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Predicting Armed Conflict, 2010–2050[1]

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The article predicts changes in global and regional incidences of armed conflict for the 2010–2050 period. The predictions are based on a dynamic multinomial logit model estimation on a 1970–2009 cross-sectional data set of changes between no armed conflict, minor conflict, and major conflict. Core exogenous predictors are population size, infant mortality rates, demographic composition, education levels, oil dependence, ethnic cleavages, and neighborhood characteristics. Predictions are obtained through simulating the behavior of the conflict variable implied by the estimates from this model. We use projections for the 2011–2050 period for the predictors from the UN World Population Prospects and the International Institute for Applied Systems Analysis. We treat conflicts, recent conflict history, and neighboring conflicts as endogenous variables. Out-of-sample validation of predictions for 2007–2009 (based on estimates for the 1970–2000 period) indicates that the model predicts well, with an area under the receiver operator curve of 0.937. Using a $p > .30$ threshold for positive prediction, the true positive rate 7–9 years into the future is 0.79 and the False Positive Rate 0.085. We predict a continued decline in the proportion of the world's countries that have internal armed conflict, from about 15% in 2009 to 7% in 2050. The decline is particularly strong in the Western Asia and North Africa region and less clear in Africa south of Sahara. The remaining conflict countries will increasingly be concentrated in East, Central, and Southern Africa and in East and South Asia.

Motivation

The world has seen a strong decline in the amount of conflict since the end of the Cold War. This article shows that the likely future development of the incidence of internal armed conflict is a continued reduction. In 2050, the proportion of countries in conflict will be reduced to half the present rate. We define armed conflict as a contested incompatibility between a government and an organized opposition group causing at least 25 battle-related deaths during a calendar year (Themnér and Wallensteen 2011). Our predictions are based on a statistical model estimated on data on socioeconomic and demographic characteristics as well as information on previous conflicts and conflicts in neighboring countries. The data set covers 169 countries for the 1970–2009 period. We have made use of a set of explanatory variables for which the UN and the International Institute for Applied Systems Analysis (IIASA) have produced forecasts up to 2050. These predictors cover the most important structural factors that explain the onset, risk, and duration of armed conflict (Fearon and Laitin 2003; Collier and Hoeffler 2004; Collier, Hoeffler and Söderbom 2004; Hegre and Sambanis 2006). The article presents global as well as regional predictions and for individual countries.

Predictions are necessarily uncertain. They depend on a sound statistical model of what determines conflict, accurate forecasts for the predictors and are never able to account for entirely random events nor great systemic shifts such as the end of the Cold War. We present an out-of-sample evaluation that indicates that our model predicts well several years into the future, but the predictive ability obviously is better for countries that remain in the same state (conflict or no conflict) than those that change. Despite the uncertainty involved, we believe making predictions of internal armed conflict has several potential advantages:[2]

First, an ability to predict conflicts before they happen is useful to help prevent conflicts and avoid much human suffering. We predict, for instance, a 21% probability that Tanzania has a conflict in 2030. If this is a good prediction, the UN should monitor the country closely in order to be able to move early if this conflict should happen and seek measures to address the underlying causes of conflict.

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[2] See Hewitt (2010) for a related project and a further discussion.

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Second, even though country-level predictions are uncertain, we show it is possible to generate quite accurate regional- and global-level predictions. The true positive prediction rate 7–9 years into the future is 0.79 and the false positive rate 0.085.[3] The primary reason that we predict a 50% reduction in the global incidence of conflict is that infant mortality rate (IMR) and education levels, among our most important predictors, are projected to improve globally over the next few decades. Our results, then, show that the implementation of policies that help increase education levels and reduce poverty (as measured by IMRs) do have an impact on global conflict levels. Predictions of the sort we develop here can help assess the benefits of such policies in terms of conflict reduction.

Third, the prediction methodology developed can be extended to calculate the expected reduction in conflict risk from interventions such as UN peace-keeping missions (Hegre, Hultman and Nygård 2011b). These risk-reduction estimates, again, can be used to greatly improve the cost-benefit calculations of these policies along the lines of Collier, Chauvet and Hegre (2009).

Finally, predictive ability is an excellent criterion to evaluate the quality of the empirical models used by scholars who are primarily interested in showing that certain causal mechanisms work to facilitate or prevent conflicts. One thing is that our simulations indicate the amount of uncertainty in such models. Another is that the complete effect of interventions that for instance improve education in a country is not restricted to the change in the risk of conflict onset in that country the year after. This risk reduction also transmits into neighboring countries, since education reduces the risk that these countries experience a destabilizing conflict in the neighborhood.

Our predictor variables are a combination of conflict history and development variables. The poverty reduction that the UN expects to continue over the next decades is the main driver of our results.

Prediction Methodology: Simulation

Our simulation approach is based on a statistical model of how the probabilities of conflict onset, escalation, and termination depend on a set of exogenous variables such as population size and IMRs.[4] These probabilities, however, are dependent on the conflict history in each country and in their immediate neighborhood (Gleditsch 2007). This can be captured by including variables ''neighbor in war'' or ''previous conflict'' in the statistical model. This makes forecasting more complex, however. If we predict an onset of a new conflict in a country for a given year, this will be reflected as a change in the ''neighbor in war'' variable for its neighbors or ''previous conflict'' for subsequent years and therefore affect the probabilities of experiencing conflict for other countries and for the future. A statistical model can estimate these relationships, but only simulation techniques allow researchers to take these complexities fully into account when attempting to forecast conflict levels. The simulation procedure reported below is designed to model this endogeneity completely and flexibly.

Transition Probability Matrix

Our goal is to predict the conflict state for all countries in the world. Table 1 cross-tabulates the conflict level observed in all countries in the 1970–2009 period with the conflict level these countries had the year before. In 2009, our data set comprises 169 countries. The three conflict levels reported in the Uppsala/PRIO conflict data set (Themnér and Wallensteen 2011) are ''no conflict'' or <25 battle-related deaths reported in a year; ''minor conflict'' or between 25 and 999 battle-related deaths per year; and ''major conflict,'' which occurs when more than 1,000 battle-related deaths per year are reported. Table 1 is called a transition probability matrix since it specifies the annual probabilities of transition from each of the three states to each of the states.[5] These probabilities are the row proportions given in parentheses in the table. 0.966 or 96.6% of the countries that had no conflict in year $t-1$ did not have conflict in year t. A 2.93% of them transitioned into minor conflict, and 0.4% into major conflict. Over the 1970–2009 period, the average probability of transition from ''no conflict'' to ''major conflict'' was therefore 0.004. The multinomial logit model we describe below allows us to estimate these probabilities as functions of explanatory variables. This estimated transition probability matrix is at the core of our simulation procedure and allows us to predict which conflict level a country is at in a given year and transitions between each level.

Simulation Setup

The general setup of the simulation procedure is shown in Figure 1. In short, it involves the following steps: (1) specify and estimate the underlying statistical model (see section Dynamic Multinomial Logit Model); (2) make assumptions about the distribution of values for all exogenous predictor variables for the first year of simulation and about future changes to these. In this article, we base the simulations on UN projections for demographic variables and IIASA projections for education (Conflict Predictors); (3) start simulation in first year. We start in 2001 for out-of-sample validation of our candidate models (Out-of-Sample Prediction Assessment) and in 2009 for the actual forecasts (Prediction Results 2010–2050); (4) draw a realization of the coefficients of the multinomial logit model based on the estimated coefficients and the variance–covariance matrix for the estimates; (5) calculate the nine probabilities of transition between levels (cf. Table 1) for all countries for the first year, based on the realized coefficients and the projected values for the predictor variables; (6) randomly draw whether a country experiences conflict, based on the estimated probabilities (Dynamic Multinomial Logit Model); (7) update the values for the explanatory variables. A number of these variables, most notably those measuring historical experience of conflict and the neighborhood conflict variables, are contingent upon the outcome of step 6; (8) repeat (4)–(7) for each year in the forecast period, for example, for 2009–2050, and record the simulated outcome; and (9) repeat (3)–(8) a number of times to even out the impact of individual realizations of the multinomial logit coefficients and individual realizations of the probability distributions.

[3] Using a $p > .30$ threshold for positive prediction.

[4] In this article, we treat these variables as exogenous. We relax this assumption in other outputs of the project, for example, Hegre, Nygård, Strand, Gates and Flaten (2011a).

[5] Taylor and Karlin (1998) discuss in detail transition probability matrices and related concepts.

Table 1. Transition Probability Matrix: Conflict at t vs. at $t-1$, 1970–2009

	Conflict level at t			
Conflict at $t-1$	*No conflict*	*Minor conflict*	*Major conflict*	*Total*
No conflict	5116 (0.966)	156 (0.029)	23 (0.004)	5295 (1.000)
Minor conflict	145 (0.207)	481 (0.689)	72 (0.103)	698 (1.000)
Major conflict	24 (0.070)	70 (0.205)	247 (0.724)	341 (1.000)
Observations	5285	707	342	6334

Row proportions in parentheses.

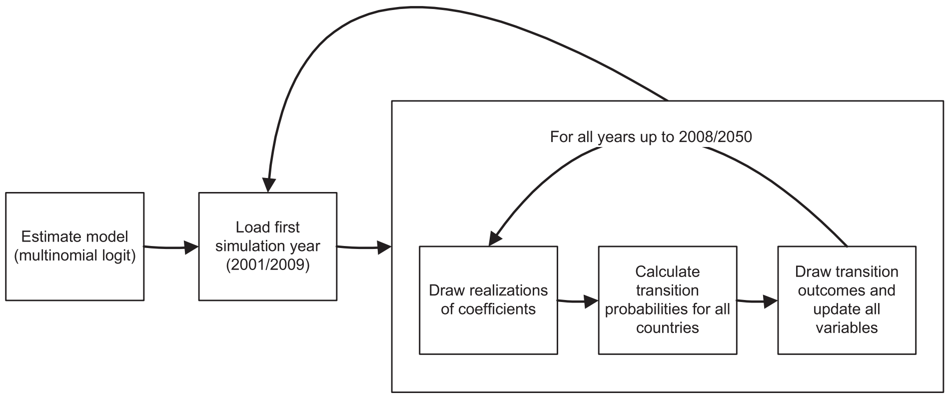


Fig 1. Simulation Flow Chart

A data set with observed and projected data and a matching parameter file are the main inputs to the program. The output is the simulated data. The software consists of three main components: (i) a Stata ado file reading the parameter file, performing the estimations, and drawing estimates; (ii) a C# class library running the simulation and outputting the results; (iii) A C++ program written as a Stata plug-in used to transfer data between Stata and the simulator. The interface to manage the simulation is the parameter file with mathematical expressions controlling how the variables are updated in the simulation. We use a general math parser to evaluate these expressions (MuParser).[6] The main simulation program is designed so that other models than the multinomial logistic model can be added. The expression parser can be extended with custom functions to enable complex interactions between the variables.

Dynamic Multinomial Logit Model

One may estimate the transition probability matrix using a multinomial logit model with the conflict level at t as the outcome variable and the level at $t-1$ as a set of dummy variables. This type of model is often referred to as a ''dynamic multinomial model''.[7] In the multinomial model (see Greene 1997:914–917) for the three outcomes ($j=0$: ''no conflict,'' $j=1$: ''minor conflict,'' $j=2$: ''major conflict''), the probabilities of the three outcomes are given by:

$$p(Y_i = j) = \frac{e^{x\beta_j}}{\sum_{k=0}^{2} e^{x\beta_k}} \tag{1}$$

To identify the model, we set ''no conflict'' as the base outcome. The estimates β_1 reported below, then, are interpreted as the impact of the explanatory variable on the probability of being in ''minor conflict'' relative to ''no conflict''. The β_2 estimates approximate the probability of ''major conflict'' relative to ''no conflict''.

If we enter only the state at $t-1$ as explanatory variable(s) (i.e., lagged dependent variables), the predicted probabilities from estimating this model are identical to those reported in Table 1. In addition, the model accounts for a set of explanatory variables, discussed in Conflict Predictors. The estimates for the lagged dependent variables and the constant terms then estimate the transition probability matrix for the case where all explanatory variables are zero. We refer to this as the ''underlying transition probability matrix'' below.

Using a ''dynamic multinomial logit model'' allows capturing variables that may increase the risk of conflict onset, but not its duration. This is achieved by adding interaction terms between the state at $t-1$ and predictor variables. The transition probability matrix in Table 1 only takes the state at $t-1$ into account. We also include information on the conflict state at earlier points in time by adding to the model a function of the number of years in each state up to $t-2$.

Our dynamic multinomial logit model sets this article apart from other recent conflict prediction projects. Hewitt (2008, 2010), Rost et al. (2009), and Goldstone et al. (2010) all restrict their attention to the *onset* of conflict, exclude countries with ongoing conflicts, and base their estimations on logistic regression. Since we predict onset and termination simultaneously, we are able to predict the global and regional incidence of armed conflict.

[6] The math parser is a set of programs that translate instructions such as a function in text form to executable code. See http://muparser.sourceforge.net/ for details.

[7] Przeworski, Alvarez, Cheibub and Limongi (2000), for instance, refer to their related model as a dynamic probit model.

Conflict Predictors

We specify a model with explanatory variables that have been shown to be related to the risk of conflict, and for which good projections up to 2050 are available. In this section, we discuss previous research on these indicators' relationship to the risk of armed conflict and detail the specific operationalizations and the data sources used.

