Evaluating the scope and intensity of the conflict trap: A dynamic simulation approach

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Abstract
Several studies show that internal armed conflict breeds conflict by exacerbating conditions that increase the chances of war breaking out again. Empirically, this ‘conflict trap’ works through four pathways: conflicts increase the likelihood of continuation, recurrence, escalation, and diffusion of conflict. Past empirical studies have underestimated the scope and intensity of the conflict trap since they consider the impact of conflict only through one of these pathways and rarely across sufficiently long time periods. This article shows that simulation and forecasting techniques are useful and indeed necessary to quantify the total, aggregated effect of the conflict trap, over long time periods and across countries. We develop a country-year statistical model that allows estimating the probability of no conflict, minor conflict, and major conflict, and the probabilities of transition between these states. A set of variables denoting the immediate and more distant conflict history of the country are used as endogenous predictors in the simulated forecasts. Another set of variables shown to be robustly associated with armed conflict are treated as exogenous predictors. We show that the conflict trap is even more severe than earlier studies have indicated. For instance, if a large low-income country with no previous conflicts is simulated to have two to three years of conflict over the 2015–18 period, we find that it will have nine more years of conflict over the 2019–40 period than if peace holds up to 2018. Conversely, if a large low-income country that has had major conflict with more than 1,000 battle-related deaths in several of the past ten years succeeds in containing violence to minor conflict over the 2015–18 period, we find that it will experience five fewer years of conflict in the subsequent 20 years than if violence continues unabated.

Keywords
conflict diffusion, conflict escalation, conflict recurrence, conflict trap, forecasting, simulation

Introduction
Internal armed conflict remains a major societal problem in many parts of the world. Over the past couple of decades, these conflicts disproportionately occur in a group of less than 50 countries that transition in and out of conflict – the ‘bottom billion’ population of the world (Collier, 2007). Structural factors that tend to facilitate conflict – poverty, poor governance, and non-participation in the modern, global economy – are clustered. This convergence, however, is intensified by the ‘conflict trap’ (Collier et al., 2003).
The presence of a conflict trap is well established in the literature, but we know little about its size and severity. In this article we show that the conflict trap is more intense than suggested by previous studies. If a country similar to Tanzania experiences two to three years of conflict over the 2015–18 period, we find that it can expect nine additional years of conflict over the subsequent 20 years compared to a scenario where peace continues up to 2018. Conversely, if a country like Nigeria succeeds in de-escalating its conflicts to less than 1,000 battle-related deaths in three out of four years over the 2015–18 period, the number of years with major conflict over the subsequent two decades will be reduced by 50%.

Quantifying the substantive effect of a phenomenon like the conflict trap is an essential complement to the focus on statistical significance in previous studies. Assessing the intensity of the conflict trap is demanding, however, since the ‘trapping effects’ extend far beyond the country year for which we have direct statistical estimates—they involve a set of factors active over a significant period of time, and work through several channels. We identify four empirical pathways for the conflict trap: an onset of a conflict increases the risk of conflict in the next year (pathway 1: continuation); it increases the risk of future conflict in the same country (2: recurrence); it (often) leads to intensified fighting that subsequently is harder to end (3: escalation); and it often spreads to neighboring countries (4: diffusion). Thanks to recent analyses disaggregated to the country-year level we now have fairly precise estimates for annual effects along each of these pathways. However, these studies fail to take into account the combined effect of them as well as their long-run implications. A comprehensive analysis of the conflict trap cannot be done by simply discussing the estimates from statistical models conducted at a disaggregated level of analysis, but requires the use of simulations based on the disaggregated statistical estimates. Such simulations are common in forecasting applications and also used in some of the articles in this special issue (e.g. Witmer et al., 2017).

We utilize the forecasting/simulation framework developed in Hegre et al. (2013) to assess the extent to which the outbreak of conflict affects the risk of future conflict in the same country, its neighborhood, and regionally. Since the conflict trap is related to onset, termination, and recurrence of conflict, we study the incidence of conflict. In our specification, we model how the risk of conflict depends on the conflict history of the country itself as well as its neighborhood, a set of risk factors established as robustly related to conflict, and time-invariant country effects.

To assess the intensity of the conflict trap, we conduct a set of statistical ‘experiments’ within our simulations. For instance, we investigate the model’s implications for the future risk of conflict in the group of previously peaceful low-income countries if one of them experiences conflict in the 2015–18 period. These experiments allow us to report a measure akin to an ‘average treatment effect’ of conflict, such as the one for Tanzania referred to above. The estimated magnitude of the conflict trap indicated by our results for low-income countries is considerable and larger than shown in previous studies. This estimate of the substantive effect has important implications for a policymaker that considers taking costly steps to prevent the escalation to armed conflict in a country in crisis. In deciding how to respond to a crisis, it makes a difference for a policymaker that a successful intervention that results in the prevention of armed conflict in the short run also helps avoid armed conflict for most of the subsequent two decades. In comparison, if the detrimental effect of an onset of fighting is contained to the next two years, intervention might be seen as carrying higher than expected costs and risks. As such, our results and estimation methodology can support decisions that allocate limited resources to conflict prevention and peacekeeping operations.

The article reviews the literature and discusses the different pathways through which a conflict trap operates, looks at some descriptive statistics related to the conflict trap, describes and discusses the statistical model and the simulation technique, performs out-of-sample evaluation of a set of candidate models for the simulation, reports the simulation results, and analyzes the intensity of the conflict trap.

### Why conflict traps

Multiple explanations for the presence of the conflict trap have been established. The literature points to both societal and economic impacts of war and to how both of these impacts are transmitted to neighboring countries through diffusion effects.

#### Societal impacts

Wartime transformation of social actors, structures, norms, and practices have long-lasting effects on society...
that fundamentally alter the likelihood that violence becomes entrenched. Social networks are reshaped through political mobilization, military socialization, identity transformation, polarization, and militarization of local authority (Wood, 2008). Internal conflicts commonly result in intense intergroup anger, hate, and fear, and in the buildup of ‘organizational capital’ for conflict, that render fighting self-perpetuating and fuel escalation. These effects routinely linger on after the conflict – battle-hardened war veterans are imperfectly reintegrated in society and remain interlinked through informal networks that can be used to re-recruit them into rebel armies (Humphreys & Weinstein, 2007).

Conflict strengthens the hand of the military establishment, and often contributes to excessive and counter-productive government military spending. Moreover, protracted armed conflicts often bring into power individuals that do well out of war (Wood, 2008), and will be inclined to continue to fight or revert to violence if post-conflict tensions re-escalate. Such individuals often function as ‘spoilers’ in post-conflict peace processes and are likely to continue to use violence to secure power and interests (Stedman, 1997).

