflict and peace inside the trap and use draws from the state's growth distribution to estimate the long-term impact of entering into conflict. Our main result is that entering conflict leads to an average GDP per capita loss of close to 20%, a loss of 30% in the 75th percentile, and a decline of close to 45% in the 90th percentile.

The conflict trap framework we propose offers a useful way of making sense of some of the cross-sectional variation we see in the data. But it does this through a dynamic model of changing risks. This implies that countries are not doomed because of their characteristics but, instead, their conflict cycles are worse. We demonstrate this using a simple machine learning model that combines factors stressed by the literature to define a group of conflict-prone countries. The trap dynamics they exhibit are indeed slightly worse but conflict episodes have a very similar effect on growth for them. Using our simulation approach we show that the 90th percentile in this sample suffers a loss of more than 50% of GDP per capita when entering the trap. The 90th percentile in the relatively peaceful sample still suffers a loss of 35%. Helping countries escape the trap faster is extremely important. Preventing countries from falling into the trap would yield even larger gains.

Our article relates to a large literature on the costs of conflict. Most closely related is the overview article by Rohner and Thoenig 2021 which also focuses on the role of conflict traps and development. They identify a series of what they call *war traps* wherein self-reinforcing dynamics lead to vicious cycles of poverty and violence. They discuss how conflicts deteriorate material conditions and social ties, which in turn constitutes a powerful breeding ground for future violence. They conclude that studying the impact of conflict on development without taking into consideration conflict traps may lead to seriously wrong conclusions on the role of conflict in development. We contribute to this literature by proposing a conceptual framework to better capture the developmental impact of the conflict trap empirically. In contrast to the conventional approach, our estimates do not arise from a specific assumption regarding the conflict history but are only conditional on having an outbreak of conflict.

Our model of the conflict trap is directly related to the literature in Macro studying economic growth in emerging economies. 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. We argue here that this is the kind of growth behavior that conflict traps generate, i.e. they do not simply cause year-to-year volatility but longer episodes of low and high growth. Intense armed conflict could therefore be one reason for the empirical pattern observed by Aguiar and Gopinath 2007.

Finally, we also contribute to an older 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 2011; 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 levels. This allows us to run a robustness check of our findings distinguishing the predictably affected countries. We also argue, however, that thinking of risk as something that is fixed at the country level seems an oversimplification. Countries can and do escape ongoing episodes of open violence. The change of risk from 20 percent to around 2 percent shown in Figure 1 is substantial when compared to predictable cross-country risk.[6]

The following section outlines the conceptual model of the conflict trap and its calibration and estimation. The simulation method is then described in Section 3. In Section 4, we present and discuss the results, followed by our conclusions in the final section. A discussion of predictable country conflict and trap risk, as well as various robustness checks, are discussed in the appendices.

2 Model

2.1 A Model of the Conflict Trap

This section presents our empirical model of the conflict trap. Our central assumption is that the transition between conflict and peace can be described by a discrete-time Markov process. The state space is composed of a state of conflict, multiple states of post-conflict peace collectively referred to as unstable peace, and a state of stable peace. As shown in Figure 1, the multiple post-conflict peace states embody the conflict trap, as they generally exhibit a higher risk of conflict resurgence. This is empirically confirmed later, in the model estimation. On the other hand, stable peace represents a state that is not conditioned by a conflict trap, which means, transitions to conflict are as likely as if the country would have had no conflict to start with.

Then, when a country is in the state of conflict, it can either stay in conflict or transition to the first year of post-conflict peace. When a country is in this first year, it can either return to conflict or transition to the second year of post-conflict peace. This pattern repeats until the country reaches τ consecutive years of post-conflict peace. It can then go back to conflict or enter stable peace. τ determines the threshold of consecutive post-conflict years of peace needed to escape from the conflict trap.

The state space is defined as $S = \{0, 1, \ldots, i, \ldots, \tau, \tau + 1\}$ with s_t being the state at period t. 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*. Finally, when $s_t = \tau + 1$, the country is in *stable peace*.

By the structure of the Markov process we assume, a country can only transition in two directions. 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.

