# The Straw that Broke the Camel's Back: Separating Close Calls from True Onsets in Conflict Prediction

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**Abstract**

Conflict forecasting seeks to correctly anticipate events of armed violence. While the field has made significant advancements, differentiating between close calls and true onsets has been overlooked despite its potential to improve our ability to predict new outbreaks of war. In this paper, we investigate why some countries with a high predicted risk of conflict experience limited violence only. We argue that the processes stalling the transition into active conflict display recurring patterns that can be leveraged to enhance conflict prediction. Against this backdrop, we introduce a methodological innovation of the *Shape finder* aimed at separating the underlying processes of true onset from stalling escalation, where low-intensity violence does not surpass a certain level. Based on the escalation spiral framework, we elaborate pathways to and away from conflict onset. Combining UCDP GED data with unpublished data on low-intensity violence that never reached the UCDP threshold, we apply a hurdle model to identify the dynamics that drive countries into armed conflict. Our preliminary results indicate that the *Shape finder* is able to separate contexts that consistently lead to armed conflict from those where intensity remains low, and that this information increases the model's ability to anticipate true onsets. Our findings highlight that the relationship between a predicted high risk and conflict onset is context specific.

*Keywords:* Conflict onset, high-risk, false-positives, escalation, de-escalation

In many forecasting contexts, including conflict prediction, the general aim is to correctly predict the occurrence of events. Conflict early-warning systems increasingly leverage advanced machine learning tools to account for processes driving political violence (Hegre et al. 2019; Mueller et al. 2024a; Raleigh et al. 2010). Predicting the outbreak of new conflict, however, remains a key challenge (Mueller and Rauh 2022). This difficulty is driven by the general low baseline risk of armed conflict (i.e., wars are rare events), but from a policy perspective, failing to anticipate onset cases yields missed opportunities. To prevent countries from falling into the *conflict trap*, the most effective intervention occurs before the initial onset of armed violence (Mueller et al. 2024b). Once a country experiences armed conflict, the probability that violence remains at that level is high, while a de-escalation is unlikely. Moreover, intervening at an early stage is less costly than missing an opportunity to act in a timely manner, due to the tremendous suffering armed conflict causes and the surge in intervention costs once violence has escalated.

In recent decades, conflict forecasters have made significant methodological, theoretical and empirical advances to improve the forecast of the actual incidence of violence. This is based on the premise that our models correctly captured the underlying processes driving violence. While existing conflict prediction models perform well when anticipating dynamics in ongoing armed violence (see Rød et al. 2024 for a review), conventional conflict predictors have proven less informative for new outbreaks, even where the predicted risk of conflict onset is high. Current conflict models extract insufficient signal from the chain of events leading up to conflict onset. In addition, we lack a good scholarly understanding of why the final determinants that push high-risk cases towards armed violence – i.e., *the straw that breaks the camel's back* – pass under our radar.

However, despite the rarity of war, armed escalation does not occur out of *nowhere*. Even cases that caught experts by surprise, such as the Gaza war in 2023, can retrospectively be assigned to preceding build-ups. Indeed, there was mass protest in Israel in reaction to an attempted judicial overhaul (Gidron 2023) right until the $7^{th}$ of October. At the same time, current forecasting approaches are yet to leverage the over-predicted onsets that never materialize. Against this backdrop, we argue that a better mechanism to differentiate between high-risk cases that actually transition to armed conflict and those that do not is required to further advance early warning.

In this study, we investigate why some countries with high predicted risk of conflict experience limited violence only. Departing from the escalation spiral framework as put forward by Pruitt and Kim (2004; 2016), we develop two distinct models: one for conflict onset and one for stalled escalations. To predict new outbreaks of armed conflict in previously peaceful settings, we leverage temporal dynamics in preceding, less violent forms of political contention, including protests and low-intensity armed conflict, as well as in processes that may halt escalation. We use the *Shape finder* methodology (Schincariol et al. 2025) to find the most similar historical analogs where low-intensity violence *did* or *did not* transition to higher levels.

To test our approach, we combine the standard UCDP Georeferenced Event Dataset (Sundberg and Melander 2013) fatalities data with unpublished events of low-intensity violence from the UCDP repository, granted specifically for our research purposes. Jointly, these conflict data provide the most complete case universe of low-intensity violence that may reach conflict onset. We deploy the *Shape finder* approach as a hurdle model, matching on sequences of low-intensity violence in countries without conflict, and subsequently uncovering the specific contexts that either spur escalation or prevent further intensification.

Our preliminary results indicate that we are able to successfully discriminate truly dangerous contexts from averted onsets. Indeed, separating escalatory and de-escalatory contexts yields a marginal improvement in out-of-sample performance. This suggests that patterns from both preceding, less violent political contention and stalled escalations can improve our ability to correctly predict true onsets, highlighting a gateway to explore, theoretically and empirically, what makes high-risk cases resilient against war.

This study makes three main contributions. Methodologically, we demonstrate the *Shape finder*'s versatility by extending the original approach to cases where autoregressive and structural predictors say less about how contention is likely to unfold. Our approach to trace simultaneous processes to predict rare events carries relevance also to other fields with high class imbalances. Theoretically, our study suggests that drivers and hampers of violence work differently for early-stage contention depending on which context they appear in. We identify the most dangerous settings based on a limited number of variables. Empirically, we are able to separate true escalatory dynamics from close calls, which may help policy-makers prioritize decision-making and resources to where they are most needed. The separation of processes in forecasting bears relevance both to the field of conflict prediction and to the wider forecasting literature.

## Literature Review

Predicting the onset of conflict is relevant for both early warning and conflict research more generally.[1] Albeit implicit, the overarching rationale of conflict forecasting is to increase the predictive performance for actual conflict (Hegre et al. 2013; Rød et al. 2024). This rational has prompted significant methodological advancements (Bazzi et al. 2022; Brandt et al. 2011; Chadefaux 2023; Hegre et al. 2021; Vesco et al. 2022), including the use of sophisticated machine-learning techniques (D'Orazio and Y. Lin 2022; Malone 2022; Radford 2022) and exploring novel data sources (Mueller et al. 2024a). Some scholars even make advances in both areas simultaneously (Brandt et al. 2022; Croicu 2025).