Violent conflicts affect countries’ institutions. Contrary to the notion of war as anarchy, new social orders with clear rules of conduct often emerge during conflict. Variation in wartime social order is likely to influence the challenges and opportunities for reconciliation, reconstruction, and development after conflict has ended (Arjona, 2009, 2014).

Not all of the effects of war are negative. For instance, violence has been shown to increase community social cohesion (Gilligan, Pasquale & Samii, 2014), collective action (Bellows & Miguel, 2009), and post-conflict political mobilization (Bellows & Miguel, 2009; Blattman, 2009). Less socially motivated individuals may be more likely to flee, and those who cannot leave pull together in order to cope with threats and trauma (Gilligan, Pasquale & Samii, 2014). On balance, however, the net societal effect of war is likely to increase the risk of future hostilities.

Economic effects
The conflict-trap mechanism that has received most attention in the literature is conflict’s impact on economic growth and diversification. Buildings and infrastructure are destroyed, and valuable human capital lost through death, injury, or flight from the carnage. Financing the war itself is costly, and is often done by incurring debts (Slantchev, 2012) or inflation-driving money printing. Trade and finance are also disrupted (Bayer & Rupert, 2004), and mobile capital flees (Collier, 1999). Civil wars thus degrade human and capital stock, commerce, and the government’s capacity to collect revenues and provide essential services.

The effect of war on GDP per capita has been estimated to be about 2% annually (Collier, 1999; Gates et al., 2012; 175–176) and up to 20% in aggregate (Cerra & Saxena, 2008; Mueller, 2012: 442). Collier (1999) finds that short wars ‘cause continued post-war [GDP] decline, […] but sufficiently long wars give rise to a phase of rapid growth’ (Collier, 1999: 175–176). He attributes the continued decline in GDP after short wars to post-war environments being less capital-friendly than before the war.

The detrimental effect of conflict on the economy increases the risk of continued or renewed conflict – indeed, poverty is among the most important structural conditions that facilitate internal armed conflict (Collier & Hoeffler, 2004; Fearon & Laitin, 2003; Hegre & Sambanis, 2006). Adding to this, armed conflict adversely affects the structure of the economy (Collier, 1999). Since land-specific capital such as agriculture and other primary commodity extraction is less mobile, conflict transforms societies into more primary-commodity dependent economies that are more vulnerable to conflict (Collier et al., 2003; Collier & Hoeffler, 2004: 84).

A considerable portion of the negative economic effects of conflict occur at the microeconomic level and are only partially reflected in the measure of gross domestic product (Blattman & Miguel, 2010). These effects, however, are at least as important in priming societies for renewed violence. Shocks such as civil war and drought negatively affect human-capital formation both in terms of health and skills. Malnutrition due to such shocks negatively affects height for age and schooling completed, both of which harm lifetime labor productivity (Alderman, Hoddinott & Kinsey, 2006; Bundervoet, Verwimp & Akresh, 2009). Not only civilians are affected; the human capital accumulation of combatants is also interrupted. Youth who had been abducted and served as child soldiers during Uganda’s civil war attained lower levels of schooling, had less skilled employment, and achieved lower earnings (Blattman & Annan, 2010).

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2 Correspondingly, initiatives to promote disarmament, demobilization, and reintegration of combatants (DDR) seek to dismantle such ‘organizational capital’ (see e.g. United Nations, 2000; Walter, 1999). The importance within DDR programs of providing credible guarantees on the terms of the peace agreement highlights the deep security dilemmas generated by previous fighting.
Diffusion effects

Conflicts tend to cluster in space. There are two overlapping reasons for this: factors that are causally linked to conflict (such as land-based economies) tend to clump together, and conflict is contagious. Several studies show that there is a cross-border spillover effect even when controlling for the presence of these clustered factors (Collier et al., 2003; Hegre & Sambanis, 2006; Gleditsch, 2007). The magnitude of this effect is somewhat unclear, and some studies find only a weak effect of neighboring conflict (Hegre et al., 2001). Collier et al. (2003) argue that conflict diffusion primarily happens indirectly through economic cross-border spillover effects. These occur by increasing the ‘perceived risk to would-be investors and divert foreign direct investment away from neighbors at peace’ (Murdoch & Sandler, 2002: 96). Murdoch & Sandler (2004: 150) find that ‘a country in a region with three or more civil wars may be equally impacted as a country experiencing a civil war’. Other mechanisms lead to more direct conflict diffusion. One stems from collateral damage whereby battles close to the border destroy infrastructure and capital. More importantly, Salehyan & Gleditsch (2006) point to the importance of ethnic kin groups in neighboring countries, especially when combined with significant refugee flows.

Reassessing the intensity of the conflict trap

Four pathways

Armed conflicts alter societies and their neighborhoods in multiple ways. Empirically, these effects can be traced through four pathways: an onset of a conflict increases subsequent risk of conflict (pathway 1: continuation); the risk of future conflict in the same country (2: recurrence); escalation (3: escalation); and cross-border diffusion (4: diffusion). The pathways are interlinked, and a comprehensive assessment of the conflict trap requires an analysis of their combined impact. Traditional statistical studies (e.g., those reviewed in Collier et al., 2003; Blattman & Miguel, 2010) cannot account for the combined impact across all these pathways, since they only discuss the effect of individual parameter estimates for the next time period in their empirical analyses. Hence, they do not aggregate over multiple pathways and over multiple subsequent years.

In what follows, we use the definition and dataset of the UCDP/PRIO Armed Conflict Database (Gleditsch et al., 2002; Pettersson & Wallensteen, 2015).3 The UCDP records conflicts at two levels: minor conflicts that pass the 25 battle-related deaths threshold but have fewer than 1,000 deaths in a year, and major conflicts that pass the 1,000 annual deaths threshold. Since the conflict trap is related to onset, termination, and recurrence of conflict, we study the incidence of conflict – the proportion of a group of countries that is coded as being in minor or major conflict in a given year, simultaneously assessing the determinants of onset and duration of conflict (Bleaney & Dimico, 2011).

Continuation. A conflict trap is present if a conflict at time \( t \) increases the likelihood of conflict at some subsequent year \( t + k \). This occurs since conflicts clearly persist over time (Collier et al., 2003; Fearon, 2004) – the pathway of continuation. This pathway is illustrated in Figure 1. The left panel shows Kaplan-Meier estimates of the survivor function for conflict spells. A conflict spell is defined as one or more consecutive years with at least 25 battle-related deaths per year, within a given country. The Kaplan-Meier estimator is a non-parametric estimate of the survivor function. More precisely, it is an estimate of the probability of remaining in conflict after a certain time, \( t \), measured in years after the last conflict outbreak.

