Reconceptualizing Conflict Emergence

Evidence from Machine Learning

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Declaration

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Abstract

Despite extensive research on the causes of civil war, many explanations remain contested. Critical theoretical omissions and methodological shortcomings inhibit our understanding of conflict emergence. Civil war is treated as a dichotomous phenomenon (peace/war), which overlooks the fact that armed conflict typically arises from preceding low-intensity collective action, such as protests and rebel mobilization. This dissertation makes two main contributions: (1) Integrating structural and procedural theories to develop a reconceptualization of conflict emergence, and (2) leveraging tools from machine learning to capture the complexity of civil war.

Civil war is a multistaged process, comprising initial collective action (*stage i*) and the transition to civil conflict (*stage ii*). Armed conflict entails significant risks and logistical challenges, making a direct link between structural risk factors and civil war seem implausible. Instead, less extreme types of collective action, such as protest, terrorism, and low-intensity armed violence, constitute a critical precursor to civil conflict. Collective action mediates the relationship between structural risk factors and civil conflict. In particular, there are two pathways to civil war: The protest and the clandestine pathway. Protests might gradually transition to armed violence, or the non-state group immediately decides to pursue violence, yet needs to mobilize first. The continued interactions between the non-state group and the government might spark an escalation process, where both sides consecutively apply heavier tactics, ultimately leading to more substantial levels of armed conflict.

Null-hypothesis significance testing encounters key challenges when studying intricate phenomena, potentially producing models that fall short in accurately capturing the underlying data-generating process. Conversely, machine learning allows constructing an empirical model with high complexity, capable of mirroring the non-linear and conditional associations in civil conflict data, while ensuring to discard sample noise. Post-hoc interpretability tools are leveraged to reveal how each variable affects the prediction, which assists in deriving theoretical conclusions. Machine learning is likewise relevant from a practical perspective, given that conflict early warning can inform policymakers where and when to intervene.

This thesis contains four papers, each addressing a unique aspect of the topic. *Paper i* explores the interactions between grievances and opportunity to uncover stereotypical pathways to civil war onset. *Paper ii* demonstrates that structural risk factors predict collective action more broadly, rather than civil war exclusively, and investigates similarities and differences in the causes of collective action. *Paper iii* identifies dangerous protest patterns that precede high fatalities in civil conflict, and argues that protest is a dynamic phenomenon, whose inherent mechanisms go beyond what static protest events can account for. *Paper iv* introduces a new conflict prediction model—the 'Onset catcher'—derived from a reconceptualization of conflict emergence and therefore tailored towards anticipating conflict onsets.

Keywords: Civil conflict, conflict emergence, collective action, machine learning

Acknowledgments
At the beginning of the PhD, I received three pieces of advice: *A good PhD is a finished PhD*, *a PhD is a marathon and not a 100-meter race*, and *the PhD will be the longest and shortest time of your life*. Especially the last one couldn't be truer. Now approaching the end, I realize that I gained much more from the people in my environment than just great inspirational quotes.

First and foremost, I want to thank my supervisor (mein Doktorvater), *Thomas Chadefaux*, whose constant guidance and support over the last four years greatly enhanced the quality of my research. You have delivered feedback with a great level of nuance, insight, speed, and frequency. On many occasions, people heard me say: Thomas saved my paper, and this does not only apply to providing great ideas for titles ('the outrage gap') but for the framing, design, and presentation choices more broadly. With your help, I could advance my research to (hopefully) good pieces of work. From the beginning, you have treated me as a colleague rather than a student. Collaborating with you on numerous projects helped me to hone my research skills, particularly in terms of thinking creatively/outside of the box (you are really good at this), and regarding how to set up research papers, how to write academically, and when and how to submit papers for review. Without your supervision, all of these things would have taken me much longer to learn, and I truly feel like I turned into a junior scholar under your guidance.

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List of Papers

1. Frank, H. (2025). "Grievances and Opportunity: Uncovering Causal Complexity in Civil War Onsets".
2. Frank, H. (2025). "To Demonstrate or Fight: Similarities and Differences in the Causes of Collective Action".
3. Frank, H., & Chadefaux, T. (2025). "From Protests to Fatalities: Identifying Dangerous Temporal Patterns in Civil Conflict Transitions".
4. Frank, H. (2025). "From Structure to Action: Anticipating Onsets in Civil Conflict".

Contents

1 *Introduction*

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Replication Material
The data and code for this analysis are available here: https://github.com/hannahhfrank/phd_thesis_reconceptualizing_conflict_emergence/tree/main/introduction.

Use of Generative Artificial Intelligence
ChatGPT-3.5 and higher (https://chatgpt.com/) was consulted as a coding assistant when implementing the empirical analysis. For checking spelling and grammar, suitable tools were used as add-ons in Overleaf (i.e., Grammarly, Writefull, and LanguageTool).

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Reconceptualizing Conflict Emergence: Evidence from Machine Learning

Abstract

Existing research on the causes of civil war can be divided into structural and procedural approaches. The former investigates structural background factors, and the latter explores how state-dissident interactions produce civil war. Despite decades of research, many associations between structural risk factors and civil war onset remain contested. The underlying argument of this dissertation is that addressing theoretical omissions and methodological shortcomings can enhance our understanding of conflict emergence. Collective action mediates the relationship between structural risk factors and civil war. By integrating structural and procedural theories, this thesis proposes a reconceptualization of conflict emergence along two stages: Initial collective action *(stage i)* and the transition to civil conflict *(stage ii)*. When seeking to uncover the intricate associations in the causes of civil war, machine learning tools are advantageous over null-hypothesis significance testing. Against this background, this dissertation identifies stereotypical pathways to civil war onset *(paper i)*, investigates similarities and differences in the causes of collective action *(paper ii)*, studies how protests transition to civil conflict *(paper iii)*, and proposes a conflict prediction model to anticipate conflict onsets *(paper iv)*.

Keywords: Civil war, multistaged phenomenon, collective action, machine learning

1.1 Introduction

Existing research on the causes of civil war puts forward structural and procedural approaches (Blair and Sambanis 2020). The former focuses on slow-changing background factors that increase the risk of armed violence, and the latter investigates how the interactions between the government and the non-state actor might produce violent outcomes. Despite decades of research, many associations between structural risk factors and civil war onset remain contested (see Malone 2021 for a discussion). The underlying argument of this dissertation is that addressing theoretical omissions and methodological challenges can enhance our understanding of conflict emergence.[1]

Existing research on the causes of civil war studies armed conflict as a dichotomous phenomenon: A country either experiences *peace* or *war* (Bartusevičius and Gleditsch 2019). This practice omits that armed violence usually originates from preceding low-intensity collective action, thereby ignoring an important aspect of how civil conflict evolves.[2] By integrating structural and procedural theories, this thesis proposes a reconceptualization of conflict emergence along two stages: Initial collective action *(stage i)* and the transition to civil conflict *(stage ii)*.

A certain combination of structural risk factors indicates that there is conflict in society. The non-state actor selects a strategy from a 'repertoire of collective action' to pursue their interests (Tilly 1977), which can be less (e.g., protest, riots) or more violent (e.g., terrorism, low-intensity armed conflict). The continued interactions between the government and the non-state group might trigger an escalation process,

[1]Similar arguments on the multistaged character of civil war and the methodological challenges of null-hypothesis significance testing were proposed in my master's thesis (see Frank 2021). These ideas are further developed in the presented dissertation.

[2]This thesis follows the tradition of understanding civil war as inherent, and thereby emerging from previous contention (Lichbach et al. 2003).

where both sides apply increasingly heavier tactics (McAdam 1983; Pruitt and Kim 2016), ultimately producing more substantial levels of civil conflict.

Despite the large number of studies on the drivers of armed violence, many associations remain contested due to inconclusive empirical findings. Since civil war is a highly complex phenomenon, correctly specifying a statistical model becomes challenging. While machine learning has been proposed as a potential remedy, ensuring a correct model specification by navigating the over- and underfitting trade-off (Colaresi and Mahmood 2017), the black-box character of many machine learning algorithms remains a prime obstacle. Converse to the seemingly atheoretical nature of machine learning, there are post-hoc interpretability tools that reveal how each variable affects the prediction (Molnar 2025), thereby assisting in deriving theoretical conclusions. In addition to using machine learning for validating civil conflict theory, this dissertation contributes to the field of conflict prediction, a thriving field due to its practical relevance (Bara 2020; Rød et al. 2024).

To engage with these theoretical and methodological challenges, this dissertation contains four papers. "Grievances and Opportunity" (*paper i*) identifies stereotypical pathways to civil war onset, while maintaining the unique character of each case. "To Demonstrate or Fight" (*paper ii*) shows that there are marked similarities but also differences in the causes of collective action, considering more or less violent forms. "From Protests to Fatalities" (*paper iii*) investigates how the interactions between protesters and the government might drive non-violent collective action towards violence. "From Structure to Action" (*paper v*) introduces the 'Onset catcher', which is a conflict prediction model tailored towards onset cases.

This dissertation makes three main contributions. First, it proposes a reconceptualization of conflict emergence, emphasizing how structural risk factors may prompt civil conflict by transitioning through non-violent and/or violent collective action.

While this claim might appear intuitive, government-dissident interactions have long been ignored in the civil war literature (Young 2013), and civil war is still commonly perceived as dichotomous (Bartusevičius and Gleditsch 2019). By discarding events that precede violent escalation, existing research conceals an essential aspect of how civil conflict emerges.[3]

Second, this dissertation leverages interpretable machine learning when validating civil conflict theory. In spite of the advantages of machine learning when unpacking complex phenomena, political scientists remain skeptical about predicting as opposed to explaining. Yet, there are off-the-shelf tools that can be used to extract theoretical conclusions from black-box machine learning models, going beyond a simple out-of-sample evaluation (Masís 2023; Molnar 2025).

Third, this dissertation contributes to the field of conflict prediction by addressing a key area where existing models fall short: Conflict onsets (Mueller and Rauh 2022). The proposed reconceptualization of conflict emergence informs the inner workings of the Onset catcher, predicting the number of fatalities in civil conflict, conditional on a high preceding risk of collective action.

1.2 Structural and Procedural Theories

Existing research on the causes of civil war emerges along structural and procedural approaches (Blair and Sambanis 2020). Structural approaches focus on slow-changing background conditions that are associated with an increased risk of armed violence. Procedural approaches focus on the interactions between the government and the non-state actor, ultimately driving violent escalation.

Structural approaches have proposed a long list of potential risk factors for the

[3] Similar observations are made by Demirel-Pegg (2011), probing how protest waves lead to civil conflict through radicalization and militarization. The author criticizes existing work for omitting escalation processes and bridges between structural approaches and contentious politics.

onset of civil conflict (e.g., Trinn and Wencker (2021) derive 107 explanatory variables). These background conditions run along the themes of conflict history (e.g., previous war, new state), demography (e.g., population size, ethnicity), geography (e.g., terrain, climate), economy (e.g., natural resources, prosperity), and politics (e.g., regime characteristics) (Dixon 2009). The corresponding associations are substantiated with grievances- and opportunity-based explanations.

The grievances argument contends that relative deprivation causes frustration, which might prompt aggression and, by extension, civil conflict if individual behavior aggregates (Dollard et al. 1939; Gurr 2016). Relative deprivation is a discrepancy between reality and expectation: An individual is denied access to the living conditions that they believe should be attainable (Gurr 2016). The comparisons between reality and expectation are often linked to cultural cleavages, where a majority group dominates the minority (Fearon and Laitin 2003). Indeed, ethnically divided countries are considered inherently more challenging to govern (Horowitz 1985).

The opportunity argument claims that organized violence originates from opportunity, such as low opportunity costs if individuals have little to lose from engaging in rebellion, due to poor economic prospects (Collier and Hoeffler 2004). In this view, armed conflict can be an economic activity if rebels receive payment. Alternatively, opportunity originates from weak state capacity, given that weak states are unable to deter mobilization against the government (Fearon and Laitin 2003). When facing a weak government, the non-state actor might perceive their chances of successfully overthrowing the regime as high, which enhances recruitment capabilities as more individuals are inclined to participate (Jakobsen et al. 2013).

Following some important null findings for the grievances argument (Collier and Hoeffler 2004; Fearon and Laitin 2003), the approach was reconceptualized, proposing that cultural diversity itself is not a driver of armed violence but exclusion from political power along ethnic lines (Wimmer et al. 2009). As politicians favor coethnics to strengthen their support base, ethnic cleavages organize the political arena (Cederman et al. 2010). Individuals who are systematically excluded from political power are more willing to engage in armed action against the government.

Rather than seeing the grievances- and the opportunity-based argument as competitors, the literature began investigating how both interact (Bara 2014; Bormann and Hammond 2016; Dyrstad and Hillesund 2020). Civil war is caused by grievances *and* opportunity, given that a non-state actor needs to be willing and able to initiate armed action (Bara 2014). Based on a set of common indicators for grievances and opportunity, Bara (2014) performs a Qualitative Comparative Analysis (QCA), and uncovers four quasi-sufficient conditions for ethnic conflict: Conflict trap, bad neighborhood, ousted rule, and resource curse.

While the civil war literature is strongly dominated by structural approaches, procedural theories can be derived from the field of contentious politics (McAdam et al. 2001), which is a sub-discipline in the study of social movements. The contentious politics paradigm can be summarized in five points: (1) Different forms of political contention, such as protests, rebellions and civil wars, have similar causes, (2) these causes can be categorized into common mechanisms and initial scope conditions, (3) the interactions between the government and the non-state actor define which type of contention occurs, (4) there are 'repertoires of collective action' comprising various tactics that can be used by claim-makers, and (5) political contention is a dynamic phenomenon (Tarrow 2015).

While the contentious politics paradigm investigates different types of collective action together, there was a shift towards studying civil war exclusively in the early 2000s, without explaining why armed conflict should be singled out (Cunningham and Lemke 2014). Nevertheless, more recent research has been conducted on how the interactions between government and dissenters drive violent escalation (Hultquist 2017; Rød and Weidmann 2023; Young 2013). The basic idea of those approaches is that state repression pushes moderates towards violent tactics. States commonly apply repressive means to non-state groups attempting to challenge the status quo (Davenport 2007). In contrast to the government's intentions, state repression can backfire through a process of micromobilization where dissenters become even more committed as a reaction to repression (Opp and Roehl 1990).

1.3 A Reconceptualization of Conflict Emergence

Existing research treats civil war as a dichotomous phenomenon: A country is either at *peace* or at *war* (Bartusevičius and Gleditsch 2019). This equalizes cases such as March 2010 in Syria with March 2010 in Germany (White et al. 2015). While Syria experienced mass protests and quickly spiraled into civil war, Germany saw no noticeable collective action and no armed violence. The common practice of lumping those cases together into one category of *peace* omits an important aspect of how civil war emerges (Bartusevičius and Gleditsch 2019).

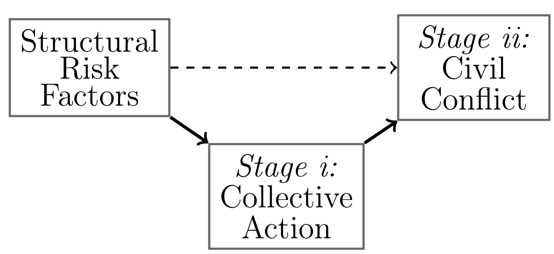


Figure 1.1: Civil war is a multistaged process, comprising initial collective action (*stage i*), and the transitions to civil conflict (*stage ii*). Collective action mediates the relationship between structural risk factors and civil conflict.

The main argument of this thesis is that collective action mediates the relationship between structural risk factors and civil war (Figure 1.1). The proposed reconceptualization of conflict emergence integrates structural and procedural theories and suggests that civil conflict develops in two stages. A certain combination of structural risk factors prompts collective action, in particular, protests, riots, terrorism, and low-intensity armed conflict *(stage i)*. Thereafter, the continued interactions between the government and the non-state actor might trigger an escalation process, ultimately producing more substantial levels of civil conflict *(stage ii)*.

A certain combination of structural risk factors causes conflict in society. Conflict is a contested incompatibility, which implies that the interests of two groups are mutually exclusive and that both sides act to promote their preference (Bartusevičius and Gleditsch 2019). To maintain the status quo, the government seeks to repress any challenge to the political leadership (Davenport 2007). While the state response appears almost deterministic, the behavior of the opposition is less predictable. In particular, the non-state actor selects a strategy from a 'repertoire of collective action', which comprises a set of tactics that can be used by claim-makers to advance their interests (Tilly 1977). These tactics can be more or less violent, ranging from protesting and striking to lynchings and killings.

A direct link between structural risk factors and civil war onset seems implausible, due to the great risks of escalating armed action to the level of a war. At the outset, the non-state actor prefers less violent collective action, which has a higher chance of success (Stephan and Chenoweth 2008), or seeks to pursue violent tactics but needs to build military capabilities first (Malone 2021). This implies two pathways to civil war: The protest and the clandestine pathway.[4]

In the protest pathway, the non-state actor selects less violent forms of collective action (protests, riots) to openly pressure the government into making concessions. Protest might transition to armed violence along two mechanisms: Protest escalation or protest capture (Rød and Weidmann 2023). In the former, protesters gradually

[4]These labels are inspired by Lewis (2017), who suggests that civil conflict can start similarly to social movements (protest pathway) or after secret mobilization (clandestine pathway).

adopt more violent means of contention based on the belief that non-violent tactics have failed. In the latter, an already existing armed group sees protests as a window of opportunity to initiate armed action against the government.

In the clandestine pathway, the non-state actor selects violent means but needs to mobilize first (Malone 2021). When procuring military capabilities, the non-state group might steal battle equipment from the state (Jackson 2010), loot the civilian population (Azam 2006), or extract resources from another non-state actor (Fjelde and Nilsson 2012). Rebel mobilization produces initial fatalities from terrorism and low-intensity armed conflict.

Initial collective action might transition to more substantial levels of civil conflict along continued interactions between the government and the non-state actor. The former engages in tactical adaptations, where the repression apparatus is adjusted to the tactics of the opposition, and the latter in tactical innovations to better counter the repressive response from the state (McAdam 1983). These interactions underpin an escalation process, where both sides consecutively use heavier tactics (Pruitt and Kim 2016), gradually pushing collective action towards armed violence.

1.4 Existing Approaches and the New Argument

While the idea that civil war is a multistaged phenomenon is not novel, previous research has two main limitations. Stage one is perceived as non-violent and potentially non-collective, and only structural explanations are considered. To overcome these shortcomings, the newly proposed reconceptualization of conflict emergence understands *stage i* as collective, comprising non-violent and violent tactics, and integrates structural and procedural theories on the causes of civil war.

The existing research on the staged character of civil war differentiates between two phases: Claims and contentious action (Cunningham et al. 2017; Germann and

Sambanis 2021; White et al. 2015) or contested incompatibility and armed conflict (Bartusevičius and Gleditsch 2019). These authors argue that claim-making occurs if a non-state actor announces a certain goal, such as overthrowing the government or independence, and a contested incompatibility implies that conflict actors actively pursue their interests through extra-institutional non-violent tactics.

Existing arguments on the staged character of civil war establish the first stage as non-violent and potentially non-collective. Indeed, claim-making can be entirely non-collective, given that no coordinated action is required. This practice continues to omit an important aspect of conflict emergence by not considering the possibility of prior collective action. Civil war can originate from institutional forms of collective action, in particular protests, as seen in Myanmar, Syria, and Egypt. Alternatively, civil conflict is preceded by initial fatalities from terrorism and low-intensity armed violence, which are produced during rebel mobilization.

Existing staged models on the causes of civil war exclusively rely on structural explanations and ignore how the interactions between the government and the non-state actor might produce more substantial levels of violence. They either investigate which structural factors are associated with which stage, taking an exploratory approach (Bartusevičius and Gleditsch 2019; Germann and Sambanis 2021) or assign grievances to the occurrence of claims and opportunity to the onset of civil war (Cunningham et al. 2017; White et al. 2015).

This practice neglects that armed conflict is a dynamic phenomenon. Grievances and opportunity are a necessary but not sufficient condition, given that the resulting collective action may or may not transition to civil war (Florea 2017). Once collective action occurs, tactical interactions between the government and the non-state group can spark an escalation process (McAdam 1983), where both sides consecutively use heavier tactics (Pruitt and Kim 2016), ultimately producing more extreme violence.

1.5 Methodological Challenges

Despite the immense volume of studies, there is little consensus on the causes of civil war, given that quantitative research continues to produce inconclusive findings (see Malone 2021 for a discussion). For instance, the effect of ethnic exclusion from political power has been demonstrated as positive (Cederman et al. 2010), while the effect of ethnic diversity has been found to be negative (Collier and Hoeffler 2004), or absent (Fearon and Laitin 2003). The association between inequality and political contention has been shown to be positive, negative, nonlinear, or null (Østby 2013). The effect of temperature on the risk of civil war onset has been presented as positive (Burke et al. 2009), or absent (Buhaug 2010). Finally, the effect of regime type has been found to be negative (Collier and Hoeffler 2004), or inverted U-shaped (Hegre et al. 2001), while the nonlinear relationship remains disputed (Vreeland 2008). Going beyond these relevant examples, the noticeable disagreement on the drivers of armed violence extends to the literature as a whole.

Most recently, Trinn and Wencker (2021) derive eleven consensus variables from a systematic review of existing research: Regime type (curvilinear or linear), regime change, political discrimination, hybrid regime, GDP per capita, economic growth, ethnic diversity, population size, rough terrain, and hydrocarbon exports. Importantly, the authors investigate a total of 107 explanatory variables, but only eleven are classified as robust. While few in number (Blattman and Miguel 2010; Cederman and Vogt 2017; Dixon 2009; Hegre and Sambanis 2006; Hoeffler 2012; Mason and Mitchell 2016; Sambanis 2002; Trinn and Wencker 2021), attempts to summarize the state of the literature have consistently demonstrated that the majority of explanations for civil conflict are non-robust to model specification.

Quantitative peace research mostly relies on null-hypothesis significance testing

(NHST). In addition to p-values being imprecise and heavily dependent on research design (Gelman and Loken 2014), corresponding methods produce unstable results when studying intricate phenomena. Civil wars are often characterized as random or puzzling (Gartzke 1999; Kalyvas 2003) and are driven by structurally and temporally complex mechanisms (Beck et al. 2000; Chadefaux 2014). NHST encounters three main challenges when studying the causes of civil war: Nonlinearity, non-additivity, and establishing causal effects in the context of high causal complexity.

Nonlinearity

The associations between structural risk factors and civil war are suspected to be nonlinear (Beck et al. 2000). For example, both democracies and autocracies have a lower risk of civil conflict in comparison to anocracies, presenting a mix of both democratic and autocratic institutions (Hegre et al. 2001). Conventional regression models assume that the relationship between the independent and dependent variable is linear. If the relationship is not linear, the coefficients could be biased, discarding the effect of an outlying subpopulation (Schrodt 2014). A linear model is too simple in the context of civil conflict and cannot learn nonlinear associations from the data (Colaresi and Mahmood 2017). This discrepancy is understood as underfitting, which occurs if a statistical model only mirrors parts of the data-generating process (Colaresi and Mahmood 2017).

While it is possible to include nonlinear effects in a linear model, it appears more suitable to learn the types of associations from the data, based on two main concerns. First, it is unclear which associations are linear, which are nonlinear, and if nonlinear, nonlinear how: U-shaped, S-shaped, or J-shaped. This situation is referred to as the 'researcher degrees of freedom' (Simmons et al. 2011). Researchers are incentivized to experiment with different model specifications, which might produce false positive findings or rather an overfitted model that incorrectly picks up noise from the sample (Colaresi and Mahmood 2017).

Second, even if the researcher knew which variables to transform and how, the nonlinear terms are highly correlated with the original variables. The resulting multicollinearity can bias regression coefficients (Schrodt 2014). This issue is particularly severe in the context of high causal complexity, which likely requires nonlinearizing several independent variables.

Non-additivity

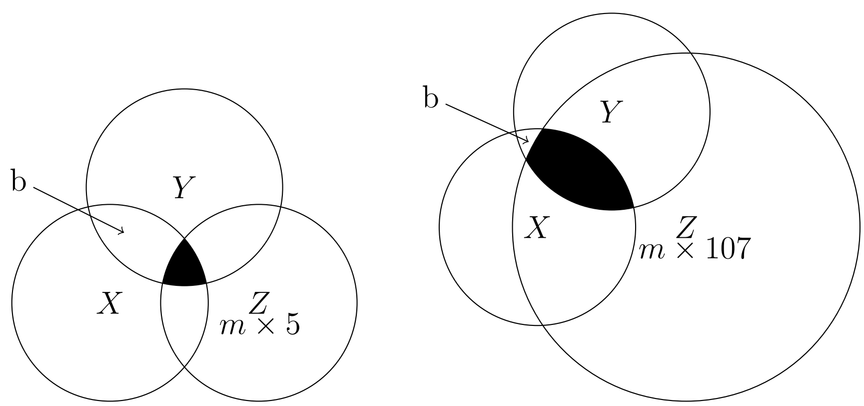
The correlations between structural risk factors and civil conflict are believed to be non-additive and dependent on certain scope conditions (Beck et al. 2000). For instance, the association between inequality and civil conflict has been shown to be conditional on regime type, natural resources, or population growth (Østby 2013). In NHST, effects are additive by default and interpreted *under control* of the other independent variables. In case of non-additive, multiplicative effects, regression coefficients might be unstable, given that effects change with the inclusion or removal of control variables. An additive model cannot account for conditional relationships and underfits the data-generating process (Colaresi and Mahmood 2017).

While it is possible to include multiplicative terms in an additive model, it seems safer to learn the types of interactions directly from the data. Similar to the issue of nonlinearity, interaction effects cause concerns about the 'researcher degrees of freedom' (Simmons et al. 2011) and multicollinearity (Schrodt 2014).

Establishing Causal Effects

Most social scientists agree that omitted-variable bias is the biggest threat to causality. In an experimental design, cases are randomly assigned to treatment and control groups, which means that confounding factors are similarly distributed and therefore have no effect on the outcome (Kellstedt and Whitten 2018). True experiments in the social sciences are rare, and researchers opt for natural experiments, where the treatment gets randomly assigned by a natural process (Dunning 2012). The main disadvantage of experimental designs is the lack of applicability, particularly when investigating the potentially complex interactions of *causes* rather than *a cause* (Diener et al. 2022). Consequently, quantitative research on the drivers of civil conflict often relies on observational designs.

In observational designs, researchers seek to establish a causal effect through controlling for alternative explanations (Kellstedt and Whitten 2018). However, the relationship between regression and causality remains contested, as it is often unclear whether the statistical model is correctly specified. Since experimental designs lack applicability and NHST's link to causality remains contested, establishing a causal effect is challenging to begin with.



(a) Low causal complexity (b) High causal complexity

Figure 1.2: Venn diagram illustrating the trade-off between omitted variable bias and multicollinearity. b is the causal effect of X, Y is the dependent variable, and Z is a matrix ($m \times n$) of control variables, with m rows and n columns. Each control variable z_i is associated with X and Y. The larger the Z circle, the more control variables need to be included in the model to avoid omitted-variable bias. The size of the control matrix in terms of n indicates the causal complexity of Y. The number of alternative explanations increases with n, and the phenomenon becomes more causally complex. The visualization is adapted from Kellstedt and Whitten (2018, p. 212).

Establishing a causal effect is even more challenging for complex phenomena. The causal effect of X on Y is denoted by b, while Z is a $m \times n$ matrix where m

refers to rows and n to columns, containing a set of control variables (Figure 1.2). The variables in the control matrix are correlated with both X and Y, as indicated by the intersection, which means that they need to be included in the model to avoid omitted-variable bias (Kellstedt and Whitten 2018). If Z does not contain all relevant controls, the area shaded in black is incorrectly assigned to the effect of X, hence leading to a biased estimation of b. Only the area that exclusively belongs to X is used when estimating b. For low causal complexity, where the set of control variables is comparatively small ($Z = m \times 5$), this is reasonably straightforward (left panel, Figure 1.2).

For high causal complexity, where the number of control variables is high ($Z = m \times 107$), a correct model specification becomes challenging (right panel, Figure 1.2).[5] Navigating between omitted-variable bias and multicollinearity almost naturally produces 'garbage can' models (Schrodt 2014). To avoid omitted-variable bias, all causally relevant variables need to be controlled for. However, the more predictors are included, the higher the correlation among them, which means that X's unique area becomes smaller and smaller until there is only little data leverage left to estimate the causal effect b (Kellstedt and Whitten 2018). 'Garbage can' models have large numbers of independent variables, which are mostly insignificant, or might have biased coefficients due to the weak data basis (Schrodt 2014). Such models tend to be overfitted, picking up noise from the sample, which yields false positive findings (Colaresi and Mahmood 2017).

A dilemma emerges. High causal complexity requires including large sets of control variables, thereby producing a 'garbage can' model with at best insignificant and at worst biased coefficients (Schrodt 2014). Excluding controls is no solution, as the resulting omitted-variable bias could distort the estimated causal effects. Coef-

[5]The most recent review identifies a total of 107 potential independent variables, when seeking to explain civil conflict (Trinn and Wencker 2021).

ficients in a 'garbage can' model are highly unstable, flipping from negative to null, to positive, depending on the model specification (Schrodt 2014). This explains why findings on the same explanatory factor change from study to study.

1.6 A Case for Interpretable Machine Learning

Machine learning has long been proposed as a potential remedy to the issues illustrated above (Beck et al. 2000; Colaresi and Mahmood 2017; Ward et al. 2010). Every sample has a systematic and a noise component (Carsey and Harden 2014). The systematic component refers to the true data-generating process, which is the causal mechanism that produces a certain phenomenon. Noise is introduced through measurement error or other idiosyncrasies of the cases that are randomly selected. The goal is to mirror the data-generating process while discarding noise.

There are two potential issues: Underfitting and overfitting (Colaresi and Mahmood 2017). The former occurs if a model only detects parts of the data-generating process and therefore does not provide an accurate explanation of the outcome. The latter occurs if the model accidentally picks up noise as signal and performs poorly when explaining the same outcome in a different sample. 'Garbage can' models suffer from both under- and overfitting, as they pick up noise while omitting nonlinear and conditional associations (Beck et al. 2000; Schrodt 2014).

At the heart of machine learning lies the bias-variance, or rather, the underfitting-overfitting trade-off (Colaresi and Mahmood 2017; Hastie et al. 2017). An algorithm with low complexity, such as linear regression, has low variance, meaning that the model works similarly well in another sample, but high bias, as it cannot account for intricate associations. An algorithm with high complexity, such as a decision tree, has low bias, as it accurately mirrors the data-generating process; yet the model might also pick up noise, leading to poor performance on new data. The ideal lies in the middle: A model with sufficient complexity (low bias), while maintaining the ability to generalize (low variance).

Machine learning identifies the ideal cut-off between underfitting and overfitting through out-of-sample validation (Hastie et al. 2017), thereby having a higher chance at accurately mirroring the data-generating process. Using out-of-sample validation, the model becomes as complex as necessary, while guarding against overfitting by ensuring that findings still generalize (Colaresi and Mahmood 2017). This implies that machine learning can overcome issues of non-additivity and nonlinearity, while evading the pitfalls of 'garbage can' models. Surely, machine learning cannot isolate a causal effect and returns correlations instead. However, it appears as a convincing alternative when validating civil conflict theory. In NHST, avoiding omitted-variable bias produces 'garbage can' models, which have a weak data basis to estimate b, and effects become untrustworthy (Kellstedt and Whitten 2018; Schrodt 2014).

While these arguments are fairly well established, social scientists remain skeptical, since machine learning models are black boxes (Masís 2023). A white-box model, for example, a linear regression, has simple inner workings, which means that it is clear how the independent variables relate to the outcome. A black-box model, such as a Random Forest or a Neural Network, has complex inner workings, and it is no longer accessible how the model makes predictions. However, this insight is needed to generate scientific knowledge (Masís 2023).

Conversely to the machine learning sceptics, off-the-shelf interpretability tools exist. These methods serve to derive post-hoc interpretations, similar to how humans make decisions (Masís 2023). Most often, it is unclear how the human brain arrives at a certain decision, but we can request a person to explain their reasoning. Interpretable machine learning takes this approach by asking the model to demonstrate how each variable affects the prediction.

1.7 A *Simple* Civil War Model

To illustrate how interpretable machine learning can overcome the methodological challenges of NHST, in particular, nonlinearity, non-additivity, and establishing causal effects (multicollinearity), a *simple* civil war model is constructed, using prominently discussed variables to explain and predict fatalities in civil conflict:[6]

1. Number of fatalities ($t-1$ and $log+1$)
2. Exponential time since last civil conflict
3. Exponential time since last civil war
4. At least one fatality in neighborhood ($t-1$)
5. Infant mortality
6. GDP per capita ($log+1$)
7. GDP growth
8. Oil rents ($log+1$)
9. Population size ($log+1$)
10. Share of male population 15-19 years
11. Ethnolinguistic fractionalization (ELF) index
12. Expected years of male schooling
13. Temperature
14. Freshwater withdrawals ($log+1$)
15. Electoral democracy
16. Liberal democracy
17. Egalitarian democracy
18. Civil liberties
19. Exclusion by social group

An OLS model is contrasted with a machine learning approach, using Random Forest (Breiman 2001) and tools from interpretable machine learning (Molnar 2025).[7] The regression model is presented in Table 1.1.[8] Three variables stand out due to

[6]The level of analysis is country-year. More details on the variables are provided in Table A1 (Appendix A). Missing values are filled in with linear interpolation and mean imputation based on the procedures explained in Section C.1 (Appendix C). The countries in Gleditsch and Ward (1999) comprise the sample after dropping microstates, countries with extensive missingness (i.e., Taiwan, Bahamas, Belize, Brunei Darussalam, Kosovo, North Korea, Montenegro, Somalia, Kuwait, and Solomon Islands), and states that no longer exist, yielding a sample of 164 countries. The temporal coverage is 1989—2023. Only the years that a state was independent are considered.

[7]A Random Forest averages predictions across several decision trees, which are obtained using a bootstrap sample (Hastie et al. 2017). Decision trees recursively divide observations into subgroups based on a series of input variables and corresponding split values.

