The 'conflict trap' reduces economic growth in the Shared Socioeconomic Pathways*

Elisabeth A. Gilmore[1], Håvard Hegre[2,3], Gudlaug Olafsdottir[2], and Kristina Petrova[2]

[1]Department of International Development, Community and Environment, Clark University
[2]Department of Peace and Conflict Research, Uppsala University
[3]Peace Research Institute Oslo

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Abstract

Armed conflict and economic growth are inherently coupled; armed conflict substantially reduces economic growth, while economic growth is strongly correlated with a reduction the propensity of armed conflict. Here, we investigate these interactions by simulating the incidence of armed conflict and its effect on economic growth simultaneously along the economic pathways defined by the Shared Socioeconomic Pathways (SSPs). We argue that GDP per capita projections through the 21st century currently in use are too optimistic since they disregard the harm to growth caused by conflict. Our analysis indicates that the correction required to account for this is substantial – expected income is 25% lower on average across countries when taking conflict into account. The correction is particularly strong for the more pessimistic SSPs 3 and 4 where expected future incidence of armed conflict is high. There are strong regional patterns with countries with contemporaneous conflicts experiencing much higher conflict burdens and reduced economic growth by the end of century. Today's most marginalized societies will be more vulnerable to the impact of climate change than indicated by existing income projections.

Keywords: armed intrastate conflict, economic feedback, shared socioeconomic pathways

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1 Introduction

In making forecasts for future socioeconomic scenarios, one of the most critical inputs is the Gross Domestic Product (GDP) and its rate of growth over the long run (Christensen, Gillingham, and Nordhaus, 2018). Extended end-of-century GDP projections are important in the projection of the impacts and economic costs of climate change (Rose, Diaz, and Blanford, 2017). Reflecting the importance of GDP as an indicator of socio-economic development, GDP projections have been used to project energy and land use (Riahi et al., 2017; Popp et al., 2017), food prices (Popp et al., 2017), quality of governance (Andrijevic et al., 2020), and even armed conflict (Hegre et al., 2016).

Most prominent among the GDP projections in use is the ENV-Growth model developed by Dellink et al. (2017). This model builds projections of future economic growth, using a convergence framework and interacting key long-run drivers of population, total factor productivity, physical capital, employment and human capital, and energy and fossil fuel resources (specifically oil and gas). The projections are specified as operationalizations of each of the five Shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2014), and cover the entire 21th century.[1] Other projections have also been developed, e.g. Crespo Cuaresma (2017) and Leimbach et al. (2017). These are built on fairly similar assumptions and are highly correlated with the Dellink et al. (2017) projections.[2]

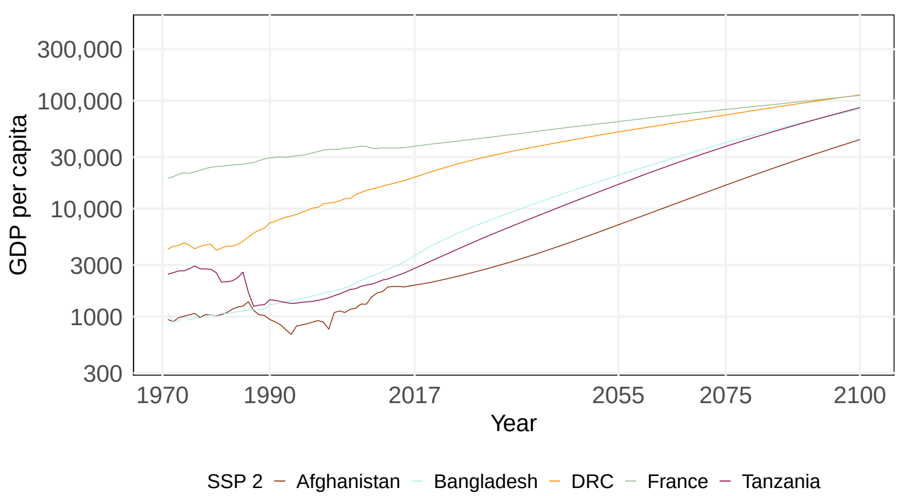


Figure 1. ENV-Growth projections for five countries from Dellink et al. (2017): Afghanistan, Bangladesh, the Democratic Republic of Congo, France and Tanzania, SSP2, 2017–2100.

Figure 1 shows GDP per capita projections according to the ENV-Growth model for the 'middle-of-the-road' scenario SSP 2 for one high-income country (France), two lower-middle income countries (Bangladesh and Tanzania) and two low-income countries (Afghanistan and Democratic Republic of Congo). By 2100, the model suggests that the incomes of Afghanistan, Bangladesh, and the Democratic Republic of Congo (DRC) have converged with France, and that Tanzania will join the happy family

[1]The SSPs were developed by the climate change research community to harmonize the assumptions that modelers make in developing projections of the costs of mitigation and adaptation to climate change. In addition to GDP, the SSPs define alternative bounding scenarios for variables such as population and education.

[2]In this article, we only discuss the Dellink et al. (2017) since data for the other projections proved difficult to obtain.

only a few decades later.

Are these projections plausible? Dellink et al. (2017) emphasize that they disregard external shocks or other non-economic factors affecting productivity or technological transfer, such as governance or environmental damages. One such growth-inhibiting shock is internal armed conflict. Organized political violence is often so detrimental to a country's economy that it has been termed 'development in reverse' (Collier et al., 2003). A number of independent studies agree that the armed conflicts that historically have afflicted 15–25% of all countries at any time, leads to an annual growth shortfall of 2% per conflict year (Collier, 1999; Gates et al., 2012).[3] Afghanistan has had continuous armed conflict since the 1970s (Pettersson and Öberg, 2020). Ignoring this constraint on Afghanistan's future growth trajectory seems unrealistic. Neglecting this feedback means that we are likely to overestimate future GDP (Buhaug and Vestby, 2019) for Afghanistan and other conflict-prone countries. This ignorance is not necessary – approximations to the risk of armed conflict in the future are available, as demonstrated in Hegre et al. (2016) and Witmer et al. (2017).

To demonstrate how the dynamics of armed conflict and GDP interact over the long-term, we develop in this article the first endogenous, joint projections for GDP per capita and armed conflict. We use these new GDP pathways to adjust the ENV-Growth GDP per capita projections for the plausible losses due to destructive armed conflict. To simulate armed conflict and its implications for GDP, we develop empirical models of the onset and duration of conflict and the effect of conflict on GDP growth, as well as a simple model of economic growth. We then jointly simulate these outcomes using the forecasting approach outlined in Hegre et al. (2013) and Hegre et al. (2016). We run the simulation for each of the five SSP scenarios, and revise the ENV-Growth model results based on the simulated prevalence of armed conflict.

2 Material and methods

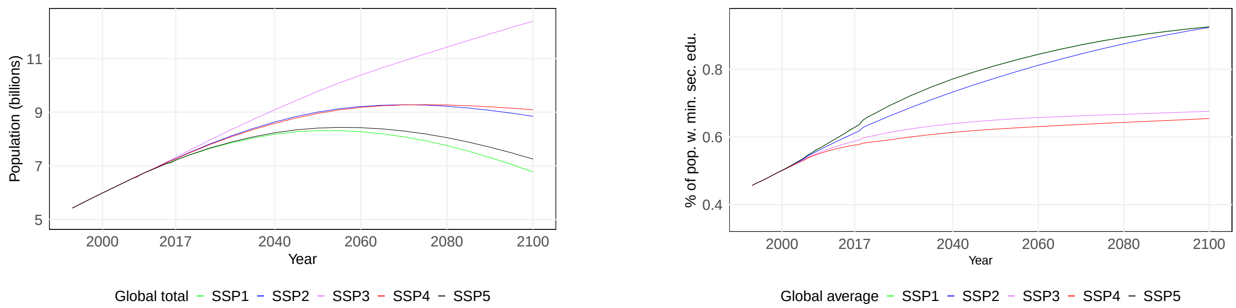
We estimate a set of simple linear and logistic regression models of the relationships between economic growth and armed conflict that reproduce the consensus view on the empirical relationship between these. We then run two matched sets of simulations for each of the SSPs: one where we jointly simulate armed conflict and GDP growth, and one where we simulate GDP growth while ignoring armed conflict. For each combination of SSP, country, and year, we calculate the difference in simulated log GDP per capita between each pair of matched simulations. Given its prominence and sophistication, we take the Dellink et al. (2017) model as our point of departure and develop an armed conflict correction to these projections. The final step, then, is to correct the Dellink et al. (2017) projections by subtracting the calculated differences.

2.1 Data

We develop our models of armed intrastate conflict with data from the 2017 update of the UCDP/PRIO Armed Conflict Dataset (Gleditsch et al., 2002; Allansson, Melander, and Themnér, 2017), which records conflicts between governments and organized armed actors with a political motivation that lead to at

[3] See Section A.1 for a review of these studies.

least 25 battle-related deaths in a year. Historic GDP per capita is derived primarily from the World Development Indicators (WDI, World Bank, 2017) – the same set of sources as used by Dellink et al. (2017).



(a) Population

(b) Education

Figure 2. Projections from KC and Lutz (2017). Total global population (2a), and average global proportion of population with secondary education (2b). Education levels are unweighted averages of countries' education level.

The exogenous country-level variables in our model are total population, population growth, and rates of secondary education attainment. As projections for these, we use results from IIASA published in *Global Environmental Change* (KC and Lutz, 2017). Figure 2 shows observed and projected total global population under each of the five SSPs as well as the proportion of the population that have completed upper secondary education. SSP1 (sustainability; green line) and SSP5 (conventional development; black line) have optimistic assumptions regarding population growth and expansion of education. SSP4 (inequality; red line) assume minimal expansion of education and higher population growth, whereas SSP3 (fragmentation; purple line) have similarly pessimistic education expansion assumptions and an even stronger population growth. SSP2 (blue line) is a middle-of-the-road scenario.

2.2 Statistical models

We estimate a set of statistical models to quantify the short-term effect of conflict on growth and vice versa. We use country years as our unit of analysis.

Modeling the effect of armed conflict on economic growth

First, we model the effect of armed conflict on economic growth in two separate models. The dependent variable is the difference in log GDP per capita from one year to the next.

The results from our two growth models are reproduced in Table 1.[4] They are deliberately simple and contain only terms for which we have authoritative projections up to the end of the century. We include the natural log of the proportion of the population above 15 with at least lower secondary education. The estimate is positive – an educated workforce is essential for picking up the technological innovations that underpin long-term growth (Knutsen, 2013). A log-transformed version of this variable

[4] Table 1 and 2 show results from estimating model on one of the imputed datasets (see Appendix B.2). Results using the other nine imputations are very similar.

Variable	Growth model I Coefficient	Std. error	Growth model II Coefficient	Std. error
Intercept	0.0072	0.014	0.0243	0.014
Log education	0.0912	0.027	0.0856	0.027
Population growth	–0.5885	0.189	-0.6402	0.189
Conflict	–0.0233	0.004	-0.0980	0.011
Log population	–0.0104	0.008	-0.0170	0.008
Int. Population x conflict			0.0260	0.003
Country decay fixed effects	Yes		Yes	
R-squared	0.202		0.208	
F-statistic	10.91		11.25	

Table 1. Fixed-effects OLS results, two growth models, 1960–2016. Detailed results in Appendix C.1 Tables A-2

was found to fit the data best, suggesting that the main differences in growth rates are between countries that have very low education levels and those that have medium or high levels. In and of itself, the education variable suggests that most developing countries will maintain high future growth rates in the SSP1 and SSP5 scenarios where education assumptions are optimistic, but lower ones in SSP3 and SSP4.

We also include the change in log population. Since the dependent variable is change in log GDP per capita, this variable is bound to have a strong effect: the higher the population growth, the stronger must the economy perform to increase income per capita. The results indicate that increasing population growth by 1% decreases economic per capita growth by almost 0.6%. Since projected growth rates are quite different across SSPs, this variable indicates further differences between the scenarios, again lifting up expected growth rates for SSP1 and SSP5, and depressing them for SSP4 and in particular for SSP3.

Moreover, the model includes fixed effects to model unobserved differences in growth capacity between countries after accounting for population growth and education. When forecasting, we assume that these differences gradually disappear – over time, they are reduced at a constant rate. We assume a half-life of 20 years, so that the modelled differences are reduced to 1/16 of the historical estimate by 2100.

We model the impact of armed conflict on growth by including data from the UCDP/PRIO armed conflict dataset (Allansson, Melander, and Themnér, 2017) that records whether at least 25 people were killed in a political conflict between a government and an organized non-state armed group. Markets typically react quickly to conflicts, more quickly than with a year's lag, so we have decided to not lag this variable as is common in many studies. Large-scale violent conflicts erupting in a year typically destroy and distort economies immediately, so that they affect growth rates in the same year. Our estimates are close to what found in the studies reviewed above (Collier, 1999; Gates et al., 2012) – a median-sized conflict typically take in excess of 2% off growth in the affected country.