3 The Uppsala Conflict Data Project (UCDP) defines a conflict as a contested incompatibility that concerns a government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths. A civil (or intrastate) conflict occurs between a government and a non-government party. We focus on 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 average duration of a conflict was 4.9 years and the median was two years, but 10% of the conflict spells last more than 20 years. The right panel shows the smoothed hazard function for the probability of conflict termination. The hazard function is the (annual) probability of transition from conflict to non-conflict at $t$ given that the conflict has lasted up to $t$. This probability decreases strongly during the first five years, and countries become ‘trapped’. But does this trap persist even after the conflict has ended?

Recurrence. A conflict at time $t$ increases the likelihood of conflict at $t + k$ also because conflicts have a tendency to recur once ended (Beck, Katz & Tucker, 1998; Hegre et al., 2001, 2013; Fearon & Laitin, 2003). Many conflicts are indeed restricted to a single ‘spell’ – about one-third of all conflict countries have no recurrences. The conflict trap, however, also manifests itself as an increased risk of conflict recurrence, that is, of experiencing several conflict spells. Over the period 1945 to 2014, there were 159 conflict recurrences in 98 countries, defined as new conflict outbreaks after a period of minimum one year of post-conflict peace. To illustrate this recurrence pathway, Figure 2 shows corresponding Kaplan-Meier estimates for post-conflict peace spells. In this case, the survivor function represents how long a country emerging from a conflict remains at peace before entering into a new, recurring, conflict. The median duration of post-conflict peace spells was seven years. Here, too, the hazard function decreases over time. In this case, the hazard function refers to the probability of transitioning from peace to conflict. The function shows that each additional year of peace increases the chance of continued peace. Countries that manage to avoid conflict recurrence for a few years stand a much better chance of exiting the conflict trap.

Escalation. The third pathway is escalation or de-escalation of conflict. Here conflict at $t$ increases the likelihood of a higher-intensity conflict at $t + k$. This conflict-trap pathway has received much less attention in the literature than continuation, recurrence, and diffusion.

Hegre et al. (2013) show that in the period 1970 to 2009, around 10% of countries that had a minor conflict at $t$ experienced an escalation of that conflict to major status at $t + 1$. Accounting for this pathway is important because major armed conflicts have a much lower likelihood of ending than minor armed conflicts. Around 20% of all countries that had a minor armed conflict at $t - 1$ were in peace at $t$. The corresponding figure for major armed conflict was only 7% (Hegre et al., 2013). Accounting for the risk of escalation and de-escalation is therefore crucial for understanding the likely future conflict trajectory of a country.

Diffusion. The fourth and final conflict-trap pathway works through increasing the risk of conflict at time $t + k$ in a country if conflict is active in that country’s neighborhood at time $t$. The diffusion pathway is illustrated in the map in Figure 3. It shows the highest observed conflict intensity for the world’s countries over the period 2001–14. Conflicts cluster in space. Consequently, it is necessary to take into consideration the risk of conflict contagion in order to capture the effect the conflict trap has on countries’ neighbors that in turn causes subsequent instability to the entire region.

Why a dynamic simulation framework is necessary

To fully assess the scope and intensity of the conflict trap all four pathways must be taken into consideration. In order to do this, it is necessary to go beyond the traditional, simple interpretation of the parameter estimates of a model. Below, we specify in detail a model that operationalizes the four pathways (see Table V). It contains parameters for conflict in the previous year, in neighboring countries, and summaries of conflict history over the past few decades. Simply considering the individual parameter estimates clearly is insufficient.
given the overlap of information between them. Tools such as Clarify (Tomz, Wittenberg & King, 2003) are helpful in that they allow interpreting multiple coefficients simultaneously. However, Clarify is severely limited in the sense that it can only assess how variables affect the predicted probabilities one step ahead. This is insufficient since the four pathways of the conflict trap work over multiple years. If a conflict breaks out in hitherto peaceful country $i$ in year $t$, applying Clarify to the model sketched above would allow us to estimate the increased risk of conflict in year $t + 1$ in country $i$ and neighboring country $j$. However, the risk of conflict in countries $i$ and $j$ will also be affected in year $t + 2$ and subsequent years. If the increased risk is translated into actual fighting in country $j$ the chance of war in its neighboring country $k$ is also affected. The effect of the initial outbreak of war in country $i$ is propagated in time and space well beyond year $t + 1$. Clarify is of little help when we want to estimate long-term impacts of the initial conflict.

Moreover, only interpreting the short-term impact of the regression coefficients would severely underestimate the conflict trap. To assess the complete magnitude of the conflict trap, it is necessary to simulate all the possible trajectories that might follow a year of conflict. Furthermore, it is necessary to simulate over at least a couple of decades to fully capture the long-term combined impact of conflict along all the four pathways of continuation, recurrence, escalation, and diffusion.

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5 See Online appendix A-3 for a demonstration.

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### Table I. Simulation algorithm

| Step | Description |
|------|-------------|
| 1.   | Estimate ‘random-effect’ parameters capturing country-specific propensity for conflict |
| 2.   | Draw a realization of the random-effect parameters |
| 3.   | Estimate multinomial logistic regression model regressing conflict on a set of risk factors (1950–2014) |
| 4.   | Based on estimated coefficients and the variance-covariance matrix, draw realizations of parameter coefficients |
| 5.   | Load first simulation year (2015) |
| 6.   | Loop for every year: |
|      | (a) Calculate probabilities of transition between no conflict, minor conflict, and major conflict, based on: |
|      | • Realized coefficients and projected values for predictors |
|      | • Projected data for population, time since independence, and socio-economic development |
|      | (b) Draw transition outcomes (no conflict, minor conflict, or major conflict) and update predictors |
| 7.   | Repeat procedure multiple times for each model specification |
| 8.   | Out-of-sample model evaluation or summary of results |

### Estimating the size of conflict trap

To this end, we have developed a simulation framework that enables us to assess the size, magnitude, and severity of the conflict trap both within a specific country and in the country’s neighboring countries. We utilize the simulation technique developed by Hegre et al. (2013) summarized in Table I. Here, we build a dynamic forecasting framework, the backbone of which is an estimate of the matrix of transition probabilities between the conflict states of no
conflict, minor conflict, and major conflict. A sample transition probability matrix, based on observed transitions in sub-Saharan Africa, is reported in Table II. It shows, for instance, that in this region, 94.7% of all country-years at \( t - 1 \) without conflict were followed by no conflict, but that 5.1% of these were followed by minor conflict at \( t \). Furthermore, a country with minor conflict had a probability of .573 of minor conflict the year after.