6. We show this in Appendix A by using country characteristics stressed by the literature to predict country risk with machine learning. The predicted values of this prediction have a standard deviation of 10 percentage points.

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 obviously not realistic. Much of the conflict literature is linking armed conflict outcomes to their colonial history or geographic features. Some countries will have a higher baseline likelihood of conflict. However, we show in the appendix that predicting which countries will get stuck in the trap is surprisingly difficult.

To capture the impact of conflict on development we focus on real GDP per capita. Denote $GDP_t(\boldsymbol{s^t})$ as the real GDP per capita when the Markov process is at period t, with $\boldsymbol{s^t} = \begin{pmatrix} s_0 & s_1 & \dots & s_t \end{pmatrix}$ being the history until time t. The realization of the state affects $GDP_t(\boldsymbol{s^t})$ by determining the distribution from which the growth shock u_{t+1} is drawn, i.e., $u_{t+1}|s_{t+1} \sim f_{i=s_{t+1}}$. Then, at each period, $GDP_t(\boldsymbol{s^t})$ updates according to

$$GDP_{t+1}(\boldsymbol{s^t}, s_{t+1}) = GDP_t(\boldsymbol{s^t})(1 + u_{t+1}) \tag{1}$$

For example, if $s_2 = 0$, the growth shock u_2 is drawn from the distribution 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 f_0 to be low when compared to the other elements of the growth vector. This kind of model will lead to dynamics in which countries cycle back and forth between high and low growth episodes. Importantly, the transition matrix will capture the self-reinforcing nature of peace, so that lasting peace makes it more likely that countries escape the trap altogether.

2.2 Calibration and Estimation

We calibrate and estimate the model using the number of battle-related fatalities from the UCDP/GED and GDP (in constant 2015 US$) together with population data from the World Bank's World Development Indicators (WB/WDI).[7] These give a dataset for the years 1989-2021 and over 190 countries. The

7. We are using the "best" estimate of fatalities summing all types of violence and aggregating all fatalities for each country-year.

data is a yearly cross-country panel data so we use t to denote year and j to denote country.

Our definition of conflict is based on surpassing the threshold of violence intensity that significantly harms the economy. We quantify violence intensity using the number of battle-related deaths per capita.[8] 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. The results are displayed in Figure 2 below. 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 at the 5% level. Therefore, 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.[9] According to this definition, we have 700 conflict country-years which makes our definition relatively inclusive when compared to the standard 1000 fatalities threshold with 400 conflict country-years.

To provide a more extensive study of the conflict trap, we define three specifications, each distinguished by the data employed. Alongside utilizing the complete dataset, we partition it into two subsets: one composed of a less conflict-prone sample and another composed of a more conflict-prone sample. The sample partition allows us to quantify the effects of more and less pervasive types of conflict traps. We reduce the problem of ad-hoc ways of splitting the data through a summary measure of conflictousness derived from the conflict literature. First, we use machine learning to predict the extent to which a country will experience the conflict trap using a set of variables used in the cross-country literature: geographical features, ethnic and religious composition, natural resources, and political institutions. We find that predicting the extent of the conflict trap in this way is relatively hard ex-ante with an R-squared of less than 20 percent. Second, we use the fitted value from this exercise to generate two samples with the most similar total number of years of conflict.[10] In the larger and less conflict-prone sample, countries have low predicted conflict scores. In the smaller and more conflict-prone sample, countries have higher scores. 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*. For more details on the sample partition methodology, see Appendix A.

From Figure 1 we know that the risk of renewed outbreak next year stabilizes for higher states. We choose $\tau = 7$ so be sure to have enough observations to have meaningful transition likelihoods.[11] This leads to a total of 9 states, which is common to all specifications.

8. See Mueller 2016 for a more detailed analysis along these lines using subnational data.

9. In Appendix B we show robustness checks for more restrictive thresholds which lead to even larger estimates of the developmental impact of internal armed conflict. See Figure A3.

10. The less conflict-prone sample has a total of 348 conflict years, whereas the more conflict-prone sample has a total of 356 conflict years.