Finally, the models include log total population in the country. Although population size is unlikely to affect growth rates in themselves, there are reasons to expect that armed conflict, defined with a fixed fatality threshold, has less of an impact in large countries than small ones. In growth model I, we include only log population as a predictor without an interaction term. In growth model II, we add a multiplicative interaction term between log population size and conflict. The estimates for the main terms do not have a straightforward interpretation in the presence of fixed effects and the population

Variable	Conflict model I Coefficient	Std. error	Conflict model II Coefficient	Std. error
Log population	0.3174	0.051	0.3093	0.051
Log GDP per capita$_{t-1}$	–0.1251	0.073	-0.2777	0.089
Log education	–2.1863	0.513	–2.1426	0.518
Log GDP per capita growth $_{t-1}$	–0.1644	0.419	–0.2462	0.425
Conflict$_{t-1}$	3.5430	0.529	0.7279	1.028
Conflict$_{t-2}$	1.0430	0.196	1.0431	0.196
Conflict$_{t-3}$	0.7573	0.166	0.7402	0.166
Conflict history decay1	–2.1405	1.555	-2.0240	1.554
Conflict history decay10	1.7335	0.369	1.6161	0.370
Conflict-GDP per capita int.			0.3453	0.110
Temporal fixed effects	Yes		Yes	
Regional fixed effects	Yes		Yes	

Table 2. Logistic regression results, conflict model(s), 1960–2016, geographical clusters, main terms. Complete results for conflict model I are reproduced in Appendix Table A-5, and for conflict Model II in A-10. Results for the other regional clusters are found in Appendix Tables A-5–A-8 (model I) and Tables A-10–A-13 (model II).

growth term, but the interaction term indicates that the negative effect of conflict is somewhat smaller the larger the country is. The goodness of fit of the model does not improve much when adding the interaction term – F-statistics for the two models are quite similar. In the simulations below, we average over the models, but give the simpler model a weight of 0.75 and the interaction model one of 0.25.

Modeling the effect of economic growth on armed conflict

Table 2 shows the results from estimating a logit model with armed conflict as the dependent variable. It includes the same exogenous variables as the growth model, that also have been shown to be among the most important predictors of armed conflict (Hegre and Sambanis, 2006). Countries with large populations have a higher probability of conflict (Raleigh and Hegre, 2009), and countries that have high average incomes (Fearon and Laitin, 2003), high growth rates (Collier and Hoeffler, 2004; Miguel, Satyanath, and Sergenti, 2004) or high education levels (Thyne, 2006) are less likely to have conflict. The model includes a number of variables capturing the countries' conflict history. Countries with recent past conflict are very likely to see conflict re-occurrence (Collier, Hoeffler, and Söderbom, 2008), as modeled by the two 'conflict history decay' variables.[5] The lagged conflict variables capture that armed conflicts tend to last for many years. An interaction term with GDP per capita models that middle-and high-income countries are likely to have as long conflicts as low-income countries if they break out (Fearon, 2004).

In addition to these variables, we include a set of temporal dummy variables – one for each five-year period. Historically, there have been clear global shifts in conflict propensities. The period dummies capture that more conflicts started and fewer ended during the 1980s than during the 1970s. The estimate for the final period (2011–2016) is slightly higher than earlier periods, reflecting the recent

[5]The 'conflict history decay' variables are constructed as $z = 2^{-t/\alpha}$ where t is the number of years since last conflict in a country and α a half-life parameter. The variable has the value 1 just after conflict and is reduced by 50% every α years. The decay function with $\alpha = 10$ has the strongest impact. 20 years after a past conflict, the risk of conflict is still 50% higher than for similar countries with no past conflict.

increase in conflicts globally (Pettersson and Eck, 2018).[6] These are set to zero in the simulated years, apart from the 2011–2016 cluster.

The model also includes a set of geographical 'cluster variables' to model unobserved, time-invariant country characteristics that translate into different underlying conflict propensities. Since there is no variation on the dependent variable for many countries, a fixed-effects logistic regression model would fail to produce predictions for these. Instead, we define categorical variables that include multiple countries. To even out the arbitrariness of grouping countries, we use four different groupings or clusters. In addition to the geographic cluster used in the model in Table 2, another clusters on countries' values for democracy and GDP per capita (the development cluster), a third on former colonial power (the political history cluster), and the final generates a random grouping of countries. See Section B.3 for details and estimation results for the other models.

The models are estimated without an overall intercept term, so each of the temporal/cluster dummy terms are interpreted as a time- or cluster-specific intercept. Variation over time is not large, implying that global changes in our exogenous variables capture global trends in conflict history reasonably well.

Again, we use the projections for population size and for education levels. Countries' conflict histories are updated throughout the simulation procedure.

2.3 Simulation procedure

To generate the conflict-corrected GDP per capita projections we expand the 'dynamic simulation' procedure used in Hegre et al. (2013) and Hegre et al. (2016). We simulate probabilities of armed intrastate conflict as well as GDP growth per capita, allowing the simulations to inform one another. The version used here is summarized in Figure A-1. The procedure implies estimating a set of underlying statistical models (Tables 1 and 2), assuming the projections for population and education from IIASA for 2017–2100 (Figure 2) are exogenous to conflict and growth. We also assume that the country fixed effects and cluster dummies are exogenous, but reduce their importance in the future by letting them decay with a half-life of 20 years as the simulations reach into the future.

In a number of repeated simulations, we draw realizations of model coefficients based on the estimated coefficients and the variance-covariance matrix for the estimate; calculate probability distributions for conflict and growth rates for year t_0, based on the realized coefficients and the predictor variables, and randomly draw realized conflict and growth rates based on these. We then update the values for the variables measuring historical experience of conflict and growth in the country and neighborhood. After drawing realized conflict and growth for a year, we add the simulated growth to the previous year's logged GDP per capita to obtain a new value for the simulated GDP per capita, and repeat for each year in the forecast period 2017–2100, and record the simulated outcomes for growth, GDP per capita, and conflict. The updated conflict, growth, and GDP per capita variables are then used when simulating the next years values for these three variables. We label the procedure a 'dynamic simulation' since the outcomes we draw affect the incidence of conflict at time steps $t + 2, t + 3$, etc.[7]

To even out uncertainty about model specifications, we run simulations for both sets of growth

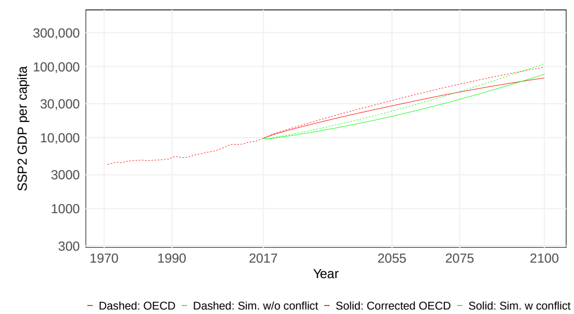
[6]Detailed results are shown in Appendix C.2 and C.3.

[7]See Hegre et al. (2013) and Hegre et al. (2016) for further details.

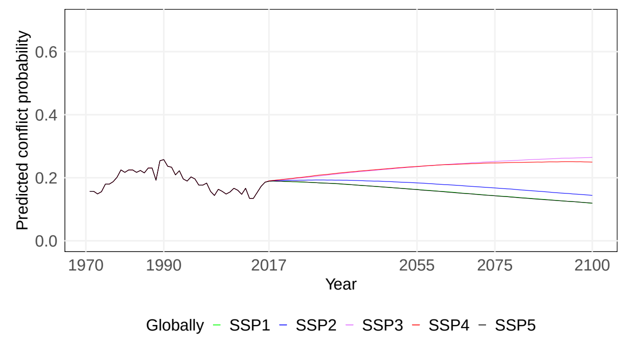
models (Table 1) and conflict models (Table 2) and average over the results. In 40% of the simulations we have no cluster variables in the conflict models, and the remaining 60% are distributed equally over the four cluster definitions.[8]

3 Results: Correcting the GDP per capita projections 2017–2100

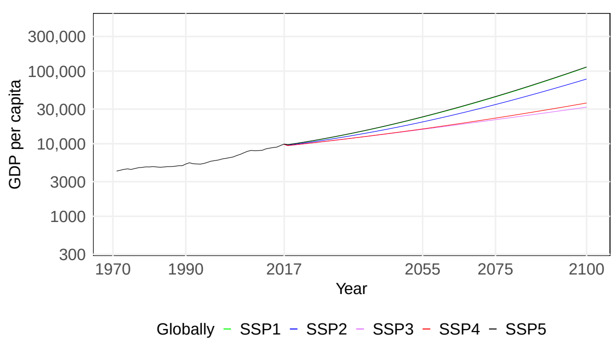
Figure 3a compares the projected growth rates in Dellink et al. (2017) with ours.[9] The red dashed line shows the unweighted global average in their projections as well as the historical trend. By the end of the century, the ENV-Growth model expects global average income to be close to \$100,000, ten times higher than the current average.



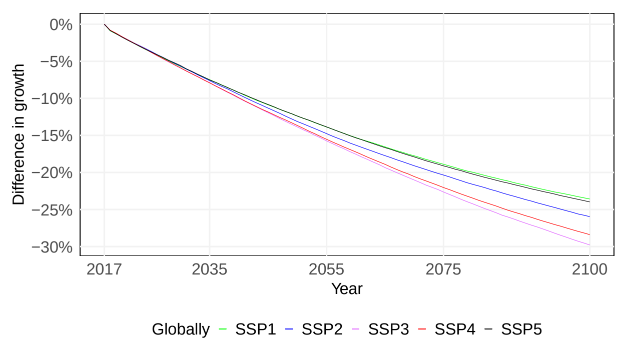
(a) Dellink et al. (2017) vs. ours, corrected and uncorrected, SSP2. Global unweighted average, 2017–2100.



(b) Simulated conflict projections, globally



(c) Simulated GDP projections, globally, model incorporating simulated conflict in growth predictions



(d) Difference between simulated GDP projections with and without simulating conflict, globally.

Figure 3. Simulation results, global unweighted averages, 2017–2100. SSP1 (green), SSP2 (blue), SSP3 (pink), SSP4 (red), SSP5 (black).

Our first set of simulations makes use of the estimates in Table 1, but in this set we do not simulate armed conflict but rather set the conflict variable to 0 for all countries for all years 2017–2100. This unrealistically optimistic scenario mirrors the assumptions in Dellink et al. (2017). The green dotted line in Figure 3a shows the unweighted global average GDP per capita for this scenario. The most important

[8] The results for the remaining conflict models are reported in Appendix C.2 and C.3.

[9] In all the figures presented in this article, 'averages' are the averages by year of all countries' log GDP per capita. We do not weight by population. Hence, if large countries such as China and India have higher GDP per capita than the median country we underestimate average income. The choice to average over log scores rather than levels pull the average toward the median.

thing to note from these results is that average growth for an SSP over the century in our projections are quite similar to the corresponding projections from Dellink et al. (2017). The growth paths are different – since convergence is what drives the Dellink et al. (2017) model, growth in low-income countries is initially high but slow down as they approach the levels of the rich countries. In their model, growth rates in the first decades of the projections are considerably higher than the historical average up to 2016. In our empirical model, per-capita growth rates increase toward the end of century since population growth is decreasing swiftly in developing countries. Although the two growth models are different in structure, the large-scale economic changes underlying our conflict simulations are roughly similar to those using the Dellink et al. (2017) projections, ensuring that the corrections we derive below are based on a roughly comparable set of scenarios.

3.1 Simulated projections of conflict and GDP per capita

The projected global proportions of countries in conflict is shown in Figure 3b. We have assumed that the intercept for the 2011–2016 period remains constant up to the end of the century – i.e. that the underlying unexplained conflict propensity of the past six years will continue (recall that this was higher than in the preceding five-year periods).

The results are roughly in line with earlier studies using the same basic setup (Hegre et al., 2016). Since we are using more elaborate and credible projections for education (KC and Lutz, 2017) than this earlier study, the forecasts for SSP 3 and 4 are somewhat more optimistic than the previous study. The forecasts for SSP 1, 2, and 5, on the other hand, are more pessimistic, since we here include the corrected growth projections in the conflict forecasts. Still, the simulations for SSP1 and SSP5 suggest a clear decline in conflict, driven by the moderate population growth and robust expansion of education under these scenarios (see Figure 2). Conversely, the forecasts for SSP3 and 4 suggest an increasing incidence of conflict (per country, if not per capita), driven by high population growth and a slow expansion of education levels. It is worth noting that these models exclude features that we cannot model into the future, and hence the simulations can only rely on the effect of structural change captured by the variables included in the analysis. Hence, efforts through mediation, peacekeeping and negotiation are not included, nor is any change in fundamental aspects such as changes in resource revenues or political power dynamics. These factors are all likely to shape the future conflict trajectory for a given country.

There is considerable uncertainty regarding these simulations. Sources of this estimated uncertainty are the imputations of exogenous variables, the uncertainty of the parameter estimates in our statistical model, the different country-level intercepts due to our region variables, and the noise implied by random draws of growth rates given the growth model. Figure 3c shows simulated global average GDP per capita from the model that takes future conflict into account.

