Barcelona School of Economics

WORKING PAPERS

Dynamic Early Warning and Action Model

BSE Working Paper 1355| June 2022

Hannes Mueller, Christopher Rauh, Alessandro Ruggieri

Dynamic Early Warning and Action Model*

Hannes Mueller
IAE (CSIC), BSE and CEPR

Christopher Rauh
University of Cambridge, CEPR

Alessandro Ruggieri
University of Nottingham

9 June 2022

Abstract

This document presents the outcome of two modules developed for the UK Foreign, Commonwealth Development Office (FCDO): 1) a forecast model which uses machine learning and text downloads to predict outbreaks and intensity of internal armed conflict. 2) A decision making module that embeds these forecasts into a model of preventing armed conflict damages.

The outcome is a quantitative benchmark which should provide a testing ground for internal FCDO debates on both strategic levels (i.e. the process of deciding on country priorities) and operational levels (i.e. identifying critical periods by the country experts).

Our method allows the FCDO to simulate policy interventions and changes in its strategic focus. We show, for example, that the FCDO should remain engaged in recently stabilized armed conflicts and re-think its development focus in countries with the highest risks. The total expected economic benefit of reinforced preventive efforts, as defined in this report, would bring monthly savings in expected costs of 26 billion USD with a monthly gain to the UK of 630 million USD.

Keywords: prevention; forecasting; internal armed conflict; dynamic optimisation.

*Mueller: hannes.mueller@bse.eu, Rauh: cr542@cam.ac.uk, Ruggieri: aruggierimail@gmail.com. We thank Manohar Gannavarapu, Luis Ignacio and Francesco Slataper for excellent research assistance. We also thank the team at the FCDO for their cooperation, with a special thanks to Peter Rowan and Tom Wilkinson Interviews with Elizabeth Drew, James Martin and Phoebe White had a profound impact on the focus of this report. All errors remain, unfortunately, ours. Hannes Mueller acknowledges financial support from the Spanish Ministry of Economy and Competitiveness, through the Severo Ochoa Programme for Centres of Excellence in RD (CEX2019-000915-S). This material has been funded by UK aid from the UK government trough a grant Agreement with the Fundació d'Economia Analítica (www.fea.cat); however the views expressed do not necessarily reflect the UK government's official policies.

1 Introduction

Armed conflicts pose significant challenges for the international community. Predicting conflict outbreaks and escalation, and assessing the best timing and nature of interventions is fundamental for policy makers to reduce death tolls and economic costs of armed violence. Policies to address armed conflict should thus be developed within a framework that integrates forecasts of future events into a dynamic model of optimal decision making. While such models are regular tools of the economics literature and have been applied to financial crises, debt burdens, pandemics and climate change, they haven't been used to study conflicts. This project fills this gap.

The contribution of this project is two-fold. First, we develop a forecast framework which is able to track the entire conflict cycle, from forecasting new outbreaks, escalation of conflict and de-escalation out of conflict to the re-emergence of conflict in post-conflict phases where countries are particularly fragile. We do this through a cutting-edge machine learning model which integrates a text-based forecast of conflict outbreaks with geo-spatial and temporal forecast of conflict dynamics during conflict. The estimated risks are made accessible through the webpage: `https://conflictforecast.org/`.

Second, we build a theoretical framework for optimal interventions which embeds the forecasting module and can be used as a laboratory to study costs and benefits of different intervention strategies and locations, from pre-conflict prevention, to de-escalation and post-conflict stabilization. We develop a theoretical model for optimal decision making and integrate this with a new forecast framework for the entire conflict cycle.

The key novelty is that our model exploits dynamic policy simulations based on forecasts which are derived from supervised and unsupervised machine learning and natural language processing (NLP) of millions of news articles. The final policy framework allows policy preferences to be reflected in monthly warning flags, country priority rankings, and cost simulations. This supports the GSRA priority area of Early Warning by providing predictive conflict forecasting, early warning flags, priority ranking and cost simulations which we fine-tuned in a testing-phase with FCDO staff.

1.1 Expected study impact

Our goal is to provide a testing ground for the introduction of quantitative benchmarks in FCDO decision-making. Two potential impacts are particularly important:

The forecasting module provides country experts with the ability to have an objective benchmark of conflict outbreak risk and intensity forecast at the national and sub-national level. This benchmark is comparable across time and between countries. This should allow experts to escalate within the hierarchy of the FCDO which, in turn, should be able to improve the organizational responses.

The decision making module provides a benchmark for strategic decisions as it allows the FCDO to reflect on its understanding of countries under a *development* or *conflict* aspect. Our interviews with FCDO staff and our quantitative analysis both point strongly to the need of focusing to specific situations without ongoing armed violence. We show that this could save considerable resources, even under mild assumptions on the effectiveness of preventive policies. The costing exercise we conduct also allows country experts inside the FCDO to bring this strategic understanding to the country level through the evolution of prevention gains over time.

1.2 Overview over project outputs

This project develops the following outputs.

1) A forecasting module: Cutting-edge machine learning model which integrates a text-based forecast of conflict outbreaks with geo-spatial and temporal forecast of conflict dynamics during conflict. This module provides:

- A forecast of the intensity of expected violence for those countries with a recent conflict history and a forecast of the geo-spatial distribution within these countries. This dimension will be added to the predictions of the webpage `conflictforecast.org` and can be explored interactively.
- A complete ranking of over 170 countries and 10,677 grid cells across the world according to the risk that they experience an outbreak of armed conflict.

The forecast module provides the raw material for the optimal intervention module in which interventions are analysed regarding how much resources they save in the future either by preventing an escalation, de-escalating or stabilising a country.

2) Optimal intervention module: A dynamic model which allows policy makers to trade-off the many dimensions of costs caused by conflict with the costs of intervention under uncertainty. This module delivers alternative scenarios in which persistent policy actions will be simulated within an infinite horizon with discounting. We assess optimal interventions along the conflict cycle under three scenarios regarding their effectiveness (pessimistic, neutral, optimistic). These scenarios have been worked out in cooperation with FCDO staff to make them as relevant and realistic as possible.

The final result is a monthly intervention list together with the expected gains from engaging in the indicated optimal interventions. These gains are displayed along dimensions most relevant to the FCDO, including economic output contraction, fatalities, displacement of refugees, cost of future ODA, and costs for UK exports.

1.3 Overview over the report

This report will first provide background information on the research and the preparatory interviews conducted with FCDO staff. We then discuss the data collected for the project and the forecast methodology.

Section 5 develops the core concept of the report - the idea of conflict *states* which we then use to link the forecasts to outcomes, model the idea of interventions as affecting the likelihood of escalation and simulate future paths with and without interventions.

Finally, in section 6 we discuss the optimal decision making module. We first discuss the fundamental trade-offs that determine the benefits of de-escalation and stabilization. We then briefly discuss the module and present results both at the strategic level and for the country expert view.

2 Study background

2.1 Academic research

Armed conflicts are characterized by what the literature calls the *conflict trap* or *war trap*.[1] These are repeated cycles of armed violence which have a large death-toll, lead to persistent outflows of refugees and prevent countries from developing economically. Dealing with armed conflict is therefore similar to other policy areas with escalating costs, like epidemics or financial contagion, in that policy decisions need to be taken repeatedly to prevent outbreaks and escalations. Decision making requires good data, reliable risk evaluations, and a conceptual framework that helps evaluate the options at hand.

War traps often drive the analysis in academic research and policy circles as most outbreaks and escalations of violence happen in a context of recent or ongoing armed conflicts. As a result, existing conflict forecast models are also caught in the conflict trap. It is possible to reach excellent forecast precision in the context of ongoing or recent conflict dynamics but hard to predict the location of new outbreaks of violence. Existing early warning models like ViEWS or the PREVIEW system have therefore shifted away from predicting outbreaks of violence altogether. Instead, they focus on predicting conflict incidence or escalations and de-escalations which can be predicted much more accurately with conflict history.

In our previous research we have show that, using supervised machine learning and natural language processing (NLP) based on millions of news articles, it is possible to predict the hard-to-predict conflict outbreaks.[2] Our method has been tested in a real out-of-sample competition with other research teams world-wide and in which we achieved the lowest and second-to-lowest mean square forecast error (i.e. some of the best results).[3] To provide forecasts based on our methodology and to provide a data platform for prevention efforts we have developed the webpage: conflictforecast.org. The webpage provides monthly forecasts for conflict outbreaks a year before they occur for over 170 countries – including those that do not have a recent conflict history. In past out-of-sample trials the deployed model reaches unprecedented precision in the forecast of rare conflict outbreaks.

[1]See Collier and Sambanis (2002) and Rohner and Thoenig (2021).
[2]See Mueller and Rauh (2018, 2022a).
[3]See Mueller and Rauh (2022b).

One key element of the decision-making module is the effectiveness of interventions. Existing work on costing prevention assumes extremely high levels of effectiveness. Chalmers (2007) assumes, for example, extremely high forecast ability and effectiveness leading to effectiveness of 60 percentage points being removed from the escalation likelihood. Estimates in other parts of the academic literature vary dramatically here and obviously depend on the intervention studied and the method used. Estimates reach from empirical results which suggest a negative impact of foreign aid on conflict intensity (Nunn and Qian (2014)) to evidence on substantial gains from local efforts and institutional changes (Blattman et al (2014)). A review conducted for DFID in 2016 concluded that the evidence base for prevention policy is weak (Cramer et al (2016)). Newer evidence on, for example, peacekeeping (Hegre et al (2019)) power-sharing (Mueller and Rohner (2018)) and education (Rohner and Saia (2020)) point towards strong reductions in conflict risk but more research is needed. We will therefore make the assumptions that interventions are relatively ineffective and fail with a likelihood of over 90 percent.

2.2 FCDO interviews

We conducted interviews and unstructured conversations with a number of FCDO experts over the course of six months between August 2021 and February 2022. The first goal of these interviews was to find out about preventive efforts in FCDO and how they are conducted in practice. But we also wanted to collect subjective perceptions and estimates on the costs of different FCDO efforts and their effectiveness.

2.2.1 Takeaways for our team

The interviews were a big success. They led to a complete re-think of our project on two important dimensions. The first main take-away for our team was that the monetary costs of prevention might not be huge as the influence of the UK government depended much more on the preexisting relationship and leverage over conflict parties. That said, we also learned of a rich policy environment in which financial resources could make a difference through the of funding local initiatives of community engagement, helping address economic exclusion or supporting ongoing negotiations. The policy proposals were diverse but clearly indicated that most staff believe in possible gains from funding a bottom-up, as well as a top-down approach in which engagement with local grass-roots actors provides feedback for the more standard top-down approach. We have taken this on-board by avoiding any assumptions on intervention costs, and instead focusing on one-off gains from intervention without a full dynamic optimization that would require intervention cost estimates.

The second main takeaway for us was that there would be no way of knowing effectiveness through interviews. There is very little consistent gathering of data on this issue and opinions diverged dramatically depending on the personal experience and country focus. We will, therefore, take an agnostic approach in this area as well by assuming that initiatives succeed with a likelihood of 2, 5 or 10 percent. We will call this our pessimistic, neutral and optimistic scenarios. We think that these are conservative assumptions in light of the academic literature but it should be kept in mind that some interventions could escalate conflict.

2.2.2 Takeaways for the FCDO

However, the interviews also revealed some areas in which our report could be useful for strategy debates inside the FCDO. It appeared that a conflict perspective was sometimes hard to maintain without a violent, ongoing conflict. We also observed that significant resource was devoted to countries with ongoing, high-intensity conflicts such as Afghanistan, Ethiopia and Nigeria. Our conversations with staff and material requested for us to provide all reinforced this impression. During the duration of our project the Ukraine crisis started and it was clear that FCDO staff was re-directed towards this issue. This is understandable given the importance of high-intensity conflict, but it is also representative of the shifts in attention that we observed. The end of violence will often mean an immediate shift of attention away from a situation. We show that this might be inefficient, i.e. these shifts come at a monetary and human cost.

This is linked to a second issue which is that the shift in and out of a "development" focus compared to a "conflict" focus is not easy to coordinate without some objective criterion. Often, a country expert will receive news about the danger of an escalation but it is not clear whether there should be a response at the organizational level. Our forecasts provide a real opportunity here as they are an objective measure of tracking developments at the country level. In addition, a framework such as the one we present can provide an estimate of the economic gains from reinforced efforts in de-escalation/stabilization. This can be held against what the UK hopes to achieve with ODA as we will show in the final section.

Finally, our emphasis on the conflict trap as a critical determinant of policy success resonates strongly with country experts. One expert stressed the fact that a key element for peace seems to be the faith, social fabric and cultural constraints for violence. The flip-side of this are legacies and trauma of past violence that still lingers in local communities in many countries that suffered civil conflict. We put this sort of non-reversibility at the heart of our model approach and are therefore able to provide quantitative estimates of the costs and the benefit of prevention. Moreover, we are also able to show that there are indeed important trade-offs the FCDO faces when conducting preventive effort which might be driving the organisation away from it.

3 Data sources

The key data-set for our effort comes from the Uppsala Conflict Data Program (UCDP) Georeferenced Event Dataset (GED). For descriptions of this data see Pettersson et al (2021) and Sundberg and Melander (2013). We define armed conflict based on this data and the World Bank's population data. Armed conflict is defined by a country suffering more than 5 fatalities per 1 million population. We maintain this definition throughout the country-level analysis and will describe a situation with lower intensity as not in armed conflict.

The second main data source for our project is the webpage `https://conflictforecast.org/`. It provides us with a set of conflict risk estimates and escalation likelihoods which we discuss in detail below. We also rely on the news topics that we use for the estimation of conflict risk in the analysis of the gender index described below. These are automatically generated news summaries which summarize news reporting in each country/month across 15 dimensions. We give names to these news topics like "religious tensions" or "armed conflict". The topics and their share for every country can be explored on the webpage.

We have gathered data on the UK's Statistics on International Development by DAC code from the FCDO, World ODA and UK aggregate ODA from the OECD, data on population and GDP in 2015 constant USD from the World Bank. Considerable effort went into coding all peacekeeping missions since the 1990s, their starting point, troop size and budget from UN reports.

Finally, we produced a *gender index* by searching our entire database of over 6 million news articles for gendered words like *woman, man, boy, girl....* This led to a data set of a monthly "maleness" of country news coverage. This maleness is positively correlated with several of news our topics "religious tensions", "politics", "foreign policy", "armed conflict" and "power and negotiation" and negatively correlated with the topics "civilian life", "health and emergencies" and "sports". We have not, however, managed to improve the conflict risk forecast through the gender index. We find that the gender index does not change in a robust way to the onset of conflict, either.

3.1 Regional data collection

We updated the news text corpus as part of the project. The base corpus on which we draw predictions relies on different API queries that filter newspaper articles based on country and capital names. In order to compliment the existing corpus, we created a whole new set of sub-national queries that span the first level administrative divisions of all the countries. In order to achieve this, we firstly consider the Wikipedia's list of administrative divisions. This leads to about 4,000 new administrative divisions from which we obtained a coverage of more than 200,000 articles. Some of the countries with highest coverage are China, Iran, Russia, India or Afghanistan.

4 Forecast module

The basis for this report comes from the webpage `https://conflictforecast.org/`. Specifically we rely on two forecasts: 1) a model that forecasts armed conflict outbreaks twelve months ahead of time and 2) a model that predicts the (log of the) average number of fatalities within the next twelve months. In both cases we use the "best" model. This model uses features that capture conflict dynamics, such past violence levels and the time that has passed since the last conflict episode, and combines them with 15 news topics which we generate from over 6 million news articles using a topic model. The methodology is described in detail in Mueller and Rauh (2022 a,b).

In what follows we show data for the period January 2010 to February 2022. Performance is always measured through rolling forecasts in which the information set of, say August 2012, is taken as given and the model forecasts the period after August 2012. That is, we are careful not to use future information when predicting the future. We then use the actually observed outbreaks of violence to measure our forecasting performance. In this way we are able to give realistic performance measures.[4]

One reasonable performance measure for highly unbalanced classes like conflict outbreaks

[4] We have started to analyse forecasts that were made public on the webpage starting a year ago and this exercise suggests that performance is indeed similar to what we measure within-sample. In the 3 months ahead best model for armed conflict outbreaks, for example, the mean area under the curve of the receiver operating characteristics curve (ROC-AUC) is 0.91.

is precision. We therefore focus on presenting precision/recall curves for armed conflict onset. Figure 1 shows the performance for all outbreaks of violence, i.e. those that follow directly after previous conflicts and those that occur in previously peaceful countries. Performance here is relatively good. The precision is around 80 percent for 50 percent recall. This means that if the model suggests that a conflict will break out within the next 12 months it really does so with a likelihood of 80 percent. A recall of 50 percent means that the model is able to spot about half of all outbreaks. However, this really good performance is driven by the conflict trap. It is relatively easy to predict that conflict will break out in places that just suffered from conflict. Many countries enjoy brief stints free from violence before going back to armed conflict. Our best model picks this up and produces a high precision for a high recall.

Figure 1: Precision/Recall Curve for all Outbreaks

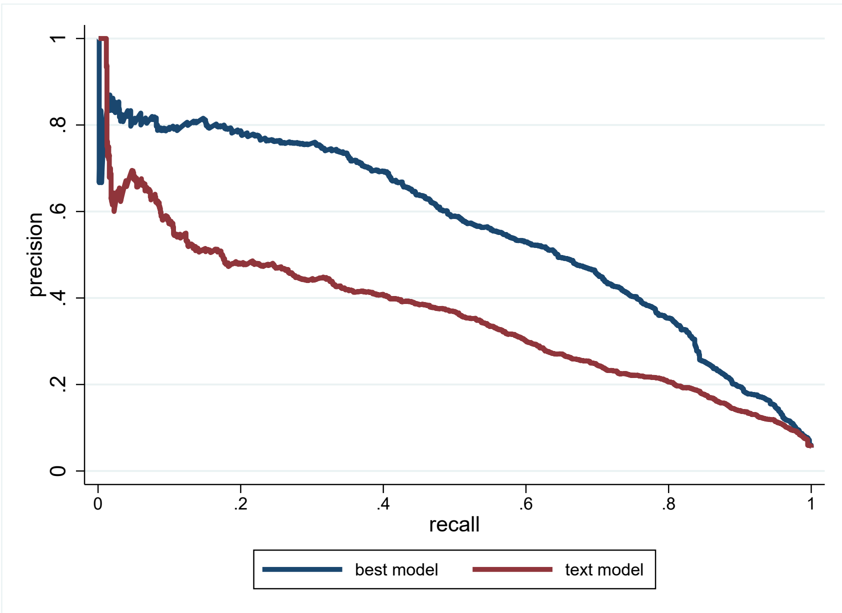
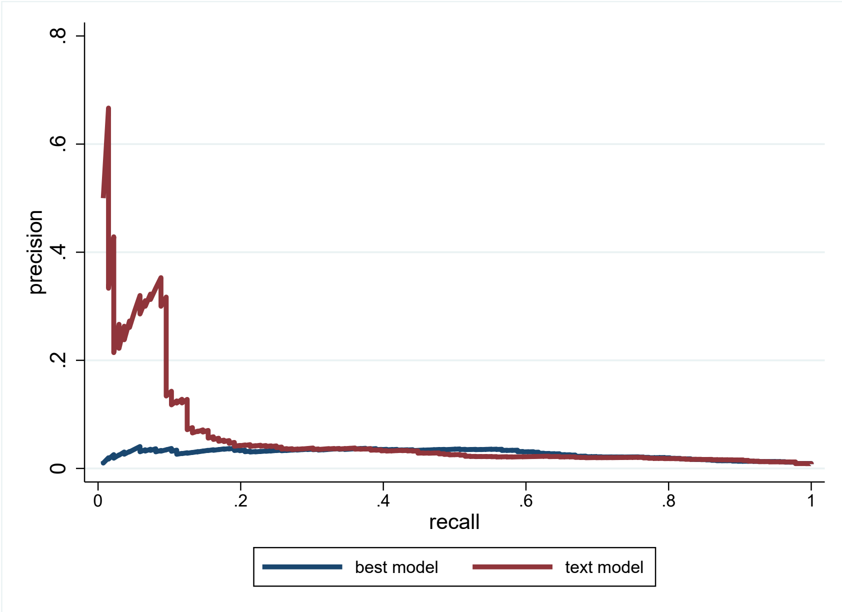


Figure 2 shows how precision changes outside the conflict trap. Here we look only at onsets which occur after at least 5 years of peace. These are outbreaks in countries which have been in peace for a relatively long time and can therefore be placed outside the conflict trap. Performance falters with precision being closer to 20 or even just 10 percent for reasonable values of recall.

The mean square error of the best intensity model is 0.0001419. It is much harder to

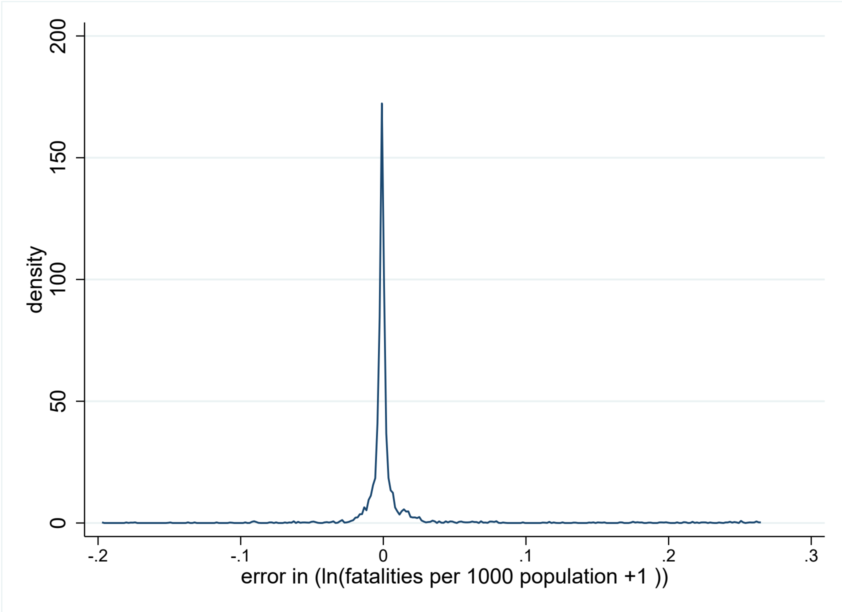
Figure 2: Precision/Recall Curve for Outbreaks After 5 Years of Peace



give an intuitive understanding for how good this is. Figure shows the distribution of simple errors where a positive number indicates that the actual number of fatalities was higher than the prediction, whereas negative numbers indicate an overestimate. There is a very strong concentration of errors close to 0. This is a constant over-prediction of violence for country/months with no violence. Then there is a little bump to the right. These are escalations that were not foreseen by the model. Finally, we see very large errors, both positive and negative, where the time-series of fatalities broke within the forecast window. It is these kind of breaks that we try to forecast with the onset models.

The intensity model is less good in picking up breaks in the time-series but understands trending escalations and de-escalations extremely well. First, see the example the times series of violence for Ethiopia with the forecast from the same month in Figure 4. The model shows some anticipatory peaks before the most recent escalation. This lies in the nature of these sudden escalations that, unless the model is trained specifically for sudden outbursts, it will have a hard time picking these up. The problem is common to all models that are specialized in forecasting incidence or intensity. However, the model does allow the country expert to understand how the model evaluates the escalation in terms of future outlook (red dashed line shoots up) and also allows for tracking stabilization.

