Challenging the status quo: Predicting violence with sparse decision-making data

Konstantin Bätz, Ann-Cathrin Klöckner, and Gerald Schneider

aUniversity of Konstanz; bUppsala University

ABSTRACT
This article addresses the discrepancy between the explanation and the prediction of political violence through the development of different models that approximate the decision-making on war and peace. Borrowing from the crisis bargaining literature, the prediction models particularly consider the situational attributes through which players can challenge the status quo. We distinguish between direct and indirect proxies of a weakening of the status quo and show that adding decision-making data can improve the accuracy of cross-sectional forecasting models. The study, which demonstrates the increased conflict risk due to the COVID-19 pandemic and thus another development upsetting the status quo, discusses the usefulness of decision-making forecasts through various case study illustrations.

KEYWORDS
Africa; civil war; decision making; prediction

Este artículo aborda la discrepancia entre la explicación y la predicción de la violencia política mediante la elaboración de diversos modelos que se acercan a la toma de decisiones sobre la guerra y la paz. Inspirados en las publicaciones sobre negociaciones de crisis, los modelos de predicción consideran, en particular, las características situacionales a través de las cuales las piezas claves pueden desafiar el statu quo. Distinguiemos entre indicadores directos e indirectos de un debilitamiento del statu quo y demostramos que la incorporación de datos sobre la toma de decisiones puede mejorar la precisión de los modelos de previsión transversal. El estudio, que demuestra el aumento del riesgo de conflicto durante la pandemia de la COVID-19 y, por lo tanto, otro acontecimiento que altera el statu quo, analiza la utilidad de las previsiones para la toma de decisiones mediante diferentes ejemplos de casos prácticos.

Cet article aborde la divergence entre l’explication et la prévision de la violencia politique par le développement de différents modèles qui permettent une estimation des prises de décisions sur la guerre et la paix. S’inspirant de la littérature sur les négociations de crises les modèles de prévision prènnent...

CONTACT
Gerald Schneider
gerald.schneider@uni-konstanz.de
Graduate School of the Social and Behavioural Sciences, University of Konstanz, Konstanz, Germany

This article was originally published with errors, which have now been corrected in the online version. Please see Correction (http://dx.doi.org/10.1080/03050629.2022.2051024).

Supplemental data for this article can be accessed on the publisher’s website.

© 2022 The Author(s). Published with license by Taylor & Francis Group, LLC.

This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives License (http://creativecommons.org/licenses/by-nc-nd/4.0/), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited, and is not altered, transformed, or built upon in any way.
Introduction

Historical accounts of the origins of wars as well as cutting-edge models of armed conflict rest on the realist conjecture that war starts with a challenge to the status quo. One heretic strand within the realist literature, the power transition approach, maintains that the risk of war grows when an emerging power is dissatisfied with the current situation (Organski and Kugler 1980). The crisis bargaining literature has formalized this intuition, demonstrating that the utility of the status quo in comparison to the costs of conflict influences the risk of an escalatory confrontation (e.g. Morrow 1989).1

Although the crisis bargaining model has made some inroads into the literature on civil wars (e.g. Nygård and Weintraub 2015), comparative studies largely resort to structural conditions to explain the escalation of internal political violence. Theoretical models that focus on such slowly changing variables have been the backbone of early attempts to predict internal unrest (e.g. Rost, Schneider, and Kleibl 2009). Although such predictors are crucial for risk assessments, they might not reflect well the triggering events that quickly move society closer to the brink of war. Unsurprisingly, several studies have started to focus on explicit early warning signals, such as the killing of journalists that often forebode political violence (e.g. Gohdes and Carey 2017). Other possibilities to include possible conflict triggers, at least in an indirect way, arise through news reports about growing risks of wars (e.g. Chadefaux 2014) or the shifting anticipation of impending violence by financial markets (e.g. Schneider, Hadar, and Bosler 2017).2

The scarcity of news reports from some African states and of mature financial markets on this continent prevent us from using such information within the ViEWS prediction competition (Hegre, Vesco, and Colaresi 2022; Vesco et al 2022) that seeks to assess the predictive accuracy of

---

1This hypothesis also reflects the etymological roots of “status quo” in the Latin phrase in statu quo res erant ante bellum (“in the state in which matters were before the war”).

2The literature on forecasting violent conflicts has been reviewed, among others, by Hegre et al. (2017).
divergent forecasting models across Africa. To overcome the lack of encompassing information on short-term causes of escalations and de-escalations, we collect data on proxy conflict triggers and argue in line with the crisis bargaining literature that attempts to predict new, accelerating or declining political violence need to consider how political actors are enabled to challenge the status quo.