We assume that predictors are exogenous to conflict. This assumption is not likely to be true—armed conflict certainly has an impact on IMRs and education (Gates, Hegre, Nygård and Strand 2010; Iqbal 2010). Modeling this endogeneity between conflict and predictors would be beyond the scope of this article. A proportion of the effect from conflict on predictors, however, is captured by our conflict history variables and, in particular, by the interaction terms between conflict history and the predictors.

Baseline Model Predictors

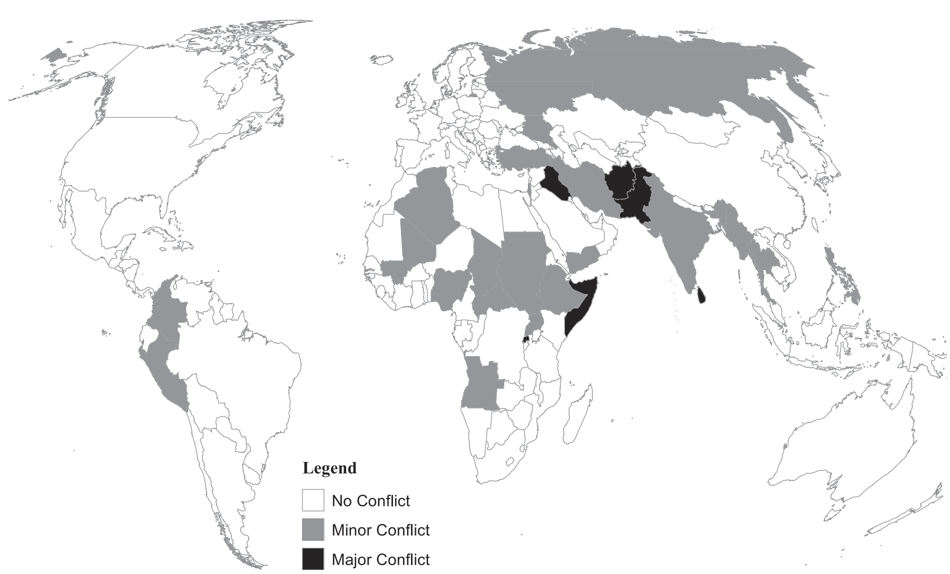
Conflict History

Our conflict data are from the 2010 update of the UCDP/PRIO Armed Conflict Dataset (Gleditsch, Wallensteen, Eriksson, Sollenberg and Strand 2002; Themnér and Wallensteen 2011), which records conflicts at two levels. Minor conflicts are those that pass the 25 battle-related deaths threshold but have less than 1,000 deaths in a year. Major conflicts are those conflicts that pass the 1,000 annual deaths threshold. We only look at internal armed conflicts and only include the countries whose governments are included in the primary conflict dyad (i.e., we exclude other countries that intervene in the internal conflict). The conflict countries in 2009 are shown in Figure 2. We include information on conflict status (no conflict, minor, or major conflict) at $t-1$, the year before the year of observation. This is coded as two dummy variables $c1_{t-1}$ and $c2_{t-1}$ for minor and major conflicts, respectively.

It is clear that conflicts, when ending, have a high risk of recurrence. Collier, Hoeffler and Söderbom (2008) estimate the risk of conflict reversal to be around 40% during the first post-conflict decade, and Elbadawi, Hegre and Milante (2008) find an even higher rate using a more inclusive definition of conflict. These studies, however, often fail to acknowledge that conflicts have strong adverse impact on major conflict risk factors. In particular, conflicts may strongly depress average income. Collier, Elliot, Hegre, Hoeffler, Reynal-Querol and Sambanis (2003, ch. 4) show that there is a ''conflict trap'' tendency. They estimate that about half of all post-conflict countries return to conflict. A third of the post-conflict countries succeed in keeping the peace beyond the first 10 years, but these enter a category classified as ''marginalized countries at peace'' (roughly the same as the ''bottom billion'' countries without conflict; cf. Collier 2007). This group of countries is characterized by low incomes and sluggish growth and has a markedly higher risk of conflict than other countries. Only one-sixth of post-conflict countries end up in the group of ''successful developers,'' drastically reducing conflict risk (Collier et al. 2003:109). To capture the impact of conflict history further back in time, we also record in three variables the log of the number of years in each of the three states up to $t-2$. In practice, we only make use of $\ln(t)_0$—the number of consecutive years without conflict up to $t-2$. These variables are referred to jointly as ''conflict history'' variables below. Countries that have recently become independent have low values for all the conflict history variables.

Neighborhoods and Regions

Figure 2 illustrates that conflicts are clustered in a few geographical regions. This clustering is partly due to the fact that some risk factors such as poverty are also geographically clustered. However, several studies show that there is a cross-border spill-over effect even when controlling for the presence of these factors (Collier et al. 2003;



Source: Themnér and Wallensteen (2011)

Fig 2. Map of Conflicts Ongoing in 2009

Hegre and Sambanis 2006; Gleditsch 2007). Some studies point to the importance of ethnic kin groups in neighboring countries, especially in conjunction with significant refugee flows (Salehyan and Gleditsch 2006). Others argue that detrimental economic effects of conflict contaminate neighbors (Murdoch and Sandler 2004).

The neighborhood of a country A is defined as all n countries $[B_1 \ldots B_N]$ that share a border with A, as defined by Gleditsch and Ward (2000). More specifically, we define ''sharing a border'' as having <100 km between any points of their territories. The spatial lag of conflict is a dummy variable measuring whether there is conflict in the neighborhood or not. Since the dependent variable is nominal, we construct two spatial lags, one for minor conflicts and one for major conflicts. Islands with no borders are considered as their own neighborhood when coding the exogenous predictor variables, but have by definition no neighboring conflicts.

Since our aim is to predict, we are best served by a spatial lag of conflict as our measure of neighborhood effects. In our estimated models, we rely on observed levels of conflict in the direct neighborhood of each country. In our simulation models, we update these variables based on the simulated results—if a conflict is simulated to erupt, the values for the neighboring countries change. We also include the neighborhood average of each predictor variable as another set of exogenous predictor variables in the model.

We define nine regions as shown in Figure 3. The list is a revised version of the UN region definition. These regions are used as predictor variables in our models. Dummy variables that capture inter-regional heterogeneity should improve the quality of predictions for the immediate future, since they help maximizing the explained variance in the observed data. We cannot be certain that it improves predictions for the future beyond the first decade, however, since it may be untenable to assume that this heterogeneity persists indefinitely.

Temporal Dummies

There are good reasons to believe that the underlying transition probability matrix for a country with a given set of characteristics is not constant over the observed period. At least we know that the end of the Cold War led to the eruption of an unusually high number of new conflicts, but at the same time increased the number of conflict terminations (Elbadawi et al. 2008). Among many other possible specification, we explored models with temporal dummy variables for the 1970–1988 and 1989–2000 periods. The temporal dummies did not improve the predictive ability of the models, however, and none of the models we use include any of them.

Other Predictors

Population

Greater populations are associated with increased conflict risks, and a country with the population size of Nigeria has an estimated risk that is about three times higher than a country the size of Liberia.[8] The increase in the risk of conflict does not increase proportionally with population, however—the per-capita risk of civil war onset decreases with population size.[9]

Studies of the duration of civil war find little evidence that population size affects how long conflicts last (Collier et al. 2004; Fearon 2004; Buhaug and Lujala 2005). Whether the severity of conflict is increasing in a country's population is contested. Lacina (2006) does not find this to be the case, but Gleditsch, Hegre and Strand (2009) do. Even the results in the latter study imply that the per-capita risk of being killed in battle is much higher in small countries than in large ones.

All demographic variables used for this analysis originate from the World Population Prospects 2006 (United Nations 2007) produced by the United Nations Population Division. This is the most authoritative global population data set, providing estimates of demographic indicators for all states in the international system between 1950 and 2005 and providing projections for key variables for the 2005–2050 period.

Total population is defined as the de facto population in thousands in a country as of 1 July of the year indicated. The measure has been log-transformed following an expectation of a declining marginal effect on conflict risk of increasing population size.

The UN population data provide several different demographic projection scenarios taking into account different assumptions about future trends in fertility, mortality, and international migration. For this project, we use the three main scenarios from the population projections. These differ from each other exclusively as a result of different assumptions regarding future fertility trajectories, with a high, medium, and low fertility scenario (see United Nations 2007, for details). For countries that currently (i.e., in 2005) experience high fertility levels, the three different fertility trajectories display considerable uncertainty concerning total population size estimates by 2050.

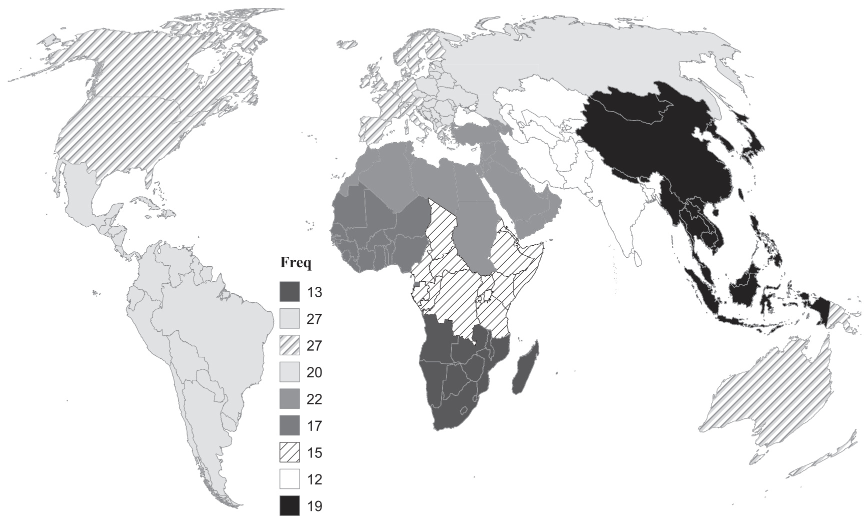
Education

Thyne (2006) finds that higher levels of primary enrollment, secondary male enrollment, greater education expenditure, and higher literacy levels are associated with lower conflict risk. The pacifying effect of education has also been noted in other studies. Secondary male enrollment is associated both with lower risk of outbreak of civil war (Collier and Hoeffler 2004) and with shorter wars (Collier et al. 2004). Barakat and Urdal (2009) replicate Thyne's findings using male secondary school attainment rates and low-intensity armed conflict onset data. Hence, there appears to be a consensus in the empirical literature that higher education levels reduce conflict risks.

The education data originate from a new data set for the 1970–2000 period compiled by the International Institute for Applied Systems Analysis (Lutz, Goujon, Samir, and Sanderson 2007). The data set is based on individual-level educational attainment data from recent Demographic Health Surveys (DHS), Labour Force Surveys (LFS), and national censuses. Historical estimates are constructed by five-year age groups and gender using demographic multistate methods for back projections and taking into account gender- and education-specific differences in mortality. The data set measures educational attainment using definitions and categories that are consistent over countries and time, representing a vast improvement over previous education data. By disregarding national classification systems, the standardization of education categories facilitates cross-national and time series comparison of education levels. For this study,

[8] This is based on an estimate of 0.3, typical for cross-national logistic regression models with a log population variable. See Raleigh and Hegre (2009) for references and a discussion.

[9] This is also noted by Collier and Hoeffler (2004).



Regions: South and Central America and the Caribbean (27 countries with data); Western Europe, North America, and Oceania (27); Eastern Europe (20); Western Asia and North Africa (22); West Africa (17); East and Central Africa (15) Southern Africa (23); South and Central Asia (12); Eastern and South-East Asia (19).

Fig 3. Map of Regions

we follow Barakat and Urdal (2009) and employ a measure of male secondary education, defined as the proportion of men aged 20–24 years with secondary or higher education of all men aged 20–24.

A recent addition to Lutz, Goujon, Samir, and Sanderson (2007) is a projection scenario for educational attainment until 2050 (Samir, Barakat, Goujon, Skirbekk, Sanderson and Lutz 2010). Our base scenario is the General Trend Scenario, for which the projection takes into account the current (2000) distribution of educational attainment, assumptions about education-specific fertility, mortality, and migration rates, and assuming that a country's educational expansion will converge on an expansion trajectory based on the historical global trend. In addition to the General Trend Scenario, we have constructed two alternative educational scenarios. The low education scenario is based on an assumption of no improvement in relative educational attainment after 2008, that is, that the share of young men receiving secondary education is constant. This is consistent with the IIASA Constant Enrollment Ratio scenario. The high education scenario assumes a trajectory with an annual increase in enrollment, which is 0.5% higher than the baseline trend scenario, converging towards 100% of young men aged 20–24 having secondary education.

While the back-projection techniques applied by IIASA provide uninterrupted time series, the problem with the limited number of countries covered (120 countries only) has been ameliorated by imputation based on male secondary enrollment data from Barro (2000), covering the same period as the IIASA data. After this first procedure for imputation, a total of 27 countries in our data set were still lacking education data. For 24 of these countries, UNESCO has data on secondary male enrollment, but only for a limited number of years around year 2000. Based on the UNESCO data, we matched the missing observations with cases we found to be reasonably similar and assumed the same trajectory for the historical data. We primarily use countries from the same region as models, but for the few cases where we could not identify a neighboring country with a reasonably similar enrollment profile, we used a model country with an apparently similar education profile from another region. The data on future levels of education and the residual countries from the previous step were then imputed based on the model country approach. For some countries, we assumed a slightly higher or lower trajectory than the model country, based on differentials in enrollment rates in year 2000.[10]

Youth Bulges

A few cross-national studies address the relationship between young age structure and armed conflict. Esty, Goldstone, Gurr, Harff, Levy, Dabelko, Surko and Unger (1998) find some effect of youth bulges on ethnic conflict, while Collier and Hoeffler (2004) and Fearon and Laitin (2003) report to have initially included youth bulges, but not found any relationship. Cincotta, Engelman and Anastasion (2003) and Urdal (2006) report increasing risks of minor armed conflict onset associated with youth bulges. An emerging consensus is that youth bulges appear to matter for low-intensity conflict, but not for high-intensity civil war.