3.2 Correcting the ENV-Growth projections

Figure 3d shows the cumulative difference in (unweighted) global GDP per capita between simulations where we ignore armed conflict and those where we take them into account. We calculate this by running two pairs of simulations of our economic growth model for the 2017–2100 – one where we assume there will be no conflicts anywhere and one where we simulate how much growth-reducing conflict to expect

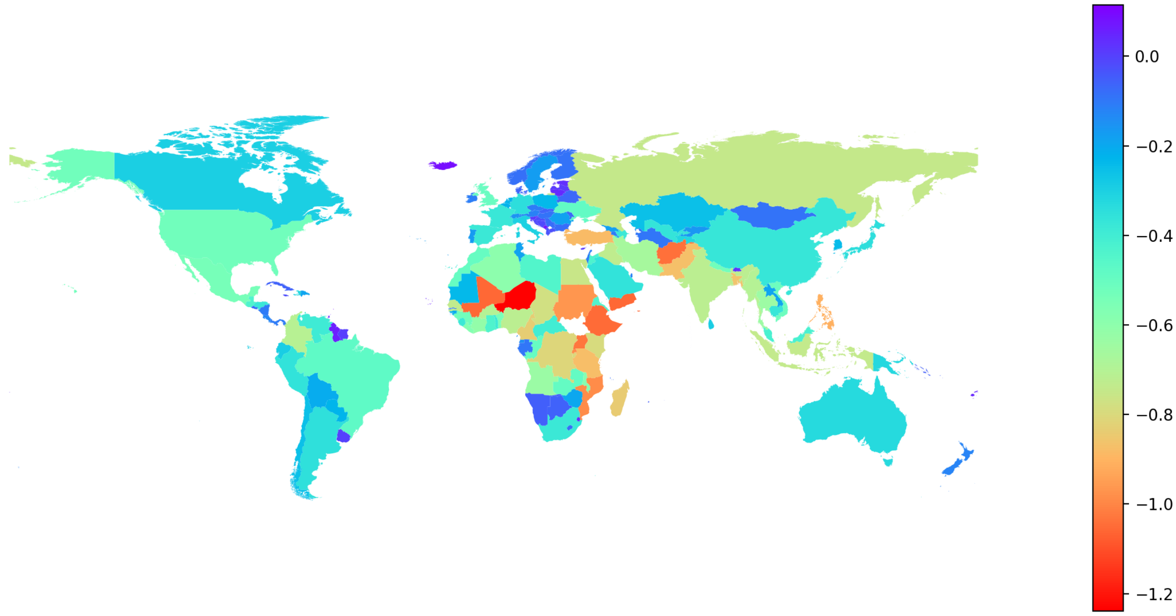


Figure 4. Cumulative correction in SSP2 for logged GDP per capita by 2100, expressed as difference in log income. A log difference of –0.2 is equal to a 18.1% correction, –0.5 corresponds to -39.3%, and –1 to –63.2% correction.

over the period. While doing so, we simultaneously update correct the growth paths of countries that experience conflict using the growth model in Table 1. The difference is our quantification of the correction required to account for the growth impeded by armed conflict – every year we simulate that a country is in conflict, the country has a growth rate that is on average 2.3% lower, as estimated in Table 1. Over the 84 years of simulation, these growth losses accumulate, especially in the SSPs where projected conflict levels are high. In the low-conflict SSP5, the unweighted average GDP per capita is more than 30% lower in 2100 than what conflict-ignorant projections indicate. For the high-conflict SSP3 and SSP4 scenarios, unweighted average GDP per capita is more than 35% lower. In these scenarios, the low underlying economic growth rate compounds the effect in a conflict trap, since a higher population growth and lower education levels depresses income, increases expected conflict levels, which decrease growth rates even more.

The final step in our correction procedure is to add the difference shown in Figure 3d to the original ENV-Growth model. Figure 3a shows the corrected and uncorrected ENV-Growth projections for the five SSPs. The original projections (again as unweighted global averages) are shown as dotted lines. We subtracted the simulated difference between simulations that ignore conflict and those that take them into account from the original projections. These corrected series are shown as solid lines in Figure 3a.

3.3 Region- and country-level results

The cumulative size of the correction in GDP per capita differs greatly between countries and regions. Figure 4 illustrates the divergence between countries in this regard for the middle-way scenario (SSP2). The further toward the red end of the scale, the larger the correction. For countries with hardly any correction to their growth projections, the color is purple. As the map shows, the corrections are greatest for countries our model suggests have a high future risk of conflict. This risk is high for countries with a recent, extended conflict history, as well as large and poor countries. Mali, Niger, Afghanistan and Ethiopia tick off many of these boxes, and the simulated effect of conflict on future economic growth over time is large. Their future income levels compared to a peaceful counterfactual are much more reduced than, for instance, Iceland or New Zealand that have a very low risk of future conflict. The correction is plausible for some countries. Afghanistan, for example, have been continuously at war for forty years and may conceivably continue to be so for many decades. If the war takes off 2% annually from the real growth potential of the country, the loss easily accumulates to a 50% loss over a century.

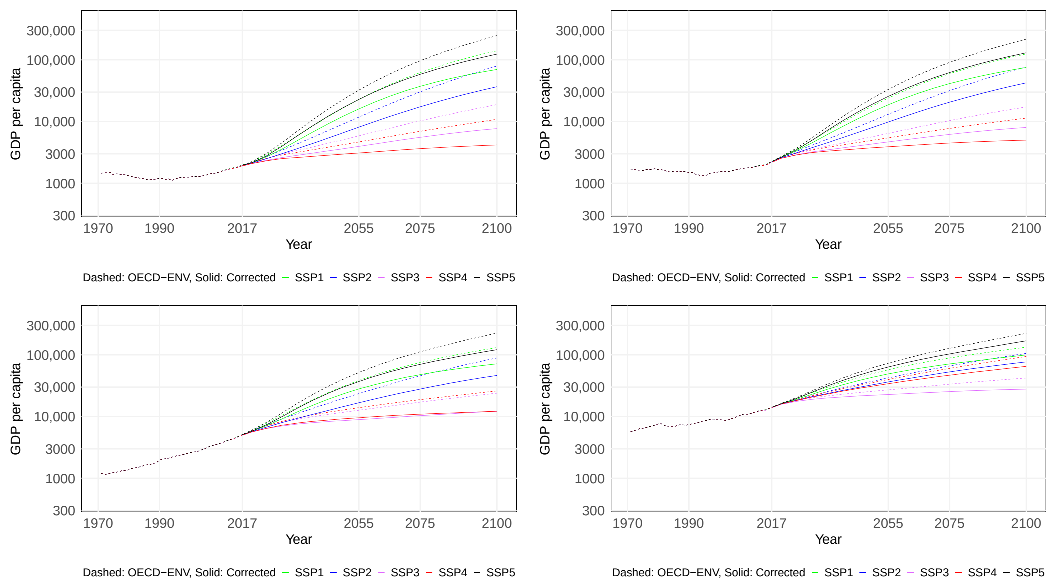
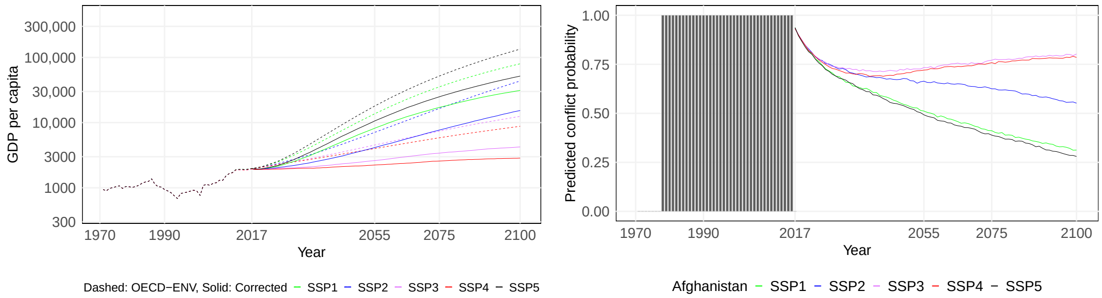


Figure 5. Corrected projections with simulated projections (2017-2100), regional differences. Top left: East Africa, top right: West Africa, bottom left: South Asia, bottom right: Latin America.

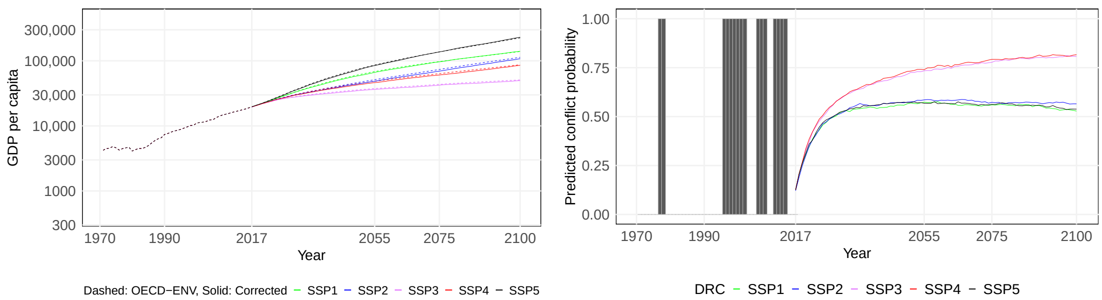
Disaggregating the projected levels of GDP per capita by region further illustrates important differences. Figure 5 shows the corrected and uncorrected ENV-Growth projections for the five SSPs for four regions. The correction for this scenario is substantial in East Africa (top left), reflecting a higher frequency of simulated conflicts. The correction is less marked in West Africa (top right) which historically has been more peaceful than its Eastern neighbors. Likewise, the correction is even smaller in Latin America (bottom right), a region where armed conflict is approaching obsolescence. In South Asia, on the other hand, our correction is substantial. Several countries in the region, e.g. India, Pakistan, and Myanmar, have had virtually continuous conflict since independence, and our models suggest that this will continue for a few more decades based on the inputs included.

Moving further down to the country level we return to the five illustrative cases shown earlier, to further understand how the data that go into the simulations differ, and how this shapes the outcomes. Comparing the effect of our corrections of GDP per capita in Afghanistan, a country with a long history of internal armed conflict, and France, which has enjoyed peace throughout the period that we study, important differences emerge. Figure 6 shows corrected and uncorrected GDP per capita and conflict for Afghanistan, the Democratic Republic of Congo (DRC), Bangladesh, Tanzania, and France. The

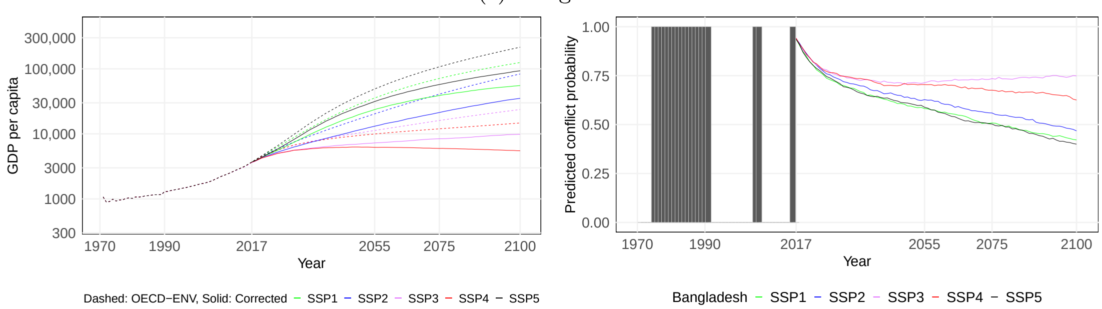
(a) Afghanistan



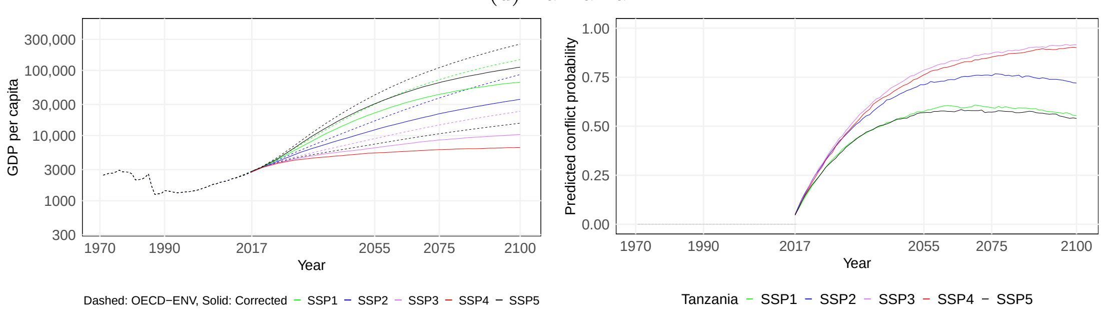
(b) Democratic Republic of Congo



(c) Bangladesh



(d) Tanzania



(e) France

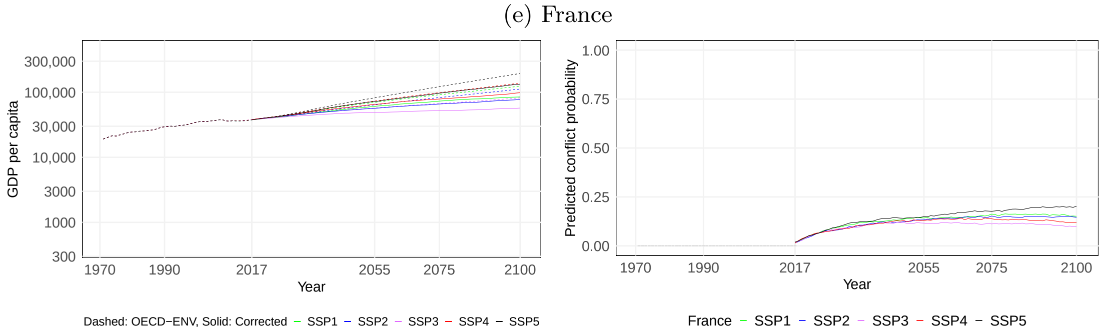


Figure 6. Historical observations and projections, individual countries

left column shows the ENV-Growth (Dellink et al., 2017) projections as well as these projections with our correction, for each SSP. The right column shows the conflict projections for each SSP.