We estimate this matrix of transition probabilities using a multinomial logistic model with the conflict level at \( t \) as the outcome variable, and the level at \( t - 1 \) as a set of dummy variables (step 3 in Table I). By adding variables denoting various risk factors, including the conflict history of the country and its neighbors, we can estimate the transition probability matrix contingent on these risk factors and projected and simulated changes to these. For the first year of the simulation, the procedure calculates the transition probabilities based on the last observed values for conflict history and exogenous risk factors (step 6a). It then draws a conflict outcome for the first year based on these probabilities (step 6b). Thereafter it moves to the next year and calculates an updated conflict history based on the draw, retrieves projections for the exogenous variables, re-estimates the transition probabilities, and draws a conflict outcome for this year. This is repeated until the last year of the simulation. This simulation framework allows us to dynamically forecast future incidence of conflict as a function of risk factors, the country’s own short-term and long-term conflict history, and the conflict history of the country’s neighbors. The forecasts are obtained through simulating conflict events in a country as implied by the estimates from the statistical model. In the simulation, conflict at \( t \) affects the conflict risk for country \( i \) and the neighboring countries \( j \) at time \( t + 1 \), and the risk of conflict at \( t + 2 \) and so on and so forth.

This procedure allows us to estimate the impact of the conflict across all pathways. If a minor conflict breaks out in a hitherto peaceful country, the procedure captures that this increases the estimated risk of conflict in that country in many years afterwards, as well as the risk of conflict in neighboring countries. The estimates from our statistical model, for risk of onset, recurrence, and escalation of such a conflict, are likewise reflected in several subsequent transitions. As long as we can assume that the estimated transition probabilities (contingent on projected risk factors) are correct, the model yields fairly accurate predictions in aggregate. The ability to forecast over at least 25 years is important, since the effects of armed conflicts often linger for at least as long as that.

### Risk factors

**Conflict history**

All models tested include the dependent variable lagged by one year, implemented as two dummy variables – one denoting whether there was a minor conflict at \( t - 1 \) and the other denoting whether there was a major conflict at \( t - 1 \). We explore two models of the effect of past conflict up to two years before the year of observation. First, we test the performance of a model that includes the log of the number of consecutive years in a given state up to and including \( t - 2 \). There are three of these: \( \ln(t_0) \), which is the log of the number of years with no conflict; \( \ln(t_1) \), the log of consecutive years with minor conflict up to \( t - 2 \); and \( \ln(t_2) \), the number of years with major conflict. These parameters allow the model to distinguish clearly between a country such as Tanzania with close to 50 years of peace and Burundi with much more recent conflict. The smoothed hazard functions shown in Figures 1 and 2 indicate that the logs of the numbers of years are adequate representations of how the probabilities of war and peace change over time.

A model only relying on the \( \ln(t_2) \) variables, however, may not be sufficiently flexible to capture the dynamics of the more recent past. We therefore also specify a model with lagged dependent variables for each of the years \( t - 2 \) to \( t - 5 \).

**Neighboring conflict**

We define the neighborhood of a country \( i \) as all \( j \) countries \([i \ldots j_N]\) with some part of their territory less than 100 km from the territory of \( i \) (Gleditsch & Ward, 2000). The spatial lag of conflict is a dummy variable measuring whether there is at least one conflict in the

Table II. Observed annual transition probability matrix, sub-Saharan Africa 1960–2013

| State at \( t - 1 \) | No conflict | Minor conflict | Major conflict |
|---------------------|-------------|----------------|---------------|
| No conflict         | 1,524 (.947)| 82 (.051)      | 4 (.003)      |
| Minor               | 76 (.307)  | 142 (.573)     | 30 (.121)     |
| Major               | 7 (.063)   | 27 (.243)      | 77 (.694)     |
| Total               | 1,607 (.816)| 251 (.128)    | 111 (.056)    |

\( ^6 \) In what follows, we use the term ‘country’ for states in the international system, and the term ‘state’ to denote a given value for the dependent variable (e.g., no conflict, minor conflict, or major conflict).
neighborhood or not. Islands with no borders are considered as their own neighborhoods when coding the exogenous predictor variables, and 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 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.

Socio-economic development
To measure economic development we utilize log GDP per capita from the World Bank’s World Development Indicators (World Bank, 2010). This dataset covers the period 1960 to 2014. Beyond 2014, we use the SSP2 projections constructed using the OECD ENV-Growth model (using an augmented Solow growth model with representations of human capital and fossil fuel usage, Chateau & Dellink, 2012). We treat economic development as exogenous in this analysis. Although we consider this simplification as appropriate here, we treat GDP per capita as endogenous in Hegre, Hultman & Nygård (2015).

Additional controls
Greater populations are associated with increased conflict risks. 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 (Raleigh & Hegre, 2009). We include a measure of total population from the UN’s World Population Prospects (United Nations, 2007) and projections from the IIASA and Wittgenstein Centre for Demography and Global Human Capital model (Samir et al., 2010).

The measure has been log-transformed assuming a declining marginal effect of increasing population size on conflict risk. We also control for the log of the number of years the country has been independent based on the Gleditsch & Ward (1999) list of independent states. This measure covers aspects of state consolidation not captured by economic development.

Time-invariant and country-level unobserved heterogeneity
It is clear that there may be country-level heterogeneity not accounted for by the other predictors. The conflict trap may not be the consequence of the recent conflict history, but rather of structural conditions that go further back in time. Fixed-effects models are unsuited to our purpose since they do not yield useful estimates for countries without any conflicts over the observation period, countries for which we also want to have forecasts.

We estimate two multilevel logistic models with conflict as dependent variable (one for minor and one for major armed conflict) and the variables discussed above as predictors, as well as country-specific ‘random-effects’ intercepts (Gelman & Hill, 2007; StataCorp, 2013). From this model, we collect predicted mean country-specific random effects as well as the country-specific standard errors of these estimates (step 1 in Table I). These mean country-specific random effects can be interpreted as a measure of the propensity for a country of experiencing conflict that is not explained by the other risk factors included in the model. This propensity is assumed to be normally distributed across countries, but time-invariant within.