Our focus on decision-making indicators allows us to mirror the data-generating process of armed conflict closely, which, by definition, involves a change in the status quo level of violence. We contend that attempts to predict new or slowing political violence need to consider the possibility that a country moves to a new political equilibrium and that political violence is an option that certain actors consider using or abandoning. Forecasts of internal violence must therefore take the decision-making context into account that enables actors to challenge the current peaceful or violent power arrangement.

To evaluate our argument, we compare models that include direct and indirect correlates of a changing status quo and that are thus proxies of the decision-making process on war and peace. The direct measures are based on expert evaluations of the conflict structure of a country and anticipated events, such as scheduled elections that can upset the status quo. Indirect proxies encompass indicators that are potentially changing fast, such as the number of reported cases of COVID-19 infections, as well as some proxies that influence the status quo more slowly, but that have nevertheless a high conflict potential.

The model evaluation shows that adding direct and indirect decision-making data improves the accuracy of the forecasts. We find that including socio-economic factors increases the predictive power of the baseline model, indicating that the economic environment determines the decision-making process of actors in a conflict. Second, political triggers, like scheduled elections and leadership changes, are key in predicting political violence. Lastly, and most interestingly in the current environment, we find that the inclusion of public health variables relating to the current COVID-19 pandemic improves our predictions significantly.

**Direct and Indirect Measures of the Decision-Making Context**

Conflict forecasts frequently rely on judgmental information from a pool of a more or less arbitrary selection of experts. However, as these experts have incentives to dramatize a conflict situation, their forecasts often fail (Schneider, Hadar, and Bosler 2017). Kahneman (2011, 225) reasons that predicting violence is especially difficult as it occurs in an environment with low validity and writes: “Unreliable judgments cannot be valid

---

3Blair and Sambanis (2020) develop a similar argument and call for the inclusion of “procedural” variables. For a critique and response, see Beger, Morgan, and Ward (2021) and Blair and Sambanis (2021), respectively.
predictors of anything.” In light of the mixed experience with dramatizing media pundits and other conflict “oracles,” some studies have used descriptions by insiders with deep knowledge about a particular conflict as an input to decision- or game-theoretic models from which predictions are derived across a wide range of applications (e.g. Bueno de Mesquita 2011; Schneider, Finke, and Bailier 2010). Unlike the experts consulted by mass media, these specialists assess the current conflict situation without making an explicit forecast. We use some of the information that the ViEWS project has developed as an input to our models.

 Nonetheless, direct assessments of the conflict structure that country experts provide have the disadvantage that they are snapshots of the current situation and potentially ignore events and developments that might alter the political landscape in the future. This is the reason why we also include indirect proxies of developments that might affect the status quo and that are predictable, at least partially. We differentiate here between socio-economic and political factors that have the potential to alter the decision-making context quickly and to move a country closer to the brink of new or intensified violence. Among the often rather indirect predictors of a changing status quo, we have selected variables that the conflict literature deems as potential triggers.

 Figure 1 offers a summary of the decision-making models that we have developed to predict conflict at the monthly level across the African nations; the online Supplementary Appendix provides more detailed information. To make the forecasts comparable to the models within the ViEWS competition, we resort to a baseline model that is based on the conflict history of a country and its neighboring regions. Adding decision-theoretic variables to this null model will thus mainly be useful for countries that might fall victim to “new” violence after a period of stability or that are likely to experience a substantial escalation of an ongoing armed conflict.

<table>
<thead>
<tr>
<th>Task 1</th>
<th>Task 2</th>
<th>Task 3</th>
<th>Task 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>M0: Basic</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>M1: soc-econ triggers</td>
<td>Yes</td>
<td>Yes, no C-19</td>
<td>Yes, no C-19</td>
</tr>
<tr>
<td>M2: pol triggers</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>M3: conflict structure</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Previous conflict, country + month dummies</td>
</tr>
<tr>
<td>Economic factors, Public health (C-19)</td>
</tr>
<tr>
<td>Leadership, Elections</td>
</tr>
<tr>
<td>Number of actors, Political polarization</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Estimation Period</th>
<th>01/09-08/20</th>
<th>01/09-12/16</th>
<th>01/09-12/13</th>
<th>01/09-06/20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Testing Period</td>
<td>10/20-03/21</td>
<td>01/17-12/19</td>
<td>01/14-02/16</td>
<td>07/20-09/20</td>
</tr>
</tbody>
</table>