Age-specific population numbers are provided by the United Nations (2007), and youth bulges are measured as the percentage of the population aged 15–24 years of all adults aged 15 years and above. For the youth bulge measure, the three scenarios yield identical estimates until 2024 since the relevant youth cohorts were already born by 2005. Beyond 2025, the different fertility assump-

[10] The following model countries were used (the corresponding countries for which education data were imputed are in brackets): Tunisia (Libya; Lebanon; Yemen), Rumania (Yugoslavia; Albania at a 10% lower trajectory), Paraguay (Surinam), Papua New Guinea (Solomon Islands), Malaysia (Brunei), Macedonia (Bosnia-Herzegovina; Moldova; Belarus at a 10% lower trajectory), Kyrgyz Republic (Tajikistan), Ethiopia (Burundi, Angola), Costa Rica (Cape Verde), Benin (Guinea-Bissau; Equatorial Guinea), Bangladesh (Bhutan), Bahrain (Qatar; United Arab Emirates at a 10% lower trajectory; Oman at a 10% lower trajectory), Armenia (Georgia, Azerbaijan), Vietnam (Laos at a 10% lower trajectory). For the three remaining countries for which neither database had any information on education levels, we chose a neighboring model country that we assumed could act as a reasonable proxy: Ethiopia (for Somalia and Djibouti), Vietnam (for North Korea, but at a 10% lower trajectory).

tions lead to significant variation in the youth bulge projections for many countries.

Infant Mortality

IMR has been promoted as an alternative measure of level of development (Goldstone 2001), capturing a broader set of developmental factors than the standard measure of income levels (GDP per capita). Esty et al. (1998) report very strong effects of infant mortality on state failure and conflict. Urdal (2005) and Abouharb and Kimball (2007) find high IMRs to be strongly associated with an increased risk of armed conflict onset. Generally, infant mortality appears to perform very similar to other measures of general development.[11]

IMR is defined as the probability of dying between birth and exact age 1 year, expressed as the number of infant deaths per 1000 live births. Our data are taken from the UN Population Division (United Nations 2007), which also provides a projection up to 2050. Given the considerable fluctuations in infant mortality associated with different economic, social, and political conditions, it is plausible to expect significant uncertainty associated with future trends. For the purpose of this analysis, we have constructed two alternative projection scenarios. For the high infant mortality scenario, we assume a correction in the IMR identical to a 0.5% increase for each successive year compared to the UN projected baseline. For the low infant mortality scenario, we conversely assume a downward correction in the infant mortality of 0.5% per year compared to the UN projected baseline. This implies that absolute variation will be greatest in countries with high levels of infant mortality and that over a 40-year period, the correction will be approximately 20% higher and 20% lower than the baseline UN projection for our high and low infant mortality scenarios, respectively. This also reflects the greater uncertainty pertaining to trends in IMR for high-mortality countries.

Neighborhood Characteristics

Countries located in poor neighborhoods have higher risk of conflict than countries in more developed regions, ceteris paribus. Neighbors that themselves have high risk of conflict are more likely to provide safe havens for rebel groups and to interfere in domestic politics. Countries in relatively rich neighborhoods are likely to have higher growth rates (Frankel and Romer 1999) and more stable political systems (Gates, Hegre, Jones and Strand 2006). To capture these effects, we include the average education levels, IMR, and youth proportion in countries' neighbors as predictors.

Oil

The effect of primary commodities on the risk of armed conflict has attracted significant attention (see e.g., Ross 2004, 2006, for recent reviews). Fearon and Laitin (2003) argue that countries that rely on primary commodities tend to be underbureaucratized for their GDP level and thus have weaker state institutions and higher risk of conflict. Collier and Hoeffler (2004) in contrast argue that the heightened risk of conflict associated with primary commodities is due to an increase in the opportunities for financing rebellion presented by such commodities. Most recently, Lujala (2010) finds that onshore oil production increases the risk of civil war onset, but that offshore production does not. She also finds that the location of the resources is crucial for its impact on the duration of the conflict; if the resources are located inside the zones of combat, the duration of the conflict is doubled.

Our oil measure comes from Fearon and Laitin (2003). It is a dummy variable coded 1 if the country gets more than one-third of its export revenues from oil or gas. For the simulations we assume that countries that were oil exporters according to this definition in 2005, continue to be this for the entire period through 2050.

Ethnic Dominance

Fearon and Laitin (2003) find no significant effect of ethnicity on risk of civil conflict, while Collier and Hoeffler (2004) find that only a variable measuring whether a country has a dominant ethnic group increases the risk of conflict onset. Recently, this finding has been brought into question, and Cederman, Girardin and Gleditsch (2009) find that border-crossing ethnic affiliations have a considerable impact on the likelihood of ethnonational civil wars. Hegre and Sambanis (2006) find that ethnic differences only impact the risk of lower levels of conflict.

The ethnic dominance variable is from Collier and Hoeffler (2004) and is coded 1 if one ethnic group in the country comprises a majority of the population. As for the oil variable, we assume that a country will have the same ethnic configuration through out the period through 2050 as it had in 2003.

Arriving at The Best Model Specification

We have a large number of predictor variables and a multitude of possible interaction terms between predictor variables and the conflict history variables. Since predictions depend on the specification of the statistical model, we need to choose among the nearly infinite number of possible specifications.

Out-of-Sample Prediction Assessment

To select the best model, we use a split-sample design where we estimated a large number of candidate models on data for the period 1970–2000. We then use our simulation program to obtain predictions for the 2001–2009 period and compare our predictions with the observed conflicts for that period (as reported in Themnér and Wallensteen 2011).[12] We also compared predictions versus observations for the three years 2007–2009 only. We ran 1,000 simulations of each model in the model selection stage.

We selected models through several steps. We first estimated a set of models consisting of the variables referred to as baseline variables above—conflict status at $t-1$, conflict history, neighborhood conflict, region, and period dummy variables, in various combinations and interaction term specifications. After having tried various specifications, we found a ''baseline'' specification that

[11] Per-capita income is among the most robust predictors of internal armed conflict. Almost all scholars find it to be associated with a high risk of the onset of conflict (Hegre and Sambanis 2006), and GDP per capita is included in virtually all studies of the risk of armed conflict onset. In the models estimated below, we do not include income as a variable. This is partly because we do not have access to good projections for this variable, partly because education levels, IMRs, and per-capita income are so highly correlated.

[12] See Ward, Greenhill and Bakke (2010) and Weidmann and Ward (2010) for applications of related procedures in conflict research.

was relatively simple but predicted as least as well as all other specifications.[13]

We then added terms based on the six country-level predictors presented above and the neighborhood averages for the IMR, education, and youth bulge variables. Each of these nine variables form set of terms consisting of the core variable (e.g., IMR or Oil) and multiplicative interactions between that variable and the three conflict history variables: $c1_{t-1}$, $c2_{t-1}$, and $\ln(t)_0$. We estimated and simulated close to 100 specifications that all included the ''baseline model'' and various combinations of the nine groups of variables, different choices for which interaction terms to include, and various constraints to allow terms appear only in one of the two equations or to be similar in both equations. Which terms are included in each model are reported in Tables A1 and A2.

We report results from the split-sample evaluation of the nine best-performing models in Table 2. We want to identify the model that yields the predictions from 1970–2000 data that most closely reflect what we actually observed in 2001–2009. Evaluations of predictions are more straightforward for dichotomous variables than for variables with three categories, so we group the cases where we predict either minor or major conflict into one category and compare with a similarly dichotomous observed variable. Column 2 in the table reports the Akaike Information Criterion (AIC) and the number of parameters for the models. The model with the lowest AIC gives the best balance between goodness of fit and complexity (Claeskens and Hjort 2008:22–64). We then summarize all simulated outcomes for each country-year as the share of simulations where we predict conflict and the share where we predict no conflict. These predicted shares are in turn paired with the observed outcomes. We look into predictions of incidence of conflict, of onsets of conflict, and terminations of conflict. As a goodness-of-fit measure, we use the area under the receiver operator curve (AUC—''Area Under the Curve'').[14] The AUC is equal to the probability that the simulation predicts a randomly chosen positive observed instance as more probable than a randomly chosen negative one. The ROC curves for the models (incidence 2007–2009) are presented in Figure 4. The black line is the ROC curve for the combined model.

The AUCs for incidence of conflict over the 2001–2009 period are reported in column 3. In columns 4–6, we report the AUC for onset, termination, and incidence of conflict for the 2007–2009 period, still based on estimates for 1970–2000. Column 7 reports 95% confidence intervals for the incidence AUC. The final columns report the true positive rates (TPR, also referred to as sensitivity)—the number of conflict country years in 2007–2009 that were correctly predicted as well as the false positive rates (FPR or 1 – specificity)—the number of no-conflict country years that were incorrectly predicted (false positives). Columns 8–9 report the TPR and FPR if we consider a conflict to be predicted if conflict occurs in more than half of the simulations, that is, predicted probability $p > .5$. Columns 10–11 report the rates if $p > .3$.

Table 2. Area Under the Curve (AUCs) for Six Models Estimated on Data for 1970–2000

		2001–2009	2007–2009							
							$p > .50$		$p > .30$	
Model	*AIC (no. of parameters)*	*Incidence AUC*	*Onset AUC*	*Termination AUC*	*Incidence AUC*	*Incidence CI*	*TPR*	*FPR*	*TPR*	*FPR*
23	2474.32 (26)	0.937	0.837	0.828	0.945	(0.924, 0.965)	0.561	0.032	0.740	0.085
43	2453.75 (56)	0.930	0.853	0.830	0.937	(0.908, 0.966)	0.534	0.035	0.767	0.081
45	2457.13 (60)	0.928	0.832	0.821	0.934	(0.904, 0.964)	0.548	0.032	0.781	0.069
48	2451.22 (78)	0.930	0.843	0.825	0.935	(0.908, 0.961)	0.521	0.030	0.849	0.104
66	2454.31 (42)	0.940	0.840	0.839	0.942	(0.918, 0.966)	0.603	0.030	0.794	0.078
67	2455.77 (71)	0.926	0.830	0.812	0.935	(0.910, 0.961)	0.534	0.035	0.822	0.101
96	2448.43 (39)	0.939	0.839	0.836	0.942	(0.919, 0.966)	0.575	0.030	0.767	0.067
97	2438.85 (49)	0.931	0.840	0.829	0.936	(0.907, 0.966)	0.466	0.025	0.740	0.069
98	2448.43 (39)	0.940	0.834	0.827	0.942	(0.919, 0.965)	0.589	0.030	0.767	0.078
Combined		0.937	0.837	0.830	0.944	(0.920, 0.967)	0.633	0.034	0.794	0.085

Predictions compared to observed conflicts 2001–2009 and 2007–2009.
AIC: Akaike Information Criterion.

[13] This model had three region dummies, no temporal dummies, a neighborhood conflict variable that merge major and minor conflicts, and interactions between neighborhood conflict and conflict history variables.

[14] See Hosmer and Lemeshow (2000:156–164) for an introduction to Receiver Operator Curves, AUC, and the related concepts of sensitivity (or True Positive Rate) and specificity (1—False Positive Rate) in the context of logistic regression.

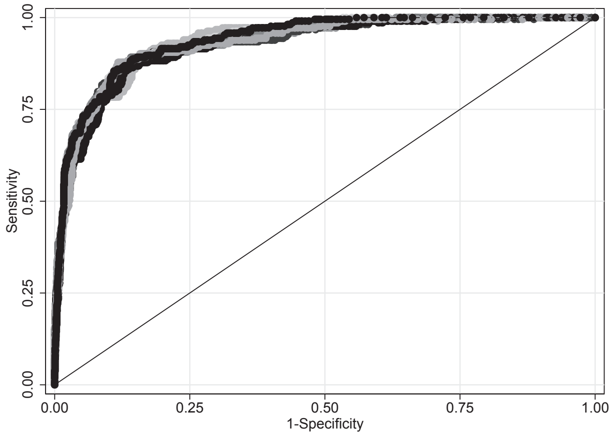


Fig 4. Receiver Operator Curves (ROC), 2001–2009

The likelihood ratio tests indicate that the more complex models (48 and 67) fit the data better than the simpler models. Still, the complex models do not predict better than the simpler in terms of the incidence AUCs (nor AIC). Model 23 incorporates information only on conflict history, neighborhood conflicts, and the population size of the country and predicts as well as models with all indicators. This may not be so surprising, since the effect of the predictors over the past decades are reflected in countries' conflict history. The correlation between $\ln(t)_0$ and ln(IMR), for instance, is −0.46. As is clear from the estimation results (Tables A1 and A2), however, the predictors have explanatory power, and we expect the more complex models to predict better beyond the first decade since they reflect better future changes in our predictors. The most complex models also tend to predict onset and termination somewhat better than the more simple models. The confidence intervals for the various AUCs indicate, however, that we do not have a firm basis for concluding it is clearly better than the other 8 models. We have reasons to believe that predictions are sensitive to model specification (cf. Hegre and Sambanis 2006, see On Uncertainty in Predictions for an assessment). Rather than making a possibly arbitrary choice, our predictions for the 2011–2050 period are based on the average over all nine specifications in Table 2.