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

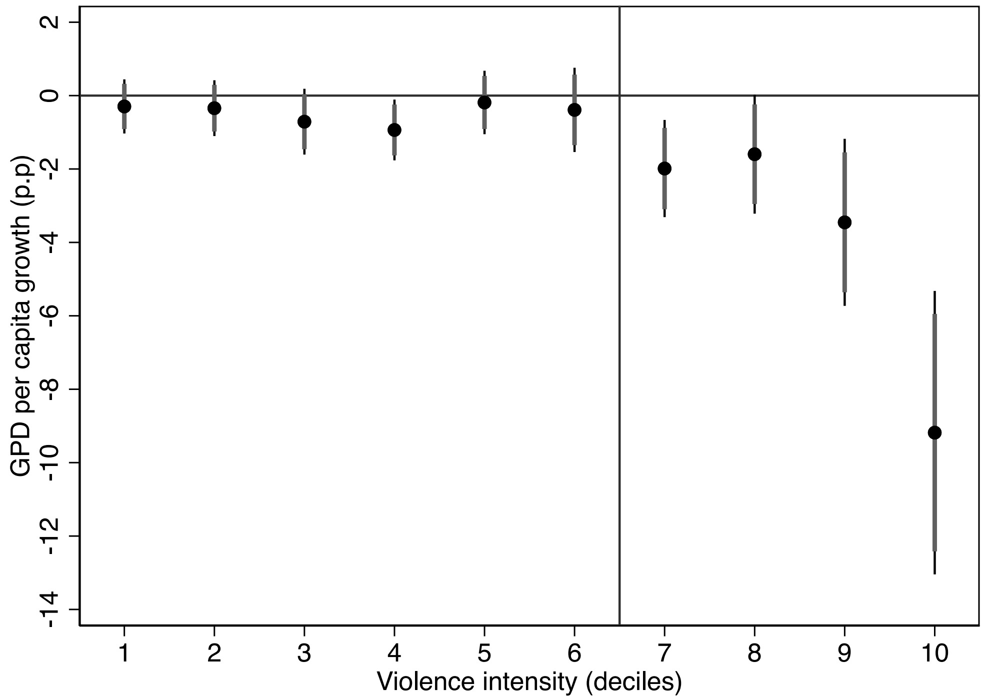

Figure 2: Violence intensity and economic growth

Notes: Figure 2 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.

The transition matrix is estimated using the relative frequencies of the observed transitions. 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.[12] 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 the trap.[13]

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 5.88 years for the conflict one. Meanwhile, the expected number of periods in the conflict trap is 15.49 for the peaceful sample and 26.01 for the conflict one. Note that

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

the pattern of high persistence in conflict and falling risks in post-conflict is robust across samples. With our distinction into peaceful sample and conflict sample, we are merely capturing a small fraction of the intensive margin with an R-squared of 0.2 out-of-sample with a machine learning model.[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	0.7	0.21	0.11	0.06	0.05	0.07	0.04	0.06	0.01
CS	0.82	0.25	0.24	0.16	0	0.04	0.09	0.1	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 relative frequencies of the observed transitions. $\hat{\pi}_i$ 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 Appendix A.

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 period t. The regression equation is

$$Growth_{jt} = \sum_{i=0}^{\tau+1} \beta_i d_{ijt} + \mu_j + \gamma_t + \varepsilon_{jt}, \tag{2}$$

where μ_j and γ_t represent country and time fixed effects respectively. The results for each specification are shown in Table 2. In all specifications, a year in conflict lowers growth by more than 3 percentage points. This result lies inside the bounds of the literature but is a relatively large coefficient given that we classify a lot more years as conflict compared to the standard 1000 fatalities threshold.[15] The coefficients of the rest of the states are small and insignificant in all specifications.[16]

An important caveat applies to this way of deriving the growth vector. 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, and Rohner and Thoenig 2021 conclude that these probably still constitute a lower bound. The causal interpretation is also in line with the finding that more intense violence is associated with more dramatic declines in growth as shown in Figure 2. In any case, we are using these estimates here because they are the best possible estimates with a reasonable claim to identification and outside validity.