Figure 1. Overview of tasks and models.
The socio-economic model includes some relatively stable features, such as the GDP of a country as well as its regime type, but also more quickly changing economic indicators, such as inflation. GDP and regime type provide the background conditions within which a conflict might take place or escalate. As the political economy literature has shown, food price shocks and inflation crises increase the conflict potential within states (e.g. Fjelde 2015). Price shocks signal shortages and could potentially prolong a violent conflict, even though they are not necessarily related to the mass mobilizations and the possible conflict onsets that follow from them (Bazzi and Blattman 2014). Similarly, natural resource income has been shown to be associated with conflict, which is why we include oil prices in our empirical analysis. In line with the empirical literature, we expect that fighting will decline during a religious holiday, especially during Ramadan (Reese, Ruby, and Pape 2017).

We attribute a similar potential to upset the political power balance to public health crises, such as the COVID-19 pandemic. Mehrl and Thurner (2021) show in an early study that this global crisis, and the policy measures associated with it, has had heterogeneous effects across the world and that the lockdowns occurring in the Middle East can be linked with an increase in conflict. Kraemer et al. (2020) suggest that the Ebola outbreak of 2018 was more severe in conflict-affected regions of the Democratic Republic of Congo and that the violence intensified in regions experiencing this earlier pandemic. As the time series for the Corona crisis is too short for inclusion in the ViEWS competition, we include it in a separate model.

A further model includes political triggers. Scheduled elections provide a window of opportunity for the opposition to voice its discontent and thus create uncertainty over the sustainability of the status quo. A rich empirical literature in this vein shows that electoral violence is a regular attribute of a diverse range of political systems (e.g. Birch, Daxecker, and Höglund 2020), frequently triggering violence if the anticipated or realized victory is narrow or if the election fraud is too blatant. The risk of a challenge to the status quo also grows with the biological age of an already elderly leader and with the dissatisfaction of the political elite, which translates into an increased probability of a coup d’état. As the literature demonstrates, coups and internal violence are intertwined. While ongoing civil wars are associated with a higher risk of the military trying to overthrow the government (Bell and Sudduth 2017), failed attempts also result in the onset or intensification of internal violence (Gassebner, Gutmann, and Voigt 2016).

**Research Design**

Our predictive models build on the ViEWS environment. The dependent variable is the log of the number of casualties in a country month,
ln\_ged\_best\_sb.\(^4\) The present work, as well as the VIEWS prediction competition, focuses exclusively on state-based violence, as the \(sb\) suffix indicates. As the structural and political explanations of conflict refer to the state level, we consider the country-month level as the appropriate unit of analysis. Moreover, key input variables, such as inflation, growth, or COVID-19 related deaths, are not available at the grid level of analysis. Additionally, we analyze the \(ged\_dummy\_sb\) variable that takes the value 1 if there is state-based violence in a given country-month, and 0 otherwise for theoretical reasons: the variables we suggest as predictors of political violence should also predict whether a discrete change takes place. For instance, a leadership change should not only increase the number of casualties but also make the occurrence of violence more likely in the first place.

Figure 1 displays key features of our models as well as the estimation and testing periods of the different tasks. Broadly put, we start with a simple lag model M0, which we then extend through the inclusion of socioeconomic variables (M1), political triggers (M2), and salient features of the conflict structure (M3).

The models are set up cumulatively. This means that all variables and specifications included in M0 are also constitutive for M1, and all characteristics of M1 also appear in M2, and so on. We use M0, based only on lags of previous conflict, country dummies, and month dummies, to establish a baseline to which we then compare the other three models. M1 in turn adds socioeconomic triggers, including economic factors like GDP per capita, inflation, oil- and food prices, and the VDem polyarchy index. In addition, this model includes data on COVID-19 casualties, caseloads, testing capacities, and the number of hospital beds. These last two indicators capture the government’s response to the pandemic. All COVID-19 proxies are measured on a per capita basis, whenever such information is available. Lastly, this model also includes a Ramadan dummy that considers if a month was overlapping with this religious holiday.\(^5\)

M2 adds political triggers, in particular the age of the political leader, life expectancy in their home country, and actual and anticipated elections. We also include here a coup-risk variable, taken from the REIGN dataset. Finally, M3 adds the conflict structure variables. These capture the number of active political actors as well as their political polarization.