[8]An Ordinary Least Squares (OLS) regression model is suitable for the continuous outcome. Since armed conflict is a rare event, the number of fatalities is heavily right-skewed, which can cause

	Dependent variable: Fatalities (log+1)				
	(1)	(2)	(3)	(4)	(5)
Number of fatalities ($t-1$)	0.657** (0.032)	0.647** (0.033)	0.641** (0.032)	0.642** (0.032)	0.633** (0.031)
Exponential time since civil conflict	−0.030 (0.042)	−0.054 (0.044)	−0.057 (0.044)	−0.061 (0.043)	−0.061 (0.044)
Exponential time since civil war	0.020 (0.040)	0.094^o (0.049)	0.091^o (0.050)	0.096^o (0.050)	0.088^o (0.049)
Fatality in neighborhood ($t-1$)	−0.182* (0.073)	−0.137* (0.064)	−0.139* (0.064)	−0.140* (0.064)	−0.168** (0.065)
Infant mortality		0.005* (0.003)	0.008** (0.003)	0.008** (0.003)	0.005^o (0.003)
GDP per capita ($log+1$)		−0.101 (0.063)	−0.072 (0.066)	−0.070 (0.066)	−0.059 (0.066)
GDP growth		−0.023** (0.006)	−0.022** (0.006)	−0.022** (0.006)	−0.021** (0.006)
Oil rents ($log+1$)		−0.004 (0.087)	−0.006 (0.084)	−0.006 (0.083)	−0.017 (0.080)
Population size ($log+1$)			0.355^o (0.205)	0.413* (0.209)	0.404^o (0.218)
Male population, 15-19 years			0.022 (0.025)	0.021 (0.025)	0.026 (0.026)
Ethnolinguistic fractionalization			0.967 (0.598)	0.949 (0.607)	1.128* (0.567)
Expected years of male schooling			−0.028 (0.028)	−0.026 (0.028)	−0.026 (0.028)
Temperature				−0.044 (0.037)	−0.041 (0.036)
Freshwater withdrawals ($log+1$)				−0.136 (0.105)	−0.115 (0.107)
Electoral democracy					1.796 (1.152)
Liberal democracy					0.158 (1.501)
Egalitarian democracy					−0.617 (1.518)
Civil liberties					−2.238** (0.720)
Exclusion by social group					0.526 (0.569)
Constant	3.212** (0.272)	3.270** (0.467)	−3.742 (3.600)	−3.653 (3.629)	−3.569 (3.778)
R-squared adj.	0.776	0.782	0.782	0.782	0.786
Observations	5625	5625	5625	5625	5625

^{o} p<0.1, * p<0.05, **p<0.01. The parentheses show standard errors, which are clustered by country. Country-fixed effects are included.

Table 1.1. OLS regression model with the number of fatalities in civil conflict ($log+1$) as dependent variable and a set of commonly discussed independent variables.

showing inconsistent results, taking the state of the literature as a reference point. (1) For the exponential time since the last civil war, the coefficient suggests that the more time has passed, the higher the fatalities, although this effect is not significant (expectation is a negative slope, Collier et al. 2003). (2) If one neighbor had at least one fatality in the previous year, the number of deaths in civil conflict decreases (ex-

heteroskedasticity and unreliable standard errors (Carsey and Harden 2014). A common solution is to log-transform the outcome. Standard errors are clustered by country, and country fixed-effects are included. Right-skewed independent variables are likewise log transformed ($log+1$).

pectation is a positive slope, Buhaug and Gleditsch 2008). (3) Finally, oil rents have a negative, although not significant, effect on the number of casualties (expectation is a positive slope, Ross 2004b).

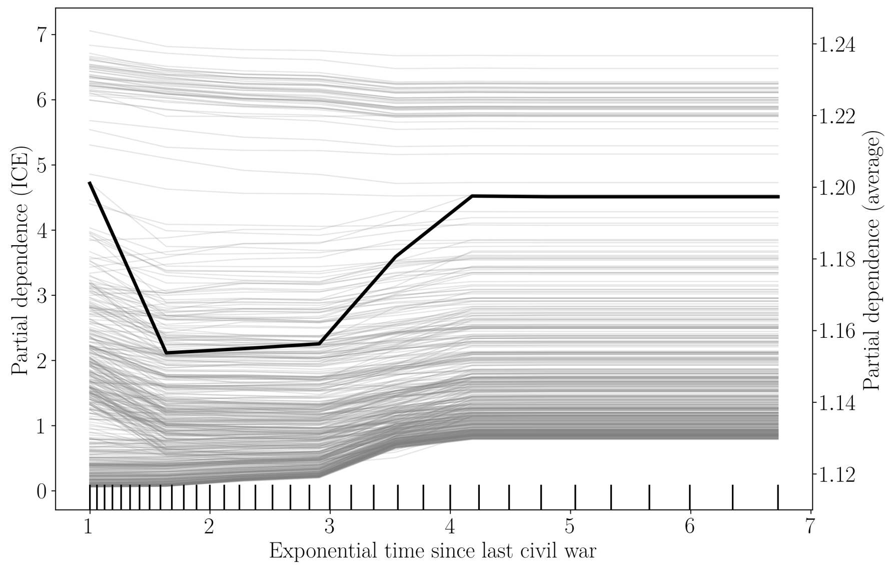


Figure 1.3: Partial dependency plot for the exponential time since the last civil war.[a] Individual Conditional Expectation (ICE) on the left y-axis and average on the right y-axis. The association between time since civil war and fatalities in civil conflict is U-shaped.

[a]Partial dependence (PD) plots show the marginal effect of X on the prediction of Y across different values of X (Masís 2023). The plot averages the Individual Conditional Expectation (ICE). ICE is calculated for each case by replacing X with a grid, while the remaining features take the observed values. The partial dependence (PD) is the average. For better visibility, the ICE curves are limited to cases with a high range.

The regression model presents a non-significant, positive effect for the time since the last civil war. More consistent with the literature, the machine learning approach shows a negative correlation immediately after an event, suggesting that the number of fatalities is higher the more recent the last civil war (Figure 1.3). The individual curves (gray) suggest that the association is negative/U-shaped for some cases, while positive for others, ultimately producing a U-shaped pattern when aggregated. This finding suggests that the effect is conditional, which is uncovered by the machine learning approach, while the OLS model only accounts for the average.

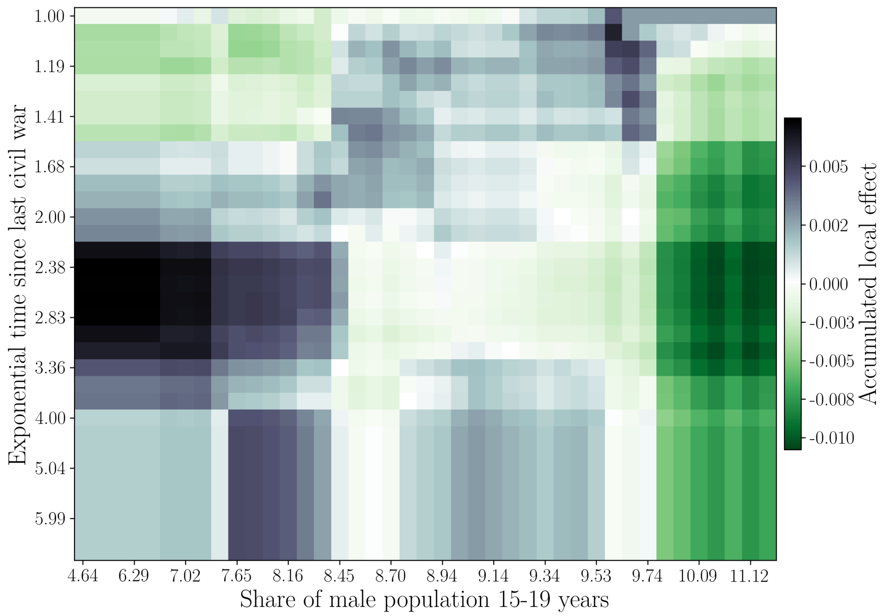


Figure 1.4: Interactive ALE plot for the exponential time since the last civil war and male population aged between 15-19 years.[a] The association between time since civil war and fatalities in civil conflict is positive if there are no youth bulges.

[a]Interactive Accumulated Local Effect (ALE) plots illustrate how much the predicted outcome changes across different values on a grid, accounting for two features simultaneously (Molnar 2025). The plots show the second-order association, which is the effect on the outcome that is produced exclusively by the interaction.

Time since the last civil war has a positive correlation if the share of the male population aged between 15-19 years is low (Figure 1.4). A large fraction of young males, also referred to as a youth bulge, increases the risk of armed conflict, given that young men are more easily recruited for violent contention (Urdal 2006). This means that the proportion of young males is an indicator for recruitment capabilities, with low values implying poor chances of successfully recruiting enough individuals. Consequently, the non-state actor might require more time to regroup after fighting ends, creating longer pauses between distinct armed conflicts. This applies particularly to civil war, as opposed to civil conflict, which arguably involves greater levels of destruction and longer remobilization phases to begin with.

The regression model returns a negative coefficient for fatalities in the neigh-

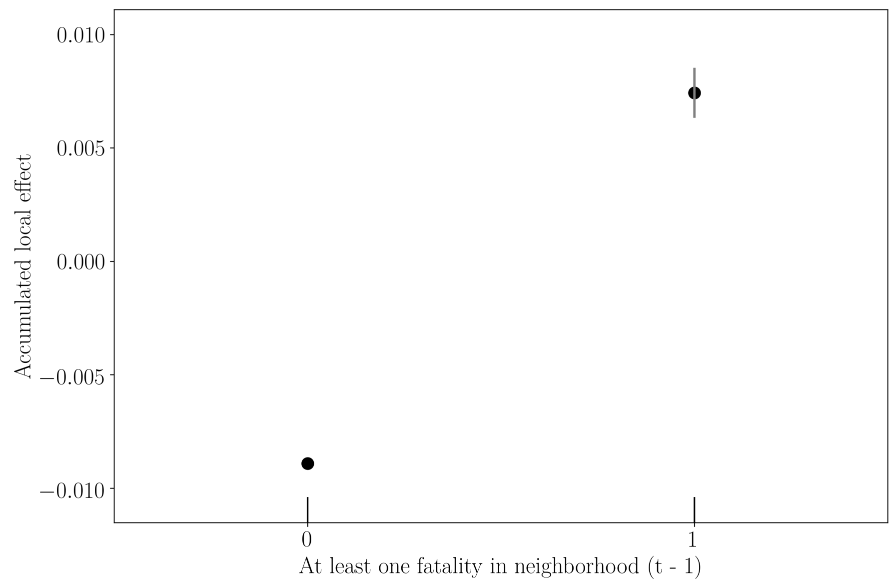


Figure 1.5: ALE plot for the neighborhood effect.[a] The predicted fatalities from civil conflict are higher if a country has at least one neighbor with at least one fatality in the previous year.

[a]Accumulated Local Effects (ALE) denote how much the prediction changes on average across different values of X (Molnar 2025). The feature space is divided into intervals. For each observation, the value of X is replaced by the upper and lower bounds of the interval, and the change in the predicted outcome is calculated. These differences are then aggregated over intervals.

borhood. More consistent with the literature, nearby armed conflict increases the number of fatalities in the machine learning approach (Figure 1.5). This is due to the spill-over of violence, transnational linkages between conflicts, or the geographic clustering of conflict risk factors (Forsberg 2016). The OLS model includes four strongly correlated variables, since they are different measures of the same data: Fatalities in civil conflict. The resulting multicollinearity can lead to biased coefficients, due to an insufficient data basis (Kellstedt and Whitten 2018; Schrodt 2014).

The regression model presents a non-significant, negative effect of oil rents. The machine learning approach suggests a more complex association: The effect is funnel-shaped (Figure 1.6). High oil rents increase *and* decrease the number of fatalities. For one, trade with oil can provide rebels with sufficient funds to initiate armed action, natural resource dependence erodes state capacity, and oil depletion might intensify local grievances (Ross 2004a). For another, not all oil exporters suffer from the *oil curse*. Countries like Norway and the United Kingdom have large oil deposits *and* are rich democracies (Ross 2013). The pattern in Figure 1.6 suggests that the effect of oil is conditional.

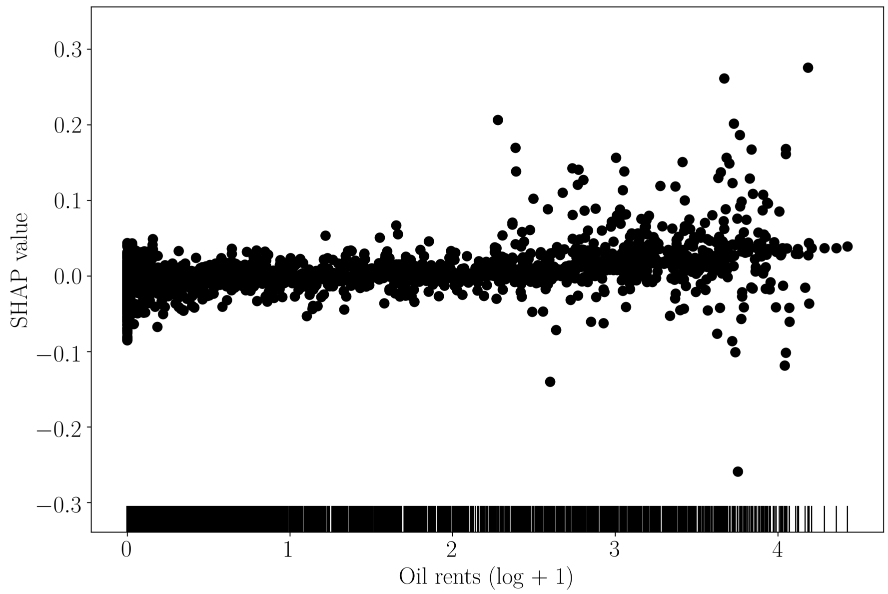


Figure 1.6: SHAP value plot for oil rents ($log + 1$).[a] The correlation between oil and fatalities is funnel-shaped.

[a]SHapley Additive exPlanations (SHAP) denote the average marginal contribution of a variable across coalitions (Molnar 2025). Coalitions are certain combinations of predictors, and the marginal contribution is the change in the predicted outcome after removing the variable. A positive value implies that the outcome increases, and a negative value means that the outcome decreases.

The effect of oil is conditional on GDP per capita (Figure 1.7). Oil *increases* the predicted fatalities if GDP per capita is low, yet *decreases* the risk of civil conflict in rich countries. Income is a key indicator for opportunity costs, and individuals might have too much to lose from engaging in armed conflict if economic prospects in the regular economy are good (Collier and Hoeffler 2004). This seems to nullify the danger of oil, a key enabler for a non-state group to recruit individuals (Ross 2004a), which is arguably dependent on low opportunity costs.

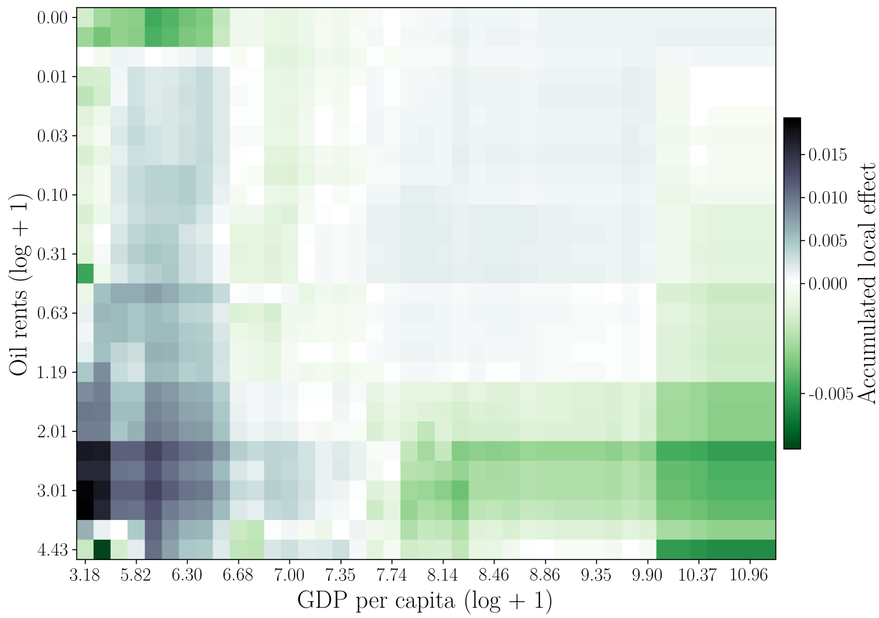


Figure 1.7: Interactive ALE plot for oil rents (log+1) and GDP per capita (log+1). The correlation between oil and fatalities is positive for low GDP per capita, and negative for high GDP per capita.

1.8 Contributions to the Field of Conflict Prediction

Conflict prediction has been established as a relevant subfield of peace and conflict research (Bara 2020; Rød et al. 2024). This is for two important reasons: (1) Conflict prediction has high practical relevance since early warning can inform policymakers where and when to intervene (Hegre et al. 2017), and (2) there is the hope that machine learning can overcome some of the methodological challenges prevalent in the civil war literature (Beck et al. 2000; Colaresi and Mahmood 2017; Ward et al. 2010). While this dissertation uses machine learning to validate theory, it likewise contributes to the field of conflict prediction.

The academic field of conflict prediction is dominated by two main approaches: The Violence & Impacts Early-Warning System (VIEWS) (Hegre et al. 2019; Hegre et al. 2021; Hegre et al. 2022) and *Conflict forecast* (Mueller and Rauh 2022; Mueller et al. 2024). Both projects have unique strengths. VIEWS uses structural variables on economic development, conflict history, and political institutions (Hegre et al. 2022), and therefore excels at predicting a baseline level of armed violence (Schincariol et al. 2025). However, the model encounters difficulties when seeking to anticipate conflict onsets, given that structural background factors are too time-invariant to forecast the precise timing of a new outbreak (Blair and Sambanis 2020).

Taking this as a point of departure, *Conflict forecast* tackles the "hard problem of conflict prediction" (Mueller and Rauh 2022, p. 2442), which are cases with no immediate conflict history. Augmenting variables on past armed violence, the project extracts topics from news articles to measure political tensions, and predicts the total number of fatalities in the next three or twelve months.[9] While *Conflict forecast* puts forward a novel approach, the model's reliance on news responds to political turmoil more immediate to armed conflict and might produce an early warning signal only after violent escalation is already underway.[10]

Based on the reconceptualization of conflict emergence, preceding low-intensity collective action is a more robust precursor to the outbreak of civil conflict. Protests might unfold over months before a potential transition to armed violence (e.g., Israel and Egypt), and non-state actors commonly mobilize for several consecutive years (Malone 2019), during which recruitment produces initial fatalities from low-intensity armed conflict. Complementing *Conflict forecast* and VIEWS, this dissertation introduces the 'Onset catcher', which is a hurdle model, anticipating fatalities in civil conflict conditional on a high preceding risk of collective action.

[9] *Conflict forecast* predicts fatalities from state-based conflict, non-state conflict, and one-sided violence (Mueller and Rauh 2022), which makes it challenging to use the model as a benchmark. For this reason, VIEWS is the default reference for predictive performance.

[10] This argument relates to the criticism by Jäger (2016), stating that news-based conflict prediction models are essentially tautological, given that they forecast armed conflict with conflict.

1.9 Conclusion

This dissertation develops a reconceptualization of conflict emergence. Civil war is a multistaged process, comprising initial collective action *(stage i)* and the subsequent transition to civil conflict *(stage ii)*. Different aspects of the reconceptualization are investigated with conflict prediction, using tools from interpretable machine learning to derive theoretical conclusions. Four main findings are put forward.

Paper i: Civil wars are highly complex phenomena and emerge along stereotypical pathways rather than sufficient conditions. These pathways present intricate combinations of grievances and opportunity, and civil war onsets can be grouped based on similarity. While common pathways to civil war onset exist, every case is likewise unique, presenting a specific manifestation of the underlying logic, which limits the applicability of causal mechanisms across cases. This is in line with the assertion that civil war is inherently unexplainable (Gartzke 1999).

Paper ii: Different forms of collective action have similar causes and should be studied together. Structural risk factors predict collective action more generally, rather than civil war exclusively, which implies that structural factors might prompt civil conflict by transitioning through protest and/or low-intensity armed conflict. Despite marked communalities, less (protests, riots) and more extreme contention (terrorism, low-intensity armed conflict) have distinct characters, which applies particularly to protest, a regular form of political participation in democracies.

Paper iii: Protest is a dynamic phenomenon. The interactions between protesters and the government produce recurring patterns in protest over time. Going beyond recent activity, sequences of protest events contain unique information on when non-violent collective action might escalate. There are three types of dangerous protest patterns which precede high fatalities in civil conflict: A gradual escalation of protest intensity, a substantial decline following a peak, and a U-shape where protest drops and then resurges. These patterns emerge from an escalation process or the strategic decision-making of the non-state group.

Paper iv: Using structural risk factors to filter out country-months with a high baseline risk of collective action yields a subsample of cases. For this subsample, the preceding risk of collective action serves to predict conflict onsets, which are observations with non-zero fatalities and a value of zero in the previous month. This implies that civil conflict emerges along two stages: Initial collective action (*stage i*), and the transition to more substantial armed violence (*stage ii*). Preceding collective action is a key precursor to civil conflict.

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2 *Grievances and Opportunity: Uncovering Causal Complexity in Civil War Onsets*

Grievances and Opportunity: Uncovering Causal Complexity in Civil War Onsets

Hannah Frank

Replication Material
The data and code used for the analysis can be accessed here: `https://github.com/hannahhfrank/phd_thesis_reconceptualizing_conflict_emergence/tree/main/interpretability`.

Use of Generative Artificial Intelligence
For implementing the empirical analysis, ChatGPT-3.5 and higher (`https://chatgpt.com/`) served as a coding assistant, and when brainstorming ideas for how to visualize the findings. In addition, grammar and spell checkers were used as add-ons in Overleaf (i.e., Grammarly, Writefull, and LanguageTool).

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Grievances and Opportunity: Uncovering Causal Complexity in Civil War Onsets

Abstract

Civil wars are highly complex phenomena, often described as puzzling, random, or stochastic. Rationalist explanations contend that uncertainty and incentives to bluff might cause a high-risk situation, but the mechanisms ultimately producing war are largely stochastic. This means that outbreaks of violence are inherently unexplainable. Rather than seeking to establish sufficient conditions, as emphasized by existing complexity-based explanations, it might be useful to think about civil war onsets in terms of stereotypical pathways. Every onset is assigned to the closest pathway, while allowing for the possibility that each case presents a unique manifestation of the underlying logic. This paper uncovers stereotypical pathways to civil war by leveraging machine learning tools, which are advantageous when studying intricate phenomena. The analysis reveals eight distinct civil war pathways: Economic crisis, opportunity, grievances, weak state capacity, oil curse, bad neighborhood, climate, and large population. The derived clusters illustrate how the combination of grievances and opportunity produces civil war onsets. While common pathways to civil war exist, every onset has a unique character, limiting the extent to which causal mechanisms apply across cases.

Keywords: Civil war onset, complexity, pathways, interpretable machine learning

2.1 Introduction

After some initial rivalry between grievances and opportunity-based explanations, scholars began exploring how the interaction of both might cause civil war onset (Bara 2014; Bormann and Hammond 2016; Dyrstad and Hillesund 2020). Grievances and opportunity can interact and reinforce each other, given that the willingness to fight against the government facilitates mobilization, which in turn increases the chances of success and thereby the group's recruitment capabilities.

Civil war is a highly complex phenomenon, often described as puzzling, random, or stochastic (Gartzke 1999; Kalyvas 2003). Rationalist explanations ascertain that civil war is caused by uncertainty: The combination of private information, incentives to bluff, and the resulting danger of miscalculations (Fearon 1995). If civil war is caused by uncertainty and incentives to bluff, the onset of civil war becomes inherently unexplainable, given that a stochastic component, unique to each situation, ultimately leads to the onset of war (Gartzke 1999). Rather than seeking to establish sufficient conditions, it might be useful to think about civil war onset in terms of stereotypical pathways. Each case is assigned to one pathway while allowing for the possibility that additional structural factors and triggering events produce a unique manifestation of the underlying mechanism.

This paper seeks to uncover stereotypical pathways to civil war using tools from interpretable machine learning. Ten prominently discussed indicators for grievances and opportunity are used to predict civil war onsets, which are country-years with at least $1,000$ fatalities from civil conflict (N. P. Gleditsch et al. 2002), preceded by two years below that threshold (adapted from Bara 2014). The Random Forest Classifier (Breiman 2001) is selected due to the algorithm's ability to mirror complex associations. Considering only onset cases, SHAP values are obtained, which denote how each variable affects the prediction (Molnar 2025), and therefore serve to derive theoretical conclusions. To find stereotypical pathways, the SHAP values are grouped with hierarchical clustering (Hastie et al. 2017).

The analysis reveals eight distinct civil war pathways: (1) *Economic crisis* are cases with negative economic growth, (2) *Opportunity* includes countries with low opportunity costs, (3) *Grievances* combines cases with high ethnic exclusion, (4) *Weak state capacity* groups onsets with low regulatory quality, (5) *Oil curse* illustrates how low regulatory quality and oil-dependence are intertwined, (6) *Bad neighborhood* contains countries in conflict hot-spots, (7) *Climate* shows the effect of high and low temperatures, and (8) *Large population* indicates that populous countries are more vulnerable to armed violence.

While common pathways to civil war onset exist, every case likewise has a unique character, which is accounted for in this analysis. Some cases even fall outside the assigned stereotypical pathway. For example, the civil war in Ukraine-2014 belongs to the *oil curse* pathway but has a clear geopolitical component (UCDP 2025k), and the Chechen Civil Wars emerged as separatist conflicts amid the dissolution of the Soviet Union (UCDP 2025g), while being part of the *climate* pathway. Another idiosyncratic case is Israel, which only marginally fits into the clusters, due to being a rich democracy.

This paper produces two main findings. Armed conflict is costly, rendering it unreasonable to assume that one factor alone would cause it. Conversely, grievances and opportunity interact and reinforce each other to trigger civil war onset. The uncovered civil war pathways combine both mechanisms, and the most dangerous situations are those with political opportunity/grievances (i.e., weak state capacity), economic opportunity/grievances (i.e., low education and low GDP per capita), and social opportunity/grievances (i.e., high ethnic exclusion).

Second, civil wars are highly complex phenomena, and extracting common pathways only works to a certain degree. While shared pathways emerge from the data, every onset likewise has its unique character, limiting the extent to which causal mechanisms apply across cases. This is in line with the assertion that civil conflict is inherently unexplainable, given that only a stochastic mechanism can account for how uncertainty and incentives to bluff lead to war (Gartzke 1999).

2.2 Grievances versus Opportunity

The literature on the causes of civil war is dominated by three lines of argument: Grievances, economic opportunity, and political opportunity. The oldest theoretical model on the causes of civil war proposes that armed conflict is prompted by aggrieved individuals when frustration turns into aggression (Dollard et al. 1939). The frustration itself originates from grievances, which arise if individuals are dissatisfied with their current living conditions and believe that more should be attainable, also known as relative deprivation (Gurr 2016). Relative deprivation often refers to comparisons between cultural groups, where a majority holds power over the minority (Fearon and Laitin 2003).

Beginning in the early 2000s, Collier and Hoeffler (2004) and Fearon and Laitin (2003) put forward alternative theoretical arguments for the causes of civil war. For one, Collier and Hoeffler (2004) suggest that civil war occurs if individuals have low opportunity costs, which refer to the income that is lost if an individual joins a rebel group, instead of employment in the regular economy. For another, Fearon and Laitin (2003) argue that civil war emerges due to political opportunities, where a weak central government enables rebels to hide and mobilize in the periphery of the country. Both articles pit the opportunity argument against the grievances approach and find that grievances are a weak explanatory factor for civil war onset.

As a reaction to the grievance null finding, scholars have pointed towards a reconceptualization of the approach (Cederman et al. 2010; Wimmer et al. 2009). Earlier work relied on diversity indicators, such as ethnic fractionalization, measuring the probability that two randomly selected citizens belong to different ethnic groups (e.g., Collier and Hoeffler 2004; Fearon and Laitin 2003). Conversely, Wimmer et al. (2009) claim that it is not diversity that causes civil war, but exclusion from political power along ethnic lines. If ethnic groups are not accurately represented in government, the legitimacy of the state falters, which enables ethnic leaders to mobilize coethnics for armed action. With a new dataset on politically relevant ethnic groups, the authors demonstrate that the more severe political exclusion, the higher the probability of civil war onset.

2.3 Grievances and Opportunity

After initial rivalry between grievances and opportunity-based explanations, scholars began to argue that civil war is most likely caused by both (Bara 2014; Bormann and Hammond 2016; Dyrstad and Hillesund 2020). Using Qualitative Comparative Analysis (QCA), Bara (2014) uncovers four quasi-sufficient explanations for ethnic conflict: (1) 'Conflict trap', which combines cases with conflict history and political exclusion, (2) 'Bad neighborhood' are onsets with political instability and transborder ethnic kin experiencing armed conflict, (3) 'Ousted rulers' integrates political instability with ethnic exclusion from political power, and (4) 'Resource curse' are cases with natural resources, exclusion and political instability.

Both grievances and opportunity are required for civil war onset to occur. Enough individuals need to have a reason to engage in rebellion, and the rebel group needs to be able to mobilize effectively (Bara 2014). Moreover, grievances and opportunity can be mutually reinforcing. Grievances make individuals more willing to engage in armed action against the state, thereby facilitating mobilization for collective action (Gurr 2016). Initially, a rebel group is weak and needs to obtain sufficient military capabilities to attack the government (Larson and Lewis 2018). As more individuals join, a window of opportunity emerges. The stronger the military capabilities of the non-state group, the higher the chances of winning. The higher chances of success, in turn, enhance mobilization as more individuals are motivated to participate if they believe concessions from the government are possible (Jakobsen et al. 2013).

In addition to the cyclic relationship, grievances and opportunity are even directly intertwined, as they often cannot be distinguished theoretically or empirically. Most correlates of civil war onset can be substantiated by both types of arguments (see Bara 2014 for a similar discussion). For instance, low GDP per capita is positively associated with civil war onset because grievances provide motivation, because low income enhances recruitment capabilities, or because low GDP per capita indicates weak state capacity (Jakobsen et al. 2013). Oil increases the risk of civil war, since income from oil can provide rebels with the opportunity to initiate armed action, since oil dependency erodes state capacity, or since oil depletion intensifies local grievances (Ross 2004). Food insecurity might prompt armed conflict due to grievances of the ones affected, due to the decline in agricultural production leading to higher unemployment, or due to food insecurity signaling weak state capacity (Martin-Shields and Stojetz 2019).

2.4 The Complexity of Civil War

Civil wars are highly complex phenomena, often described as puzzling, random, or stochastic (Gartzke 1999; Kalyvas 2003). In this context, complex systems are dynamic, self-organizing entities, comprised of a multitude of components that interact with each other and the environment (Brosché et al. 2023; De Coning 2020).

Civil wars are structurally and temporally complex. Structural complexity originates from the unique interests of actors: The political elite might promote a certain goal while private actors pursue their individual interests (Kalyvas 2003). The causal relationships in the context of civil war are likely nonlinear and conditional on specific scope factors (Beck et al. 2000). In terms of temporal complexity, certain structural aspects might produce a high-risk situation—a powder keg—but a spark—some triggering event—is needed to ignite armed escalation (Chadefaux 2014). While armed conflict has long been described as a complex system, this notion is not sufficiently integrated into the study of civil war onsets (Brosché et al. 2023).

Existing complexity-based approaches (i.e., Bara 2014) remain constrained by seeking to establish sufficient conditions for civil war onset. These approaches omit that every civil war has a unique character, given that they are caused by uncertainty, or rather a lack of information, making onsets theoretically indeterminate (Gartzke 1999). Instead of focusing on certain formulas to substantiate civil war onset (e.g., if a and b or if c and d), explanations for civil conflict should be approached as stereotypical pathways, maintaining the unique character of war.

Rationalist explanations contend that actors should be able to agree to a negotiated settlement before violence erupts, given the high costs of armed conflict (Fearon 1995). However, negotiated settlements can be undermined by uncertainty. Every conflict actor has private information concerning military capabilities and resolve. Since this information is unknown to the other side, both actors have strong incentives to misrepresent, which can cause war due to miscalculations.

Against this backdrop, Gartzke (1999) ascertains that uncertainty and incentives to bluff yield a theoretically indeterminate explanation for the outbreak of war. These conditions might produce a high-risk situation, but miscalculations are caused by a lack of information and are therefore largely stochastic and unique to each context.

The systematic component of a situation does not cause war, but the unpredictable one, which means that there is no reproducible relationship between causal factors and civil war onset. The author concludes that war is unexplainable as it is caused by uncertainty, incentives to bluff, *and* randomness.

If the onset of war cannot be explained, sufficient conditions for new outbreaks of violence simply do not exist. Against this background, I argue that civil war is not driven by the combination of conditions a, b, and c, but by how conditions a, b, and c, unfold in a specific context, which might likewise see conditions d and e, and a potentially unobservable condition f. Due to the stochastic component, each civil war is caused by a unique manifestation of the underlying causal mechanism, which cannot be translated to other cases.

If civil war is inherently unexplainable, this needs to be reflected when studying civil war onset. Rather than seeking to uncover sufficient conditions, civil war emerges along stereotypical pathways (e.g., conditions a, b and c). For example, a country with an oil-dependent economy, weak state capacity, and an authoritarian regime might be more prone to armed violence (Ross 2013). Alternatively, political marginalization along ethnic lines can produce fertile ground for armed conflict, especially if the excluded segment of society is large, which enhances mobilization capabilities (Cederman et al. 2010). These stereotypical pathways might manifest in different ways, and a specific situation could see further observable (conditions d and e) and unobservable explanatory factors (condition f). The effect of oil might be particularly severe if revenues are distributed along ethnic lines, where only the majority benefits and the minority misses out (Basedau and Richter 2014).

When studying civil war onset, it seems reasonable to extract stereotypical pathways that apply across cases, focusing on the interaction of grievances and opportunity. Matching stereotypical pathways to actual onset cases allows for the possibility that other relevant structural factors and/or more immediate triggers, observed and/or unobserved, ultimately produce civil war onsets. The stochastic component of each case is accounted for, while uncovering underlying mechanisms that might generalize across cases.

2.5 Building a Civil War Model

By uncovering stereotypical pathways to civil war onset, this paper aims to investigate the causal complexity in the causes of civil conflict. For this purpose, a list of independent variables is proposed, including prominently discussed indicators for grievances and opportunity:[1]

1. Fatalities in neighborhood ($t-1$ and $log+1$)
2. GDP per capita ($log+1$)
3. GDP growth
4. Population size ($log+1$)
5. Oil rents
6. Temperature
7. Ethnic exclusion
8. Male education
9. Liberal democracy
10. Regulatory quality

Civil war has an international dimension, since armed violence clusters geographically and temporally (Buhaug and K. S. Gleditsch 2008). There are three explanations for this: (1) Structural risk factors might cluster in space, (2) armed violence in one country might prompt civil war in a neighboring state due to the spill-over of fighters and military equipment, and (3) one civil war might rage in several countries simultaneously through connectedness of conflict issues and actors (Forsberg 2016). The first variable in the model is the total *fatalities in the neighborhood* ($t-1$ lag and $log+1$).

[1] Table B1 in Appendix B contains more information on the variables and data sources.

Civil war might be caused by low opportunity costs (Collier and Hoeffler 2004). Opportunity costs refer to the income that an otherwise employed person would lose in the peaceful labor market. If economic prospects are poor, an individual might be more easily recruited into a non-state group based on the promise of receiving payment (Jakobsen et al. 2013). Participation in armed action becomes an economic activity. Common proxies for opportunity costs are: *GDP per capita* ($log + 1$), *GDP growth*, and *male education* (see Collier and Hoeffler 2004).