We draw 50 realizations of the random effects for each country with mean equal to the mean country-specific random effect and variance equal to its standard error (step 2 in Table I). We then enter these as covariates in the multinomial logistic regression model used in the simulation – essentially making the model the logistic regression equivalent of a shared ‘frailty model’ in

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7 See Hegre et al. (2016) for details regarding projections for GDP and population.
8 Treating development as exogenous is obviously a simplification. In practical terms, it is not very substantial for our purpose. A typical war reduces GDP per capita by up to 20%. According to the estimates in Table V, this increases the risk of major armed conflict onset by about 10%, and the risk of minor conflict by about 5%. The estimated risk of continued conflict is largely unaffected by development. Although substantial, these effects are small relative to the estimated effect of past conflict – the presence of a minor conflict at \( t \) increases the probability of minor or major conflict at \( t + 1 \) by a factor of 20–40, for instance (see discussion of these results below). Out-of-sample evaluation showed that models with endogenous GDP per capita did not perform better than the models presented below.
9 In Hegre, Hultman & Nygård (2015), we are interested in the economic costs of conflict in addition to the social costs, and use a similar setup to quantify the economic benefits of successfully containing and preventing armed conflicts.
10 As discussed at some length in Raleigh & Hegre (2009), country population size and considerations of per-capita impact are important aspects of armed conflict. The analysis we present here could usefully be expanded along these lines. In Online appendix A-4 we elaborate briefly on this issue.
11 These models are clearly ‘throwing the baby out with the bathwater’ (Beck & Katz, 2001). The random effects are estimable also for countries without any change for the dependent variable.
12 The results from these estimations as well as illustrations of the country-specific effects are presented in Online appendix A-1.
duration analysis. To capture the uncertainty of these estimates, we run a large number of simulations for each of these 50 realizations and aggregate over these simulations before presenting the results. The estimated results from the multilevel models are reported in the Online appendix as Tables A-1 and A-2. Mean estimated country-specific effects are reported as maps in the Online appendix Figures A-1 and A-2. These conform to expectations – China, for instance, has a lower risk of conflict than expected from the remainder of the model. India has a lower risk of major conflicts than expected, but a higher risk of minor ones.

Out-of-sample evaluation

To demonstrate the predictive power of the simulation framework and to arrive at an optimal model specification, we ran a series of out-of-sample evaluation tests. As argued persuasively in Ward, Greenhill & Bakke (2010), evaluation of predictive performance is essential for studies that seek to provide policy advice. Out-of-sample evaluation helps preventing overfitting models to the data used for estimation, and models that do well in such evaluations are more likely to be generalizable outside the data that are available (see Colaresi, 2017). This is particularly important when models are as complex as those presented here. We specified six models listed in Table III based on the different combinations of the risk factors discussed above. These were estimated on data for the 1950–2001 period. We then simulated as described above for the years 2002–14, in accordance with our definition of the conflict trap as the risk of armed conflict in any of a number of subsequent years $t + k$. We then compared the simulated conflict level to the observed conflict level in this period. Estimation results for the six models are reported in Online appendix Tables A-3 to A-8.

The baseline model only includes the lagged dependent variable, log population size, log GDP per capita, and time since independence. Model 2 includes random effects. Model 3 adds the lagged dependent variable for each of the five preceding years. Model 4 adds neighborhood variables to the five-year lag model. Models 5 and 6 are similar to Models 3 and 4, but with log of number of consecutive years in peace, minor conflict, or major conflict up to $t - 2$ instead of the lagged dependent variables.

Evaluations of forecasts are more straightforward for dichotomous variables than for variables with three categories; hence we group the cases where we predict either minor or major conflict into one category, ‘conflict’, and compare with the corresponding observed variable. We evaluate using three metrics: the area under the receiver operator curve (AUROC), the area under the precision recall curve (AUPR), and the Brier score.

The receiver operator curve is a plot of the true positive rate ($TP$) against the false positive rate ($FP$) for all combinations of these values in the data. A perfect model would produce an AUROC value of 1. A perfect receiver operator curve would plot a line going from the lower-left corner to the top-left and then straight to the top-right corner. The AUROC is equal to the probability that the simulation predicts a randomly chosen positive observed instance as more probable than a randomly chosen negative one. Here, that means the probability that a randomly drawn conflict-year will have a higher predicted risk of conflict than a randomly drawn peace-year. AUROCs, however, have two drawbacks: they are too optimistic when dealing with highly skewed variables such as conflict, and they neglect the relative importance of true positives vs. false positives. Therefore, we also report the AUPR and the Brier scores.

The AUPR overcome the AUROC drawbacks by comparing true positives to both false negatives and false positives. AUPR plots ‘precision’, true positives over all predicted positives $\frac{TP}{TP + FP}$, against ‘recall’, true positives over all observed positives $\left(\frac{TP}{TP + FN}\right)$. Unfortunately, AUPR does not have an intuitive interpretation that parallels the AUROC, but a well performing model would plot a line going from the upper-left corner to the upper-right corner before dropping to the lower-right corner.

### Table III. Models for out-of-sample evaluation

| Model | Conflict lags | Time since conflict | Neighboring conflict | Random effects | GDP per capita | Population & time indep. |
|-------|---------------|---------------------|----------------------|----------------|----------------|-------------------------|
| 1 (baseline) | No | No | No | No | Yes | Yes |
| 2 (1 + RE) | No | No | No | Yes | Yes | Yes |
| 3 (2 + lags) | Yes | Yes | No | Yes | Yes | Yes |
| 4 (3 + neigh) | Yes | Yes | Yes | Yes | Yes | Yes |
| 5 (2 + lns) | No | Yes | No | Yes | Yes | Yes |
| 6 (5 + neigh) | No | Yes | Yes | Yes | Yes | Yes |
The Brier score is the average of the squared difference between the predicted probability and the observed outcome. Brier scores are considered a proper scoring rule since they are ‘best’, that is, smallest, at the true observed probability (Gneiting & Raftery, 2007; Brandt, Freeman & Schrodt, 2014).

Figure 4 reports the AUROC (left panel) and precision-recall plot (right panel). Table IV reports the AUROC, AUPR, and Brier scores. The out-of-sample evaluation allows us to answer two model-selection questions: does (1) adding conflict history variables, and (2) the random country effects, add to the predictive power of the model? Columns 5–7 in Table IV report the rank for each model across the evaluation metrics. These results show that adding the random effects parameters (M2) increases the predictive ability of the models considerably. Adding the additional conflict trap variables also increases predictive power, but the logged time in status variables (M5) do much better than the additional conflict lags (M3, M4). Adding neighborhood variables (M6) again improves on M5 across all metrics. All metrics agree in ranking Model M6 as the best model. We therefore base the simulations presented below on this model.

The fact that the most complex model performs unambiguously better in the out-of-sample evaluation

13 Proper scoring rules are particularly attractive since they, by definition, give an ‘assessor an incentive to reveal her true probability function rather than to hedge (e.g. supply equal probabilities for each event)’ (Brandt, Freeman & Schrodt, 2014: 948).