Since stable peace is the omitted category, we normalize growth for this state to 0, i.e. $\hat{f}_8 = 0$.

14. We also show in the appendix that predicting the share of conflict years for a country is even more difficult out of sample with an R-squared of only 0.16.
15. The reason is that defining conflict relative to population is a better model of conflict damage.
16. These results are robust to a more demanding specification with country time trends which we show in Table A5 in the Appendix.

Table 2: Estimation of the growth vector

	Aggregate Sample	Peaceful Sample	Conflict Sample
		GDP per capita Growth	
Conflict	-0.0320***	-0.0330**	-0.0328**
	(0.00823)	(0.0114)	(0.0112)
1st Year Post-conflict Peace	0.00481	0.00588	0.00325
	(0.00761)	(0.0108)	(0.00936)
2nd Year Post-conflict Peace	0.00176	0.00525	-0.00467
	(0.00713)	(0.0102)	(0.00740)
3rd Year Post-conflict Peace	0.000921	0.000604	-0.00213
	(0.00633)	(0.00787)	(0.0110)
4th Year Post-conflict Peace	0.00608	0.00632	0.00157
	(0.00562)	(0.00652)	(0.0106)
5th Year Post-conflict Peace	0.000295	-0.000311	-0.00113
	(0.00503)	(0.00547)	(0.0101)
6th Year Post-conflict Peace	0.00217	-0.00120	0.00452
	(0.00461)	(0.00481)	(0.0103)
7th Year Post-conflict Peace	0.00155	-0.00434	0.0136
	(0.00417)	(0.00439)	(0.00930)
Observations	5730	4707	1023
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
(Within country) R^2	0.122	0.175	0.0843

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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
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 Appendix A.

For the rest of the states, we use the estimates from our regressions and their standard error to construct the growth distribution of each state. Formally, for $h < \tau + 1$, $\hat{f}_h = \mathcal{N}(\hat{\beta}_h, \hat{\sigma}_h^{SE})$ with $\hat{\sigma}_h^{SE}$ being the standard error of β_h. Therefore, the estimated growth vector is given by the growth estimates with a 0 added, i.e., $\hat{\boldsymbol{f}} = \begin{pmatrix} \mathcal{N}(\hat{\beta}_0, \hat{\sigma}_0^{SE}) & \mathcal{N}(\hat{\beta}_1, \hat{\sigma}_1^{SE}) & \dots & 0 \end{pmatrix}$. 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.

A striking aspect of Table 2 is that the different samples do not show dramatic differences in their growth estimates. This indicates that any variation between samples in the simulation results can be mainly attributed to differences in conflict dynamics, rather than variations in the impact of conflict itself. Furthermore, a year of conflict reduces growth that year by 3 percentage points. This is a significant amount but it is totally unclear from this whether such a number, derived with country fixed effects, can explain large cross-country differences.

3 Simulation of the Conflict Trap

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.

Countries start with $GDP_0 = 100$ and in the state of conflict.[17] We make stable peace absorbing ($\hat{\pi}_8 = 0$) to capture the net aggregate effect of the conflict trap. This leads to a fair comparison with the benchmark in which the country remains in stable peace and stays there. Then, we draw transition paths from the estimated transition matrix and the growth shocks from the corresponding distribution in the growth vector. The simulation has $T = 30$ periods and it is repeated $N = 100,000$ times to get a good sense of the distribution of the loss over time.

4 Results

The results of the simulations for each specification are shown in Figure 3. Since all countries start in conflict, the average loss increases sharply. Then, as time goes by, more countries reach absorbing stable peace which means that growth converges back to the benchmark's growth rate.

In the aggregate sample, the average loss in GDP per capita after 30 years is almost 20%. 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%. This is a large effect. The median growth of GDP per capita in the 30 years between 1990 to 2020 was about 50 percent. In other words, doing better or worse inside the conflict trap can explain substantial changes in the long run.[18]

When comparing the two other specifications, the higher conflict tendency of the conflict sample leads to significantly greater losses, the average loss is almost double that of the peaceful one. More strikingly, the 90th percentile of the conflict sample reaches losses above 50%. Still, 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.