The predictive performance is quite good. The TPR or sensitivity of the combined model with $p > .50$ as the cutoff is 0.63, implying that the model correctly predicts conflicts in about 16 of the 26 countries that had conflict in 2009. The FPR with $p > .50$ cutoff is 0.030—among the 143 non-conflict countries in 2009, the model only predicts conflict in about four countries. The precision rate, or the proportion of country years with positive predictions that are correctly predicted, is 0.79. With a $p > .30$ cutoff, the model has a TPR of 79.4% corresponding to about 21 of 26 countries, with a false positive rate at .078 or 11 out of 143 countries. The precision rate in that case is 0.65. Before turning to the results for the 2010–2050 period, it is useful to take a closer look at predictions for 2009 for individual countries.

Table 3 lists for a set of countries the proportions of the 18,000 simulations in which the simulation procedure yielded a minor or a major conflict. The table includes all countries with conflict in 2009 as well as all countries with predicted risk of conflict higher than 0.15 (on average over the nine models). The table is sorted by conflict status in 2009 as reported in Themnér and Wallensteen (2011) (reported in column 2) and then by our simulated probability of conflict, either level. Column 3 indicates the conflict history known in 2000 and therefore available as the initial state for the simulation procedure. Columns 4–6 report the proportion of simulations with minor, major, or either minor or major conflict. These figures are our predicted probabilities of conflict. The two right-most columns report the highest and lowest predicted probability over the nine models.

Cells with values larger than 0.50 in the three main columns have a dark shade, those with values larger than 0.30, a lighter shade. They point to predicted conflicts, given cutoffs of $p > .5$ and $p > .3$, respectively. Nineteen true positives given $p > .3$ are indicated in ''Either'' column in the top half of the table, and 12 false positives in the lower half.[15] We predict five of the six major conflicts in 2009, but fail to predict the conflict in Iraq. Iraq falls below the 0.30 line because of the 1997–2000 period with no recorded conflict in the data set.[16] The recent conflict history is a very important predictor, and even four years of no conflict reduces the estimated risk considerably. We fail to predict the conflict in Sri Lanka given a $p > .5$ threshold since it scores relatively well on the socioeconomic development indicators—the exogenous variables also contribute significantly to the quality of predictions.[17]

All the minor conflicts that are correctly predicted given the cutoff $p > .3$ were ongoing in 2000. The countries with more distant conflicts (Peru, CAR, Mali, Yemen, Nigeria, and Thailand) turn up with conflicts in between 8% and 30% of the simulations. The 12 false positives turn up in the list either because they had conflict in 2000 (e.g., DRC, Nepal, Sierra Leone) or have less recent conflicts but are either populous (e.g., Bangladesh) or poor (e.g., Niger). Predicting correctly the intensity of conflicts is harder. Given $p > .3$, the model predicts correctly the major conflict in Afghanistan and minor conflict in Colombia, Ethiopia, India, Israel, Uganda, the Philippines, and Chad.

Table 4 shows the estimated AUCs for each of the nine regions. The model predicts well, except for three regions: in North America and Western Europe, it fails to predict the complete absence of conflicts after 2001.[18] Both in West Africa and East and Central Africa, the conflict landscape displayed an unusual amount of change. The year 2000 (the last year with data in these estimations) saw a considerably higher incidence of conflict than the following years—over 20% of the region was in conflict, as compared to only 11% 8 years later.

Final Model

We now turn to the predictions for the 2010–2050 period. Tables A1 and A2 show the results of re-estimating the nine model specifications for the entire 1970–2009 period. The first table contains the estimates for the minor conflict equation, the second those for major conflicts.

[15] These figures deviate somewhat from those reported in Table 2 since that table refers to 2007–2009, and Table 3 to 2009 only.

[16] The same applies to Somalia, although the country was certainly not peaceful in 1997–2000—the UCDP/PRIO dataset records the warfare in these years as *nonstate* conflict because of the absence of a functional central government.

[17] The conflict in Sri Lanka ended in 2010.

[18] The observed incidences of conflict referred to here are shown in Figure 6.

Table 3. Highest Predicted Risk of Conflict in 2009

Country	Conflict observed 2009	Conflict up to 2000	Minor	Major	Either	Either Lowest	Either Highest
Afghanistan	Major	2000	0.139	0.748	0.887	0.825	0.920
Rwanda	Major	2000	0.346	0.237	0.583	0.423	0.688
Pakistan	Major	1996	0.280	0.180	0.460	0.374	0.528
Sri Lanka	Major	2000	0.174	0.274	0.448	0.348	0.815
Somalia	Major	1996	0.223	0.122	0.345	0.186	0.435
Iraq	Major	1996	0.193	0.099	0.291	0.206	0.363
Colombia	Minor	2000	0.855	0.028	0.883	0.830	0.932
Sudan	Minor	2000	0.199	0.607	0.806	0.643	0.883
Ethiopia	Minor	2000	0.467	0.285	0.752	0.674	0.814
Myanmar	Minor	2000	0.647	0.105	0.752	0.679	0.831
India	Minor	2000	0.404	0.347	0.751	0.708	0.795
Angola	Minor	2000	0.280	0.407	0.688	0.532	0.773
Israel	Minor	2000	0.653	0.021	0.674	0.630	0.835
Uganda	Minor	2000	0.433	0.232	0.660	0.623	0.698
Algeria	Minor	2000	0.233	0.394	0.627	0.583	0.678
Philippines	Minor	2000	0.461	0.122	0.583	0.453	0.653
Chad	Minor	2000	0.396	0.172	0.568	0.517	0.615
Russia	Minor	2000	0.178	0.232	0.406	0.305	0.503
Turkey	Minor	2000	0.297	0.104	0.401	0.319	0.499
Iran	Minor	2000	0.263	0.123	0.386	0.189	0.619
Peru	Minor	1999	0.231	0.068	0.299	0.235	0.394
Central African Republic	Minor	1997	0.160	0.126	0.286	0.215	0.336
Mali	Minor	1994	0.168	0.043	0.211	0.178	0.246
Yemen	Minor	1994	0.113	0.063	0.177	0.133	0.219
Nigeria	Minor	1970	0.104	0.052	0.156	0.114	0.205
Thailand	Minor	1982	0.061	0.024	0.085	0.046	0.161
Congo, DRC	No	2000	0.320	0.422	0.742	0.645	0.861
Indonesia	No	2000	0.575	0.122	0.697	0.643	0.763
Nepal	No	2000	0.445	0.117	0.561	0.488	0.658
Burundi	No	2000	0.291	0.243	0.535	0.366	0.634
Mozambique	No	1992	0.210	0.154	0.363	0.170	0.467
Uzbekistan	No	2000	0.228	0.134	0.362	0.276	0.559
Sierra Leone	No	2000	0.282	0.077	0.359	0.271	0.454
Congo	No	1999	0.170	0.183	0.353	0.208	0.498
Egypt	No	1998	0.226	0.112	0.337	0.268	0.401
Niger	No	1997	0.268	0.062	0.331	0.254	0.439
Guinea	No	2000	0.246	0.068	0.314	0.258	0.396
Bangladesh	No	1992	0.205	0.107	0.312	0.281	0.360
Eritrea	No	1999	0.195	0.102	0.297	0.151	0.414
Mexico	No	1996	0.199	0.071	0.269	0.188	0.329
Senegal	No	2000	0.197	0.052	0.248	0.177	0.353
Djibouti	No	1999	0.164	0.081	0.245	0.191	0.362
South Africa	No	1988	0.127	0.102	0.229	0.135	0.333
Kenya	No	1982	0.118	0.089	0.207	0.158	0.243
Liberia	No	2000	0.172	0.033	0.205	0.161	0.244
Guatemala	No	1995	0.148	0.046	0.194	0.095	0.259
Cambodia	No	1998	0.136	0.051	0.187	0.151	0.249
Papua New Guinea	No	1996	0.128	0.045	0.173	0.102	0.200
Guinea-Bissau	No	1999	0.136	0.033	0.167	0.108	0.231
Cameroon	No	1984	0.089	0.079	0.168	0.120	0.209
Malawi	No	–	0.092	0.070	0.16	0.049	0.299
Lesotho	No	1998	0.117	0.045	0.161	0.117	0.207
Burkina Faso	No	1987	0.124	0.035	0.158	0.075	0.250
Azerbaijan	No	1995	0.086	0.064	0.150	0.094	0.230

Dark shade: Predicted conflicts, cutoff of $p > 0.5$. Light shade: cutoff of $p > 0.3$.

Space constraints preclude a detailed discussion of these estimates, but a brief review helps evaluating the predictions presented below. First, the lagged conflict and conflict history variables model the strong tendency for internal conflicts to last for several subsequent years. The negative estimates for the ''$\ln(t)_0$'' variable indicates that the probability of both levels of conflict increases the longer the country has been without conflict up to $t - 2$. The positive estimate for ''$\ln(t)_1$'' in the minor conflict equation shows that the risk of remaining in minor conflict increases with conflict duration. The year after a minor conflict has broken out, the odds of minor conflict in the year after is estimated to be about 10 times higher than before the onset. When the conflict has lasted for three years, the odds are almost 30 times higher. After 10 years, the estimated odds are more than 100 times

TABLE 4. Area Under the Curve (AUC) for Model 66, By Region

Region	*AUC 2001–09*	*CI*
Latin America and the Caribbean	0.981	(0.973, 0.989)
North America and Western Europe	0.824	(0.762, 0.886)
Eastern Europe	0.962	(0.943, 0.982)
Middle East and North Africa	0.956	(0.947, 0.965)
West Africa	0.589	(0.545, 0.633)
East and Central Africa	0.821	(0.799, 0.843)
Southern Africa	0.982	(0.975, 0.989)
Central Asia	0.930	(0.916, 0.944)
South-West Asia	0.917	(0.902, 0.931)

higher. The estimates for ''$\ln(t)_2$'' show the same pattern for major conflict.

The log population variable is positive and strongly significant, and there are clear signs of spill-over from conflicts in a country's neighborhood. High IMRs increase the risk of conflict onset, but are less important predictors of conflict continuation. Youth bulges have little impact on conflict onset, but seem to increase the tendency for conflicts to continue and to escalate to major conflict. Education is not important in most of these models controlling for the other variables. Countries with ''ethnic dominance'' have more conflict than countries with other ethnic configurations, whereas countries heavily dependent on oil may have a higher risk of onset of major conflict than non-oil dependent countries.

Controlling for these variables, we find some regional residual variation. Most importantly, West African countries have much less major conflicts than their socioeconomic and demographic indicators imply.

Prediction Results 2010–2050

We then generated predictions for the 169 countries for which we have data. We ran 2,000 separate simulations for each of the nine models and report the average results across model specifications if nothing else is noted.

Figure 5 shows the observed incidence of conflict from 1960 to 2009 and the corresponding simulated incidence for 2010–2050. The black line represents the proportion of countries in any level of conflict. The gray line plots the proportion in major conflict. The observed proportion for both conflict levels increased steadily up to 1992 and then declined to the year 2003, after which the incidence of conflict again increased somewhat. Our simulations imply that we are likely to see a continuation of the decreasing trend from the 1995–2009 period over the next few decades, from 15.1% in 2009 to 7.1% in 2050. The decline is equally strong for major conflicts—from 3.5% in 2009 to 1.6% in 2050. The shaded areas denote the 80% confidence interval for the predicted proportion.[19] In 80% of the simulations, the global proportion in conflict in 2050 is between 4.7% and 10.7%. The corresponding confidence band for major conflict is (0.6%, 3.6%).

The simulation shows an immediate decrease for minor conflicts from 2009 to 2010 and thereafter a steady decrease over the remaining years. The immediate reduction is to some extent an artifact of the simulation procedure and due to a swift predicted transition from the initial (observed) distribution of conflicts to the steady-state distribution implied by the estimated transition matrix.[20]

The predicted decline in global conflict is mainly driven by the expected improvements in infant mortality and education as well as the decline of youth bulges. An obvious objection to this prediction is that infant mortality and education were improving also in the 1970–1990 period, at a time when the incidence of conflict increased strongly.[21] How can we claim that what occurred in this period will not occur in the next few decades?

The apparent puzzle is not likely to be due to omitted time-invariant variables. We have tried a large number of temporal dummies. Despite the obvious conflict-driving effect of the Cold War, none of these improve the predictive power of the model. In other words, the estimated transition probability matrix (given our predictors) was the same in 1980 as in 2000. Puzzlingly, we have not been able to identify any change in the conditional transition probabilities over time—the conditional probabilities that generate our predictions also seem to underlie the 1970–1990 period.

Two processes can explain the increase in conflict incidence within the confines of our model. The first is the process of decolonization. In 1970, the median age of countries was 43 years. In 2009, it was 60 years. This is reflected in our $\ln(t)_0$ variable, which has a low value when countries have existed for only a few years and is estimated to be a powerful predictor. The average value for this variable in 2009 is much lower than in the 1970s and the 1980s, partly explaining that conflicts accumulated at a higher pace then than they will in the future.[22]

The second process is a slow convergence toward a *steady-state incidence* of conflict (Collier et al. 2003:95).[23] Few countries had conflict in the first year of independence.[24] Initially, ''too few'' countries were in conflict, and the process of falling into conflict is relatively slow. The risks of conflict onset in many newly independent countries were high according to our model, but typically only about 0.10. It takes 2–3 decades before most countries have fallen into the ''conflict trap''.