14 The evaluation metrics exhibit some disagreement in their comparisons of the models. In particular, the Brier score ranks the simple baseline model favorably. The AUROC and AUPR measures generally agree on how to rank the models. These measures exhibit different strengths and weaknesses, as discussed above. Since all metrics agree on the best model, we omit a detailed discussion of them here.
Analyzing the conflict trap

To analyze the effect of the conflict trap we re-estimate M6 on data for 1950–2014. The estimation results are shown in Table V. The results are broadly in line with previous research (Hegre & Sambanis, 2006). Here, we only discuss the estimates most relevant to the conflict trap. Since baseline probabilities are relatively small, what we write in terms of change in odds of conflict is roughly similar to the corresponding change in probability of conflict.

The estimates for conflict at $t - 1$ are all large and positive. For a country with size and poverty levels similar to Liberia’s, a minor conflict at $t - 1$ increases the odds of minor conflict by a factor of 36 relative to if there was no conflict at $t - 1$, and the odds of major conflict are 52 times higher. If there was major conflict at $t - 1$ in a country with these characteristics, odds of minor conflict are estimated to be 26 times higher, and odds of major conflict 460 times higher. The estimates for the interaction terms between lagged conflict, population, and GDP per capita are comparatively small, and do not alter these estimates significantly.

A period of peace alters the risk of conflict significantly. After 20 years of non-interrupted peace, the risk of major conflict in a newly independent country similar to Liberia is 84% lower. For a country that has been independent longer, the effect is somewhat smaller.

For a country that is not in conflict itself, a conflict in a neighboring country increases odds of minor conflict



\begin{table}
\centering
\begin{tabularx}{\textwidth}{l|cc|cc}
\hline
& \textbf{Minor conflict} & & \textbf{Major conflict} & \\
\hline
Minor conflict, _{-1} & 3.063^{***} & (11.39) & 3.514^{***} & (7.69) \\
Major conflict, _{-1} & 2.498^{***} & (7.24) & 5.244^{***} & (11.18) \\
Time in peace, _{-2} & -0.139 & (-1.30) & 0.0163 & (0.08) \\
Time in minor, _{-2} & 0.241 & (1.60) & -0.109 & (-0.49) \\
Time in major, _{-2} & 0.0104 & (0.03) & 0.0598 & (0.20) \\
log(Population) _{-2} & 0.149* & (2.01) & 0.291* & (2.12) \\
log(Population) _{-1} * Minor conflict, _{-1} & 0.164 & (1.90) & -0.102 & (-0.67) \\
log(Population) _{-1} * Major conflict, _{-1} & -0.0373 & (-0.29) & -0.0129 & (-0.07) \\
log(Population) _{-1} * Time in peace, _{-2} & 0.0207 & (0.80) & -0.0285 & (-0.51) \\
log(GDPcap) _{-2} & -0.212* & (-1.98) & -0.430* & (-2.08) \\
log(GDPcap) _{-1} * Minor conflict, _{-1} & -0.139 & (-1.21) & 0.212 & (1.01) \\
log(GDPcap) _{-1} * Major conflict, _{-1} & 0.176 & (1.01) & 0.165 & (0.68) \\
log(GDPcap) _{-1} * Time in peace, _{-2} & -0.0559 & (-1.65) & -0.0103 & (-0.14) \\
Time since independence & -0.0407 & (-0.33) & -0.334* & (-2.05) \\
Neighboring conflict & 0.827^{***} & (3.19) & 0.416 & (1.26) \\
Neigh. conflict * Conflict, _{-1} & -1.527^{***} & (-4.63) & -0.885* & (-2.01) \\
Neigh. conflict * Time in peace, _{-2} & -0.312^{**} & (-2.61) & -0.0978 & (-0.46) \\
Time since neigh. conflict & 0.0820 & (0.66) & 0.290 & (1.79) \\
Minor random effect & 1.146^{***} & (8.29) & 0.310 & (1.47) \\
Major random effect & 0.223 & (1.83) & 1.443^{***} & (6.81) \\
constant & -2.722^{***} & (-3.92) & -4.241^{***} & (-3.66) \\
\hline
N & 8,269 & & & \\
AIC & 3,714.9 & & & \\
ll & -1,815.4 & & & \\
\hline
\end{tabularx}
\caption{Estimation results, armed minor conflict (left) and major conflict (right), 1950–2014}
\end{table}

15 Liberia’s population in 2012 was about 4.3 million and its GDP per capita about 440 USD. In log form, these numbers are 8.375 and 6.095, respectively. In combination with the estimates in Table V, this means odds of minor conflict are \( \exp(3.063 + .164 \cdot 8.375 - .139 \cdot 6.095) = 36.2 \) times higher when minor conflict at $t - 1$ is 1 than if minor conflict at $t - 1$ is 0.

16 The log of 20 is about 3. Change in odds is then \( \exp(-3.34 - .0163 - .00285 - 3 - 8.375 - .0103 - 3 - 6.095) = 0.157 \).
by a factor of 2.3. According to these estimates, the effect is negligible if the country at risk of conflict spillover is in conflict itself, or if it has been at peace for about 20 years or more.

**Quantifying the scope and intensity of the conflict trap**

In order to be able to quantify the scope and intensity of the conflict trap, our strategy now is to use these estimated results together with the simulation framework discussed above to produce a large number of *alternative futures* for a set of comparable countries. We create 96,000 simulations of future conflict trajectories for all countries over the next 26 years – the simulated risk of conflict in that country for every year from 2015 until 2040. Then we group these simulations into ‘scenarios’ according to whether they yield an onset of conflict in the first four years of the simulations (2015–18). These simulations all start from the same conditions in terms of development, conflict history, and neighborhood characteristics in 2014, but then diverge (on conflict status, history, and neighborhood characteristics) in a multitude of directions. This gives us several large sets of simulations that differ in terms of how much conflict these countries experienced between 2015 and 2018. This initial variation is used to group the simulations into three ‘scenarios’ or quasi-experimental ‘treatments’ as explained below. We quantify the size and intensity of the conflict trap by comparing these ‘scenarios’ in terms of their impact on simulated incidence of conflict over the subsequent 26 years.

To even out country-specific effects we look at a group of 13 ‘low-income previously peaceful countries’ that have not seen any internal armed conflict in the last 20 years. All of them have GDP per capita less than USD 2,000. By in some of the 96,000 simulations, at least one country in the group will experience conflict in the 2015–18 period; in some, none of them will.

The forecasts are grouped into three ‘scenarios’ according to the 2015–18 projections. The scenarios are: (1) continued peace, (2) onset of minor conflict, and (3) onset of major conflict. All simulations where none of the 13 countries have conflict fall into the ‘continued peace’ scenario. The ‘minor conflict’ scenario groups together all simulations with at least one year of minor or major conflict, but a maximum of one year of major conflict among the 13 countries. ‘Major conflict’ groups simulations with more extensive conflict than that. From 2019 onwards, the simulations in all scenarios unfold according to the transition probabilities indicated in Table V and the values for the risk factors. This allows us to calculate how much more conflict these countries subsequently see if conflict breaks out compared to if all remain at peace over the initial four years. The difference in the amount of conflict observed in these simulated subgroups is interpretable as the (group) average treatment effect of conflict.