Note that our novel approach leads to a nuanced interpretation of the results, which differs from the conflict literature where aggregate losses are typically reported conditioning on the duration of conflict.[19]

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

18. 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 A4 in Appendix B.

19. For example, Collier 1999 reports a 30% decrease in GDP per capita for countries experiencing 15 years of civil war,

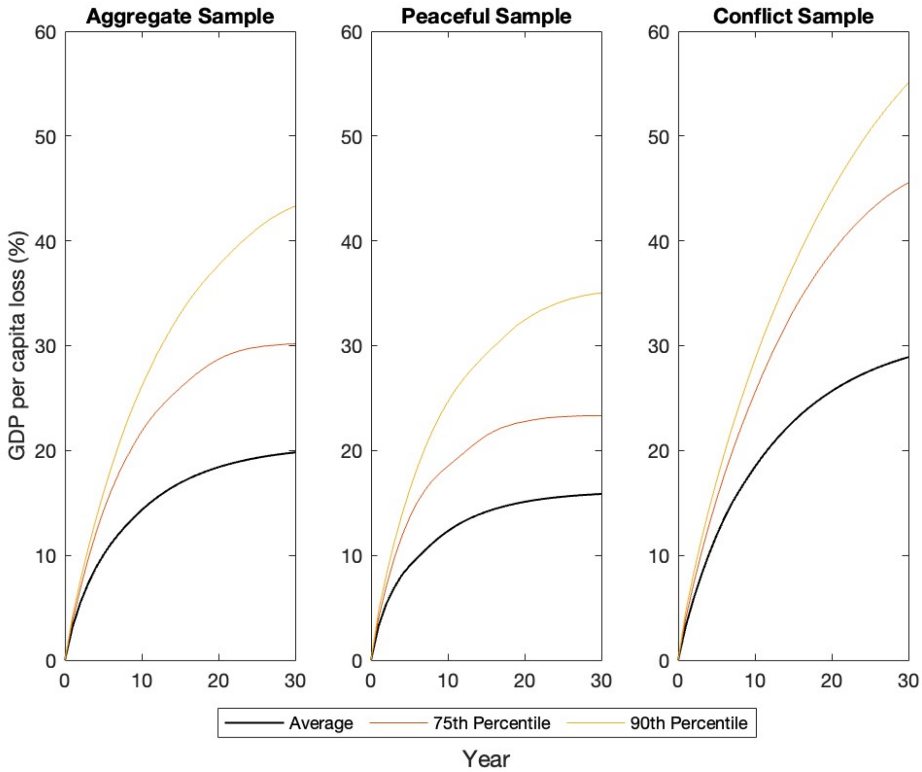

Figure 3: Evolution of GDP per capita loss

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 $N = 100,000$. The methodology for sample partitioning is described in Appendix A.

Instead, we only impose a starting year in conflict, and the rest of the incurred losses are a result of the estimated conflict dynamics, i.e., the conflict trap. This emphasizes the importance of conflict prevention by underscoring the long-term loss induced by one random year of conflict.

5 Conclusion

The aim of this study is to enhance our comprehension of the long-term developmental consequences of conflict. We have argued that when thinking about the developmental impact of conflict the conflict trap should take centre stage. To achieve this, we propose a conceptual framework that combines a model trap dynamics with within-country estimates of economic costs.

The simulation results indicate that entering conflict will induce an average loss in GDP per capita

while De Groot et al. 2022 find that country loses, on average, 15.7% of its potential GDP per capita during the war-torn 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%. This is despite the fact that only one outbreak of conflict is imposed, and the remainder of the losses are due to the estimated conflict dynamics inside the conflict trap. This highlights the relevance of conflict prevention.

Our model is modular in the sense that other cost aspects of conflict can be linked to the states and then simulated using the framework. One could, for example, replace the cross country regression with case study results. More generally, the idea of clustering observations into states holds promise for other applications where dynamic costs arise from trap dynamics. Health issues like cancer or social issues like crime, for example, will have similar dynamics.