Low GDP per capita also indicates weak state capacity, which provides opportunity for violence by making the government either unaware or unable to prevent it (Fearon and Laitin 2003). Simultaneously, weak state capacity can lead to a poor provision of public goods, which fuels grievances (Fjelde and De Soysa 2009). Another measure of state capacity is *regulatory quality*, denoting whether the government can effectively manage the private sector (Kaufmann and Kraay 2024).

Regime type (*liberal democracy*) likewise offers opportunity when autocratic and democratic characteristics concur (Fearon and Laitin 2003; Hegre et al. 2001). While autocratic regimes have strong repressive means to counter opposition, democratic regimes represent their citizens' interests and have non-violent conflict resolution tools (Hegre 2014). Regimes in the middle are the most vulnerable, unwilling to be accountable to their citizens, and unable to prevent collective action.

Regime type also relates to grievances, given that political exclusion becomes salient if it runs along ethnicity (Cederman et al. 2010). Politicians may attempt to gain legitimacy with ethnic favoritism, which organizes the political arena according to ethnic cleavages. Seeking to enhance their standing, individuals systematically excluded from political power might resort to armed action. *Ethnic exclusion* denotes the fraction of the population that is excluded from political power, summing across politically relevant ethnic groups (Vogt 2021).

Population size (*log*+1) is linked to civil war onset because: (1) Large populations provide opportunity, i.e., the chance of recruiting enough individuals is higher the more people are potentially available, (2) large countries are inherently more difficult to govern, offering opportunity to mobilize in the periphery of the state, and (3) population concentration can help overcome coordination problems (Raleigh and Hegre 2009). There is also a grievances component, since the provision of public goods might be hampered in large countries (Fox and Bell 2016).

There are four causal mechanisms to substantiate the positive association between *oil rents* and civil war onset: (1) Trade with oil can provide the required start-up funds to initiate mobilization against the state, (2) oil abundance might produce grievances if its benefits are not distributed equally or if oil extraction deteriorates the living conditions of locals, (3) if oil deposits are located in one part of a country, this may prompt separatist movements, and (4) oil abundance might increase the risk of civil war indirectly, where the government's reliance on income from oil erodes state capacity (Ross 2004).

Although the association between climate and armed violence is contested (Buhaug 2010; Burke et al. 2009), there is evidence that extreme *temperature* increases the risk of conflict (Burke et al. 2015). There are four potential explanations: (1) Climate change might intensify competition over resources such as water and crop, (2) climate-induced displacement can produce conflict in host regions, due to increased demand for goods and services, (3) weather conditions can influence economic performance, and (4) high temperatures might prompt aggressive behavior, which can cause armed conflict if aggregated (Wischnath and Buhaug 2014).

2.6 Data

The level of analysis is country-year. To build the sample, the countries in K. S. Gleditsch and M. D. Ward (1999) are taken as the point of departure. Microstates, states that no longer exist (e.g., Yugoslavia), and states with extensive missingness are dropped, given that imputation techniques can produce unreliable results for countries completely missing.[2] In addition, it seems reasonable to remove microstates (e.g., Monaco and Liechtenstein), due to their systematically different character from non-microstates. The final sample comprises 162 countries with a temporal coverage of 1989—2023, which is defined by the Uppsala Conflict Data Program (UCDP).[3]

To code the outcome—civil war onset—data on the number of fatalities in civil conflict are required, which are obtained from the UCDP Georeferenced Event Dataset (Sundberg and Melander 2013) by summarizing the *best* fatality estimates over country-year. Data sources for the inputs are the World Bank (CCKP 2024; World-Bank 2025a; World-Bank 2025b), the Ethnic Power Relations dataset (Vogt et al. 2015), and the Varieties of Democracy data (V-Dem 2024). Missing values are filled in with linear interpolation and mean imputation, accounting for a train-validation split. Since multivariate imputation can produce unrealistic dents in the time trends (Honaker and King 2010), time series warrant a simple approach.[4]

2.7 Research Design

The empirical strategy relies on machine learning, which requires dividing the data into a training and a validation set. The first 70% of years (1989—2013) are used during training, and the remaining 30% (2014—2023) for optimizing hyperpa-

[2]These countries are dropped due to missingness: Taiwan, Bahamas, Belize, Brunei Darussalam, Kosovo, North Korea, Djibouti, Azerbaijan, Haiti, Moldova, Turkmenistan, and Zambia.

[3]Only the years that a country was independent are included (e.g., South Sudan 2011—2023).

[4]For more details on how missing values are imputed, refer to Section C.1 in Appendix C.

rameters of the model. Since the data are time series, the temporal order needs to be accounted for in the split (Roberts et al. 2017).

The dependent variable is civil war onset, taking a value of *one* for each country-year with at least 1,000 fatalities in civil conflict, and *zero* otherwise (N. P. Gleditsch et al. 2002). For an onset to occur, the two preceding years need to remain below that fatality threshold (adapted from Bara 2014). This coding yields 58 onset cases (Table B2 in Appendix B lists all cases). The variable is constructed conservatively by discarding left-censored onsets, or rather, cases with 1,000 fatalities in 1989 or 1990, since data on the two preceding years are not available. This leads to fewer onsets, which is preferred due to the intensive character of the design.

Random Forest

The Random Forest Classifier (Breiman 2001) is used for the dichotomous outcome, which is an excellent choice when seeking to uncover causal complexity, given that the algorithm can capture nonlinear and conditional associations (Molnar 2025). To obtain more robust forecasts, Random Forests combine predictions from several decision trees through bootstrap aggregation (Hastie et al. 2017). Decision trees (Figure 2.1) begin with all observations at the top node and recursively split them into subgroups until a stopping criterion is satisfied. The predicted outcome is the maximum class in each final node, or predicted probabilities are returned as the relative proportion of cases assigned to $Y = 1$ (scikit-learn 2025a).

The sequence of features and split values is selected by minimizing the Gini impurity (Hastie et al. 2017). The Gini impurity is defined as

$$G = \sum_{k=1}^{K} \hat{p}_{mk}(1 - \hat{p}_{mk}) \tag{1}$$

where $\hat{p}_{mk}$ is the proportion of observations assigned to class k in the m^{th} node. For example, the Gini impurity after the first split to the left is $G = \frac{1}{4} * (1 - \frac{1}{4}) + \frac{3}{4} * (1 - \frac{3}{4}) =$

0.375, and after the first split to the right $G = \frac{5488}{5543} * (1 - \frac{5488}{5543}) + \frac{55}{5543} * (1 - \frac{55}{5543}) = 0.02$. By comparing the relative frequencies across classes, the Gini impurity denotes the diversity of each node, where zero implies a perfect split (Tangirala 2020).

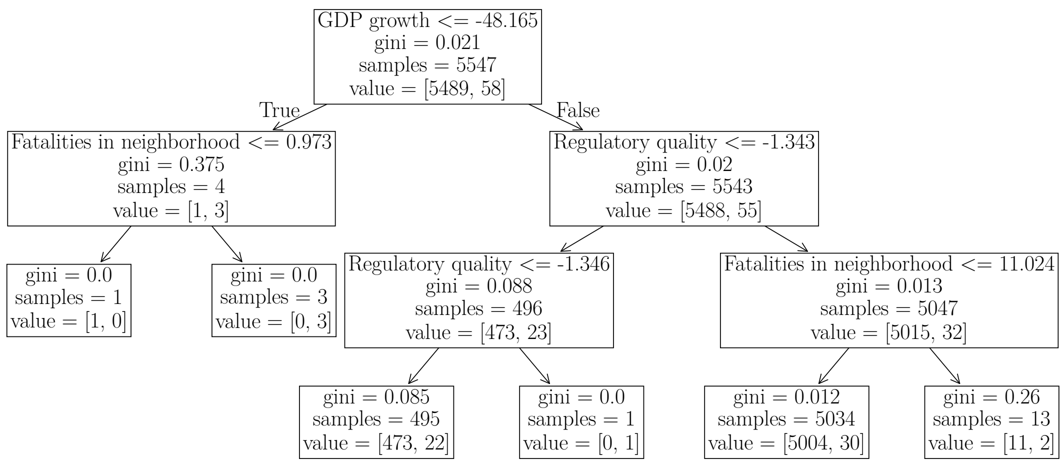

Figure 2.1: Decision tree example, predicting civil war onset with the following independent variables: GDP per capita ($log + 1$), fatalities in neighborhood ($t - 1$ and $log + 1$), GDP growth, population size ($log + 1$), oil rents, ethnic exclusion, and regulatory quality.

Decision trees can capture nonlinear and conditional associations (Molnar 2025). In the sample, 5489 observations have no civil war onset, while 58 experience one. The first split divides cases based on economic performance (Figure 2.1). The four cases that have a $\leq -48.165\%$ GDP growth rate are contained in the left subgroup, and the 5543 observations with a higher value are passed on to the right side. Instead of assuming that economic performance has a linear effect on the probability of civil war onset, the decision tree identifies certain cutoff values to differentiate between low- and high-risk cases.

After the first split, observations on the left side are split again based on whether fatalities in the neighborhood ($t - 1$ and $log + 1$) are ≤ 0.973 (Figure 2.1). One case is passed to the left and three to the right. The right node then contains three onset cases with negative GDP growth *and* some ($exp^{0.973} - 1 = 1.646$) fatalities in the neighborhood. Instead of focusing on additive effects, the decision tree accounts for several variables simultaneously, thereby uncovering conditional associations.

Decision trees are seldom used on their own due to their high variance (Hastie et al. 2017). Especially if fully grown, decision trees can capture complex associations, where each final node contains one case. While such a model has low bias by accurately mirroring the data-generating process, it is likely overfitted. If a decision tree is used on new data, the results could change dramatically.

Several decision trees can be combined in a Random Forest (Hastie et al. 2017). To reduce the similarity between constituent models, each tree is grown using a bootstrap sample, and only a random selection of variables is considered at each split. The final predictions are obtained in majority vote over B trees, where $\hat{C}_b(x)$ denotes the predicted class of the b^{th} tree,

$$\hat{C}_{rf}^{B}(x) = majority\,vote\,\{\hat{C}_b(x)\}_1^B \tag{2}$$

Random Forests have several hyperparameters, such as the number of trees and the maximum depth (scikit-learn 2025b), which control the complexity of the algorithm. The hyperparameters are optimized in the validation data. The training data (1989—2013) are used to fit different value combinations, and out-of-sample predictions are returned for the validation partition (2014—2023). The combination with the highest accuracy returns the final model. This step is essential, making the algorithm as complex as possible, while ensuring that findings still generalize (Colaresi and Mahmood 2017). As a consequence, the model has a better chance at accurately mirroring the complex data-generating processes that drive civil war onset.

While a Random Forest can account for nonlinear and conditional effects, the algorithm is a black box. The inner workings of the model are no longer comprehensible, and it is unclear how the inputs relate to the output (Masís 2023). To interpret Random Forests, post-hoc interpretability tools are needed, such as Shapley values and their fast adaptation, SHapley Additive exPlanations (SHAP).

Shapley Values

Originally a concept from game theory, Shapley values (Shapley 1953) denote the payout of a player by forming coalitions with others. Putting this into the context of machine learning, the player is variable X, the game is the prediction task, the payout is the impact of X on the forecast, and coalitions are all possible combinations of the remaining independent variables in the model (Molnar 2025). Shapley values signify the average marginal contribution of each variable over different sets of control variables. The marginal contribution is the change in the predicted outcome when dropping X from the model. A positive Shapley value implies that the predicted outcome increases, and a negative value suggests that the predicted outcome decreases. The reference for the change is the mean forecast.[5]

SHapley Additive exPlanations

Shapely values are often unfeasible due to their high computational costs: The number of coalitions increases exponentially with the number of independent variables (Molnar 2025). To speed up computational time, a fast adaptation was proposed—SHapley Additive exPlanations (SHAP)—which comes in different variants. For this application, KernelSHAP is selected, which takes two shortcuts: Only a subsample of coalitions is considered, and rather than calculating the marginal contribution directly, it is approximated by replacing the absence of a feature with a random observation from the data (Molnar 2025).

[5] Consider the following example (adapted from Molnar 2025). The outcome is the house selling price, and the inputs are: Pets allowed, size, location, and year of construction. Taking pets allowed as X, the remaining independent variables make up eight coalitions: None, size, location, year, size and location, size and year, location and year, and size, location, year. The marginal contribution is the change in the predicted house selling price when removing *pets allowed* from the model. The final Shapley value is the average marginal contribution across coalitions.

While a range of interpretability tools exist, SHAP values are particularly appealing due to their solid statistical foundation (Molnar 2025). After training the Random Forest on the full sample, the 58 onset cases are filtered out. For each onset case, one SHAP value for each independent variable is obtained. This process yields a matrix with cases in columns and features in rows.

Hierarchical Clustering

To uncover stereotypical pathways, the SHAP values are sorted into k groups using hierarchical clustering. At the outset, the hierarchical clustering algorithm considers each case individually and recursively merges two groups based on similarity until all observations are included in one cluster (Hastie et al. 2017). Similarity is given by Ward's method (J. H. Ward 1963), which merges cases based on minimizing the sum of squared errors between observations assigned to the cluster and the centroid, which is the mean of all constituents.

Rather than clustering on the inputs, SHAP values are preferred, which allows for grouping civil war onsets according to feature importance instead of the observed values on the independent variables. For predictors like temperature, it is expected that both extremely high and low temperatures have the strongest impact on the probability of civil war onset. The SHAP values are then matched with the independent variables, and pathways are derived from the clustering solution.

The number of pathways is learned inductively from the data. Recursively merging observations produces a dendrogram (see upper panel Figure 2.2), which is cut at a certain height to obtain k clusters. The number of clusters is set to $k = 8$. Based on visually inspecting the groupings in the dendrogram, eight clusters emerge as an *ideal* choice.[6]

[6] The number of clusters $k = 8$ is verified with the inertia criterion, using the k-Means clustering algorithm. k-Means divides observations into k groups by minimizing the within-cluster dissimilarity (Hastie et al. 2017). Inertia denotes the within-cluster Euclidean distance, comparing each case

2.8 Findings

The SHAP value analysis reveals eight distinct pathways to civil war onset: (1) *Economic crisis* are cases with negative economic growth, (2) *Opportunity* includes countries with low opportunity costs, (3) *Grievances* combines cases with high ethnic exclusion, (4) *Weak state capacity* groups onsets with low regulatory quality, (5) *Oil curse* illustrates how regulatory quality and oil are intertwined, (6) *Bad neighborhood* contains countries in conflict hot-spots, (7) *Climate* shows the effect of high and low temperatures, and (8) *Large population* indicates how populous countries are more vulnerable to armed violence.

The upper panel in Figure 2.2 presents the SHAP values. The darker the color, the higher the value, and the more important the variable for the case. The horizontal lines differentiate between clusters. The lower panel in Figure 2.2 shows the value combinations for the independent variables. Positive values are presented in blue and negative ones in green. Matching the SHAP values with the independent variables allows for the interpretation of the clusters.

The eight pathways illustrate how the combination of grievances and opportunity prompts civil war. For civil war onset to occur, there needs to be economic opportunity/grievances (e.g., low GDP per capita and low male schooling), political opportunity/grievances (e.g., weak state capacity), and social opportunity/grievances (e.g., high ethnic exclusion). While cases can be grouped based on similarity, every onset has a unique character, which is accounted for in this analysis.

to the centroid, which is the mean of all cases assigned to one cluster (Rykov et al. 2024). A lower inertia implies a better fit of the clustering solution to the underlying data structure. Minimizing the inertia criterion is not suitable, since the score decreases monotonically with the number of clusters (Rykov et al. 2024). Instead, the elbow method recommends selecting k based on when the inertia reduction begins to level off. Figure B.1 in Appendix B presents the inertia for different values of k. There is a noticeable reduction when $k = 8$.

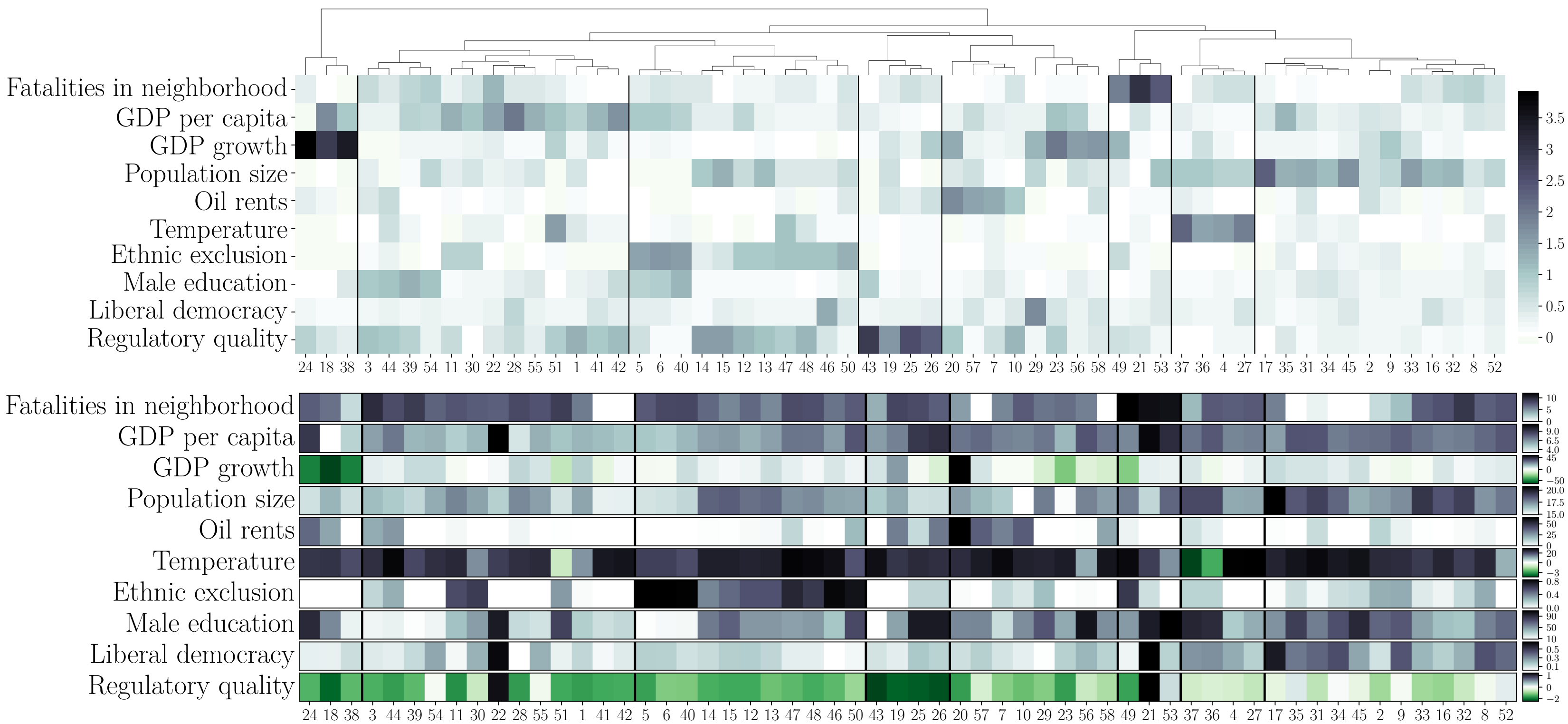

Figure 2.2: The upper panel shows SHAP values for each onset case (in columns) over the ten variables included in the model (in rows). A darker blue shading implies a higher SHAP value and therefore a higher importance of the variable for the case. The onset cases are clustered into eight groups as indicated by the dendrogram and the horizontal lines. The lower panel shows the corresponding values on the independent variables. For variables with only positive values, the darker the blue shading, the higher the value. For variables with positive and negative values, the negative values are shown in green. Each case has a number, which corresponds to the indices in Table B2 in Appendix B.

Cluster 1: Economic Crisis

The first cluster contains onset cases with negative economic growth, low GDP per capita, and weak regulatory quality. Cluster 1 is called *economic crisis* given that it combines negative growth, with a limited state capacity to manage recession.[7]

The civil war literature has prominently linked economic conditions to the onset of civil war (Collier and Hoeffler 2004; Miguel et al. 2004). Economic decline and the resulting poor unemployment chances produce low opportunity costs. Armed conflict can be seen as an economic activity where individuals obtain income through employment as rebel soldiers. Alternatively, negative growth might correspond to relative deprivation, where an individual receives less than they believe should be attainable (Gurr 2016). Relative deprivation might emerge from a sudden drop in the living conditions of one group (Gurr 1970), as seen during a recession if one segment of society is hit particularly hard. The cluster analysis demonstrates the conditional effect of economic decline on weak state capacity and low income. In these contexts, the government is unable to implement counter-cyclical fiscal policies as would be possible in rich countries.

Iraq-1991 (case 18) and Rwanda-1994 (case 38) illustrate those mechanisms. Both countries were plagued by previous armed conflict, which is known to have tremendous economic impacts, reducing economic growth by destroying human capital, state institutions, and disrupting trade and government spending (Murdoch and Sandler 2004). The third case in the cluster—Libya-2011 (case 24)—falls slightly outside this logic. In contrast to the negative economic growth, Libya-2011 has a high GDP per capita. Due to its oil resources, Libya is counted among the wealthiest countries in Africa (Siebens and Case 2012), and the drop in economic growth resulted mainly from the political turmoil itself, by disrupting oil trade (AEO 2012). While assigning

[7] Table B3 in Appendix B presents the observed values on the independent variables.

Libya to the *economic crisis* pathway, the analysis maintains the unique character of the case, illustrating how political unrest might shock the economic performance in reasonably prosperous countries.

Cluster 2: Opportunity

The second cluster entails cases with low GDP per capita, low male education, weak state capacity, and fatalities in the neighborhood. This selection of onset cases is called *opportunity*.[8] Poor economic prospects and weak state capacity provide an opportunity to initiate armed action against the government.

GDP per capita is connected to civil war based on grievances and opportunity. For one, poor individuals are more likely to rebel, seeking an improvement to their situation (Gurr 2016). For another, low GDP per capita leads to low opportunity costs, where an individual's lost income in the regular economy is too little to prevent them from joining a non-state actor (Collier and Hoeffler 2004). At the same time, low GDP per capita is an indicator of weak state capacity, which relates to political opportunities given that weak states cannot credibly deter rebel mobilization (Fearon and Laitin 2003).

Sierra Leone (cases 41, 43) and Uganda (cases 54, 55) illustrate the opportunity cost argument. The RUF's (Revolutionary United Front) fight for power was opportunistic rather than ideological (UCDP 2025f). Opportunistic rebel groups depend on material incentives for recruitment (Weinstein 2007), where low opportunity costs facilitate mobilization. The LRA (Lord's Resistance Army) has similar characteristics to the RUF. Initially, the LRA presented themselves as sent by God to liberate the people from the oppressive government, but quickly transitioned into a causeless group by attacking the civilian population (UCDP 2025d).

[8] Table B5 in Appendix B presents the observed values on the independent variables.

Not every case aligns with the opportunity cost mechanism. Most notably, Israel-2023 (case 22) diverges markedly, having a high GDP per capita, a high value for liberal democracy, and strong regulatory quality. While these three indicators are indeed the most important, the value combinations differ from the remaining cases in the cluster. The fact that Israel-2023 stands out as a unique case is less surprising considering its background. Israel has experienced comparatively low levels of armed violence since the last Gaza war in 2014, when the conflict escalated to a magnitude and scope unprecedented in the region (UCDP 2025c).

Another unique case in the *opportunity* cluster is South Sudan-2014 (case 44), which more closely resembles the logic of the oil curse (Ross 2013). Upon independence, the governing mode in South Sudan was highly patrimonial and reliant on a constant flow of revenues to pay supporters, when a shutdown of oil exports was the spark that ignited the powder keg (De Waal 2014). Nevertheless, oil *can* play a key role in the opportunity mechanism, given that trade with oil enables a rebel group to mobilize and recruit individuals (Ross 2004).

Cluster 3: Grievances

This cluster integrates countries with high ethnic exclusion, low male education, low GDP per capita, weak state capacity, and high population size. The emerging pathway is called *grievances*, illustrating how exclusion from political power paired with opportunity can produce civil war onset.[9]

Ethnicity becomes a salient cause of armed conflict if political exclusion runs along ethnic cleavages (Cederman et al. 2010). The positive effect of ethnic exclusion is conditional on opportunity. Low opportunity costs arise if an individual has low prospects of obtaining sufficient income in the regular labor market (Collier and

[9] Table B6 in Appendix B presents the observed values on the independent variables.

Hoeffler 2004). Alternatively, opportunity stems from weak state capacity, rendering the government more vulnerable to armed action (Fearon and Laitin 2003). A third source of opportunity emerges in populous countries, due to reduced coordination costs and the larger pool of potential recruits (Raleigh and Hegre 2009).

Prominent cases in the *grievances* cluster are Burundi (cases 5, 6), Rwanda-2001 (case 40), the Democratic Republic of Congo (DRC) (cases 12, 13, 14, 15), and the Syrian Civil War (case 50), which all align remarkably well with the grievances theory. The Belgian colonial occupation had established Tutsi dominance in various aspects of society, such as politics, employment, and education, which produced resentment among Hutus (Ngaruko and Nkurunziza 2005), ultimately leading to the Rwandan Genocide. The DRC is markedly featured in this cluster, having experienced armed violence for decades, due to ethnic divisions, low opportunity costs, and weak state capacity (Ndikumana and Emizet 2003). During the so-called Arab Spring, protests erupted in Syria, demanding political liberalization, which was countered with harsh repression by the Assad regime (Hof and Simon 2013). While arguably having the so-called Arab Spring as its unique background, the conflict has a clear sectarian origin, since Assad belongs to the Alawite minority, which has ruled the country for decades, as opposed to the majority Sunni population, systematically excluded from political power (Hof and Simon 2013).

Cluster 4: Weak State Capacity

The fourth cluster filters out onset cases with the lowest values for regulatory quality and is therefore called *weak state capacity*.[10]

State capacity is linked to civil war through three mechanisms: (1) Coercion, which implies that a strong state is more capable of either deterring or effectively

[10] Table B4 in Appendix B presents the observed values on the independent variables.

preventing the emergence of insurgency, (2) co-optation, which suggests that strong states can provide goods and services to their citizens to prevent them from joining the opposition, and (3) cooperation, where strong states signal the ability to enforce laws, creating trust in political institutions (Fjelde and De Soysa 2009). Since the non-state actor is usually the weaker party in civil conflict, its initial survival depends on its ability to operate undetected (Fearon and Laitin 2003). Weak state capacity provides an opportunity to mobilize, given that the government is either unaware or unable to counter it.

Somalia-2007 (case 43) presents an extreme manifestation of the *weak state capacity* pathway, having the lowest regulatory quality among all cases. The country has been without a functioning central government since 1991, when attempts to install a new executive body were met with armed resistance, culminating in the emergence of Al-Shabaab (UCDP 2025h). Iraq-1997 (case 19) illustrates the interaction between weak state capacity and oil-dependence, given that the country has substantial oil deposits but suffers from corruption, which produces fertile ground for armed conflict (Le Billon 2005). With its comparatively high GDP per capita, Libya (cases 25, 26) stands out as before.

Cluster 5: Oil Curse

The fifth cluster of civil war onsets comprises cases with low regulatory quality, negative economic growth, and high oil rents. Cluster five is called *oil curse.*[11]

Oil abundance is a curse rather than a blessing, given its correlation with civil conflict (Ross 2013). Oil can provide rebels with the required start-up funds to initiate mobilization against the state, oil extraction can intensify local grievances, and oil-dependency erodes state capacity, thereby making a country more vulnerable to

[11]Table B8 in Appendix B presents the observed values on the independent variables.

armed violence (Ross 2004). The *oil curse* cluster illustrates the potential detrimental impact of oil-dependency on economic performance, which can reduce economic growth if political institutions are weak (Antonakakis et al. 2017).

This cluster contains cases with large oil deposits, such as Iraq-2004 (case 20), Yemen (cases 57, 58), Chad-2006 (case 7), and Congo-1997 (case 10). After Yemen's oil-dependent economy was hit by the fuel and financial crisis in 2008 (Breisinger et al. 2011), the country failed to manage a peaceful transition amid the so-called Arab Spring and spiraled into civil war (UCDP 2025l). Chad illustrates how oil increases the price of political power. When the country started exporting oil, jealousy and competition intensified, and the government invested in strong military capabilities to repress challengers, producing a powder keg for armed violence (Gould and Winters 2012). Similarly, Congo shows how access to oil wealth might prompt civil war, as a disputed attempt to democratize destabilized the political system, and the resulting uncertainty intensified competition over oil (Englebert and Ron 2004).

Not all cases in the *oil curse* cluster have high oil rents. Ukraine-2014 (case 56), Liberia-2003 (case 23), and Myanmar-2021 (case 29) stand out, but are connected to the pathway based on their negative economic growth. Upon further inspection, all three countries have unique backgrounds. Amid the country's EU rapprochement and ousting of the pro-Russia president, a separatist conflict emerged in Eastern Ukraine, preceding Russia's full-scale invasion in 2022 (UCDP 2025k). The Second Liberian Civil War was caused by the failure to address the underlying root causes of the first war, i.e., political and socio-economic marginalization, combined with an incomplete post-conflict demobilization process (Kieh 2009). In reaction to the military takeover, widespread protests erupted in Myanmar and quickly transitioned into armed action, facilitated by the numerous non-state armed groups already active in the country (UCDP 2025e).

Cluster 6: Bad Neighborhood

The sixth cluster contains Sudan-2023 (case 49), Israel-2014 (case 21), and Turkey-2016 (case 53), which have high fatalities in the neighborhood. The cluster is called *bad neighborhood*.[12]

Armed conflict has an international dimension due to the clustering of risk factors, the spill-over of weapons and soldiers from neighboring conflicts, or the interconnectedness of armed violence across borders (Forsberg 2016). The spill-over mechanism is most clearly observable in the case of Turkey-2016. When Turkey joined the international coalition against the so-called Islamic State (IS), the armed conflict escalated along the Turkish-Syrian border, as the government attempted to push back the IS from its state territory (UCDP 2025j).

While Sudan-2023 and Israel-2014 are arguably located in a conflict hotspot (i.e., Sub-Saharan Africa and the Middle East), the latter markedly stands out based on its characteristics: High regulatory quality, GDP per capita, male education, and liberal democracy. A similar observation applies to Turkey, which has high education and high GDP per capita, albeit a low value for liberal democracy.

Cluster 7: Climate

The *climate* cluster contains cases with high and low temperatures, conditional on large population size and fatalities in the neighborhood.[13]

Extreme temperatures can cause armed conflict due to intensified competition over resources, climate-induced displacement, or the resulting drop in economic performance (Wischnath and Buhaug 2014). However, the impact of climate on armed conflict is conditional on vulnerability, such as poverty and weak state capacity (Buhaug and Von Uexkull 2021). The pathway analysis demonstrates that the effect

[12] Table B9 in Appendix B presents the observed values on the independent variables.
[13] Table B10 in Appendix B presents the observed values on the independent variables.

of temperature is accentuated by large population size, providing mobilization capacity (Raleigh and Hegre 2009), and fatalities in the neighborhood, likewise creating opportunity due to the spill-over of violence (Forsberg 2016).

Burkina Faso-2022 (case 4), Mali-2022 (case 27), and Russia (cases 36, 37) all show extreme temperatures. Burkina Faso and Mali are located in the Sahel, a region most affected by climate change, experiencing intense temperature hikes that destroy farmland (Pavia and Simões 2025). Both Chechen Civil Wars are assigned to the *climate* pathway but are unique cases. Amid the dissolution of the Soviet Union, a separatist movement emerged in the Chechen Republic, which was violently crushed by the Russian government (UCDP 2025g). Instead of low temperature, Russia itself seems particularly vulnerable to separatist conflict, given its large territory, ethnic diversity, and geographic concentration of ethnic groups (Hughes 2001).

Cluster 8: Large Population

The final cluster groups cases with high population size, a robust predictor of armed conflict (Hegre and Sambanis 2006), and is therefore called *large population*.[14]

High population size makes countries more vulnerable to armed violence due to the increased chances of successfully mobilizing enough individuals, the opportunity stemming from the inherent challenges of governing large territories, and the reduced coordination costs in concentrated populations (Raleigh and Hegre 2009). The following countries are included in the cluster: India-1999 (case 17), the Philippines (cases 34, 35), Nigeria-2013 (case 31), Algeria-1994 (case 2), Colombia (cases 8, 9), Pakistan (cases 32, 33), Ethiopia-2020 (case 16), and Turkey-1992 (case 52).

Upon further inspection, population size appears to be a facilitator rather than a root cause of civil war. This claim is illustrated by Ethiopia-2020 and India-1999.

[14] Table B7 in Appendix B presents the observed values on the independent variables.

After the TPLF (Tigray People's Liberation Front) ruled Ethiopia for decades, a process of political liberalization ousted the group from political power, and armed violence escalated to unprecedented levels after delayed elections (UCDP 2025a). The Indian government has been engaged in armed conflict with numerous non-state actors, most protracted in Kashmir. The territory remains contested since Pakistan became independent and quickly saw the emergence of a separatist movement: The Kashmir insurgents (UCDP 2025b).

Sri Lanka-2006 (case 45) falls outside the *large population* cluster, indeed having a population size close to the sample mean. Instead, the Sri Lankan Civil War has a clear ethnic component. For decades, Sri Lanka was engulfed in violent conflict between the Sinhalese majority and the Tamil minority fighting for independence (UCDP 2025i). While assigning Sri Lanka-2006 to the *large population* cluster, the pathway analysis maintains the unique character of the case.

2.9 Conclusion

Civil wars are highly complex phenomena, often described as puzzling, random, or stochastic (Gartzke 1999; Kalyvas 2003). Rationalist explanations contend that war is caused by uncertainty, incentives to bluff, and the resulting danger of miscalculations (Fearon 1995). Since uncertainty is essentially a lack of information, civil war onsets become theoretically indeterminant, driven by a stochastic component that is unique to each case (Gartzke 1999). Instead of seeking to establish sufficient conditions (i.e., Bara 2014), civil war should be studied along stereotypical pathways. Every onset is assigned to the closest pathway while maintaining its unique character, or rather, its stochastic component.

This paper uncovers the causal complexity of armed conflict using tools from interpretable machine learning. Ten prominently discussed indicators for grievances and opportunity are used to predict civil war onset. The Random Forest classifier (Breiman 2001) is selected due to the algorithm's ability to mirror complex associations. Filtering out onset cases, SHAP values are obtained, which denote how much each feature affects the predicted outcome (Molnar 2025). The values are clustered, deriving a set of pathways to civil war onset.