There is also an ongoing debate on the role of theory in conflict forecasting (Beger et al. 2021; Blair and Sambanis 2021; Colaresi and Mahmood 2017). Several forecasting studies involve theory testing (Ward et al. 2010), while fewer make use of prediction for theory development and evaluation (Croicu 2025; Dorff et al. 2020). However, there is an increasing use of causal machine-learning and interpretation methods to critically evaluate prediction models (Chadefaux 2017; Hegre et al. 2021) or use forecasting to validate the results from inference-by-design (Croicu and Kreutz, forthcoming). Despite these recent advancements, predicting new conflict outbreak remains "the hard problem of conflict prediction" (Mueller

[1] Other strands in the literature seeking to answer why some countries with a high conflict risk sometimes experience limited political violence involve research on causes of peace (e.g. Posner 2004; Hancock and Mitchell 2007) and resilience (Krause 2018); third-party prevention efforts (e.g. Beardsley et al. 2017; Tir and Karreth 2018; Cunningham et al. 2025); and government repression and civil strife remaining nonviolent (e.g. Ritter and Conrad 2016). We relate to conflict risk primarily as probability in a forecasting setting.

and Rauh 2022, p. 2442). There are two main reasons: first, conflict onset is rare, and second, traditional indicators of conflict are insufficiently tailored towards new outbreaks of violence.

### Limits of Traditional Conflict Predictors

While standard predictors of armed violence might work well for ongoing war, they do not apply equally to contexts of no violence and new outbreaks. Conflict history – the most powerful predictor for ongoing armed conflict (Croicu 2025; Hegre et al. 2025; Ward et al. 2010) – is by construction not useful for predicting violence in previously peaceful societies.

The low predictive power of structural risk indicators resonates with theoretical considerations. During political crises or heightened tension imminent to an escalation of hostilities, factors other than structural variables (e.g., conflict history, GDP per capita, and population size) are relevant to explain why some high-risk cases escalate to armed conflict while others do not. Instead, less intense political violence, such as geopolitical tensions (Chadefaux 2014) or protests (Rød et al. 2025), can help predict conflict onsets.

### Armed Conflict as Rare Event

Wars are rare events, just like earthquakes and pandemics, meaning that we see few such instances globally. While this is a great fact for humanity, the underlying data structure poses statistical issues known as the 'class imbalance problem.' An imbalanced classification task has a majority class and a minority class. To minimize the prediction error, a statistical model is encouraged to always predict the majority class (*peace*) and to simply ignore the minority one (*war*). Such a model will have a high true-negative rate but a low true-positive rate.

Due to the class imbalance problem, the best-performing conflict prediction models are often atheoretical, no-change models, where predictions cluster around the mean (Vesco et al. 2022), or null models (which always predict zero fatalities). Such models are, however, not helpful to predict conflict onset. The class imbalance has partly motivated a transition towards more nuanced prediction targets such as escalation (Hegre et al. 2022; Vesco et al. 2022) and probability distributions (Hegre et al. 2025; Brandt et al. 2014). These options better reflect actual conflict dynamics and the uncertainties surrounding them.

### Existing Conflict Prediction Models

In the scientific field of conflict prediction, three approaches are identified. *The Violence & Impacts Early-Warning System* (VIEWS) is the most comprehensive early-warning system and uses a large set of structural background factors (e.g., conflict history, economic performance, political institutions) to predict fatalities in state-based armed conflict (Hegre et al. 2024). While excelling at predicting a baseline level of armed conflict, the slow-moving nature of the structural variables makes VIEWS less well-suited to anticipate conflict onsets.

Another approach is proposed by *Conflict Forecast* (Mueller et al. 2024a), leveraging news data to forecast fatalities in armed violence. The project can be seen as a complement to VIEWS, due to its specific focus on new conflict outbreaks. At the same time, news-based forecasting has been accused of being tautological (Jäger 2016), predicting conflict with preceding political tensions rather than extracting true precursors.

Finally, the *Shape finder* (Schincariol et al. 2025) is a risk-taking model aimed at predicting dynamics in ongoing war. Its autoregressive setup, i.e., predicting fatalities in the future with fatalities in the past, is optimal for capturing variability in ongoing violence, but cannot anticipate onsets. By definition, the *Shape finder* model always predicts zero fatalities for cases that only take zero as inputs.

### The Role of False-Positives

Existing conflict prediction models continue to perform poorly at predicting onsets, and likewise show a tendency to over-predict new outbreaks when they *do not* occur. In the quest to capture the few onsets there are, most efforts are directed towards enhancing the model's ability to capture the dynamics leading to onsets, while over-predictions (i.e., so-called false-positives) have been systematically overlooked. However, accounting for processes that prevent armed escalation in high-risk contexts, or better understanding what pushes hostile situations towards new outbreaks of violence (i.e., what *breaks the camel's back*) might further enhance conflict prediction.

Against this background, we propose to take a double grip on the processes driving and stalling the escalation to armed violence. Cases where we observe a high predicted risk but no conflict onset offer a window of opportunity to learn something novel from false alarms. Specifically, we seek to identify the contexts under which high-risk cases *might* and *might not* escalate to more substantial levels of armed violence.

## Theoretical framework

To understand the dynamics under which low-intensity violence does or does not escalate into conflict onset, we apply the escalation spiral framework by Pruitt and Kim (2004). Below, we develop two distinct conflict outcomes: the escalatory trajectory leading to onset (i.e., protest and clandestine pathways), and the de-escalatory trajectory that stalls escalation before conflict outbreak, through pathways of victory or compromise.