\(^4\)We conduct our main analysis with the first difference of this variable, \( \delta \ln\_ged\_best\_sb\), the results without transformation are included in the online Supplementary Appendix. The source of this outcome variable is UCDP–GED, for details, see https://ucdp.uu.se/downloads/.

\(^5\)Other holidays that have a fixed calendar date will be subsumed by the month dummies included in all model specifications.
Data availability limits the time periods available for model fitting. The data from the ViEWS survey, for instance, which is the backbone of M3, is only available between 2018 and the beginning of 2021. The fact that we have access to around 350 country-months for the whole African continent compounds this problem.\(^6\) Hence, we cannot compute predictive values for time periods before 2018. Unfortunately, none of the tasks set by the competition allow us to meaningfully test our conflict structure variables. The COVID-19 related variables face similar problems, as they are not available before 2020. To still address the relevance of the COVID-19 pandemic and the ViEWS survey data, we predict the violence that is related to the pandemic with data from the spring and summer of 2020, going above and beyond the tasks formulated in the prediction competition (dubbed “task 4” in Figure 1). Lastly, we lose around 10\% of predictions when moving from the basic model 0 to model 1 and further due to the missingness of independent variables in specific country months. To alleviate this problem, we have substituted missing predictions from lower-level models. For example, the prediction for Libya in February of 2017 is missing in the predictions computed by model 1. Instead of leaving this prediction out, we substitute it with the basic model’s prediction for Libya in February of 2017.

Computationally, we rely on the scikit-learn python package (Pedregosa et al. 2011) provided in a user-friendly version by the ViEWS project.\(^7\) Within this environment, we specify random forest regressions with 200 trees per forest. The main evaluation criterion is the mean squared error (MSE). We do not set a limit for the depth per tree. These kinds of models are highly demanding in terms of computing power. We have thus conducted our computations remotely on the bwUniCluster2 High-Performance Computing Cluster.

In accordance with the parameters set out by the competition, our predictions are presented in a “step by step” fashion: For each model, we estimate seven different step-ahead predictions. The steps, denoted by \(s\), determine which data is used for the predictions. For instance, if \(s = 3\), the prediction at time \(t\) is based on the data up to and including \(t-3\). This allows us to compare the quality of forecasts disaggregated by how far into the future they predict.

**Prediction Competition Results**

In accordance with the three tasks given by the competition, we provide forecasts for three distinct testing periods. The first of these is a true out-
of-sample test for the period from October 2020 to March 2021. Task 1 represents the “true out-of-sample forecasts,” finalized and submitted before the forecasting period started and the outcome variables were realized. In Figure 2, we compare the performance of our model to that of the ViEWS benchmark. Our model consistently performs better than the benchmark in terms of forecasting error. Mean squared errors are consistently lower, even though the differences are small. Our forecasts in task 1 were based on Covid-19 data, the socio-economic structure variables, and political trigger variables.

As indicated, tasks 2 and 3 exclude the public health variables, as the COVID-19 pandemic falls outside of the test range. Additionally, the conflict structure variables are unusable for all tasks apart from task 4 discussed below. While they are included in the task 2 testing period, their coverage begins within this period. Hence, there are zero observations on which the model could be trained. Consequently, we can only implement and discuss model 0, a reduced model 1, and model 2 here. However, as indicated above, we have decided to also include a fourth testing period (task 4). This testing period covers the COVID-19 pandemic, providing ideal test conditions for the public health variables. We consciously chose an interval that covers the latter half of our sample of COVID-19 data, such that the Random Forest model has sufficient training data available to make precise forecasts.

The results of our predictions are summarized in graphical form below. To attain these, we manually computed the mean squared errors (MSEs) for all models separately. Each graph displays the different steps ahead on its x-axis, while the y-axis indicates the magnitude of the MSE. The MSE is a “deviation

---

8The full results for all tasks and all models are provided in online Supplementary Appendix C.
"meaning a lower value indicates a better prediction performance for a given step. For instance, panel d of Figure 3 shows that in step $s = 2$, the basic model has the lowest MSE score around 0.2 and performs best, followed by the model with political triggers, with MSEs of around 0.3 and 0.4, respectively. The socio-economic model performs worst in step 2, having the highest MSE. This flips in the next step, $s = 3$, where the basic model performs worst while the models with socio-economic triggers and with political triggers perform better.