The first four countries are all low- or lower-middle income and have a high projected probability of armed conflict. In the case of Afghanistan and DRC, they also have long conflict histories, whereas the predictions for Bangladesh and Tanzania are pulled up by their large population sizes. Toward the end of the century, all these countries are forecasted to see more than 25 deaths in 75% of the years under the pessimistic scenarios SSP 3 and 4. Under the optimistic scenarios, the simulations yield conflict in about half of the years. These forecasts seem high, but recall that population in 2100 is projected to exceed 200 million in both Tanzania and DRC in SSP 3 and 4, and well over 100 million in the low-population growth scenario. With a fixed threshold of 25 deaths in the definition of armed conflict, population size is a major predictor of conflict (Raleigh and Hegre, 2009).

The income corrections for these four countries is substantial. In Afghanistan under SSP4, Dellink et al. (2017) projects an increase in GDP per capita to about 10,000 dollars, whereas income with our correction is slightly below the current levels of 2,000. For SSP5, where Dellink et al. (2017) projects Afghanistan's income to reach the implausible value of 140,000 dollars, the correction is still about 75%.

Also in France, the model forecasts conflict in a good proportion of the simulations – highest in SSP5, where the IIASA projects France's population to increase to 125 million. Here, though, the estimated correction to income is much smaller than in the other countries.

4 Conclusions and next steps

This work improves the understanding of links between climate change, economic development and civil conflict as well as produces forecasts of future conflict burdens that are consistent with widely used climate change scenarios. The ENV-Growth model (Dellink et al., 2017) underlying much climate change research clearly over-estimates future growth in conflict-prone countries. While there are a number of issues that remain to be addressed, we successfully model the effect of the conflict trap on economic growth over the course of the 21st century. In so doing, we provide a first indication of how the ENV-Growth projections of GDP per capita can be corrected for the effect of armed conflict. Globally, our corrected projections are close to 25% lower than the original at the end of the century for the most optimistic Shared Socioeconomic Pathways, and more than 30% lower in the least optimistic ones. The correction is largest for currently poor and vulnerable countries with a conflict history, and suggests that the resources these societies will have available for adapting to climate change and other challenges are much lower than assumed in studies that rely on currently available projections.

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Supplementary Information

A Background

A.1 Previous studies on armed conflict and growth

Armed conflict, especially civil war or intrastate conflict, adversely affects many dimensions of socioeconomic development such as human health and education and has been termed 'development in reverse' (Collier et al., 2003). As many of these development indicators are also robust correlates of the onset and duration of armed conflict (e.g. Fearon and Laitin, 2003; Hegre and Sambanis, 2006), the delay in development may lead to increases in both the duration of conflict as well the onset of future conflict and thus, result in a 'conflict trap' (Collier et al., 2003; Hegre, Nygård, and Ræder, 2017). Collier, Hoeffler, and Söderbom (2008) estimate that there is an approximate 40% risk of conflict reversal in the first decade after the termination of conflict.

One of the primary pathways for this reversal is the reductions in economic growth that occur due to the onset and continue over the duration of the conflict (Gates et al., 2012; Hegre, 2018). Thus, expectations for both future economic growth patterns as well as future armed conflict events have profound implications for global stability.

Since 1945, over 57% of all countries that have had one conflict have experienced at least one more (Walter, 2011). The "conflict trap" – the higher propensity for renewed conflict once conflict has occurred – has been a defining characteristic of armed intrastate conflict. In part, the same country-level characteristics that led to the first onset of conflict may still be present after its termination. Collier et al. (2003) argue, however, that conflict also exacerbates these factors and thus increases the likelihood of future conflict . As income levels and economic growth are robust correlates of conflict propensity (Blattman and Miguel, 2010; Fearon and Laitin, 2003; Hegre and Sambanis, 2006), the disruption of economic growth both during and post conflict is of specific concern. During the conflict, economic growth is affected first through the direct diversion of economic resources to military spending. More profoundly, economic growth is damaged by the effects of the conflict through the destruction of physical capital such as infrastructure, capital flight, the destruction of social capital and the promotion of opportunistic and criminal behavior (Collier, 1999). Further, economic growth continues to lag due to continued military spending and corruption as well as changes to the structure of the economy. Namely, there is likely to be a heavier reliance on natural resource extraction which is independently associated with both decreases in economic growth and an increased propensity for conflict (Lujala, 2010; Ross, 2004; Sachs and Warner, 1995).

The consensus is that conflict has an immediate impact on economic growth by slightly more than 2% per year (Collier, 1999; Staines, 2004; Gates et al., 2012; Mueller, 2017; de Groot, Bozzoli, and Brück, 2015). After 7 years of conflict, then, GDP per capita is 15% lower than it would have been in the absence of conflict (Collier et al., 2003). Using a synthetic approach to generating the counterfactual GDP growth scenarios, Costalli, Moretti, and Pischedda (2014) confirmed the central estimate and further showed strong regional differences which they attribute to an interaction with ethnic fragmentation. The severity and the duration of the conflict have also been associated with additional effects on economic growth. Koubi (2005) evaluated the effect of the severity measured in battle deaths of both interstate and intrastate conflict. She found that severity has a significant negative effect on economic growth and further that intrastate conflict is the sole driver of this effect. There is also evidence that in addition to the severity, the duration, especially the duration of conflict in neighboring countries, can have an additional negative impact on growth (Murdoch and Sandler, 2004).

After the termination of conflict, the rate of economic growth does revert to its pre-conflict growth levels. Conflicts of short duration cause continued post-war GDP decline (Collier, 1999). However, there is also evidence of higher and more rapid GDP growth at the conclusion of longer conflicts. For example, Chen, Loayza, and Reynal-Querol (2008) found a 2.4% per year acceleration in growth after conflict, although this higher growth is temporary. This is consistent with Elbadawi, Hegre, and Milante (2008) who found a 2% per year growth in the first five year period after the termination of conflict, but lower growth in the subsequent five years. Gates et al. (2010) confirm that over ten years, post-conflict countries recover at least part of the economic losses. Hoeffler, Ijaz, and Billerbeck (2011) estimating that on average it takes approximately 15 years to revert to pre-conflict income levels, although some of this loss may be permanent (Collier et al., 2003).

The climate change research community has formulated a set of scenarios that outline socioeconomic conditions that would present greater or lesser challenges to mitigation and adaptation (Moss et al., 2010; O'Neill et al., 2014). Known as the Shared Socioeconomic Pathways (SSPs), these five pathways are designed to span a wide range of possible future worlds from present to 2100 to be used to investigate a wide range of climate impacts, especially those that have an interaction with the socioeconomic system. In our previous effort, Hegre et al. (2016) investigated how future changes to socioeconomic factors – namely, population, economic growth and educational attainment – affect the global and country-level patterns of intrastate conflict without feedback into the scenarios. We found that the scenarios produced a range of conflict outcomes with the scenarios with lower GDP/capita growth and educational attainment over the course of the century experiencing higher propensities for intrastate conflict, especially in regions which already experience conflict. We also found that scenarios with lower economic growth, although with higher levels of educational attainment, have the same propensity for conflict as scenarios with higher economic growth. Thus, we concluded that the SSP that outlines a 'sustainability' scenario - referred to as SSP1 - facilitates both climate mitigation and global stability. However, revised GDP pathways for armed conflict will have implications for both the incidence of armed conflict and GDP growth. Further, the GDP growth will influence GHG emissions and the implied climate effects for each SSP and the costs and challenges of mitigation and adaptation. Here, we further the literature by modeling these 'feedbacks' between the implied levels of armed conflict for each SSP, GDP growth and the potential challenges for climate policies.

A.2 Shared socioeconomic pathways

We use the five future scenarios outlined by the shared socioeconomic pathways (SSPs), known as SSPs 1 through 5. The scenarios are meant to represent plausible futures that capture challenges to mitigating greenhouse gases (GHG) and adapting to the impacts of climate change. The SSPs are described in detail in Moss et al. (2010) and summarized in Table A-1. The most optimistic scenario

Pathway	Total factor productivity	Speed of convergence	Fossil fuel dependence	Population growth	Education levels
SSP1 Sustainability	High	Medium	Low	Low	High
SSP2 Middle of the road	Medium	Medium	Medium	Medium	Medium
SSP3 Fragmentation	Low	Low	High	High	Low
SSP4 Inequality	Medium	Medium	High	Medium	Low
SSP5 Conventional development	High	High	High	Low	High

Table A-1. Characteristics of the five shared socioeconomic pathways. Table adapted from Dellink et al. (2017)

(SSP1) is characterized by a higher rate of economic growth and a lower environmental impact through population stabilization. The SSP3 pathway is characterized by rapid population growth and weak economic growth.

The GDP in the SSPs is developed using the OECD economic projection model (ENV-Growth). In this model, economic growth is represented by an augmented Solow growth model based on OECD data. Physical capital is here assumed to have a depreciation rate of 5%. Human capital is measured using age- and gender-specific education levels, expressed as an index that is multiplied by the labor available. This model estimates that an educated workforce is more productive than a less educated one. The OECD model explicitly incorporates value added by natural resource extraction, specifically the oil and gas sector. Built on a Solow framework, a specific implication of the model is that countries with lower GDPs will experience higher initial growth rates towards convergence at regional level. Technology transfer is assumed to be smooth, so that factor productivity approaches parity over a number of decades. They do not incorporate armed conflict or other political constraints that might impede technology transfer or productivity improvements. We do not have access to the complete ENV-Growth modeling apparatus. Hence, in what follows we estimate using our own modeling tools the extent to which armed conflict impedes economic growth over the coming decades, and use these estimates to calculate corrected ENV-Growth projections.

B Methods

B.1 Simulation procedure

To generate the conflict-corrected GDP per capita projections we expand the 'dynamic simulation' procedure presented in Hegre et al. (2013). The version used here is summarized in Figure A-1. The procedure implies estimating a set of underlying statistical models (Tables 1 and 2 as well as those presented in Appendix C), assuming the projections for population and education from IIASA for 2017–2100 (Figure 2) are exogenous to conflict and growth. In a number of repeated simulations, we draw realizations of model coefficients based on the estimated coefficients and the variance-covariance matrix for the estimate; calculate probability distributions for conflict and growth rates for year t_0, based on the realized coefficients and the predictor variables, and randomly draw realized conflict and growth rates based on these. We then update the values for the variables measuring historical experience of conflict and growth in the country and neighborhood. After drawing realized conflict and growth for a year, we add the simulated growth to the previous year's logged GDP per capita to obtain a new

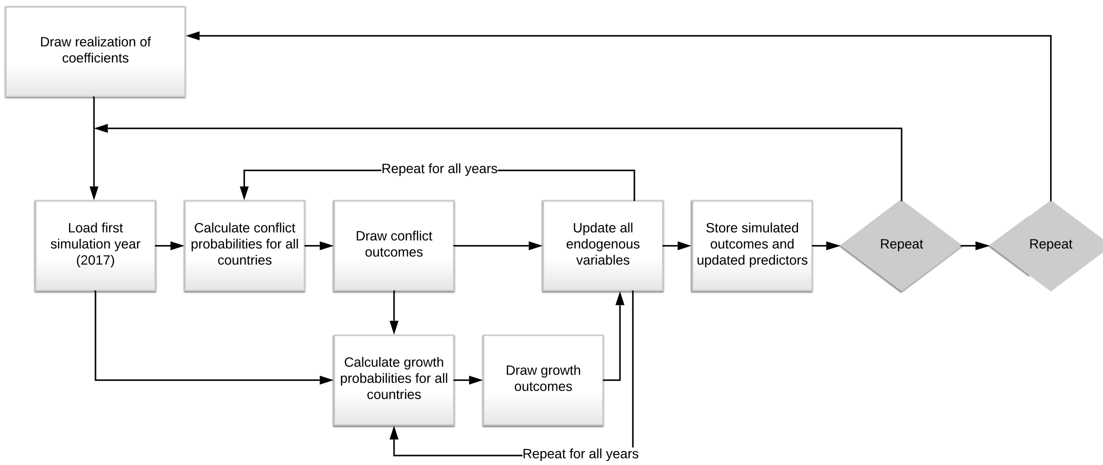

Figure A-1. Simulation procedure.

value for the simulated GDP per capita, and repeat for each year in the forecast period 2017–2100, and record the simulated outcomes for growth, gdp per capita, and conflict. The updated conflict, growth, and GDP per capita variables are then used when simulating the next years values for these three variables. We label the procedure a 'dynamic simulation' since the outcomes we draw affect the incidence of conflict at time steps $t + 2, t + 3$, etc.[10]

B.2 Imputation

The input data were completed to cover all countries for all years in the training data by various procedures. First, multiple sources were consulted (e.g. supplementing WDI data with data from Penn World Tables). When individual years were missing, we used linear interpolation. For remaining missingness, we used Amelia to multiply impute observations. We loop over five imputed datasets in the simulations, reestimating the models for each imputation and using the corresponding imputed dataset for the exogenous variables.