### Escalatory Trajectory

Armed conflict does not occur out of nowhere. Instead, more substantial armed violence is preceded by initial contentious politics, such as protests and low-intensity armed violence. If conflict emerges in society and remains unresolved by existing institutions, the non-state actor might engage in contentious politics. Contentious politics revolve around interactions between the government and a collective of claim-makers, where the latter puts forward demands concerning the former (Tilly and Tarrow 2012). Political contention occurs through a range of tactics, such as demonstrating, striking, and road blockades (i.e., less violent), but also kidnappings, terrorist attacks, and direct killings (i.e., more violent). Against this background, there are two pathways to civil war onset: the protest and the clandestine pathway.

#### The Protest Pathway

In the protest pathway, the claim-makers opt for less violent forms of contention (i.e., protest, riots) due to the higher chances of success (Chenoweth 2023; Stephan and Chenoweth 2008). Non-violent resistance increases the legitimacy of a movement, and state repression is more likely to backfire when the opposition remains peaceful. Nevertheless, peaceful collective action might transition to civil conflict if the majority of protesters believe that non-violent tactics have failed and that armed resistance is the only option left (Rød and Weidmann 2023). Alternatively, protest transitions to violent conflict if an existing armed actor perceives mass protest as a window of opportunity to attack the government (ibid.).

### The Clandestine Pathway

Conversely, the claim-makers might opt for violent resistance at the outset, but need to mobilize first, given that non-state actors have no immediate access to arms. The non-state actor often operates undetected and therefore has the strategic advantage of waiting to attack until sufficient military means are procured (Malone 2021). Rebel mobilization is at the heart of the clandestine pathway. Obtaining military capabilities may produce initial fatalities from remote violence and other forms of low-intensity organized violence: (i) *state-based conflict*, as the claim-makers might attempt to steal arms directly from the government (Jackson 2010), (ii) *one-sided violence*, as the non-state actor might extract resources from the civilian population (Azam 2002), or (iii) *non-state conflict*, as the claim makers seek to extract capabilities from other groups (Fjelde and Nilsson 2012).

### Escalation Spiral

The continued interactions between the government and the non-state actor might prompt an *escalation* process, where both parties apply heavier tactics (Pruitt and Kim 2016). Contentious politics is a dynamic phenomenon where the behavior of the government is tailored towards the tactics of the opposition (i.e., tactical adaptation), and the claim makers modify their approaches to better evade state repression (i.e., tactical adaptation) (McAdam 1983). These strategic interactions push collective action towards more violent manifestations, ultimately leading to civil conflict. More substantial levels of armed conflict, in this way, are preceded by certain patterns in low-intensity collective action, which are produced by the interactions of government and claim-makers (Schincariol et al. 2025).

## De-Escalatory Trajectory

In contentious settings, there are several mitigating processes that can take place and avert conflict onset, in particular, two possible outcomes of the escalation spiral itself: victory and compromise (Pruitt and Kim 2016; Wallensteen 2015). We begin by recognizing that not all societies are equally receptive to conflict triggers. Indeed, some societal factors place *structural* limits on the likelihood of escalation.

### Resilience Against Conflict

First, social cohesion and cultural tightness might absorb or divert grievances into less contentious claim-making. Specifically, the ethno-political bargaining structure and presence of regional autonomy makes armed contention less likely to begin with (Buhaug et al. 2021; Germann and Sambanis 2021; Hillesund 2022; Mustasilta 2019). Second, the population may be less susceptible to rebel recruitment if individuals perceive that there are alternative routes to subsistence and political engagement. We consider alternative types of organized violence, such as gang violence and criminal activity, where recruits can obtain monetary profit. Shifting patterns in the landscape of political violence, therefore, depend on the relative benefits connected to such activities (Gutiérrez-Sanín and Wood 2017; Kalyvas 2019).

Lastly, the way claims have been catered for, including as the result of a peace process (Kreutz 2018), affects dissidents' trust that their grievances will be taken into account through regular politics. In democratizing countries, institutional checks and balances offer conflict-resolution mechanisms and alternative routes for voicing demands (Dudouet 2013). Even in more risk-prone hybrid regimes (i.e., anocracies), the accountability mechanisms of democratic institutions have been found to exert a constraining effect on elite-based and popular dissent (Fjelde et al. 2021). Peace agreement signatories are invested in the negotiated political process in which they have continued bargaining power. The organizational capacities of the former rebel constituencies may also change in the wake of a peace process, as warring groups demobilize as part of the negotiated settlement (Kreutz 2018).

Conversely, when societal resilience is low and conflict parties find themselves in an escalatory spiral, we theorize two distinct de-escalatory routes away from conflict outbreak: the victory pathway, where the government gains ground, and the compromise pathway, where the parties engage in talks, with or without the support of third-party actors.

### The Victory Pathway

During early-stage contention, we define victory as obtaining long-term rather than temporary advantages over the opponent. A theoretical implication of this pathway is that we may observe short-term escalation before a significant reduction in violence. Faced with growing resistance, governments may opt for preemptive repression to deter future dissent (Walter 2006; Ritter and Conrad 2016; Bartusevičius and Skaaning 2018; Bartusevičius and K. S. Gleditsch 2019). Power asymmetries speed up these processes. Limited domestic support (Shellman et al. 2013) as well as rival group competition, in-group fighting and fragmentation (Bakke et al. 2012) may reduce the relative power and capabilities of certain non-armed actors, facilitating their defeat at the earliest stages of contention.

### The Compromise Pathway

A compromise is sought when both parties perceive that they can achieve their demands more effectively through a negotiated settlement. According to general bargaining theory, conflict is a sub-optimal outcome given that bargaining should lead to better results than fighting, unless hindered by uncertainty and commitment problems as well as issue indivisibility (Fearon 1995). Research on restraint in civil war shows that non-state groups limit their use of violence in the proximity of negotiations, to position themselves as legitimate political actors and credible negotiating partners (Jo et al. 2021; Stanton 2016). If talks are perceived as a viable option, groups on the brink of armed struggle may instead seek to increase their chances of achieving concessions at the negotiating table.

## Data

We currently retrieve our variables from seven different data sources. Jointly, they cover the period January 1997 to December 2024 for predictors, and one additional year for data on fatalities, meaning that we can produce predictions up to December 2025.