Regional Predictions

Figure 6 shows the projected incidence of conflict with 80% confidence bands for the nine regions shown in Figure 3. We also show the average forecasts for IMR, secondary education, and youth proportion for each

[19] The lower bound in the confidence interval is the 10th percentile in the distribution of shares of countries in conflict, and the upper bound the 90th percentile. Since there is a discrete number of countries, the confidence interval has a step shape. The confidence interval is roughly similar throughout the prediction period. Since the measure is the aggregate proportion of countries in conflict, there is a strong pull towards an equilibrium proportion where the number of random events that take countries out of conflict is balanced by those that bring countries into conflict. This pull is sufficiently strong to counter the increasing uncertainty at the country level. Since the state at t is a function of what happened before t, uncertainty increases with every simulation period.

[20] Since the average probability of conflict termination is higher than that of conflict onset, the simulation first removes conflicts with low predicted probability such as those in Sri Lanka and Thailand and then more slowly fills in high-risk countries without conflict in 2009 (e.g., DRC, Indonesia, and Nepal).

[21] We are grateful to Joe Hewitt for raising this important issue.

[22] Moreover, the newly independent countries in the 1990s have a lower underlying risk of conflict according to our model than the new countries in the 1960s.

[23] See Taylor and Karlin (1998:199–205) for a general discussion of such convergence processes.

[24] Among the countries that became independent in the 1950s and 1960s, the exceptions were Vietnam, Malaysia, Cameroon, Zaire, and Angola.

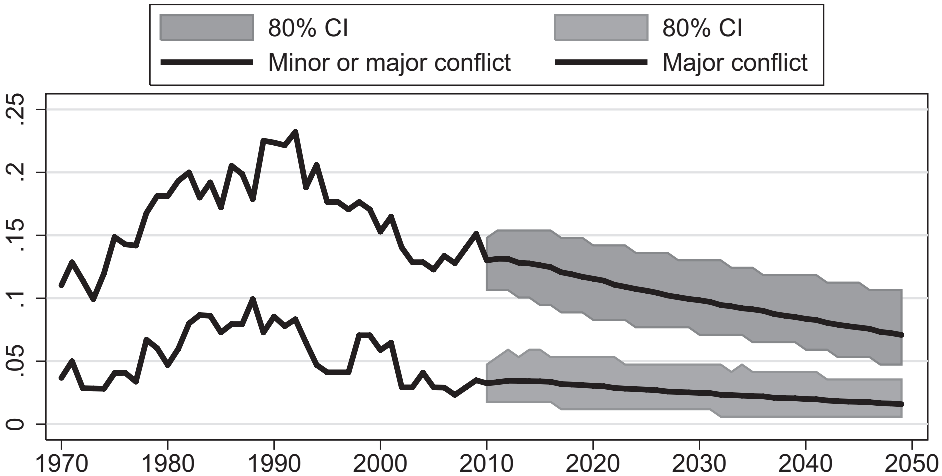


FIG 5. Observed and Simulated Proportion of Countries in Conflict, Averaged Over Nine Model Specifications, Both Conflict Levels, All Countries, 1960–2050

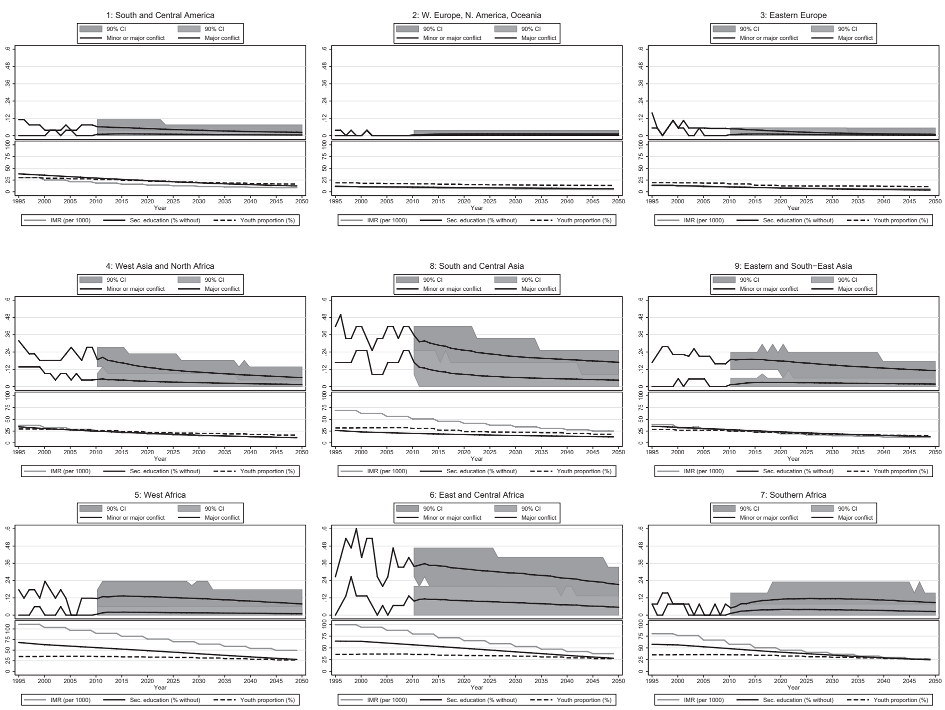


FIG 6. Predicted Share of Countries in Conflict and Average Predictor Values, by Region, 1995–2050

region. To maximize legibility, we transform the education variable slightly so that all three are positively correlated and have roughly similar range.[25]

The decline in the incidence of conflict is not uniform across different parts of the world. Europe and the Americas are projected to experience continued decrease from low levels. From 2030 onwards, it is most likely that these regions have no conflicts at all. As shown in Table 5 below, the proportion of simulations with conflict is reduced to about 0.10 even for current conflict countries such as Colombia and Peru, and the predicted risk in European countries with recent conflict is negligible from the first years of simulation.

Our forecasts are most optimistic for the ''Western Asia and North Africa'' region, where the incidence of conflict is predicted to be reduced by almost two thirds, from over 27% in 2009 to 6.2% in 2050. The incidence of major conflict drops from 4.5% to 1.5%. The favorable demographic and socioeconomic forecasts for this region are likely to bring this region close to the recent conflict levels of South and Central America. The forecasts for the socioeconomic variables for these two regions are almost identical—all three indicators are between 25 and 40 in 2000 and decreasing to about half that level over the 50-year period. Although we do model a strong conflict trap tendency, the conflict trap is not sufficiently strong to prevent this currently conflict-prone region from reducing the incidence of conflict to something closer to that observed in similar regions.

[25] That is, we report education in % of population in age group *without* education.

Table 5. Highest Predicted Risk of Conflict in 2017, 2030, and 2050

		2017			2030			2050		
Statename	*2009*	*Minor*	*Major*	*Either*	*Minor*	*Major*	*Either*	*Minor*	*Major*	*Either*
Ethiopia	Minor	0.792	0.096	0.889	0.692	0.118	0.810	0.613	0.093	0.707
India	Minor	0.618	0.180	0.806	0.538	0.167	0.705	0.485	0.133	0.619
Philippines	Minor	0.746	0.057	0.803	0.575	0.050	0.626	0.380	0.034	0.414
Myanmar	Minor	0.627	0.111	0.738	0.493	0.087	0.580	0.388	0.056	0.444
Thailand	Minor	0.611	0.070	0.680	0.360	0.045	0.405	0.208	0.026	0.234
Afghanistan	Major	0.335	0.331	0.665	0.304	0.174	0.478	0.293	0.129	0.413
Algeria	Minor	0.546	0.102	0.648	0.327	0.081	0.407	0.169	0.036	0.205
Sudan	Minor	0.437	0.207	0.644	0.403	0.171	0.574	0.354	0.107	0.461
Pakistan	Major	0.401	0.237	0.638	0.344	0.167	0.511	0.284	0.105	0.389
Congo, DRC	–	0.358	0.211	0.568	0.309	0.168	0.470	0.235	0.101	0.337
Somalia	Major	0.327	0.231	0.558	0.251	0.119	0.370	0.143	0.057	0.200
Angola	Minor	0.342	0.203	0.545	0.302	0.155	0.457	0.221	0.092	0.313
Uganda	Minor	0.346	0.166	0.512	0.294	0.133	0.427	0.215	0.083	0.298
Russia	Minor	0.337	0.164	0.501	0.150	0.076	0.225	0.066	0.031	0.097
Chad	Minor	0.340	0.145	0.485	0.227	0.101	0.328	0.149	0.069	0.217
Rwanda	Major	0.315	0.168	0.484	0.307	0.154	0.461	0.239	0.092	0.332
Nigeria	Minor	0.382	0.097	0.478	0.352	0.065	0.418	0.271	0.040	0.311
Burundi	–	0.296	0.157	0.453	0.270	0.130	0.399	0.184	0.068	0.252
Colombia	Minor	0.362	0.082	0.444	0.178	0.041	0.219	0.092	0.020	0.112
Turkey	Minor	0.325	0.100	0.424	0.189	0.054	0.243	0.117	0.029	0.145
Mali	Minor	0.374	0.040	0.415	0.235	0.028	0.264	0.139	0.016	0.154
Iraq	Major	0.257	0.127	0.385	0.121	0.053	0.174	0.067	0.025	0.091
Iran	Minor	0.254	0.105	0.359	0.156	0.063	0.222	0.110	0.037	0.147
Niger	–	0.315	0.042	0.357	0.240	0.031	0.271	0.155	0.016	0.171
CAR	Minor	0.215	0.128	0.344	0.161	0.084	0.245	0.086	0.040	0.126
Peru	Minor	0.271	0.064	0.335	0.125	0.029	0.154	0.058	0.012	0.071
Yemen	Minor	0.193	0.085	0.279	0.113	0.043	0.156	0.057	0.020	0.077
Sri Lanka	Major	0.173	0.100	0.273	0.062	0.031	0.093	0.032	0.014	0.046
Indonesia	–	0.188	0.062	0.250	0.198	0.057	0.255	0.164	0.037	0.201
Nepal	–	0.158	0.063	0.220	0.106	0.042	0.148	0.073	0.027	0.100
Morocco	–	0.154	0.055	0.209	0.114	0.034	0.148	0.062	0.018	0.080
Mozambique	–	0.120	0.066	0.185	0.184	0.081	0.264	0.165	0.060	0.225
Cote D'Ivoire	–	0.157	0.027	0.184	0.150	0.023	0.173	0.098	0.014	0.112
Bangladesh	–	0.117	0.052	0.168	0.145	0.053	0.198	0.132	0.044	0.176
Israel	Minor	0.100	0.029	0.129	0.029	0.008	0.037	0.014	0.003	0.017
Georgia	–	0.080	0.049	0.130	0.034	0.019	0.054	0.015	0.007	0.022
Uzbekistan	–	0.085	0.041	0.125	0.069	0.040	0.108	0.061	0.032	0.094
Azerbaijan	–	0.073	0.050	0.124	0.060	0.054	0.113	0.037	0.031	0.068
Kenya	–	0.079	0.046	0.124	0.132	0.068	0.201	0.128	0.059	0.187
Congo	–	0.074	0.049	0.123	0.071	0.047	0.118	0.045	0.026	0.071
Cambodia	–	0.086	0.033	0.120	0.078	0.028	0.105	0.050	0.016	0.066
Senegal	–	0.101	0.017	0.119	0.092	0.015	0.107	0.073	0.011	0.084
South Africa	–	0.079	0.040	0.118	0.105	0.044	0.148	0.089	0.028	0.117
Mexico	–	0.085	0.030	0.116	0.107	0.033	0.140	0.080	0.019	0.099
Guinea	–	0.097	0.016	0.113	0.087	0.015	0.101	0.051	0.007	0.058
Burkina Faso	–	0.094	0.018	0.112	0.136	0.021	0.158	0.112	0.015	0.128
Tanzania	–	0.070	0.038	0.108	0.145	0.063	0.208	0.177	0.057	0.234
Eritrea	–	0.076	0.031	0.107	0.061	0.023	0.084	0.038	0.015	0.053
Egypt	–	0.076	0.030	0.106	0.083	0.028	0.110	0.062	0.019	0.081
Cameroon	–	0.066	0.039	0.104	0.091	0.060	0.148	0.080	0.049	0.129
China	–	0.068	0.033	0.102	0.117	0.050	0.168	0.145	0.045	0.190
USA	–	0.079	0.020	0.098	0.085	0.021	0.106	0.086	0.020	0.105
Sierra Leone	–	0.077	0.018	0.095	0.078	0.017	0.095	0.045	0.012	0.057
Liberia	–	0.080	0.012	0.092	0.081	0.011	0.092	0.063	0.006	0.069

The forecasted trend for Africa south of Sahara is much more pessimistic, with only a reduction in incidence of about one-third. East and Central Africa has had considerably more frequent conflicts than other parts of Africa in recent decades. In 2009, five of the 15 countries in the region were in conflict, two of them major conflicts. The simulation indicates a decrease also in this region, to about 20% in conflict and 6% in major conflict. The forecasts for West Africa are considerably lower. Despite the serious conflicts in Liberia, Sierra Leone, and Côte d'Ivoire, the region has had a lower incidence of conflicts than comparable regions (such as East and Central Africa). In particular, relatively few conflicts have reached the level of major conflict, as reflected in the dummy variable for the region shown in Table A2. The forecasted trend in the incidence of con-