Figure 3: Error in the Prediction of Intensity



Our model also shows its strength in the Colombian case shown in Figure 5 where escalations in the period 2010-2014 are picked up before they occur. Partly, this is due to the model being able to "interpret" conflict dynamics, but it also comes from the text features. We have added additional Figures B42, B43 and B44 for Ethiopia, Egypt and Pakistan to the Appendix. The case of Pakistan is worth highlighting as it shows a significant stabilisation over time. All data can also be seen on the web page `https://conflictforecast.org/`. The intensity forecasts can be reached by clicking on a country or searching in the search bar and then choosing the "violence intensity" and "12 months ahead" options from the menu on the right.

4.1 Grid cell level predictions

Conflict is not only concentrated in certain countries, but also in certain regions within countries. We, therefore, build a model in order to predict conflict at the grid cell level, i.e. a world map segmented into almost 65,000 cells with a size of $55km \times 55km$.

As a first step, we need to adapt our national news coverage to the regional level. In order to do so, we write an algorithm to detect locations in news articles based on words appearing close to prepositions of locations. We then retrieve the geographic coordinates of

Figure 4: Nigeria: Intensity Forecast

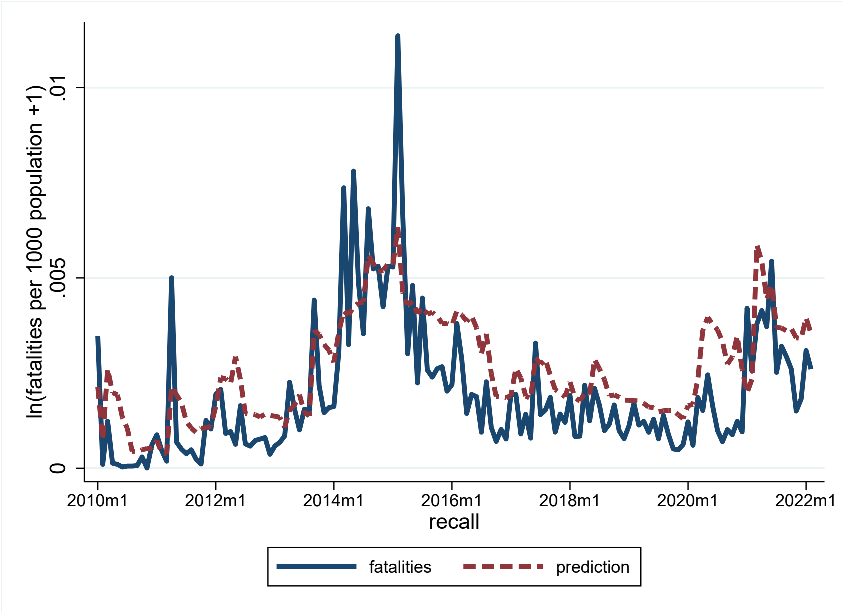
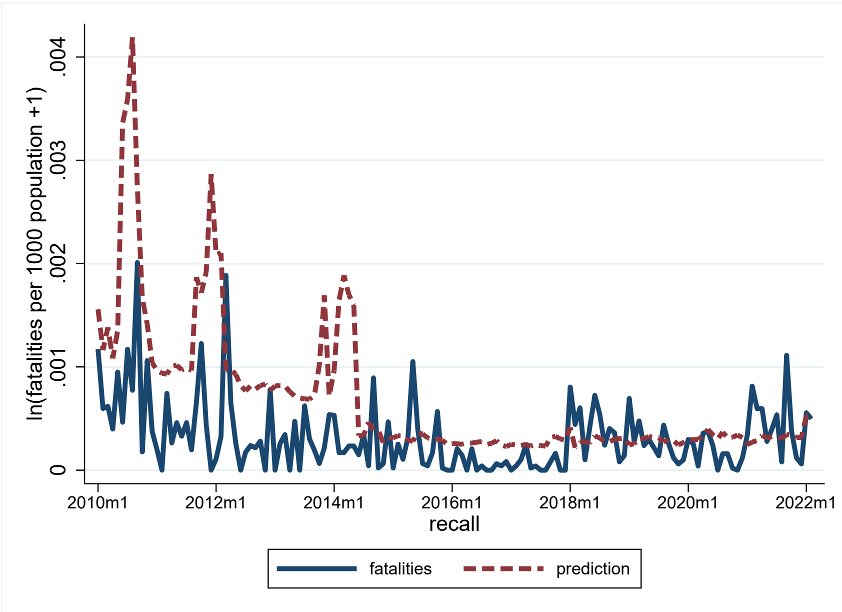


Figure 5: Colombia: Intensity Forecast

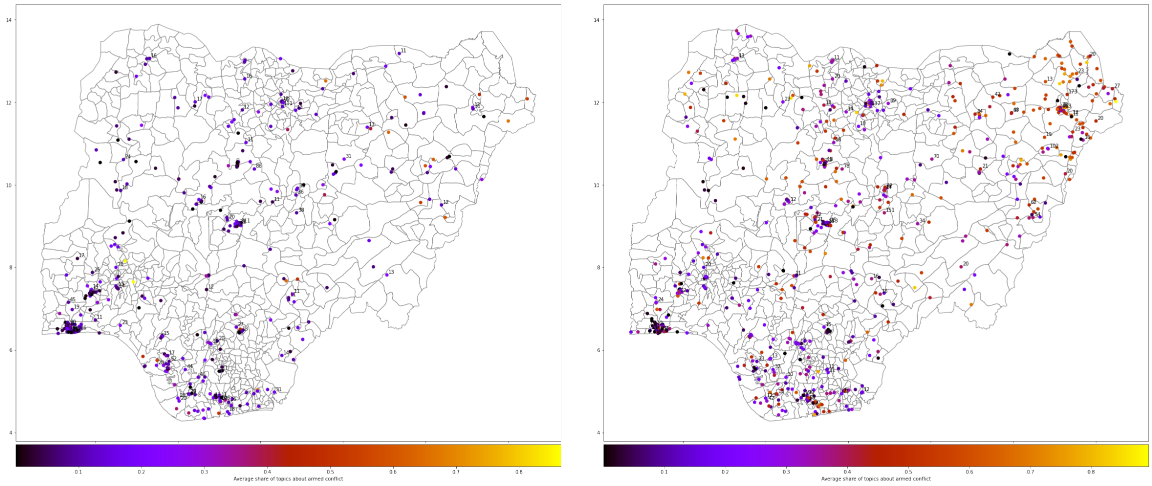


said locations so that we can assign them to the grid cells. Equipped with the geographical information contained in each article, we compute the average news coverage for each grid cell as a convex combination of national news and grid cell specific news. The more frequently a location is mentioned, the less weight national news receive.

In Figure 6 we show an example of local reporting for Nigeria, where each dot is a detected location in an article and panel A and B are from two time periods. The coloring of the dots represent the intensity of reporting about conflict, with a yellow shade indicating more conflict reporting. In panel B, it is clear that much more reporting about conflict has been taking place in the Northeastern region of Borno.

Figure 6: Locations mentioned in newspaper articles and their conflict topic share in two different time periods in Nigeria

Panel A: Nigeria 1985-2009 Panel B: Nigeria 2010-today



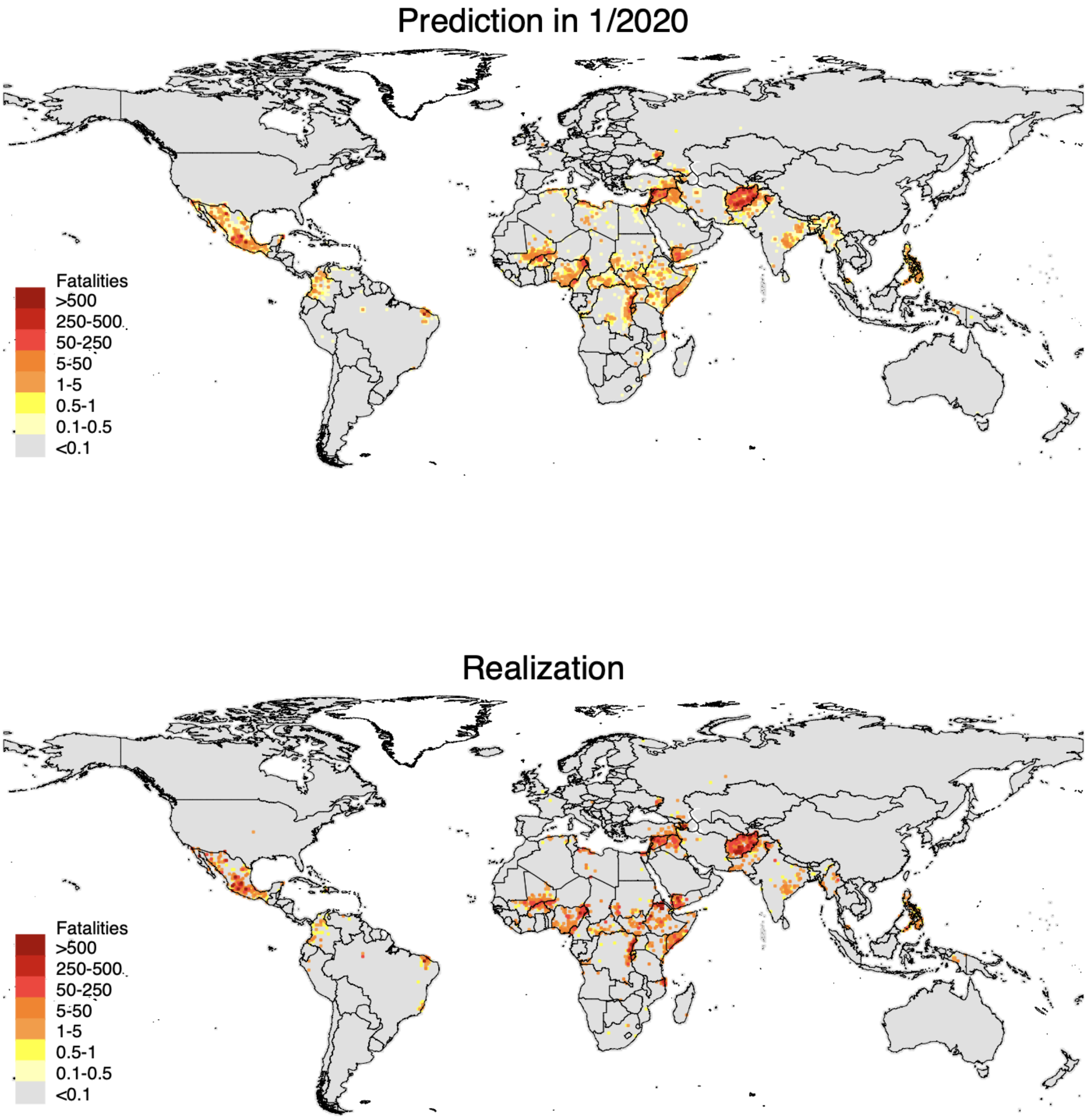
Notes: Each dot represents a location mentioned in an article. A yellow share indicates high conflict reporting.

The rest of the prediction model setup at the grid cell is similar to the country level model with a random forest serving as the prediction algorithm. One additional aspect is that we leverage much more geographic variation of conflict taking place in neighboring cells in order to capture potential spillovers. Moreover, we include some geographic characteristics highlighted by the literature such as distance to the capital, prevalence of diamonds, and mountainous terrain. As outcomes, we predict conflict incidence and outbreak in terms of at least one battle death, and intensity in terms of log(fatalities+1). For each of these outcomes, we predict with a twelve month horizon and in the evaluation sample only look at December, i.e. the prediction for the following calendar year, in order to avoid double counting.

4.1.1 Results when predicting an outbreak at the grid cell level

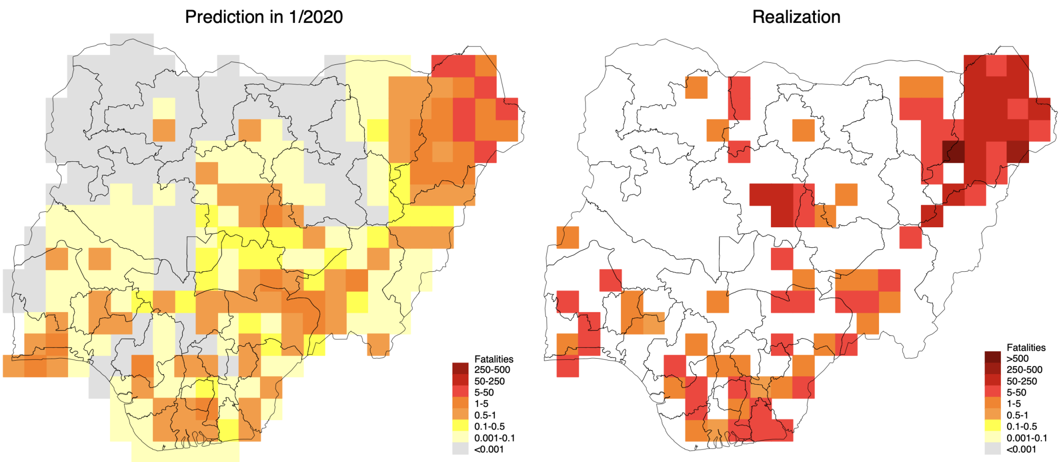
In Figure 7 we present out-of-sample predictions (left) and realizations (right) of battle deaths for the next twelve months following January 2020 across the globe, with darker shades of red indicating the highest intensity levels. In Figure 8, we show the same predictions and realizations for Nigeria.

Figure 7: World map of intensity prediction (top) and realization (bottom)



Overall the results are extremely promising. In Figure 9 we evaluating the results across out-of-sample predictions of outbreaks of violence from 2016 to 2022. The left panel shows

Figure 8: Nigerian map of intensity prediction (left) and realization (right)

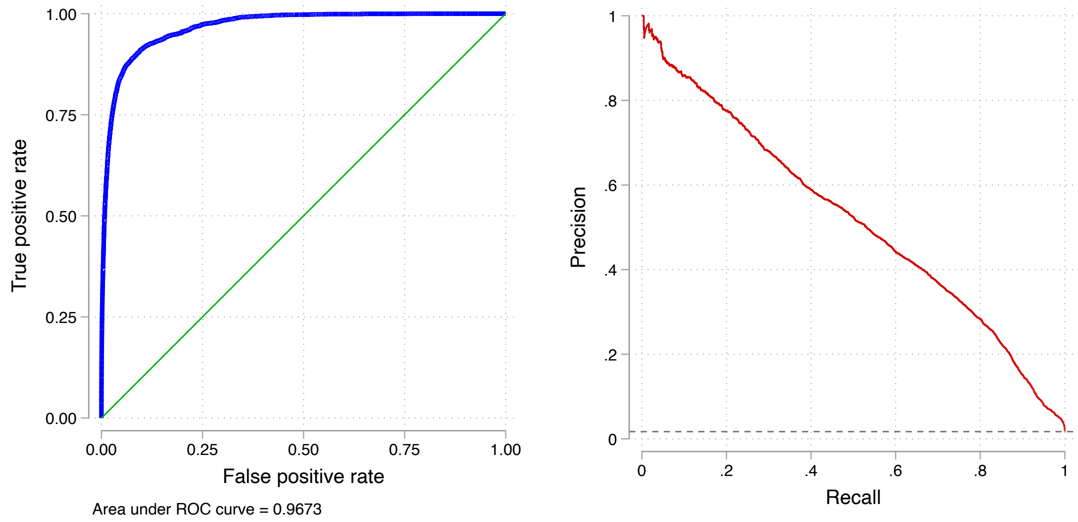


the receiver operating curve (ROC) plotting the false positive rate on the x-axis and the true positive rate on the y-axis. The 45 degree indicates the performance of a random predictor. One summary measure of prediction performance for binary outcomes is the area under the curve (AUC), which is 0.97 in our case. The right panel displays the precision/recall curve for the onset of any violence. The high predictive performance is validated, with, for instance, a precision of 0.5 at a true positive rate of 0.5. This means that when ranking all of our predictions, we correctly identify 1,750 outbreaks when ringing the alarm bell 3,500 times.

In Figure 10 we bin predicted probabilities and then plot the realized probabilities and their 95% confidence interval on the y-axis. We, further, split the sample into cells that have only had one month of peace (left), 2-12 months of peace (middle), or at least a year without a battle death (right). We see that for all three of these samples the realized probabilities are very close to the 45 degree line, i.e. the predicted probabilities.

In Figure 11 we look deeper into the specifics of grid cell level predictions and investigate whether the model performance varies when slicing the sample depending on how many neighboring cells are in conflict. We plot the closest cell in conflict on the x-axis and the performance in terms of ROC AUC on the y-axis for the corresponding sample. We see that moving away from conflict in a geographic sense improves the predictive power in terms

Figure 9: ROC and precision/recall at grid cell level



of the AUC. If the closest cell in conflict is at least 5 cells away, the AUC is above 0.90. However, even for close by conflicts the AUC always is above 0.80. Remember that here we are comparing amongst very dangerous cells, given that they have a neighbor in conflict.

We have included the forecast of outbreaks at the cell level on our webpage `https://conflictforecast.org/` under the option "subnational view".

Figure 10: Predictions versus realizations depending on time since last conflict

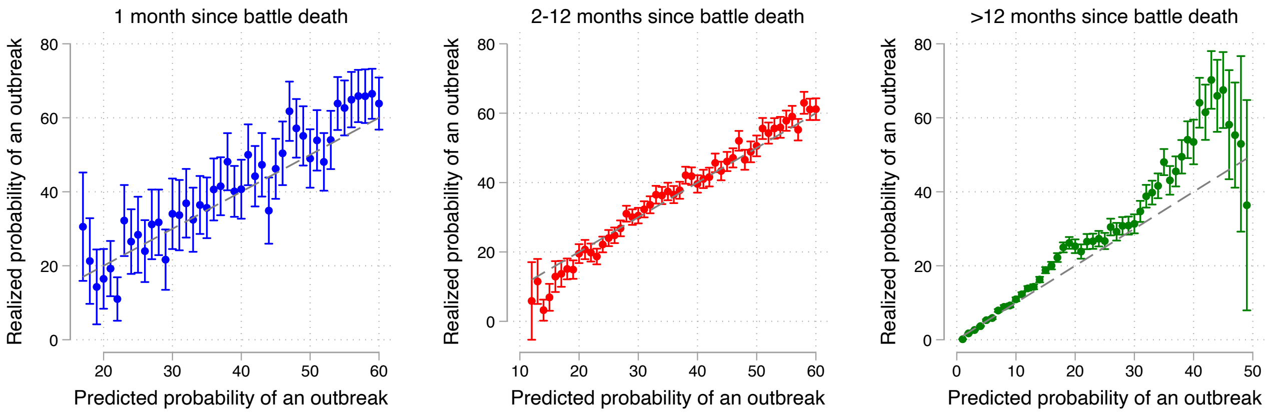
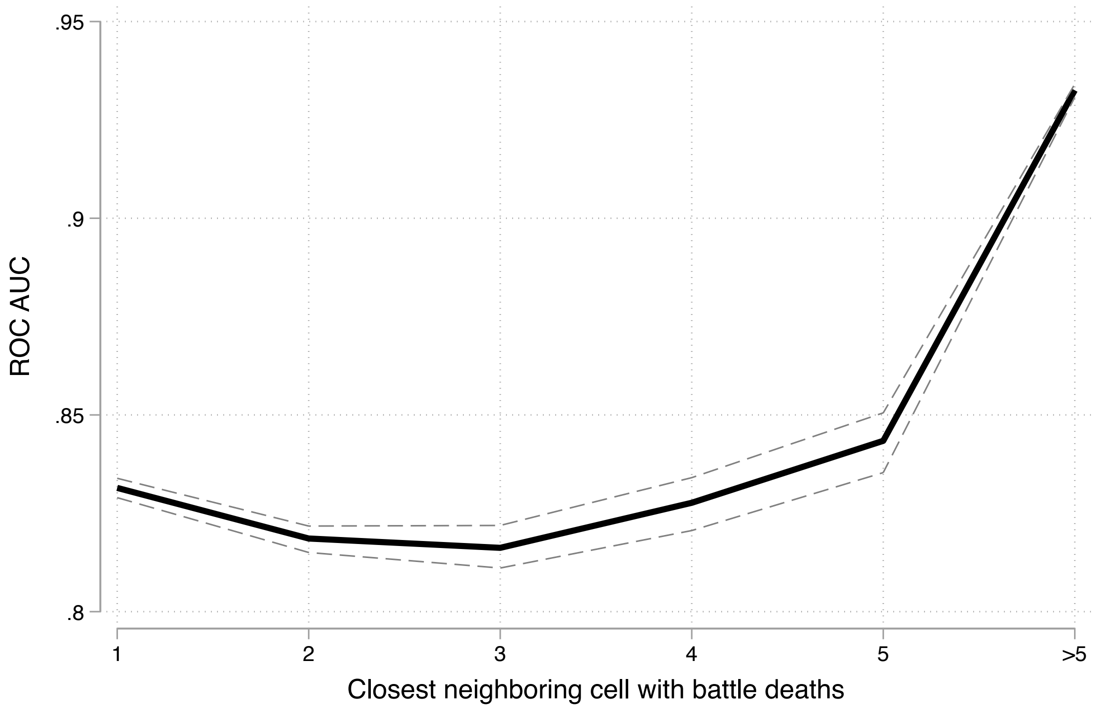


Figure 11: ROC AUC depending on closest grid cell currently in conflict

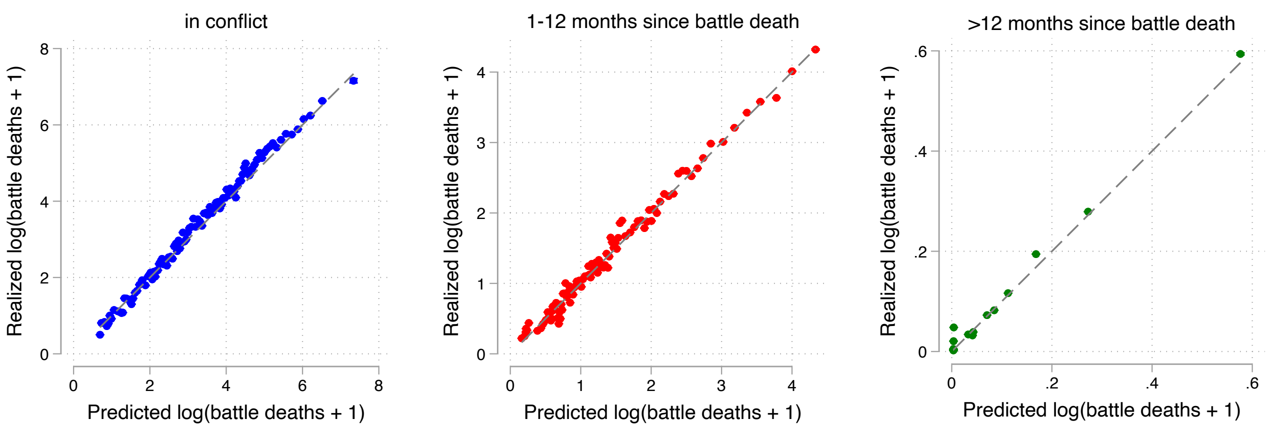


4.1.2 Results when predicting intensity at the grid cell level

Next we turn the evaluation of the forecasting performance in terms of intensity. We find that the correlation between predicted and realized log(fatalities+1) is 0.70 across all predictions, and 0.58 when looking at only cases with at least one battle death.