### Fatality Data from the UCDP

We use fatality data from the UCDP both as target outcome (state-based fatalities) and to create predictors related to conflict history. For our target outcome to cover the full case universe of true and averted onsets, we combine three sources of fatality data:

1. *UCDP GED* (Sundberg and Melander 2013): For event-level data on active armed conflicts over the period 1989–2025.
2. *Candidate Event Dataset* (Hegre et al. 2020): Including events from 2018–2025 recorded by the UCDP with a high probability of being included in the final annual version of UCDP GED.
3. *Raw and unpublished UCDP data*: For cases that never reached the UCDP threshold for active armed conflict (25 battle-related deaths in a calendar year) in the period 1989–2017.

The unpublished fatality data constitute a unique feature of this research. While the Candidate Events Dataset was first released in 2018, similar event data have been recorded unsystematically by the UCDP since 1989, but in a more systematic fashion since 2010. In that sense, these data are a precursor to the published Candidate events, and provide us with a case universe of stunted onsets before 2018. While the coverage is uneven between 1989–2009, that period will only be part of the data partition used for training our models.

### Data Sources for Predictors

For the predictor variables, we rely on the following additional sources:

1. *Varieties of Democracy (V-Dem)* (Coppedge et al. 2024) for predictors related to levels of democracy, democratic institutions, state repression, and civil society relations.
2. Event data on collective action from *ACLED* (Raleigh et al. 2010).

3. Structural indicators related to conflict risk and societal resilience from the *World Bank's Development Indicators (WDI)*, the *World Population Prospects (WPP)*, and the *Ethnic Power Relations (EPR)* dataset (Vogt et al. 2015).
4. Data on pre-talks and negotiations from the *PA-X database* (Bell and Badanjak 2019).

5-7. From the UCDP infrastructure, we use three additional datasets:

— *Managing Intrastate Low-Intensity Conflict (MILC)* data (Melander et al. 2009), with indicators for *direct*, *indirect* and *bilateral* talks, as well as for arbitration, good offices, fact-finding, observer mission, and PKOs. This is the cleanest measure of early-stage, third-party mediated talks we could find, though coverage is short (1993–2004), and many preventive measures are used after conflict onset.

— *UCDP Peace Agreements Dataset* (Pettersson et al. 2019), relevant for conflict dyads once recorded as active by the UCDP.

— *UCDP Dyadic Dataset* (Davies et al. 2025; Harbom et al. 2008) to build dummy variables at the country–month level for whether any state-based violence in that month was over (1) territory, (2) government, or (3) both.

8. Finally, we plan to include news data as indicators of pre-talks and upcoming elections.

## Model Specification

### Baseline Risk Index

The literature has established structural risk factors for the onset of civil war (e.g., GDP per capita, population size, regime characteristics). Instead of assigning these structural risk factors directly to armed violence, we argue that they indicate a baseline risk of conflict. If there is conflict in society, the non-state actor decides how to address the underlying incompatibility. To separate the contexts at higher risk of conflict onset from those with a lower baseline risk, we construct a structural risk index based on established risk factors for conflict onset, using the training data ($\leq$ 2021).[2]

[2] VIEWS similarly includes a large set of structural variables on conflict history, economic development, and political institutions, and excels at predicting a baseline level of armed violence (Hegre et al. 2019; Hegre et al. 2021; Hegre et al. 2024).

The following structural variables are included in the risk index (see also Figure 7):

* GDP per capita (`wdi_ny_gdp_pcap_kd`)
* Population size (`wdi_sp_pop_totl`)
* Liberal democracy index (`vdem_v2x_libdem`)
* Civil liberties index (`vdem_v2x_civlib`)
* Male 15-24/male 15+ ratio (`youth bulge`)
* The $t-1$ lag of the cumulative number of state-based fatalities (`cum_best_t1`)

These variables are inverted (if required) and *min–max* normalized, which yields an additive index by taking the mean value for each country-year. The risk index ranges from 0 to 1. Larger values imply a greater baseline risk of armed conflict (Figure 1). We consider cases above 0.5 as high-risk countries.

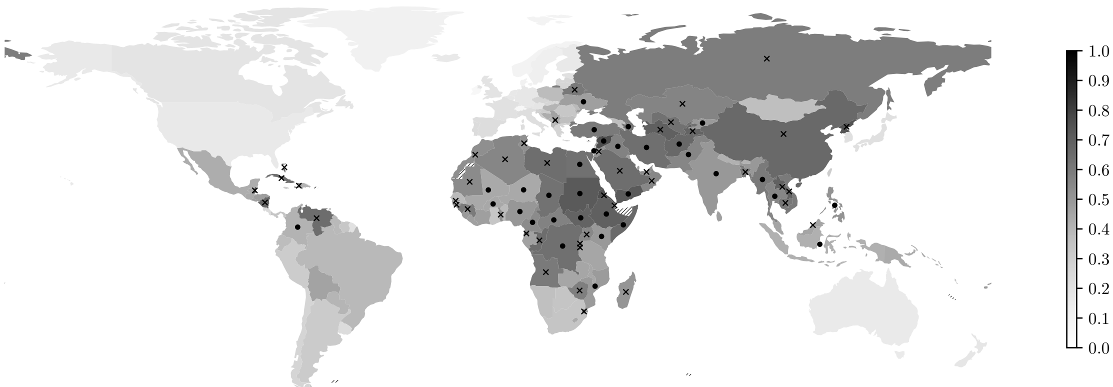


Figure 1: Conflict *risk* index on the cumulative $t-1$ number of fatalities, population size, GDP per capita, civil liberties index, liberal democracy index, and youth bulge. Solid marker indicates cases with ongoing armed conflict in 2021, and *X* signals *high risk* countries.

**Baseline Resilience Index**

We similarly construct a baseline resilience index, based on our theoretical argumentation that not all societies are equally susceptible to conflict triggers and that some sociocultural factors discourage (renewed) armed contention. We construct the resilience in a similar way to the risk index, including the following variables (see also Figure 7):

* Indicators on clan-based structures and community ties from V-Dem and EPR, to capture ethno-political bargaining structure and social cohesion, which are expected to dampen contentious tendencies.
* The count of peace agreements at different levels from the PA-X and the UCDP Peace Agreements datasets, as well as the MILC indicators of talks with third-party facilitation for the 1993–2004 subsample.
* Other types of organized violence/crime (TBD), pointing towards alternative recruitment routes for other types of violence, which may explain why some countries do not see armed conflict onset but higher levels of other forms of violence.