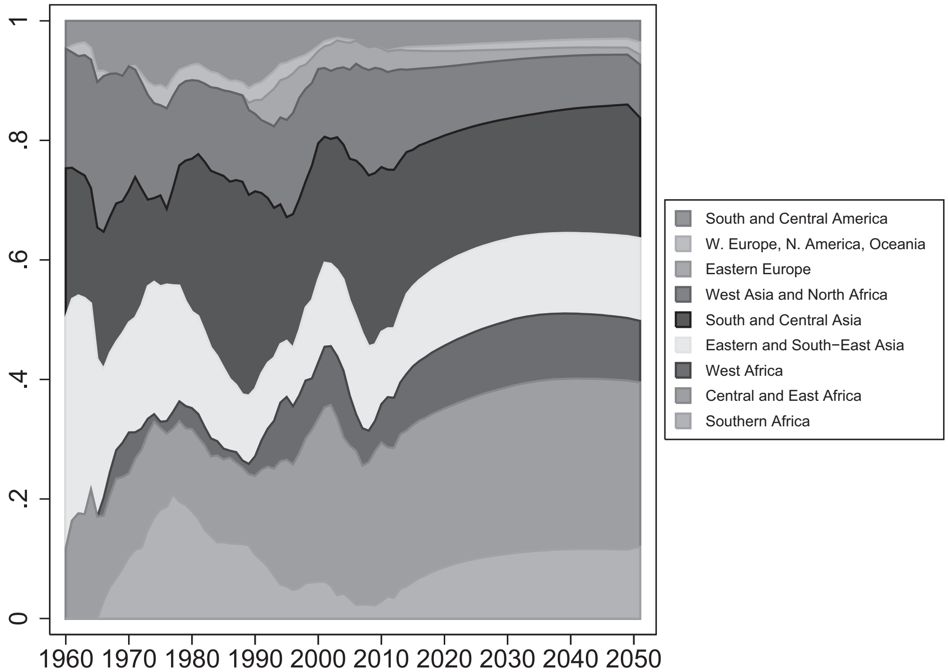


FIG 7. Regions' Predicted Share of Conflicts, 1960–2050

flict is almost flat, however. As the plot for the predictors show, West Africa is in general poorer than East and Central Africa. In our simulations, this causes the incidence of conflict to increase slightly from the 12% observed in 2009 and then slowly decrease from 2015 to under 8% in 2050.

The forecasts for Southern Africa are similar to those for West Africa. In this case, the low level of conflict is associated with a higher level of socioeconomic development in this region than for the rest of Sub-Saharan Africa. We predict a clear increase in the incidence of conflict up to 2025—on average, about two of the 19 countries in the region are in conflict every year at the peak.

The two Eastern Asian regions have also had a high incidence of conflict in the 1960–2009 period. This is particularly true for South and Central Asia. We predict a considerable decrease in conflict for this region, from about 40% in 2009 to <20% in 2050. The amount of conflict in Eastern and South-East Asia was lower in 2009, but we forecast a more moderate reduction in conflict incidence here than in the rest of Asia. The two Eastern Asian regions show a less positive development than West Asia/North Africa, despite the fact that living conditions improve at least as rapidly here. This is mainly because of the large populations in the Eastern countries.

Figure 7 shows the proportion of predicted conflicts by region. The uneven decline of conflicts means that an increasing share of the world's conflict will be in South and East Asia. Our three SSA regions are located at the bottom of the figure and display an increasing fraction. This figure also shows the remarkable forecasted decline in conflicts in Western Asia and North Africa.

Country-Level Predictions

Figure 8 shows the proportion of simulations with conflict (either level) for all countries in the years 2011, 2017, 2030, and 2050. Dark shades represent high risk of conflict. It shows how the forecasted patterns of conflict gradually changes from being dominated by recent conflict countries in 2011 to be more evenly distributed, with conflict concentrated in large, poor countries.

Table 5 shows the simulated risk of conflict in 2017, 2030, and 2050 for the set of countries listed in Table 3, as well as whether they had conflict in 2009. The simulations imply that the major conflicts in Afghanistan, Pakistan, and Afghanistan are more likely to continue up to 2017 than to end, although they are more frequently simulated as minor than as major conflicts. The simulation predicts the termination of the conflicts in Sri Lanka and Iraq, and possibly also in Rwanda. The minor conflicts in Ethiopia, India, the Philippines, Myanmar, Thailand, Algeria, Sudan, Angola, Uganda, and Russia are also predicted to be in conflict in 2017. The forecasts further imply that conflicts are likely to (re-)commence in DR Congo.

The column labeled ''Major'' shows the proportion of simulations with major conflict in the given country. Major conflict risks are predicted to be highest in Afghanistan, Sudan, Pakistan, DR Congo, Somalia, and Angola, due to the seriousness of the recent conflicts in these countries.

Twenty-six countries exceed the $p > .30$ threshold. Table 2 indicated a true positive rate of 0.794 and a false positive rate of 0.085 eight years into the future. Our simulations indicate that about 12%, or 20 countries, will be in conflict in 2017. Together, these figures imply that 16 of the 26 countries are likely to be in conflict. More importantly, we are not likely to miss many conflicts—the out-of-sample evaluation indicates that only about four countries not among these 26 will have conflict in 2017.

Hewitt (2008, 2010) and Rost, Schneider and Kleibl (2009) also publish lists of the countries with the highest

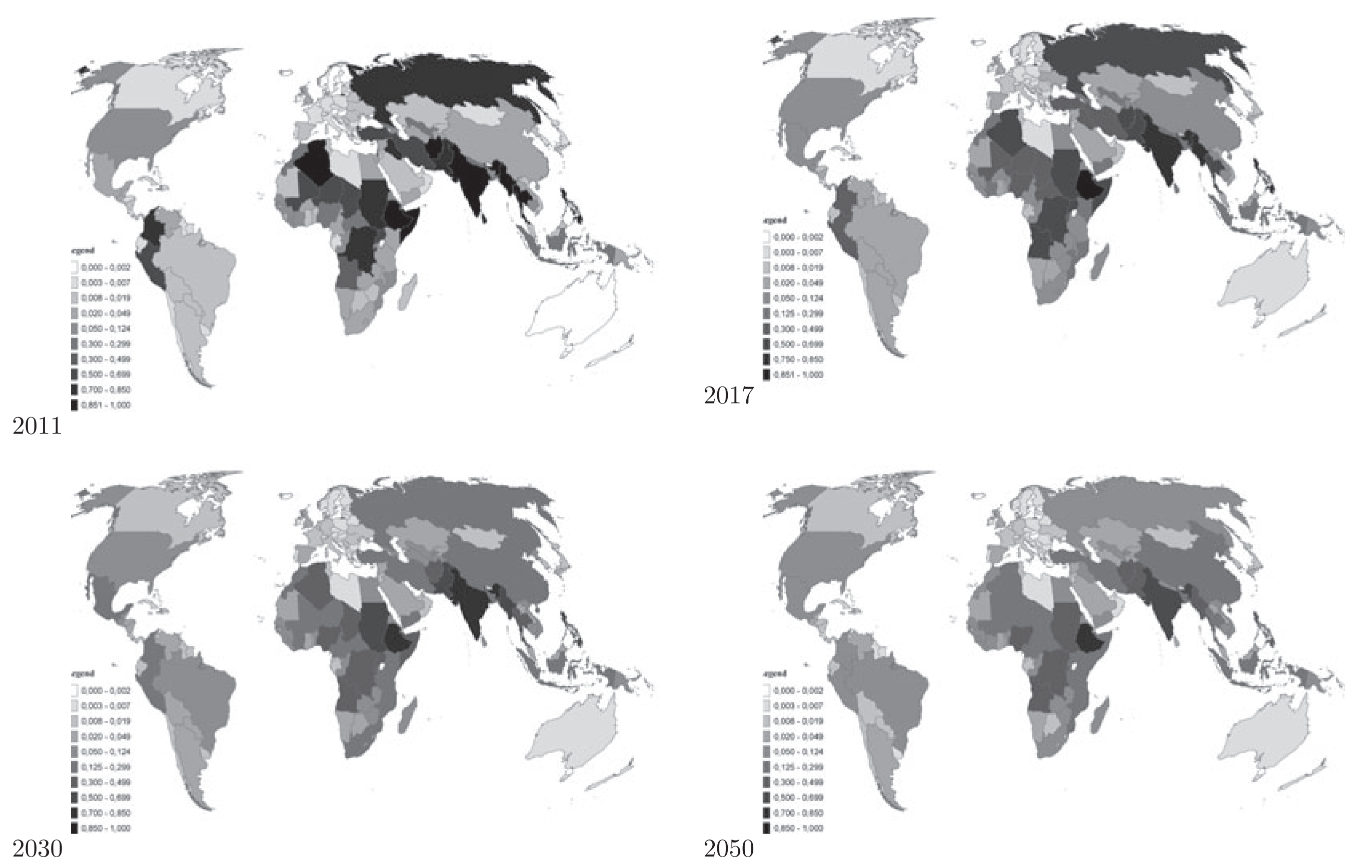


Fig 8. Map of Conflict Predictions in Selected Years. Proportion of simulations in minor or major conflict

risk of conflict onset. The predictions are not directly comparable, but many similarities exist.[26] African countries are disproportionally represented in all these lists—Iraq and Afghanistan are the only non-African countries among the top 25 in Hewitt (2010), and Rost et al. (2009) have 16 African out of 25.

Twenty-five of the 30 most conflict-prone countries in Table 5 had conflict in 2009. What can these predictions tell us that we did not know in advance? For example, the predictions point out how anomalous the conflict in Israel is.[27] Moreover, countries follow very different risk trajectories over the next decades of simulations. Many of the current conflict countries are likely to escape the conflict trap over the next decades—the predicted risk of conflict is at least halved from 2017 to 2050 in countries such as Thailand, Algeria, Pakistan, Somalia, Russia, Chad, Colombia, Iraq, Peru, and Sri Lanka. Other countries remain conflictual—this is particularly true for India and Ethiopia, large countries with long conflict histories.

Some countries that have no recent conflicts are predicted to increase the risk of conflict over the next decades. This is the case for Mozambique, Kenya, Burkina Faso, Tanzania, Cameroon, and China. China has conflict in 19% of simulations in 2050, mainly because of its large size. For many countries, a major reason for the estimated stability or increase in conflict risk is strong population growth. According to the medium UN population projections, 29 countries are estimated to at least double their populations between 2009 and 2050, 24 are in Sub-Saharan Africa. The population of the fastest growing country, Niger, is estimated to increase by close to 250% in this period, from less than 16 million to more than 53 million people. Our conflict estimates thus reflect an assumption that more people correspond to more conflict. The African countries further have a high risk of conflict because they are poor, have low education and high infant mortality, and are neighbors to other countries with high conflict risk.

On Uncertainty in Predictions

The out-of-sample evaluation of the models presented in Arriving at the Best Model Specification indicates how accurately our simulations predict conflict eight years into the future. In this section, we discuss the various sources of uncertainty in our predictions.

Uncertain Parameter Estimates

The first source of uncertainty is that of the parameter estimates in the models underlying the simulations, as indicated by the standard errors reported in Tables A1 and A2. Large standard errors means that the relationship between conflict and our predictors is relatively uncertain and limit the accuracy of the predictions we can make. This uncertainty is accounted for in our predictions through drawing ''realizations'' of parameter

[26] Rost, Schneider and Kleibl (2009) only predict major conflicts and censor ongoing conflict years. Hewitt (2008, 2010) predict the onset of a wider set of political instability events (as do Goldstone, Bates, Epstein, Gurr, Lustik, Marshall, Ulfelder and Woodward 2010). Moreover, these studies include predictors such as regime type and state repression for which we do not have forecasts up to 2050.

[27] But Israel is a special case in our dataset, since all predictors are coded for Israel excluding the occupied Palestinian territories, but the conflict variable for both sets of territories. Our predictions, then, are implicitly assuming that occupation ceases in 2010.

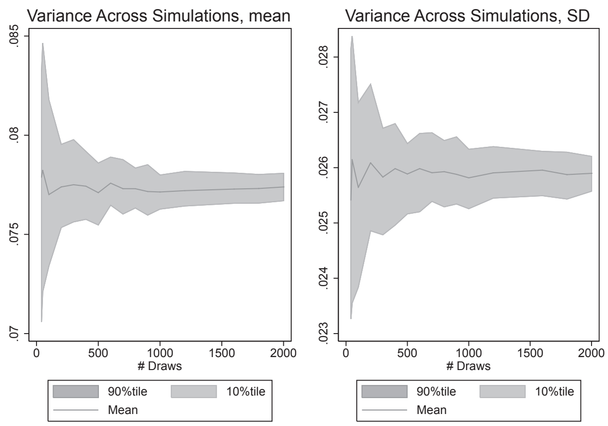


FIG 9. Convergence of Simulation Estimates

estimates using the variance-covariance matrix, so that our estimated confidence intervals reflect this uncertainty.

Limited Number of Simulations

The second source of uncertainty derives from running a limited number of repeated simulations. We ran tests to ascertain that 18,000 simulations are sufficient to obtain correct estimates for the variance of the global proportion of countries in conflict. Figure 9 was produced by drawing multiple random samples from the simulated data. The plots illustrate the number of simulations needed for the results to converge to a stable estimate. From the 18,000 simulations, we first drew 50 independent samples of N = 40 simulations and calculated the mean proportion of simulations in conflict over the 50 samples and the variance around this. We then increased the *N* of theses samples gradually from 40 to 2,000. Figure 9 plots the mean and the variance across the samples. It shows that both the mean and the variance converge to a stable value when *N* exceeds 500–1,000 simulations.