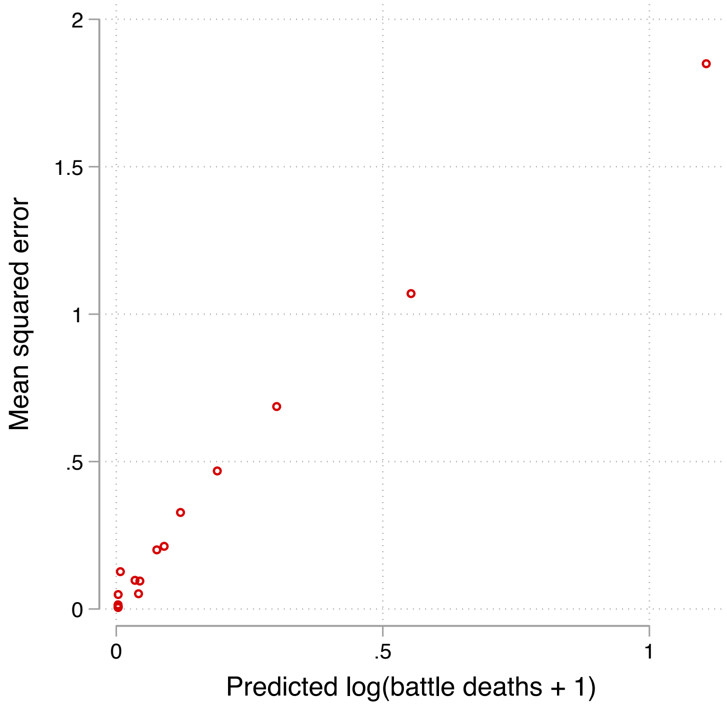
In Figure 12 we plot the relationship between predicted intensity on the x-axis and realizations on the y-axis for log(fatalities+1) on the left and for the absolute number of battle deaths on the right. Each dot is the mean within a percentile, and the 95% confidence interval is so small that it is hardly visible. We see a strong positive relationship between predictions and realizations. Moreover, we see that this predictive performance holds no matter whether we split the sample into cells that have only had one month of peace (left), 2-12 months of peace (middle), or at least a year without a battle death (right). For all three of these samples the realized intensities are very close to the 45 degree line, i.e. the predicted intensities.

Figure 12: Predictions versus realizations depending on time since last conflict



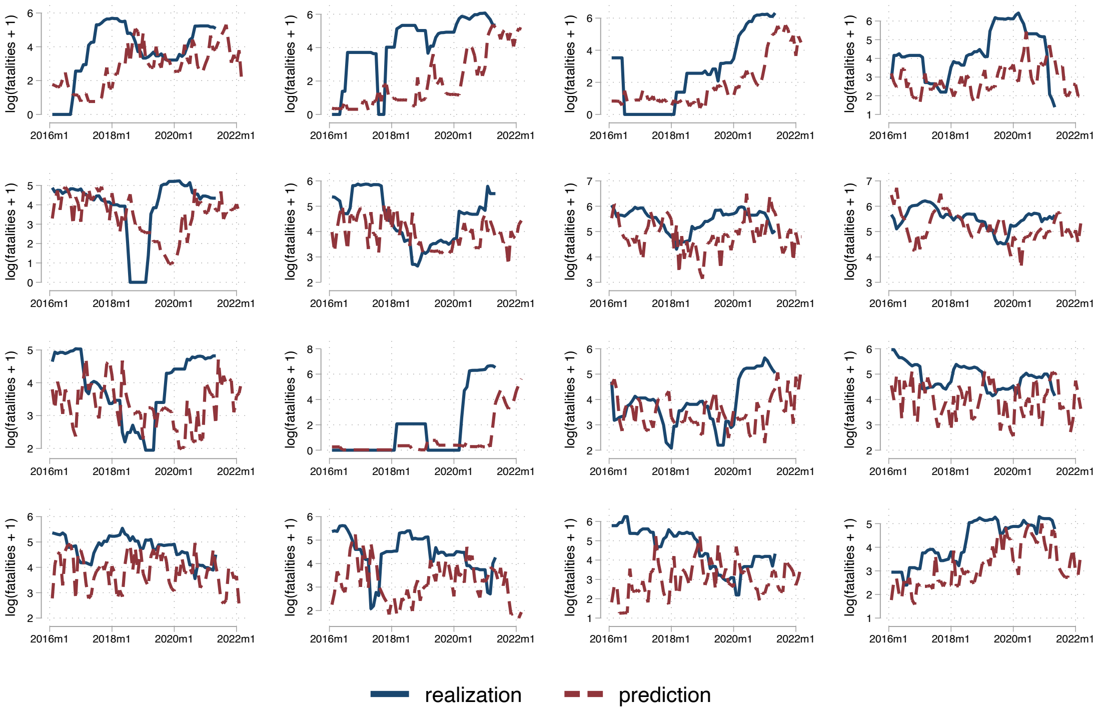
The overall mean squared error is 0.038 and Figure 13 shows how it increases with the magnitude of the prediction. Each dot represents the mean squared error within a percentile of predictions. The relationship is nearly linear showing how much harder it is to predict the intensity when battle deaths are high.

Figure 13: Relation between size of prediction and mean squared error



In Figure 14 we see realizations and predictions in terms of log(fatalities + 1) for the 16 cells with the most total fatalities in Nigeria. We see that the cells present very different profiles but that the model tends to do a good job at generating the observed patterns. While sudden large spikes are hard to foresee, cycles of violence and the corresponding intensities are predicted with high accuracy.

Figure 14: Realizations and predictions of intensity for the 16 most deadliest cells in Nigeria



5 The conflict states

5.1 Introduction

We link the forecast module of the previous section to the optimal decisions model through what we call conflict *states*. These states should be thought of as warning flags which have been raised. The higher the state, the worse is the future outlook. Overall, our model has 13 states:

- 5 states pre-conflict (outbreak risk model) to capture early prevention opportunities
- 3 states post-conflict (outbreak risk model) to capture late prevention opportunities
- 5 states in conflict (intensity model) to evaluate stabilization opportunities

We use two forecast models to construct these states. For months without ongoing armed conflict (more than 5 fatalities per 1 million inhabitants) we use an outbreak risk model. We take the forecast model of armed conflict, 12 months ahead and split the data into observations with and without a recent history of armed conflict. For observations without a recent history we split the data into 5 groups. This will include many observations from stable, democratic, developed countries. However, it is possible that some of these countries suffer escalations like those observed in Chile, Spain or Russia.

Observations with a recent history of armed conflict but without ongoing conflict are split into 3 groups. These observations should be thought of sitting inside the conflict trap but at various degrees of stabilization. Here we have countries like Egypt, Pakistan or Indonesia.

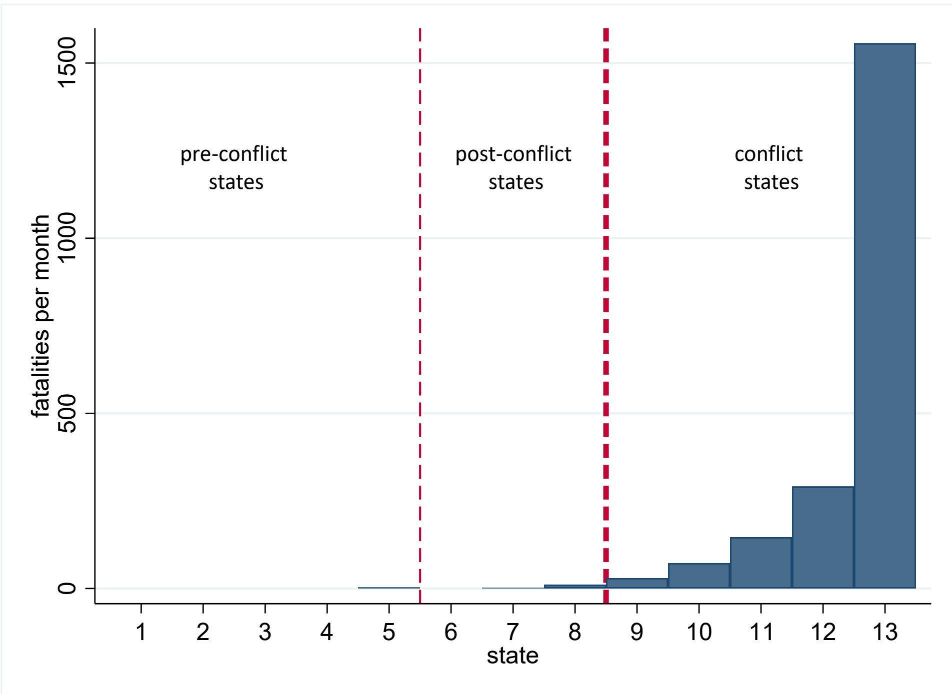
For months with ongoing armed conflict we use the intensity forecasts to define states. We use this to split the data in 5 groups with increasing intensity forecast. Keep in mind that intensity of the ongoing conflict and the forecast are strongly correlated so that these 5 states will often capture conflict of different intensities.

5.2 A characterization of conflict states

In the decision making module we will link each of the states with data on fatalities, population, GDP, total ODA, UK ODA, refugees and UK exports in a model framework. Each state can be linked to these dimensions of costs through a simple averaging of the costs or other statistical methods.

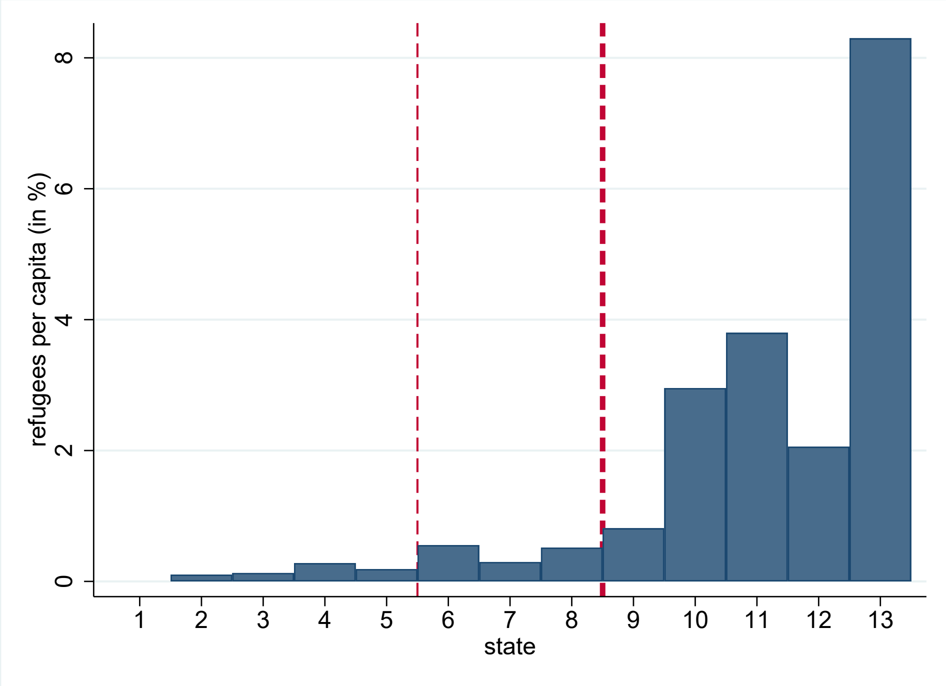
As an example see Figure 15 which shows the average number of fatalities in our 13 states. We have marked the three phases of conflict through vertical dashed lines. To the left are states 1 to 5, the pre-conflict states. Next come the post-conflict states 6 to 8. These states are peaceful but in countries with a recent history of armed conflict. To the right are the conflict states 9 to 13.

Figure 15: Average Number of Fatalities in the 13 States



The fatalities associated with each state are shown as blue bars. Remember that we define armed conflict through relatively high levels of violence so that there is some violence in pre-conflict and post-conflict states. But it is clear from this Figure that it is the last states which are responsible for a disproportional level of fatalities. On average, every time a country spends a month in state 13, 1,500 persons lose their life. Every time a country

Figure 16: Average Number of Refugees per Capita in the 13 States



spends a month in state 12 it suffers 250 fatalities. In our model we will always take a per capita view, i.e. we divide fatalities by the respective population. The resulting figure is shown in the Appendix.

Figure 16 shows the number of refugees as a share of population for the different states. Again, we see a clear distinction between the conflict states and all other states. This is because refugees tend to quickly return to their home country once intense violence recedes. In the Appendix we explain how we cost refugees.

Just to understand the world response to these risks we also show the cost of peacekeeping and World ODA and UK ODA in Figures 17 and 18. ODA is almost linearly increasing with risk. One factor behind this pattern is that ODA goes to poorer countries and poorer countries also tend to be more fragile so that this association is partly spurious. We will account for this through country fixed effects regression in our costing exercise (discussed in the appendix). However, there is a striking pattern which is particularly visible in the UK ODA which suggests a particular focus on states 5 and 8. We will return to this important fact as it could suggest that policy already targets these key states because of their conflict risk. We will argue that spending categories do not clearly indicate that de-escalation or institutional robustness are key goals of UK ODA in state 5.

Figure 17: World ODA in the 13 States

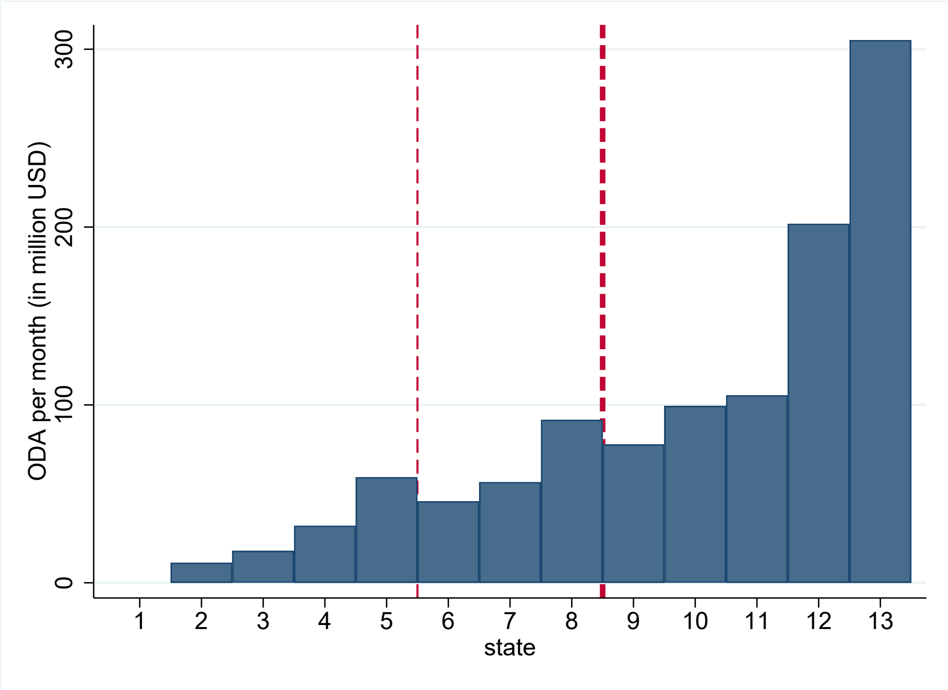
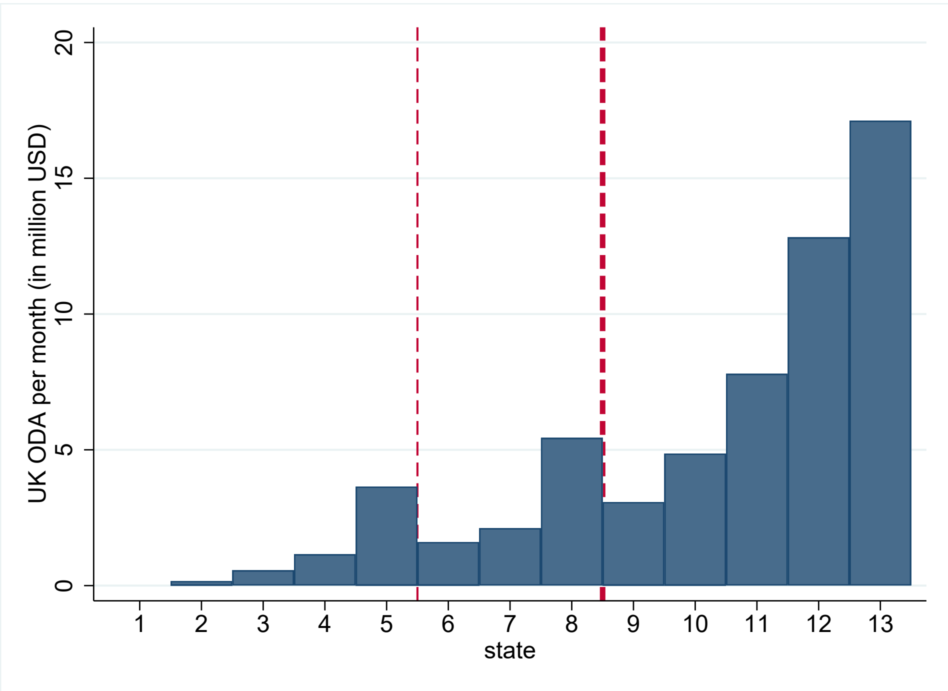
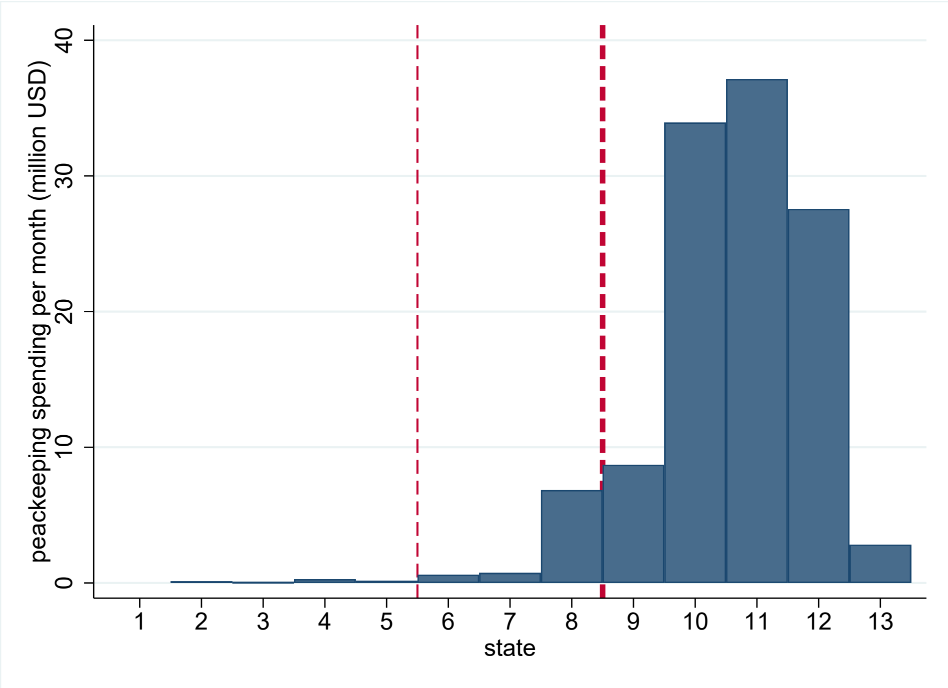


Figure 18: UK ODA in the 13 States



Peacekeeping spending patterns are shown in Figure 19. We know that peacekeeping is directly related to conflict and it is interesting to note that efforts concentrate in what we call the conflict states, i.e. peacekeeping is actually implemented in situations with an ongoing armed conflict. We also see some engagement in state 8 which is very indicative of the special role of this state in the perception of the international community.

Figure 19: Peacekeeping Spending in the 13 States



We use the conflict states to simulate costs along 5 different monetary cost dimensions:

- Lost GDP due to falling growth during armed conflict
- Loss of life due to conflict
- Refugees that live outside their country
- ODA spending (World and UK) required during conflict and after conflict
- Loss in UK exports

Details underpinning this cost estimate are discussed in the appendix. We translate the loss of life and refugees into monetary values and summing them to the loss in GDP and

ODA spending. Our estimate of the total cost are therefore costs both to the international community and the affected population. By far the most important component in terms of monetary cost is the loss in GDP as we do no assume that losses in the GDP stock are recovered which implies that costs accumulate over time.

But it is also possible to focus on non-monetary values like lives lost or the number of refugees by translating these numbers back from their monetary equivalents.

5.3 A simple way of capturing the complex dynamics of conflict

The key ingredient for our model is a tool which is called a *Markov chain* model. This is a simple model to capture complex dynamics. The idea of the model is to link states to each other over time by calculating the probability that one state leads to another. We apply this on a month-to-month basis to study how states are linked to each other.

The probabilities of moving from one state to another are combined into what is called a *transition matrix*, where the rows identify each of the possible states today, the columns describe each of the state tomorrow, and the entries are the probability of moving from a given state today to a given state tomorrow. In the Appendix we describe the entire transition matrix used in the current analysis.

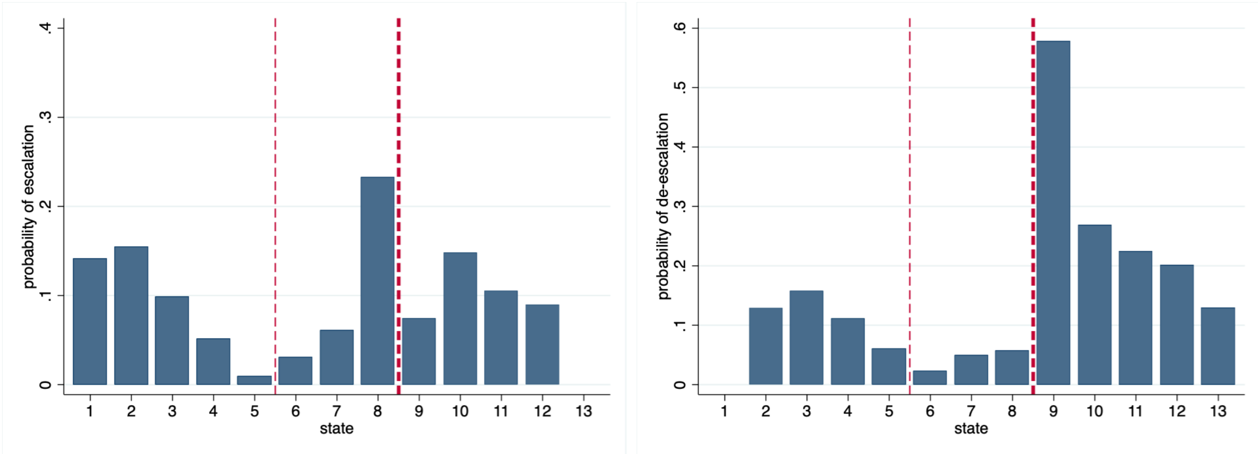
Here we discuss two main features embedded in the transition matrix, the probability of escalation and the probability of de-escalation. In panel (a) of Figure 20 we report the probability of escalation, which is the probability of moving to riskier states in the future conditional on the current state, which are displayed in the x-axis. By construction, this probability is zero in state 13, which is assumed to be the riskiest state. In panel (b) of Figure 20 we report the probability of de-escalation, which is the probability of moving to less risky states in the future, conditional on the current state. By construction, this probability is zero in state 1, which is assumed to be the less risky state.