The analysis reveals eight distinct civil war pathways: (1) *Economic crisis* are cases with negative economic growth, (2) *Opportunity* includes countries with low opportunity costs, (3) *Grievances* combines cases with high ethnic exclusion, (4) *Weak state capacity* groups onsets with low regulatory quality, (5) *Oil curse* illustrates how low regulatory quality and oil-dependence are intertwined, (6) *Bad neighborhood* contains countries in conflict hot-spots, (7) *Climate* shows the effect of high and low temperatures, and (8) *Large population* presents how populous countries are more vulnerable to armed violence.

This study has two main implications. First, both grievances and opportunity are required for civil war onset, producing certain combinations of structural risk factors. Civil war entails great risks, and it is implausible to believe that one factor alone would prompt armed escalation to 1,000 fatalities. The SHAP value analysis illustrates how grievances and opportunity interact to create violent outcomes, combining political opportunity/grievances (i.e., weak state capacity), economic opportunity/grievances (i.e., low GDP per capita and low male schooling), and social opportunity/grievances (i.e., high ethnic exclusion).

Second, while there are common pathways to civil war, every onset presents a unique manifestation of the underlying mechanism. Some cases even diverge from the assigned cluster, such as Ukraine, having a clear geopolitical component (UCDP 2025k), and the Chechen Civil Wars, which emerged as separatist conflicts amid the dissolution of the Soviet Union (UCDP 2025g). Another idiosyncratic case is Israel.

As a rich democracy, Israel fits only marginally into the pathways. Civil wars have high causal complexity and might be driven by their own causal mechanisms, which do not generalize to other settings. This finding is supported by the rationalist claim that civil war onsets are inherently unexplainable, given that they are caused by uncertainty, incentives to bluff *and* randomness (Gartzke 1999).

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3 *To Demonstrate or Fight: Similarities and Differences in the Causes of Collective Action*

To Demonstrate or Fight: Similarities and Differences in the Causes of Collective Action

Hannah Frank

Replication Material
The data and Python code used for this analysis can be accessed here: `https://github.com/hannahhfrank/phd_thesis_reconceptualizing_conflict_emergence/tree/main/structural`.

Use of Generative Artificial Intelligence
ChatGPT-3.5 and higher (`https://chatgpt.com/`) served as a coding assistant during the empirical analysis, and to correct spelling and grammar, suitable add-ons in Overleaf were used (i.e., Grammarly, Writefull, and LanguageTool).

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To Demonstrate or Fight: Similarities and Differences in the Causes of Collective Action

Abstract

Existing research on the causes of civil war focuses on correlations between structural background factors and armed conflict. However, the great risks and logistical challenges of armed violence make a direct link between structural factors and civil war seem implausible. Civil conflict is a dynamic phenomenon and commonly emerges from preceding and less violent collective action, such as protests, riots, terrorism, and low-intensity armed conflict. Instead of singling out civil war, it appears more reasonable to consider different types of collective action together. This paper uncovers similarities and differences in the causes of collective action and finds that structural risk factors perform reasonably similarly when predicting low-intensity collective action in comparison to civil war. Theoretical arguments apply across outcomes, most evidently for population size and the cyclical nature of political contention. Simultaneously, the analysis highlights the unique character of less violent forms of collective action, i.e., protest and riots, for example, regarding the importance of mobile phones. While structural risk factors might prompt civil war by transitioning through protest and/or low-intensity armed violence, collective action is a non-sufficient condition for civil war, which applies particularly to protest.

Keywords: Collective action, protest, civil war, similarities and differences

3.1 Introduction

Existing research on the causes of civil war emphasizes structural factors that are associated with an increased risk of armed violence (Cederman et al. 2010; Collier and Hoeffler 2004; Fearon and Laitin 2003). While the literature assigns those variables exclusively to civil war onset, they prompt collective action more broadly (Cunningham and Lemke 2014), or if anything, low-intensity forms of collective action exclusively. Due to the great risks and logistical challenges of armed violence, a direct link between structural background factors and civil war appears implausible. Armed conflict is a dynamic phenomenon and frequently emerges from preceding and less violent collective action.[1] Structural risk factors cause collective action, which may or may not transition to civil war (Florea 2017).

The conflict literature has shifted towards singling out civil war (Cunningham and Lemke 2014), concealing potential synergies among various forms of collective action. Instead, different types of collective action should be studied together. This paper puts forward two main arguments: (1) There are similarities and differences in the causes of collective action, and (2) structural risk factors predict collective action more generally, instead of civil war exclusively, given that collective action is a key precursor to more substantial levels of civil conflict. A certain configuration of structural background factors produces conflict in society, and the non-state group decides how to address the resulting incompatibility, selecting a strategy from a 'repertoire of collective action' (Tilly 1977). A 'repertoire of collective action' refers to a set of tactics, such as protesting, striking, but also kidnappings and killings, commonly used by claim-makers to promote group objectives.

There are two pathways to civil war: The protest and the clandestine pathway

[1] This paper follows the tradition of seeing civil war as inherent in prior contentious politics (Lichbach et al. 2003).

(cf. Lewis 2017). In the former, the non-state actor opts for less violent forms of collective action (i.e., protests). At the outset, non-violent tactics are preferred due to their higher chance of success (Stephan and Chenoweth 2008). In the clandestine pathway, the non-state actor selects violent forms of collective action but needs to mobilize first (Malone 2021). During mobilization, the non-state actor might extort military capabilities from the government (Jackson 2010), the civilian population (Azam 2006), or another non-state group (Fjelde and Nilsson 2012), which produces initial fatalities from terrorism and low-intensity armed conflict.

Structural risk factors of civil war run along five themes: Conflict history, demography, geography, economy, and politics (Dixon 2009). The resulting thematic models are used to predict six outcomes: More than 25 protest or riot events, or at least one fatality from terrorism, battles, non-state conflict, or one-sided violence. Two civil war benchmarks are constructed, predicting whether civil conflict surpasses 25 or 1,000 deaths. The Random Forest Classifier (Breiman 2001) is used for the out-of-sample evaluation. Finally, differences and similarities in the causes of collective action are uncovered with SHAP values (Molnar 2025).

This paper puts forward two main findings. First, the empirical analysis shows that structural risk factors predict different types of collective action reasonably similarly. This implies that structural risk factors prompt collective action more broadly rather than civil war exclusively. While conflict history is the most important theme for the 1,000 and 25 civil war benchmarks, politics and demography perform best for protest and battles. Structural risk factors might lead to civil war by transitioning through protest and/or low-intensity armed violence.

Second, there are similarities in the causes of collective action; specifically, the probability of collective action increases with population size, and political contention has a cyclical character. However, there are also marked differences, highlighting the unique character of less (i.e., protest, riots) and more violent forms (i.e., terrorism, low-intensity armed conflict), as the former occurs more frequently in economically developed countries. Moreover, access to digital communication seems to be important for protest and riots, while less important for terrorism and low-intensity armed conflict. Collective action is a non-sufficient condition for civil war, which applies particularly to protests.

3.2 Structural Theories on the Causes of Civil War

The literature on the causes of civil war was strongly shaped by structural theories that assign slow-changing background factors, most prominently population size, GDP per capita, mass education, and political exclusion, to the occurrence of civil war onset (Cederman et al. 2010; Collier and Hoeffler 2004; Fearon and Laitin 2003). Most of these studies define civil war onset as armed violence between the government and a non-state group, causing at least 1,000 battle deaths in a year (N. P. Gleditsch et al. 2002). Structural risk factors of civil war can be categorized into five themes: Conflict history, demography, geography, economy, and politics (Dixon 2009).

Conflict History: A recent violent past increases the likelihood of continuing or renewing armed conflict, or in other words, a country with armed violence in the previous year is likely to experience armed violence also this year (Quinn et al. 2007; Walter 2004). This correlation is explained by the 'conflict trap', where previous armed violence leaves an economic, political, and societal legacy that increases the risk of recurring conflict (Collier et al. 2003).

Demography: Certain demographic characteristics make a country more vulnerable to civil war onset, based on providing recruitment opportunities. For example, the risk of civil war is positively associated with large population size (Raleigh and Hegre 2009) and youth bulges, which are large fractions of young men (Urdal 2006).

While ethnicity is prominently discussed in the field, cultural differences on their own are not a sufficient condition for violence, yet they can become salient under certain conditions, such as ethnic exclusion from political power and cultural mobilization (Cederman et al. 2010; Posner 2004).

Geography: Some geographic characteristics may increase the risk of armed violence. Civil war has an international dimension, given that armed conflict is known to cluster in hotspots (Buhaug and K. S. Gleditsch 2008), mostly in Africa, Asia, and the Middle East (Davies et al. 2024). Climate is related to the risk of civil war (Burke et al. 2009), in particular, if temperature and precipitation patterns diverge from the norm (Burke et al. 2015; Hendrix and Salehyan 2012). During the initial stage of insurgency, rebels need to procure military resources without being discovered by the government (Fearon and Laitin 2003; Larson and Lewis 2018). Certain geographic conditions, such as mountains, produce rough terrain that hampers state presence, providing opportunities to mobilize (Fearon and Laitin 2003).

Economy: Civil war predominantly occurs in poor countries. Most notably, GDP per capita is considered one of the most robust predictors of civil war onset (Hegre and Sambanis 2006). Moreover, there is a negative correlation between education and civil war, or rather, mass education reduces the risk of armed conflict (Collier and Hoeffler 2004; Thyne 2006). Civil war can be an economic activity. Poor economic prospects lead to low opportunity costs, which means that the foregone income is not high enough to prevent individuals from joining a rebel group (Collier and Hoeffler 2004). Closely related, natural resources are linked to an increased risk of civil war (Ross 2004b; Vesco et al. 2020). Revenues from natural resources can provide rebels with funding, and natural resource wealth erodes state capacity, making a country more vulnerable to armed conflict (Ross 2004a).

Politics: The risk of civil war is associated with weak governing capacity, given that weak states offer opportunity to mobilize in secret (Fearon and Laitin 2003). There is a relationship between regime type and civil war since democracies and autocracies have a lower risk of armed conflict compared to regimes that show characteristics of both, so-called anocracies (Fearon and Laitin 2003; Hegre et al. 2001). Another factor playing into the political opportunity structure is access to digital communication. Such technology enables the coordination of collective action and thereby facilitates armed operations (Pierskalla and Hollenbach 2013).

3.3 Similarities and Differences in Collective Action

Starting in the 1960s, political scientists began examining why some countries experience more violence than others (Cunningham and Lemke 2014). These studies did not prioritize civil war but considered violence more broadly, such as turmoil, rebellion, military coups, guerrilla warfare, or total conflict-related fatalities. Only in the 2000s has there been a shift towards researching civil war exclusively (Cunningham and Lemke 2014). This shift conceals the potential synergies between civil conflict and other types of collective action.

While largely missing from the study of civil war, the similarities in the causes of collective action have long been noted by the social movement literature. The school of contentious politics (McAdam et al. 2001; Tarrow 2015) ascertains that various forms of political contention, such as revolutions, social movements, and civil wars, have similar causes that can be identified as repeating mechanisms and processes. Contentious behavior develops in the context of the state, and political opportunities determine which type of contention is deployed by claim makers (Tarrow 2015). There are 'repertoires of collective action', or rather, common tools for voicing shared claims, such as protesting, rioting, kidnappings, and killings (Tilly 1977), which are generated through the interactions between government and challenger (McAdam

1983). Claim-makers select a strategy from the repertoire based on previous experiences and the behavior of the state (Tilly 1977). This suggests that conflict can be addressed with different tactics and varying degrees of violence.

If different forms of collective action have similar causes, they need to be studied together. Rather than signaling out civil war, structural risk factors prompt collective action more broadly (Cunningham and Lemke 2014). For example, political exclusion along ethnic lines might cause civil conflict (Cederman et al. 2010). However, violent tactics are only one approach to managing ethnic diversity, and ethnic groups might opt for non-violent collective action, such as demonstrations, instead (Cebotari and Vink 2013). The severity of political exclusion affects whether ethnic groups protest or select more violent forms of collective action (Choi and Kim 2018).

At the same time, less and more violent forms of collective action have a unique character. While civil conflict is a rare event and markedly falls outside the institutional channels of political participation, protests frequently occur in democracies when citizens voice demands to their government. Despite intense protest activity, including non-violent and violent tactics, as observed during Black Lives Matter (Shuman et al. 2022), civil conflict is considered unlikely in those situations.

3.4 Collective Action as Precursor to Civil Conflict

Civil conflict does not break out as a surprise, but it is usually preceded by less intense forms of collective action, or rather, collective action mediates the relationship between structural risk factors and civil war (Figure 3.1). In my understanding, collective action refers to more or less violent collective behavior, where several individuals act together. Surely, not all collective action relates to armed conflict, and the type needs to have a certain potential for violence. The following are considered: Protests, riots, terrorism, and low-intensity armed conflict.

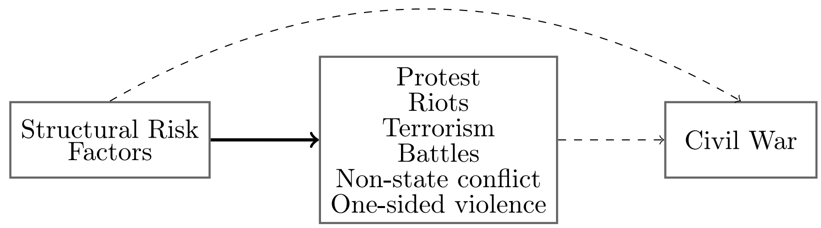


Figure 3.1: Collective action mediates the relationship between structural risk factors and civil war. A combination of risk factors prompts collective action, in particular, protest, riots, terrorism, and low-intensity armed conflict. Collective action may or may not transition to civil war.

A certain combination of risk factors produces conflict in society, which refers to a situation in which two actors attempt to seize the same object at once (Wallensteen 2019). At the heart of conflict lies an incompatibility, implying that the interests of two actors are mutually exclusive (Bartusevičius and K. S. Gleditsch 2019). Conflict can be economic, political, or cultural, concerning the distribution of wealth, political power, or social ranking. Indeed, conflict is a *natural* component of society, and it becomes contested when actors actively pursue their interests (Bartusevičius and K. S. Gleditsch 2019).

As conflict emerges between the government and a non-state actor, both sides seek to advance their objectives. To secure the immediate regime survival, the government applies repression to any challenger of the status quo (Davenport 2007; Young 2013). While the response of the state is more predetermined, the non-state group selects a strategy from a 'repertoire of collective action' which is a set of tactics commonly used by claim-makers to pursue their interests (Tilly 1977).

Against this background, a direct correlation between structural factors and civil war seems implausible. Escalating armed violence to the dimension of a war entails great risks and logistical challenges. In the beginning, the non-state group likely opts for less risky and less extreme forms of collective action. Non-violent collective action has a higher chance of success due to enhancing the group's legitimacy (Stephan and

Chenoweth 2008). Even if the non-state actor wants to pursue violent tactics, they need to mobilize first, producing a considerable gap between group foundation and the onset of civil conflict (Malone 2019). This reveals two distinct pathways to civil war: The protest and the clandestine pathway (cf. Lewis 2017).

In the protest pathway, the non-state actor selects less violent collective action from the repertoire (i.e., protests and riots) and openly seeks to pressure the government into making concessions.[2] Indeed, protest is a key driver of societal change, and nonviolent resistance doubles the chances of success in comparison to violent contention (Stephan and Chenoweth 2008). Nevertheless, protest can transition to civil conflict if the majority of protesters conclude that non-violence has failed and that violence is the only remaining option (Rød and Weidmann 2023). Alternatively, protest continues until it loses momentum or until the government and the non-state actor agree on a compromise to address the underlying incompatibility.

The clandestine pathway contends that the non-state actor selects violent forms of collective action from the repertoire. However, the group has no immediate access to arms and needs to mobilize first. Several years may pass between the formation of a non-state group and the onset of civil conflict, during which the rebels prepare for military action (Malone 2019). Rebel mobilization is not a deterministic process, given that a significant fraction of non-state groups disappear before more substantial levels of violence are documented (Lewis 2017).

At the outset, the non-state group is weak and seeks to obtain sufficient military capabilities without being captured by government troops (Larson and Lewis 2018). During mobilization, the non-state group acquires military resources through violent and nonviolent strategies. By appealing to social endowments, such as shared

[2] A protest is a nonviolent demonstration, where the government might respond with force, and riots are demonstrations, where both sides, the government and the protesters, may engage in violent behavior (ACLED 2023).

ethnicity and grievances, individuals might participate because they believe in the proclaimed cause of the non-state actor (Weinstein 2007). While nonviolent recruitment is challenging to observe empirically, violent recruitment is manifested in low-intensity armed conflict, including initial fatalities from terrorism, battles, non-state conflict, and one-sided violence.[3]

The less resourceful non-state actor might perceive terrorist tactics as a cheap alternative to impose substantial costs on the government (Kydd and Walter 2006). An emerging rebel group could attempt to steal military means directly from the state, which is considered a low-cost, high-reward strategy (Jackson 2010). Violence against civilians can be used as a way to extract resources from the local population (Azam 2006). The government might also target civilians, attempting to undermine favoritism for the non-state actor through intimidation and direct violence (Valentino et al. 2004). A final strategy for rebel mobilization is capturing military means from an already existing non-state actor (Fjelde and Nilsson 2012).

Two claims can be derived from the theoretical discussions. First, while different forms of collective action have similar causes, there are also potential differences. The protest and clandestine pathways are not mutually exclusive and can occur simultaneously, implying that different forms of collective action have similar causes. However, the two distinct pathways highlight the unique character of less and more violent contention. Protest can be an entirely peaceful means of political participation. Rather than lumping both pathways together, this paper explores similarities *and* differences in the causes of collective action.

Second, structural background factors predict collective action more broadly,

[3]Terrorism is understood as the use of violence or threat thereof by a non-state actor to spread fear and to coerce a change to the status quo (GTD 2021). Low-intensity armed conflict has three forms: Battle events take place between the government and a non-state group (state-based conflict after excluding government—government dyads), non-state conflict occurs between two non-state actors, and one-sided violence refers to violence against civilians, committed by the government or a rebel group (UCDP 2025).

rather than civil war exclusively, given that civil war emerges from preceding less violent collective action. Therefore, collective action is a key precursor to civil war, and structural risk factors might cause more substantial levels of armed violence by transitioning through protest and/or low-intensity armed conflict.

3.5 Data

The data are on the country-year level of analysis. The countries in K. S. Gleditsch and Ward (1999) comprise the sample, after removing microstates and countries that no longer exist (e.g., Yugoslavia). Microstates are systematically different than non-microstates, which justifies excluding them. Another set of countries is removed due to extensive missingness.[4] The final sample contains 168 states. The temporal coverage is 1989—2023, defined by the Uppsala Conflict Data Program (UCDP).[5] Due to different temporal coverages, the protest, riots, and terrorism models only use a subset of cases. The Armed Conflict Location and Event Dataset gathers data for certain years only, depending on the country, and the Global Terrorism Database is only available until 2020, and all data for 1993 were lost (GTD 2021).

Data on the outcomes are obtained from the UCDP Georeferenced Event Dataset (Sundberg and Melander 2013), the Armed Conflict Location and Event Dataset (ACLED) (Raleigh et al. 2010), and the Global Terrorism Database (GTD) (LaFree 2010). After summarizing the event data on the country-year, six binary outcomes are coded: More than 25 protest events, more than 25 riot events, at least one fatality

[4] The following countries are excluded due to extensive missingness in the World Bank or V-Dem data: Taiwan, Bahamas, Belize, Brunei Darussalam, Kosovo, and North Korea. ACLED collects data on several additional territories (e.g., Antarctica and La Réunion), which are not considered, except for Palestine, which is assigned to Israel due to being a crucial case. GTD events in Palestine are likewise assigned to Israel. GTD does not collect data on several countries in K. S. Gleditsch and Ward (1999) (e.g., Oman and Cape Verde). To ensure a comparison across a constant spatial coverage, fatality counts from terrorism are set to zero for those countries.

[5] Only the years that a country was independent are included (e.g., South Sudan begins in 2011).

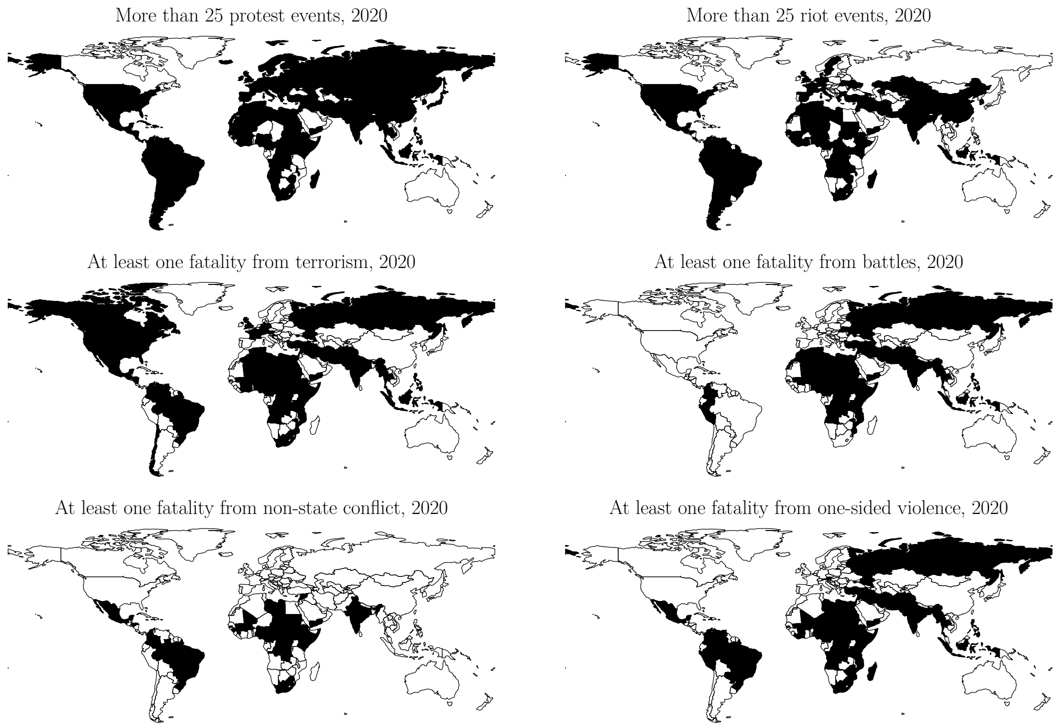


Figure 3.2: Black shading indicates if the country-year experienced more than 25 protest events (upper left), more than 25 riot events (upper right), at least one fatality from terrorism (middle left), at least one fatality from battles (upper right), at least one fatality from non-state conflict (lower left), or at least one fatality from one-sided violence (lower right).

from terrorism, at least one fatality from battles, at least one fatality from non-state conflict, and at least one fatality from one-sided violence (Figure 3.2). For protests and riots, it is important to apply a threshold because both occur too regularly across different contexts. Protests and riots need to have a certain level of intensity, which is achieved with a 25-event threshold.[6]

Data on the predictors are obtained from the World Bank (CCKP 2024; World-Bank 2025a; World-Bank 2025b), the Ethnic Power Relations Dataset (core and ethnic dimensions) (Bormann et al. 2017; Vogt et al. 2015), the terrain replication data from Nunn and Puga (2012), the United Nations Development Program (UNDP

[6]The 25-fatality threshold is commonly used in peace research (N. P. Gleditsch et al. 2002). For this paper, the 25-fatality threshold is understood as a cutoff, coding country-years as *one* which surpasses 25 events.

2024), the Varieties of Democracy data (V-Dem 2024), and the Rulers, Elections, and Irregular Governance data (Curtis et al. 2021). The independent variables run along the five themes of conflict history, demography, geography, economy, and politics (Dixon 2009). A list of indicators is included in Table C1 (Appendix C).

Since missing values in conflict data are substantial and not random, it is necessary to impute them. Missing observations are filled in using a combination of linear interpolation and mean imputation, as well as multivariate imputation if countries are completely missing. Simple imputation is preferred because multivariate techniques can produce unrealistic results for time series (Honaker and King 2010). The imputation takes the temporal order into account.[7]

3.6 Research Design

This paper validates whether structural risk factors predict collective action more broadly, instead of civil war exclusively. Building on this, similarities and differences in the causes of collective action are explored. The research design follows two steps. First, a set of thematic models is used to predict different forms of collective action. The out-of-sample performance is compared to two civil war baselines. Second, interpretable machine learning is applied to derive theoretical conclusions from the black-box machine learning models, which serves to uncover similarities and differences in the causes of collective action.

The analysis presented by Cunningham and Lemke (2014) is extended in three main ways. Instead of a small subset of correlates—GDP per capita, ethnic fractionalization, regime type, mountainous terrain, population size, and political instability—the theoretical claims are validated against a large number of independent variables, producing more extensive empirical evidence. Second, civil conflict commonly

[7]More details on the imputation are provided in Section C.1 in Appendix C.

emerges from preceding protest cycles (e.g., in Egypt and Myanmar), making protest a key type of collective action yet being absent from Cunningham and Lemke (2014). Third, this paper relies on predictive rather than regression modeling.

Predictive modeling has two main advantages. First, machine learning algorithms are highly flexible, able to account for nonlinear and conditional effects (Beck et al. 2000; Colaresi and Mahmood 2017), which makes them more suitable for the intricate data-generating processes that drive political contention. Second, predictive modeling produces strong evidence since out-of-sample performance offers a direct tool for comparing models across themes and outcomes (Shmueli 2010). In-sample evaluation can bias performance: A model that works well in-sample could do so by picking up noise rather than a systematic component of the data-generating process (Carsey and Harden 2014).

The Machine Learning Approach

In machine learning, models are validated based on out-of-sample performance. For this purpose, all available observations are divided into three partitions: Training, validation, and test. The country-years between 1989–2016 are in the training data, 2017–2018 is the validation partition, and 2019–2023 the test set.[8] Splitting observations like this is necessary for time series because conventional cross-validation would ignore the temporal order, which can bias model performance due to data leakage (Roberts et al. 2017). The hyperparameters of the algorithm are optimized in the training data: The first 80% of the training data are used to validate different combinations in the remaining 20% of cases.

The Random Forest Classifier (Breiman 2001) is selected as the algorithm, which

[8]The data partition is a compromise between the varying temporal coverage of UCDP (1989—2023) and ACLED (1997—2023 and shorter). A longer training period is required to include enough observations in the protest and riot models.

is the default in conflict prediction due to its good performance on conflict data (Muchlinski et al. 2016; Wang 2019). To produce more stable forecasts, a Random Forest model aggregates predictions from several decision trees (Hastie et al. 2017). A decision tree repeatedly splits observations into subgroups to classify cases into $y = 0$ and $y = 1$. At the outset, all data points are included at the top. Using one independent variable and a specific cutoff value at a time, the cases are divided into two sub-nodes. The splitting continues until each final node contains one observation, or until a stopping criterion applies.

A decision tree has a specific sequence of predictors, and each predictor has a unique cutoff for splitting observations (Hastie et al. 2017). These values are learned by minimizing the Gini impurity. For each split, the variable and cutoff that produce the lowest Gini impurity are selected. Gini impurity denotes the diversity of a node by comparing the relative proportions of cases assigned to each class (Tangirala 2020). A lower value implies a better partition. At the end of this process, every observation is assigned to one final node, and the probability of $y = 1$ is returned by the relative frequency of positive cases (scikit-learn 2025a).

Decision trees are not frequently used on their own, since they produce high-variance results, or rather, they are prone to overfitting (Hastie et al. 2017). The Random Forest model averages several decision trees, which reduces variance and leads to more stable results. When growing each tree in the forest, the algorithm only considers a random selection of variables and a bootstrap sample of cases. The final prediction across all trees is the mean relative frequency of $y = 1$ for each observation (scikit-learn 2025b).

Random forests have several hyperparameters, such as the number of trees and the minimum number of cases in the final nodes (scikit-learn 2025b), which are optimized in the training data using a random search. A grid of possible hyperparameter combinations is produced. Taking a random selection of 100 possible combinations, the first 80% of observations in the training data are used for validation in the remaining 20% of country-years. The combination with the best accuracy returns the final model to produce predictions for the validation and test data.

For each outcome, five thematic models are constructed: Conflict history, demography, geography, economy, and politics (Dixon 2009). To enhance interpretability, the thematic models are combined, producing one ensemble per outcome. An ensemble integrates predictions from several constituent models and commonly performs better than just one model alone (Page 2018). In more technical terms, an ensemble returns the weighted average across predictions from different models (Montgomery et al. 2012). The weights are derived from the performance in the validation data, assigning a higher weight to well-performing models. Performance is indicated by the inverse of the Brier score ($1 - Brier$), which denotes the mean squared difference between the predicted probability of $y = 1$ and the actual class (Hegre et al. 2019). The weights are *min-max*-normalized, ensuring that the best-performing model has a value of one and the worst-performing model weights zero. Before calculating the weighted additive index, the weights are converted to sum up to one.

Evaluation Metrics

The prediction accuracy of the collective action models is compared to two theoretical baselines, predicting whether there was a minor or major civil war, which is denoted by the 25 and 1,000 fatality thresholds (adapted from N. P. Gleditsch et al. 2002). The thresholds are applied as a cutoff, coding country-years that surpass this level as *one*. The outcomes battles, 25-fatality, and 1,000-fatality are different operationalizations of the same underlying data, the death counts in civil conflict, which entails combat events between the government and non-state actors (N. P. Gleditsch et al. 2002). However, the level of intensity distinguishes these concepts, with battles likewise including low-intensity armed violence based on removing any cutoff. This is in line with the idea that civil war originates from preceding low-intensity battle, and allows for validating the theoretical expectation that structural risk factors predict other types of collective action equally well as civil war.

The out-of-sample performance is evaluated with two metrics, commonly applied to classification tasks: The Area Under the Precision-Recall Curve (AUPR) and the Area under the Receiver Operating Characteristic Curve (AUROC).[9] The Precision-Recall Curve displays the precision against the recall (Hegre et al. 2019). Recall denotes the true-positive rate ($TPR = \frac{TP}{TP+FN}$), which divides correctly predicted positive cases, or rather true positives (TP), by the sum of all $y = 1$ cases, counting true positives and false negatives (FN). Precision ($Pr = \frac{TP}{TP+FP}$) denotes the share of true positives (TP) compared to all positive predictions, also including false ones (FP). This metric is particularly useful for rare events, given that it indicates how well the model performs for cases with $y = 1$ (Hancock et al. 2023).

The Receiver Operating Characteristic Curve shows the true-positive rate against the true-negative rate (Hegre et al. 2019). The true-positive rate ($TPR = \frac{TP}{TP+FN}$) divides observations where the predicted class is 1 and the actual class is 1 (TP) by the total number of positive cases, including both true positives (TP) and false negatives (FN). Conversely, the true-negative rate ($TNR = \frac{TN}{FP+TN}$) refers to ob-

[9]Selecting an evaluation metric to compare across outcomes is challenging, given that the baseline prevalence affects the size of the score. AUPR can be misleading due to its non-fixed baseline (Saito and Rehmsmeier 2015). While AUROC has a fixed baseline of 0.5, denoting that the classification is as good as random, the baseline in AUPR depends on the proportion of positive cases. Outcomes with a high prevalence have a higher AUPR, therefore making protest ($\bar{y} = 0.7909$ in test data) and civil war ($\bar{y} = 0.0476$ in test data) incomparable. The Brier score is another option, denoting the mean squared difference between the predicted probability of $y = 1$ and the actual classification (Hegre et al. 2019). Like AUPR, comparing Brier across outcomes can be misleading, given that the prevalence of $y = 1$ affects the size (Hoessly 2025). Low prevalence (e.g., civil war) leads to better performance. While there is no *ideal* option, AUPR is often deemed superior for imbalanced outcomes (Hancock et al. 2023).

servations where the predicted class is 0 and the actual class is 0 (TN), divided by the total number of negative cases, including false positives (FP) and true negatives (TN). This metric indicates how well the model discriminates between positive and negative cases (Yang and Gilbert 2017).

SHapley Additive exPlanations (SHAP)

Machine learning models are black boxes. Other than in the case of linear regression, it is unclear how each variable relates to the outcome, while this information is needed when validating theory (Masís 2023). To derive theoretical conclusions from black-box machine learning models, post-hoc interpretability tools are required, which uncover how the model makes predictions (Masís 2023; Molnar 2025).

This paper uses SHapley Additive exPlanations (SHAP)—a fast adaptation of Shapley values (Shapley 1953)—to uncover similarities and differences in the causes of collective action. SHAP values signify the *effect* of each independent variable on the predicted outcome, taking the mean forecast as baseline (Molnar 2025). In more technical terms, SHAP is the average marginal contribution of each variable across coalitions. A coalition is a specific combination of the remaining independent variables, and the marginal contribution is the change in the prediction when removing X from the model. While there are several interpretability tools, SHAP values are particularly appealing due to their solid statistical foundation (Molnar 2025).

A positive SHAP value implies that X increases the predicted outcome, while a negative value suggests that the outcome decreases, taking the mean forecast as a baseline (Molnar 2025). For each variable, one SHAP value for each observation is obtained. These can be plotted against the values of X, producing something similar to a marginal effect plot. Ensuring an easier comparison across outcomes, the SHAP values are binned over X, and the distributions are shown with violin plots.

3.7 Findings

The empirical analysis follows two steps. First, the out-of-sample performance is compared. For each outcome (i.e., protest, riots, terrorism, battles, non-state conflict, one-sided violence, 25 fatalities, and 1,000 fatalities), there are five thematic models, in addition to an ensemble. Second, SHAP values are presented to explore similarities and differences in the causes of collective action.

This paper puts forward two main findings. First, structural risk factors predict other types of collective action equally well. While conflict history is most important for the two civil war benchmarks, politics and demography are the best-performing themes for protests and battles. Structural background factors might cause civil war by transitioning through protest and/or low-intensity armed conflict. Second, there are similarities in the causes of collective action, most pronounced for population size and the cyclical nature of political contention, while less violent forms likewise have a unique character. Collective action is a non-sufficient condition for civil war, which applies particularly to protest.

Out-of-sample Evaluation

The results support the proposed theoretical claims if the collective action models have a similar or better out-of-sample performance than the two civil war benchmarks (1,000 and 25 fatalities). Indeed, the collective action and civil war models perform reasonably similarly, at least if the ensembles are concerned (Figure 3.3).[10]

Starting with the ranking of thematic models within each outcome, the ensembles (indicated by the ///-shading) have the highest bars, signifying good performance

[10]Tables C2—C4 in Appendix C contain the numerical results. The tables also include the Brier score. Figure 3.3 is limited to AUPR and AUROC, given that Brier rewards outcomes with low prevalence (Hoessly 2025). Less surprisingly, the 1,000-fatality model is the best performer on Brier; yet, when considering the ensembles, all outcomes perform similarly.