Uncertainty About Correct Model Specification

How to specify the statistical model is a third source of uncertainty. Our out-of-sample evaluation indicated that the nine model specifications we use predict better than the 90 or so models we also tried, but we have little basis for judging which of the nine are better than the other. Figure 10 shows the predicted global proportion of countries in conflict for each of the nine model specifications.

The figure shows that the simulated global proportion of countries in conflict depends on the model specification. Model m23 is the model with only log population, neighboring conflicts, and region variables (see Table A1). Since this model includes none of the predictors that the statistical model implies reduces the risk of conflict, the simulations indicate no reduction in its incidence over the next decades. The other models display considerable variation in predicted global incidence of conflict. This variation is taken into account in the results presented in Prediction Results 2010–2050, as they are based on the average over all these nine models.

Optimistic and Pessimistic Scenarios

The predictions presented so far depend on the accuracy of the UN/IIASA forecasts. How does the projected global incidence of conflict change if the world develops differently? In Conflict Predictors, we described two alternative forecasts for the demographic and socioeconomic variables. We combine these alternatives into one ''optimistic'' and one ''pessimistic'' scenario. Figure 11 shows the predicted global incidence of conflict (both levels) for the three scenarios. The solid line represents the neutral scenario used in all previous simulations. The dotted line shows the simulated global incidence for the optimistic scenario. Here, IMRs decrease annually 0.5% quicker than the UN projection, and education levels increase 0.5% more rapidly. The demographic variables are assumed to follow UN's low-population growth scenario. The dashed line shows the corresponding simula-

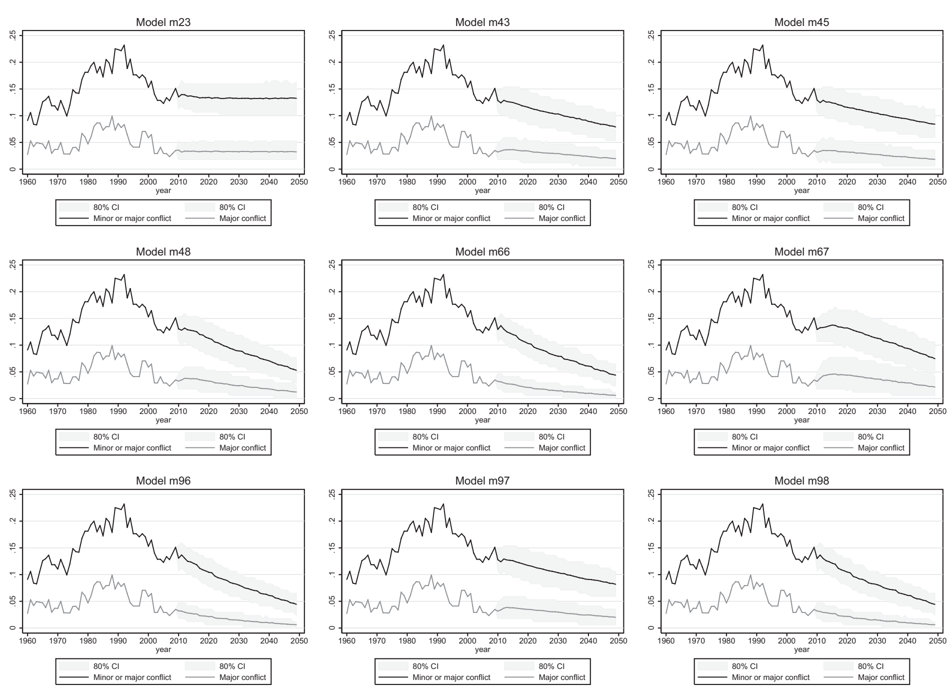


FIG 10. Observed and Simulated Proportion of Countries in Conflict, Either Conflict Level, by Model Specification, 1960–2050

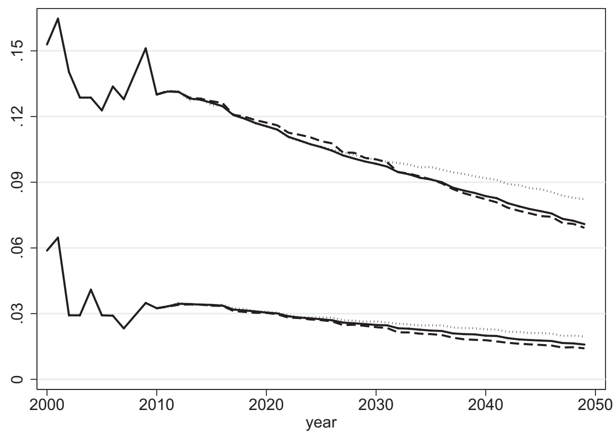


Fig 11. Observed and Simulated Proportion of Countries in Conflict, Three Scenarios for Predictor Variables, Both Conflict Levels, All Countries, 1960–2050. Solid line: Neutral scenario. Dotted line: optimistic scenario. Dashed line: pessimistic scenario

tion results for the pessimistic scenario where education levels remain constant at the 2008 level in all countries, the demographic variables follow the UN high-population growth scenario, and IMRs decrease at 0.5% lower annual rate than the UN projection.

The simulated incidence of conflict does not vary much over the three scenarios. This source of uncertainty is moderate relative to the uncertainties due to statistical estimation.

Conclusion

We have specified a model to predict the incidence of minor and major conflicts based on education and demographic variables for which we have observations back to 1970s and projections up to 2050. We use out-of-sample validation to select a model specification and to assess the predictive ability of the model. This implied estimating a set of models for the 1970–2000 period, predicting conflict up to 2009, and comparing with the actual conflicts observed in 2007–09. The assessment indicates a true positive rate 7–9 years into the future of 0.63 with probability threshold $p > .5$, and 0.79 with $p > .5$. The corresponding false positive rates were 0.030 and 0.085.

Our predictions indicate that the global incidence of conflict is likely to continue to decrease from the current level and probably be reduced to about half of the present number of conflict countries in 2050. We have taken into account several sources of uncertainty and argue that a considerable share of the uncertainty due to model specifications have been taken into account. The predictions are obviously dependent on the UN/IIASA forecasts that we use, but even a pessimistic projection generates a clear decline in the predicted incidence of conflict. We also conclude that over the next few decades, an increasing proportion of conflicts will occur in East, Central, and Southern Africa as well as in East and South Asia.

Our exogenous poverty and demography variables contribute strongly to the predictions. The poverty reduction that the UN expects to continue over the next decades is the main driver of the reduction in conflict that we predict. In addition, the recent conflict history also contributes strongly to the simulated outcome. We have shown that a few years of peace changes the subsequent risk considerably. This finding highlights the importance of assistance to post-conflict countries in the form of peacekeeping operations and other interventions. Although we do predict a strong decline in the incidence of conflict, such interventions will continue to be important in the years ahead.

The project presented here has considerable expansion potential. First, it should take into account other variables found to be important to predict internal armed conflict such as economic growth, political institutions, and UN peace-keeping operations. In Hegre et al. (2011b), we evaluate the effectiveness of UN peace-keeping operations based on the procedure developed in this article. A major obstacle to incorporating these variables, however, is that we do not have adequate forecasts for them. Moreover, they are clearly endogenous to conflict, and their inclusion requires an expansion of the simulation procedure. Another extension is to use the simulation methodology to develop much more precise cost-benefit estimates of possible interventions (e.g., UN peace-keeping operations) along the lines of Collier et al. (2009). The simulation procedure enables constructing a much more realistic counterfactual than the methods used in previous studies.

Appendix

TABLE A1. Estimates 1970–2009, All Models, Minor Conflict Equation

	(m23)	(m43)	(m45)	(m48)	(m66)	(m67)	(m96)	(m97)	(m98)
$c1_{t-1}$	0.440 (0.292)	2.255 (1.814)	2.671 (1.850)	1.628 (1.958)	0.416 (0.296)	−0.421 (1.709)	0.340 (0.195)	1.641 (1.490)	0.340 (0.195)
$c2_{t-1}$	2.499 (0.534)***	−0.202 (3.389)	0.283 (3.406)	0.825 (3.475)	2.398 (0.536)***	−1.697 (3.120)	2.341 (0.515)***	−0.0505 (3.050)	2.341 (0.515)***
$\ln(t)_0$	−1.209 (0.0799)***	−1.243 (0.0844)***	−1.243 (0.0845)***	−1.238 (0.0851)***	−1.151 (0.0820)***	−1.243 (0.0849)***	−1.163 (0.0761)***	−1.250 (0.0839)***	−1.163 (0.0761)***
$\ln(t)_1$	1.206 (0.112)***	1.145 (0.115)***	1.147 (0.115)***	1.093 (0.116)***	1.174 (0.113)***	1.130 (0.114)***	1.174 (0.113)***	1.162 (0.113)***	1.174 (0.113)***
$\ln(t)_2$	0	0	0	0	0	0	0	0	0
Oil	0 (.)	0 (.)	0 (.)	−0.0421 (0.430)	−0.0383 (0.167)	0.0556 (0.426)	−0.0417 (0.167)	0 (.)	−0.0417 (0.167)
Oil·$c1_{t-1}$	0 (.)	0 (.)	0 (.)	−0.0823 (0.518)	0 (.)	−0.174 (0.515)	0 (.)	0 (.)	0 (.)
Oil·$c2_{t-1}$	0 (.)	0 (.)	0 (.)	−0.343 (0.640)	0 (.)	−0.524 (0.635)	0 (.)	0 (.)	0 (.)
Oil· $\ln(t)_1$	0 (.)	0 (.)	0 (.)	0.0332 (0.189)	0 (.)	−0.00993 (0.186)	0 (.)	0 (.)	0 (.)
Ethn. dom.	0 (.)	0 (.)	0 (.)	−0.170 (0.337)	0.336 (0.130)**	−0.151 (0.333)	0.335 (0.130)**	0 (.)	0.335 (0.130)**
Ethn.dom.·$c1_{t-1}$	0 (.)	0 (.)	0 (.)	0.777 (0.401)	0 (.)	0.863 (0.394)*	0 (.)	0 (.)	0 (.)
Ethn.dom.·$c2_{t-1}$	0 (.)	0 (.)	0 (.)	−0.165 (0.529)	0 (.)	−0.0493 (0.518)	0 (.)	0 (.)	0 (.)
Ethn.dom.· $\ln(t)_1$	0 (.)	0 (.)	0 (.)	0.183 (0.144)	0 (.)	0.169 (0.143)	0 (.)	0 (.)	0 (.)
ln(IMR)	0 (.)	−0.103 (0.316)	0.0268 (0.332)	0.0491 (0.339)	0.375 (0.158)*	0.467 (0.153)**	0.369 (0.157)*	−0.0110 (0.171)	0.369 (0.157)*
ln(IMR) ·$c1_{t-1}$	0 (.)	−0.215 (0.402)	−0.264 (0.405)	−0.0925 (0.416)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
ln(IMR) ·$c2_{t-1}$	0	−0.148 (0.531)	−0.214 (0.535)	−0.231 (0.550)	0 (.)	0 (.)	0 (.)	−0.163 (0.459)	0 (.)
ln(IMR) · $\ln(t)_1$	0 (.)	0.281 (0.133)*	0.272 (0.134)*	0.297 (0.136)*	0 (.)	0 (.)	0 (.)	0.243 (0.0551)***	0 (.)
Youth	0 (.)	0.0143 (0.0388)	0.0125 (0.0391)	−0.0164 (0.0409)	−0.0275 (0.0217)	−0.0696 (0.0306)*	−0.0271 (0.0216)	0 (.)	−0.0271 (0.0216)
Youth·$c1_{t-1}$	0 (.)	0.0000801 (0.0489)	−0.00115 (0.0491)	0.000826 (0.0500)	0 (.)	0.0245 (0.0384)	0 (.)	−0.00471 (0.0287)	0 (.)
Youth·$c2_{t-1}$	0 (.)	0.108 (0.0724)	0.104 (0.0726)	0.0971 (0.0732)	0 (.)	0.112 (0.0626)	0 (.)	0.112 (0.0625)	0 (.)
Youth· $\ln(t)_1$	0 (.)	−0.00825 (0.0167)	−0.00763 (0.0167)	−0.0118 (0.0169)	0 (.)	0.0201 (0.00892)*	0 (.)	0 (.)	0 (.)
ln(Population)	0.235 (0.0397)***	0.367 (0.0987)***	0.353 (0.0994)***	0.373 (0.104)***	0.286 (0.0450)***	0.306 (0.0962)**	0.288 (0.0447)***	0.363 (0.0689)***	0.288 (0.0447)***
ln(Pop.)·$c1_{t-1}$	0 (.)	0.00504 (0.126)	−0.00755 (0.127)	−0.0213 (0.131)	0 (.)	0.0396 (0.125)	0 (.)	−0.0233 (0.106)	0 (.)
ln(Pop.)·$c2_{t-1}$	0 (.)	−0.0404 (0.190)	−0.0410 (0.190)	−0.0432 (0.198)	0 (.)	0.0357 (0.196)	0 (.)	−0.0536 (0.119)	0 (.)
ln(Pop.)· $\ln(t)_1$	0 (.)	−0.0573 (0.0413)	−0.0532 (0.0414)	−0.0522 (0.0427)	0 (.)	−0.0178 (0.0389)	0 (.)	−0.0618 (0.0308)*	0 (.)
Education	0 (.)	−1.782 (0.799)*	−1.633 (0.835)	−1.438 (0.855)	−0.534 (0.434)	−1.072 (0.769)	−0.560 (0.427)	−1.729 (0.722)*	−0.560 (0.427)
Education·$c1_{t-1}$	0 (.)	0.0582 (1.076)	−0.0575 (1.087)	0.0765 (1.123)	0 (.)	0.662 (0.928)	0 (.)	0.479 (0.850)	0 (.)
Education·$c2_{t-1}$	0 (.)	2.516 (1.478)	2.353 (1.483)	2.230 (1.523)	0 (.)	2.942 (1.300)*	0 (.)	2.472 (1.432)	0 (.)
Education· $\ln(t)_1$	0 (.)	0.473 (0.326)	0.454 (0.328)	0.352 (0.336)	0 (.)	0.0618 (0.306)	0 (.)	0.439 (0.285)	0 (.)
Neighb. IMR	0 (.)	0 (.)	−0.281 (0.216)	−0.529 (0.230)*	−0.462 (0.214)*	−0.546 (0.226)*	−0.437 (0.206)*	−0.304 (0.165)	−0.437 (0.206)*
Neighb. education	0 (.)	0 (.)	−0.454 (0.610)	−0.0576 (0.649)	−0.0897 (0.628)	−0.238 (0.642)	0.0228 (0.577)	−0.602 (0.490)	0.0228 (0.577)
Neighb. youth	0 (.)	0 (.)	0 (.)	0.102 (0.0328)**	0.0984 (0.0312)**	0.102 (0.0324)**	0.0996 (0.0310)**	0 (.)	0.0996 (0.0310)**
Neighb. conflict	0.0535 (0.142)	0.614 (0.225)**	0.646 (0.226)**	0.662 (0.228)**	0.0588 (0.146)	0.633 (0.224)**	0 (.)	0.704 (0.209)***	0 (.)
Neighb. c.·$c1_{t-1}$	−0.0624 (0.193)	−0.608 (0.265)*	−0.612 (0.265)*	−0.612 (0.267)*	−0.0705 (0.195)	−0.618 (0.263)*	0 (.)	−0.648 (0.245)**	0 (.)
Neighb. c.·$c2_{t-1}$	−0.711 (0.334)*	−1.298 (0.386)***	−1.295 (0.386)***	−1.303 (0.389)***	−0.707 (0.336)*	−1.355 (0.384)***	−0.652 (0.306)*	−1.351 (0.376)***	−0.652 (0.306)*
Neighb. c.· $\ln(t)_1$	0.175 (0.0535)**	−0.120 (0.0953)	−0.128 (0.0957)	−0.136 (0.0964)	0.166 (0.0544)**	−0.125 (0.0954)	0.181 (0.0409)***	−0.153 (0.0892)	0.181 (0.0409)***
W. Asia & North Africa	−0.812 (0.306)**	−0.291 (0.367)	−0.375 (0.374)	−0.0223 (0.396)	0.00139 (0.374)	−0.0393 (0.400)	0.0173 (0.372)	−0.420 (0.354)	0.0173 (0.372)
West Africa	0.234 (0.199)	−0.256 (0.224)	−0.153 (0.244)	−0.0497 (0.253)	0.00124 (0.248)	−0.0608 (0.252)	−0.00792 (0.246)	−0.166 (0.239)	−0.00792 (0.246)
Southern Africa	0.255 (0.136)	−0.00749 (0.154)	0.0674 (0.166)	0.0399 (0.179)	0.0279 (0.170)	0.0432 (0.177)	0.0260 (0.169)	0.0636 (0.162)	0.0260 (0.169)
Constant	−3.209 (0.412)***	−4.498 (1.104)***	−3.641 (1.327)**	−5.505 (1.514)***	−5.393 (1.328)***	−4.853 (1.475)**	−5.518 (1.276)***	−3.038 (0.989)**	−5.518 (1.276)***