B.3 Cluster variables

Clustering criteria

Estimates of how economic development and other variables affect conflict propensity may suffer from omitted-variable bias due to time-invariant country characteristics (Green, Kim, and Yoon, 2001). Tanzania may be more peaceful than DRC for specific but unmeasured reasons. Unfortunately, the fixed-effects specification that works fine in the growth model cannot be used in the conflict model. Given that we have a binary dependent variable it would lead us to drop all countries that have not had any variation in the dependent variable, i.e. that have remained peaceful throughout the training period.

An alternative solution implies including four 'region' or 'cluster' variables to account for unobserved unit-specific differences in conflict propensity. The first cluster variable (geography – 'geo') groups

[10] See Hegre et al. (2013) and Hegre et al. (2016) for further details.

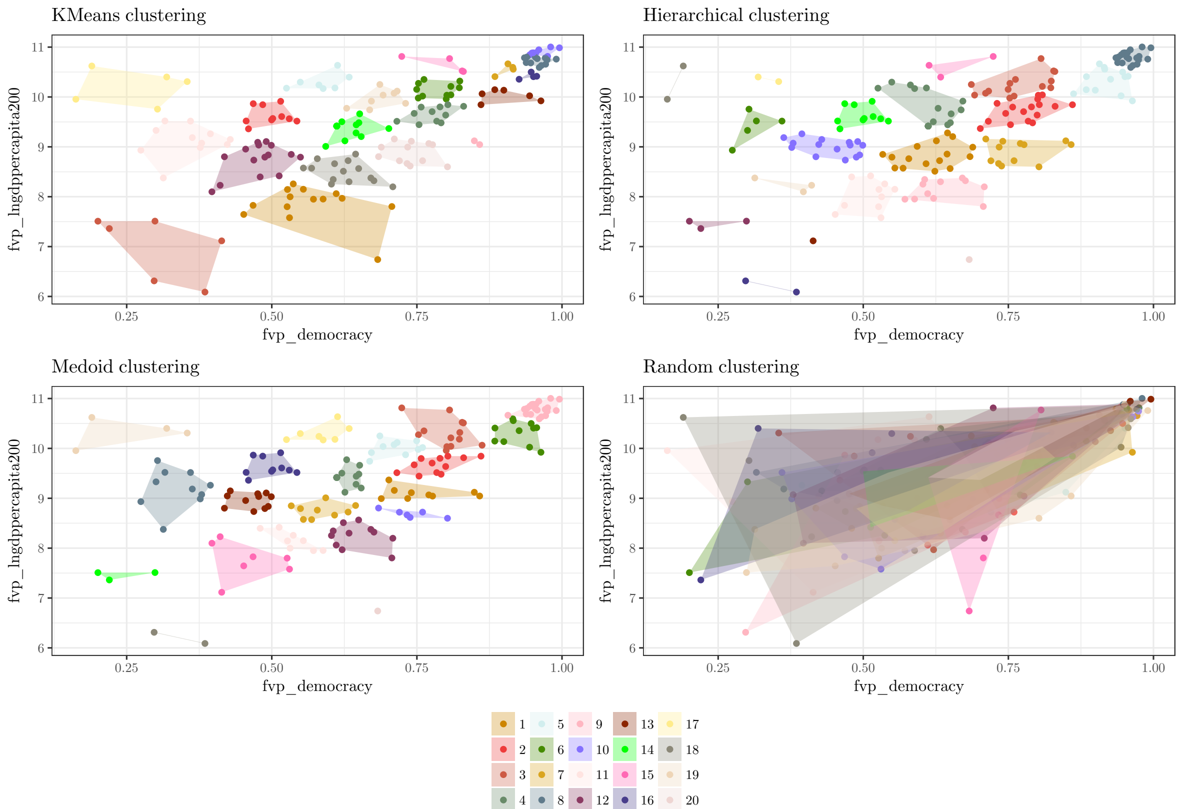

Figure A-2. Clustering results on democracy/GDP per capita

countries in terms of their geographic locations, grouping together countries that are close to each other in terms of geographic coordinates. Another clusters countries together in terms of their values for democracy and GDP per capita, grouping countries with similar institutional-political development together. A was defined in terms of shared political history ('ph') (e.g., having same former colonial power). The final variable is simply a random grouping. Each country belongs to one and only one category within each of these regions. All the region variables were slightly tweaked to ensure there is variation for all variables including the conflict variable within the groups, allowing the estimation of the logistic regression model without cases dropping out.

In our simulation procedure, we estimated four logistic regression models, one for each set of region variables but otherwise identical. Each of the region variables function as a region-specific intercept. We then ran five sets of simulations including each of these as well as one set without any clusters. Estimation results are shown in Appendix C.2 and C.3 below. In the results presented as main results, we take the average of the simulated outcomes for each of these models, in order to gain a more accurate baseline conflict propensity measure for each country than just running it with one such cluster region. Inspecting PR and ROC curves in an out-of-sample evaluation (not shown here) indicates that this setup gives more accurate conflict predictions than a model without such region variables.

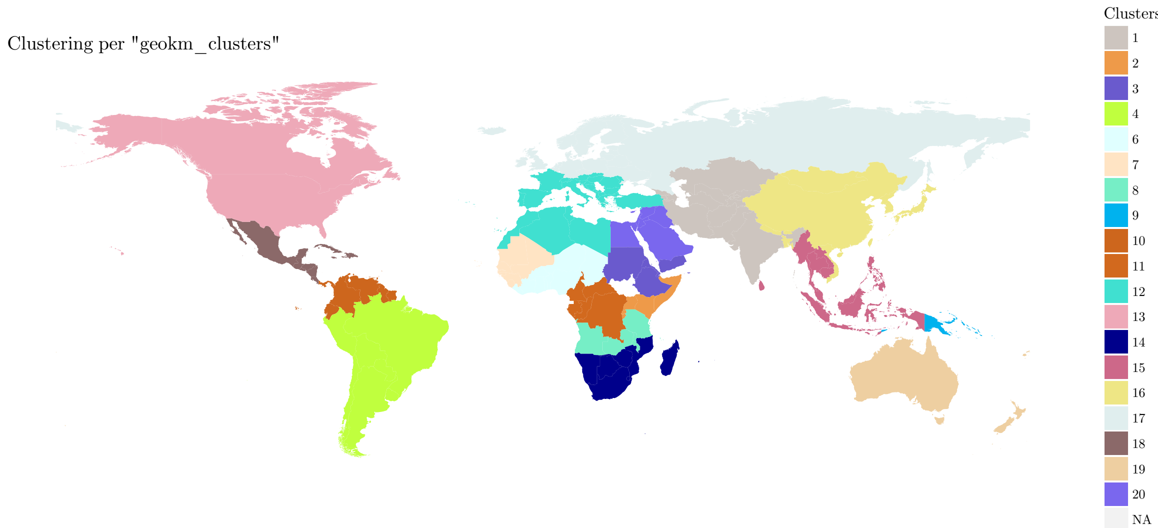

Figure A-3. World map of K-Means clustering on capital latitude and longitude (geographical cluster)

Clustering methods

We explored three methods to identify clusters. Figure A-2 shows how the methods compare when seeking clusters in terms of democracy and GDP per capita. We chose to use the k-means clustering method which gave the most complete solution for all cluster definitions, grouping almost all countries distinctly. This is an unsupervised learning algorithm that clusters data by minimizing the sum of squared Euclidean distances between data points and their respective cluster centroids. That is, the algorithm iterates through two steps following a random assignment of data points to a cluster: first, data points are reassigned to to the cluster whose centroid is closest, and then the new centroid of each cluster is calculated. This procedure is repeated until the within-cluster variation cannot be reduced any further and each data point is optimally grouped.

Figure A-3 shows the geographical K-Means clustering solution. In the simulation, we merged some of these clusters to ensure there were non-zero counts of conflict observations in each of them. We also explored hierarchical and medoid clustering approaches but did not find them to improve results relative to k-means.

C Complete results, statistical models

In this Appendix section we present results for the fixed effects (growth models) and temporal and regional terms (conflict models). All models are estimated for one of the imputed data sets.

C.1 Growth models

Dep. Variable:	delta_ln_gdp1	**R-squared:**	0.202
Model:	OLS	**Adj. R-squared:**	0.184
Method:	Least Squares	**F-statistic:**	10.91
Date:	Mon, 22 Feb 2021	**Prob (F-statistic):**	5.49e-249
Time:	11:45:25	**Log-Likelihood:**	6894.7
No. Observations:	7614	**AIC:**	-1.344e+04
Df Residuals:	7440	**BIC:**	-1.223e+04
Df Model:	173		

	coef	**std err**	**t**
Intercept	0.0072	0.014	0.510
conflict1	-0.0233	0.004	-5.353
ln_educ1	0.0912	0.027	3.427
ln_pop1	-0.0104	0.008	-1.281
delta_ln_pop1	-0.5885	0.189	-3.109
gwno_f_2_decay	0.0147	0.026	0.570
gwno_f_20_decay	-0.0064	0.016	-0.402
gwno_f_40_decay	0.0023	0.015	0.150
gwno_f_41_decay	0.0085	0.016	0.543
gwno_f_42_decay	0.0180	0.015	1.172
gwno_f_51_decay	-0.0316	0.019	-1.683
gwno_f_52_decay	-0.0137	0.020	-0.683
gwno_f_53_decay	-0.0357	0.024	-1.459
gwno_f_70_decay	0.0338	0.023	1.452
gwno_f_90_decay	0.0396	0.016	2.476
gwno_f_91_decay	0.0221	0.015	1.435
gwno_f_92_decay	0.0074	0.015	0.483
gwno_f_93_decay	0.0032	0.015	0.205
gwno_f_94_decay	0.0125	0.016	0.776
gwno_f_95_decay	0.0084	0.018	0.476
gwno_f_100_decay	0.0582	0.019	3.072
gwno_f_101_decay	0.0103	0.016	0.629
gwno_f_110_decay	-0.0308	0.023	-1.343
gwno_f_115_decay	-0.0377	0.023	-1.665
gwno_f_130_decay	0.0209	0.015	1.376
gwno_f_135_decay	0.0274	0.016	1.708
gwno_f_140_decay	0.0433	0.027	1.614
gwno_f_145_decay	0.0068	0.015	0.450
gwno_f_150_decay	0.0226	0.015	1.460
gwno_f_155_decay	0.0128	0.015	0.845
gwno_f_160_decay	0.0151	0.018	0.844
gwno_f_165_decay	-0.0006	0.017	-0.037
gwno_f_200_decay	0.0264	0.020	1.338
gwno_f_205_decay	0.0005	0.018	0.025
gwno_f_210_decay	-0.0115	0.015	-0.746
gwno_f_211_decay	-0.0121	0.016	-0.777
gwno_f_220_decay	0.0120	0.020	0.615
gwno_f_225_decay	-0.0315	0.018	-1.763
gwno_f_230_decay	0.0191	0.018	1.054
gwno_f_235_decay	0.0144	0.015	0.934
gwno_f_260_decay	-0.0051	0.019	-0.268
gwno_f_290_decay	0.0051	0.016	0.314
gwno_f_305_decay	-0.0248	0.017	-1.423
gwno_f_310_decay	-0.0117	0.016	-0.723
gwno_f_316_decay	-0.0185	0.017	-1.093
gwno_f_317_decay	-0.0034	0.019	-0.176
gwno_f_325_decay	0.0078	0.019	0.406
gwno_f_339_decay	-0.0260	0.019	-1.339
gwno_f_340_decay	-0.0402	0.174	-0.231
gwno_f_341_decay	-0.0052	0.026	-0.202
gwno_f_343_decay	-0.0621	0.020	-3.134
gwno_f_344_decay	0.0087	0.019	0.467
gwno_f_346_decay	0.0052	0.018	0.287
gwno_f_347_decay	-0.2097	0.243	-0.864
gwno_f_349_decay	-0.0136	0.022	-0.608
gwno_f_350_decay	-0.0041	0.015	-0.274
gwno_f_352_decay	-0.0172	0.022	-0.777
gwno_f_355_decay	-0.0073	0.017	-0.438
gwno_f_359_decay	-0.3012	0.019	-15.930