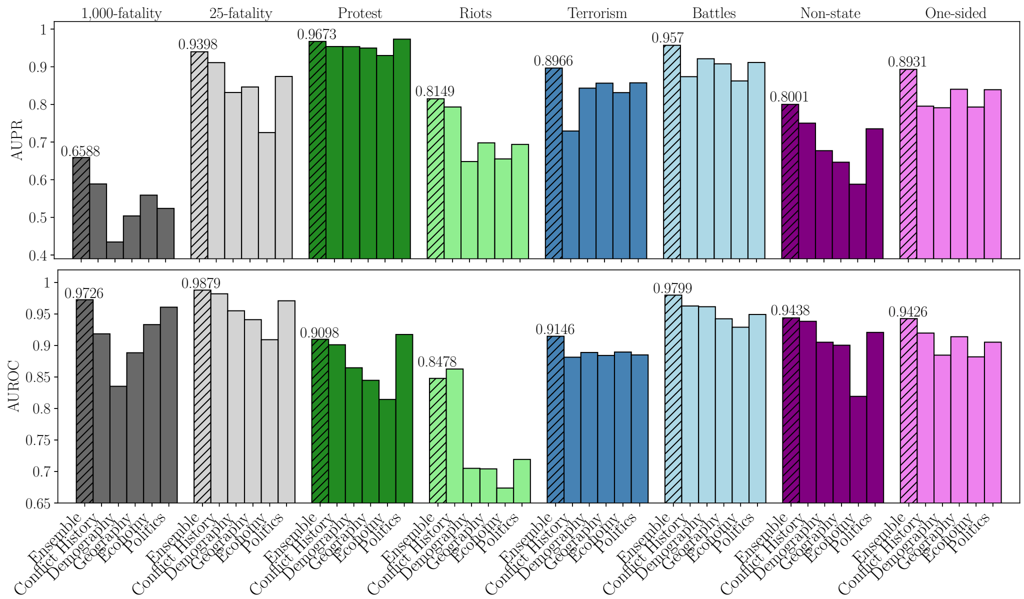


Figure 3.3: Area Under the Precision-Recall Curve (AUPR, upper panel) and the Area Under the Receiver Operating Characteristic Curve (AUROC, lower panel) across outcomes and themes: Conflict history, demography, geography, economy, and politics. Protests are shown in dark green, riots in light green, terrorism in dark blue, battles in light blue, non-state conflict in purple, and one-sided violence in pink. Two civil war benchmarks are included, indicating whether fatalities surpass 25 (gray) or 1,000 (dark gray) deaths. The ensembles are indicated by the ///-shading.[a]

[a]An alternative visualization of the results is included in Figure C.1 in Appendix C, showing AUROC and AUPR against each other in a scatter plot. The ensembles (X-markers) are clustered in the upper right corner, signifying good performance on AUPR and AUROC.

on AUPR and AUROC. For the civil war benchmarks, conflict history is the second-best performer. While conflict history is likewise important for less violent collective action, politics is the best-performing theme for protest, and demography the second-best for battles. Conflict history is most important for civil war, which implies that more substantial levels of armed violence originate from preceding civil conflict. Politics and demography are more relevant for protest and battles, which demonstrates that structural risk factors are more strongly associated with collective action rather than civil war. Structural factors might prompt civil war by transitioning through protest and/or low-intensity armed conflict

Next, model performance is compared across outcomes. For one, the ensembles suggest that there is no noticeable difference in out-of-sample performance, using structural risk factors to predict protest, riots, terrorism, and low-intensity armed conflict, in comparison to civil war, given that the heights of the ///-bars are reasonably similar. While protest is the best and 1,000-fatality the worst performing model on AUPR, this result is misleading due to the metric's non-fixed baseline, yielding higher AUPR scores for outcomes with higher prevalence, such as protests (Saito and Rehmsmeier 2015). The finding suggests that structural risk factors predict different types of collective action equally well.

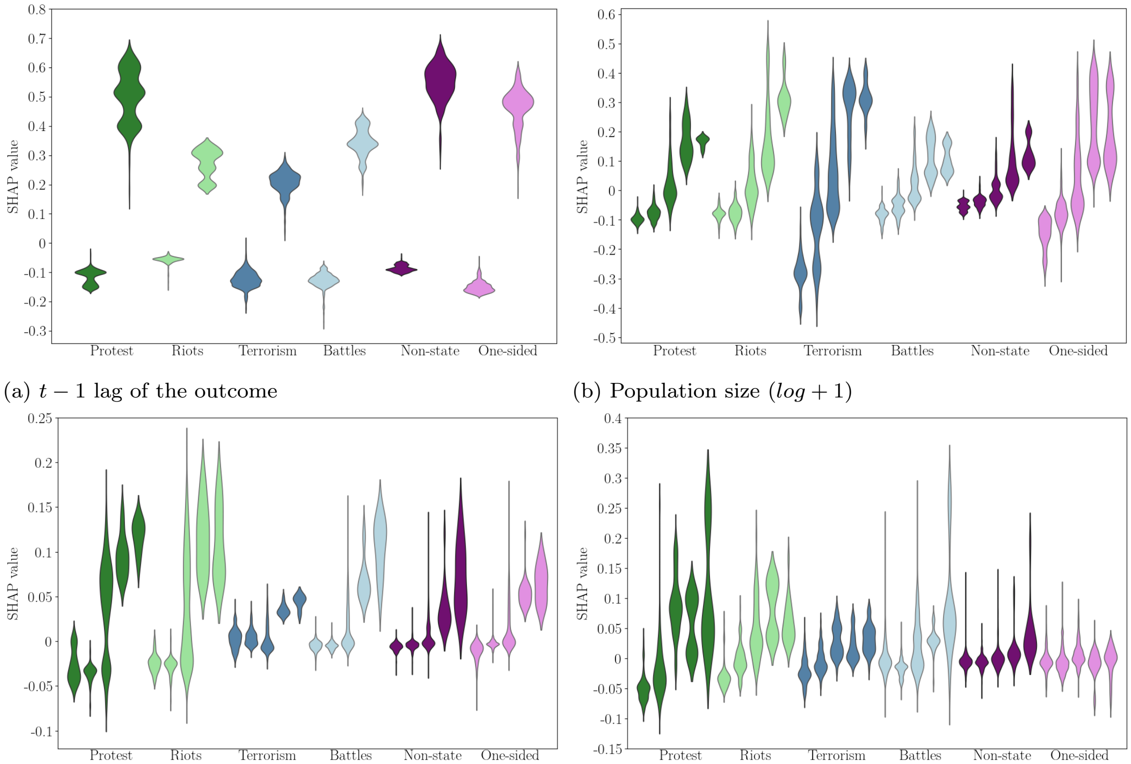
For another, the ensemble models reveal a clear ranking: Battles and 25-fatality perform best, and protest and riots worst. The somewhat lower AUROC scores for protest and riots already single out low-intensity collective action, in contrast to more violent contention, such as terrorism and armed conflict. This notion is further unpacked in the next section.

Differences and Similarities in the Causes of Collective Action

This section explores similarities and differences in the causes of collective action. A substantial share of associations is similar across outcomes. The larger the population size and the higher the consumer price index, the higher the probability of collective action, considering protest and low-intensity armed conflict.

However, there are also marked differences, grouping protests with riots, and terrorism with low-intensity armed conflict. Mobile phones seem to be relevant for protests and riots, yet not important for terrorism and low-intensity armed conflict. While different types of collective action have shared causes, they also have a unique character depending on the level of violence. Focusing on the specific most important predictors, the following paragraphs discuss similarities and differences.[11]

[11]The main text focuses on the most striking findings, selected among the most important variables. Additional plots are included in Figures C.3—C.12 in Appendix C.



(a) $t-1$ lag of the outcome

(b) Population size $(log+1)$

(c) Consumer price index $(log+1)$

(d) Level of water stress $(log+1)$

Figure 3.4: The associations between structural risk factors and different types of collective action are similar, as illustrated by (a) $t-1$ lag of the outcome, (b) population size, (c) consumer price index, and (d) level of water stress. The continuous variables are binned into categories for better visibility. Protests are shown in dark green, riots in light green, terrorism in dark blue, battles in light blue, non-state conflict in purple, and one-sided violence in pink.

Similarities

Battle events have a strong autoregressive character (Figure 3.4a). Conflict history is the most important predictor for ongoing armed violence (Mueller and Rauh 2022). This pattern is explained by the 'conflict trap': Civil violence leaves countries more vulnerable to armed conflict in the future through eroding state institutions and interpersonal relationships (Collier et al. 2003).

The cyclic nature applies to collective action more broadly. Protests commonly emerge in waves, where protest intensity increases and decreases consecutively (Koopmans 1993). Each wave is driven by diffusion and exhaustion (Tarrow 2011). Protests are initiated by activists and quickly diffuse to incorporate a larger share of society.

After reaching peak intensity, participation exhausts amid the repressive response from the state. If the underlying issue remains unresolved, protesters might initiate another protest cycle.

The probability of collective action increases with population size (Figure 3.4b). This is a robust finding in the civil war literature, substantiated by three arguments: (1) More potential recruits are available in more populous countries, (2) large countries are more challenging to govern, leading to a weak state reach into rural areas, and (3) high population concentration reduces coordination costs, which facilitates mobilization for collective action (Raleigh and Hegre 2009).

The same ideas apply to protests and riots, as more populous countries, by construction, experience higher event counts. Protests predominantly occur in urban regions, where population density is high. The positive association between population size and protest is substantiated by similar arguments: (1) Population concentration decreases coordination costs and lowers the risk of arrest, and (2) large populations are more challenging to govern, while the potentially hampered provision of public goods fuels grievances and protests (Fox and Bell 2016).

The consumer price increases the predicted probability across outcomes (Figure 3.4c). When the cost-of-living soars, citizens are likely to demonstrate, demanding that the government act. Starting in 2022, the COVID-19 pandemic and Russia's invasion of Ukraine have accelerated food and electricity prices, which prompted a wave of protest across the globe (Hossain and Hallock 2022). In this context, citizens see access to food and electricity as a basic human right, and if governments are unable to provide, protest is a measure for holding politicians accountable (Hossain and Hallock 2022).

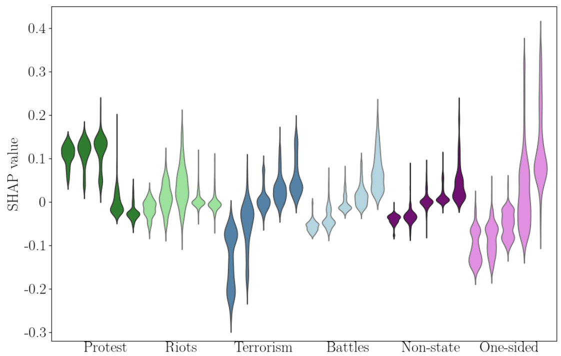
For more violent forms of collective action, the positive correlation is strongest for battle events and non-state conflict. A high consumer price index suggests that food prices are increasing, and the resulting food insecurity can prompt armed violence, in particular non-state conflict (Hendrix and Brinkman 2013). Competition for crop, land, and water can lead to communal violence between and among herders and farmers, as seen in the form of cattle raiding in Kenya, Nigeria, Sudan, and Uganda (Brinkman and Hendrix 2011).

Water scarcity can increase the probability of battle events (Figure 3.4d). Several potential mechanisms substantiate this association: (1) Water scarcity causing conflict among consumers directly, (2) a disruption of market prices leading to inflation and intensified grievances, (3) water pressure prompting migration flows and conflict in host societies, (4) a reduced provision of public goods, when state resources get tied up to counter water stress, and (5) water scarcity hampering overall economic productivity (Hendrix and Salehyan 2012).

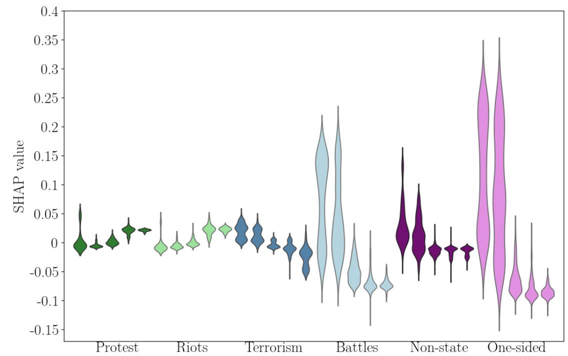
Water pressure is also linked to small-scale conflict, such as rioting, in economically less developed countries due to reduced opportunity costs (Almer et al. 2017). Since water is a key input to farming, pastoralism, and mining, water stress hampers productivity and intensifies competition. Instead of engaging in economic activity, individuals participate in contention over water. In addition, water stress can prompt communal violence between communities with distinct identities, such as herders and farmers (Döring 2020). The Lake Turkana Basin in Kenya has experienced non-state violence for decades, as ethnic groups in the region, most of whom are nomadic pastoralists, are heavily dependent on grazing land (Ngonge et al. 2023).

Differences

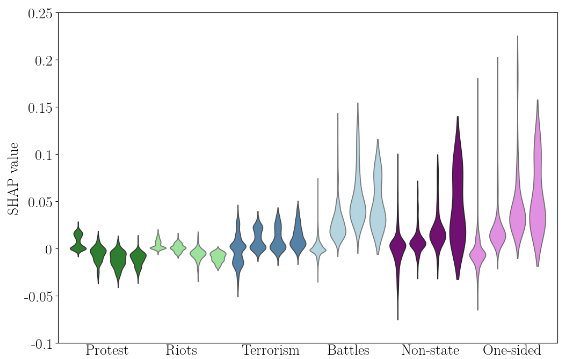
While the causes of collective action show some similarities, there are also marked differences, grouping less and more violent forms, in particular, protest with riots, and terrorism with low-intensity armed conflict. The differences in the causes of col-



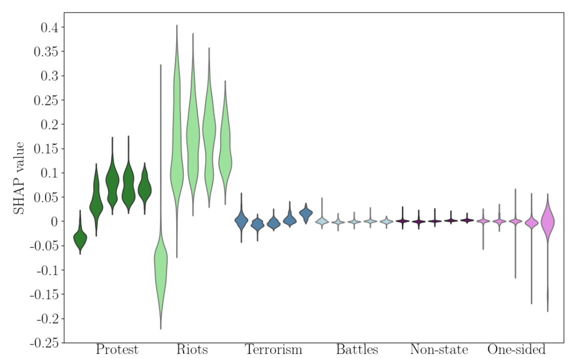
(a) Share of male population 0-14 years



(b) Expected years of schooling for females



(c) Oil rents ($log + 1$)



(d) Mobile phone subscriptions

Figure 3.5: The associations of structural risk factors vary across different types of collective action, as illustrated by (a) share of male population 0-14 years, (b) expected years of schooling for females, (c) oil rents, and (d) mobile phone subscriptions. The continuous variables are binned into categories for better visibility. Protests are shown in dark green, riots in light green, terrorism in dark blue, battles in light blue, non-state conflict in purple, and one-sided violence in pink.

lective action are most pronounced for youth bulges and mobile phone subscriptions. The findings suggest that protests and riots occur more frequently in prosperous and low-intensity armed conflict in poor countries.

For the percentage of male children, terrorism and low-intensity armed conflict display a positive association (Figure 3.5a). Despite being a clear violation of international law, children under the age of 18 are still commonly involved as combatants in armed conflict (UN 2025). In more general terms, youth bulges can prompt political violence, given that a larger share of young men increases the prevalence of grievances in society and provides opportunity, as young men are more easily recruited by a non-state actor (Urdal 2006).

The correlation between expected years of schooling for females and more violent forms of collective action is negative (Figure 3.5b). Civil war might be caused by low opportunity costs as indicated by low levels of education (Collier and Hoeffler 2004). Opportunity costs refer to the income that an individual might lose by joining a non-state group. If economic prospects are poor, engaging in rebellion might become an economic activity if rebels are given the prospect of payment.

Conversely, the correlation of male children with less violent collective action is negative, suggesting that the higher the percentage, the lower the predicted probability of protest events (Figure 3.5a). Similarly, the association of female schooling is positive: The higher the female schooling, the higher the predicted probability of protest and riots (Figure 3.5b). A low percentage of male children is an indicator of a low fertility rate, a main consequence of economic development (Hafner and Mayer-Foulkes 2013). Equally, female schooling is a common proxy for gender equality and, by extension, economic development (Kabeer and Natali 2013). These results mean that economic development decreases the probability of more violent collective action, while less violent contention occurs more frequently in prosperous countries. Specifically protest is a regular form of political participation in democracies and usually remains non-violent.

There is a positive association between oil rents and more violent forms of collective action (Figure 3.5c). Oil is related to civil conflict based on three mechanisms: (1) Income from oil might provide the financial means to initiate armed action against the state, (2) oil depletion can intensify grievances of the local population, especially if oil revenues are not equally distributed, and (3) oil can erode state capacity if the government becomes overly dependent on trade with oil (Ross 2004a).

Oil is also correlated with non-state conflict and civilian targeting. If several non-state actors operate in an area with oil deposits, they might engage in inter-rebel armed violence to gain control (Fjelde and Nilsson 2012). Rebel groups in resource-rich environments attract opportunistic individuals and need to allow a certain level of looting as part of their recruitment strategy (Weinstein 2007).

Conversely, the association between oil rents and less violent collective action is negative. While oil exporters commonly experience oil-related protests (Gayle 2024), oil rents indicate a dependency on oil rather than abundance (Basedau and Richter 2014). Countries like Norway and the United Kingdom have large oil deposits, *and* a diversified economy to avoid dependency on revenues from oil (Ross 2013). While oil deposits might even foster peace, oil dependency combined with low abundance can cause civil war (Basedau and Richter 2014).

Nevertheless, there is also anecdotal evidence that oil can prompt protest, which gradually transitions to civil conflict. Nigeria has large oil deposits, and its economy became dependent on oil revenues after the intensification of oil depletion in the 1980s (Frynas 2001). The oil fields are located in the Niger Delta, which experienced intense protest amid the increasing oil production, decrying environmental degradation and the marginalization of local interests (Frynas 2001). Protests transitioned into more violent forms of contention as heavily armed groups began operating in the area (Obi 2009). Kidnappings of oil workers and ransom payments likely enabled the purchase of more sophisticated weapons (Obi 2009).

Another interesting difference between less and more violent forms of collective action is revealed by mobile phone subscriptions. Access to mobile phones increases the predicted probability of riots and protests (Figure 3.5d). While phone subscriptions arguably also relate to economic development, mobile phones play a key role in organizing protests, given that they allow sharing information in real time and lower the coordination costs of collective action (Neumayer and Stald 2014). Instead of having to coordinate beforehand, mobile phones can be used to distribute updates as events unfold, in particular concerning crowd control measures and other repressive responses by the state.

In comparison, battles are uncorrelated with mobile phones. Non-state groups might rely on other ways of communication due to the high risks of being discovered. Cellphones can enhance the counterinsurgency capabilities of the state: The government can monitor cellphone activities to capture rebels, and civilians may use cellphones to transmit information to the state (Shapiro and Weidmann 2015). At the same time, mobile phones can increase the risk of armed violence, due to lowering coordination costs and the opportunity to free ride (Pierskalla and Hollenbach 2013). Digital communication allows rebels to coordinate in real time, and by distributing anti-government propaganda, the non-state actor can increase support. Both arguments are reflected in the U-shaped association for terrorism.

3.8 Conclusion

Existing research on the causes of armed conflict focuses on structural risk factors (Cederman et al. 2010; Collier and Hoeffler 2004; Fearon and Laitin 2003). However, an immediate connection between background conditions and civil war onset seems unrealistic. Escalating armed violence to the level of war entails great risks and logistical challenges. Initially, the non-state actor favors less violent forms of collective action due to the higher chances of success (Stephan and Chenoweth 2008), or they need to mobilize first (Malone 2021), which implies that collective action is a key prerequisite for civil war. Structural factors cause collective action, which may or may not transition to more extreme manifestations of violence (Florea 2017).

This paper puts forward two main findings. First, structural risk factors perform reasonably similarly when predicting other forms of collective action, if compared to the 25 and 1,000-fatality civil war benchmarks. While conflict history is the most important theme for civil war, politics and demography are most relevant for protest and battles. This suggests that structural background factors might prompt civil war by transitioning through protest and/or low-intensity armed conflict.

Second, similar theoretical arguments apply across outcomes, most evidently for population size and the cyclic nature of political contention. At the same time, less violent forms of collective action, i.e., protests and riots, have a unique character, which is revealed by mobile phones and proxies for economic development. Protest is a common tool for citizens in rich democracies to voice their opinions and has a low risk of violent escalation in those contexts. However, protest *can* be an early-warning signal for armed conflict (Rød et al. 2023). Differentiating between peaceful protest and protest dynamics, signaling an increased risk of violence, is an important area of future research. The presented findings emphasize that collective action is a non-sufficient condition for civil war, in particular protest.

This paper has three implications. First, structural risk factors prompt collective action more broadly. When conflict emerges in society, claim makers select a strategy from a 'repertoire of collective action' (Tilly 1977). Those strategies can be less (i.e., protest and riots) or more violent (i.e., terrorism and low-intensity armed conflict). Collective action is a key precursor to civil conflict, and structural risk factors might lead to more substantial levels of armed violence by transitioning through protest and/or low-intensity armed action.

Second, if collective action mediates the relationship between structural factors and civil conflict, the predicted probability of collective action delineates a subsample of high-risk cases. This subsample seems particularly relevant when seeking to anticipate conflict onsets, an area where existing conflict prediction models still perform poorly (Mueller and Rauh 2022).

Third, this paper illustrates how interpretable machine learning can be leveraged to validate civil conflict theory. Machine learning produces an empirical model that is as complex as necessary, while ensuring that findings still generalize (Colaresi and Mahmood 2017). Thereafter, tools from interpretable machine learning serve to extract theoretical insights from the black-box models (Molnar 2025).

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4 *From Protests to Fatalities: Identifying Dangerous Temporal Patterns in Civil Conflict Transitions*

This paper is co-authored with my supervisor, Thomas Chadefaux. My contribution to the paper is as follows: Leading the empirical analysis and parts of the write-up. For the empirical analysis, we adapted sections of the Python code from another co-authored project (e.g., how to implement subsequence time series clustering for different window lengths). The adapted parts were written by Thomas Schincariol, who has kindly allowed us to reuse his work.

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Replication material
The data and Python code to run the analysis are available here: `https://github.com/hannahhfrank/phd_thesis_reconceptualizing_conflict_emergence/tree/main/protest`.

Use of Generative Artificial Intelligence
For the empirical analysis, ChatGPT-3.5 and higher (`https://chatgpt.com/`) was consulted as a coding assistant, and when correcting spelling and grammar, suitable add-ons in Overleaf were used (i.e., Grammarly, Writefull, and LanguageTool).

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From Protests to Fatalities: Identifying Dangerous Temporal Patterns in Civil Conflict Transitions

Abstract

Why do some protests escalate into civil conflict while others do not? Protest can turn violent when participants believe that non-violent action has failed, or when existing rebel groups perceive protests as a strategic opportunity to initiate armed action. However, armed violence does not occur spontaneously, and armed escalation typically follows periods of strategic calculations and tactical adaptations over time. This suggests that recent protest activity (e.g., at $t-1$) is insufficient to explain transitions to civil conflict. Instead, the continued interactions between protesters and the state produce dangerous protest patterns. In this context, we develop a novel methodology to extract temporal patterns from time series of protest events, combining statistical inference and predictive modelling. Using country-month data on protest and battle events, we identify three dangerous protest patterns that precede high fatalities in civil conflict: (1) A gradual escalation of protest intensity, (2) a sharp decline following peak activity, and (3) a U-shaped trajectory. These shapes are indicative of the non-state actor's strategic decision-making.

Keywords: Protest, civil conflict, temporal patterns, time series clustering

4.1 Introduction

There is marked variation in the outcomes of protest movements: Some transition into armed conflict, whereas others conclude peacefully. For example, the so-called Arab Spring saw Tunisia and Egypt navigate comparatively peaceful regime transitions, while Syria, Libya, and Yemen spiraled into civil war (Massoud et al. 2019). Explaining and predicting which protest movements will turn violent remains a central challenge in the study of political contention and the onset of civil conflict.

Traditional explanations for protest-to-civil conflict transitions emphasize mechanisms such as protest escalation, where non-violent movements radicalize over time, and protest capture, where armed groups perceive protest as a window of opportunity to initiate armed violence (Rød and Weidmann 2023). Those theories are often operationalized through static indicators, such as protest counts including temporal lags (e.g., $t-1$). However, static protest lags assume that recent activity is the main predictor of armed escalation, which overlooks temporal dynamics of dissident-state interactions over several preceding months. Civil conflict entails great risks for both the government and the non-state actor, which means that actors carefully monitor the evolving situation before pursuing violent tactics.

In this paper, we argue that sequences of protest activity contain unique information about whether a protest movement will spiral into civil conflict or not. Rather than viewing protest as a static signal, we conceptualize it as a dynamic phenomenon driven by interaction, adaptation, and escalation (cf., McAdam 1983; Tarrow 2011). We contend that certain recurring protest shapes, or rather, patterns in the intensity of protest over time, serve as early warning signals for civil conflict.

Adapting the framework in Rød and Weidmann (2023), these shapes capture the strategic calculations of protest movements and existing non-state armed groups, including their responses to repression, shifts in tactics, and decisions to initiate armed action. Rapid escalations followed by abrupt government crackdowns or the transition from small to widespread protests may signal a higher likelihood of violent conflict. Such patterns can indicate a tactical shift among protesters or suggest that the government is sufficiently preoccupied with managing protest, offering a window of opportunity to an existing armed group. This paper's main objective is to find dangerous protest shapes that precede high fatalities in civil conflict.

To uncover these patterns, we develop a two-step empirical strategy. First, we apply time series clustering techniques (Aghabozorgi et al. 2015) to identify recurring patterns in protest intensity across country-month time series data. This inductive approach enables us to capture meaningful temporal structures without imposing ex ante assumptions on the shape of protests over time. Second, we test the explanatory power and predictive value of these patterns using null-hypothesis significance testing and out-of-sample forecasting.

Our analysis reveals three distinct protest shapes that precede high fatalities in civil conflict: (1) A gradual escalation of protest intensity, (2) a sharp decline following high-intensity protest, and (3) a U-shaped pattern in which protest activity declines and resurges before violence erupts. These protest patterns are inferred back to the theoretical framework, developed by Rød and Weidmann (2023), who propose that protest might transition to armed conflict along two mechanisms: *Protest escalation* or *protest capture*.

Our paper makes three main contributions. Theoretically, we expand upon static models of protest escalation and protest capture by identifying the temporal patterns through which these mechanisms might manifest over time. Understanding the transition from protest to armed conflict requires actually 'taking time seriously', not only as a control variable but as a central object of analysis. Methodologically, we introduce a new approach for extracting dynamic variables from contentious event data, which improves explanatory power and predictive performance over conventional lag-based models.[1] Empirically, we offer a framework for identifying high-risk protest patterns, with implications for conflict prevention. Indeed, protest activity can be an early warning signal for armed violence (Rød et al. 2023).

4.2 Temporal Patterns in Protest

Protests commonly emerge in wave-like patterns with consecutive increasing and decreasing intensity (Koopmans 1993).[2] Protest is a dynamic phenomenon where the behavior of the protesters depends on the behavior of the state and vice versa (Pierskalla 2010). Thus, protest patterns are produced by the interactions between protesters and the government. Each protest wave is driven by diffusion and exhaustion (Tarrow 2011). At the outset, protest is initiated by early risers, and protest participation gradually diffuses. The government perceives the emerging protest as a threat and responds with state repression (Davenport 2007). Depending on the context, state repression takes less or more violent forms, for example, pepper spray versus live ammunition (Chenoweth et al. 2017). However, the government *always* responds with some form of repression to dissidence (Davenport 2007).

State repression reveals the personal costs of protest, and as a consequence, participation exhausts (Tarrow 2011). To counter the declining protest activity, early risers undergo tactical innovations, where protest strategies are modified to better evade the government's repressive response (McAdam 1983). Tactical innovations

[1] A similar methodological approach is explored by K. S. Gleditsch et al. (2024), using cluster analysis and dynamic time warping to extract groups from fatality time series.

[2] Protest intensity refers to the count of protest events in a given period. A higher number of protest events indicates higher protest intensity. While the number of participants might be a more suitable measure for protest activity (Biggs 2018), relying on the number of events is in line with common practice (e.g., Della Porta 2008; Koopmans 1993; Rød and Weidmann 2023).

prompt a new wave of mobilization as protest activity surges again. While protesters innovate their tactics, the government seeks tactical adaptations, where the repression apparatus is tailored to counter the emerging protest tactics (McAdam 1983). This leads to a more powerful repression, and intensity declines once more.

Protest waves often occur in succession, where one wave prompts another. The shape of each wave is determined by the chess-like interplay of tactical innovations and adaptations (McAdam 1983). Therefore, patterns in sequences of protest events contain information about the broader course of protest. Such patterns can indicate a tactical shift among dissidents or suggest that the government is sufficiently focused on managing protest, offering a window of opportunity to an existing armed group (cf. Rød and Weidmann 2023). Following this, we argue that certain protest patterns are precursors for a protest-to-civil conflict transition. Our goal is to identify dangerous protest patterns, which precede high fatalities in civil conflict.[3]

4.3 The Transition from Protest to Civil Conflict

Existing research argues that protest transitions to civil conflict through continued interactions of protesters and the government (e.g., Della Porta et al. 2018; Rød et al. 2023; Rød and Weidmann 2023). Against this background, Rød and Weidmann (2023) identify two mechanisms: *Protest escalation*, where protest gradually shifts from non-violence to violence, and *protest capture*, where protests create strategic opportunities for existing rebel groups.

Protest escalation occurs when non-violent protesters adopt violent tactics. At the outset, non-violent tactics are preferred due to their higher likelihood of achieving concessions (Stephan and Chenoweth 2008). While intended to suppress dissent,

[3]Protest is a public demonstration where protesters remain non-violent, while the state might use violent tactics to counter protest (ACLED 2023). Civil conflict refers to armed conflict between a government and a non-state group (N. P. Gleditsch et al. 2002).

state repression can backfire, intensifying protests and radicalizing movements by creating divisions between moderates and extremists (Tarrow 2011). This is particularly true if institutionalized channels for political participation are closed off (Rød and Weidmann 2023). Emotional responses to state violence, such as moral outrage, further legitimize the shift toward armed resistance (Wood 2001). This dynamic leads to civil conflict when protesters perceive that non-violent tactics have failed and that violent tactics are the only option (Rød and Weidmann 2023).

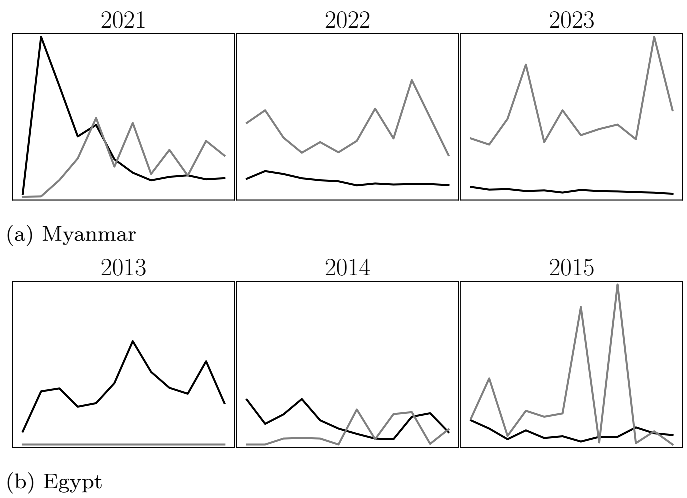


Figure 4.1: The number of protest events (black) and the number of fatalities in civil conflict (gray). There is co-variation between protest and civil conflict, with high protest counts followed by peaks in fatalities. All data are *min-max* normalized at the country level.

The protest escalation mechanism seems to apply in the case of Myanmar (Figure 4.1a). In 2021, the military seized political power with a coup, which was countered by a wave of protest demanding the return to democratic rule (UCDP 2025b). The military responded with repression, which prompted protesters to arm, forming the People's Defence Force, an armed wing of the pro-democracy government. Violent conflict escalated as the People's Defence Force launched an armed campaign against the military, which was joined by already existing rebel groups.

Protest capture describes how protests create opportunities for existing rebel groups (Rød and Weidmann 2023). State repression often stretches resources thin and undermines government control in peripheral regions. While state resources are focused on countering protests, rebel groups exploit these conditions to mobilize, recalculating their chances of success based on the state's weakened capacity.

While this dynamic seems relevant in the Burmese context as well, we find further anecdotal evidence for this mechanism in Egypt (Figure 4.1b). Amidst the so-called Arab Spring, protests erupted in Egypt, which led to the overthrow of Mubarak and the transfer of power to an elected president (Khan et al. 2020). Despite this comparatively peaceful transition, political instability remained high, and the military seized power two years later (UCDP 2025a). In 2014, the country experienced escalating armed violence in the Sinai, mostly driven by the Islamic State.

4.4 Actually 'Taking Time Seriously'

Civil conflict involves high temporal complexity, including intricate patterns of aggression, appeasement, and escalation (Chadefaux 2022; Chadefaux 2023). Similarly, protests commonly follow wave-like patterns of escalation and de-escalation, with sudden peaks and declines in intensity (Della Porta 2008). Despite acknowledging the dynamic character, much of the existing research remains constrained by static approaches that fail to capture the temporal complexity of protest-to-civil conflict transitions. This paper contributes to the emerging literature linking protest to civil conflict (i.e., Rød et al. 2023; Rød and Weidmann 2023), while offering an alternative take that explores temporal dynamics in protest.

Understanding the transition from protest to civil conflict requires a theoretical framework that accounts for the strategic calculations of protesters and existing non-state groups. Building on the work of Rød and Weidmann (2023), we argue that the escalation of protest to armed conflict is not a sudden event, but rather a gradual development shaped by the dynamic interactions between protesters, the state, and existing rebel groups. Civil conflict entails great risks. The government is in danger of being overthrown, while the non-state actor faces severe repression, punishment, and death. Given these high stakes, actors carefully monitor the evolving situation before committing to violence. Thus, protest movements often unfold over several months, with their trajectory determined by the interactions between state repression, protest activity, and the strategic decisions of existing armed groups.

The transition from non-violence to violence depends on how protesters and rebel groups interpret the state's responses over time rather than just at $t-1$ (i.e., Rød and Weidmann 2023). Protesters may initially rely on non-violent tactics, but repeated governmental crackdowns signal that peaceful means have failed. When government forces show a continued unwillingness to engage constructively, protesters may come to believe that violent escalation is the only option. Alternatively, rebel groups in peripheral regions observe protest activity at the center, carefully assessing whether consecutive protest cycles indicate a weakened state capacity. If the state appears increasingly preoccupied with suppressing protest over several consecutive months, rebels may believe that a strategic window of opportunity has emerged.

The interactions between protesters and the government generate discernible patterns in the sequences of protest events. These sequences may indicate either escalating confrontations or a weakening of state capacity, both of which serve as precursors to civil conflict. When seeking to anticipate protest-to-civil conflict transitions, it is essential to analyze entire protest sequences rather than focusing on recent events. By doing so, we can identify dangerous protest shapes, or rather, temporal patterns in sequences of protest events that precede high fatalities in civil conflict.