Standard errors in parentheses.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table A2. Estimates 1970–2009, All Models, Major Conflict Equation

	(m23)	(m43)	(m45)	(m48)	(m66)	(m67)	(m96)	(m97)	(m98)
$c1_{t-1}$	1.066 (0.504)*	3.170 (3.070)	3.087 (3.102)	2.204 (3.416)	1.036 (0.512)*	−1.934 (2.862)	1.014 (0.500)*	2.954 (2.943)	1.014 (0.500)*
$c2_{t-1}$	2.956 (0.663)***	4.348 (3.943)	4.121 (4.007)	3.803 (4.325)	2.746 (0.675)***	−1.443 (3.765)	2.728 (0.675)***	4.541 (3.258)	2.728 (0.675)***
$\ln(t)_0$	−1.577 (0.163)***	−1.569 (0.160)***	−1.574 (0.160)***	−1.571 (0.160)***	−1.497 (0.166)***	−1.589 (0.159)***	−1.502 (0.166)***	−1.572 (0.161)***	−1.502 (0.166)***
$\ln(t)_1$	0	0	0	0	0	0	0	0	0
$\ln(t)_2$	1.305 (0.167)***	1.255 (0.170)***	1.260 (0.170)***	1.244 (0.172)***	1.275 (0.169)***	1.239 (0.172)***	1.272 (0.169)***	1.255 (0.170)***	1.272 (0.169)***
Oil	0 (.)	0 (.)	0 (.)	1.960 (0.687)**	0.270 (0.233)	1.907 (0.654)**	0.261 (0.232)	0 (.)	0.261 (0.232)
Oil·$c1_{t-1}$	0 (.)	0 (.)	0 (.)	−1.849 (0.776)*	0 (.)	−1.756 (0.745)*	0 (.)	0 (.)	0 (.)
Oil·$c2_{t-1}$	0 (.)	0 (.)	0 (.)	−2.071 (0.826)*	0 (.)	−2.051 (0.794)**	0 (.)	0 (.)	0 (.)
Oil· $\ln(t)_1$	0 (.)	0 (.)	0 (.)	−0.865 (0.364)*	0 (.)	−0.822 (0.352)*	0 (.)	0 (.)	0 (.)
Ethn. dom.	0 (.)	0 (.)	0 (.)	0.433 (0.598)	0.566 (0.195)**	0.338 (0.584)	0.555 (0.193)**	0 (.)	0.555 (0.193)**
Ethn.dom.·$c1_{t-1}$	0 (.)	0 (.)	0 (.)	0.214 (0.665)	0 (.)	0.357 (0.649)	0 (.)	0 (.)	0 (.)
Ethn.dom.·$c2_{t-1}$	0 (.)	0 (.)	0 (.)	−0.204 (0.722)	0 (.)	−0.00606 (0.705)	0 (.)	0 (.)	0 (.)
Ethn.dom.· $\ln(t)_1$	0 (.)	0 (.)	0 (.)	0.00562 (0.279)	0 (.)	0.0147 (0.275)	0 (.)	0 (.)	0 (.)
ln(IMR)	0 (.)	1.962 (0.646)**	1.981 (0.657)**	2.031 (0.666)**	0.753 (0.238)**	0.467 (0.153)**	0.727 (0.228)**	1.836 (0.616)**	0.727 (0.228)**
ln(IMR) ·$c1_{t-1}$	0 (.)	−1.832 (0.735)*	−1.825 (0.734)*	−1.692 (0.748)*	0 (.)	0 (.)	0 (.)	−1.561 (0.694)*	0 (.)
ln(IMR) ·$c2_{t-1}$	0 (.)	−2.110 (0.785)**	−2.054 (0.789)**	−1.984 (0.802)*	0 (.)	0 (.)	0 (.)	−1.933 (0.760)*	0 (.)
ln(IMR) · $\ln(t)_1$	0 (.)	−0.294 (0.273)	−0.292 (0.274)	−0.263 (0.270)	0 (.)	0 (.)	0 (.)	−0.245 (0.255)	0 (.)
Youth	0 (.)	−0.140 (0.0745)	−0.145 (0.0743)	−0.186 (0.0766)*	−0.0532 (0.0352)	−0.0980 (0.0561)	−0.0525 (0.0351)	−0.150 (0.0744)*	−0.0525 (0.0351)
Youth·$c1_{t-1}$	0 (.)	0.175 (0.0844)*	0.176 (0.0842)*	0.178 (0.0862)*	0 (.)	0.0770 (0.0638)	0 (.)	0.178 (0.0839)*	0 (.)
Youth·$c2_{t-1}$	0 (.)	0.248 (0.0971)*	0.246 (0.0973)*	0.237 (0.0993)*	0 (.)	0.126 (0.0783)	0 (.)	0.253 (0.0963)**	0 (.)
Youth· $\ln(t)_1$	0 (.)	0.0464 (0.0342)	0.0462 (0.0341)	0.0423 (0.0335)	0 (.)	0.0173 (0.0169)	0 (.)	0.0520 (0.0339)	0 (.)
ln(Population)	0.246 (0.0606)***	0.203 (0.174)	0.213 (0.175)	0.180 (0.182)	0.346 (0.0702)***	0.247 (0.175)	0.344 (0.0698)***	0.363 (0.0689)***	0.344 (0.0698)***
ln(Pop.)·$c1_{t-1}$	0 (.)	0.194 (0.203)	0.198 (0.204)	0.220 (0.210)	0 (.)	0.171 (0.204)	0 (.)	0.0609 (0.126)	0 (.)
ln(Pop.)·$c2_{t-1}$	0 (.)	0.147 (0.238)	0.158 (0.239)	0.211 (0.249)	0 (.)	0.160 (0.246)	0 (.)	0 (.)	0 (.)
ln(Pop.)· $\ln(t)_1$	0 (.)	0.0598 (0.0800)	0.0625 (0.0804)	0.0720 (0.0811)	0 (.)	0.0409 (0.0774)	0 (.)	0 (.)	0 (.)
Education	0 (.)	0.704 (1.165)	1.171 (1.248)	0.476 (1.434)	0.174 (0.656)	−0.820 (1.404)	0.0700 (0.598)	0.662 (1.084)	0.0700 (0.598)
Education·$c1_{t-1}$	0 (.)	−1.428 (1.478)	−1.486 (1.494)	−0.331 (1.679)	0 (.)	1.334 (1.563)	0 (.)	−0.828 (1.377)	0 (.)
Education·$c2_{t-1}$	0 (.)	−1.774 (1.721)	−1.860 (1.749)	−0.754 (1.916)	0 (.)	1.460 (1.726)	0 (.)	−1.389 (1.646)	0 (.)
Education· $\ln(t)_1$	0 (.)	−0.203 (0.585)	−0.245 (0.592)	0.119 (0.640)	0 (.)	0.120 (0.635)	0 (.)	0.0182 (0.415)	0 (.)
Neighb. IMR	0 (.)	0 (.)	−0.0917 (0.305)	−0.393 (0.318)	−0.250 (0.303)	−0.197 (0.303)	−0.181 (0.253)	0 (.)	−0.181 (0.253)
Neighb. Education	0 (.)	0 (.)	−0.909 (0.868)	−0.589 (0.944)	−0.371 (0.914)	−0.373 (0.919)	0 (.)	−0.602 (0.490)	0 (.)
Neighb. Youth	0 (.)	0 (.)	0 (.)	0.133 (0.0483)**	0.138 (0.0468)**	0.137 (0.0475)**	0.143 (0.0449)**	0 (.)	0.143 (0.0449)**
Neighb. conflict	0.249 (0.270)	0.785 (0.479)	0.801 (0.482)	0.895 (0.508)	0.192 (0.277)	1.057 (0.501)*	0.168 (0.274)	0.704 (0.209)***	0.168 (0.274)
Neighb. c.·$c1_{t-1}$	−0.0190 (0.325)	−0.596 (0.517)	−0.610 (0.519)	−0.685 (0.545)	−0.0334 (0.330)	−0.889 (0.536)	−0.00791 (0.318)	−0.648 (0.245)**	−0.00791 (0.318)
Neighb. c.·$c2_{t-1}$	−0.653 (0.403)	−1.187 (0.570)*	−1.217 (0.572)*	−1.280 (0.597)*	−0.609 (0.410)	−1.522 (0.588)**	−0.587 (0.408)	−1.120 (0.373)**	−0.587 (0.408)
Neighb. c.· $\ln(t)_1$	0.158 (0.0919)	−0.199 (0.208)	−0.212 (0.210)	−0.232 (0.215)	0.140 (0.0933)	−0.284 (0.212)	0.148 (0.0922)	−0.153 (0.0892)	0.148 (0.0922)
W. Asia & North Africa	−0.581 (0.430)	0.285 (0.542)	0.319 (0.556)	0.709 (0.593)	0.632 (0.584)	0.714 (0.582)	0.659 (0.581)	0.296 (0.539)	0.659 (0.581)
West Africa	−1.132 (0.497)*	−1.823 (0.521)***	−1.889 (0.540)***	−1.639 (0.552)**	−1.682 (0.548)**	−1.630 (0.552)**	−1.691 (0.547)**	−1.907 (0.524)***	−1.691 (0.547)**
Southern Africa	0.337 (0.192)	−0.0758 (0.215)	−0.0695 (0.232)	0.0209 (0.249)	−0.0386 (0.243)	0.0128 (0.248)	−0.0601 (0.236)	−0.0929 (0.214)	−0.0601 (0.236)
Constant	−4.632 (0.692)***	−9.231 (2.381)***	−8.648 (2.577)***	−11.04 (3.007)***	−10.36 (2.177)***	−8.331 (2.708)**	−10.81 (1.885)***	−9.419 (2.231)***	−10.81 (1.885)***
N	5942	5942	5942	5942	5942	5942	5942	5942	5942
ll	−1568.6	−1521.6	−1519.9	−1503.0	−1537.2	−1513.0	−1537.4	−1521.5	−1537.4

Standard errors in parentheses.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

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