	coef	std err	t
gwno_f_360_decay	0.0121	0.016	0.779
gwno_f_365_decay	-0.0631	0.023	-2.800
gwno_f_366_decay	-0.1814	0.023	-7.871
gwno_f_367_decay	-0.1954	0.021	-9.148
gwno_f_368_decay	-0.1144	0.019	-5.952
gwno_f_369_decay	-0.0760	0.017	-4.359
gwno_f_370_decay	-0.0679	0.016	-4.217
gwno_f_371_decay	-0.2773	0.020	-13.594
gwno_f_372_decay	-0.3142	0.019	-16.584
gwno_f_373_decay	-0.1356	0.017	-8.036
gwno_f_375_decay	-0.0310	0.019	-1.606
gwno_f_380_decay	-0.0165	0.016	-1.040
gwno_f_385_decay	-0.0276	0.020	-1.393
gwno_f_390_decay	-0.0358	0.019	-1.874
gwno_f_395_decay	-0.0262	0.025	-1.062
gwno_f_402_decay	0.0040	0.038	0.106
gwno_f_404_decay	0.0106	0.017	0.610
gwno_f_411_decay	0.0100	0.015	0.659
gwno_f_420_decay	0.0025	0.018	0.139
gwno_f_432_decay	0.0490	0.017	2.853
gwno_f_433_decay	0.0299	0.016	1.840
gwno_f_434_decay	0.0292	0.016	1.839
gwno_f_435_decay	0.0079	0.016	0.487
gwno_f_436_decay	0.0274	0.017	1.584
gwno_f_437_decay	0.0271	0.017	1.559
gwno_f_438_decay	0.0214	0.016	1.335
gwno_f_439_decay	0.0488	0.017	2.847
gwno_f_450_decay	-0.0148	0.016	-0.924
gwno_f_451_decay	0.0153	0.016	0.980
gwno_f_452_decay	0.0223	0.016	1.400
gwno_f_461_decay	0.0054	0.016	0.347
gwno_f_471_decay	0.0361	0.017	2.143
gwno_f_475_decay	0.0527	0.026	2.008
gwno_f_481_decay	0.0013	0.018	0.072
gwno_f_482_decay	-0.0120	0.016	-0.753
gwno_f_483_decay	0.0510	0.017	3.076
gwno_f_484_decay	0.0142	0.016	0.867
gwno_f_490_decay	0.0102	0.020	0.518
gwno_f_500_decay	0.0607	0.019	3.184
gwno_f_501_decay	0.0375	0.018	2.108
gwno_f_510_decay	0.0404	0.021	1.890
gwno_f_516_decay	0.0310	0.016	1.907
gwno_f_517_decay	0.0500	0.016	3.047
gwno_f_520_decay	-0.0004	0.016	-0.028
gwno_f_522_decay	-0.0292	0.018	-1.590
gwno_f_530_decay	0.0834	0.025	3.306
gwno_f_531_decay	0.1085	0.016	6.822
gwno_f_540_decay	0.0484	0.018	2.766
gwno_f_541_decay	0.0559	0.018	3.053
gwno_f_551_decay	0.0149	0.015	0.958
gwno_f_552_decay	0.0017	0.015	0.112
gwno_f_553_decay	0.0279	0.016	1.783
gwno_f_560_decay	0.0205	0.018	1.146
gwno_f_565_decay	0.0119	0.018	0.647
gwno_f_570_decay	0.0288	0.017	1.703
gwno_f_571_decay	0.0363	0.019	1.942
gwno_f_572_decay	0.0109	0.019	0.572
gwno_f_580_decay	0.0143	0.017	0.826
gwno_f_581_decay	-0.0152	0.019	-0.796
gwno_f_590_decay	0.0194	0.018	1.075
gwno_f_600_decay	0.0590	0.019	3.061
gwno_f_615_decay	0.0374	0.017	2.170
gwno_f_616_decay	0.0340	0.015	2.230
gwno_f_620_decay	-0.0611	0.016	-3.885
gwno_f_625_decay	0.0635	0.019	3.285
gwno_f_626_decay	-0.0931	0.422	-0.221
gwno_f_630_decay	0.0330	0.021	1.557

	coef	std err	t
gwno_f_640_decay	0.0650	0.022	2.950
gwno_f_645_decay	0.0689	0.017	4.001
gwno_f_651_decay	0.0547	0.021	2.583
gwno_f_652_decay	0.0203	0.016	1.249
gwno_f_660_decay	-0.0038	0.017	-0.224
gwno_f_663_decay	0.0024	0.017	0.140
gwno_f_666_decay	0.0198	0.017	1.175
gwno_f_670_decay	0.0128	0.016	0.792
gwno_f_678_decay	0.0451	0.018	2.488
gwno_f_690_decay	0.0100	0.015	0.659
gwno_f_692_decay	0.0012	0.028	0.044
gwno_f_694_decay	0.0012	0.028	0.044
gwno_f_696_decay	0.0012	0.028	0.044
gwno_f_698_decay	0.0100	0.015	0.659
gwno_f_700_decay	0.0525	0.017	3.009
gwno_f_701_decay	-0.1091	0.020	-5.586
gwno_f_702_decay	-0.1971	0.018	-11.075
gwno_f_703_decay	-0.1122	0.019	-5.992
gwno_f_704_decay	-0.0677	0.016	-4.291
gwno_f_705_decay	-0.0434	0.016	-2.760
gwno_f_710_decay	0.1068	0.041	2.629
gwno_f_712_decay	0.0078	0.020	0.390
gwno_f_731_decay	0.0062	0.019	0.328
gwno_f_732_decay	0.0483	0.017	2.779
gwno_f_740_decay	0.0113	0.022	0.513
gwno_f_750_decay	0.1080	0.041	2.639
gwno_f_760_decay	0.0303	0.019	1.592
gwno_f_770_decay	0.0748	0.027	2.737
gwno_f_771_decay	0.0673	0.027	2.461
gwno_f_775_decay	0.0888	0.020	4.408
gwno_f_780_decay	0.0472	0.016	3.023
gwno_f_781_decay	0.0360	0.020	1.784
gwno_f_790_decay	0.0457	0.018	2.564
gwno_f_800_decay	0.0770	0.022	3.437
gwno_f_811_decay	0.0444	0.016	2.714
gwno_f_812_decay	0.0461	0.015	2.997
gwno_f_816_decay	0.0566	0.022	2.568
gwno_f_820_decay	0.0410	0.016	2.608
gwno_f_830_decay	0.0100	0.015	0.659
gwno_f_835_decay	-0.0034	0.041	-0.084
gwno_f_840_decay	0.0553	0.021	2.625
gwno_f_850_decay	0.0849	0.029	2.913
gwno_f_860_decay	-0.0036	0.118	-0.031
gwno_f_900_decay	-0.0040	0.015	-0.257
gwno_f_910_decay	0.0077	0.015	0.501
gwno_f_920_decay	-0.0277	0.019	-1.445
gwno_f_940_decay	-0.0044	0.020	-0.217
gwno_f_950_decay	-0.0220	0.022	-1.014

Omnibus:	5077.400	**Durbin-Watson:**	1.555
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	32065373.151
Skew:	-1.411	**Prob(JB):**	0.00
Kurtosis:	320.907	**Cond. No.**	1.09e+03

Table A-2. Complete Results, growth model I (1), 1960–2016

Dep. Variable:	delta_ln_gdp1	**R-squared:**	0.208
Model:	OLS	**Adj. R-squared:**	0.190
Method:	Least Squares	**F-statistic:**	11.25
Date:	Tue, 23 Feb 2021	**Prob (F-statistic):**	1.95e-259
Time:	13:02:56	**Log-Likelihood:**	6923.1
No. Observations:	7614	**AIC:**	-1.350e+04
Df Residuals:	7439	**BIC:**	-1.228e+04
Df Model:	174		

	coef	**std err**	**t**
Intercept	0.0243	0.014	1.700
conflict1	-0.0980	0.011	-8.981
ln_educ1	0.0856	0.027	3.227
ln_pop1	-0.0170	0.008	-2.094
delta_ln_pop1	-0.6402	0.189	-3.393
ln_pop1:conflict1	0.0260	0.003	7.462
gwno_f_2_decay	0.0385	0.026	1.492
gwno_f_20_decay	0.0029	0.016	0.183
gwno_f_40_decay	0.0044	0.015	0.288
gwno_f_41_decay	0.0084	0.016	0.537
gwno_f_42_decay	0.0181	0.015	1.189
gwno_f_51_decay	-0.0377	0.019	-2.010
gwno_f_52_decay	-0.0219	0.020	-1.095
gwno_f_53_decay	-0.0486	0.024	-1.987
gwno_f_70_decay	0.0474	0.023	2.037
gwno_f_90_decay	0.0504	0.016	3.149
gwno_f_91_decay	0.0190	0.015	1.239
gwno_f_92_decay	0.0137	0.015	0.900
gwno_f_93_decay	0.0082	0.015	0.534
gwno_f_94_decay	0.0074	0.016	0.464
gwno_f_95_decay	0.0036	0.017	0.207
gwno_f_100_decay	0.0487	0.019	2.571
gwno_f_101_decay	0.0164	0.016	1.011
gwno_f_110_decay	-0.0413	0.023	-1.807
gwno_f_115_decay	-0.0486	0.023	-2.147
gwno_f_130_decay	0.0228	0.015	1.504
gwno_f_135_decay	0.0309	0.016	1.932
gwno_f_140_decay	0.0623	0.027	2.321
gwno_f_145_decay	0.0065	0.015	0.432
gwno_f_150_decay	0.0197	0.015	1.280
gwno_f_155_decay	0.0169	0.015	1.123
gwno_f_160_decay	0.0231	0.018	1.294
gwno_f_165_decay	-0.0054	0.017	-0.325
gwno_f_200_decay	0.0242	0.020	1.231
gwno_f_205_decay	-0.0029	0.018	-0.163
gwno_f_210_decay	-0.0066	0.015	-0.433
gwno_f_211_decay	-0.0100	0.015	-0.648
gwno_f_220_decay	0.0249	0.020	1.275
gwno_f_225_decay	-0.0309	0.018	-1.733
gwno_f_230_decay	0.0253	0.018	1.400
gwno_f_235_decay	0.0149	0.015	0.971
gwno_f_260_decay	0.0107	0.019	0.567
gwno_f_290_decay	0.0160	0.016	0.978
gwno_f_305_decay	-0.0236	0.017	-1.354
gwno_f_310_decay	-0.0094	0.016	-0.582
gwno_f_316_decay	-0.0156	0.017	-0.924
gwno_f_317_decay	-0.0042	0.019	-0.222
gwno_f_325_decay	0.0204	0.019	1.054
gwno_f_339_decay	-0.0304	0.019	-1.569
gwno_f_340_decay	-0.0197	0.173	-0.114
gwno_f_341_decay	-0.0155	0.026	-0.609
gwno_f_343_decay	-0.0682	0.020	-3.449
gwno_f_344_decay	0.0059	0.019	0.320
gwno_f_346_decay	0.0037	0.018	0.204
gwno_f_347_decay	-0.2457	0.242	-1.016
gwno_f_349_decay	-0.0197	0.022	-0.883
gwno_f_350_decay	-0.0027	0.015	-0.179
gwno_f_352_decay	-0.0272	0.022	-1.228
gwno_f_355_decay	-0.0064	0.016	-0.390
gwno_f_359_decay	-0.3035	0.019	-16.108

	coef	std err	t
gwno_f_360_decay	0.0186	0.016	1.197
gwno_f_365_decay	-0.0738	0.023	-3.281
gwno_f_366_decay	-0.1894	0.023	-8.239
gwno_f_367_decay	-0.2012	0.021	-9.446
gwno_f_368_decay	-0.1183	0.019	-6.178
gwno_f_369_decay	-0.0654	0.017	-3.755
gwno_f_370_decay	-0.0658	0.016	-4.103
gwno_f_371_decay	-0.2816	0.020	-13.852
gwno_f_372_decay	-0.3125	0.019	-16.555
gwno_f_373_decay	-0.1295	0.017	-7.692
gwno_f_375_decay	-0.0321	0.019	-1.672
gwno_f_380_decay	-0.0152	0.016	-0.965
gwno_f_385_decay	-0.0294	0.020	-1.490
gwno_f_390_decay	-0.0368	0.019	-1.930
gwno_f_395_decay	-0.0389	0.025	-1.578
gwno_f_402_decay	-0.0185	0.038	-0.491
gwno_f_404_decay	0.0021	0.017	0.119
gwno_f_411_decay	0.0132	0.015	0.872
gwno_f_420_decay	-0.0068	0.018	-0.377
gwno_f_432_decay	0.0499	0.017	2.916
gwno_f_433_decay	0.0322	0.016	1.992
gwno_f_434_decay	0.0264	0.016	1.670
gwno_f_435_decay	0.0066	0.016	0.409
gwno_f_436_decay	0.0290	0.017	1.678
gwno_f_437_decay	0.0291	0.017	1.683
gwno_f_438_decay	0.0202	0.016	1.265
gwno_f_439_decay	0.0495	0.017	2.897
gwno_f_450_decay	-0.0110	0.016	-0.683
gwno_f_451_decay	0.0184	0.016	1.184
gwno_f_452_decay	0.0272	0.016	1.713
gwno_f_461_decay	0.0021	0.015	0.137
gwno_f_471_decay	0.0386	0.017	2.296
gwno_f_475_decay	0.0571	0.026	2.184
gwno_f_481_decay	-0.0095	0.018	-0.525
gwno_f_482_decay	-0.0121	0.016	-0.762
gwno_f_483_decay	0.0647	0.017	3.892
gwno_f_484_decay	0.0127	0.016	0.781
gwno_f_490_decay	0.0110	0.020	0.563
gwno_f_500_decay	0.0611	0.019	3.220
gwno_f_501_decay	0.0439	0.018	2.471
gwno_f_510_decay	0.0474	0.021	2.222
gwno_f_516_decay	0.0372	0.016	2.293
gwno_f_517_decay	0.0545	0.016	3.331
gwno_f_520_decay	0.0094	0.016	0.606
gwno_f_522_decay	-0.0355	0.018	-1.940
gwno_f_530_decay	0.0656	0.025	2.598
gwno_f_531_decay	0.1049	0.016	6.612
gwno_f_540_decay	0.0568	0.017	3.247
gwno_f_541_decay	0.0610	0.018	3.338
gwno_f_551_decay	0.0153	0.015	0.994
gwno_f_552_decay	0.0090	0.015	0.596
gwno_f_553_decay	0.0288	0.016	1.847
gwno_f_560_decay	0.0257	0.018	1.443
gwno_f_565_decay	0.0042	0.018	0.229
gwno_f_570_decay	0.0205	0.017	1.213
gwno_f_571_decay	0.0277	0.019	1.482
gwno_f_572_decay	-7.713e-05	0.019	-0.004
gwno_f_580_decay	0.0171	0.017	0.991
gwno_f_581_decay	-0.0258	0.019	-1.357
gwno_f_590_decay	0.0085	0.018	0.471
gwno_f_600_decay	0.0633	0.019	3.294
gwno_f_615_decay	0.0356	0.017	2.072
gwno_f_616_decay	0.0342	0.015	2.252
gwno_f_620_decay	-0.0622	0.016	-3.972
gwno_f_625_decay	0.0614	0.019	3.188
gwno_f_626_decay	-0.0545	0.420	-0.130
gwno_f_630_decay	0.0269	0.021	1.274