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Online Appendices

A Predicting Conflict and the Conflict Trap

How much of the conflict that occurred in the period 1989-2022 is predictable through predetermined country characteristics? To answer this question we construct a dataset of country characteristics from various sources like the replication dataset of Nunn and Puga 2012 (legal origins, continent dummies, ruggedness, % fertile soil, % desert, distance to coast, longitude and latitude), Montalvo and Reynal-Querol 2005 (ethnic polarization/fractionalization and religious polarization/fractionalization), and the WB/WDI (natural resource dependence of GDP, GDP, and population). We impute missing values through a clustering method that uses continent, longitude, and latitude to match countries.

We use two simple models to predict the conflict trap: 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 use only variables that are pre-determined to this period: a set of continent dummies, 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. This does not affect the R-squared substantially.

We then use cross validation to tune hyperparameters $(lasso - alpha : 0.0001, randomforest - max\_depth : 4, min\_samples_leaf : 20, n\_estimators : 500)$ and to calculate the R-squared statistics. For the random forest, the 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 (ensemble). In Figure A1 below we show the importance in the random forest. This suggests that GDP per capita levels are a main driver of fragility. To provide an impression of the fit of the model we show the within-fitted values on the x-axis when compared to the actual variation on the y-axis in Figure A2.

When predicting the extent of conflict (defined as the share of years with a civil war) use the same method and get an R-squared of 0.16 in the overall model, 0.15 with the random forest, and 0.12 in the lasso. We think it is worth highlighting that we have used all possible factors that are typically thought to be important by the conflict literature. The fact that the R-squared is a mere 0.16 when trying to predict out-of-sample shows how important country idiosyncrasies are. We know that we know nothing.

Codes for both of these forecasting tasks will be made available on GitHub after publication.

B Appendix Figures

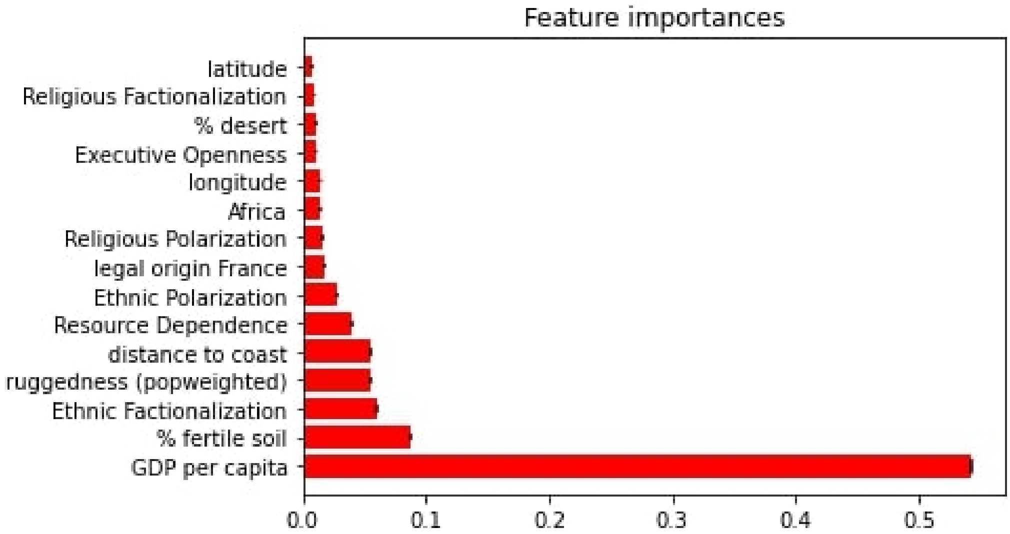

Figure A1: Importances of Random Forest when Predicting Conflict Trap

Notes: Figure A1 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).