Existing approaches for time dependency, such as lagged predictors, decay functions, or cumulative event counts (e.g., Rød et al. 2023; Rød and Weidmann 2023), are limited. Modeling temporal dependencies requires incorporating long sequences of past events, which can lead to overfitting and lower statistical power. Moreover, traditional lag-based methods fail to account for the varying speeds at which protest patterns emerge. For instance, a recurring pattern of up-down-up in protest activity might unfold over four or more months, but temporal lags would miss the similarity between such events. These issues underscore the limitations of static variables in explaining the transition from protest to civil conflict.[4]

To address these limitations, we step away from seeking to establish correlations between variables at time t and instead use techniques from time series clustering. Taking entire sequences as unit of analysis, time series clustering extracts recurring patterns in series of events (Aghabozorgi et al. 2015). Applying these tools, we uncover protest patterns with an inductive approach and investigate their utility using null-hypothesis significance testing and out-of-sample validation. The extracted shapes are then inferred back to the theoretical mechanisms: *Protest escalation* and *protest capture*, as proposed by Rød and Weidmann (2023).

4.5 Data

Data on the output, the number of battle-related deaths in civil conflict, are provided by the UCDP Georeferenced Event Dataset (UCDP GED) (Sundberg and Melander 2013). Data on the input, the number of protest events, are obtained from the Armed Conflict Location and Event Data (ACLED) (Raleigh et al. 2010). The event data are aggregated to the country-month by summing the number of events and the number of fatalities, which is then the level of analysis.[5]

[4] Chadefaux (2022) and Chadefaux (2023) put forward a similar discussion on the limitations of static analyses when uncovering patterns in time series data.

[5] UCDP is the default for fatality data due to its rigorous verification process (Eck 2012). UCDP GED version 24 was downloaded from `https://ucdp.uu.se/downloads/ged/ged241-csv.zip` on the 9^{th} of August 2025. To code the outcome, we remove events between states and those that occur over several months. The ACLED data were downloaded from `https://acleddata.com/conflict-data/data-export-tool` (old export tool) on the 23^{rd} of April 2024.

The country-month level of analysis offers an ideal compromise. Taking country as spatial unit allows us to validate whether our theoretical expectations apply across diverse contexts (e.g., Israel, Sudan and Portugal, Iceland). A stronger geographic disaggregation would limit our analysis to a few countries only. More importantly, using daily data on the regional level, such as PRIO-GRID (Tollefsen et al. 2012), would result in time series with access zeros, making it difficult to differentiate between flat time series with no observations, noise, and signal. Yearly data on the other extreme are likely to conceal important temporal dynamics in protests, which often escalate and de-escalate from one month to the next.

To study transitions from protest to civil conflict, we focus on the intensity of armed violence rather than its onset. More specifically, we use the number of fatalities in civil conflict as the outcome variable, following standard practice in the literature (e.g., Lacina 2006; Trinn and Wencker 2021). This operationalization allows us to investigate whether protest dynamics are associated with the escalation or de-escalation of armed violence over time. A binary measure of civil war onset would conceal such variation, and it would also exclude cases where protests occur amid ongoing armed conflict. Indeed, the protest capture mechanism (Rød and Weidmann 2023) presumes the presence of existing armed actors, suggesting that protest-to-civil conflict transitions can unfold even in already violent situations.

The temporal coverage is determined by ACLED, which has varying periods for different countries. This means that the protest time series have different lengths, ranging between 1997—2023 and 2021—2023. We take the countries in ACLED as the point of departure. Microstates (e.g., Lichtenstein and Monaco) are excluded, since those countries systematically differ, as well as states not listed in K. S. Gleditsch and Ward (1999).[6] We also remove countries completely missing in at least one

[6]ACLED gathers data on several territories not listed in K. S. Gleditsch and Ward (1999) (e.g., Antarctica and La Réunion), which are not included. Events in Palestine are assigned to Israel due

of the data sources for control variables (i.e., Bahamas, Belize, Brunei Darussalam, North Korea, Taiwan, and Venezuela), since imputation techniques can be unreliable in this context. These procedures yield a sample of 168 countries.

A set of control variables is included, which are associated with both the occurrence of protest and civil conflict. Data on economic conditions are taken from the World Development Indicators (World-Bank 2025) and variables on political institutions from the Varieties of Democracy (V-Dem 2024). Missing values are imputed with linear interpolation and mean imputation.[7]

4.6 Research Design

Null-hypothesis significance testing is used to assess whether there is an association between protest patterns and fatalities in civil conflict, while accounting for static protest variables. By including covariates related to both protest activity and civil conflict, the regression model helps to evaluate whether protest patterns contribute explanatory power beyond standard predictors.

For extracting protest patterns, we leverage out-of-sample techniques because they allow us to identify protest patterns directly from the data rather than being constrained by assumptions. Predefining patterns can limit the scope of analysis, potentially overlooking important dynamics that fall outside the theoretical framework. By adopting an inductive approach, we can test which patterns emerge from the data while inferring back to theories on protest-to-civil conflict transitions. This ensures that our findings reflect the full complexity of protest dynamics.

Moreover, out-of-sample evaluation serves as a test of whether a variable cap-

to being a crucial case.

[7] For more details, see Section C.1 in Appendix C. While we ensure to use a train-test split during the imputation, the World Bank data are only available annually, where splitting observations by 70/30 yields different partitions than on the country-month.

tures a systematic component of the underlying data-generating process (Carsey and Harden 2014). If the inclusion of dynamic protest variables improves predictive performance in out-of-sample tests, these variables likely reflect meaningful patterns in protest beyond what static protest measures and other country characteristics can offer. Out-of-sample validation demonstrates that dynamic protest patterns are not simply noise but are indicative of broader temporal processes that help predict transitions to civil conflict.

To this end, we develop a two-step methodological approach. First, we cluster time series of protest events based on similarity in shape. This yields a set of cluster assignments, which we call dynamic covariates. These protest patterns are optimized within and across countries. Next, we use the protest patterns to explain and predict fatalities in civil conflict. The main goal is to identify dangerous protest patterns that precede high fatalities in civil conflict. The extracted dangerous shapes can then be inferred back to the theoretical mechanisms, protest escalation and protest capture, as proposed by Rød and Weidmann (2023).

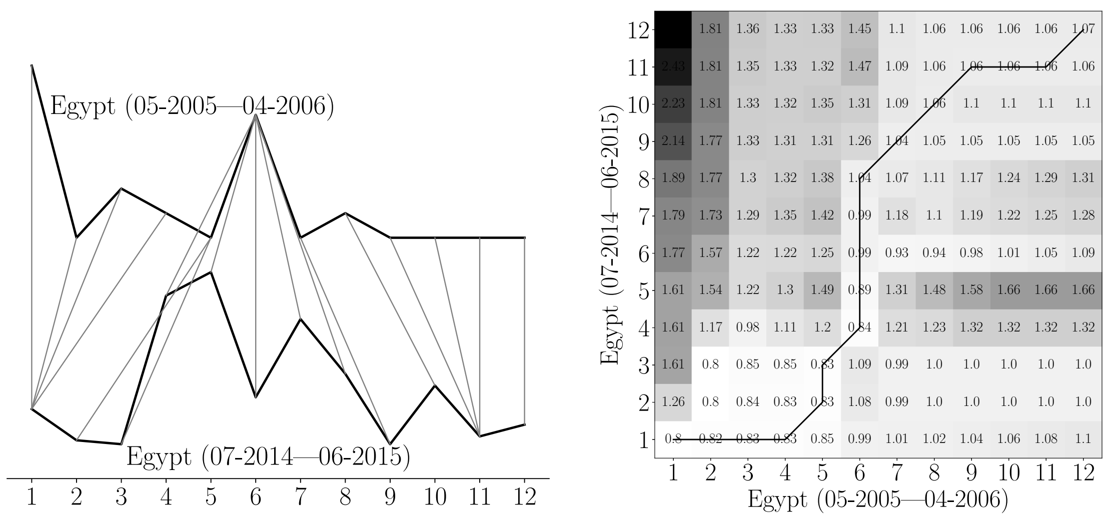
Step 1: Extracting Protest Patterns

To extract protest patterns, we apply techniques from subsequence time series clustering (Zolhavarieh et al. 2014), which allows uncovering recurring patterns in sequences of protest events. Using a moving window, each protest series is divided into a set of subsequences having a length of *win* each. Starting at index *win*, the preceding *win* observations are considered for each case at time t. Each subsequence of protest events is *min-max* normalized, and the matrix of subsequences is used as input to the clustering algorithm.[8]

Identifying recurring protest patterns requires a metric for assessing the similarity

[8] The *min-max* normalization is implemented using the following formula, $X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$. This is an important preprocessing step and allows us to match subsequences based on shape.

between subsequences, which we operationalize with their distance. Conventional distance measures can be misleading for time series data. These approaches typically enforce a linear matching between observations, where the i^{th} observation in X is compared to the j^{th} observation in Y (Keogh and Ratanamahatana 2005). This rigid alignment fails to account for variations in the speed at which similar patterns unfold. Such time shifts are particularly relevant in the context of protest, given the inherently dynamic nature of political contention.



(a) Warped time series

(b) Optimal warping path ($d = 1.066$)

Figure 4.2: (a) Dynamic Time Warping realigns time series and thereby uncovers similar but phase-shifted patterns (Keogh and Ratanamahatana 2005). Each observation in one time series is compared to multiple observations in another, finding the specific closest match. (b) The matching is derived from a cost matrix, where each cell denotes the distance between two points. The optimal warping path (black) is chosen to minimize the cost, which is the cumulative distance (d).

We select Dynamic Time Warping (DTW) as our similarity measure, which is commonly used for time series data (Keogh and Ratanamahatana 2005). DTW provides a solution by enabling more flexible comparisons between time series. Instead of a linear matching, DTW allows one point in X to be contrasted with multiple points in Y, aligning each observation with the closest reference (Figure 4.2a). This process realigns, or *warps*, the time axis to minimize the distance between two series. During the realignment, the time axis may be stretched or compressed.

In more technical terms (Keogh and Ratanamahatana 2005), a distance matrix is obtained, where each cell in the matrix denotes the distance between the i^{th} observation in X and the j^{th} observation in Y. The distance is denoted by the Euclidean distance, $\delta(i, j) = (x_i - y_j)^2$ (Figure 4.2b). Building on the cost matrix, the DTW algorithm derives the optimal warping path by minimizing the cumulative distance between both time series. Each potential warping path needs to begin and end in opposite corners, only connect to adjacent cells, and cannot go backwards.

With DTW as a similarity measure, we apply k-Means clustering to uncover recurring patterns in protest time series. k-Means is a tool for grouping observations into clusters based on similarity (Kotu 2019). With this algorithm, the subsequences of protest events are assigned to one of k clusters, selected by minimizing the distance between cases contained in each group.[9] The similarity between subsequences is given by the Dynamic Time Warping (DTW) distance. Each cluster has a centroid, which is the mean of all constituent subsequences and serves as a representative, revealing a preceding protest pattern for the observation at t.

The clustering algorithm has two hyperparameters: k, the number of clusters, and win, the window length of the subsequences. These two hyperparameters need to be optimized to find the optimal clustering solution. The optimization is implemented across and within-country.

Cross-Country Optimization

The cross-country protest patterns are validated with null-hypothesis significance testing. First, we apply the clustering algorithm to each country individually, using the full length of the protest time series. The number of clusters k and the win-

[9] The k-Means algorithm starts by randomly selecting k centroids and assigning each observation to the nearest (Kotu 2019). The centroids are recalculated based on these initial clusters, and the assignment process is repeated until convergence.

dow length win are optimized by brute force. The combination with the highest silhouette score yields the final clusters.[10] For the window length win, we consider $[5, 6, 7, 8, 9, 10, 11, 12]$ and for k, we select from $[3, 5, 7]$.

Thereafter, we seek to aggregate the within-country patterns to the cross-country level with a second round of clustering. Using the centroids obtained in the first step as input, we apply agglomerative hierarchical clustering (Hastie et al. 2017). This algorithm takes each time subsequence individually and recursively merges similar cases until all observations are combined. Subsequences are grouped based on their Dynamic Time Warping (DTW) distance. As before, the number of clusters k is optimized by brute-force search based on maximizing the silhouette score.

This two-step strategy offers an ideal compromise in the aggregation process. Using the same k-win-combination across all countries would discard any difference in the protest shapes, lumping together protests in the United States and Myanmar. In the first round of clustering, we maintain high flexibility and allow for protest shapes to be affected by country characteristics. Yet, to identify dangerous patterns, we need to generalize across countries. With the two-step clustering approach, protest shapes are gradually aggregated from the national to the global level.

Within-Country Optimization

The within-country protest patterns are validated with out-of-sample techniques. Before applying the clustering algorithm within-country, each time series is divided into a training fraction, the first 70% of observations, and a test fraction, the remaining 30% of observations. The length of these partitions varies, depending on ACLED

[10]Silhouette scores indicate how well the clusters describe the underlying data (Rousseeuw 1987). They are calculated by comparing the within cluster distance $a(i)$ to the between cluster distance $b(i)$, $s(i) = \frac{b(i)-a(i)}{max\left\{a(i),b(i)\right\}}$. $s(i)$ takes values between -1 and 1, with large scores meaning that within-cluster distance is low and between-cluster distance high (scikit-learn 2025a). This indicates that subsequences in each cluster are similar, while substantial differences exist between clusters.

coverage. We use the clustering algorithm to find protest patterns in the training data. The extracted shapes are then deployed to assign each observation in the test partition to one cluster. In this context, we rely on a brute-force approach to tune the hyperparameters: The *win*-k combination with the best out-of-sample performance yields the final within-country configuration. For *win*, we consider $[3, 5, 7, 9]$ and for k, we select from $[3, 5, 7]$.[11]

The within-country optimization is implemented for each time series, which means that each country has a unique *win*-k combination and a unique set of protest patterns. This approach allows us to account for protest dynamics, which may be country-specific. The within-country optimization offers maximum flexibility, which enhances the performance in time series forecasting, where each case is considered individually.

Step 2: Validating Protest Patterns

Having extracted cross- and within-country protest patterns, the ultimate goal is to identify dangerous protest patterns that precede high fatalities in civil conflict. For this purpose, we include the cross-country shapes in a regression model, and we add the within-country protest clusters to a static prediction model.

Null-Hypothesis Significance Testing

We use Ordinary Least Squares (OLS) regression to establish a baseline association between protest events and log-transformed fatalities in civil conflict ($log + 1$). The main independent variable is the number of protest events at t (*min-max* normalized for a fair comparison with the protest shapes), supplemented by lagged values at $t-1$, $t-2$, and $t-3$. Given the panel structure of our data, standard errors are clustered

[11] For the cross-country optimization, we opt for longer candidate values for *win* due to the two rounds of clustering. This ensures that the centroids obtained in the first round are sufficiently complex to allow for a second round of clustering.

at the country level, and a lagged dependent variable is included to capture temporal autocorrelation. To account for unobserved unit heterogeneity, we also add country fixed effects.

In addition to protest lags and country-fixed effects, we include a set of control variables that are associated with both protest activity and civil conflict. The most robust correlates of civil conflict are GDP per capita (log) and population size (log) (Hegre and Sambanis 2006). The transition from protest to civil conflict is more likely in autocratic countries, where the regime lacks popular support and protesters are particularly committed (Rød and Weidmann 2023). We control for regime characteristics by including the V-Dem indices: Liberal democracy, physical violence, political corruption, rule of law, civil liberties, and neopatrimonial rule.[12]

Having established a baseline model, we include a dummy set referencing the cross-country protest shapes (D_c). We expect that the patterns significantly explain fatalities in civil conflict, conditional on static protest variables. This would suggest that the protest shapes add unique information to the model that is not accounted for by static protest variables. In addition, we can compare the size of the slopes to determine which clusters have the strongest effect on the number of fatalities. This indicates which protest pattern is the most dangerous.

Out-of-Sample Evaluation

Next, we construct a time series forecasting model to predict the number of fatalities in civil conflict. The primary input is the number of protest events, considering both the count at t and temporal lags. The optimal value of protest lags is given by brute force. Selecting from $[t, t-1, t-3, t-5, t-11]$, the value that minimizes the out-of-sample prediction error is chosen. Similar to the regression model, we add

[12] Table D1 in Appendix D includes more detailed information on the control variables.

the same set of static controls to the protest variables (i.e., GDP per capita (*log*), population size (*log*), and regime characteristics), including the *min-max* normalized fatalities at $t-1$ (normalization based on a train-test split). The models are trained on the first 70% of observations, and predictions are returned for the last 30%. The prediction accuracy is measured by the Mean squared error (MSE)$=\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$ (scikit-learn 2025b), which is a standard choice for continuous outcomes.[13]

We validate the protest patterns using two types of algorithms, representing linear and non-linear approaches. For the linear algorithm, we use Ridge Regression (RR), which is an OLS model with an L2 penalty in the loss function to control for overfitting (Hastie et al. 2017). The L2 penalty has a hyperparameter (λ) determining the shrinkage of the slopes. To tune λ, the first 50% of the training data are used to validate candidate values in the remaining 50% of observations. The best-performing λ is used for the final model.[14]

As an extension of the static RR model, we introduce a dynamic counterpart, which we call Dynamic Ridge Regression (DRR). In the dynamic variant, we include an additional input, which is a dummy set of within-country cluster assignments (D_w). Each cluster is representative of a preceding pattern in protest for the observation at t. This process allows us to evaluate whether the protest shapes contain a unique signal beyond static protest variables. In addition, we can identify dangerous protest patterns as those that precede high fatalities.

For the non-linear model, we use the Random Forest (RF) regressor, which com-

[13] Fatalities in civil conflict are *min-max* normalized, $X_{\text{norm}} = \frac{X-X_{\min}}{X_{\max}-X_{\min}}$, based on country-specific minima and maxima and a train-test split. This is an important step since the measurement scale affects the size of the error, making high and low intensity cases incomparable.

[14] When tuning hyperparameters of the prediction models, we use a validation set, while we opt for a train-test approach for the hyperparameters of the clustering algorithm. Due to the ACLED coverage, some protest time series are short, only comprising 36 months. In this context, splitting the data into three partitions, training, validation, and test, would yield a too short validation window. This limits the robustness of the tuning, as the algorithm lacks a sufficient data basis for making a reliable selection. While a less robust approach is suitable for the hyperparameters of the prediction models, a more reliable strategy is needed for extracting protest patterns.

bines predictions from several decision trees through bootstrap aggregation (Hastie et al. 2017).[15] A decision tree partitions observations based on sequences of input variables and corresponding split values, which are selected to minimize the error. The predicted outcome is the average of all cases in the final node. The Random Forest algorithm has a range of hyperparameters (scikit-learn 2025c), and we optimize the number of trees in the training data with a 50-50 split.

By including cluster assignments, the static Random Forest is extended to the Dynamic Random Forest (DRF). Similar to the linear approach, the dynamic counterpart takes an additional input matrix, containing a dummy set of within-country cluster assignments (D_w), which are representative of preceding patterns in protest for the observation at t.

4.7 Findings

By extracting protest patterns inductively from the data, we seek to uncover dangerous protest patterns, which are then inferred back to the theoretical mechanisms, *protest escalation* and *protest capture* as proposed by Rød and Weidmann (2023). First, we discuss the findings of the null-hypothesis significance testing and thereafter the out-of-sample evaluation.

Null-Hypothesis Significance Testing

To assess whether protest patterns contribute explanatory value beyond conventional predictors, we estimate a series of Ordinary Least Squares (OLS) regressions, where the dependent variable is the log-transformed number of fatalities in civil conflict ($\log +1$). We begin with a baseline model that includes static protest variables:

[15] We choose Random Forest over Neural Networks, given that tree-based algorithms have been shown to work particularly well on conflict data (Muchlinski et al. 2016; Wang 2019).

The *min-max* normalized number of protest events at time t and its lags at $t-1$, $t-2$, and $t-3$. To account for temporal dependence, we include a lagged dependent variable. Country-level fixed effects are added to control for unobserved unit heterogeneity, and standard errors are clustered by country.

	Dependent Variable: Fatalities ($log+1$)				
	(1)	(2)	(3)	(4)	(5)
Number of Protest Events (*min-max*)	0.079* (0.033)	0.067* (0.032)	0.049 (0.037)		0.047 (0.036)
Lag 1: Number of Protest Events (*min-max*)	0.047 (0.044)	0.059 (0.053)	0.030 (0.043)		0.053 (0.053)
Lag 2: Number of Protest Events (*min-max*)	0.012 (0.033)	0.004 (0.035)	−0.004 (0.034)		−0.007 (0.036)
Lag 3: Number of Protest Events (*min-max*)	0.099* (0.046)	0.078^o (0.046)	0.079^o (0.048)		0.068 (0.049)
Cluster 1		0.081* (0.034)		0.056^o (0.033)	0.054 (0.033)
Cluster 2		0.032 (0.028)		0.024 (0.028)	0.011 (0.031)
Cluster 3		0.073* (0.037)		0.071^o (0.038)	0.061 (0.040)
Cluster 5		0.054* (0.025)		0.045^o (0.025)	0.040 (0.026)
Lag 1: Fatalities ($log+1$)	0.826*** (0.024)	0.824*** (0.024)	0.697*** (0.034)	0.697*** (0.034)	0.696*** (0.034)
Constant	−0.342 (0.277)	−0.311 (0.277)	−3.065 (3.711)	−3.166 (3.799)	−2.418 (3.633)
Country Fixed Effects	No	No	Yes	Yes	Yes
Clustered by Country	Yes	Yes	Yes	Yes	Yes
F-value (joint significance of clusters)		7.31***		3.56**	3.6**
R-squared	0.744	0.745	0.762	0.762	0.762
Number of Observations	23126	23126	23126	23126	23126

o p<0.1; * p<0.05; ** p<0.01; *** p<0.001. Country-clustered standard errors in parentheses.

Table 4.1. OLS regression on the log-transformed number of fatalities in civil conflict (log +1), using both static and dynamic protest variables. Control variables are omitted from the main text for brevity. The full results, including all controls, are reported in Appendix D (Table D2).

In the next step, we introduce a set of dummy variables referencing the cross-country protest clusters. These variables capture dynamic protest patterns and allow us to evaluate whether temporal sequences of protest activity are associated with increased fatalities, conditional on static protest indicators. As shown in Table 4.1, the inclusion of dynamic protest patterns improves model fit, as evidenced by statistically significant joint F-tests. This means that the extracted protest shapes contain unique information beyond what static protest variables can account for.

The corresponding protest patterns are shown in Figure 4.3.

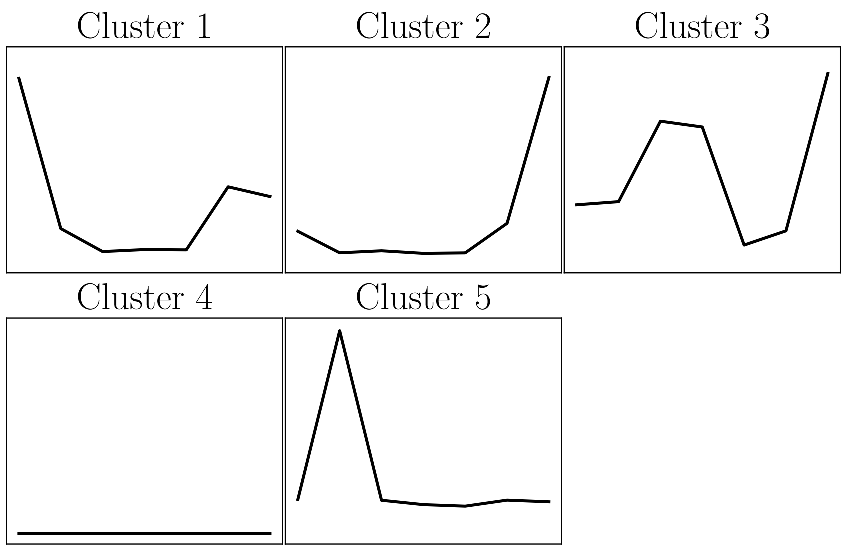


Figure 4.3: Cross-country protest patterns included in the OLS regression model. Cluster 4 is the reference category for the dummy set of cluster assignments.

Compared to the reference category, a flat pattern with no protest activity (Cluster 4), four clusters are positively and significantly linked to elevated fatalities in civil conflict. These include a gradual escalation of protest activity (Cluster 2), a sharp decline following high protest intensity (Clusters 1 and 5), and a U-shaped pattern in which protest activity declines and then resurges (Cluster 3). These results support our central claim that temporal protest sequences, rather than static measures alone, provide meaningful insight into the protest-to-civil conflict transition. In fact, none of the static protest lags reaches statistical significance when controlling for protest patterns (Model 5 in Table 4.1), which underscores the limits of static protest indicators.

The extracted protest patterns (Figure 4.3) can be inferred back to the theoretical mechanisms of protest escalation and protest capture (Rød and Weidmann 2023). In our view, the main aspect that sets both apart is whether the non-state actor is armed or not. Cluster 2 aligns with the *protest capture* mechanism, where an already mobilized rebel group perceives escalating protest activity as a window of opportunity (Rød and Weidmann 2023). The positive and significant association between this shape and fatalities in civil conflict suggests that gradually intensifying protest may signal weakened state capacity, prompting armed groups to act. Given that the non-state actor is already armed, the group can wait for a protest peak to initiate armed action.

Clusters 1 and 5, both marked by sharp drops in protest intensity after a period of substantial activity, are consistent with the logic of *protest escalation* (Rød and Weidmann 2023). These shapes might reflect a tactical pause in which protest groups, having concluded that non-violent means failed, begin preparing for armed action. Depending on how much time the non-state group needs to mobilize, the gap in protest activity can vary. That both clusters are associated with significantly higher fatalities supports the idea that protest de-escalation may be a precursor to civil conflict, not a sign of protest exhaustion.

Cluster 3 represents a theoretically novel trajectory. The U-shaped pattern, a decline in protest activity followed by another surge, is associated with the largest coefficient among all clusters in the regression model, suggesting a particularly strong link to fatalities in civil conflict. Unlike the other patterns, this temporal sequence is not directly anticipated by existing theories of escalation or capture. However, its empirical prominence invites several plausible interpretations.

One possibility is that the U-shape reflects an emerging split in the protest movement between moderates and those willing to use armed violence (cf., Tarrow 2011). A temporary decline in protest might occur due to internal reorganization, during which some parts of the movement prepare for armed action while others promote a continuation of non-violent contention. The subsequent resurgence of protest and simultaneous transition to civil conflict could represent a fragmentation of the actor between moderates and radicals, where the former initiates armed violence and the latter protest (cf., Tarrow 2011).

Alternatively, the U-shape could be a product of strategic deception. The non-state group may exploit a temporary pause in protest to secretly mobilize, using the reemergence of protest as a decoy for immediate armed action. The return of protest serves to distract the state's attention, producing a tactical advantage for the rebel group. In this context, the non-state actor can capitalize on information asymmetry, given that they commonly operate undetected (Malone 2021). The resurging protest may be a precursor to rebellion, not a sign of a new protest wave.

While we cannot adjudicate among these interpretations with the available data (i.e., cluster 1 might be reflective of these mechanisms as well, given the slight increase in protest activity at the end of the sequence), the emergence of the U-shape illustrates the advantage of our inductive approach. It demonstrates that protest trajectories can exhibit complex, nonlinear patterns that fall outside established theories. The identification of the U-shape not only strengthens the case for modeling protest as a dynamic phenomenon but also opens new avenues for theorizing how dissident strategies and state responses unfold over time.

Out-of-sample Evaluation

Out-of-sample evaluation allows us to explore if the extracted shapes can improve predictive performance, thereby signaling that protest patterns refer to some systematic component of the data-generating process, rather than sample noise (Carsey and Harden 2014). For this purpose, we compare among four model variants: A static baseline only considering protest lags (RR and RF), another static baseline which includes control variables in addition to protest lags (RRX and RFX), and then two dynamic counterparts, a model with protest patterns (DRR and DRF) and a model with protest patterns and static covariates (DRRX and DRFX). After evaluating the out-of-sample performance, we investigate whether we can identify the same dangerous protest shapes in a within-country set-up. This likewise enables us to uncover harmless protest patterns, those that lead to low fatalities in civil conflict.

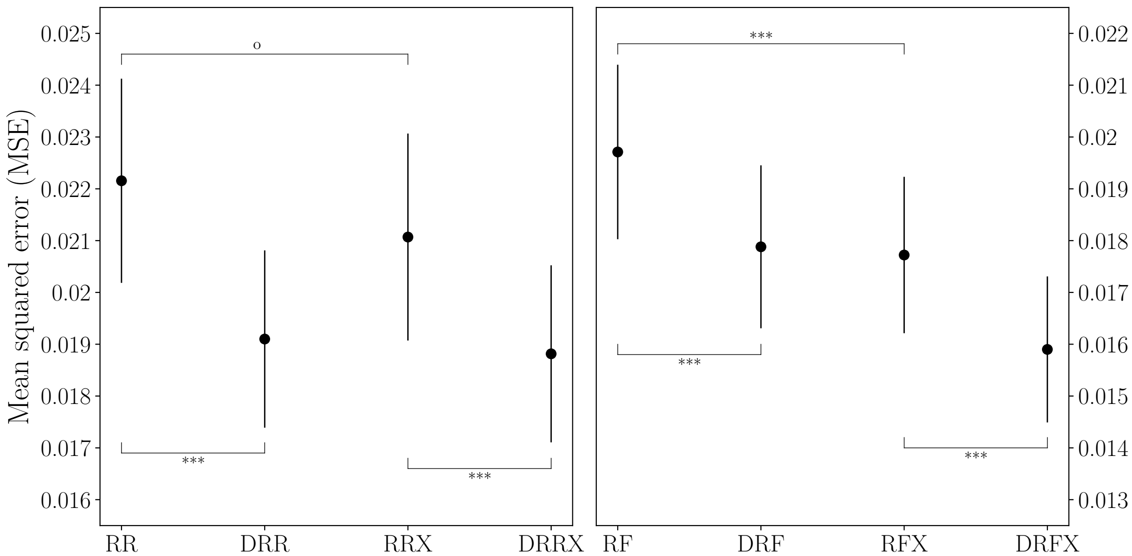


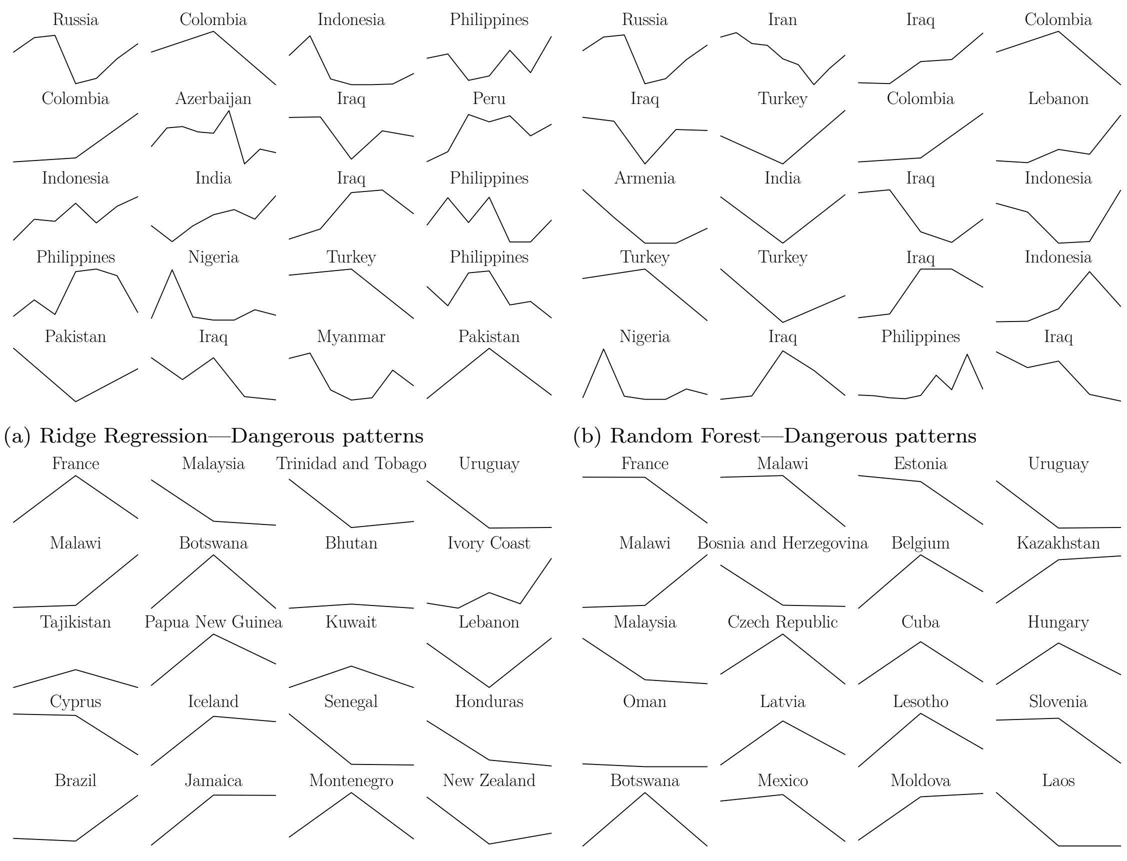
Figure 4.4: Mean squared error (MSE) in the test data for each model variant: *RR* refers to Ridge Regression, *RF* to Random Forest, *D* indicates the inclusion of dynamic covariates, and *X* denotes the static control variables. Lower MSE values correspond to better out-of-sample performance. The brackets show results of a t test with paired samples, o p<0.1; * p<0.05; ** p<0.01; *** p<0.001. The error bars denote the 90% confidence intervals ($1.65 * SD/\sqrt{n}$).

We find that including dynamic protest patterns improves prediction accuracy across all model specifications (Figure 4.4).[16] For the linear model (left panel), the largest reduction in MSE occurs when dynamic protest patterns are included. Notably, static covariates appear less relevant, as the difference between RR and RRX is not statistically significant. In the non-linear algorithm (right panel), static covariates contribute more to prediction accuracy, yet only considering dynamic protest patterns enhances performance to a similar degree. The best-performing variant is DRFX, which accounts for both static covariates and protest patterns. The predic-

[16]The numerical results are shown in Table D3 and D4 in Appendix D.

tive improvement produced by dynamic protest variables indicates that these patterns capture broader developments in protest dynamics, beyond what is accounted for by static protest lags and other country characteristics.

To distinguish between dangerous and harmless protest patterns, we compute the mean fatality count across all observations associated with that cluster, thereby capturing the typical severity of civil conflict that follows after each protest shape. Figure 4.5 displays the protest patterns with the highest and lowest fatality values, which we interpret as dangerous and harmless, respectively.