In the next section we will model policy as changing these likelihoods. We will assume that in states 1 to 8 the policy maker de-escalates, i.e. she lowers the likelihoods of escalation shown in panel a) of Figure 6. In states 9 to 13 the policy instead is assumed to stabilize, i.e. it increases the likelihood in panel b) of Figure 6.

Despite not being a conflict state, state 8 has the highest probability of escalation: coun-

Figure 20: Transition probabilities

(a) Probabilities of escalation (b) Probabilities of de-escalation



tries in state 8 have more than 20% chance of moving to states riskier than 8 in the next month on average. This makes state 8 a pivotal point as we will see later. State 5 offers a very low likelihood of escalation as escalations in this state are only possible towards states 9 to 13.

We will see that state 5 produces over-proportional benefits from de-escalation despite featuring a very low likelihood of escalation. The presence of the conflict trap in states 6 to 13 produces a mild non-reversibility at state 5. To see this, note that states 9 to 13 are much more likely to de-escalate than to escalate whereas states 6 to 8 are more likely to escalate than to de-escalate. This is what generates the conflict trap in which countries transition back and forth between conflict and post-conflict.[5]

[5]Indeed the second eigenvalue of the Markov Chain is very close to 1 which indicates that convergence to the limiting distribution is only reached slowly - an indicator for more than one point of attraction hindering convergence. We thank Tom Wilkinson for pointing this out to us.

6 Decision making module

In this section we provide the optimal decision-making model. The idea of the model is simulate a reduction in escalation likelihood for a country and compare the resulting simulated future for this country with a status quo future. To simulate possible futures we use the conflict state model and the transition matrix introduced in the previous section. These states have been linked to different outcomes and we now use this to simulate how conflict costs evolve in the long run both with and without an intervention. The difference is the gain from intervention. The resulting framework has two use cases:

- In the strategic view it allows the FCDO to understand where most dynamic gains from interventions can be expected. We contrast this with where the UK ODA resources are currently flowing.
- In the country monitoring view we provide country experts with a measure of the gains from prevention efforts over time since 2010. This can help flag situations where, for example, the lack of violence could tempt a withdrawal of resources.

It is important to stress that this is the first time such a model is developed for a policy intervention. The resulting framework should therefore be regarded as a proof-of-concept more than a fine-tuned tool. We will discuss the missing elements for a fully developed model in the conclusion section.

6.1 The fundamental trade-off in preventive action

Before we introduce the optimal decision model it helps to think about the fundamental trade-off faced by prevention policy between forecast uncertainty and conflict dynamics. This will determine which kind of intervention is optimal.

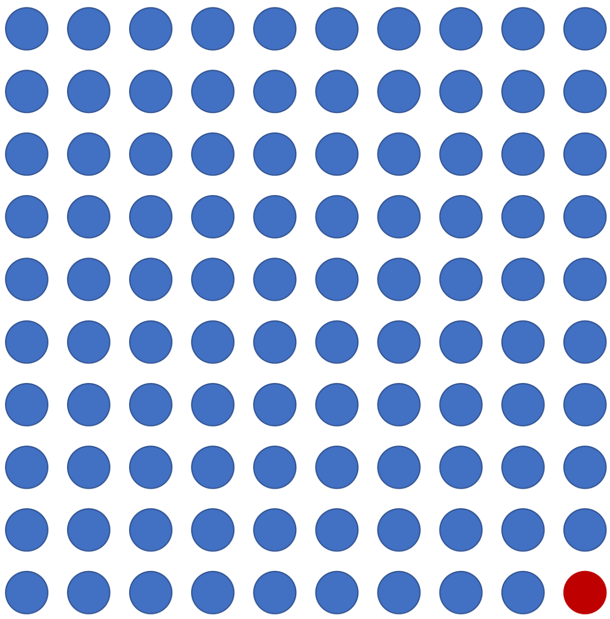
6.1.1 Forecast uncertainty

A fundamental problem of prevention policies is that they are directed towards an unknown future. This means that a policy is applied to a situation without being sure whether the application is even relevant in the context. We are used to these kind of interventions in the medical realm but it is much harder to direct development policy or foreign policy towards a conflict that has not broken out and might never break out.

In forecasting terms the crucial value to think about in these circumstances is precision.[6] Precision is the likelihood that a forecast has identified an escalation into conflict that will not stop without an intervention.

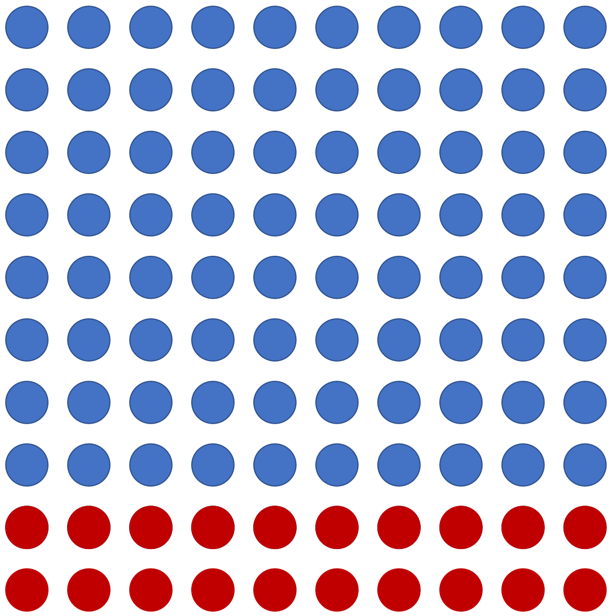
In section 5 we have discussed precision of the forecast module and we have also discussed the resulting numbers in the transition matrix in the previous section. But what does this mean for the gains from intervention? In Figure 21 we show the situation of state 5. In state 5 the likelihood that a conflict breaks out next period is around 1 percent. Assuming that interventions are linked to state 5 this implies that 99 interventions need to be conducted for 1 intervention to actually be in place at the exact moment when the escalation would otherwise occur. This makes prevention very cost-ineffective. Preventive action will only deliver large gains if the dynamic gains from prevention are large enough.

Figure 21: Illustration of Low Precision in Prevention



[6]For a simple intuition of the argument see `https://www.youtube.com/watch?v=BYQQlCVt4aE`. Recommending interventions is like recommending books.

Figure 22: Illustration of High Precision in Prevention



The situation is different in state 8 where the likelihood of escalation is substantial. If interventions are linked to state 8 the associated precision is roughly 20 percent. In other words, only 80 interventions are in vain for every 20 prevented escalations. This makes late interventions 20 times as effective just because they can be targeted better.

This argument is even stronger for the conflict states. Here the likelihood of armed conflict is almost a certainty and interventions therefore face no problem of targeting at all. It is obvious that a situation is very bad with ongoing armed conflict. Even if interventions only stabilize the situation by increasing the likelihood of a lower state next period the gains are very tangible. It is this focus on the tangible emergencies which we observed in our interviews with FCDO experts.

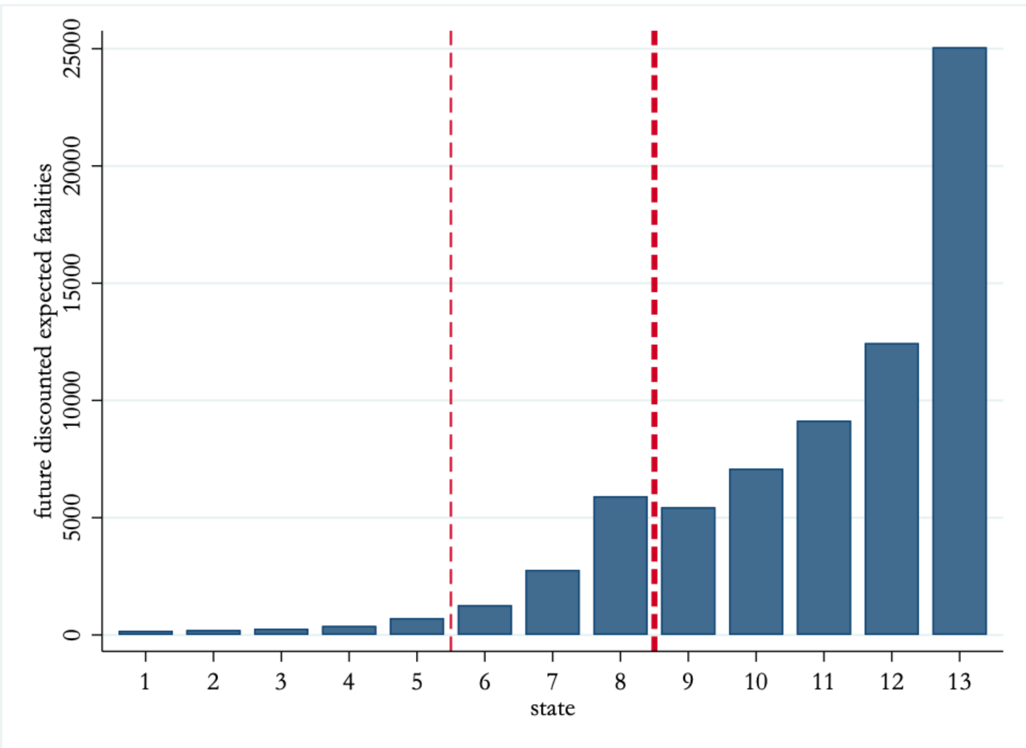
6.1.2 Conflict dynamics

The presence of the conflict trap is well-known to academics and FCDO staff. The trap is the main motivation for engaging in prevention. In our model conflict dynamics become visible in the expected values of future costs at the different states. States 6, 7 and 8 are, for example, not associated with a large number of fatalities in Figure 15 but generate large expected costs because they are part of the conflict trap.

We can use the transition matrix described in the previous section to generate an expected number of fatalities for every state. What we do here is we put ourselves into the shoes of a state and let it escalate or deescalate according to the probabilities presented before. We then check what damages the new state would lead to. We discount the result (a standard method to put less weight on the future) and add it. We then repeat this step infinitely.

This generates what is called a *present discounted values* of costs. For the absolute number of fatalities these values are displayed in Figure 23. Again we show the cost for each of the 13 states ordered from left to right in increasing risk. Whereas in Figure 15 there were no fatalities associated to states 6 to 8 now there are a significant amount of fatalities associated to these states. In fact, state 8 now looks even worse than state 9. In other words, the expected number of fatalities in peace with high risk of escalation can be higher than in conflict with very low likelihood of escalation.

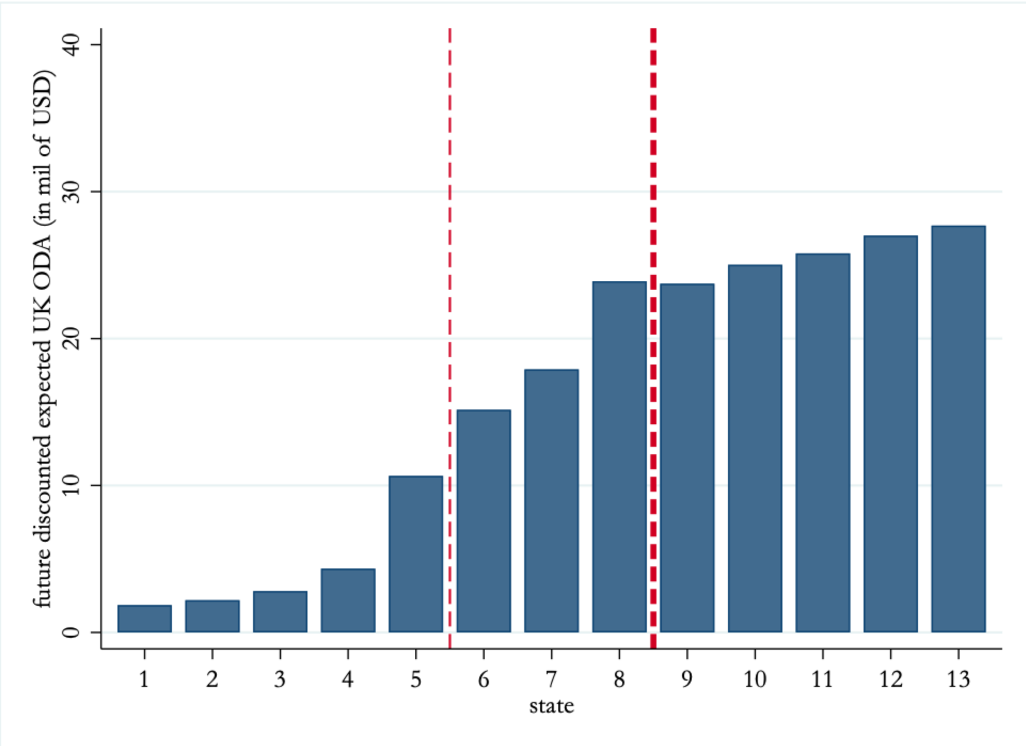
Figure 23: Future Expected Number of Fatalities in the 13 States



This is the downside of intervening in the conflict-trap. Stabilizing a country in this situation by preventing further escalation into conflict does not prevent some of the damages associated with conflict but, instead, stabilizes a relatively undesirable situation.

The situation is even more complex for ODA which, as we have shown in the previous section is often flowing to countries in the lower states 5 to 8. In Figure 24 we show that the present value of UK ODA spent increases dramatically in states 5 to 8 and then stabilizes thereafter. In other words, it is, on average, not possible to save on future expected ODA by keeping countries in state 8 because UK policy is already spending a lot of assistance in this state and because the state can still escalate in future. Gains might still be substantial in state 5 but here the trade-off with low precision is important.

Figure 24: Future Expected UK ODA in the 13 States



6.2 Optimal decision making

In this section we highlight the key ingredients of the dynamic model of intervention. The model is built on a dynamic optimization problem.[7] For every intervention, the known cost of the intervention today must be traded-off against the expected prevented damage, which we define as follows:

expected prevented damage =

likelihood of conflict × damage caused by conflict × likelihood of success

In this simple formula, three elements are used to quantify the expected prevented damage from an intervention: i) the likelihood of conflict; ii) the damage caused by the conflict; iii) the likelihood of success of an intervention.

The first ingredient, the likelihood of conflict, comes from the forecast module, which provides the probability of an outbreak, escalation and de-escalation for all countries of the world. The information contained in the forecast module is summarized by two objects: i) a set of *states*, which are indicators of conflict outlooks, and ii) a *Markov chain*, which describes the probability of moving between states over time. Both have been introduced in the previous section.

The second ingredient, the damage caused by the conflict, takes into consideration the breakdown of economic growth with conflict, the economic recovery phase post conflict, the monetary cost of population displacement, as well as the cost of aid during the reconstruction phase.

Intervention, in the form of early prevention, late prevention or stabilization, is modelled as a change in the future path of a country. Specifically, both early and late prevention are modeled as a decrease in the likelihood of escalating into conflict. On the other hand, stabilization is modeled as an increase in the likelihood de-escalating from conflict, i.e. of moving out of conflict states.

In our quantitative analysis, we consider three alternative scenarios for the the likelihood

[7]Our technical solution to this problem, the optimal stopping problem, builds on advances in economics and it is extensively discussed in the technical appendix.

of success of an intervention. In the first scenario, we assume a 5% success probability. We label this scenario as *neutral*. We compare this scenario to a *pessimistic* scenario, with a success probability of 2%, and to an *optimistic* scenario, with success probability of 10%.

Finally, by integrating our measure of expected prevented damage into a dynamic framework we are able to obtain a value for expected gains of intervention which equals the sum of present and future expected prevented damages:

$$\text{expected intervention gains} = \sum_t \beta^t \text{expected prevented damage}_t$$

where sub-index t denotes any future date t while β is a time-discount factor.

6.3 Results

6.3.1 The strategic view

We first focus on broad patterns across states in terms of expected gains from intervention. Our analysis here relies exclusively on the latest estimates of intervention gains for the entire cross-section of over 170 countries but without taking into account the most developed countries.

We call this the *strategic view* as it illustrates the kind of analysis at the strategic level that our results could support. The kind of questions we can answer at this level are:

- How should additional resources be spent to generate maximum gains?
- Are existing resources across countries allocated to maximum effect?
- Are resources spent to rebuild damages that could have been prevented?

We start with Table 1 which provides a simple country ranking based on the fatalities per capita prevented per month of intervention in Panel A. The top countries here are Yemen, Nigeria, Ukraine, Cameroon, Myanmar, Mexico, the Dem. Rep. of the Congo, Burkina Faso, the Central African Republic and Syria. According to UCDP and our definition, all of these countries were in armed conflict and our forecast indicate risk states 11 to 13 in February 2022.

In Panel B of Table 1 we instead rank countries in terms of absolute gains. Here we see a much more diverse picture with Brazil, Ethiopia and the Philippines in state 8 and India in state 5 joining the top 10. Absolute gains here are large because the countries have larger populations and this overcompensates for the low baseline risk. The case of India is particularly remarkable here as the country does not even have a recent history of armed conflict according to our definition.

Looking at the different outcomes it is clear that the prevention of fatalities will, most likely, not be the main motivation for preventive action. The magnitudes of order here are relatively small with 75 deaths per month of intervention in India for example. However, civil war is so damaging not because of the expected body count it generates but because of the overall hardship that wars bring. This becomes very clear from the substantial refugee numbers we estimate at 5 percent effectiveness. We estimate, for example, that by reinforced prevention in Nigeria over 42,000 refugee months can be prevented per month of intervention. For India, a country which is currently at pre-conflict peace the number is 14,000. It should be clear here that even the slight possibility of escalation with a 0.8 percent likelihood justifies a huge stabilization effort as an armed conflict in India would generate a humanitarian disaster.

Table 1: Example Output: Lives and Refugees Saved by Month of Intervention

Panel A: Ordered by per capita gains

Country	number of fatalities prevented with intervention of 2 percent effectiveness	number of fatalities prevented with intervention of 5 percent effectiveness	number of fatalities prevented with intervention of 10 percent effectiveness	number of refugees saved with intervention of 5 percent effectiveness	total gain (in million USD) with 5 percent effectiveness	total gain for UK (in million USD) with 5 percent effectiveness	conflict state
YEM	24	60	120	6137	752	5	13
NGA	166	414	828	42417	9648	291	13
UKR	20	49	98	5092	1575	234	12
CMR	12	30	59	3063	618	18	12
MMR	24	61	121	6277	1407	116	12
MEX	58	144	288	14875	18057	1050	12
COD	40	100	200	10333	803	18	12
BFA	5	13	27	2216	262	1	11
CAF	1	3	6	512	36	1	11
SYR	4	11	22	1856	291	10	11

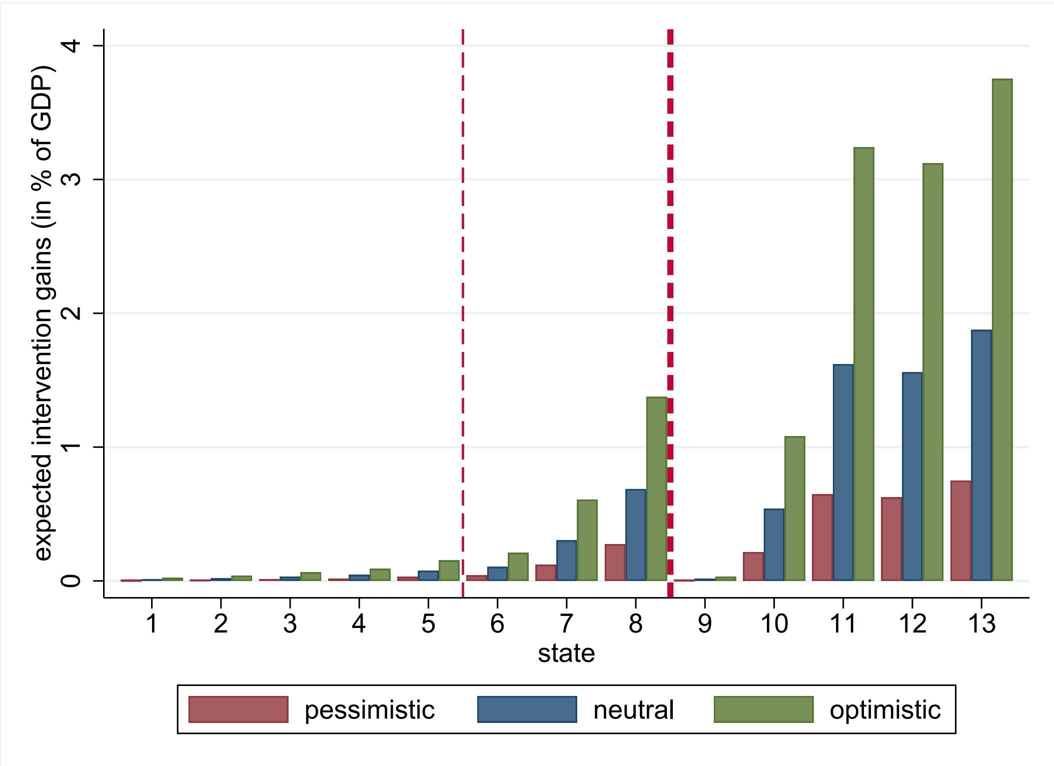
Panel B: Ordered by absolute gains

Country	number of fatalities prevented with intervention of 2 percent effectiveness	number of fatalities prevented with intervention of 5 percent effectiveness	number of fatalities prevented with intervention of 10 percent effectiveness	number of refugees saved with intervention of 5 percent effectiveness	total gain (in million USD) with 5 percent effectiveness	total gain for UK (in million USD) with 5 percent effectiveness	conflict state
NGA	166	414	828	42417	9648	291	13
MEX	58	144	288	14875	18057	1050	12
COD	40	100	200	10333	803	18	12
BRA	38	96	192	15234	12115	165	8
IND	30	75	149	14416	1986	55	5
MMR	24	61	121	6277	1407	116	12
YEM	24	60	120	6137	752	5	13
ETH	21	52	104	8239	710	18	8
PHL	20	50	99	7854	2510	37	8
UKR	20	49	98	5092	1575	234	12

Table Note: All gains are per month of intervention in place. In the case of refugees the gains are in refugee/months, i.e. number of months a refugee needs to spend time out of the country of origin. In Panel A, observations are ordered by gains per capita. This means some large countries with a lot of population do not show here. In panel B, observations are ordered by absolute gains.

The numbers in the two final columns of Table 1 are dominated by the larger economies in the top 10. For Mexico, we estimate that 18 billion USD can be saved in the long run if interventions aiming at stabilization were implemented. The benefit for the UK, through reduced ODA and increase exports is estimated to be 1 billion USD per month of intervention. The total economic long run benefit of stabilizing efforts in the Nigerian armed conflict is 9.6 billion USD per month of intervention. The benefit to the UK is estimated to be 290 million USD. If we sum the economic benefits of interventions for all countries states 5 and 8 we get a total gain of 26 billion USD per month with a gain to the UK of 630 million USD per month.