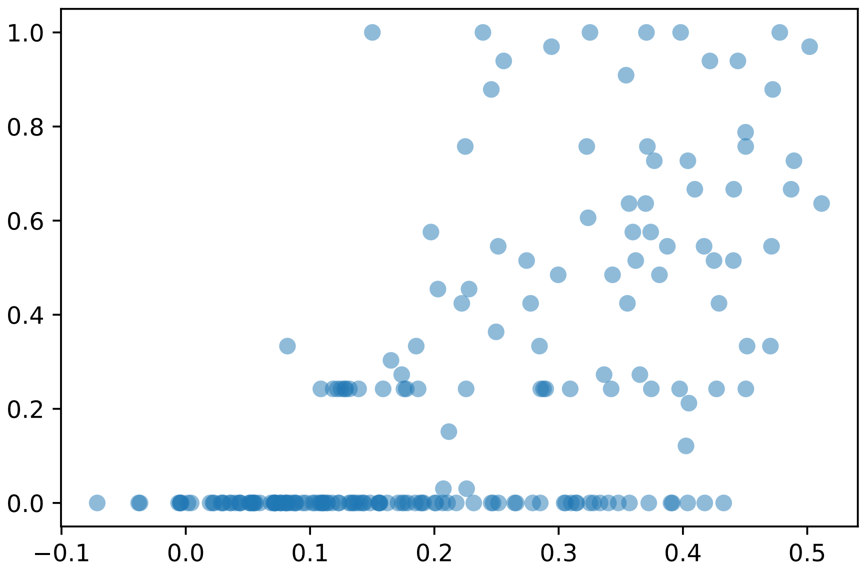

Figure A2: Fitted Values of Ensemble Model and Actual Values

Notes: Figure A2 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.

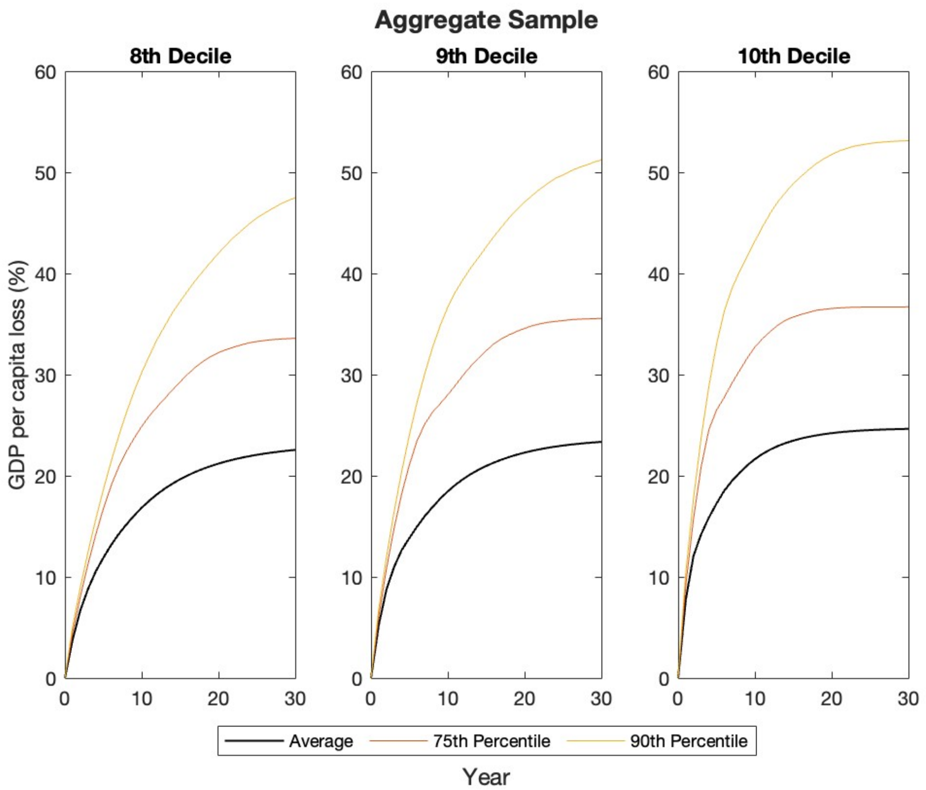

Figure A3: Evolution of GDP per capita loss for more restrictive definitions of conflict

Notes: Figure A3 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 A3) and a re-estimated growth vector (see Table A4) 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 $N = 100,000$.