(a) Ridge Regression—Dangerous patterns

(b) Random Forest—Dangerous patterns

(c) Ridge Regression—Harmless patterns

(d) Random Forest—Harmless patterns

Figure 4.5: To identify dangerous and harmless protest patterns, we calculate the mean fatalities (*min-max* normalized on the country-level, accounting for a train-test split) immediately following each protest shape. We select the protest shapes with the largest and lowest numbers of fatalities, the former being dangerous and the latter harmless.

We observe that the dangerous protest shapes identified in the cross-country analysis are also recovered in the within-country setting (upper panel of Figure 4.5), suggesting that these temporal patterns generalize across contexts. The recurrence of these shapes underscores their relevance as early warning signals for the transition to civil conflict. Cluster 2, a gradual escalation of protest activity, is frequently associated with high fatalities in cases such as India, Lebanon, and Indonesia. This pattern is consistent with the *protest capture* mechanism, in which an already mobilized group exploits protest as a window of opportunity to initiate armed action (Rød and Weidmann 2023).

Similarly, we find that clusters 1 and 5, a sharp drop in protest intensity following a period of high activity, often precede elevated fatalities, as seen in Iran, Azerbaijan, and Nigeria. This sequence aligns with the logic of *protest escalation*, where non-violent movements shift toward armed tactics (Rød and Weidmann 2023). The observed pause in protest activity may reflect a mobilization phase, during which protest groups acquire resources before engaging in armed violence. Depending on how much time the non-state group needs, the pause between protest and the transition to civil conflict can vary.

The U-shaped trajectory of cluster 3 is also uncovered within-country. In cases such as Myanmar, Russia, and Iraq, this pattern, a decline in protest activity followed by a resurgence, is associated with high fatalities. This temporal structure may reflect internal heterogeneity within protest movements, where non-violent and violent factions operate in parallel (cf., Tarrow 2011), or it may indicate strategic deception, whereby protest is used to obscure a shift towards violence.

Finally, the out-of-sample approach allows us to identify harmless protest shapes, which precede low fatalities in civil conflict (lower panel in Figure 4.5). These protest patterns show single peaks in the number of protest events. Protest is also common in democracies, which usually have a low risk of armed conflict. In those instances, protest activity is high for a single month until the incompatibility between the government and its citizens can be resolved, and protest activity stops. Such protest patterns indicate a low risk of civil conflict.

Of course, the distinction between dangerous and harmless is not perfect. This is particularly evident in the non-linear algorithm, where certain dangerous shapes resemble the up-down-up sequences also observed among patterns classified as harmless. Rather than suggesting a strict distinction, our interpretation reflects a general tendency. The goal is not to achieve a perfect categorical separation, but to identify patterns that, *on average*, are more likely to precede high fatalities.

The within-country approach offers greater flexibility, allowing protest shapes to be tailored to local characteristics. Yet, this flexibility also introduces more variability in the extracted patterns, which exhibit higher fluctuations compared to the more stable cross-country clusters (see Figure 4.3). Despite these differences, the underlying signal remains robust: Certain temporal protest patterns are more systematically associated with civil conflict than others.

4.8 Conclusion

In this paper, we argue that focusing on the immediate past of protest activity is insufficient for understanding protest-to-civil conflict transitions. Given the high risks associated with armed violence, protest is unlikely to escalate spontaneously. Instead, the non-state actor carefully monitors protest dynamics over extended periods, evaluating the evolving situation. The consecutive interactions between protesters and the state generate temporal patterns in sequences of protest events, which reflect broader developments in tactical shifts and state capacity. Against this background, we identify dangerous protest shapes, which are sequences of protest events that precede high fatalities in civil conflict.

Using null-hypothesis significance testing and out-of-sample evaluation, we uncover three types of dangerous protest shapes: (1) A gradual escalation of protest intensity, (2) a sharp decline following high protest activity, and (3) a U-shaped pattern in which protest activity declines and resurges. Our results show that the inclusion of these dynamic protest shapes enhances model performance beyond what static protest variables can explain. Their contribution to predictive accuracy suggests that these patterns capture a systematic component of the underlying data-generating process, rather than sample noise (Carsey and Harden 2014).

The shapes can be interpreted through the lens of protest escalation and protest capture (Rød and Weidmann 2023). The key distinction lies in whether the opposition group is already mobilized. *Dangerous Shape 1* is consistent with protest capture, where an existing armed group seizes the opportunity created by high protest activity. *Dangerous Shape 2* reflects protest escalation, in which a non-violent movement pauses to prepare for armed violence. *Dangerous Shape 3* is not explicitly anticipated by existing theories but may indicate overlapping phases of protest and mobilization, or the strategic use of protest as a cover for armed action.

Our findings have implications for the broader literature on contentious politics. Instead of relying on static indicators, such as the number of protest events at various time points (t, $t-1$, $t-3$, etc.), we demonstrate that studying entire time sequences is beneficial. In particular, our paper illustrates the inherently dynamic character of protest, which needs to be reflected in theory and methods. This argument applies to other types of social phenomena, where interactions between opposing actors might produce discernible temporal patterns, such as migration (Schincariol and Chadefaux 2025), or battle events (Schincariol et al. 2025).

While existing prediction models excel at forecasting a baseline risk of armed violence (Schincariol et al. 2025), anticipating onsets remains the most challenging sub-task (Mueller and Rauh 2022). Our findings imply that it is possible to identify dangerous dynamics in protest, which may indicate an increased risk of civil conflict. Extracting temporal patterns from various types of collective action, such as protests, riots, and low-intensity armed conflict, might improve upon existing prediction models when seeking to forecast new outbreaks of violence.

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5 *From Structure to Action: Anticipating Onsets in Civil Conflict*

From Structure to Action: Anticipating Onsets in Civil Conflict

Hannah Frank

Replication Material
The data and Python code written for this analysis can be accessed here: `https://github.com/hannahhfrank/phd_thesis_reconceptualizing_conflict_emergence/tree/main/procedural`.

Use of Generative Artificial Intelligence
For the empirical analysis, ChatGPT-3.5 and higher (`https://chatgpt.com/`) was consulted as a coding assistant and to brainstorm ideas for the evaluation metrics, in particular, the Onset score. When correcting spelling and grammar, suitable add-ons in Overleaf were used (i.e., Grammarly, Writefull, and LanguageTool).

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From Structure to Action: Anticipating Onsets in Civil Conflict

Abstract

Anticipating the onset of civil conflict remains the most challenging task in conflict prediction. A new outbreak of civil conflict occurs if a country-month with non-zero fatalities is preceded by a value of zero. In this paper, a reconceptualization of conflict emergence is developed, which serves to inform a novel prediction algorithm—the 'Onset catcher'—to complement existing early warning models. Rather than assuming a direct correlation between structural risk factors and civil war onset, collective action, including protests, riots, remote violence, and low-intensity armed violence, is a key precursor to more substantial levels of civil conflict. Based on a comprehensive set of structural risk factors, concerning conflict history, demography, geography, economy, and politics, a large ensemble model is constructed, predicting a latent variable, the baseline risk of collective action. The Onset catcher is a hurdle model, where *stage i* filters out high-risk cases and *stage ii* predicts the number of fatalities in civil conflict with the preceding risk of collective action. The Onset catcher demonstrates good performance for onset cases, in comparison to a range of benchmarks, which supports the validity of the proposed reconceptualization of conflict emergence. Collective action mediates between structural risk factors and more substantial levels of civil conflict.

Keywords: Civil conflict, onset cases, conflict prediction, collective action

5.1 Introduction

Civil war is a rare event, and most countries indeed will never experience it. While this is good from a humanitarian perspective, it poses challenges for conflict early warning, making conflict onsets the "hard problem of conflict prediction" (Mueller and Rauh 2022, p. 2442). Ongoing armed violence is most predictable using variables on conflict history, as demonstrated by existing models, such as the Violence & Impacts Early-Warning System (VIEWS) (Hegre et al. 2019; Hegre et al. 2021) and the Shape finder (Schincariol et al. 2025). However, those models miss conflict onsets, which are cases where armed violence occurs after zero fatalities in the preceding month. Conflict onsets are particularly relevant for policymakers, enabling them to intervene before countries become entrapped in conflict (Mueller and Rauh 2022). Civil war leaves a long-lasting economic, social, and political legacy, which accelerates the risk of renewed armed conflict due to a violent past (Collier et al. 2003).

This paper introduces a new conflict prediction model—the 'Onset catcher'—to complement existing approaches. The inner workings are derived from a reconceptualization of conflict emergence. Research on the causes of armed conflict is dominated by structural theories that explain civil war onset with slow-changing background factors (Cederman et al. 2010; Collier and Hoeffler 2004; Fearon and Laitin 2003). However, armed contention has tremendous consequences, making low-intensity collective action a key precursor to more substantial violence.[1] An immediate correlation between structural factors and civil war seems less convincing.

Initially, the non-state group opts for less violent means of collective action due to the higher chances of concessions from the government (Stephan and Chenoweth 2008), or the group seeks violent tactics but needs to mobilize first (Malone 2021).

[1] This paper approaches civil war as inherent in prior political contention (Lichbach et al. 2003).

Collective action shifts from less to more violent forms through tactical interactions between the state and the rebel group (McAdam 1983). Structural factors prompt civil war by transitioning through protest and/or low-intensity armed violence. The onset of civil conflict is preceded by a high risk of collective action.

To better understand how civil conflict emerges, a subsample of cases is of particular interest. These are country-months with a high baseline risk of collective action. The Onset catcher is a hurdle model. *Stage i* predicts the baseline risk of collective action using structural background factors and a set of outcomes: Protests, riots, remote violence, and low-intensity armed violence. The predictions on the six outcomes are combined in an ensemble, producing forecasts on a latent variable, the baseline risk of collective action. An ensemble integrates predictions from various models based on performance, where good constituent models get a higher weight (Montgomery et al. 2012). *Stage i* filters out high-risk cases which are passed on to *stage ii*. In *stage ii*, the number of fatalities in civil conflict is predicted, conditional on the preceding risk of collective action ($t-1$) surpassing a threshold. Otherwise, the model predicts zero. The input for *stage ii* is a matrix of temporal lags for the latent variable, the risk of collective action.

This paper demonstrates that the Onset catcher outperforms the VIEWS ensemble and a structural baseline when predicting conflict onsets. Despite a tendency to overpredict, at times substantially, the model works reasonably well for low-intensity cases and likewise demonstrates *some* ability to capture the high-intensity onsets in Sudan-2023 and Israel-2023. Simultaneously, there are clear limits to predictability, and new outbreaks of violence rightfully remain the "hard problem of conflict prediction" (Mueller and Rauh 2022, p. 2442).

This paper has two main implications. First, rather than establishing one model as superior, algorithms should be optimized for sub-tasks, such as predicting a baseline level of armed conflict (i.e., VIEWS), variability (i.e., Shape finder), or conflict onsets (i.e., Onset catcher). The resulting constituent models contribute unique information and can be combined to generate more robust forecasts. Second, the results highlight the validity of the developed reconceptualization of conflict emergence, emphasizing that collective action mediates between structural risk factors and civil war. Structural risk factors might prompt civil war by transitioning through protest and/or low-intensity armed violence.

5.2 The Field of Conflict Prediction

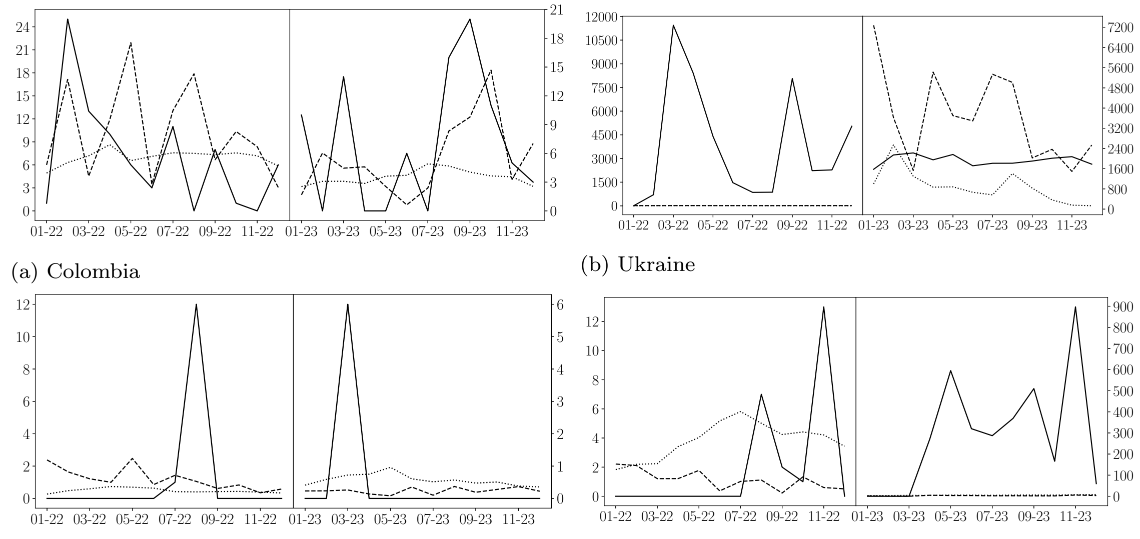
Conflict prediction has established itself as a relevant subfield of peace and conflict research. Forecasting dynamics in armed conflict has high practical relevance (Hegre et al. 2017), and machine learning tools might carry the capacity to clarify some theoretical inconsistencies in the literature (Beck et al. 2000; Colaresi and Mahmood 2017; Ward et al. 2010). Despite the good performance of existing models (see Rød et al. 2024 for a review), anticipating the onset of armed violence remains a challenge (Mueller and Rauh 2022). The reason for this has long been noted. Pandemics, earthquakes, and civil wars are rare events, which means that they occur infrequently (King and Zeng 2001; Mueller and Rauh 2022). A variable measuring their presence has access zeros (*peace*) and only a few ones (*war*).

While this is good from a humanitarian perspective, this data structure causes issues for statistical methods, also referred to as the 'class imbalance problem' (Japkowicz and Stephen 2002). An imbalanced classification task has a majority and a minority class, where the former far outweighs the latter in terms of relative size. To minimize the prediction error, a statistical model is encouraged to always predict the majority class and to simply ignore the minority one, leading to a high true-negative but a low true-positive rate. The 'class imbalance problem' is even more severe for small datasets and outcomes that are complex (Japkowicz and Stephen 2002), both of which apply to civil war.

The 'class imbalance problem' biases conflict prediction models towards zero. The minority class is discarded, and the model focuses entirely on the majority one (Japkowicz and Stephen 2002), thereby producing fatality predictions close to zero. This dynamic is intensified by evaluation metrics roughly referencing the prediction error, such as accuracy and the Mean squared error (MSE), which are often the default choice. When used for optimization, the model will discriminate against the minority class, as zero is the best guess to minimize the error (Hossin and Sulaiman 2015). While a null model, always predicting zero, is difficult to beat in terms of error, such a model is useless for policymakers and uninformative for researchers seeking to understand the causes of armed conflict better.[2]

Armed violence is inherently challenging to predict; yet conflict forecasters might nevertheless agree on a hierarchy of sub-tasks. Predicting a baseline level of armed violence works comparatively well using variables on conflict history (Mueller and Rauh 2022). The most advanced conflict prediction model—the Violence & Impacts Early-Warning System (VIEWS) (Hegre et al. 2019; Hegre et al. 2021)—is an ensemble model, forecasting the number of fatalities in armed conflict with variables on past conflict, economic development, and political institutions (Hegre et al. 2022). While the VIEWS ensemble performs well at minimizing the prediction error, the model produces conservative forecasts, clustered around the mean fatality count (upper panel, Figure 5.1). This implies that the model is *risk-averse*, missing variability in fatality time series, such as sudden escalations and drops in battle intensity over time (Schincariol et al. 2025).

[2] A similar discussion is put forward by Schincariol et al. (2025), stating that the right-skewed nature of the outcome prduces *risk-averse* predictions, which is exacerbated by evaluations metrics such as the MSE.



(a) Colombia

(b) Ukraine

(c) Peru

(d) Sudan

Figure 5.1: The count of fatalities in state-based armed conflict (solid), VIEWS predictions (dotted), and Shape finder predictions (dashed).[a] VIEWS produces conservative forecasts, while the Shape finder can capture variability, albeit with an increased tendency to overpredict (upper panel). Both models miss conflict onsets, which are country-months with non-zero fatalities preceded by a value of zero (lower panel).

[a]The predictions and actual fatalities are obtained from the replication material for Schincariol et al. (2025), downloaded from `https://github.com/ThomasSchinca/ShapeFinder_conflict` on the 11^{th} of August 2025.

Complementing the *risk-averse* VIEWS ensemble, Schincariol et al. (2025) construct a *risk-taking* model—the Shape finder—optimized to capture variability in fatality time series. The Shape finder is an autoregressive approach and makes predictions based on repeating shapes in fatality data. Each input time sequence is compared to a selection of past cases, and the aggregated future of the closest matches serves as the predicted outcome. While the Shape finder excels at mirroring the ups-and-downs in casualties over time (Figure 5.1a), *risk-taking* does not always pay off. The model has an increased tendency to overpredict (Figure 5.1b), especially if a high-intensity input is followed by de-escalation.

Reverting to the hierarchy of sub-tasks in conflict prediction, as already established, ongoing armed violence is most predictable using variables on conflict history

(Mueller and Rauh 2022). On the other extreme are idiosyncratic cases, or rather, events that caught experts by surprise (Cederman and Weidmann 2017). Such cases are often deemed unpredictable and illustrate where the limits of predictability might lie. This leaves new outbreaks of violence in the middle, which still constitutes "the hard problem of conflict prediction" (Mueller and Rauh 2022, p. 2442) due to the low baseline risk of armed conflict.

Despite the unique strengths of VIEWS and the Shape finder, both models face difficulties when seeking to anticipate conflict onsets (lower panel, Figure 5.1). Conflict onsets are cases where fatalities occur without an immediate conflict history. The number of conflict-related deaths is non-zero at t and preceded by a value of zero in the previous month. The Shape finder has hard-coded these instances, always predicting zeros for *flat* input sequences (Schincariol et al. 2025), and therefore completely discards onset cases. Similarly, the VIEWS ensemble misses sudden and single peaks (e.g., Peru) and larger conflict onsets (e.g., Sudan), due to predicting a baseline level of armed violence.

This is concerning, given that conflict onsets are most relevant for policymakers, potentially enabling them to intervene before countries become entrapped in conflict (Mueller and Rauh 2022). Once a country has experienced high-intensity armed violence, the probability that armed conflict continues on that level is high, while a de-escalation is less likely and a return to peace is essentially impossible (Mueller et al. 2024). This means that the most effective intervention time is before the initial onset of civil conflict.

This paper proposes a novel conflict prediction model—the 'Onset catcher'—tailored towards anticipating conflict onsets, or rather, country-months with non-zero fatalities, preceded by a value of zero in the previous month. The Onset catcher is a hurdle model, and the algorithm's inner workings are derived from a reconceptualization of conflict emergence.

Most research approaches civil war as a dichotomous phenomenon: A country can experience *peace* or *war* (Bartusevičius and Gleditsch 2019). This practice neglects that the category *peace* might contain a diverse set of cases, including countries with stable democratic institutions, authoritarian regimes, mass protest, or initial low-intensity armed action, such as remote violence. Civil war is a multistaged process, comprising collective action (*stage i*) and the transition to civil conflict (*stage ii*). By ignoring the possibility that civil war originates from previous collective action, a key aspect of how armed conflict emerges is unaccounted for.

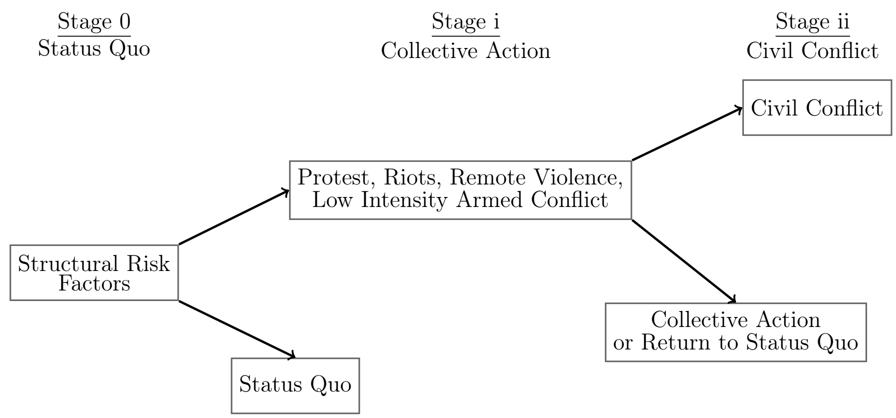


Figure 5.2: Collective action mediates between structural risk factors and civil conflict. A certain configuration of structural background factors indicates that there is conflict in society. Initially, the non-state group opts for less violent forms of collective action (e.g., protests and riots) or needs to mobilize first (e.g., remote violence and low-intensity armed conflict). The continued interactions between the government and the non-state actor might drive tactics towards violence.

5.3 A Reconceptualization of Conflict Emergence

Existing research on the causes of armed conflict seeks to establish correlations between structural background factors and civil war onset (Cederman et al. 2010; Collier and Hoeffler 2004; Fearon and Laitin 2003). Based on the potentially catastrophic consequences of armed violence, an immediate association between structural risk factors and civil war seems less convincing. The proposed reconceptualization of conflict emergence contends that civil war is a multistaged process. A certain combination of structural background factors prompts initial collective action (*stage i*), and collective action might gradually transition to civil conflict (*stage ii*). This implies that collective action mediates the relationship between structural risk factors and civil conflict, or rather, collective action is a key precursor to more substantial levels of armed violence (Figure 5.2).

Structural risk factors provide an indication of whether society is prone to experiencing conflict. Conflict refers to a contested incompatibility where the positions of two actors on the same matter cannot be combined, and opponents promote their mutually exclusive interests (Bartusevičius and Gleditsch 2019). Civil conflict occurs between the government and a non-state actor, which is an organized group not part of the government (UCDP 2025d). Based on the emerging incompatibility, the non-state actor seeks to change the status quo through collective action.

Following the 'law of cohesive responsiveness', the government commonly relies on state repression when challenged by the opposition (Davenport 2007). In contrast, the non-state actor has more options and selects a strategy from a 'repertoire of collective action' which is a set of available tactics for promoting group interests (Tilly 1977). When confronted with a choice, the non-state actor likely opts for less violent contention, such as protests and riots. Non-violent tactics have higher success chances due to enhancing the legitimacy of demands and deteriorating the standing of the government if the state responds with repression (Stephan and Chenoweth 2008). Even if the non-state actor prefers to pursue violence, the group has no standing army and needs to mobilize first (Malone 2021). Rebel recruitment produces initial fatalities from remote violence and low-intensity armed conflict.

Collective action is a dynamic phenomenon, driven by the interactions between government and opposition (McAdam 1983). Those interactions are strategic, where the behavior of the former depends on the behavior of the latter and the other way around (Young 2013). The government engages in tactical adaptations and the non-state actor in tactical innovations (McAdam 1983). More precisely, the government adjusts its responses to the tactics of the non-state group, either applying repressive means or seeking compromise. The non-state actor changes its strategies according to the behavior of the government, shifting between more or less violence to evade repression or cooperate with the state.

The tactical interactions between government and non-state actor can prompt violent escalation. Escalation occurs if two conflict actors gradually shift from less to more violent forms of contention (Pruitt and Kim 2016). *Side a* applies contentious tactics to the other, producing some structural changes in how they perceive the situation. As a reaction, the other side counters with a heavier tactic as before, in turn prompting a structural change in the first actor. The resulting spiral drives violent escalation. The escalation process can run along two pathways: The protest and the clandestine pathway.[3]

In the protest pathway, the non-state actor initially selects less violent forms of collective action from the repertoire: Protest and/or riots.[4] Civil conflict might be preceded by high protest and riot activity, where the non-state actor openly seeks to pressure the government into making concessions. Two theoretical mechanisms explain how protest might transition to armed conflict: Protest escalation and protest capture (Rød and Weidmann 2023).

Protest escalation contends that protesters gradually shift towards armed violence. The government likely responds with state repression to the emerging protests (Davenport 2007). State repression splits protesters into a moderate faction, seeing

[3] These terms are derived from Lewis (2017), observing that civil conflict can emerge similar to social movements (protest pathway) or after remote rebel mobilization (clandestine pathway).

[4] Protest is a non-violent demonstration where only the government uses violent tactics, and riots occur when both protesters and the state engage in violent behavior (ACLED 2023).

violence as illegitimate, and a radicalized subgroup willing to use violent tactics to pursue their interests further (Tarrow 2011). After several protest waves, the latter might come to believe that non-violent action has failed and that violence is the only remaining option (Rød and Weidmann 2023).

Protest capture implies that an already existing armed group perceives protest as a window of opportunity (Rød and Weidmann 2023). As the government attempts to keep protests under control, state resources get tied up, making the government appear weak. Since the non-state actor usually operates undetected, they have the strategic advantage of being able to decide when to initiate armed action (Malone 2021). This dynamic might have contributed to the onset in Israel-2023. In January, mass protests erupted as a reaction to a proposed judicial reform and continued as a regular movement (Gidron 2023) until the Hamas-led attack on 7^{th} of October. This example illustrates that even in cases where armed escalation occurs seemingly as a surprise, there are early warning signals in preceding collective action.

In the clandestine pathway, the non-state group selects violent forms of collective action from the repertoire; yet, more substantial armed conflict likely occurs with a time lag, given that the non-state actor needs to transition into an army-like organization first. Indeed, there is evidence that rebel groups mobilize for several years between foundation and the onset of civil conflict (Malone 2019). Rebel mobilization produces initial fatalities from remote violence, battles, non-state conflict, and one-sided violence.[5]

Initial fatalities occur as the non-state actor seeks to build military capabilities. To procure military means, the rebel group might resort to stealing from the govern-

[5]Remote violence refers to asymmetric battle events, using military tactics such as explosives, bombings, and gunfire (ACLED 2023). Battles occur between the government and a non-state actor (UCDP's state-based category after removing government—government events), non-state conflict takes place between two non-state groups, and one-sided violence is violence against civilians (UCDP 2025d).

ment (Jackson 2010), to looting the civilian population (Azam 2006), or to extracting resources from another non-state actor (Fjelde and Nilsson 2012). One-sided violence might also be committed by the state, perceiving civilian targeting as a way to deter support for the rebel group (Valentino et al. 2004). While the non-state actor has the advantage of organizing under cover (Malone 2021), acquiring arms can draw the attention of the government. The state might attempt to put an end to the emerging insurgency through air strikes and other remote violence.

Certainly, collective action is a non-sufficient condition for civil war. In particular, protest is a regular form of political participation in democracies, which commonly have a low probability of armed violence. In those settings, protest activity might be high over several months until the incompatibility is resolved or until protesters quit. Similarly, rebel mobilization is not deterministic, since many non-state groups dissolve before causing more severe levels of armed action (Lewis 2017). Instead of escalating to civil conflict, collective action might continue until it loses momentum, and a return to the status quo takes place.

An escalation spiral has two potential outcomes: Victory or compromise (Pruitt and Kim 2016). Victory occurs if one actor overwhelms the other and fully imposes their will. Alternatively, both sides could meet in the middle and agree on a compromise, or rather, a solution that partially advances both interests. Negotiations can kick off a de-escalation spiral, which is the mirror image of escalation (Pruitt and Kim 2016). When addressing each other, the government and the non-state actor consecutively use less violent forms of contention. This prompts structural changes on both sides, and actors start perceiving the situation more positively.

5.4 Data

The level of analysis is the country-month. Data on the outcome (*stage ii*), the number of fatalities in civil conflict, are obtained from the UCDP Georeferenced Event Dataset (Sundberg and Melander 2013). The event data are aggregated over country-month. The temporal coverage is 1989—2023.[6] The Armed Conflict Location & Event Data (ACLED) has varying temporal coverage depending on the country, which is accounted for by removing country-months where no data were collected when predicting protests, riots and remote violence. The countries in Gleditsch and Ward (1999) comprise the sample, after removing microstates, countries that ceased to exist (e.g., Yugoslavia), and some countries due to extensive missingness, yielding a final sample of 168 countries.[7]

The data are divided into a training set—1989-2021—and a test set—2022-2023. To ensure comparability, this data partition is informed by VIEWS. For constructing ensembles, a validation set is required, which entails all months between 2020—2021. The prediction window is 12 months, and to make live forecasts, the preceding 12 months before the prediction window are used as inputs (i.e., 2021 for predictions in 2022, and 2022 for predictions in 2023).

To obtain predictions for the baseline risk of collective action (*stage i*), an ensemble model is constructed. Instead of just integrating thematic models, the ensemble technically is an ensemble of ensembles, considering a set of binary outcome variables on different types of collective action: At least one protest, riot, or remote violence event, and at least one fatality from battles, non-state conflict, or one-sided violence.

[6] Only the years that a state was independent are considered (e.g. South Sudan begins in 2011.)

[7] Microstates (e.g., Monaco and Liechtenstein) have a systematically different character, which justifies excluding them. The following countries are removed due to extensive missingness in the World Bank and V-Dem data: Taiwan, Bahamas, Belize, Brunei Darussalam, Kosovo, and North Korea. ACLED includes additional territories (e.g., Vatican City and Greenland), which are not considered. Events in Palestine, being a crucial case, are assigned to Israel.

Data on protest, riots, and remote violence are obtained from ACLED (Raleigh et al. 2010), and data on low-intensity armed conflict from the UCDP (Sundberg and Melander 2013).

Each outcome is predicted using a set of structural risk factors, running along the themes of conflict history, demography, geography, economy, and politics (Dixon 2009). Table C1 in Appendix C contains a complete list of variables.[8] Data sources for the independent variables are: The World Bank (CCKP 2024; World-Bank 2025a; World-Bank 2025b), the Ethnic Power Relations Dataset (the core and ethnic dimensions datasets) (Bormann et al. 2017; Vogt et al. 2015) the terrain replication data from Nunn and Puga (2012), the United Nations Development Program (UNDP 2024), the Varieties of Democracy data (V-Dem 2024), and the Rulers, Elections, and Irregular Governance Dataset (Curtis et al. 2021). Missing values are filled in with linear interpolation, mean imputation, and multivariate imputation, taking the temporal order into account.[9]

5.5 The Onset Catcher

The 'Onset catcher' is a hurdle model derived from the reconceptualization of conflict emergence (Figure 5.3). Civil war is a multistaged process, comprising collective action (*stage i*) and the transition to civil conflict (*stage ii*). *Stage i* predicts the baseline risk of collective action, using a set of structural risk factors on different types of collective action: Protest, riots, remote violence, and low-intensity armed violence. Combining predictions on the six outcomes, an ensemble of ensembles pro-

[8]While the level of analysis is country-month, most data are only available annually (except REIGN, UCDP, and ACLED), and then take a constant value within years. While this approach leads to data leakage (e.g., the GDP is counted at the end of the year, and the data in Nunn and Puga (2012) are time-invariant), this approach is in line with common practice (Hegre et al. 2022). Since the Onset catcher returns *live* forecasts, the data leakage only affects the training period.

[9]For more details on how missing values were imputed, consult Section C.1 in Appendix C.

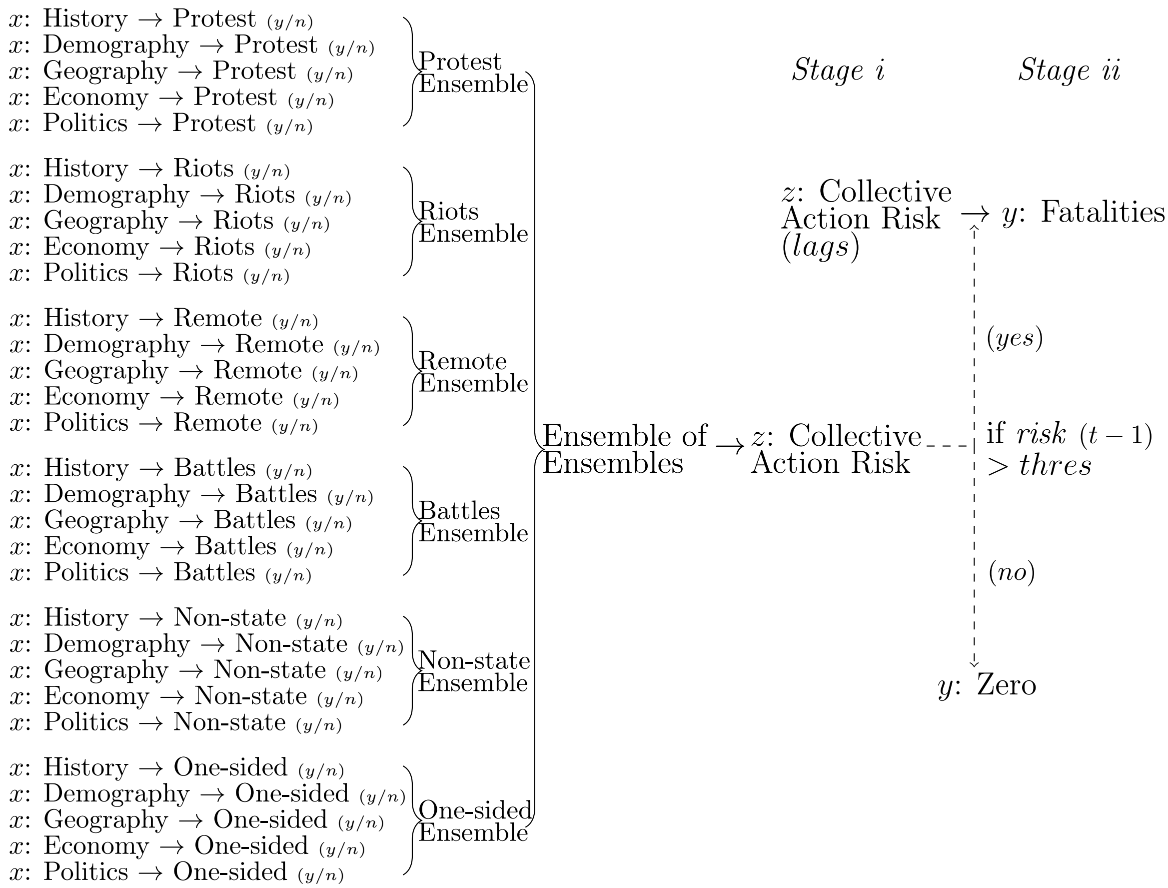


Figure 5.3: *Stage i* predicts the baseline risk of collective action, using structural risk factors and a set of outcomes: Protest, riots, remote violence, battles, non-state conflict, and one-sided violence. Combining predictions on the six outcomes, an ensemble of ensembles produces forecasts on a latent variable, the baseline risk for collective action. *Stage ii* predicts the number of fatalities in civil conflict, conditional on the preceding $(t-1)$ risk of collective action surpassing a threshold (*thres*). Otherwise, the model predicts zero. In *stage ii*, the input is a matrix of temporal lags for the risk of collective action, the latent variable (z).

duces forecasts on a latent variable, the baseline risk of collective action. This stage serves to filter out high-risk cases for *stage ii*. In *stage ii*, the number of fatalities in civil conflict is predicted, conditional on the preceding risk of collective action $(t-1)$ surpassing a certain threshold. Otherwise, the model predicts zero. The inputs for *stage ii* are temporal lags for the risk of collective action.