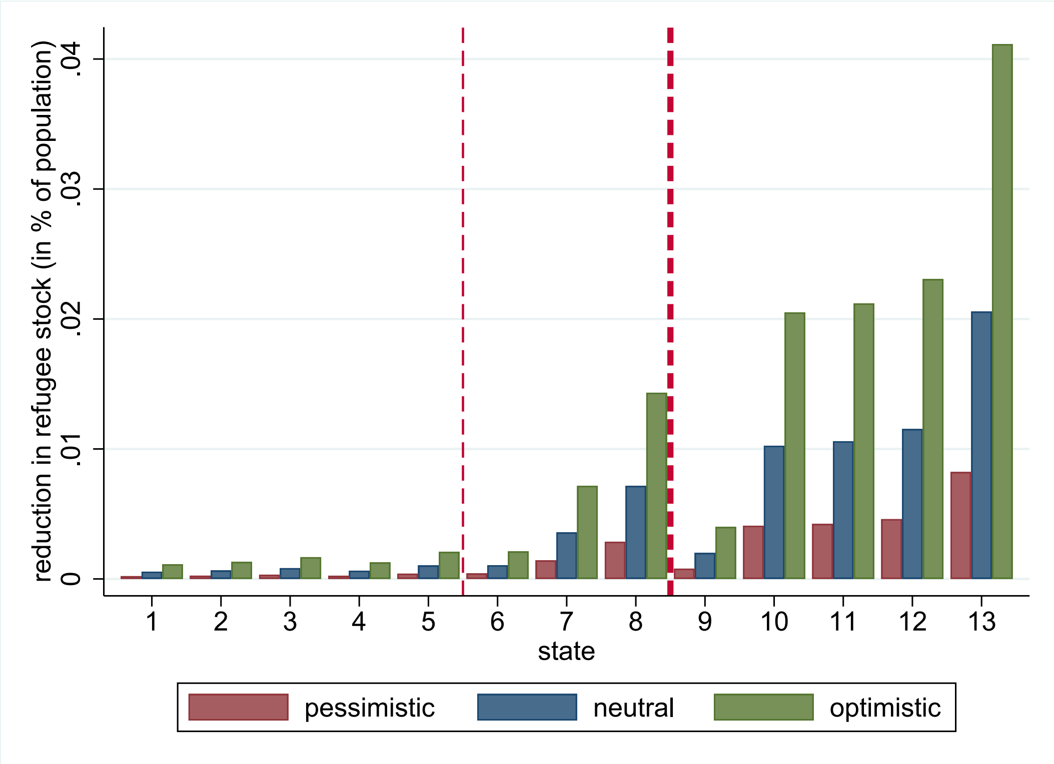
Figure 25: Average expected intervention gain across states



Figures 25 to 28 give insights into the model that generates the data we provide to FCDO. They report the average expected intervention gains for the different states in the data. As in Panel A of Table 1, expected intervention gains are expressed in proportion to GDP or population to make the different countries in the data comparable to each other. In each figure the thin dashed line separates pre-conflict from post-conflict states, while the thick dashed line separates the post-conflict states from the conflict ones.

Surprisingly, expected gains are not monotonic with respect to the riskiness of the states, meaning they don't always increase when we move from less risky to more risky states. Compare for instance the average gains in state 9 against those in less risky states. Gains in state 9 are generally lower than the gains achievable in any of the post-conflict states (states 6 to 8) and some of the pre-conflict states (states 1 to 5). Often it is even better to de-escalate in state 8 than to stabilize in state 10.

Figure 26: Average expected refugees prevented across states

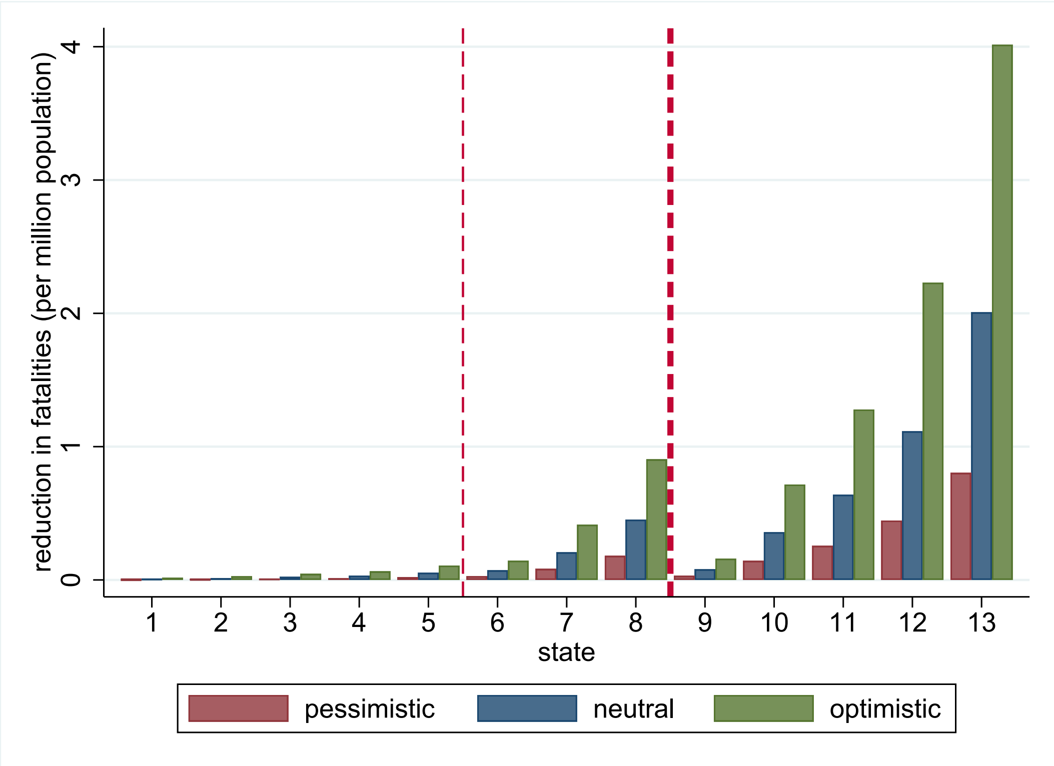


Compare this to Figures 17 and 19 which indicate substantial effort both in terms of ODA and peacekeeping spending in state 9. The contrast is particularly stark in peacekeeping in state 10 compared to state 8. Keeping the peace in state 8 is sometimes more beneficial than keeping it in state 10. It is very likely also much cheaper as there is less or no ongoing violence in state 8. But peacekeeping efforts are a lot higher in state 10, on average.

Turning toward the magnitude of the average expected gain, keep in mind that these are per month of intervention. So Figure 25 shows that interventions in state 8 saves about 0.7 percent of GDP in the long run in the neutral scenario - each month that de-escalation is conducted. Interventions in state 5 save 0.08 percent per intervention in the neutral scenario.

Remember that this is the benefit of a policy with incomplete forecasting and only 5 percent effectiveness. Interventions in state 13 save 1.9 percent of GDP per intervention in the neutral scenario.

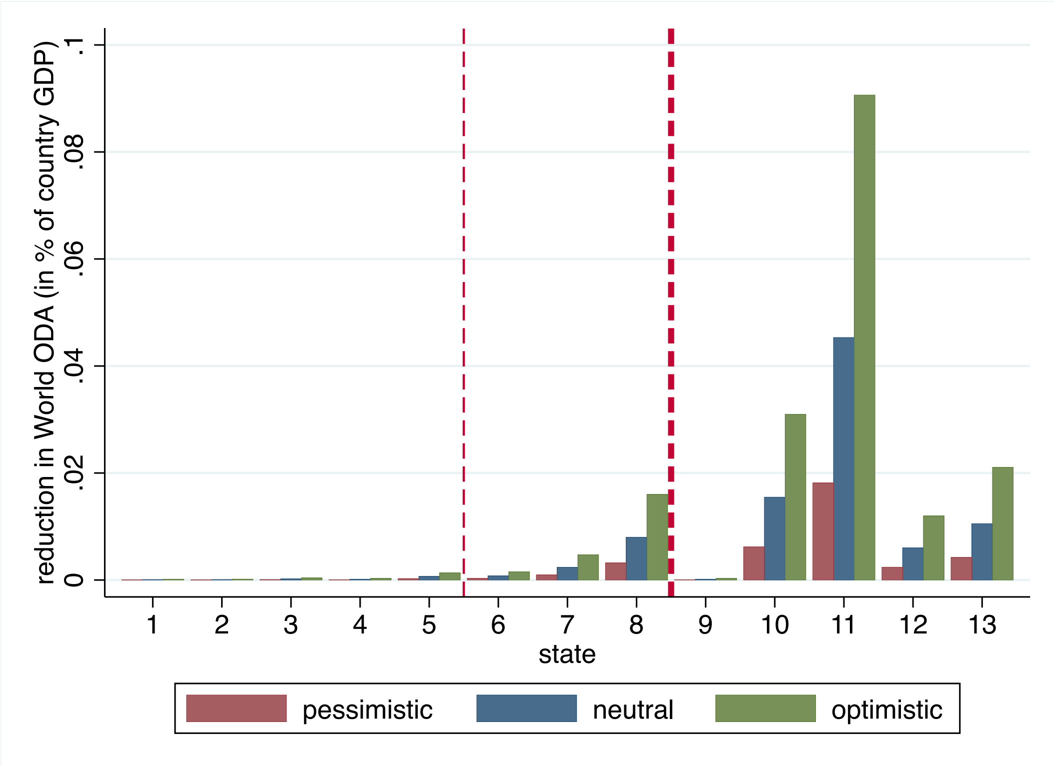
Figure 27: Average expected fatalities prevented across states



To gain a feel for what these numbers mean it helps to look into the countries at the respective states and the absolute gains associated with intervention as we did in Table 1. The countries which our model currently puts at state 13 are Nigeria and Yemen. The total expected gains from stabilizing these two conflicts with a likelihood of 5 percent are 10 billion USD, 49,000 refugees would be prevented. Both of these gains accrue every month with the attempt of stabilization. It is, however, not clear how cost-effective intervention here can be. Stabilizing Nigeria, even with just 5 percent likelihood, might require a heavily militarized intervention which might cost more than 10 billion USD per month.

Examples of countries in state 8 are Colombia, the Philippines, Kenya, the Lebanon and Ethiopia. The expected gains of implementing this policy in all 15 countries which are currently in state 8 would be close to 20 billion USD per month of intervention and would prevent close to 50,000 refugees per month of intervention. In the pessimistic scenario this

Figure 28: Average expected ODA prevented across states



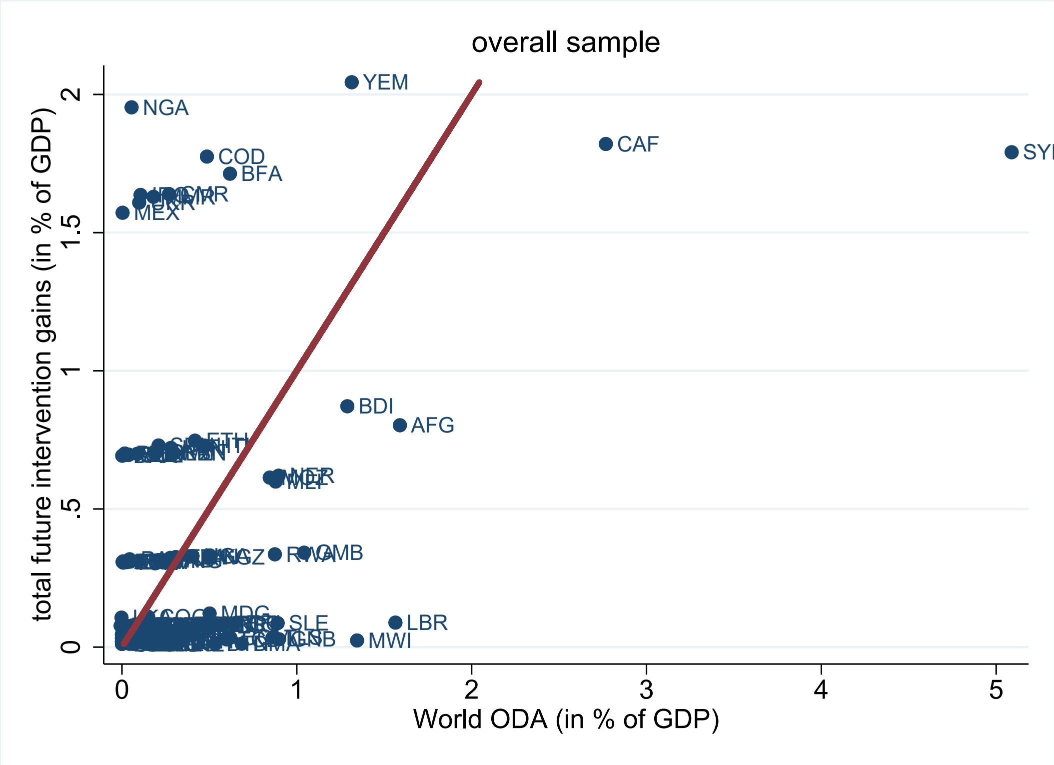
falls to 8 billion USD and 20,000 refugees.

However, intervention in state 8 might still be very expensive as armed actors are typically mobilized, recent violence leads to difficult negotiations and the population is traumatized and has fled the country in parts. All this is not the case in state 5. This state offers lower gains but intervention costs are also, potentially, much lower as violence is, if present at all, not intense or focused on specific parts of a larger country. Examples here are Tunisia, India, Indonesia, Thailand and Chile. The gains of intervention in all 26 countries in this state in the neutral scenario are 5 billion USD per month and the policy would prevent 25,000 refugees per month of intervention.

Figure 28 shows gains in terms of saved World ODA spending. Given that ODA is not focused on the conflict states the gains from late interventions are lower here. Interventions in state 8 deliver a relatively large benefit.

A detailed analysis of UK ODA shown in the appendix suggests that ODA as a tool for stabilization or de-escalation does not focus on the early states but is, instead, focused much more on the conflict states, i.e. ODA explicitly takes into account the risk of armed conflict

Figure 29: Contrasting World ODA with Gains from De-esclation and Stabilization

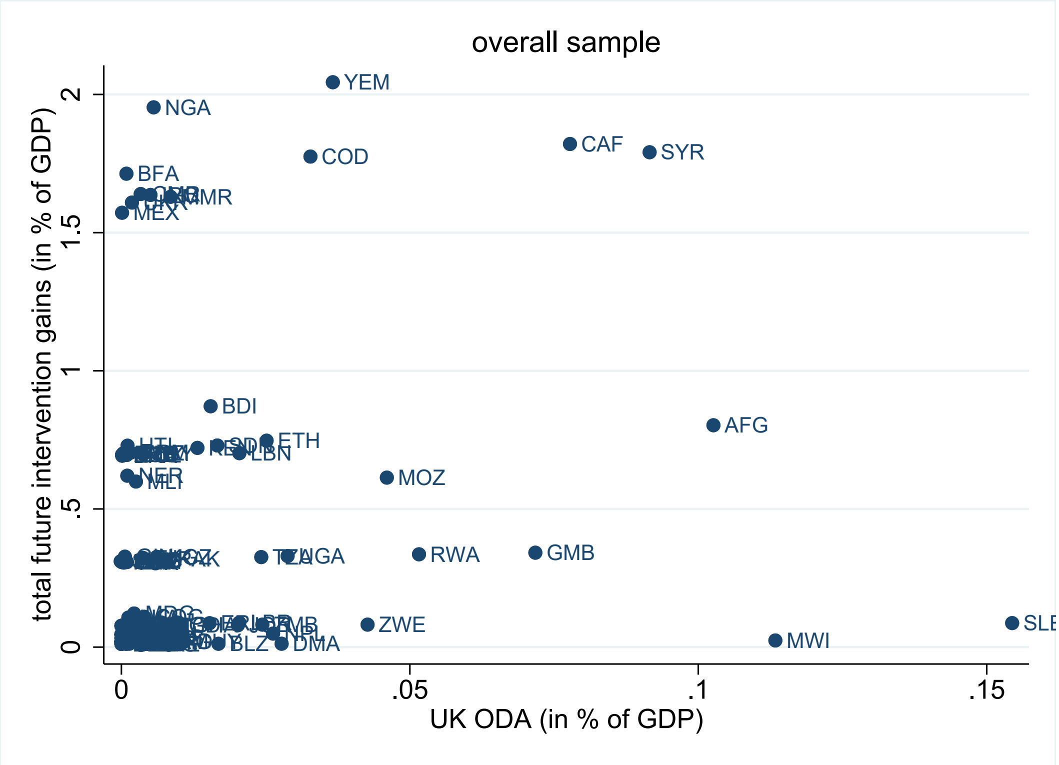


once it has broken out. Some of the patterns we see for state 8 are compatible with a specific goal of de-escalation through institutions building and civil society support but it is hard to know for sure without going further into detail.

Some of the most interesting spending categories are, perhaps, spending related to economics and business as these seem to be much more concentrated in the states 5 to 8. Of course, causality here could run both ways with ODA being faded out during conflict. But it is interesting to observe the relatively high spending in states 6 to 8. This could be both targeted at reconstruction or even an explicit de-escalation tool. But from interviews with FCDO staff we know that the development focus sometimes ignores conflict aspects so that it is difficult to interpret this pattern as spending directly targeted at stabilization.

This is important when we interpret Figures 29 and 30 which show where World ODA and UK ODA are spent respectively and contrast this with the intervention gains our model would predict. We see hardly any relationship. In Figure 29 we see the magnitudes involved are substantial where humanitarian aid around the Syrian civil war is costing over 5 percent of the Syrian GDP every month.

Figure 30: Contrasting UK ODA with Gains from De-esclation and Stabilization



In Figure 29 we show for the UK that substantial resources are spent in countries like Syria or the Central African Republic whereas much less is spent on a large number of countries with similar gains. Figure 30 also shows a dramatic variation across countries which is hidden behind the simple averages we have shown in Figure 18. We find that countries like Afghanistan, Malawi and Sierra Leone attract large shares of the overall spending in the lower conflict risk classes. The contrast between Sierra Leone and Nigeria, for example, is quite stark.

6.3.2 The Country View

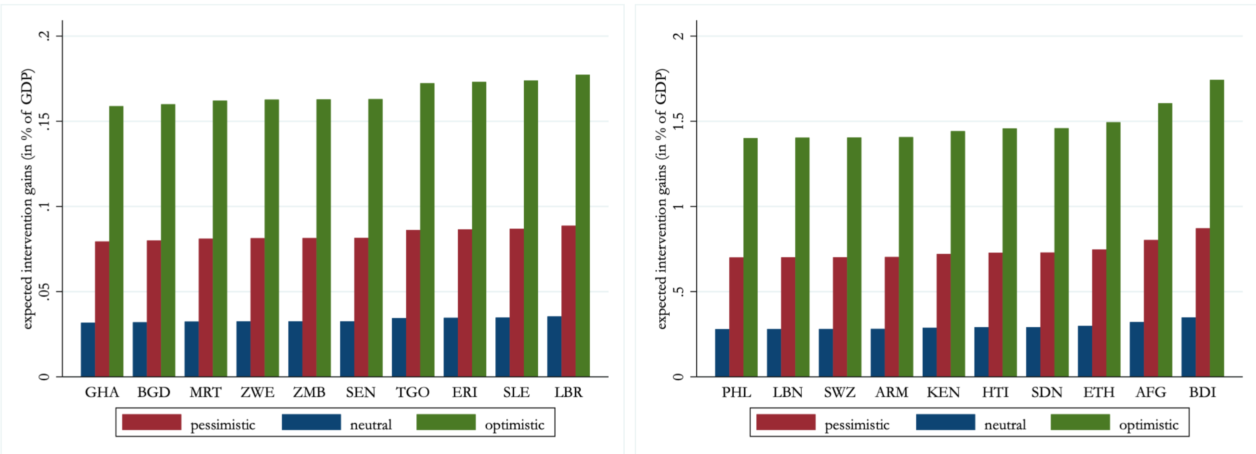
We now shift our focus to the case of a few specific countries. First, we are going to discuss the countries that provide top gains in states 5 and 8 as these states play a critical role in our analysis. Then, we move to a dynamic analysis and discuss how the expected gains evolved over time in some selected countries as a function of their conflict cycle.

We begin by providing a simple rank of countries in states 5 and 8 in terms of their total expected gains from intervention. Figures 31 report the expected gains of intervention computed under the neutral scenarios as of February 2022, for countries with the 10 highest gains in state 5 (panel a) and in state 8 (panel b). For comparison, for each of these countries we report the gains under the pessimistic and the optimistic scenarios. The gains are expressed in % of GDP.

Among the countries with highest expected gains in state 5 we find Liberia, Eritrea, together with Zimbabwe and Bangladesh. Among the countries with highest expected gains in state 8, there are Burundi, Sudan but also Armenia and the Philippines. These are countries where early or late prevention respectively could generate gains per month that range from around 0.1% of GDP (for countries in state 5) to 1% of GDP (for countries in state 8).

Figure 31: Expected intervention gains across countries

(a) countries in state 5 (b) countries in state 8

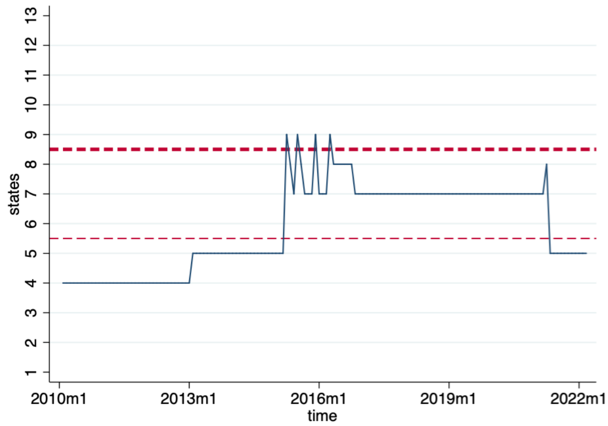


Notes: Each bar denotes the expected intervention gains computed in % of GDP in a pessimistic (red), neutral (blue) and optimistic (green) scenarios. Panel (a) reports the 10 countries with highest gains in state 5. Panel (b) reports the 10 countries with highest gains in state 8.

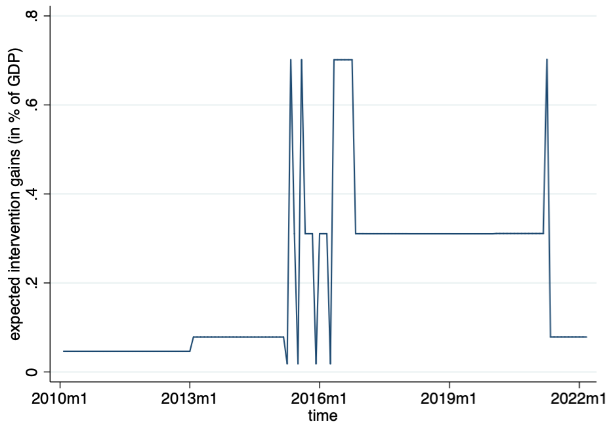
The simulation of the decision making module also allows us to track countries over time and compute expected gains in different points in times as a function of the conflict state they were in. We show-case this dynamics for two specific countries: Tunisia and the Democratic Republic of Congo. In both cases we will now treat UK ODA spending as an indication an intervention in the sense of our model, i.e. as an attempt to change conflict dynamics for the better. This allows us to evaluate the timing of these UK interventions.