	coef	std err	t
gwno_f_640_decay	0.0537	0.022	2.441
gwno_f_645_decay	0.0713	0.017	4.157
gwno_f_651_decay	0.0604	0.021	2.857
gwno_f_652_decay	0.0237	0.016	1.460
gwno_f_660_decay	0.0006	0.017	0.036
gwno_f_663_decay	-0.0005	0.017	-0.031
gwno_f_666_decay	0.0443	0.017	2.584
gwno_f_670_decay	0.0186	0.016	1.157
gwno_f_678_decay	0.0470	0.018	2.602
gwno_f_690_decay	0.0132	0.015	0.872
gwno_f_692_decay	0.0074	0.028	0.265
gwno_f_694_decay	0.0074	0.028	0.265
gwno_f_696_decay	0.0074	0.028	0.265
gwno_f_698_decay	0.0132	0.015	0.872
gwno_f_700_decay	0.0548	0.017	3.150
gwno_f_701_decay	-0.1107	0.019	-5.690
gwno_f_702_decay	-0.1920	0.018	-10.816
gwno_f_703_decay	-0.1137	0.019	-6.091
gwno_f_704_decay	-0.0599	0.016	-3.804
gwno_f_705_decay	-0.0381	0.016	-2.429
gwno_f_710_decay	0.1365	0.041	3.356
gwno_f_712_decay	0.0018	0.020	0.092
gwno_f_731_decay	0.0107	0.019	0.572
gwno_f_732_decay	0.0597	0.017	3.433
gwno_f_740_decay	0.0295	0.022	1.336
gwno_f_750_decay	0.0498	0.042	1.200
gwno_f_760_decay	0.0171	0.019	0.899
gwno_f_770_decay	0.0659	0.027	2.416
gwno_f_771_decay	0.0641	0.027	2.353
gwno_f_775_decay	0.0757	0.020	3.758
gwno_f_780_decay	0.0511	0.016	3.283
gwno_f_781_decay	0.0214	0.020	1.058
gwno_f_790_decay	0.0487	0.018	2.739
gwno_f_800_decay	0.0720	0.022	3.225
gwno_f_811_decay	0.0541	0.016	3.307
gwno_f_812_decay	0.0495	0.015	3.229
gwno_f_816_decay	0.0701	0.022	3.181
gwno_f_820_decay	0.0474	0.016	3.023
gwno_f_830_decay	0.0132	0.015	0.872
gwno_f_835_decay	0.0044	0.041	0.106
gwno_f_840_decay	0.0348	0.021	1.642
gwno_f_850_decay	0.0696	0.029	2.391
gwno_f_860_decay	-0.0359	0.118	-0.305
gwno_f_900_decay	0.0022	0.015	0.142
gwno_f_910_decay	0.0095	0.015	0.620
gwno_f_920_decay	-0.0309	0.019	-1.615
gwno_f_940_decay	-0.0179	0.020	-0.885
gwno_f_950_decay	-0.0328	0.022	-1.514

Omnibus:	4878.903	**Durbin-Watson:**	1.559
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	32001713.286
Skew:	-1.267	**Prob(JB):**	0.00
Kurtosis:	320.594	**Cond. No.**	1.12e+03

Table A-3. Complete Results, growth model II (1), 1960–2016

C.2 Conflict models with no interaction term

In this section, we show estimates for the first conflict model for each of the five region definitions: political history (Table A-4), geography (Table A-5), development (Table A-6), random regions (Table A-7), and no clusters (Table A-8). Estimates for the variables of core interest that change over time differ only moderately between models.

Political history clusters

Dep. Variable:	conflict1	**No. Observations:**	7267
Model:	Logit	**Df Residuals:**	7238
Method:	MLE	**Df Model:**	28
Date:	Mon, 22 Feb 2021	**Pseudo R-squ.:**	0.6525
Time:	11:45:23	**Log-Likelihood:**	-1146.7
converged:	True	**LL-Null:**	-3299.6

	coef	**std err**	**z**
ln_pop1	0.3637	0.056	6.484
l1_ln_gdp1	-0.1113	0.089	-1.249
l1_delta_ln_gdp1	-0.1673	0.412	-0.406
l1_conflict1	3.5667	0.529	6.748
l2_conflict1	1.0538	0.197	5.347
l3_conflict1	0.7455	0.166	4.479
decay_10_cw0_conflict1	1.7351	0.372	4.665
decay_1_cw0_conflict1	-2.2498	1.560	-1.442
year5_c_f_1971	-3.2756	0.736	-4.453
year5_c_f_1976	-3.1099	0.726	-4.283
year5_c_f_1981	-3.2899	0.729	-4.510
year5_c_f_1986	-3.0228	0.717	-4.215
year5_c_f_1991	-3.2155	0.713	-4.513
year5_c_f_1996	-3.5006	0.709	-4.934
year5_c_f_2001	-3.5854	0.716	-5.006
year5_c_f_2006	-3.4413	0.728	-4.725
year5_c_f_2011	-3.1959	0.727	-4.394
ph_fv3_f_decay	-0.4306	0.294	-1.464
ph_fv5_f_decay	-0.6328	0.277	-2.287
ph_fv7_f_decay	0.4640	0.216	2.153
ph_fv9_f_decay	-0.1709	0.195	-0.875
ph_fv11_f_decay	-0.2840	0.217	-1.306
ph_fv14_f_decay	0.3588	0.217	1.656
ph_fv16_f_decay	-0.5664	0.229	-2.473
ph_fv18_f_decay	-0.0612	0.256	-0.239
ph_fv21_f_decay	-0.0064	0.274	-0.023
ph_fv23_f_decay	-0.4352	0.251	-1.732
ph_fv25_f_decay	-0.2787	0.244	-1.141

Table A-4. Results, conflict equation with political history clusters, 1960–2016

Geographical clusters

Dep. Variable:	conflict1	**No. Observations:**	7267
Model:	Logit	**Df Residuals:**	7241
Method:	MLE	**Df Model:**	25
Date:	Mon, 22 Feb 2021	**Pseudo R-squ.:**	0.6512
Time:	11:35:05	**Log-Likelihood:**	-1151.0
converged:	True	**LL-Null:**	-3299.6

	coef	**std err**	**z**
ln_pop1	0.3174	0.051	6.268
l1_ln_gdp1	-0.1251	0.073	-1.704
ln_educ1	-2.1863	0.513	-4.260
l1_delta_ln_gdp1	-0.1644	0.419	-0.392
l1_conflict1	3.5430	0.529	6.701
l2_conflict1	1.0430	0.196	5.325
l3_conflict1	0.7573	0.166	4.561
decay_10_cw0_conflict1	1.7335	0.369	4.698
decay_1_cw0_conflict1	-2.1405	1.555	-1.377
year5_c_f_1971	-2.8824	0.644	-4.474
year5_c_f_1976	-2.6797	0.630	-4.255
year5_c_f_1981	-2.8260	0.636	-4.444
year5_c_f_1986	-2.5338	0.630	-4.024
year5_c_f_1991	-2.7313	0.623	-4.385
year5_c_f_1996	-2.9504	0.620	-4.758
year5_c_f_2001	-2.9900	0.627	-4.769
year5_c_f_2006	-2.8167	0.637	-4.425
year5_c_f_2011	-2.5471	0.636	-4.006
geo_fv3_f_decay	-0.2593	0.280	-0.925
geo_fv5_f_decay	-0.2947	0.258	-1.140
geo_fv7_f_decay	-0.4232	0.231	-1.832
geo_fv9_f_decay	0.1592	0.210	0.760
geo_fv11_f_decay	-0.2412	0.292	-0.825
geo_fv14_f_decay	-0.2383	0.267	-0.894
geo_fv16_f_decay	-0.7014	0.224	-3.124
geo_fv19_f_decay	-0.4576	0.261	-1.753

Table A-5. Results, conflict equation with geographical clusters, 1960–2016

Development clusters

Dep. Variable:	conflict1	**No. Observations:**	7267
Model:	Logit	**Df Residuals:**	7241
Method:	MLE	**Df Model:**	25
Date:	Mon, 22 Feb 2021	**Pseudo R-squ.:**	0.6488
Time:	11:40:37	**Log-Likelihood:**	-1158.7
converged:	True	**LL-Null:**	-3299.6

	coef	**std err**	**z**
ln_pop1	0.3160	0.046	6.812
l1_ln_gdp1	-0.0837	0.074	-1.135
ln_educ1	-1.7705	0.479	-3.693
l1_delta_ln_gdp1	-0.2215	0.426	-0.521
l1_conflict1	3.6700	0.522	7.026
l2_conflict1	1.0831	0.195	5.561
l3_conflict1	0.7832	0.165	4.751
decay_10_cw0_conflict1	1.8599	0.369	5.036
decay_1_cw0_conflict1	-2.5456	1.541	-1.652
year5_c_f_1971	-3.3991	0.626	-5.428
year5_c_f_1976	-3.2120	0.610	-5.267
year5_c_f_1981	-3.3888	0.610	-5.551
year5_c_f_1986	-3.1185	0.603	-5.176
year5_c_f_1991	-3.3107	0.594	-5.573
year5_c_f_1996	-3.5526	0.590	-6.017
year5_c_f_2001	-3.6187	0.595	-6.082
year5_c_f_2006	-3.4484	0.605	-5.698
year5_c_f_2011	-3.2120	0.601	-5.341
km_fv3_f_decay	-0.5534	0.219	-2.532
km_fv5_f_decay	-0.2365	0.227	-1.042
km_fv7_f_decay	-0.1084	0.224	-0.484
km_fv9_f_decay	-0.1189	0.155	-0.766
km_fv11_f_decay	-0.2272	0.200	-1.135
km_fv13_f_decay	0.1117	0.213	0.524
km_fv15_f_decay	-0.3208	0.194	-1.656
km_fv19_f_decay	-0.1489	0.166	-0.899

Table A-6. Results, conflict equation with development clusters, 1960–2016

Random clusters

Dep. Variable:	conflict1	**No. Observations:**	7267
Model:	Logit	**Df Residuals:**	7241
Method:	MLE	**Df Model:**	25
Date:	Mon, 22 Feb 2021	**Pseudo R-squ.:**	0.6492
Time:	14:47:44	**Log-Likelihood:**	-1157.6
converged:	True	**LL-Null:**	-3299.6

	coef	**std err**	**z**
ln_pop1	0.3454	0.049	6.986
l1_ln_gdp1	-0.0635	0.074	-0.860
ln_educ1	-1.7350	0.480	-3.612
l1_delta_ln_gdp1	-0.2138	0.419	-0.510
l1_conflict1	3.5771	0.524	6.820
l2_conflict1	1.0486	0.196	5.360
l3_conflict1	0.7442	0.166	4.496
decay_10_cw0_conflict1	1.8296	0.373	4.899
decay_1_cw0_conflict1	-2.2865	1.550	-1.475
year5_c_f_1971	-3.8165	0.613	-6.231
year5_c_f_1976	-3.6253	0.594	-6.099
year5_c_f_1981	-3.8084	0.594	-6.416
year5_c_f_1986	-3.5421	0.585	-6.052
year5_c_f_1991	-3.7266	0.577	-6.455
year5_c_f_1996	-3.9563	0.573	-6.907
year5_c_f_2001	-4.0042	0.577	-6.943
year5_c_f_2006	-3.8567	0.585	-6.591
year5_c_f_2011	-3.6187	0.580	-6.240
rm_fv3_f_decay	0.2047	0.159	1.283
rm_fv5_f_decay	0.1805	0.181	0.998
rm_fv7_f_decay	0.2188	0.220	0.996
rm_fv9_f_decay	-0.2592	0.179	-1.448
rm_fv11_f_decay	-0.2532	0.205	-1.233
rm_fv13_f_decay	-0.0802	0.176	-0.457
rm_fv15_f_decay	0.0977	0.165	0.593
rm_fv19_f_decay	-0.7738	0.326	-2.371