We also look at two individual countries: Tanzania, which is the most populous country in the group of peaceful low-income countries, and Nigeria, which is also low-income but has had a considerable amount of conflict over the past two decades. Exploring the simulations for Nigeria allows us to assess the ‘peace dividend’ of an onset of peace in a country that seems trapped in conflict.

**New war in previously peaceful low-income countries**

The upper two panels of Figure 5 show the average forecasted proportion in conflict for these low-income previously peaceful countries for each of the three ‘scenarios’. The left panel refers to the simulated incidence of minor and major conflict, and the right panel to major conflict only. The green dotted lines show the forecasted incidence of conflict for the group, following simulations that yielded ‘continued peace’ up to 2018. The simulations indicate that this group will see an increased incidence of conflict from 2019 onwards. By 2025, more than 10% of simulations are in either major or minor conflict under this scenario, and in 2040 as many as 15% are. The forecasted incidence of major conflict rises to 4% by the end of the forecast. These trajectories constitute the baseline against which we will evaluate the conflict trap.

The ‘major onset scenario’ (blue solid lines) includes the simulations with the most extensive conflict. In these, more than 17% of the countries in the group had a conflict by 2018, and 7% had a major conflict.

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17 The countries in the group are: Benin, Burkina Faso, Gambia, Ghana, Kenya, Madagascar, Malawi, Mongolia, North Korea, Tanzania, Togo, Zambia, and Zimbabwe.

18 Our model, as most statistical civil war models, rate these countries as being unlikely to remain in peace, even when taking into account the country-specific random intercepts that generally indicate a low baseline risk for these countries. This is not so strange, since we have selected them for being conflict-prone according to the model, but with a peaceful history. This finding does not run counter to the general trend of declining incidence of conflict, since we predict a declining incidence of conflict in countries such as Israel/Palestine or Colombia that have had more conflicts than postdicted by the model. In Hegre et al. (2016) we forecast a continued decline in armed conflict using a closely related model.
Corresponding figures for the ‘minor onset scenario’ (red dashed lines) are 10% and 2%. After 2018, the simulated incidence of conflict – minor or major – remains at the same level, at close to 20%. The exposure to conflict in both of these scenarios has led to stable and sizable shifts in the subsequent probability of conflict. A similar shift is seen for subsequent major conflicts only in the upper-right panel.

The magnitude of the conflict trap can be inferred from the difference between the lines representing the ‘major onset’ and the ‘continued peace’ scenarios. The lower two panels of Figure 5 show this difference between scenarios in simulated incidence of armed conflict as a function of simulation time. As before, the blue solid lines show how much more simulated conflict there was in the ‘major conflict onset’ scenario compared to the ‘continued peace’ scenario. The red dotted lines show excess conflict in the ‘minor onset scenario’ relative to the baseline. As before, the left panel refers to minor and major conflict, and the right panel major conflict only. The shaded areas show one standard deviation (68%) coverage.

The figures show that simulations that started with conflict remain excessively conflictual for a long time. The difference in incidence is 15% in 2019, and decreases to about 5% by 2030. The impact of an earlier war decreases with each subsequent year of peace, but the simulated incidence of conflict in the major onset scenario does not revert entirely to the baseline scenario over the 25-year forecasting period. In 2040, the incidence of conflict (minor or major) continues to be about 5% higher than in the baseline scenario. In fact, the difference between the two scenarios is roughly constant over the last ten years of the forecasting window. This also applies to the ‘minor onset scenario’, although the difference is smaller. The distance between the scenarios is quite well defined, with non-overlapping 68% coverage regions throughout the forecasting period when we look at minor and major conflict jointly (left panels). When we concentrate on major conflicts only, there is more uncertainty given the lower frequency of such conflicts. All in all, these results indicate that the conflict trap is much more intense than accounted for in earlier studies that

Figure 5. Comparing simulated incidence of conflict between ‘continued peace’, ‘minor conflict onset’, and ‘major conflict onset’ scenarios for low-income previously peaceful countries

Upper panel: Proportion in minor + major (left) and major conflict (right), by year. Lower panel: Difference in simulated proportion in minor + major (left) and major conflict (right).
account for only one of the four empirical pathways the trap can work through.\textsuperscript{19}

Figure 6 shows the same for Tanzania as a single country. We have classified simulations where there is major conflict in at least two years in the 2015–18 period as instances of a ‘major onset’ scenario. Simulations where there is minor conflict in at least one year are classified as instances of the ‘minor onset’ scenario. Excess conflict after simulations where conflict erupts in Tanzania is evident. Since Tanzania is so populous, our model predicts a ‘baseline’ conflict probability of 34% of simulations in 2040 even if peace holds through 2018 (green dotted line, upper-left panel). In 15% of simulations there is major conflict in Tanzania. Nevertheless, this is much lower than in the ‘major onset’ scenario. In this scenario in 2018 there is conflict in Tanzania in almost all simulations. This proportion decreases slowly to about 47% in conflict in 2040, and 24% in major conflict. Again, the lower panel of figures that report the difference in incidence between scenarios and the baseline show that a major conflict onset between 2015 and 2018 essentially locks Tanzania in a conflict trap whereby it has an elevated risk of conflict, compared to the baseline, for as long as 25 years after the initial conflict onset.

The areas under the blue and red lines in the lower panels of Figure 6 indicate the long-term magnitude of the conflict trap for this hypothetical situation. In the left panel of Figure 7, we present these simulation results in cumulative form – summing years of conflict in the country from 2015 up to the given year. This is arguably the most accurate estimate of the size and intensity of the conflict trap. The blue solid line shows the difference in cumulative simulated number of years in conflict for the ‘major onset’ scenario relative to simulated conflict in the ‘continued peace’ scenario baseline. At the end of 2018, Tanzania had accumulated on average 2.5 years of conflict in the simulations classified as ‘major onset’ scenarios, which by construction is 2.5 more years than the

\textsuperscript{19}We have focused here on low-income countries. Similar results for middle-income previously peaceful countries show a similarly trapping tendency in relative terms. However, since the underlying probability of conflict in middle-income countries is much lower, a doubling of the risk of conflict has a much smaller impact on such countries.
baseline. As the trapping effects of this ‘conflict treatment’ continue, the difference between the two scenarios steadily accumulates. Ten years after the treatment (in 2028), the difference is 8.6 years. Twenty years later, it is 11.6 years. In other words, if a country like Tanzania is exposed to 2.5 years of conflict spread over a four-year period, nine more years of conflict will follow over the subsequent 20-year period, compared to the simulated conflict trajectory following four initial years of peace.