### Escalatory Model

Once the high-risk cases are identified, the main input for the escalatory trajectory (see also Figure 7), including the protest and the clandestine pathways, is low-intensity collective action using aggregated event data from ACLED (Raleigh et al. 2010). We use event counts for protests (`n_protests`), riots (`n_riots`), battles (`n_battles`), and remote violence (`n_remotes`) from ACLED, as well as fatalities in non-state conflict (`ged_ns`) and one-sided violence (`ged_os`) from the UCDP. These two data sources have different coding approaches, where ACLED has a lower threshold for including events. This works to our advantage, as it likely includes a more sensitive signal for early warning. We also consider including the lead of the V-Dem indicator series for national elections in year $t + 1$ (`v2eltype_lead12`) and/or news data, to capture upcoming elections as a potentially contentious setting.

### De-escalatory Model

The de-escalatory model includes two sets of predictors for the victory pathway and one for the compromise pathway (see also Figure 7).

#### Battlefield asymmetries

To capture strong state intelligence, where governments quell dissent at an early stage, we use the V-Dem repression indicator (`vdem_v2x_clphy`) and state-inflicted one-sided violence (`state_osv`, derived by filtering the UCDP indicator `ged_os` on instances where the government is the perpetrating actor). We include the change in the number of non-state armed actors by country-month (`distinct_side_b`), as a sign of group fragmentation or new/(re-)emerging groups, making dissent more dispersed. We also disaggregate battle deaths to capture each side's losses, considering the government and the non-state actor. High fatality counts on the rebel side should suggest a lower probability of escalation.

**Territorial consolidation**

Fatalities may increase locally as either the non-state actor seeks to consolidate territory or government intelligence aims to isolate and quell armed resistance. For each country-month, we look back at the previous six months of state-based events, compute each PRIO-GRID cell's share of the country's events in that window, and calculate the Herfindahl–Hirschman index (HHI), $\sum s_i$, where $s_i$ denotes the share of the country's events in cell $i$. A consolidating state will likely push events into fewer cells (high HHI), whereas a dispersed insurgency does the opposite.

**Pre-talks/announced negotiations**

We include the count of agreements at the pre-negotiation stage from the PA-X database, at time $t$ as well as the $t-6$ and $t-12$ lags. These indicators should provide direct evidence of the de-escalatory compromise pathway, i.e., that issues are being negotiated rather than fought over, which we expect to lower the risk of onset given high risk. We also plan to include announcements or anticipation of negotiations through news data. Another relevant variable is the incompatibility type, since issues perceived as less indivisible should increase the prospects of negotiations. Finally, from ACLED, we also consider the number of strategic developments (`n_strats`), which includes events such as "agreement, arrests, change to group/activity, disrupted weapons use, headquarters or base established, looting/property destruction, [and] non-violent transfer of territory".[3]

[3] Quoting ACLED Codebook. While these data are not systematically gathered but context-specific, they should capture signals through their context-specific relevance.

## The *Shape Finder* Adaptation

The *Shape finder* (Schincariol et al. 2025) was originally developed to predict the evolution of conflict dynamics, i.e. the intensity and location of fatalities in already ongoing conflict over a given horizon. In other words, the *Shape finder* makes predictions based on the fatalities that follow the most similar historical analogues.

Due to the autoregressive setup, the *Shape finder* cannot predict onsets. Indeed, whenever the algorithm takes only zeros as input (i.e., no ongoing armed conflict), the model returns a flat (zero fatalities) sequence for the prediction window. In this study, we adapt the *Shape finder* methodology to essentially produce a hurdle model, where matching takes place in two steps. First, we match only on fatality time series with the original *Shape finder*. Secondly, using the escalatory/de-escalatory variables summarized in Figure 7, we test whether similar contexts emerge in the matched sequences, with regards to how conflict intensity subsequently increased or decreased.

Our target outcome is the *relative increase in fatalities* for states without ongoing armed conflict, but with potential low-intensity contention, as indicated by the number of fatalities in state-based conflict. While our research problem concerns conflict onset, we develop the model to detect how low-intensity violence increases or decreases, which at later stages will be used to assess whether limited violence will surpass levels of armed conflict (N. P. Gleditsch et al. 2002). The definition of the target outcome as relative increase makes it adaptable to different fatality thresholds.

To identify countries without armed conflict, we use the UCDP threshold for armed conflict, set at 25 battle-related deaths in a calendar year. In the context of the *Shape finder*, this translates into identifying the sequences with less than 25 fatalities in a given year, considering each country in the sample individually. These are the locations of potential conflict onset. Thereafter, we predict whether the number of fatalities will increase in the next year. We use the 1989-2021 period as training data and predict for the period 2022-2025.

We exemplify our target outcome with the case of Angola (Figure 2). In 2023, Angola