Figures 3 and 4 contain two panels each. The left panel shows the results for casualty numbers (fatalities) while the right panel represents event dummy predictions. All outcome variables are first differenced. The results of task 2 are not clear-cut. The dummy models behave as posited by our
theoretical approach and deliver the expected results: including socio-economic factors and political triggers increases the accuracy for the majority of a step ahead predictions of state-based violence. This is reflected in the relative decrease of the mean squared error when comparing the basic model (M0) with the other models (M1 without political triggers, M2 including political triggers), as shown in the right panel of Figure 3. The left-hand panel displays the opposite effect: the basic model is performing no worse (in terms of MSE) than the model with socio-economic variables for steps 1 through 5, with the model with socio-economic variables and political triggers performing overall the worst.

Figure 4 shows the results from task 3 in a similar manner. These results are consistent with the ones reported for task 2, if not stronger. The forecasts most in line with theoretical expectations are in panel d, where the dummy predictions are significantly improved by the inclusion of socio-economic and political variables. The fatality predictions show the opposite dynamic. The inclusion of the theoretically grounded variables has a negative effect on accuracy in predicting the number of casualties of state-based violence. In sum, we only succeed in improving the prediction of conflict events through the addition of socio-economic and political trigger variables, reducing mean squared errors significantly.

**Decision Making Data Prediction Results**

As mentioned above, we extend our perspective to include a fourth time period for predictions, dubbed task 4. This covers July through September of 2020 and thus the height of the COVID-19 pandemic up to that point. The results for the model that uses more direct proxies of the decision
context are displayed below in a similar fashion as for tasks 2 and 3. We have continued to improve this model after the time frame of the prediction competition and added new data after the competition ended. However, none of the new data we used dates from the period after the competition deadline.

Task 4 is the only assignment that includes all data we have identified as predictively useful in the theoretical section: lags of previous conflict, the socio-economic structure, COVID-19 related variables, political triggers, and the conflict structure. Hence, it is the best representation of our theoretical efforts to predict conflict events and fatalities, even though the sample size remains exceedingly small, namely only three months.

Figure 5 shows the results for task 4, separated into two panels. The right panel shows the MSEs by step for the prediction of conflict occurrence, while the left panel provides the same metric for the prediction of fatality numbers (casualties). The accuracy of our predictions is decidedly mixed. Comparing our preferred model to the basic model, we can confirm that for the occurrence of conflict, adding theoretically motivated variables improves prediction performance for most steps. However, the basic model performs no worse in predicting casualty numbers than our preferred model specification, and significantly better for three months ahead of predictions.

The preceding sections have compared the performance of different decision-theoretic models by analyzing the accuracy of their predictions. We now proceed to compare different variables, and their contributions to our predictions, directly. Table 1 provides such a comparison. It lists the thirty most influential variables in model 3 and notes their individual importance. Unsurprisingly, lags and spatial lags are the most important features.

\[\text{Figure 6. Changes in fatalities, South Sudan.}\]

---

9In particular, the ViEWS infrastructure produces impurity-based feature importance measures (Han, Guo, and Yu 2016) for every step-ahead prediction in a given model, based on the python scikit-learn package.
The top two decision-making theoretically motivated variables are `sur_pos_avg_pw` and `kn_food_price`, which capture the power-weighted average preferred position of political actors and food prices, respectively. Multiple other conflict structure variables (i.e., variables that shape the decision-making environment of key actors), indicated by suffixes `sur_` and `surkn_` are featured prominently in Table 1, emphasizing their importance for predicting conflict. Slowly changing country attributes are also of importance, with, for instance, the VDem polyarchy index ranking in the top 10 of important variables.

We draw two conclusions from our results: firstly, the addition of theoretically motivated decision-making variables improves prediction performance in at least some cases, especially for the onset of conflict. Secondly, the inclusion of COVID-19 data is the most novel predictive element in our models. The pandemic is in many respects unique, so drawing generalized lessons for forecasting is not straightforward. However, the theoretical argument on the relevance of crises, public health or otherwise, should compel researchers to include similar data for other crises in future forecasting endeavors.