Figure 32: Gains and conflict dynamics in Tunisia

(a) Conflict states

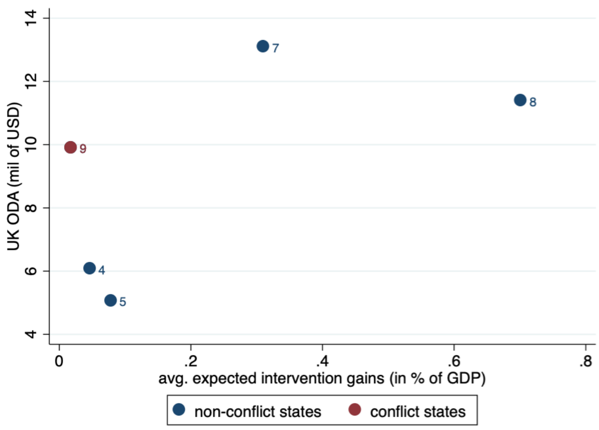


(b) Expected Intervention Gains



Notes: In Panel (a) we report the state of the country over time (blue line). Red thin dashed line separate pre-conflict from post-conflict states. Red thick dashed line separates post-conflict from conflict states. In Panel (b) we report the expected intervention gains associated to each state of the country over time.

Figure 33: Gains versus UK ODA in Tunisia



Notes: Each dot denotes the UK ODA (in mil of USD) against the expected intervention gains (in % of GDP) averaged over time separately across states. States are reported next to each dot.

In Figure 32 we report the case of Tunisia. Panel (a) reports the evolution of conflict states, meaning the conflict states Tunisia was in every month starting from January 2010 until February 2022. Panel (b) report the associated expected gains from interventions compute using a 5% effectiveness for the same time period. As highlighted in panel (a), Tunisia experienced a few months of conflicts in 2016. After the first conflict breakthrough, the country fluctuated between conflicts and post-conflict states. Quite interestingly, the gains from intervention dropped during conflicts, were higher before conflict escalation and spiked up post-conflict, suggesting that early and/or late prevention could have generated much higher benefit than stabilization.

Figure 33 scatters the amount of per-period UK ODA spending (reported in USD) against the predicted intervention gains (expressed in % of GDP), averaged across periods in each conflict state. The model predicts that large resources were employed in periods of conflict (state 9) despite very low gains from intervention. On average 10 millions USD were spent during the period in state 9, where the gains are just 0.01% of GDP. Larger gains could have been achieved if more resources were employed in early prevention in states 4 and 5. Furthermore, we find that the largest amount of resources (around 12 millions USD) were employed for post-conflict late prevention (states 7 and 8), which, as predicted by the model, delivers the highest amount of expected gains (0.7% of GDP).

Figures 34 and 35 reproduce the same analysis for the case of the Democratic Republic of Congo. Like Tunisia, the Democratic Republic of Congo has gone through a period of relative stability until the first months of 2015, when it experienced episodes of conflicts (panel a in Figure 34), immediately followed by periods of de-escalation. Over the same period of time, the model predicts that the largest expected gains would have been achieved from post-conflict intervention in states 7 to 8 rather than conflict stabilization in state 9 (panel b in 34).

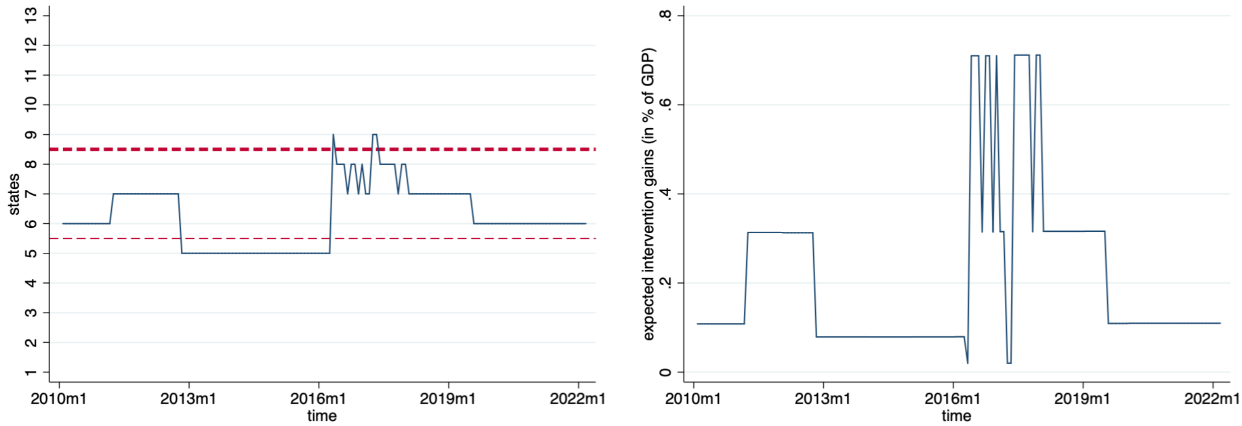
Looking at how resources were used (Figure 35), the model suggests that the largest amount of UK ODA was employed for post-conflict intervention in state 6: on average more than 20 millions USD were spent whereas our model predicts that interventions in these states generates gains of about 0.15% of GDP. Intervention gains were much higher in states 7 and 8, 0.5% and 0.8% of GDP, respectively. However, in these states, less than 5 millions USD was spent in ODA.

In the Appendix we report similar graphs for several other countries including the Ivory Coast, Burundi, Armenia, Nigeria, and the Philippines, all of which suggests that intervention gains according to our model and UK ODA spent were not aligned. Spending is typically highest during conflict stabilization whereas there are significant intervention benefits in states without ongoing violence.

Figure 34: Gains and conflict dynamics in the Democratic Republic of Congo

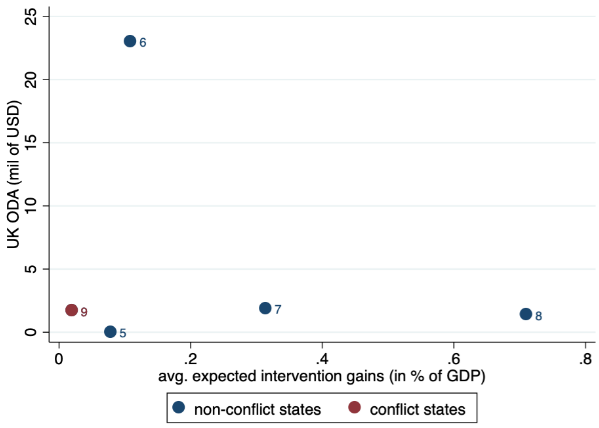
(a) Conflict states

(b) Expected Intervention Gains



Notes: In Panel (a) we report the state of the country over time (blue line). Red thin dashed line separate pre-conflict from post-conflict states. Red thick dashed line separates post-conflict from conflict states. In Panel (b) we report the expected intervention gains associated to each state of the country over time.

Figure 35: Gains versus UK ODA in the Democratic Republic of Congo



Notes: Notes: Each dot denotes the UK ODA (in mil of USD) against the expected intervention gains (in % of GDP) averaged over time separately across states. States are reported next to each dot.

7 Concluding remarks

We have shown that it is possible to integrate forecasts based on cutting-edge forecast methodologies within a model of optimal decision making to generate actionable information flows at the strategic and country-expert level. Our results should be seen as a first proof-of-concept which can serve as a quantitative benchmark when comparing the situation of different countries and within countries over time.

Future work should integrate the FCDO's policy experience deeper into the decision making model to generate more tailor-made policy recommendations. Our work here should only be regarded as a first proof of concept. A key dimension for optimal policy is the relative cost of early and late interventions. We have currently no way of integrating this as there is little data available on the costs of different policies.

Everything suggests that late interventions are more costly but the order of magnitude here matters. The expected gains per case we find suggest that, on average and in the neutral scenario, an intervention in state 8 provides a benefit of 0.7 percent of GDP whereas an intervention in state 5 saves 0.08 percent per intervention. Interventions in state 13 save 1.9 percent of GDP per intervention. This could still make interventions in state 5 more cost-effective if they are 10 times cheaper than interventions in state 8 and 25 times cheaper than interventions in state 13.

References

Blattman, Christopher, Robert Blair, and Alexandra Hartman (2014).“How to Promote Order and Property Rights under Weak Rule of Law? An Experiment in Changing Dispute Resolution Behavior through Community Education” American Political Science Review 108(1) (2014): 100-120.

Chalmers, Malcolm (2007). ”Spending to Save? The Cost-Effectiveness of Conflict Prevention”. Defence and Peace Economics, 18:1, 1-23, DOI: 10.1080/10242690600821693.

Collier, Paul and Nicholas Sambanis (2002). ”Understanding Civil War.” Journal of Conflict Resolution. 46 (1): 3–12.

Cramer, Christopher, Jonathan Goodhand, Robert Morris, Helena Pérez-Niño, Benjamin Petrini and Joshua Rogers (2014) ”Conflict Prevention Rapid Evidence Assessment.” Oxford Policy Management.

Hegre, Håvard; Lisa Hultman and Håvard Mokleiv Nygård (2019) ”Evaluating the conflict-reducing effect of UN peacekeeping operations.” The Journal of Politics 81(1): 215–232.

León, Gianmarco, and Edward Miguel (2017) ”Risky Transportation Choices and the Value of a Statistical Life.” American Economic Journal: Applied Economics, 9 (1): 202-28.

Mueller, Hannes, and Christopher Rauh (2018) ”Reading Between the Lines: Prediction of Political Violence Using Newspaper Text.” American Political Science Review 112, no. 2: 358-375.

Mueller, Hannes and Christopher Rauh (2022a) “The Hard Problem of Prediction for Conflict Prevention”, Journal of the European Economic Association.

Mueller, Hannes and Christopher Rauh (2022b) ”Using Past Violence and Current News to Predict Changes in Violence”. International Interactions, Special Issue: Forecasting in International Conflict.

Mueller, Hannes and Dominic Rohner (2018) ”Can Power-Sharing Foster Peace? Evidence From Northern Ireland”, Economic Policy, 2018, 33: 447-484.

Nunn, Nathan, and Nancy Qian (2014). "US Food Aid and Civil Conflict." American Economic Review, 104 (6): 1630-66.

Pettersson, Therese, Shawn Davis, Amber Deniz, Garoun Engström, Nanar Hawach, Stina Högbladh, Margareta Sollenberg & Magnus Öberg (2021). Organized violence 1989-2020, with a special emphasis on Syria. Journal of Peace Research 58(4).

Rohner, Dominic an Alessandro Saia (2020) Education and Conflict Evidence from a Policy Experiment in Indonesia. Working Paper.

Rohner, Dominic and Mathias Thoenig (2021). "The Elusive Peace Dividend of Development Policy: From War Traps to Macro-Complementarities". Annual Review of Economics, forthcoming in Volume 13.

Sundberg, Ralph and Erik Melander (2013) Introducing the UCDP Georeferenced Event Dataset. Journal of Peace Research 50(4).

Bazzi; Samuel, Robert A. Blair, Christopher Blattman, Oeindrila Dube, Matthew Gudgeon, Richard Peck (2021) The Promise and Pitfalls of Conflict Prediction: Evidence from Colombia and Indonesia. Review of Economics and Statistics.

World Bank (2017) United Nations and World Bank Leaders Call for Stronger International Efforts to Prevent Violent Conflict. Press release. September 21, 2017.

Mueller, Hannes, and Christopher Rauh (2018) "Reading Between the Lines: Prediction of Political Violence Using Newspaper Text." American Political Science Review 112, no. 2: 358-375.

Mueller; Hannes. (2017). "How Much Is Prevention Worth?" Background Paper for Pathways to Peace;. World Bank, Washington, DC.

United Nations, World Bank (2018) Pathways for Peace : Inclusive Approaches to Preventing Violent Conflict. Washington, DC: World Bank.

Chalmers, Malcolm (2007) Spending to Save? The Cost-effectiveness of Conflict Prevention, Defence and Peace Economics, 18:1, 1-23, DOI: 10.1080/10242690600821693 Institute for Economics and Peace (2017) Measuring Peace building Cost-Effectiveness. IEP Report, 46.

Caprioli, Mary. "Primed for violence: The role of gender inequality in predicting internal conflict." International studies quarterly 49, no. 2 (2005): 161-178.

Cohen, Dara Kay and Ragnhild Nordås (2014) Sexual violence in armed conflict: Introducing the SVAC dataset, 1989–2009. Journal of Peace Research, Vol. 51, No. 3, pp. 418-428.

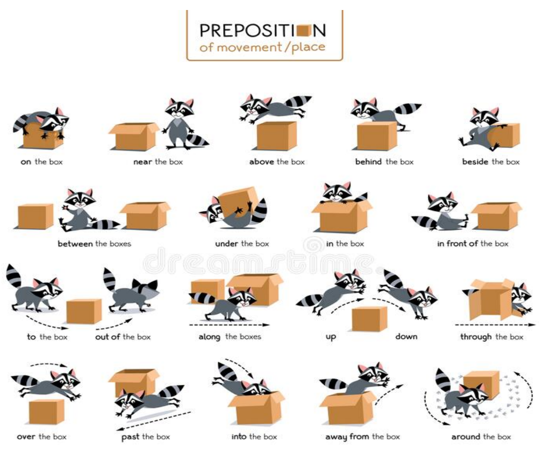
A Annex: Imputing precise spatial features to text-derived data

Our huge corpus of articles provides an irreplaceable comprehensive and world-encompassing account of any remarkable event of the last three decades. We make use of the verbally-expressed information enshrined in these accounts by representing the content of each article as point in a 15D space through latent Dirichlet allocation; thanks to this transformation, the corpus becomes a suitable train set for forecasting. The remarkable results of this training is the forecasting performance you have read above.
However, as we directed our effort toward making our forecasting models more granular, we were stifled by the paucity of the geographical information originally joined to the articles: we knew little more than the country in which the events of each articles occurred. Standard NLP packages, such as nltk, were of little help, proving unreliable and far too lax in their classifications. Because of this, we devised our own method of deriving the locations most likely concerned by the content of a text from the text itself, exploiting the fairly deterministic patterns that the English language employs to express the circumstantial complement of location.

A.1 Computational detection of geographically-significant words

The patterns our algorithm looks for are conceptually simple: we based our method on the simple fact that certain prepositions, when followed by a capitalized word (or a sequence of capitalized word), are quite unambiguous indicators of location.

The code below the fundamental bit performing the search:



The sophisticated source of our method

```
loc_prep = ['above','on','under','below','underneath','beneath','behind','between','beside','near','by','in','inside'
'within','into','out','outside','at','nearby','about','from','at','nearby','from', "north","south","west","east",
"northwest","southwest","northeast","southeast"]
loc_prep_of = ["front","top","out","north","south","west","east","northwest","southwest","northeast","southeast"]
loc_prep_to = ["next",'near',"close"]
loc_prep = loc_prep + [i.capitalize() for i in loc_prep]
loc_prep_of = loc_prep_of + [i.capitalize() for i in loc_prep_of]
loc_prep_to = loc_prep_to + [i.capitalize() for i in loc_prep_to]


def loc_detector(l_text,word):
    n = l_text.index(word)
    status = False
    if l_text[n-1]=="the":
        status = status or (l_text[n-2] in loc_prep)
        if l_text[n-2]=="of":
            status = status or (l_text[n-3] in loc_prep_of)
        if l_text[n-2]=="to":
            status = status or (l_text[n-3] in loc_prep_to)
    else:
        status = status or (l_text[n-1] in loc_prep)
        if l_text[n-1]=="of":
            status = status or (l_text[n-2] in loc_prep_of)
        if l_text[n-1]=="to":
            status = status or (l_text[n-2] in loc_prep_to)
    return status
```

Operationalization of the sophisticated source above

This deterministic method exploits only local properties of text, but it is easy to show that it is at the same time more perceptive and more scrupulous of holistic alternatives. Let's consider this article published by AP in 1983 on the protests against the Sandinista government in Nicaragua. We have highlighted what, to the human eye, are clearly locations

> Nicaragua on Thursday ordered two U.S. diplomats expelled for allegedly instigating wildcat teachers' strikes. This shows the United States government is committed to disobeying the norms of civilized coexistence and is pledged to destabilizing governments, such as the one in Nicaragua, that demand respect , Foreign Minister Miguel D'Escoto said . In Washington, State Department press officer Dennis Harter said [...] teachers in Nicaragua are on strike [...] Joel Franklin Cassman, economic attache at the U.S. Embassy in Nicaragua. Ms. Barmon was given 48 hours to leave , and Cassman was given 72 hours. Ms. Barmon is based in Honduras but had been in Nicaragua for two days, Marenco said . Cassman arrived in Nicaragua last week along with six other U . S . officials [...] It ran the front page article under the banner headline , Yankee Meddling in Chinandega. It said two U.S. officials and activists from the opposition Social Christian Party and the Labor Unification Union attended a meeting Wednesday called by teachers at two private schools in Chinandega, 80 miles northwest of Managua. [...] demonstrators broke out at an opposition rally in Nandaime, about 40 miles south of Managua. The United States retaliated by expelling Nicaragua's envoy in Washington and seven other Nicaraguan diplomats. Barricada reported teachers' strikes in two provincial cities Thursday, raising to three the number of municipalities outside Managua [...] fewer than 200 of the 800 teachers in Chinandega province walked off their jobs Wednesday. It said 70 teachers struck in El Viejo, a small town 84 miles north of Managua. In San Rafael del Sur, a town 30 miles south of Managua, all 198 teachers were on strike

We now have a benchmark to see the different outputs produced by our method and by the most common alternative, the nltk-based *geograpy* when given the same input.

```
import nltk
from geograpy.extraction import Extractor

e=Extractor(text=text)
e.find_entities()

e.places == ['Associated', 'AM','Associated','International News','Byline','DORALISA','Associated','Dateline MANAGUA'
'Nicaragua Body Nicaragua','United States','Nicaragua',"Miguel D'Escoto",'Washington','State Department','Dennis Hart
 'Nicaragua','Nicaragua','Harter','Sandinista','Dionisio Marenco','Sandinista','Kathleen Williamson Barmon','Central'
'American','Joel Franklin Cassman','Embassy','Nicaragua','Barmon','Cassman','Barmon','Honduras','Nicaragua','Marenco'
 'Cassman','Nicaragua', 'American','Marenco','Daniel Ortega','Marenco','Barricada','Sandinista National Liberation Fr
 'Yankee Meddling','Chinandega','Social Christian Party','Labor Unification Union','Chinandega','Managua','Embassy',
 'Nicaragua','Ambassador Richard Melton','Melton','Nandaime','Managua','United States','Nicaragua','Washington',
 'Barricada','Managua','Teachers','Barricada','Chinandega','El Viejo','Managua','San Rafael','Managua']

True
```

Standard package output

```
extract_places_from_text(text)
```

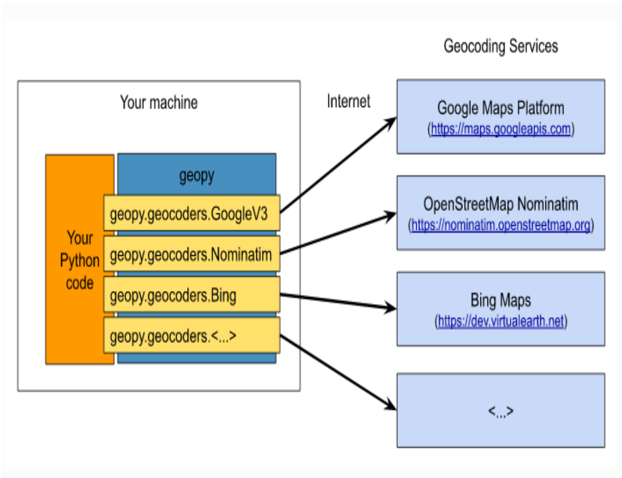
```
{'Chinandega',
 'El Viejo',
 'Honduras',
 'Managua',
 'Managua United States',
 'Nandaime',
 'Nicaragua',
 'San Rafael',
 'U S Embassy',
 'Washington',
 'Washington State Department'}
```

Our method's output

The difference both in false positives and false negatives is quite easy to appreciate. However, detecting the words signifying a position would be a rather futile exercise, given that sure a computer cannot grasp the signified, not to mention that we ourselves are often equally unable to do without a pinpoint on a map. Thus, the second crucial step of extracting usable geographic information from articles meant turning these strings of letters you see above into coordinates.

A.2 From words in a text to points on a globe

This last part was accomplished mainly by using Nominatim, an extremely useful API that gives anyone interested in automated geography access to the OpenStreetMaps data. Conceptually, it is not very different from inserting the word we think might represent a location into the search bar of Google Maps, and see what comes out. Of course, the fact that, unlike a manual search, a Nominatim query can be imputed automatically, several times per second, and returns directly coordinates rather than an image, proved extremely useful for the completion of the project. Below we show the output of an OpenStreetsMap search trough Nominatim, using the locations of the article above as input:



A schematic of our main tool

```
In [109]: locs = extract_places_from_text(text)
for i in locs:
    location = locator.geocode(i+", Nicaragua")
    try:
        if (location.latitude< 15.01 and location.latitude>10.43) and (location.longitude> -87.40 and location.longit
            cell = find_cell(location)
            print(location, location[1],cell)
    except:
        pass
```

```
Nicaragua (12.6090157, -85.2936911) 147790
Embajada de los Estados Unidos de América, Carretera Panamericana Sur, Sector Cerro Tabuya, Distrito II, Managua (Mu
nicipio), Departamento de Managua, 12000, Nicaragua (12.1311778, -86.30962194787767) 147068
Nandaime (Municipio), Granada, 44300, Nicaragua (11.756423, -86.0530799) 146348
San Rafael, Rama, South Caribbean Coast Autonomous Region, 82300, Nicaragua (12.1870386, -84.2448964) 147072
Managua (Municipio), Departamento de Managua, 10000 (CODIGO MAESTRO), Nicaragua (12.1459907, -86.2746665) 147068
El Viejo (Municipio), Chinandega, 26200, Nicaragua (12.6632331, -87.1702626) 147786
Chinandega, Nicaragua (12.8890816, -86.9577726) 147787
```

(Almost) final product

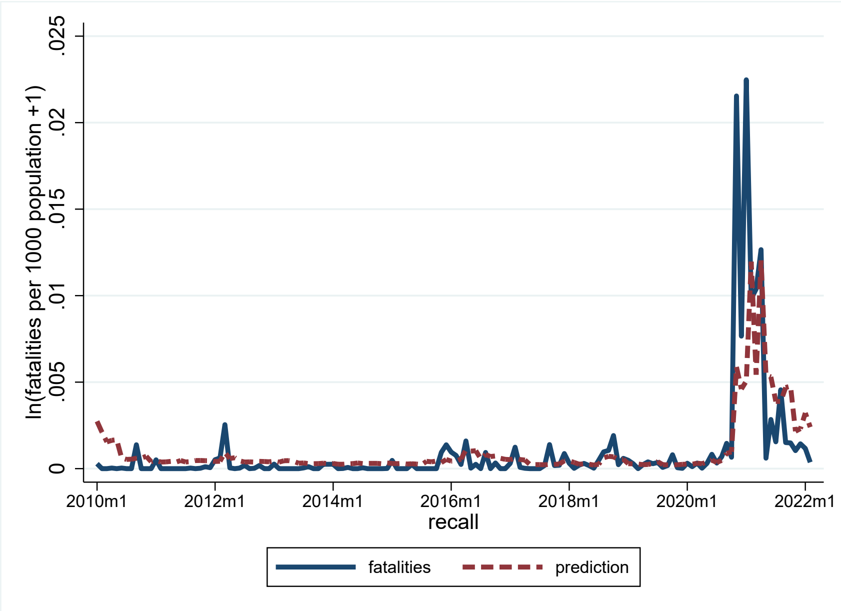
Being able to pair the LDA results (the *content* of each article) with the locations such content pertains to is a way to enable granularity and add an extremely informative feature to the training set, with the resulting improvement in overall forecasting. But it is also a way to detect qualitative and fundamental changes in the patterns of violence. Mapping the emergence of new epicenters of conflicts is not only invaluable in correctly visualizing the spatial character of events but it should also provide us with new opportunities for prevention by enabling a better understanding of local dynamics.