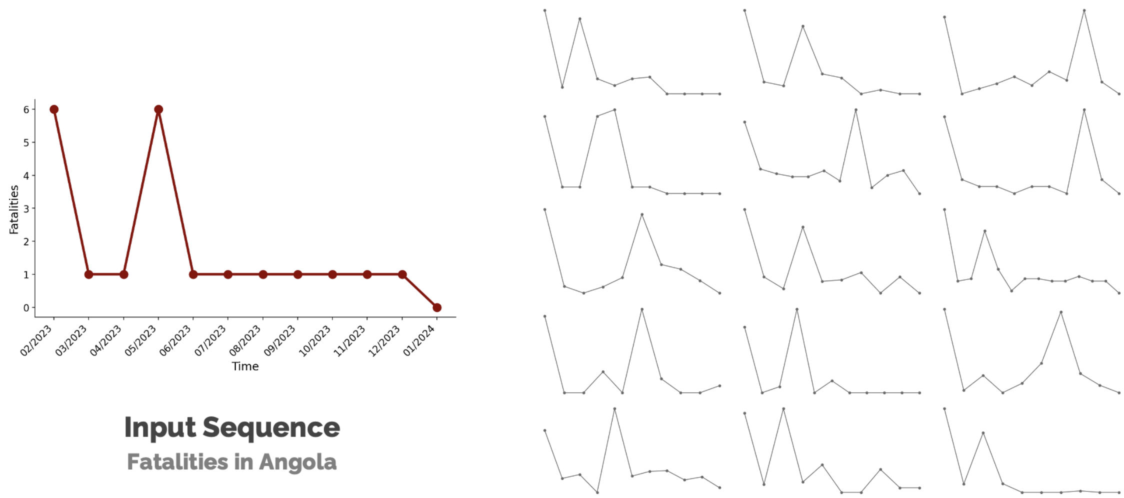


Figure 2: Example of fatality input sequence: Angola from February 2023 to January 2024 (left-panel) and similar occurrences in the historical dataset extracted by the *Shape finder* (right panel).

saw ten state-based fatalities. Our target is to predict whether there will be an increase in fatalities relative to the previous year, i.e. the number of fatalities in 2024 compared to 2023. If Angola has 15 deaths in 2024, we would classify the case as increasing.

## The *Shape Finder* as Hurdle Model

We transform the *Shape finder* into a hurdle model, focussing on previously peaceful cases only. Figure 3 below depicts the analytical procedure. At Step 1, hurdle *i* filters out cases with ongoing armed conflict based on whether the total number of fatalities in the input sequence surpasses the 25-fatality threshold. If the total fatalities in the input sequences are larger than the 25-fatality cut-off, the case is classified as active, and the original *Shape finder* is used to predict dynamics in ongoing battle. For cases without armed conflict but (i) low values on the structural risk index and/or (ii) high values on the societal resilience index, the model predicts zero fatalities for the entire prediction window.

In hurdle *ii*, Steps 2-4, we apply the original *Shape finder* to separate out cases with similar occurrences of low-intensity violence (1–24 fatalities in a year). The *Shape finder* algorithm loops over each country and derives the input shape, which are the number of fatalities over the preceding 10 months prior to the prediction window (e.g., March 2022 until December 2022

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|---|---|
| Hurdle $i$ | **Step 1.** We filter out cases without ongoing armed conflict based on whether they stay below a yearly 25-fatality threshold. |
| Hurdle $ii$ | **Step 2.** Considering one country at a time, we take the preceding 10 months before the prediction window as input. Each input has a certain shape, such as a *W*. |
| | **Step 3.** We generate a repository of historical references for fatality sequences, using overlapping subsequences with a window length between 8 and 12 months. |
| | **Step 4.** We compare the shape of the input to the historical references and extract the most similar matches. The similarity in shape is given by *Dynamic Time Warping (DTW)* which accounts for temporal distortions in time series data. This yields a filtered repository with the most similar historical analogues for each input sequence. |
| Hurdle $iii$ | **Step 5.** We fit a decision tree to identify the variable configuration under which a given fatality sequence leads to an increase in fatalities. We keep only the branches with the best split between increasing and decreasing sequences. |
| | **Step 6.** Only considering the most similar historical references, we generate predictions of relative increase or decrease in fatalities for the next 12 months following the input. |

Figure 3: The three hurdles included in the adapted *Shape finder* model.

for predictions in 2023). The *Shape finder* first takes one fatality shape as input and finds the most similar historical analogs from the historical repository. Similarity is indicated by the Dynamic Time Warping (DTW) distance, which is a distance measure commonly used for time series analysis (Keogh and J. Lin 2005). DTW allows for a non-linear alignment of sequences to produce more valid assessments on the similarities of time series with similar but phase-shifted patterns (e.g., the pattern up-down-up could extend over three, six, or ten months). The historical repository is generated using a moving window approach, considering the training data of all countries in the sample. The repository contains overlapping subsequences ranging from 8 to 12 months, which are compared to the input shape. Selecting a specific cut-off for dissimilarity, only the most similar historical references are passed on to a filtered repository.

Hurdle $iii$ takes place in Steps 5-6. Here, we identify the variable configurations that favor increases or decreases in fatalities, and filter out the contexts in which the specific fatality pattern is followed by higher intensity violence or stalling violence. We fit a decision tree on the similar cases only, including all escalatory/de-escalatory covariates and six variables of long-term trend categorizations.[4] We also consider including a variable indicating whether a given sequence yielded a false-positive (i.e., an over-prediction of violence) in the past. Then, out of the fitting process, we keep only the branches with the best split between increasing and decreasing sequences. We limit the depth of the tree to ensure interpretability of contexts, while ensuring a certain sample size per leaf.

To make the final predictions, we extract the set of covariates of the input sequence. These covariates are then compared against the contexts identified in Step 5. If they match a branch associated with a decrease in fatalities, the forecast is a decrease. On the contrary, if the branch leads to increases, an increase is forecasted. When the covariates do not match any identified branch, the overall decision tree estimated in Step 5 is used to generate the forecast.[5] This strategy offers two advantages. First, the target variable can be easily adapted from increase/decrease to onset/non-onset based on the chosen threshold for armed conflict. Then, it provides an indication of uncertainty. Predictions are considered more reliable when the input covariates match one of the identified contexts. If not, it means this conflict pattern, combined with this covariate context, is not present enough in the historical dataset to provide a confident, traceable prediction.

## Evaluating Predictive Performance

Our approach is currently only validated against the original *Shape finder*. In the long run, the goal is to evaluate the performance of our model in comparison to three benchmarks: the original *Shape finder*, the VIEWS ensemble and *ConflictForecast*. Although these models were *not* optimized to classify binary increases and decreases in the number of fatalities, and consider different forecasting horizons, a comparison would still be valuable.