<table>
<thead>
<tr>
<th>Feature</th>
<th>( s = 1 )</th>
<th>( s = 2 )</th>
<th>( s = 3 )</th>
<th>( s = 4 )</th>
<th>( s = 5 )</th>
<th>( s = 6 )</th>
<th>( s = 7 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>time_since_greq_25_ged_best_sb</td>
<td>0.64698</td>
<td>0.63108</td>
<td>0.25427</td>
<td>0.55219</td>
<td>0.45648</td>
<td>0.66175</td>
<td>0.30577</td>
</tr>
<tr>
<td>time_since_greq_25_ged_best_os</td>
<td>0.02276</td>
<td>0.03041</td>
<td>0.21062</td>
<td>0.04784</td>
<td>0.14896</td>
<td>0.09849</td>
<td>0.11118</td>
</tr>
<tr>
<td>time_since_greq_500_ged_best_sb</td>
<td>0.02386</td>
<td>0.02287</td>
<td>0.19642</td>
<td>0.08959</td>
<td>0.02044</td>
<td>0.01286</td>
<td>0.00209</td>
</tr>
<tr>
<td>splag_1_1_1_acled_count_os</td>
<td>0.00447</td>
<td>0.01653</td>
<td>0.03357</td>
<td>0.01199</td>
<td>0.01919</td>
<td>0.01037</td>
<td>0.01275</td>
</tr>
<tr>
<td>splag_1_1_1_acled_count_sb</td>
<td>0.01770</td>
<td>0.07002</td>
<td>0.02061</td>
<td>0.05018</td>
<td>0.01898</td>
<td>0.00983</td>
<td>0.01265</td>
</tr>
<tr>
<td>splag_1_1_1_acled_count_ns</td>
<td>0.01359</td>
<td>0.01165</td>
<td>0.01921</td>
<td>0.03427</td>
<td>0.02640</td>
<td>0.00479</td>
<td>0.01104</td>
</tr>
<tr>
<td>time_since_ged_dummy_os</td>
<td>0.00250</td>
<td>0.00431</td>
<td>0.01483</td>
<td>0.00308</td>
<td>0.00152</td>
<td>0.00118</td>
<td>0.06322</td>
</tr>
<tr>
<td>vdem_v2x_polyarchy</td>
<td>0.00150</td>
<td>0.00487</td>
<td>0.01467</td>
<td>0.00966</td>
<td>0.00372</td>
<td>0.00697</td>
<td>0.00175</td>
</tr>
<tr>
<td>time_since_ged_dummy_ns</td>
<td>0.08277</td>
<td>0.01446</td>
<td>0.01423</td>
<td>0.02086</td>
<td>0.09621</td>
<td>0.00363</td>
<td>0.06658</td>
</tr>
<tr>
<td>sur_pos_avg_pw</td>
<td>0.00199</td>
<td>0.00514</td>
<td>0.01350</td>
<td>0.00748</td>
<td>0.00693</td>
<td>0.00100</td>
<td>0.00780</td>
</tr>
<tr>
<td>kn_food_price</td>
<td>0.00732</td>
<td>0.00394</td>
<td>0.01272</td>
<td>0.00502</td>
<td>0.00502</td>
<td>0.00884</td>
<td>0.04818</td>
</tr>
<tr>
<td>cdum_79</td>
<td>0.00091</td>
<td>0.00045</td>
<td>0.01182</td>
<td>0.01037</td>
<td>0.00345</td>
<td>0.00494</td>
<td>0.00000</td>
</tr>
<tr>
<td>splag_1_1_ged_best_ns</td>
<td>0.00618</td>
<td>0.00649</td>
<td>0.00991</td>
<td>0.00243</td>
<td>0.00829</td>
<td>0.00119</td>
<td>0.02422</td>
</tr>
<tr>
<td>splag_1_1_ged_best_os</td>
<td>0.00161</td>
<td>0.00745</td>
<td>0.00956</td>
<td>0.00483</td>
<td>0.00323</td>
<td>0.00272</td>
<td>0.00977</td>
</tr>
<tr>
<td>kn_relative_age</td>
<td>0.00152</td>
<td>0.00641</td>
<td>0.00925</td>
<td>0.01010</td>
<td>0.01367</td>
<td>0.00674</td>
<td>0.00438</td>
</tr>
<tr>
<td>time_since_ged_dummy_sb</td>
<td>0.03854</td>
<td>0.03621</td>
<td>0.00915</td>
<td>0.01526</td>
<td>0.00490</td>
<td>0.00366</td>
<td>0.12708</td>
</tr>
<tr>
<td>surkn_pow_var</td>
<td>0.00652</td>
<td>0.00561</td>
<td>0.00882</td>
<td>0.00172</td>
<td>0.00741</td>
<td>0.00241</td>
<td>0.00176</td>
</tr>
<tr>
<td>sur_hhi</td>
<td>0.00270</td>
<td>0.01035</td>
<td>0.00878</td>
<td>0.00641</td>
<td>0.01744</td>
<td>0.00630</td>
<td>0.00379</td>
</tr>
<tr>
<td>wdi_fp_cpi_totl</td>
<td>0.04948</td>
<td>0.01417</td>
<td>0.00851</td>
<td>0.00240</td>
<td>0.00233</td>
<td>0.01402</td>
<td>0.01080</td>
</tr>
<tr>
<td>splag_1_1_acled_count_pr</td>
<td>0.00689</td>
<td>0.00227</td>
<td>0.00846</td>
<td>0.00618</td>
<td>0.00762</td>
<td>0.00306</td>
<td>0.01373</td>
</tr>
<tr>
<td>time_since_greq_100_splag_1_1_ged_best_sb</td>
<td>0.00139</td>
<td>0.00599</td>
<td>0.00835</td>
<td>0.00685</td>
<td>0.00857</td>
<td>0.00347</td>
<td>0.0261</td>
</tr>
<tr>
<td>splag_1_1_ged_best_sb</td>
<td>0.00620</td>
<td>0.00454</td>
<td>0.00803</td>
<td>0.00563</td>
<td>0.00265</td>
<td>0.02677</td>
<td>0.01764</td>
</tr>
<tr>
<td>time_since_greq_500_ged_best_os</td>
<td>0.01477</td>
<td>0.01202</td>
<td>0.00780</td>
<td>0.01263</td>
<td>0.00456</td>
<td>0.00162</td>
<td>0.08040</td>
</tr>
<tr>
<td>time_since_ged_dummy_best_ns</td>
<td>0.00457</td>
<td>0.00225</td>
<td>0.00648</td>
<td>0.00290</td>
<td>0.00777</td>
<td>0.00713</td>
<td>0.02433</td>
</tr>
<tr>
<td>reign_coupRisk</td>
<td>0.00415</td>
<td>0.00470</td>
<td>0.00645</td>
<td>0.00314</td>
<td>0.01335</td>
<td>0.00292</td>
<td>0.00447</td>
</tr>
<tr>
<td>surkn_n_actors</td>
<td>0.00176</td>
<td>0.00228</td>
<td>0.00637</td>
<td>0.00146</td>
<td>0.00400</td>
<td>0.02160</td>
<td>0.00668</td>
</tr>
<tr>
<td>sur_pos_avg</td>
<td>0.00528</td>
<td>0.00817</td>
<td>0.00598</td>
<td>0.01584</td>
<td>0.00245</td>
<td>0.00444</td>
<td>0.00188</td>
</tr>
<tr>
<td>sur_pos_std</td>
<td>0.00484</td>
<td>0.00230</td>
<td>0.00492</td>
<td>0.00772</td>
<td>0.00422</td>
<td>0.00436</td>
<td>0.00314</td>
</tr>
<tr>
<td>sur_status_quo_location</td>
<td>0.00220</td>
<td>0.00195</td>
<td>0.00477</td>
<td>0.00710</td>
<td>0.00638</td>
<td>0.00844</td>
<td>0.00147</td>
</tr>
<tr>
<td>sur_pos_std_pw</td>
<td>0.00320</td>
<td>0.00408</td>
<td>0.00476</td>
<td>0.00100</td>
<td>0.00771</td>
<td>0.00434</td>
<td>0.00242</td>
</tr>
<tr>
<td>sur_dom_power</td>
<td>0.00378</td>
<td>0.01409</td>
<td>0.00457</td>
<td>0.00245</td>
<td>0.00964</td>
<td>0.00221</td>
<td>0.00168</td>
</tr>
</tbody>
</table>