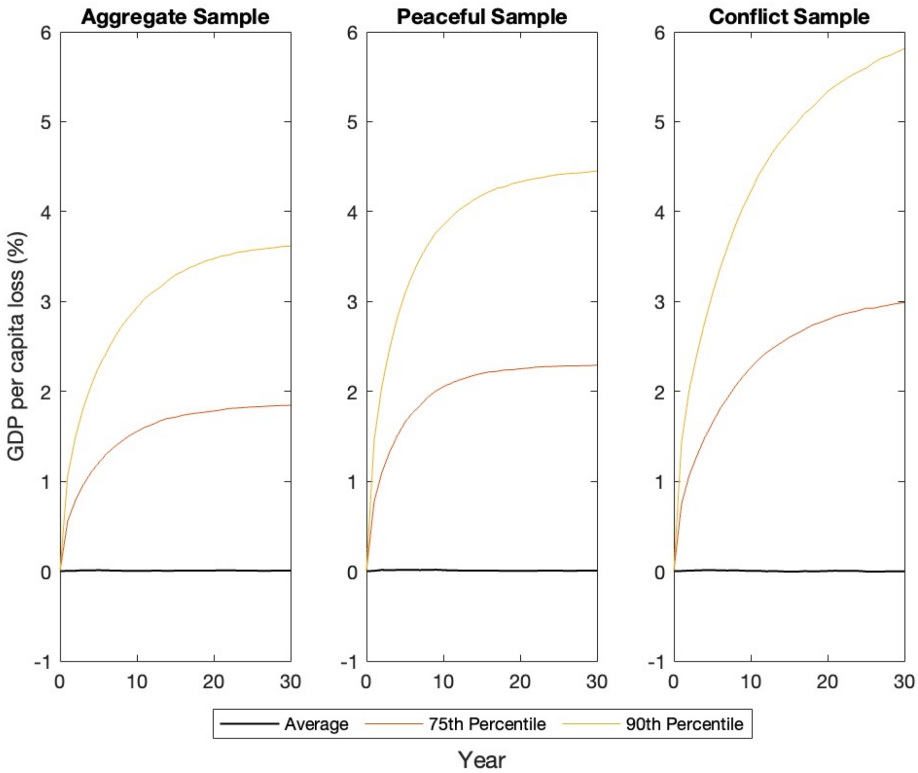

Figure A4: Evolution of GDP per capita loss due to the variation component of the estimation

Notes: Figure A4 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 $N = 100,000$. The methodology for sample partitioning is described in Appendix A.

C Appendix Tables

Table A1: The Conflict Trap

	Conflict Outbreak
1st Year Post-conflict Peace	21.79***
	(3.314)
2nd Year Post-conflict Peace	15.70***
	(3.316)
3rd Year Post-conflict Peace	8.824**
	(2.816)
4th Year Post-conflict Peace	3.297
	(1.877)
5th Year Post-conflict Peace	5.814*
	(2.530)
6th Year Post-conflict Peace	5.128*
	(2.504)
7th Year Post-conflict Peace	6.757*
	(2.926)
Beyond 7th Year Post-conflict Peace	2.314***
	(0.540)
Observations	1486
Adjusted R^2	0.125

Notes: Table A1 shows the risk of renewed outbreak for the different number of consecutive years of peace after conflict. The risk is estimated using a linear probability model, with conflict outbreak regressed on a set of dummy variables representing the number of post-conflict peace years. The regression is conducted without including an intercept term. 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: Authors' calculations based on population data from WB/WDI, and number of battle-related fatalities from UCDP/GED.

Table A2: 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 A2 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. $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$. Note that Figure 2 displays significance at the 10% level, while Table A2 indicates significance starting at the 5% level.
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 A3: 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 A3 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 relative frequencies of the observed transitions. $\hat{\pi}_i$ 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 A4: 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 A4 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
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 A5: 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 A5 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 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
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 Appendix A.