[4]The long-term trend categorization uses the aggregate fatalities (mean, max and last cumulative value) over 3 and 5 year periods, according to intensity level: 0 = zero fatalities, 1 = 1 to 24 fatalities, 2 = 25 to 99 fatalities, 3 = 100 to 999 fatalities, and 4 = >1 000 fatalities.

[5]This final step is under development. In particular, the hyperparameters are not yet optimized for the *Shape finder* (e.g., window length, maximum distance), but also the Decision Tree (e.g., max depth, min leaf sample). Additional context extraction methods will be tested, but the overall logic remains the same.

Additionally, we consider three technical baselines: the null model (i.e., always predicting zero fatalities), the $t-1$ model, and a random classifier (i.e., drawing 0/1 from a *Bernoulli* distribution based on the relative frequency of onsets in the training data). We want to evaluate the model's ability to classify both onsets and increases/decreases in fatalities correctly. There is a difference between big-blow onsets and smaller peaks in the number of fatalities. To adapt the presented design, only the categorization of the outcome would need to be changed from an increase/decrease target to onset/non-onset. In other words, what differentiates an increase from an onset is *just* a matter of intensity level.

We opt for classical classification metrics to evaluate model performance. The F1 score takes into account the ability to predict positive cases while penalizing for false positives. We use the same metric to evaluate correctly predicted fatality increases/decreases.

## Preliminary Findings

In countries with low-intensity violence, we find that the original *Shape finder* is not as risk-taking as when conflict is already ongoing. According to an initial test, using 12-month input windows from January to December spanning 2010 to 2022, out of the 100 input low-intensity sequences, the model forecasts only two increases in the following year. However, both led to a decrease in reality (i.e., false-positives), highlighting the conservative forecasts from the models optimized on the overall error, and their inability to anticipate an escalation of low-intensity conflict.

Here, we include examples of how fatality patterns are matched to escalatory and de-escalatory sequences using our approach (Figures 4, 5, and 6). Crucially, some variables theorized as de-escalatory show the opposite direction, leading to increasing fatalities in the next year, which may however depend on coding decisions (e.g., which *levels* of state repression are expected to increase or decrease the intensity of violence). Moreover, we are handling some data quality/parsing issues for certain de-escalatory variables that affects their predictive use, which may be why we see mostly violence-related indicators highlighted in the contextual patterns. The results should therefore be interpreted with caution since the model is preliminary.

The images should only be seen as indicative of what we may find with our approach.

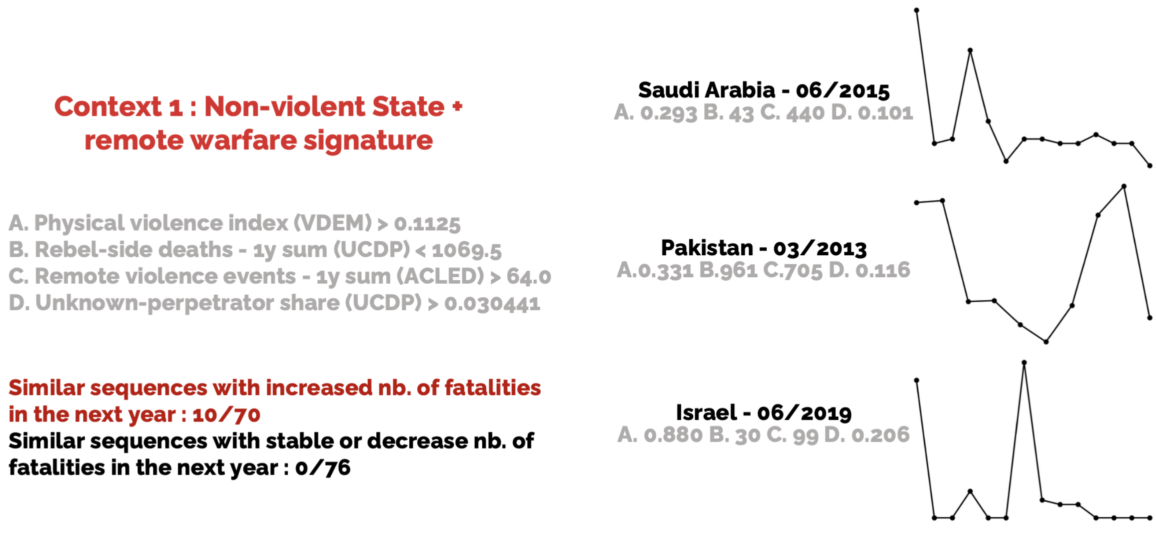


Figure 4: First increasing context example for the Angola input example, shown in Figure 2. Out of the 146 matched sequences, 10 of them fall into this context, and all of them have an increasing number of fatalities in the next year. This context is composed of four covariates (in grey). Three matching examples are displayed on the right side of the figure, along with their contextual variables.