In terms of the incidence of major conflict only, the ‘major onset’ scenario implies 1.5 years of conflict with more than 1,000 annual battle-related deaths over the four-year period. Twenty years later, the difference in cumulative years of major armed conflict in this scenario has increased to 7.9 relative to the baseline. This initial first conflict is on average followed by 6.4 years of additional conflict. In other words, if it is possible to prevent in the short term the initial conflict exposure we define as the four-year treatment here, the long-term reduction of conflict over the next 25 years is more than four times larger than the short-term reduction. For a large, low-income peaceful country like Tanzania, the potential conflict trap is substantial.

Figure 8 shows the simulated impact of the hypothetical Tanzanian conflict exposure to a neighboring country, Mozambique. The ‘major onset’ scenario in Tanzania implies a considerable increase in simulated conflict in Mozambique. In 2023, Mozambique is in conflict in 28% of simulations as compared to 20% in the baseline scenario. The conflict trap via international diffusion is considerable. The excess conflict in this scenario is also further diffused to other neighboring countries and back to Tanzania again.

Figure 7. The long-term effect of conflict in Tanzania (left), and peace in Nigeria (right): cumulative number of years with minor or major conflict, 2015–40

Figure 8. Comparing simulated incidence of conflict between Tanzania conflict-scenarios for Mozambique Proportion in minor + major (left) and major conflict (right).

Peace in a low-income country: Nigeria

Figure 9 shows the proportion of simulations in conflict 25 years into the future for Nigeria. Nigeria has had

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20 The major conflict results are not shown in the figure.
several years of major conflict over the past two decades, including all of the four years 2011–14. We grouped the simulations into three: those where Nigeria has a major conflict in at least two years (‘continued major’, solid blue line) over the 2015–18 period; those with conflict but maximum one year of major conflict (‘de-escalation’, dashed maroon line); and those with dramatically reduced incidence of armed conflict over these four years (‘cessation’, dotted green line). Given Nigeria’s long history of armed conflict, we predict a high risk of conflict 25 years into the future in the baseline scenario. In 2040, there is a minor or major conflict in about half of the simulations (green dotted line in the upper-left panel), and a major conflict in more than 10% (upper-right panel).

Mirroring what we saw for conflict in a previously peaceful country, the long-term impact of de-escalation and cessation of conflict is considerable. In 2040, excess conflict (minor or major) in the ‘continued major’ scenario relative to the ‘cessation’ scenario is about 10%. Even more notably, the difference in the incidence of major conflict is very large. In 2040, the incidence of major conflict is almost 50% lower in the ‘cessation’ scenario relative to the ‘continued major’ scenario. Twenty years after, there is still a strong effect of four years of diminished hostilities. Due to this long-term impact of containing violence, peacekeeping operations are more effective than commonly perceived.

The right panel in Figure 7 presents these results in cumulative form. It shows that the long-term effect of abating violence in a low-income conflict country is equally as large as the converse effect of conflict onset in a previously peaceful country (shown in the left panel). Containing the conflict by limiting it to less than 1,000 battle-related deaths per year for 2015–18 (i.e. from a major to a minor conflict) reduces the accumulated conflict exposure over the 2019–40 period by five years.

This finding parallels the findings reported above on the different effects of minor and major intensity conflicts. Managing a de-escalation of conflict from major to minor helps the country to break the conflict trap. This
allows the country to start the process of ending the conflict altogether. For countries at peace, in contrast, an initial onset of even a minor conflict in many cases signals the first steps into the conflict trap cycle. Consequently, a minor conflict onset is fundamentally different from a de-escalation to minor conflict – for peaceful countries a minor conflict signals a step into the conflict trap cycle, while for countries in major conflict it signals the first step out of the cycle.

Conclusion

Internal armed conflicts such as those in Syria, Sudan, and the Central African Republic have enormous human and economic costs. The need to prevent or de-escalate such conflicts is rendered even more acute by the fact that conflicts seem to have self-perpetuating effects (Collier et al., 2003). The presence of such a ‘conflict trap’ has been established in previous studies, but we have argued that the practical or substantive implications of this finding have not been clearly established.

We have shown that it is possible to quantify the magnitude of the conflict trap based on units of analysis that are sufficiently disaggregated to capture the swift changes and diffusion of risks of conflict. This requires employing a forecasting/simulation framework such as the one developed in Hegre et al. (2013) to assess how the outbreak of conflict affects the risk of future conflict in the same countries, their neighborhoods, and regionally. Aggregating the cumulative effects of conflict onset in this fashion, then, uncovers a much stronger effect of the conflict trap than is indicated by the traditional interpretation of statistical estimates.

We find that an onset of a major armed conflict in a previously peaceful low-income country results in an elevated risk of armed conflict for that country more than 20 years into the future. This implies that for a low-income country a single onset of conflict might be enough to push the country into the conflict trap. Using a country similar to Tanzania as an example to demonstrate how such quantification could be done, we show that a four-year effort that succeeds in preventing a hypothetical major conflict sustained over a four-year period will also reduce the number of years in conflict over the next 20 years by nine years – more than a 50% reduction in risk. Conversely, a cessation of hostilities in a low-income country in war lowers the likelihood of renewed conflict decades into the future.

Our results and the methods underlying them have important implications for policymakers. Since conflict prevention efforts often are costly, decisions about whether to implement them should be informed by a quantification of their long-term gains. Our study provides the means to obtain such quantifications. Since we find that previous studies have underestimated the magnitude of the conflict trap, the implication is that the international community should invest more than it currently does in identifying instances of escalating tensions (e.g. by developing better early-warning systems) and should seek to prevent the expansion of violence where the risk is high.

For low-income countries already in war, our results indicate that the international community should invest more heavily in peacekeeping capabilities. Even a limited containment of violence – often perceived as a peacekeeping failure given continued fighting – decreases the magnitude of subsequent conflict considerably. Such conflict reduction is feasible: Hegre, Hultman & Nygård (2011) show that de-escalating conflicts from major to minor status is something UN peacekeeping operations (PKOs) are especially good at. The strength of the conflict trap demonstrated here shows that such de-escalation of conflict must be the first decisive step countries take on the way out of conflict.

Replication data

The dataset and do-files for the empirical analysis in this article, along with the Online appendix, can be found at http://www.prio.org/jpr/datasets and https://havardhegre.net/replication-data/. All analyses were conducted using STATA v. 13 and R v. 3.3.1.

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