Each column represents a different step-ahead prediction, ordered by importance at step 3.
Country-Specific Results

To assess our models, we offer some case study evidence. We start out with the case of South Sudan, where our models under-predict changes in the fatality levels of September 2018. Figure 6 illustrates this tendency. After an initial de-escalation in previous months, political conflicts picked up again in September (Pinaud 2018), despite the signing of a peace agreement (United Nations 2018). Both government and rebel forces committed acts of violence against one another, but also against civilians. While our model predicts an increase in the number of fatalities in September, it expects a decline in October, the first month after the signing of the peace agreement. This is illustrated by Figure 6. Perhaps our model anticipated this fragile agreement, which was, however, not signed by all opposition parties (Security Council 2018). This would be in line with our theoretical argument: a change in the socio-economic conditions or conflict structure predicted the peace agreement, which we would, ceteris paribus, expect to decrease the level of political violence. However, the model predicted a decrease earlier than it happened. Considering that the peace agreement was not signed until mid-September (Security Council 2018), it makes sense that the mean number of fatalities for that month did not immediately decline. Overall, our model predicted no particular change in the number of fatalities in October. However, this follows a predicted change downwards for the preceding month. In reality, the number of fatalities declined in October, which, when considering the point predictions in the context of the previous month, was predicted. Thus, our model was able to predict the changes in fatalities due to a peace agreement, the monthly aggregate just appears too rough to accurately predict the timing of the changes if the change to the status quo emerges in the middle of the month.