B Annex: Data and additional results

B.1 Additional examples for Intensity Forecasts

Figures B42, B43, and B44 show the examples of Ethiopia, Pakistan and Egypt for our intensity forecasts.

Figure B42: Ethiopia: Intensity Forecast



B.2 Analysis for costs in the optimal decision-making module

We show here the statistical results that underpin the costing in the decision making module. We use the number of fatalities per 1000 population shown in Figure B45 to calculate costs from the loss of life. To do this we first multiply the per capita loss by the population of the respective country and then by 0.9 to get to millions of USD. We use 900,000 USD as the value from life from Leon and Miguel (2017).

we are calculating the costs from refugees in a starkly simplified manner. We only take into account the costs to the international community through UNHCR spending on refugees divided by the total number of refugees. In this way we arrive at a number of 100 USD per year. This is likely an underestimate as other organizations are also spending on refugees. More importantly, we are not taken into account the costs to the refugees themselves through their suffering of trauma, distress, deteriorating health and lack of education. However, we

Figure B43: Pakistan: Intensity Forecast

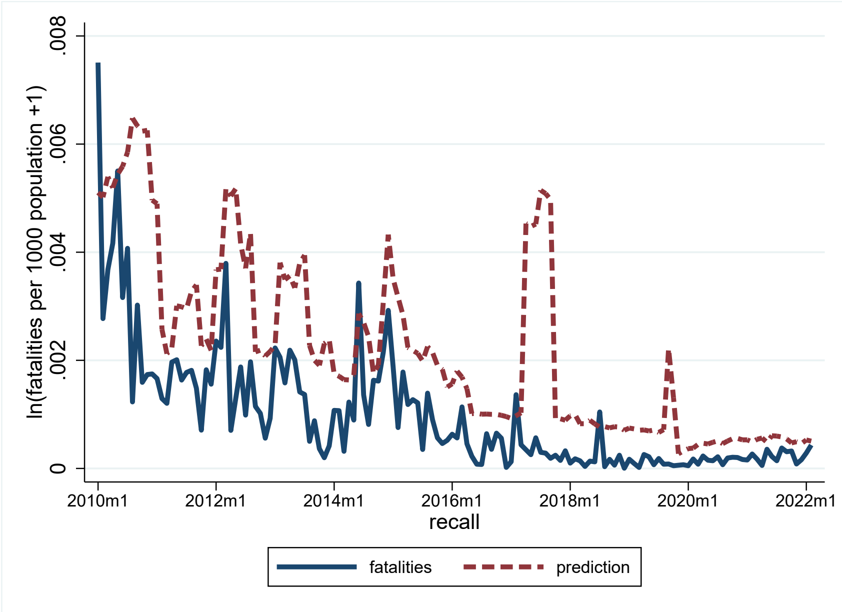
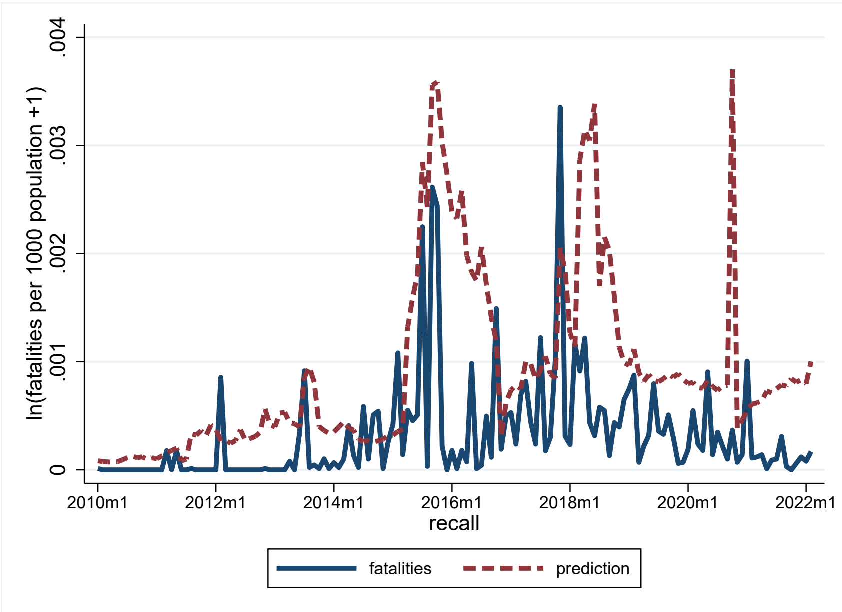


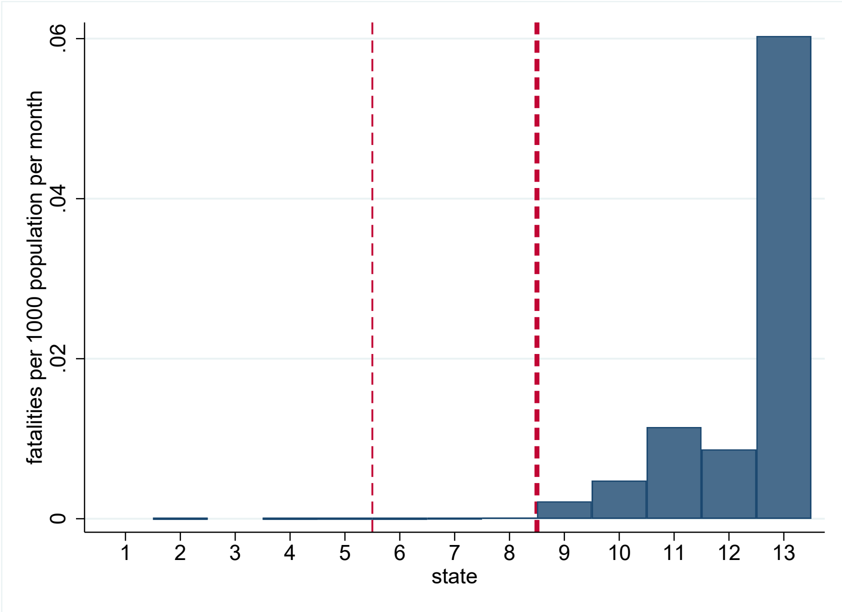
Figure B44: Egypt: Intensity Forecast



think that the suffering of the population is a main factor in declining GDP levels and the lack of a recovery post conflict and the plight of refugees is therefore captured in the, very substantial, economic costs of declining gross product.

we use simple averages in these cost factors as the causal relationship from armed conflict

Figure B45: Average Number of Fatalities per Capita in the 13 States



and fatalities/refugees is undisputed. For refugees it is worth noting that we are using stocks, not flows. We think that this is the right way of capturing the costs as every month a refugee is away from his or her home country the international community is paying this cost.

The remaining costing relies on cross country regressions. The main contribution to the total cost comes from regressions of GDP growth on the states at the country level. But we also analyzed the reaction of World ODA, UK ODa and UK exports to the affected countries using regressions with country and year fixed effects. Results are shown in Table B1. The table therefore shows the change with changes in the state compared to the baseline, omitted category of state 1 when compared within the same country and controlling for international changes through the time fixed effect.

The results show a strong association of growth and log ODA for the last states. In the case of growth the result indicate that growth collapses in years in states 11 and 13. We use the coefficients on the states 11 to 13 even thought the coefficient on state 12 is not statistically significant. These results are very much in line with the literature on the cost of conflict but also indicate a very dramatic growth collapse for the last state 13 with a contraction of over 7 percent in growth on average.

We also find very strong statistical associations of ODA with the conflict states. Our

Table B1: Cross country regression with fixed effects

VARIABLES	(1) GDP growth	(2) World ODA	(3) UK Exports	(4) UK ODA
state 2	0.00169	0.230**	0.00217	0.273***
	(0.00355)	(0.102)	(0.0550)	(0.0520)
state 3	-0.00364	0.0911	-0.0597	0.488***
	(0.00436)	(0.107)	(0.0718)	(0.0850)
state 4	-0.00499	-0.0459	0.0857	0.600***
	(0.00479)	(0.123)	(0.107)	(0.110)
state 5	0.00239	-0.0472	0.0934	0.736***
	(0.00730)	(0.152)	(0.129)	(0.145)
state 6	0.00596	-0.0195	-0.0159	0.640***
	(0.00667)	(0.174)	(0.200)	(0.161)
state 7	0.00628	-0.0337	-0.233	0.626***
	(0.00834)	(0.169)	(0.204)	(0.202)
state 8	0.00119	0.112	0.00798	0.944***
	(0.00824)	(0.183)	(0.185)	(0.228)
state 9	0.0263	0.215	-0.0907	1.011***
	(0.0227)	(0.188)	(0.208)	(0.272)
state 10	-0.0309	0.397	-0.0386	1.100***
	(0.0314)	(0.269)	(0.245)	(0.367)
state 11	-0.0547*	0.513**	-0.414	1.016**
	(0.0317)	(0.240)	(0.337)	(0.440)
state 12	-0.0339	0.869**	-0.689	1.015*
	(0.0225)	(0.348)	(0.467)	(0.583)
state 13	-0.0744**	1.081*	-0.566	0.844
	(0.0346)	(0.554)	(0.449)	(0.953)
Observations	1,674	1,729	1,891	2,248
R-squared	0.331	0.951	0.958	0.797

Notes: Robust standard errors clustered at the country level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All regressions include country and year fixed effects. States are the mean state in a year (rounded). GDP growth is the percent number of year-on-year growth of GDP where is GDP in constant 2015 USD from the World Bank. Imports is the log of exports to the country from the UK (log(exports+1)). World ODA is the log of ODA+1. UK ODA is the log of UK ODA +1

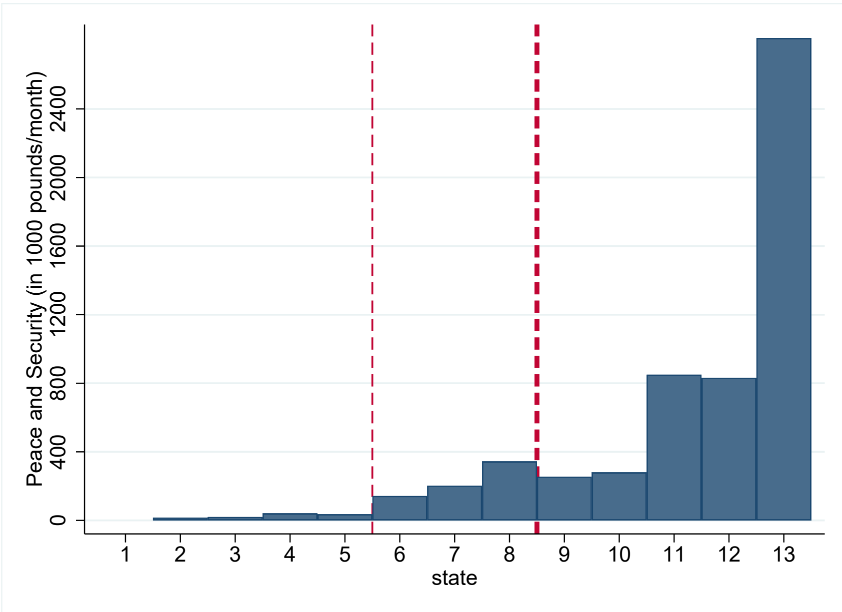
results suggest that ODA more than doubles in conflict states. There is an extremely interesting difference between overall ODA and UK ODA where the latter is increasing almost continuously with the state.

The only statistically insignificant result is on UK exports. Here we do find negative coefficients which suggest a relatively strong reaction of exports and we have used these coefficients to estimate the response. But the effects are not significant in monetary terms either and are therefore not taken into account.

B.3 Detailed analysis of UK ODA spending categories

This section provides a detailed analysis of UK ODA spending patterns by category. Average monthly spending is split by spending category and state to understand how UK ODA changes over the spending cycle. We find a dramatic increase of peace and security spending and emergency ODA in ongoing conflicts. Interestingly, even spending in the category of Government and Civil Society is much higher in states 11 to 13 than in state 8.

Figure B46: Average Monthly Peace and Security ODA by State



The most interesting spending categories are, perhaps, spending related to economics and business as these seem to be much more concentrated in the states 5 to 8. Of course, causality here could run both ways with ODA targeted at economic development and business being faded out during conflict. But it is interesting to observe the relatively high spending in states 6 to 8. This could be both targeted at reconstruction and a de-escalation tool but from intereviews with FCDO staff we know that the development focus sometimes ignores conflict

Figure B47: Average Monthly Government and Civ. Soc. ODA by State

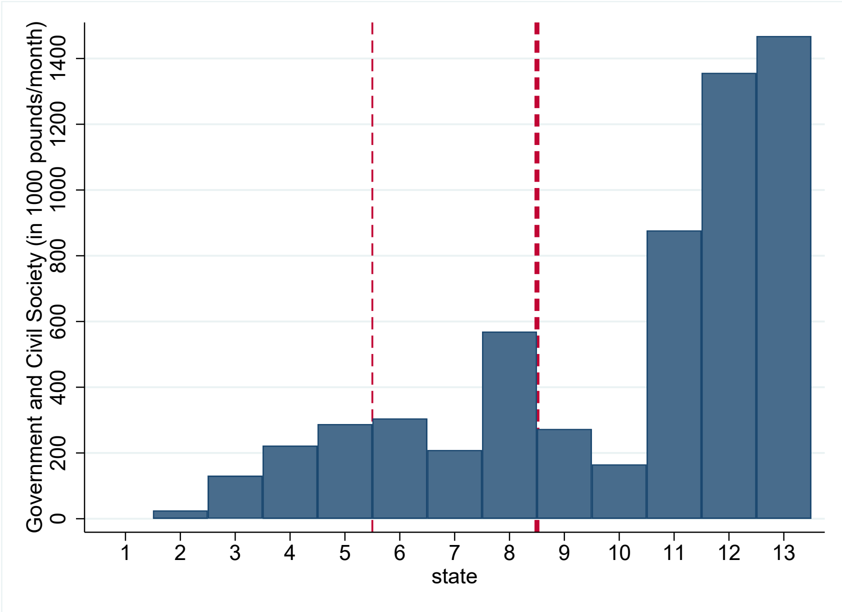
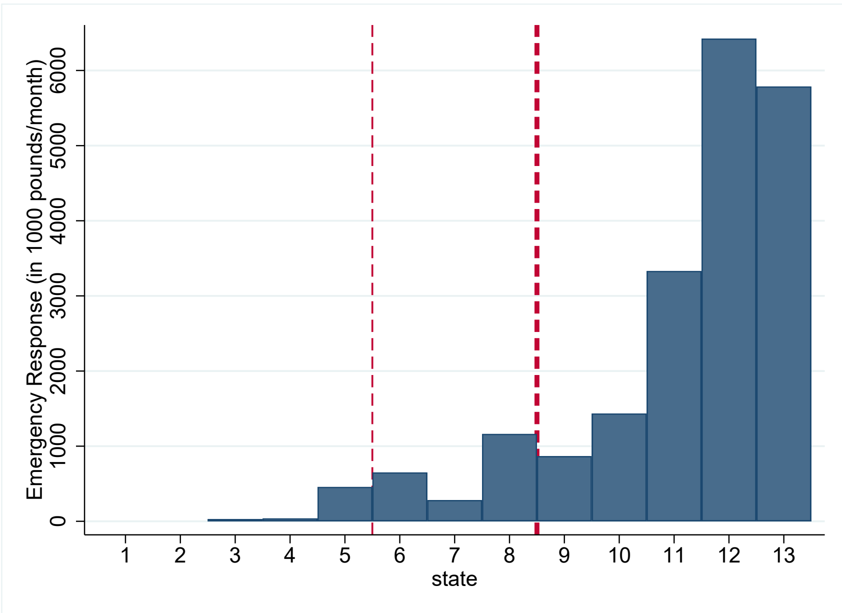
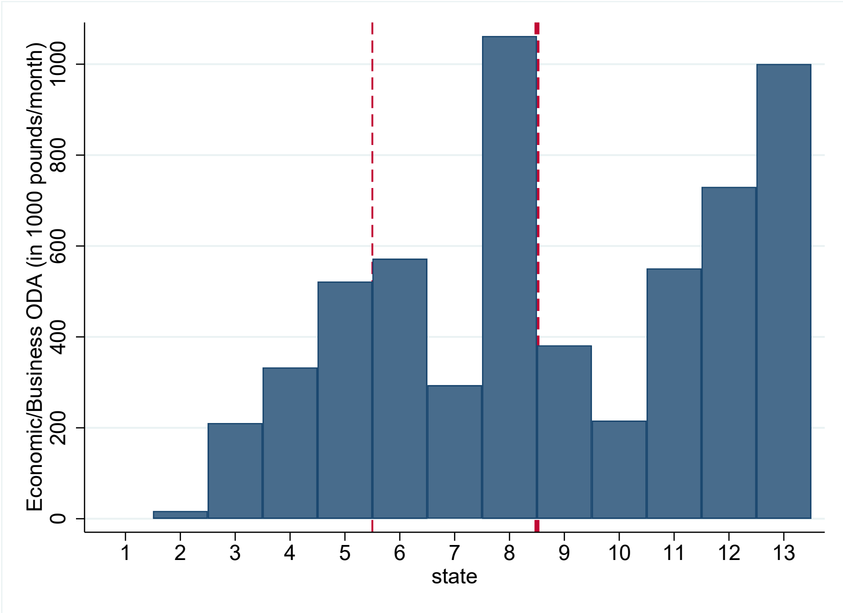


Figure B48: Average Monthly Emergency ODA by State



aspects so that it is difficult to interpret this pattern as spending targeted at stabilization.

Figure B49: Average Monthly Economic/Business ODA by State



C Annex: Optimal decision making problem

C.1 Details and numerical solution

We consider a discrete-time infinite-horizon model-environment. The environment is stationary and populated by a unique agent, a government. Each period, the government chooses whether to implement an intervention policy on a targeted country or not. The targeted country is characterized by a dimension s, which we call *state*, meant to be an indicator for conflict outlook. We assume $s \in \mathcal{S} = [1, 2, ..., S]$, ordered by how severe is the warning flag that has been raised in the targeted country, with $s = 1$ being the state with least severe conflict flag and $s = S$ being the state with most severe one. In the numerical solution, we fix $S = 13$. Depending on the state of a targeted country, a different damage is incurred. Let $-\pi(s)$ denote the damage caused by conflict in state s. We refer to $-\pi(s)$ also as per-period payoff.

Targeted countries transit between different states s over time and the likelihood of moving between states is governed by a transition function, Γ^n, which is defined as follows

$$\Gamma^n = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,S} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,S} \\ \vdots & \vdots & p_{s,s'} & \vdots \\ p_{m,1} & p_{m,2} & \cdots & p_{S,S} \end{pmatrix}$$

In the matrix Γ^n, a generic entry $p_{s,s'}$ denotes the probability of moving *tomorrow* to a state s' conditional on being *today* in a state s. By construction, each of the entry cannot be negative, $s' \geq 0$, and each row sums to one, $\sum_{s'} p_{s,s'} = 1, \quad \forall s \in \mathcal{S}$.

To capture different intervention opportunities, we group states in three categories. The first category includes 5 states pre-conflict, $\mathcal{S}^e = [1, 2, 3, 4, 5]$. An intervention implemented in state $s \in \mathcal{S}^e$ is meant to capture *early prevention opportunities*. The second category of states, $\mathcal{S}^l = [6, 7, 8]$ includes 3 post-conflict states, and any intervention in these states is meant to capture *late prevention opportunities*. Finally, the last category $\mathcal{S}^s = [9, 10, 11, 12, 13]$, includes the remaining five conflict states, and any intervention in these states is meant to represent *stabilization opportunities*.

In the model, implementing an intervention allows the government to modify the transition function so that probability mass is moved away from more risky states s', with a certain degree of effectiveness $\tau \in (0, 1)$.

Specifically, we assume the two forms of prevention (early and late) allow the government to increase in the persistency of pre-conflict states or post-conflict state respectively, meaning they allows to move probability mass from future conflict states to pre-conflict or post-conflict ones. Therefore, with prevention, the probability of moving from state $s \in \mathcal{S}^e$ to any $s' > s$ becomes:

$$p_{s,s'}(\tau) = (1 - \tau)p_{s,s'} \quad \forall s' > s$$

while the probability of remaining in the same pre- or post-conflict state $s \in \mathcal{S}^e$ becomes

$$p_{s,s}(\tau) = p_{s,s} + \tau \sum_{s'>s} p_{s,s'} \quad \forall s \in \mathcal{S}^e \cup \mathcal{S}^l$$

On the other hand, we assume stabilization allows the government to decrease the persistency of conflict states, i.e. they allow to move probability mass from the current conflict states to pre- or post-conflict ones. Therefore, with stabilization, the probability of moving from state $s \in \mathcal{S}^s$ to any $s^{'} < s$ becomes:

$$p_{s,s'}(\tau) = (1 + \tau)p_{s,s'} \quad \forall s' < s$$

while the probability of remaining in the same conflict or post-conflict states $s \in \mathcal{S}^s$

$$p_{s,s}(\tau) = p_{s,s} - \tau \sum_{s'<s} p_{s,s'} \quad \forall s \in \mathcal{S}^s$$

Let $\Gamma^i(\tau)$ be the transition function when any of the above intervention is implemented, i.e.

$$\Gamma^i(\tau) = \begin{pmatrix} p_{1,1}(\tau) & p_{1,2}(\tau) & \cdots & p_{1,S}(\tau) \\ p_{2,1}(\tau) & p_{2,2}(\tau) & \cdots & p_{2,S}(\tau) \\ \vdots & \vdots & p_{s,s'}(\tau) & \vdots \\ p_{m,1}(\tau) & p_{m,2}(\tau) & \cdots & p_{S,S}(\tau) \end{pmatrix}$$

Having defined what each intervention does, and how the transition function changes upon intervention, we can describe the optimal decision making problem of the government.

We assume the government has the option of intervening only in the current period and not anymore in the future. This feature of the model is critical, since it allows us to avoid making any assumption on the values of the intervention costs across states. When solving the decision making problem, the government compares the value of intervening today with a degree of effectiveness τ, denoted by $V^i(s;\tau)$, and equal to

$$V^i(s;\tau) = \sum_{s' \in \mathcal{S}} p_{s',s}(\tau)\tilde{V}^n(s')$$

against $V^n(s)$, which is the value of not intervening today, defined as

$$V^n(s) = \sum_{s' \in \mathcal{S}} p_{s',s}\tilde{V}^n(s')$$

Notice that the difference across the two values is in only in the transition matrix, which varies depending on whether an intervention is implemented or not, and depending on the effectiveness of the intervention.