Table A-7. Results, conflict equation with random clusters, 1960–2016

No clusters

Dep. Variable:	conflict1	**No. Observations:**	7267
Model:	Logit	**Df Residuals:**	7249
Method:	MLE	**Df Model:**	17
Date:	Mon, 22 Feb 2021	**Pseudo R-squ.:**	0.6470
Time:	11:56:23	**Log-Likelihood:**	-1164.7
converged:	True	**LL-Null:**	-3299.6

	coef	**std err**	**z**
ln_pop1	0.3124	0.047	6.655
l1_ln_gdp1	-0.0801	0.071	-1.131
ln_educ1	-1.5917	0.466	-3.417
l1_delta_ln_gdp1	-0.2513	0.423	-0.594
l1_conflict1	3.6836	0.520	7.077
l2_conflict1	1.0812	0.195	5.555
l3_conflict1	0.7719	0.165	4.687
decay_10_cw0_conflict1	1.9841	0.364	5.445
decay_1_cw0_conflict1	-2.6420	1.532	-1.724
year5_c_f_1971	-3.6914	0.594	-6.217
year5_c_f_1976	-3.5078	0.576	-6.094
year5_c_f_1981	-3.7001	0.577	-6.413
year5_c_f_1986	-3.4324	0.568	-6.048
year5_c_f_1991	-3.6324	0.559	-6.500
year5_c_f_1996	-3.8656	0.554	-6.982
year5_c_f_2001	-3.9300	0.557	-7.055
year5_c_f_2006	-3.7828	0.566	-6.688
year5_c_f_2011	-3.5332	0.560	-6.310

Table A-8. Results, conflict equation with no clusters, 1960–2016

C.3 Conflict models with an interaction term

In this section, we show estimates for the second conflict model (with interaction between GDP per capita and conflict incidence) for each of the five region definitions: political history (Table A-9), geography (Table A-10), development (Table A-11), random regions (Table A-12), and no clusters (Table A-13). Estimates for the variables of core interest that change over time differ only moderately between models.

Political history clusters

Dep. Variable:	conflict1	**No. Observations:**	7267
Model:	Logit	**Df Residuals:**	7237
Method:	MLE	**Df Model:**	29
Date:	Tue, 23 Feb 2021	**Pseudo R-squ.:**	0.6539
Time:	12:41:29	**Log-Likelihood:**	-1141.9
converged:	True	**LL-Null:**	-3299.6

	coef	**std err**	**z**
ln_pop1	0.3559	0.056	6.323
l1_ln_gdp1	-0.2432	0.100	-2.430
ln_educ1	-1.5494	0.538	-2.881
l1_delta_ln_gdp1	-0.2569	0.416	-0.617
l1_ln_gdp1:l1_conflict1	0.3414	0.110	3.098
l1_conflict1	0.7769	1.035	0.751
l2_conflict1	1.0505	0.197	5.340
l3_conflict1	0.7272	0.167	4.365
decay_10_cw0_conflict1	1.6061	0.373	4.303
decay_1_cw0_conflict1	-2.0860	1.559	-1.338
year5_c_f_1971	-2.1488	0.826	-2.601
year5_c_f_1976	-1.9604	0.821	-2.389
year5_c_f_1981	-2.1232	0.826	-2.572
year5_c_f_1986	-1.8558	0.816	-2.275
year5_c_f_1991	-2.0291	0.815	-2.491
year5_c_f_1996	-2.3005	0.813	-2.828
year5_c_f_2001	-2.3933	0.819	-2.924
year5_c_f_2006	-2.2807	0.825	-2.763
year5_c_f_2011	-2.0185	0.826	-2.443
ph_fv3_f_decay	-0.4370	0.319	-1.370
ph_fv5_f_decay	-0.6516	0.283	-2.301
ph_fv7_f_decay	0.4046	0.230	1.762
ph_fv9_f_decay	-0.1956	0.201	-0.974
ph_fv11_f_decay	-0.2380	0.218	-1.091
ph_fv14_f_decay	0.3530	0.219	1.611
ph_fv16_f_decay	-0.5622	0.234	-2.403
ph_fv18_f_decay	-0.0002	0.257	-0.001
ph_fv21_f_decay	0.0012	0.280	0.004
ph_fv23_f_decay	-0.4456	0.260	-1.713
ph_fv25_f_decay	-0.2991	0.260	-1.151

Table A-9. Results, conflict equation with political history clusters, 1960–2016

Geographical clusters

Dep. Variable:	conflict1	**No. Observations:**	7267
Model:	Logit	**Df Residuals:**	7240
Method:	MLE	**Df Model:**	26
Date:	Tue, 23 Feb 2021	**Pseudo R-squ.:**	0.6527
Time:	12:14:19	**Log-Likelihood:**	-1146.0
converged:	True	**LL-Null:**	-3299.6

	coef	**std err**	**z**
ln_pop1	0.3093	0.051	6.086
l1_ln_gdp1	-0.2770	0.089	-3.120
ln_educ1	-2.1426	0.518	-4.135
l1_delta_ln_gdp1	-0.2462	0.425	-0.579
l1_ln_gdp1:l1_conflict1	0.3453	0.110	3.147
l1_conflict1	0.7328	1.028	0.713
l2_conflict1	1.0430	0.196	5.334
l3_conflict1	0.7402	0.166	4.456
decay_10_cw0_conflict1	1.6161	0.370	4.373
decay_1_cw0_conflict1	-2.0240	1.554	-1.302
year5_c_f_1971	-1.6313	0.758	-2.153
year5_c_f_1976	-1.4062	0.749	-1.877
year5_c_f_1981	-1.5351	0.757	-2.028
year5_c_f_1986	-1.2472	0.751	-1.660
year5_c_f_1991	-1.4242	0.750	-1.900
year5_c_f_1996	-1.6349	0.748	-2.184
year5_c_f_2001	-1.6862	0.753	-2.240
year5_c_f_2006	-1.5443	0.756	-2.043
year5_c_f_2011	-1.2563	0.759	-1.656
geo_fv3_f_decay	-0.2593	0.292	-0.889
geo_fv5_f_decay	-0.2420	0.255	-0.950
geo_fv7_f_decay	-0.3794	0.235	-1.617
geo_fv9_f_decay	0.1614	0.215	0.750
geo_fv11_f_decay	-0.2901	0.296	-0.979
geo_fv14_f_decay	-0.1972	0.268	-0.735
geo_fv16_f_decay	-0.6890	0.224	-3.069
geo_fv19_f_decay	-0.3896	0.262	-1.486

Table A-10. Results, conflict equation with geographical clusters, 1960–2016

Development clusters

Dep. Variable:	conflict1	**No. Observations:**	7267
Model:	Logit	**Df Residuals:**	7240
Method:	MLE	**Df Model:**	26
Date:	Tue, 23 Feb 2021	**Pseudo R-squ.:**	0.6504
Time:	12:31:07	**Log-Likelihood:**	-1153.7
converged:	True	**LL-Null:**	-3299.6

	coef	**std err**	**z**
ln_pop1	0.3123	0.047	6.691
l1_ln_gdp1	-0.2408	0.090	-2.677
ln_educ1	-1.7160	0.485	-3.541
l1_delta_ln_gdp1	-0.3167	0.432	-0.733
l1_ln_gdp1:l1_conflict1	0.3515	0.112	3.150
l1_conflict1	0.8082	1.039	0.778
l2_conflict1	1.0799	0.194	5.553
l3_conflict1	0.7611	0.165	4.611
decay_10_cw0_conflict1	1.7515	0.370	4.731
decay_1_cw0_conflict1	-2.4279	1.542	-1.575
year5_c_f_1971	-2.1272	0.744	-2.859
year5_c_f_1976	-1.9166	0.734	-2.610
year5_c_f_1981	-2.0733	0.738	-2.810
year5_c_f_1986	-1.8101	0.731	-2.477
year5_c_f_1991	-1.9813	0.727	-2.724
year5_c_f_1996	-2.2169	0.725	-3.058
year5_c_f_2001	-2.2942	0.727	-3.155
year5_c_f_2006	-2.1555	0.731	-2.950
year5_c_f_2011	-1.8987	0.731	-2.598
km_fv3_f_decay	-0.5098	0.216	-2.356
km_fv5_f_decay	-0.1884	0.235	-0.803
km_fv7_f_decay	-0.0987	0.231	-0.427
km_fv9_f_decay	-0.1153	0.155	-0.746
km_fv11_f_decay	-0.1158	0.204	-0.569
km_fv13_f_decay	0.0575	0.225	0.255
km_fv15_f_decay	-0.3507	0.194	-1.808
km_fv19_f_decay	-0.0895	0.167	-0.538

Table A-11. Results, conflict equation with development clusters, 1960–2016

Random clusters

Dep. Variable:	conflict1	**No. Observations:**	7267
Model:	Logit	**Df Residuals:**	7240
Method:	MLE	**Df Model:**	26
Date:	Tue, 23 Feb 2021	**Pseudo R-squ.:**	0.6509
Time:	12:49:06	**Log-Likelihood:**	-1151.8
converged:	True	**LL-Null:**	-3299.6

	coef	**std err**	**z**
ln_pop1	0.3441	0.050	6.929
l1_ln_gdp1	-0.2376	0.091	-2.617
ln_educ1	-1.6631	0.480	-3.463
l1_delta_ln_gdp1	-0.2874	0.421	-0.682
l1_ln_gdp1:l1_conflict1	0.3674	0.108	3.392
l1_conflict1	0.5822	1.017	0.573
l2_conflict1	1.0470	0.195	5.356
l3_conflict1	0.7281	0.166	4.392
decay_10_cw0_conflict1	1.6788	0.375	4.473
decay_1_cw0_conflict1	-2.1258	1.553	-1.369
year5_c_f_1971	-2.3786	0.742	-3.204
year5_c_f_1976	-2.1610	0.732	-2.952
year5_c_f_1981	-2.3256	0.734	-3.167
year5_c_f_1986	-2.0636	0.728	-2.836
year5_c_f_1991	-2.2304	0.724	-3.081
year5_c_f_1996	-2.4505	0.722	-3.396
year5_c_f_2001	-2.5097	0.723	-3.470
year5_c_f_2006	-2.3984	0.725	-3.310
year5_c_f_2011	-2.1424	0.723	-2.961
rm_fv3_f_decay	0.1768	0.160	1.105
rm_fv5_f_decay	0.1769	0.184	0.961
rm_fv7_f_decay	0.2586	0.227	1.137
rm_fv9_f_decay	-0.2245	0.181	-1.238
rm_fv11_f_decay	-0.2757	0.208	-1.328
rm_fv13_f_decay	-0.0790	0.175	-0.452
rm_fv15_f_decay	0.0905	0.168	0.538
rm_fv19_f_decay	-0.7746	0.333	-2.323

Table A-12. Results, conflict equation with random clusters, 1960–2016

No clusters

Dep. Variable:	conflict1	**No. Observations:**	7267
Model:	Logit	**Df Residuals:**	7248
Method:	MLE	**Df Model:**	18
Date:	Tue, 23 Feb 2021	**Pseudo R-squ.:**	0.6489
Time:	12:55:33	**Log-Likelihood:**	-1158.4
converged:	True	**LL-Null:**	-3299.6

	coef	**std err**	**z**
ln_pop1	0.3108	0.047	6.621
l1_ln_gdp1	-0.2567	0.087	-2.936
ln_educ1	-1.5276	0.467	-3.270
l1_delta_ln_gdp1	-0.3293	0.424	-0.776
l1_ln_gdp1:l1_conflict1	0.3804	0.108	3.534
l1_conflict1	0.5735	1.012	0.567
l2_conflict1	1.0771	0.194	5.544
l3_conflict1	0.7546	0.165	4.578
decay_10_cw0_conflict1	1.8115	0.367	4.940
decay_1_cw0_conflict1	-2.4342	1.535	-1.586
year5_c_f_1971	-2.2259	0.721	-3.085
year5_c_f_1976	-2.0142	0.711	-2.833
year5_c_f_1981	-2.1865	0.715	-3.058
year5_c_f_1986	-1.9247	0.707	-2.722
year5_c_f_1991	-2.1053	0.703	-2.993
year5_c_f_1996	-2.3285	0.700	-3.324
year5_c_f_2001	-2.4053	0.701	-3.429
year5_c_f_2006	-2.2906	0.704	-3.255
year5_c_f_2011	-2.0240	0.702	-2.884

Table A-13. Results, conflict equation with no clusters, 1960–2016

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