Nigeria serves as an example of the predictive power of the model that includes political triggers and especially scheduled elections. The country held a general election on February 23rd, 2019. This resulted in high levels of political violence related to the election, leading to a high number of fatalities in events all around the country (Pinaud 2019). While soldiers and police officers were identified as the main perpetrators, violence attributed to the Boko Haram terrorist organization as well as communal unrest added to the increase in fatalities (Human Rights Watch 2019a, 2019b). Fatalities were reported both before and after the elections, with reports of 124 fatalities related to state-based violence (Pettersson and Öberg 2020). Hence, it is not surprising that the number of fatalities remained high in February. The fact that violence was already observed before the election took place is in line with our theoretical argument: elections constitute anticipable challenges to the status quo that often increase the risk of political violence.

Figure 7 compares predicted changes in the log of fatalities with the ones recorded for February of 2019. Steps 1 and 7 of the uncalibrated model
with socio-economic variables and political triggers are quite successful in predicting fatalities in an election month. It can be expected that the more extended the forecasting horizon is, the harder it is to make accurate predictions. Step 3 predictions should be more accurate, on average, than step 7 predictions. It is, therefore, encouraging that our models predicted the level of political conflict in Nigeria seven months ahead quite accurately.

**Conclusion**

One of the main challenges for the prediction of political violence is the scarcity of cross-country information on triggers that make sudden escalations and de-escalations more likely. This has contributed to the tendency in many cross-sectional forecasting studies to rely on slowly changing attributes of a political or geographic unit to predict the level of violence. While continued grievances of the population, a deteriorating climate, or similar “structural” variables constitute key early warning indicators of growing risk, they do not provide us with sufficient information about the ability of the competing political actors to challenge the status quo and to use force in doing so. Comparative conflict forecasts thus share with seismographic studies the problem that they are able to identify regions at risk quite accurately, but that they do not necessarily predict dramatic outbreaks of violence or large-scale earthquakes with the same level of precision.

This article has introduced several models that include such escalation and de-escalation triggers. The empirical evaluation supports our claim that cross-sectional prediction comparisons should strive to include information on the

**Figure 7.** Changes in fatalities, Nigeria.
key socio-economic and political developments that potentially upset the current political status quo in a country or region. We advocate that forecasting models should especially encompass well-known triggers of political violence, such as food price shocks, scheduled elections, or military coups. The article also suggests that public health crises, such as the COVID-19 pandemic have the ability to upset the balance of power of severely affected states considerably.

Admittedly, most of the decision-making variables that we used in this article are only indirect proxies of a potentially volatile political climate. One key task for future models is therefore the usage of variables that are derived from canonical theories of war and thus potentially represent the dynamics of escalating and de-escalating violence more closely. Such information would truly align the empirical models that feed into the conflict forecasts with the baseline theoretical models of political violence. Using sparse decision-making indicators does, in other words, not absolve forecasters of violence to think more deeply about the theoretical mechanisms that influence the risk of political violence within a country.

We have argued that the study of internal conflict could resort to the crisis bargaining literature that has played a pioneering role in our understanding of international wars. However, we can think about a variety of such models and hence of decision-making variables that might be collected in the next wave of the forecasting literature.

**Acknowledgments**

We would like to thank two reviewers and the participants at the 2020 ViEWS workshop on the prediction of violence for their comments as well as Remco Jansen and Paola Vesco for their assistance. We are also thankful to Rainer Rutka and the High-Performance Computing Cluster bwHPC team for their technical support.

**Disclosure Statement**

No potential conflict of interest was reported by the authors.

**Funding**

The prediction competition and the related manuscripts have been funded by ViEWS – European Research Council, Advanced Grant no. 694640.

**ORCID**

Gerald Schneider [http://orcid.org/0000-0002-0091-6217](http://orcid.org/0000-0002-0091-6217)
References