Finally, the function $\tilde{V}^n(s)$ is the continuation value, which is equal to expected discounted sums of current and future payoffs:

$$\tilde{V}^n(s) = -\pi(s) + \frac{1}{1+r}\sum_{s' \in \mathcal{S}} p_{s',s}\tilde{V}^n(s')$$

where $-\pi(s)$ is the per-period cost, which is function of the state of conflict s, while r is a discount rate. We define *gains from intervention* in this model the difference between the value of intervening today and the value of not intervening, i.e.

$$\text{gain}(s;\tau) = V^i(s;\tau) - V^n(s)$$

The *gains from intervention* can be interpreted as expected discounted damages that are prevented by intervening today. The gains depends on current state s of the targeted country and the effectiveness of the intervention. On the other hand, by construction, the gains from intervention don't depend on the value of intervention cost, since the government is assumed not to intervene in the future. Therefore, these gains should be interpreted as benefit from intervening and can be confronted against the relative cost.

C.2 Calibration

In the quantitative analysis, we impose a discount rate r of 4%, which implies a discount factor $\frac{1}{1+r}$ equal to 0.96. Moreover, we solve the model assuming three different degree of intervention effectiveness $\tau \in (0.02, 0.05, 0.1)$. We label a government with 2% effectiveness as *pessimistic*, the one with 5% effectiveness as *neutral*, and the one with 10% effectiveness as *optimistic*. Finally, the transition function under no intervention, Γ^n, is equal to:

$$\Gamma^n = \begin{pmatrix}
0.8591 & 0.1279 & 0.0086 & 0.0027 & 0.0015 & 0 & 0 & 0 & 0.0003 & 0 & 0 & 0 & 0 \\
0.1279 & 0.7179 & 0.1391 & 0.0130 & 0.0018 & 0 & 0 & 0 & 0.0003 & 0 & 0 & 0 & 0 \\
0.0130 & 0.1446 & 0.7444 & 0.0903 & 0.0062 & 0 & 0 & 0 & 0.0015 & 0 & 0 & 0 & 0 \\
0.0006 & 0.0077 & 0.1027 & 0.8380 & 0.0484 & 0 & 0 & 0 & 0.0027 & 0 & 0 & 0 & 0 \\
0.0003 & 0.0021 & 0.0021 & 0.0551 & 0.9312 & 0 & 0 & 0 & 0.0086 & 0.0003 & 0 & 0 & 0.0003 \\
0 & 0 & 0.0011 & 0 & 0.0216 & 0.9468 & 0.0227 & 0 & 0.0078 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0.0050 & 0.0440 & 0.8908 & 0.0201 & 0.0351 & 0.0033 & 0.0011 & 0 & 0.0006 \\
0 & 0 & 0 & 0 & 0.0006 & 0 & 0.0556 & 0.7115 & 0.1084 & 0.0661 & 0.0239 & 0.0267 & 0.0072 \\
0 & 0 & 0 & 0 & 0 & 0.0019 & 0.1068 & 0.4680 & 0.3495 & 0.0524 & 0.0194 & 0 & 0.0019 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.2369 & 0.0311 & 0.5845 & 0.1340 & 0.0097 & 0.0039 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1087 & 0.0019 & 0.1126 & 0.6718 & 0.0990 & 0.0058 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1070 & 0.0019 & 0.0058 & 0.0856 & 0.7101 & 0.0895 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0291 & 0.0019 & 0.0039 & 0.0019 & 0.0913 & 0.8718
\end{pmatrix}$$

With 5% effectiveness, the transition function under intervention becomes:

$$\Gamma^i(0.05) = \begin{pmatrix}
\textcolor{blue}{0.8661} & \textcolor{red}{0.1215} & \textcolor{red}{0.0081} & \textcolor{red}{0.0025} & \textcolor{red}{0.0014} & 0 & 0 & 0 & \textcolor{red}{0.0003} & 0 & 0 & 0 & 0 \\
0.1279 & \textcolor{blue}{0.7256} & \textcolor{red}{0.1322} & \textcolor{red}{0.0123} & \textcolor{red}{0.0017} & 0 & 0 & 0 & \textcolor{red}{0.0003} & 0 & 0 & 0 & 0 \\
0.0130 & 0.1446 & \textcolor{blue}{0.7493} & \textcolor{red}{0.0858} & \textcolor{red}{0.0059} & 0 & 0 & 0 & \textcolor{red}{0.0014} & 0 & 0 & 0 & 0 \\
0.0006 & 0.0077 & 0.1027 & \textcolor{blue}{0.8406} & \textcolor{red}{0.0460} & 0 & 0 & 0 & \textcolor{red}{0.0025} & 0 & 0 & 0 & 0 \\
0.0003 & 0.0021 & 0.0021 & 0.0551 & \textcolor{blue}{0.9317} & 0 & 0 & 0 & \textcolor{red}{0.0082} & \textcolor{red}{0.0003} & 0 & 0 & \textcolor{red}{0.0003} \\
0 & 0 & 0.0011 & 0 & 0.0216 & \textcolor{blue}{0.9484} & \textcolor{red}{0.0216} & 0 & \textcolor{red}{0.0074} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0.0050 & 0.0440 & \textcolor{blue}{0.8938} & \textcolor{red}{0.0191} & \textcolor{red}{0.0333} & \textcolor{red}{0.0032} & \textcolor{red}{0.0011} & 0 & \textcolor{red}{0.0005} \\
0 & 0 & 0 & 0 & 0.0006 & 0 & 0.0556 & \textcolor{blue}{0.7231} & \textcolor{red}{0.1030} & \textcolor{red}{0.0628} & \textcolor{red}{0.0227} & \textcolor{red}{0.0253} & \textcolor{red}{0.0069} \\
0 & 0 & 0 & 0 & 0 & \textcolor{blue}{0.0020} & \textcolor{blue}{0.1121} & \textcolor{blue}{0.4914} & \textcolor{red}{0.3207} & 0.0524 & 0.0194 & 0 & 0.0019 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \textcolor{blue}{0.2487} & \textcolor{blue}{0.0326} & \textcolor{red}{0.5711} & 0.1340 & 0.0097 & 0.0039 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \textcolor{blue}{0.1142} & \textcolor{blue}{0.0020} & \textcolor{blue}{0.1183} & \textcolor{red}{0.6607} & 0.0990 & 0.0058 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \textcolor{blue}{0.1124} & \textcolor{blue}{0.0020} & \textcolor{blue}{0.0061} & \textcolor{blue}{0.0899} & \textcolor{red}{0.7001} & 0.0895 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \textcolor{blue}{0.0306} & \textcolor{blue}{0.0020} & \textcolor{blue}{0.0041} & \textcolor{blue}{0.0020} & \textcolor{blue}{0.0958} & \textcolor{red}{0.8654}
\end{pmatrix}$$

where the red entries are those that reduce after the intervention, while the blue ones are those that increase.

D Annex: Further case studies

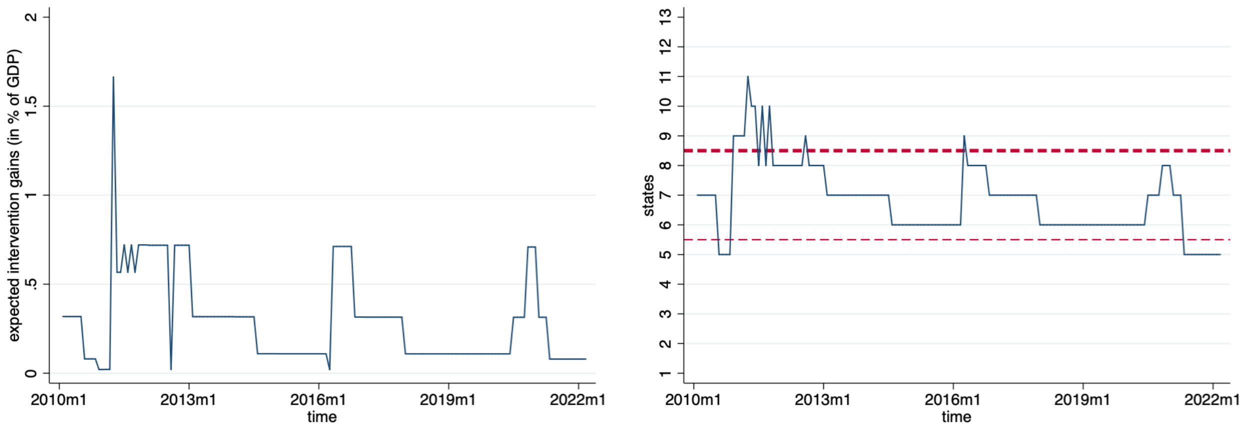
Below we highlight few other case studies of interest. We focus on intervention gains and conflict dynamics of Ivory Coast (Figure D50), Burundi (Figure D52), Armenia (Figure D54) Nigeria (Figure D56) and the Philippines (Figure D58).

D.1 The case of Ivory Coast

Figure D50: Gains and conflict dynamics in Ivory Coast

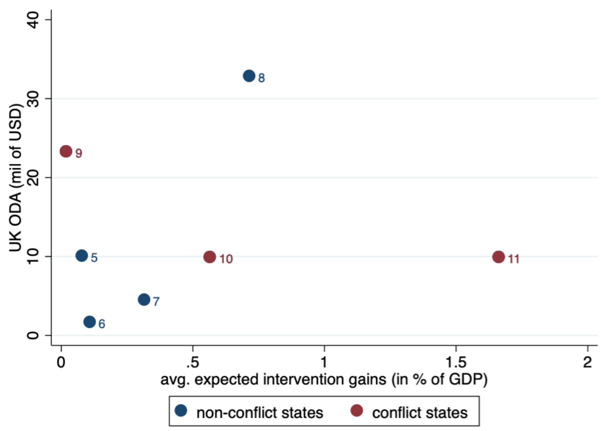
(a) Expected Intervention Gains

(b) Conflict states



Notes: In Panel (a) we report the state of the country over time (blue line). Red thin dashed line separate pre-conflict from post-conflict states. Red thick dashed line separates post-conflict from conflict states. In Panel (b) we report the expected intervention gains associated to each state of the country over time.

Figure D51: Gains versus UK ODA in Ivory Coast

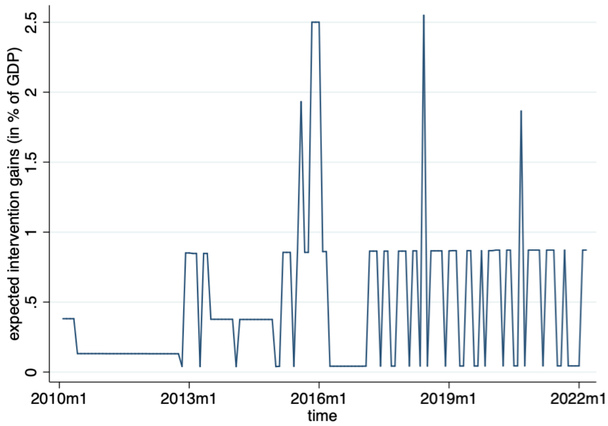


Notes: Each dot denotes the UK ODA (in mil of USD) against the expected intervention gains (in % of GDP) averaged over time separately across states. States are reported next to each dot.

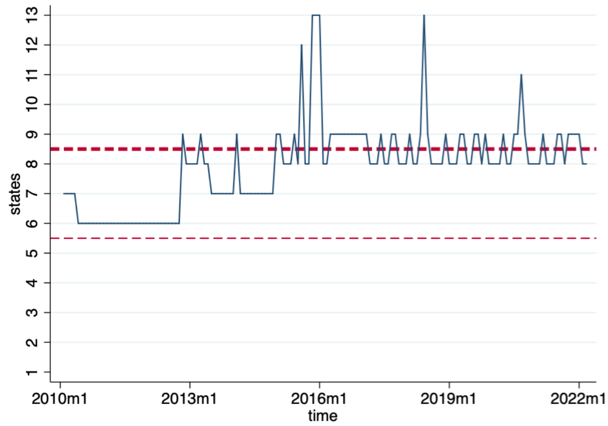
D.2 The case of Burundi

Figure D52: Gains and conflict dynamics in Burundi

(a) Expected Intervention Gains

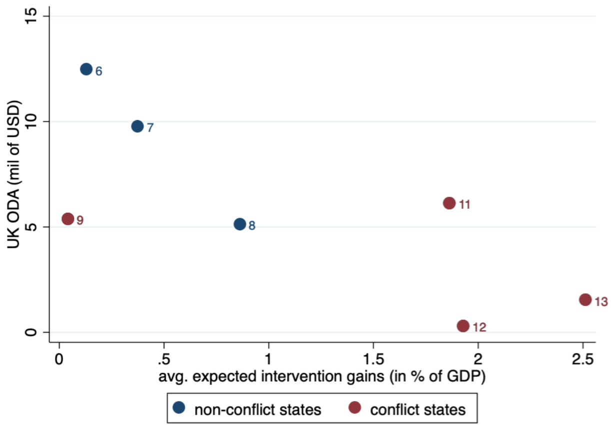


(b) Conflict states



Notes: In Panel (a) we report the state of the country over time (blue line). Red thin dashed line separate pre-conflict from post-conflict states. Red thick dashed line separates post-conflict from conflict states. In Panel (b) we report the expected intervention gains associated to each state of the country over time.

Figure D53: Gains versus UK ODA in Burundi

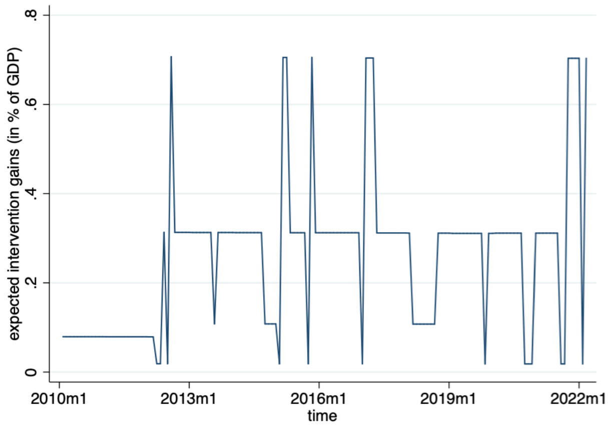


Notes: Each dot denotes the UK ODA (in mil of USD) against the expected intervention gains (in % of GDP) averaged over time separately across states. States are reported next to each dot.

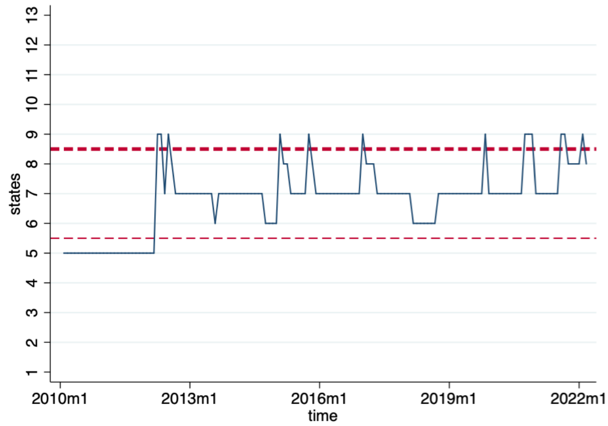
D.3 The case of Armenia

Figure D54: Gains and conflict dynamics in Armenia

(a) Expected Intervention Gains

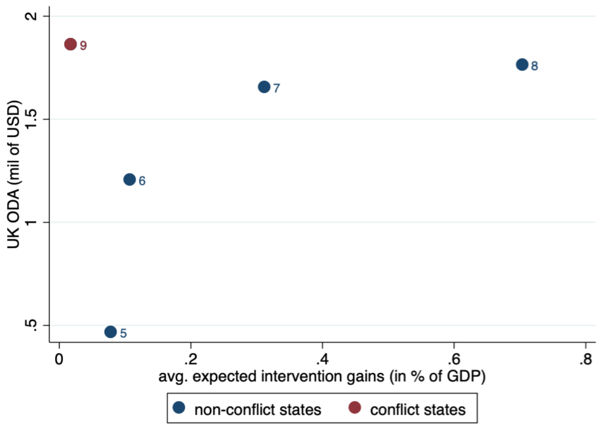


(b) Conflict states



Notes: In Panel (a) we report the state of the country over time (blue line). Red thin dashed line separate pre-conflict from post-conflict states. Red thick dashed line separates post-conflict from conflict states. In Panel (b) we report the expected intervention gains associated to each state of the country over time.

Figure D55: Gains versus UK ODA in Armenia

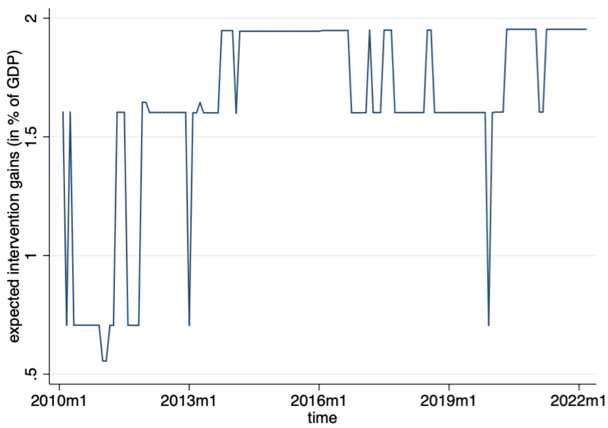


Notes: Each dot denotes the UK ODA (in mil of USD) against the expected intervention gains (in % of GDP) averaged over time separately across states. States are reported next to each dot.

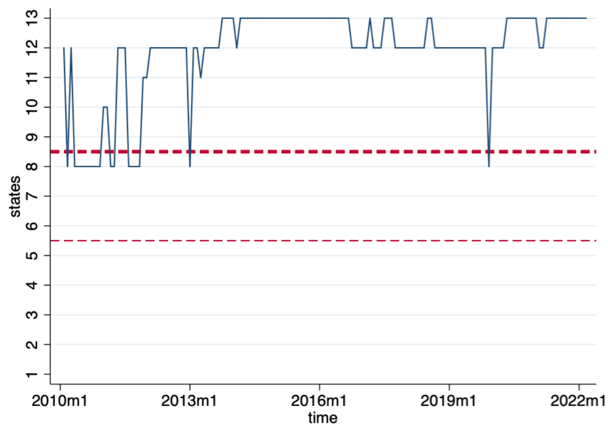
D.4 The case of Nigeria

Figure D56: Gains and conflict dynamics in Nigeria

(a) Expected Intervention Gains

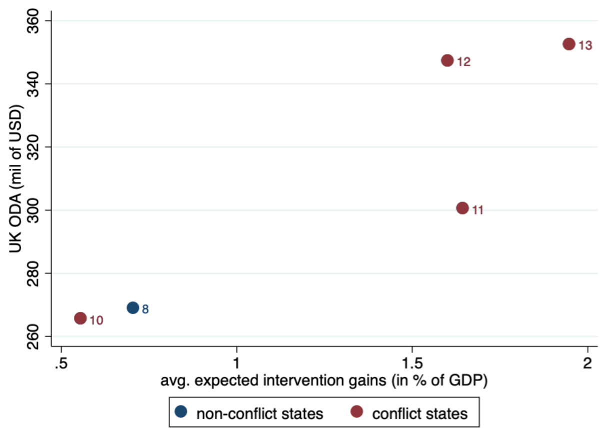


(b) Conflict states



Notes: In Panel (a) we report the state of the country over time (blue line). Red thin dashed line separate pre-conflict from post-conflict states. Red thick dashed line separates post-conflict from conflict states. In Panel (b) we report the expected intervention gains associated to each state of the country over time.

Figure D57: Gains versus UK ODA in Nigeria

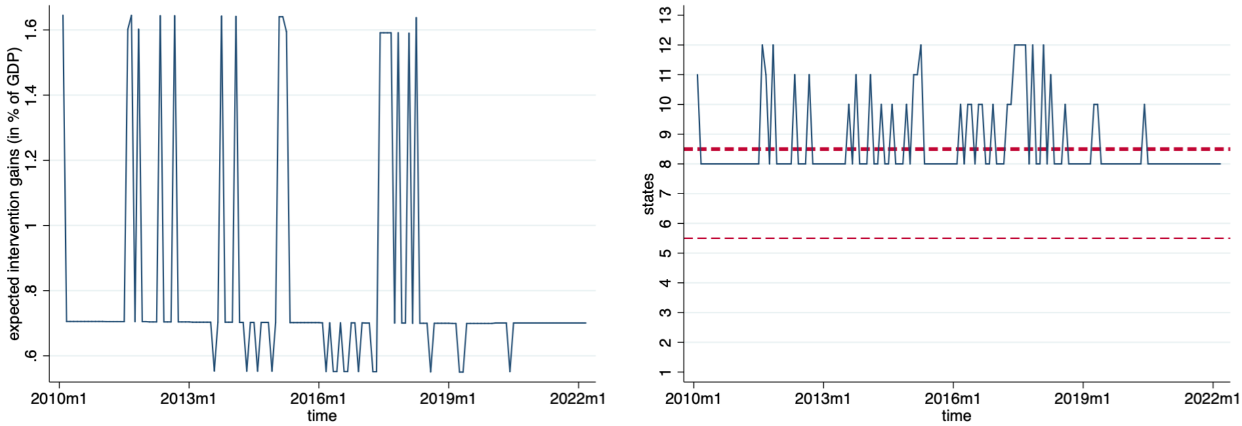


Notes: Each dot denotes the UK ODA (in mil of USD) against the expected intervention gains (in % of GDP) averaged over time separately across states. States are reported next to each dot.

D.5 The case of the Philippines

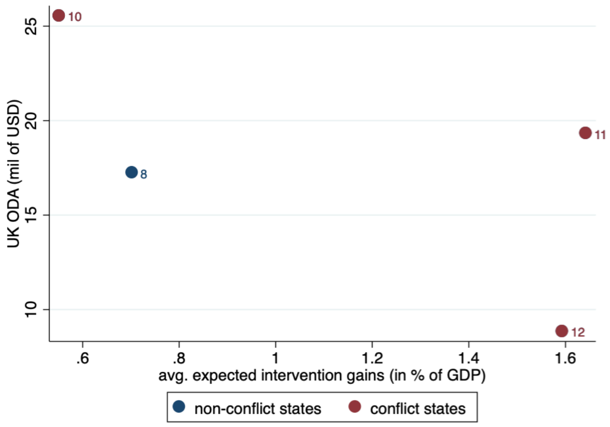
Figure D58: Gains and conflict dynamics in the Philippines

(a) Expected Intervention Gains (b) Conflict states



Notes: In Panel (a) we report the state of the country over time (blue line). Red thin dashed line separate pre-conflict from post-conflict states. Red thick dashed line separates post-conflict from conflict states. In Panel (b) we report the expected intervention gains associated to each state of the country over time.

Figure D59: Gains versus UK ODA in the Philippines



Notes: Each dot denotes the UK ODA (in mil of USD) against the expected intervention gains (in % of GDP) averaged over time separately across states. States are reported next to each dot.