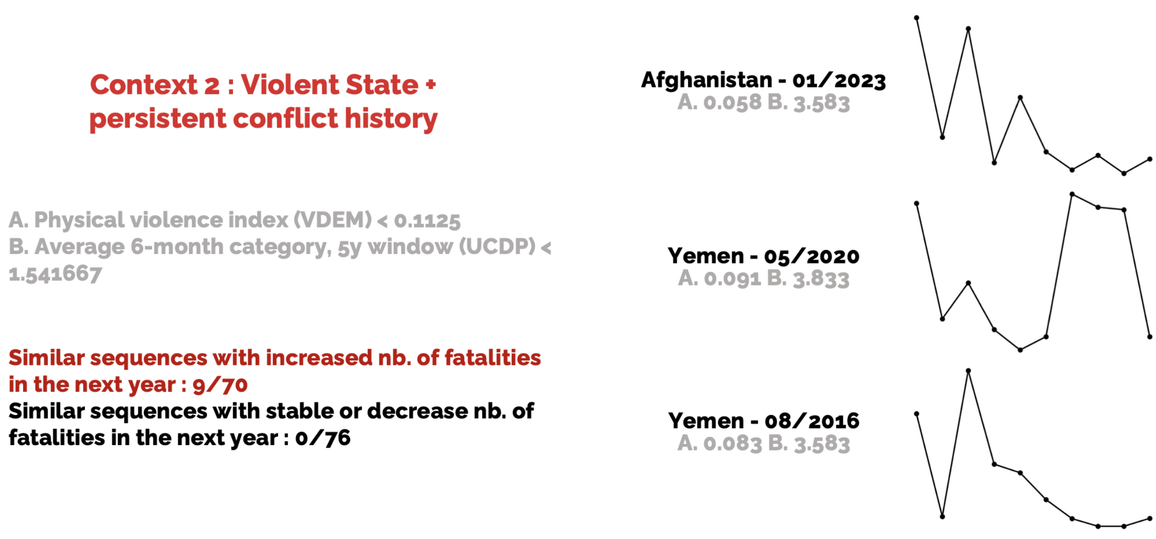


Figure 5: Second increasing context example for the Angola input example, shown in Figure 2. Out of the 146 matched sequences, 9 of them fall into this context, and all of them have an increasing number of fatalities in the next year. This context is composed of two covariates (in grey). Three matching examples are displayed on the right side of the figure, along with their contextual variables.

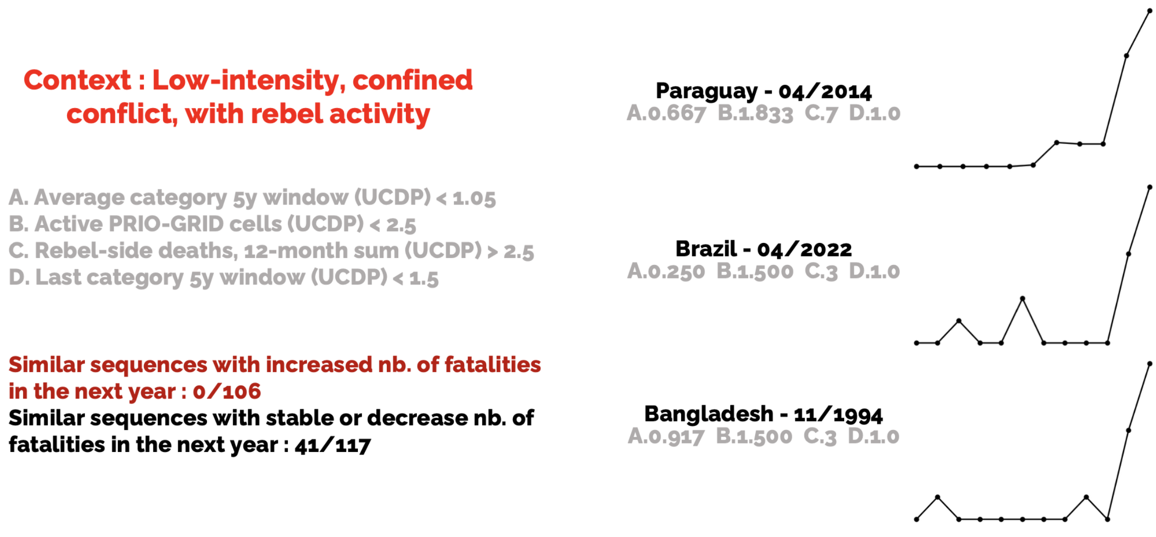


Figure 6: Decreasing context example for a fictional input example (not Angola), where a rise in fatalities was observed in the last months. Out of the 223 matched sequences, 41 of them fall into this context, and all of them have a decreasing number of fatalities in the next year. This context is composed of four covariates (in grey). Three matching examples are displayed on the right side of the figure, along with their contextual variables.

## Options for Extended Analyses

Here, we note some ideas for potential next steps:

1. *Limited violence at higher intensity levels:* We may extend our analysis by exploring whether the same approach (and predictors) help predict escalation and de-escalation at higher levels of intensity, where armed conflict or war is already ongoing.
2. *Interpretability tools for machine learning models:* Another option is to use interpretable machine learning to further uncover how the variables interplay in different risk settings. To exemplify, one could apply scoped rules after switching from decision trees to Random Forest (i.e., a black box machine-learning model) to extract the conditions under which certain variables affect the predictions.

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## Appendix

| Structural Risk Index | Baseline Resilience Index | Escalation Pathway | De-Escalation Pathway |
|---|---|---|---|
| wdi_ny_gdp_pcap_kd, wdi_sp_pop_totl, vdem_v2x_libdem, vdem_v2x_civlib, youth_bulge, cum_best_t1 | V-Dem CSO / community ties: v2cseeorgs, v2csreprss, v2csprtcpt, v2cscnsult, v2csantimv, v2psprlnks, v2pepwrses, v2pepwrsoc<br><br>EPR 2023: epr_excl_share, epr_reg_aut<br><br>PA-X later agreement stages: pax_subpar, pax_cea, pax_imp, pax_subcomp, pax_ren, pax_any, pax_any_6m, pax_any_12m<br><br>UCDP Peace Agreements: upa_any, upa_third, upa_csign, upa_terr, upa_govt, upa_any_12m<br><br>MILC Third-party engagement in low-intensity conflict, 1993–2004: milc_talks_any, milc_talks_dir, milc_talks_ind, milc_third_party, milc_in_coverage<br><br>*Tentatively: Organized crime records* | Collective action: n_protests, n_riots, n_battles, n_remotes, ged_ns, ged_os<br><br>Upcoming national elections in year $t+1$: v2eltype_lead12<br>*News data?* | Battlefield asymmetries: vdem_v2x_clphy, state_osv, distinct_side_b<br><br>GED side-disaggregate battle outcomes: ged_deaths_a, ged_deaths_b, ged_deaths_civ, ged_deaths_unk, ged_n_battles, ged_asymmetry, ged_unknown_share, ged_first_open_battle<br><br>Territorial consolidation: hhi_grid_6m, n_active_grids_6m<br><br>PA-X agreements at the pre-negotiation stage: pax_pre, pax_pre_6m, pax_pre_12m<br>*News data?*<br><br>ACLED: n_strats<br><br>Conflict incompatibility type: incomp_terr, incomp_govt, incomp_both |

Figure 7: Summary of predictor variables