Stage i. The first step requires filtering out cases with substantial collective action. For this purpose, an ensemble of ensembles is constructed, predicting a latent variable, the baseline risk of collective action. The ensemble of ensembles combines predictions on six binary outcomes: At least one protest, riot, or remote violence event, or at least one fatality from battles, non-state conflict, or one-sided violence. Each outcome is predicted using a set of variables running along the themes of conflict history, demography, geography, economy, and politics (Dixon 2009).

In *stage i*, the Random Forest Classifier (Breiman 2001) is used as algorithm, which is a powerful model when seeking to capture nonlinear and conditional associations between large sets of predictors (Molnar 2025). Since Random Forests are known to be less *tuneable* and to work well with the default hyperparameters (Probst et al. 2019), the standard settings in `scikit-learn` are kept instead of grid search optimization.[10] A Random Forest aggregates predictions over multiple decision trees to obtain more robust forecasts (Hastie et al. 2017). Decision trees classify cases by recursively splitting observations into subgroups based on a series of variables and cutoff values, which are selected by minimizing the error. In a Random Forest, each tree is grown using a bootstrap sample and a random subset of inputs. This ensures that each constituent tree adds unique information. Averaging across decision trees, the Random Forest Classifier returns predictions by majority vote, where $\hat{C}_b(x)$ is the prediction of the b^{th} tree:

$$\hat{C}^B_{rf}(x) = majority\ vote\ \{\hat{C}_b(x)^B_1\} \tag{3}$$

Stage i produces predictions for the entire sample. For country-months between 1989—2021, the forecasts are in-sample. When obtaining *live* forecast for 2022, the models are trained on the data between 1989—2020, and country-months in 2021

[10]The default hyperparameters yield better results in comparison to a random grid search in the training data. The random grid search seems to produce unreliable solutions, where the optimization selects less ideal hyperparameters than the default configuration. For those reasons, the tuning is skipped, which likewise speeds up computational time, another advantage of this approach. The Onset catcher's *live* forecasting approach requires training each model three times, when returning predictions for the validation data, for 2022 and 2023.

are used as input. When generating *live* predictions for 2023, the models are trained on data between 1989—2021, and cases in 2022 serve as input.

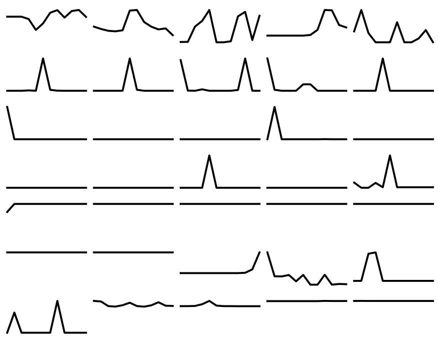
The goal is to measure a latent variable: The baseline risk of collective action. The outcome of interest is continuous, signifying the probability of collective action. Instead of classifications, Random Forest can produce probabilities as the relative proportion of observations assigned to class $y = 1$ (scikit-learn 2025b).

To obtain the final predictions in *stage i*, two rounds of ensembling are required. An ensemble combines predictions from several models and performs better than just one approach alone, given that each constituent model contributes unique information (Page 2018). In the first round of ensembling, the thematic models are integrated within the outcomes of protest, riots, remote violence, battles, non-state conflict, and one-sided violence, yielding a set of six ensembles (see Figure 5.3). Thereafter, the six ensembles are combined in an ensemble of ensembles, considering the specific temporal ranges in ACLED and UCDP. For the former, the ensemble of ensembles accounts for all six outcomes, while the remaining country-months only include the low-intensity armed conflict outcomes.

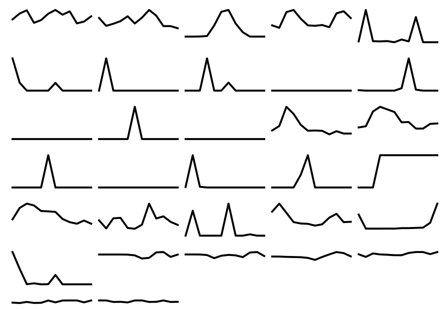
Both rounds of ensembling rely on the same strategy. The ensemble forecasts are calculated as the weighted mean across predictions for each constituent model (Montgomery et al. 2012). The weights are given by the performance in the validation data (2020—2021).[11] In more technical terms, the weights are constructed with the normalized inverse of the Brier score ($1 - Brier$), ranging between zero and one, where one is assigned to the best-performing model. The worst-performing model (i.e., riots) gets a weight of zero, effectively removing the outcome from the ensemble. Brier denotes the mean prediction error, comparing the predicted probability of $y = 1$

[11] For the first round of ensembling, the weights are based on out-of-sample performance, using all observations between 1989—2019 for training. For the second round of ensembling, the weights are given by the in-sample predictions (2020—2021) produced by the first set of ensembles.

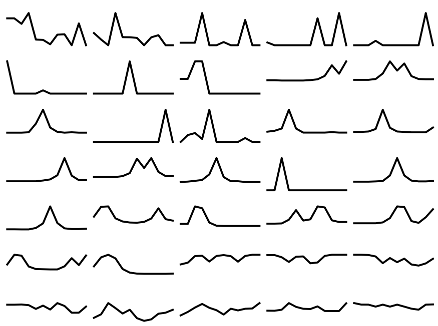
to the actual outcome (Hegre et al. 2019). Before calculating the additive index, the weights are converted to sum up to one.[12] The outcome of the ensemble of ensembles is a latent variable, signifying the risk of collective action.



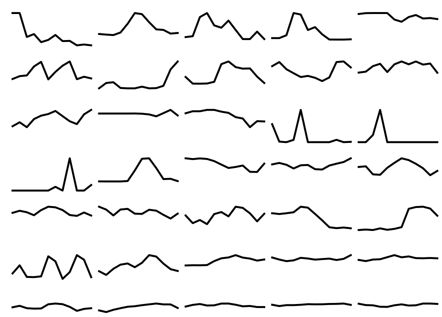
(a) Germany



(b) Armenia



(c) Benin



(d) Iran

Figure 5.4: The predicted outcome of the ensemble of ensembles is a latent variable, signifying the baseline risk of collective action. The baseline risk of collective action shows temporal and spatial variation. Countries like (a) Germany have a lower baseline risk of collective action than (d) Iran. Instead of setting the limits to zero and one, the y-axes account for the annual maxima while keeping the lower bound at *zero*. This ensures better visibility of the within-year variation but renders peaks across subplots incomparable.

The baseline risk of collective actions shows temporal and spatial variation (Figure 5.4). Germany has a lower baseline risk of collective action. As a rich democracy, Germany experiences peaks with elevated risk. Conversely, Iran has a high baseline risk of collective action. As a state with an authoritarian and religious leader, Iran

[12] For the low-intensity armed conflict ensemble, the weights are not recalculated to avoid losing another constituent model. As a result, the weights do not sum to one, and the ensemble predictions are not scaled between *zero* and *one*. This approach accounts for the fact that protest, riots, and remote violence are not included, producing a systematically lower baseline risk of collective action for the corresponding country-months.

has long experienced various forms of collective action, most recently, the Mahsa Amini protests in 2022 (Khatam 2023). Simultaneously, the government has been engaged in low-intensity armed conflict, while also having committed violence against civilians, particularly in the context of protest (UCDP 2025a).

Stage ii. The predictions from the ensemble of ensembles are used to filter out high-risk cases. *Stage ii* predicts the number of fatalities, conditional on the preceding risk of collective action ($t-1$) surpassing a certain threshold ($thres$). This means that only high-risk country-months are passed on to the second stage. For country-months below the threshold, the algorithm returns zero. Therefore, the Onset catcher is a hurdle model, forecasting the number of fatalities in civil conflict, conditional on a high preceding risk of collective action.

In *stage ii*, the predicted outcome is continuous: The number of fatalities in civil conflict. The input is a matrix of temporal lags ($lags$) on the latent variable, the baseline risk of collective action. The Random Forest Regressor is used instead of the classifier. The regressor has the same inner workings, yet the predicted outcome is the average of y, considering all cases in the final subgroup, where $T_b(x)$ is the prediction of the b^{th} tree (Hastie et al. 2017):

$$\hat{f}_{rf}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \tag{4}$$

As before, the Random Forest hyperparameters are set to the default configuration in the `scikit-learn` library. To obtain *live* predictions, *stage ii* relies on the same set-up as *stage i*. When forecasting fatalities in 2022, all country-months between 1989—2020 are used as training data, and 2021 serves as input. When producing *live* forecasts for 2023, all observations between 1989—2021 are used for training, and the inputs are obtained from 2022.

While the outcome of interest is binary (i.e., the onset of civil conflict), a continuous operationalization is preferred, as it has a higher level of information. Instead of anticipating an onset (yes/no), it appears more relevant to predict fatality counts, because this provides more actionable early warning. There is a marked difference between an onset with 10 or 1,000 fatalities. Since the Onset catcher predicts fatalities rather than onsets, a suitable metric needs to be constructed when evaluating the performance on onset cases, calculating the relative frequency of detected onsets (see below). An onset occurs if non-zero fatalities are preceded by a value of zero in the previous month.

Stage ii involves two additional hyperparameters, the number of temporal lags on the latent variable, the risk of collective action ($lags$), and the threshold for including high-risk cases ($thres$). Both hyperparameters are optimized based on out-of-sample performance in the validation data (2020—2021), using 1989—2019 for training. Considering a list of potential values for $lags = [t{-}1, t{-}2, t{-}3, t{-}4, t{-}5]$ and $thres = [0.15, 0.2, 0.25, 0.3, 0.35, 0.4]$, the value combination with the best performance in the validation partition returns the final predictions for the test data.[13] The performance is indicated by the Onset score (introduced below).

5.6 Evaluation

The performance of the Onset catcher is compared to three benchmarks: A Zero-inflated Negative Binomial (ZINB) regression, the VIEWS ensemble (Hegre et al. 2022), and a structural model, using the variables in *stage i* to predict fatalities in civil conflict directly.

ZINB regression has been proposed as a remedy to the 'class imbalance prob-

[13]The best performing values are $lags = t - 1$ and $thres = 0.35$, which leads to 12.21% of cases in the full sample being passed on the *stage ii*. Table E3 in Appendix E includes the Onset score and the Mean squared logarithmic error (MSLE) for different values of $lags$ and $thres$. Selecting a suitable threshold is more important than optimizing the number of lags.

lem' (Bagozzi 2015). ZINB predicts the number of fatalities along two processes: Logistic regression to determine whether the outcome takes a non-zero value, and count regression to forecast the continuous outcome for non-zero cases. The model specification in Bagozzi (2015) is replicated, predicting the number of deaths in civil conflict with fatality lags ($log + 1$) in both the inflation and the count process, as well as GDP per capita (*log*), GDP growth and population size (*log*) in the count stage, and GDP per capita (*log*) in the inflation stage.[14] To ensure a fair comparison, the predictions are *live*, using the Onset catcher set-up (the preceding 12 months are used as input to predict the next 12 months).

While ZINB is more of a technical baseline, the remaining benchmarks are more comprehensive approaches. The largest conflict prediction model in the academic field—Violence & Impacts Early-Warning System (VIEWS)—is an ensemble, forecasting the number of fatalities in state-based armed conflict with a long list of input variables on economic development, political institutions, and conflict history (Hegre et al. 2022). Due to being *risk-averse*, VIEWS excels at predicting a baseline level of armed violence (Schincariol et al. 2025). Instead of civil conflict, VIEWS predicts fatalities in state-based conflict, also including events between states (UCDP 2025d), and is therefore validated against the original data used to train the model. Countries in VIEWS that are not included in my sample are not considered.

The final benchmark is a structural model, using the features in *stage i* to predict (*live*, with the Onset catcher set-up) the number of fatalities in civil conflict directly. The structural benchmark serves to validate the utility of the hurdle approach, thereby allowing to infer back to the theoretical argument: Collective action is a key precursor to more substantial levels of civil conflict. If the Onset catcher per-

[14]Table E1 in Appendix E provides more information on the independent variables. Inverting the Hessian matrix in `statsmodels` fails, which means that no standard errors are available. Since the model converges, it can, however, be used for prediction where no standard errors are required.

forms better at anticipating onset cases than the structural benchmark, the empirical findings produce evidence in support of the theoretical mechanism.

For evaluating the ability to anticipate conflict onsets, a simple metric is proposed called the Onset score:

$$\text{Onset Score} = \frac{\sum_{i=1}^{D} \text{Detected Onset}_i \cdot e^{-0.01\epsilon_t}}{\text{True Onsets}} \tag{5}$$

The metric refers to the relative proportion of detected onsets over the total of true onsets. An onset occurs if a country-month with non-zero fatalities is preceded by a value of zero in the previous month. D denotes the number of detected onsets, which are predicted onsets within a $\pm$ three-month prediction error. While a certain temporal tolerance is allowed, there needs to be a penalty. ϵ_t is the temporal error, which refers to the absolute difference in the index of true and detected onset, taking values $0, 1, 2$, or 3. An exponential penalty with balancing factor -0.01 is applied to ensure that smaller temporal errors are rewarded.[15]

The Onset score obtains one value for each country, which is then averaged. The larger the Onset score, the more onsets are detected, and the smaller the temporal error. The metric takes positive values and can become larger than one. Onsets can be counted multiple times, given that every true onset is compared to every predicted one. Countries with no onsets have a value of zero.

While the Onset score indicates whether a model can catch onsets, there is no penalty for the prediction error. For example, the Onset score would signify good performance even if a model severely over- or under-predicts the actual number of fatalities, as long as the onsets are correctly detected. The second evaluation metric is the Mean squared logarithmic error (MSLE), which is equivalent to the Mean squared error, but uses log-transformed variables, and is therefore more suitable for

[15] A correctly anticipated onset is counted in full, while the exponential penalty leads to values below one depending on the temporal error. Table E2 in Appendix E shows that balancing factor -0.01 leads to an *ideal* penalty.

skewed outcomes (scikit-learn 2025a):

$$MSLE = \frac{1}{n}\sum_{i=1}^{n}(log(y_i + 1) - log(\hat{y_i} + 1))^2 \tag{6}$$

VIEWS as a *risk-averse* model and Shape finder as a *risk-taker* have complementary strengths (Schincariol et al. 2025). The former excels at predicting a baseline level of armed violence, while the latter can hit sudden peaks and declines in fatalities over time. Schincariol et al. (2025) demonstrate that a compound between VIEWS and the Shape finder outperforms both constituent models.

Similarly, this paper explores how the Onset catcher and VIEWS can complement each other. For this purpose, a simple rule is applied. If the Onset catcher predicts more than one onset, regardless of whether they are correct or not, the Onset catcher returns the final predictions. If the Onset catcher predicts one or zero onsets, VIEWS forecasts are used. This ensures that the Onset catcher is chosen for instances where frequent onsets are suspected.

5.7 Findings

The performance of the Onset catcher is compared to three benchmarks: The Zero-inflated Negative Binomial (ZINB) regression, the VIEWS ensemble, and the structural model, using the variables in *stage i* to predict the number of fatalities in civil conflict directly. While ZINB is a technical baseline, VIEWS and the structural model are more comprehensive approaches. Instead of establishing VIEWS and the Onset catcher as competitors, this paper explores how they can complement each other. The models are evaluated using the Mean squared logarithmic error (MSLE), and the Onset score, signifying how well the model anticipates onsets.

The VIEWS ensemble and the Onset catcher have unique strengths (Figure 5.5). The VIEWS ensemble has the lowest prediction error but misses all conflict onsets,

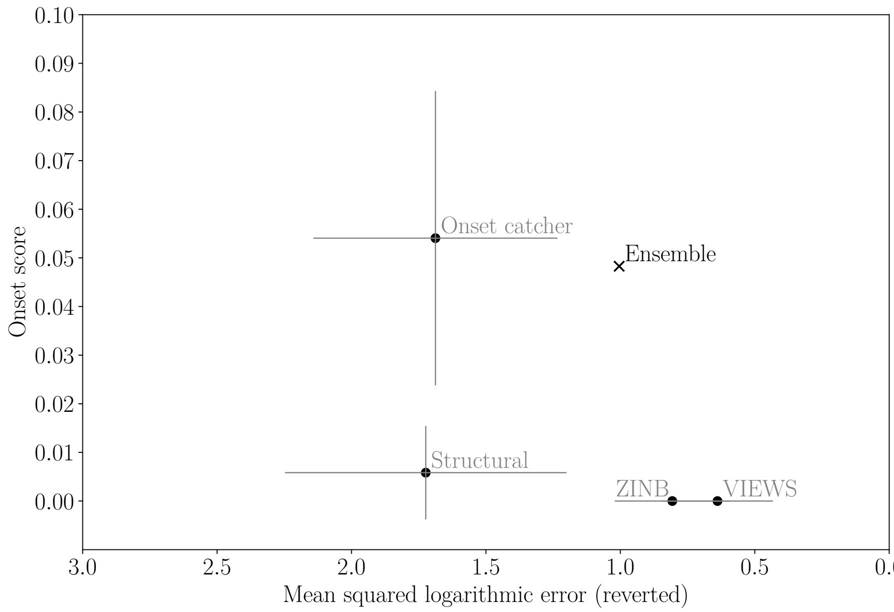


Figure 5.5: Mean squared logarithmic error (reverted) and Onset score for the Onset catcher, the three benchmarks—ZINB, VIEWS, the structural model—and the ensemble between Onset catcher and VIEWS. Well-performing models are located in the upper right corner. 90% confidence intervals ($1.65 * SD/\sqrt{n}$) are included.[a]

[a]As a robustness check, the Onset catcher is validated against the Shape finder. As a complement to the VIEWS ensemble, Schincariol et al. (2025) construct a *risk-taking* model—the Shape finder—optimized to capture variability. The Shape finder is an autoregressive algorithm and makes predictions based on repeating patterns in time series of battle deaths. While the Shape finder likewise has a high Onset score for some countries (Figures E.7 and E.8 in Appendix E), these relate to non-zero predictions after *flat* forecasts in 2022 (Figure E.9 in Appendix E). Rather than demonstrating a systematic ability to anticipate onsets, those hits are produced by the peculiarities of the algorithm. The Shape finder's inner workings discard onset cases by ignoring input sequences with only zero fatalities.

having a value of zero on the Onset score. The structural benchmark behaves similarly, yet with a slight increase in both metrics, signifying some ability to capture onsets (Onset score=0.0058), albeit with a surge in the prediction error.[16] While the VIEWS ensemble and the structural model perform well in terms of MSLE, both models encounter difficulties when anticipating conflict onsets.

This is where the Onset catcher excels. The model is most capable of anticipating

[16]To investigate which variables are particularly relevant to filter out high-risk cases, Figures E.1-E.6 in Appendix E present the feature importance scores for *stage i* (using data until 2019 to train the models). While variables on conflict history are most relevant, other indicators, such as population size, consumer price, and political stability, are likewise important.

onsets, having an Onset score of 0.054. This supports the validity of the proposed theoretical argument: Collective action is a key precursor to more substantial levels of civil conflict. However, there is an increase in the prediction error. The improvement on onset cases comes at the price of higher inaccuracy.

Policymakers encounter a key trade-off between the benefits of early intervention and the potential costs of intervening in a false positive (Mueller et al. 2024). Mueller et al. (2024) show that the benefits of early intervention outweigh the costs of intervening in a false positive case, due to the detrimental consequences of armed violence and the surge in intervention costs after violence has escalated. For policymakers, false positives, or rather overpredictions, are perhaps less concerning than false negatives, or rather underpredictions.[17] Conversely, most conflict early warning models are *risk-averse* (e.g., VIEWS), showing a tendency to systematically underpredict the number of fatalities in armed conflict, driven by the imbalanced nature of the outcome (Schincariol et al. 2025). *Risk-taking* approaches, such as the Shape finder, but also the Onset catcher, can complement existing models.

The inner workings of the Onset catcher are derived from a reconceptualization of conflict emergence. While the Onset catcher performs better at anticipating new outbreaks of violence, the model appears less suitable for cases with ongoing armed conflict, which explains the increase in the prediction error. The specific strengths of different models can be leveraged by combining forecasts, as illustrated by the ensemble between VIEWS and the Onset catcher (Figure 5.5).[18] The ensemble has a good ability to anticipate conflict onsets while maintaining a low prediction error. This emphasizes the utility of optimizing models on sub-tasks in conflict prediction,

[17]Similar arguments are included in Schincariol et al. (2025), suggesting that *risk taking* is more rewarding from a policy perspective.

[18]When evaluating the ensemble, the different outcomes, civil conflict versus state-based armed conflict, are considered. Countries with Onset catcher predictions are validated against fatalities in civil conflict, and countries with VIEWS forecasts against deaths in state-based armed conflict.

such as a baseline level of armed violence (e.g., VIEWS), variability (e.g., Shape finder), or conflict onsets (e.g., Onset catcher). When combining predictions, each model contributes unique information, which produces more robust forecasts.

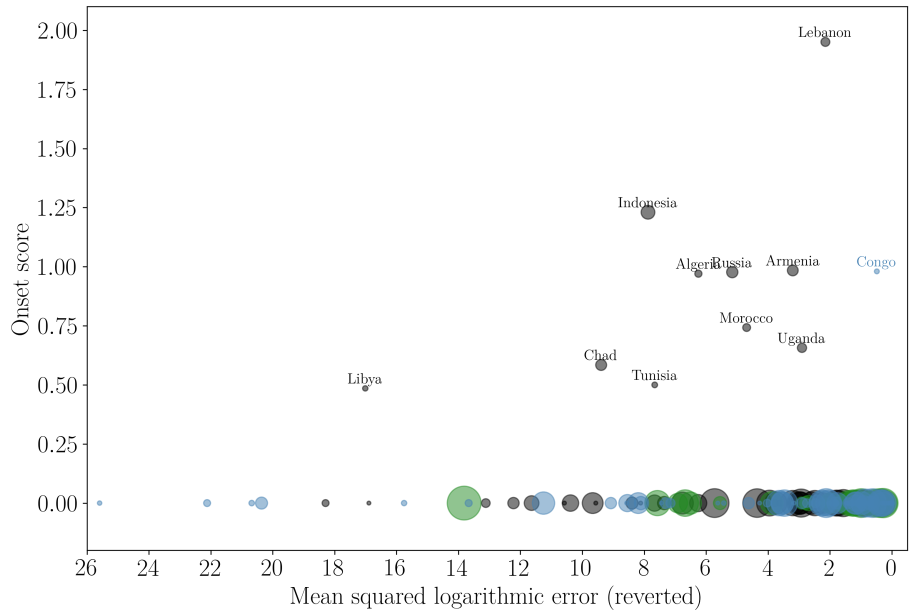
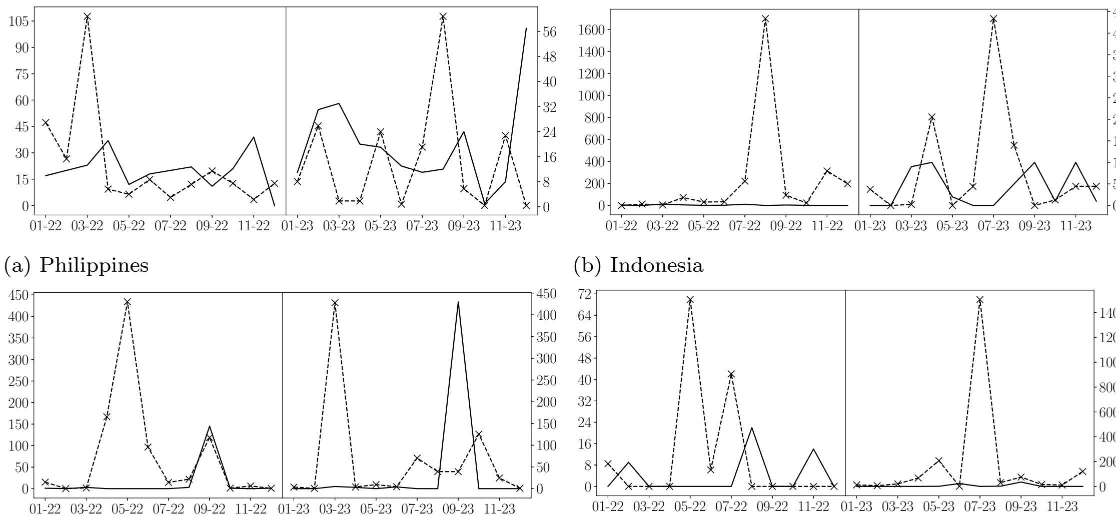


Figure 5.6: Mean squared logarithmic error (reverted) and Onset score for each country. The black markers refer to the Onset catcher, blue to the structural benchmark, and green to VIEWS. The size of the marker indicates the sum of observed fatalities in the prediction window ($log + 1$).

To uncover the conditions under which the Onset catcher performs well, the evaluation is disaggregated, showing the Onset score and the prediction error for each country (Figure 5.6). The Onset catcher (black) produces high Onset scores for countries such as Indonesia and Chad. Indicated by the size of the markers showing the actual fatalities ($log + 1$) in the prediction window, the model works well for low- and medium-intensity cases. This makes sense, given that the Onset catcher ignores dynamics in ongoing armed conflict, rendering the model less suitable to predict fatalities for cases with substantial armed violence.

Further investigating well-performing cases (Figure 5.7), the Onset catcher excels at anticipating country-months where fatalities are preceded by a value of zero.[19]

[19]Figure E.10 in Appendix E shows more examples for well-performing cases. Figure E.11 in



(a) Philippines

(b) Indonesia

(c) Azerbaijan

(d) Chad

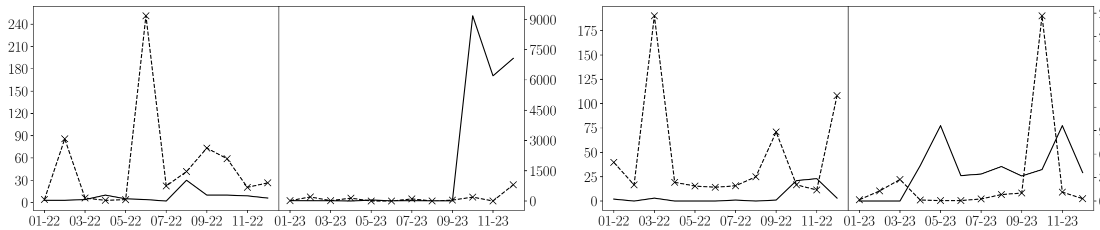
Figure 5.7: The number of fatalities in civil conflict (solid) and the Onset catcher predictions (dashed) for selected well-performing cases with high Onset score. The Onset catcher performs well for low- to medium-intensity cases but shows a clear tendency to overpredict, at times substantially.

While the model's ability to capture sudden peaks in the number of fatalities is good, the Onset catcher tends to overpredict, at times substantially (i.e., Chad and Azerbaijan). In conflict prediction, there is a trade-off between *risk-taking* and *risk-aversion*. A *risk-averse* model likely underpredicts the number of fatalities in armed conflict due to the imbalanced data structure, but *risk-taking* is not always rewarded, as it can drive up the error (Schincariol et al. 2025). This trade-off likewise applies to the Onset catcher and emphasizes the utility of the ensemble approach.

Finally, the Onset catcher's performance is validated against the two crucial cases of Israel-2023 and Sudan-2023 (Figure 5.8). The model's ability to anticipate both onsets is mixed. While the Onset catcher predicts some casualties for Israel-2023 and Sudan-2023, the number of fatalities remains markedly below the observed counts. In the case of Sudan, the Onset catcher predicts a sharp peak in the number of fatalities, several months after the actual onset, yet again showing its tendency to

Appendix E presents poorly-performing countries. In those instances, the model either completely misses onsets (i.e., Togo) or overpredicts the observed counts.

overpredict the actual counts. This issue is even more evident in the first prediction window. The Onset catcher already predicts substantial levels of armed violence in 2022, which decidedly exceed the observed values.



(a) Israel

(b) Sudan

Figure 5.8: The number of fatalities in civil conflict (solid) and the Onset catcher predictions (dashed) for the two crucial cases Israel-2023 and Sudan-2023.

The Onset catcher's mixed performance on the two crucial onset cases delineates the limits of predictability. After further inspection, both countries have a unique background. The last Gaza war occurred in 2014, and the escalation of armed violence in 2023 is unprecedented in the history of the region (UCDP 2025b). Similarly, Sudan has experienced comparatively low levels of violence since the Second Sudanese Civil War, when conflict erupted between the government and the formerly allied paramilitary Rapid Support Forces (UCDP 2025c). Some civil wars are idiosyncratic and hence inherently unpredictable (Cederman and Weidmann 2017).

5.8 Conclusion

Despite immense advancements in the field of early warning, conflict onsets remain the "hard problem of conflict prediction" (Mueller and Rauh 2022, p. 2442). This paper introduces a new conflict prediction model—the 'Onset catcher'—to complement existing approaches. The model's inner workings are derived from a reconceptualization of conflict emergence.

The literature is strongly shaped by structural approaches that explain civil war onset with risk factor combinations (Cederman et al. 2010; Collier and Hoeffler 2004; Fearon and Laitin 2003). However, an immediate association between structural factors and civil war seems less convincing due to the tremendous consequences of armed violence and the logistical challenges of organizing for armed action. Collective action mediates the relationship between structural risk factors and civil conflict. This implies that civil war originates from preceding low-intensity collective action, such as protest or rebel mobilization. Consecutive interactions between the government and the non-state group might drive tactics towards more violent manifestations of political contention (McAdam 1983; Pruitt and Kim 2016).

The Onset catcher is a hurdle model. *Stage i* predicts the baseline risk of collective action (a latent variable), using structural risk factors and a set of outcomes: Protests, riots, remote violence, and low-intensity armed violence. This stage serves to filter out high-risk cases for *stage ii*. In *stage ii*, the number of fatalities in civil conflict is predicted, conditional on the preceding risk of collective action ($t-1$) surpassing a threshold. Otherwise, the model predicts zero deaths. *Stage ii* uses temporal lags for the risk of collective action (the latent variable) as input. The empirical results demonstrate that the Onset catcher outperforms the VIEWS ensemble and a structural benchmark when anticipating conflict onsets. Nevertheless, there is a substantial increase in the prediction error.

This paper has three main implications. First, the Onset catcher is derived from a reconceptualization of conflict emergence, and the model's performance supports the validity of the proposed theoretical mechanisms. Civil war does not occur out of nowhere, but there are early warning signals in preceding low-intensity collective action, such as protest and other battle events.

Second, rather than seeking to establish one model as superior, it appears more fruitful to divide the field of conflict prediction into sub-tasks, such as forecasting a baseline level of armed contention (i.e., VIEWS), anticipating variability in fatality time series (i.e., Shape finder), or conflict onsets (i.e., Onset catcher). Each model offers unique information, producing more robust forecasts when combined.

Third, there are limits to predictability. Some civil conflicts are idiosyncratic and therefore inherently unpredictable (Cederman and Weidmann 2017). These are cases where armed conflict breaks out without any preceding tensions and are deemed by some as the real target of conflict prediction (Jäger 2016). Alternatively, this paper suggests that some aspects of armed violence are unreachable.

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6 *Conclusion*

6.1 Introduction

Despite comprehensive research on the causes of armed conflict, the literature still faces substantial barriers to establishing robust correlations between structural risk factors and the probability of civil war onset (see Malone 2021 for a discussion). This dissertation contends that both theoretical omissions and methodological shortcomings drive the lack of consensus on the causes of civil conflict. Existing research approaches civil war as a dichotomous phenomenon, given that a country can either be at *peace* or at *war* (Bartusevičius and Gleditsch 2019). The first wave of quantitative research assigns structural conditions to an increased risk of armed violence (Florea 2017), which neglects that civil war is a multistaged process, comprising initial collective action (*stage i*) and the transition to civil conflict (*stage ii*). Turning to methodological shortcomings, null-hypothesis significance testing (NHST) encounters important challenges when studying complex phenomena. By navigating the under- and overfitting trade-off, machine learning has better chances at accurately capturing the true data-generating process (Colaresi and Mahmood 2017).

Against this background, this dissertation makes two overarching contributions: (1) Reconceptualizing conflict emergence by integrating structural and procedural approaches, or rather, by theorizing about how civil conflict emerges from preceding collective action, such as protest and low-intensity armed conflict, and (2) leveraging tools from interpretable machine learning to validate theory and to advance early warning for political crises. In addressing these aspects, the presented research has a number of implications for the broader literature on the causes of civil conflict and conflict prediction.

Paper i: The complexity of armed conflict needs to be taken into account when studying its origins. Instead of searching for sufficient conditions (i.e., Bara 2014), civil wars should be investigated along stereotypical pathways. Every onset is assigned to the closest underlying logic while maintaining its unique character. *Paper i* illustrates that civil wars emerge from the interaction of grievances and opportunity. While common pathways to civil war exist, every case presents a specific manifestation of the associated causal mechanism, which suggests that explanations for civil war might not generalize across contexts. This is in accordance with the rationalist argument that wars are theoretically indeterminant as they are ultimately driven by randomness (Gartzke 1999).

Paper ii: Instead of singling out civil war, different types of collective action, in particular protest and low-intensity armed conflict, should be studied together, given that there are important similarities in their causes. Structural background factors for civil war onset are more or less equally associated with protest and low-intensity armed violence, and collective action is a key precursor to more substantial levels of civil conflict. Despite marked similarities, less and more violent forms of collective action likewise have a unique character, with the former frequently occurring in rich democracies, known for their low baseline risk of armed conflict. By extracting and aggregating SHAP values, *paper ii* demonstrates how interpretable machine learning can be used for theory validation.

Paper iii: Armed violence entails great risks, which makes a sudden protest-to-civil conflict transition seem implausible. Instead of focusing on protest activity at $t-1$ (i.e., Rød and Weidmann 2023), civil conflict is preceded by dangerous patterns in sequences of protest events, indicative of the non-state actor's strategic decision-making. Extracting temporal patterns from time series can enhance our theoretical understanding of protest dynamics, while producing potential early warning signals for armed escalation. The consecutive interactions between protesters and the government produce temporal patterns in sequences of protest events. This theoretical argument might extend to similar phenomena, such as armed conflict (Schincariol et al. 2025) and migration (Schincariol and Chadefaux 2025).

Paper iv: Civil war does not occur out of nowhere, but there are early warning signals in preceding low-intensity collective action, which can serve to predict new outbreaks of armed violence. Further advancements in the field of conflict prediction seem contingent on a stronger disaggregation of goals. Specifically, models should be optimized for sub-tasks, such as predicting a baseline level of armed conflict (i.e., VIEWS), escalation and de-escalation in battle intensity (i.e., Shape finder), or conflict onsets (i.e., Conflict forecast and the Onset catcher). The resulting predictions can be combined in an ensemble to arrive at more robust forecasts. Regardless of the good performance of existing systems (Rød et al. 2024), conflict prediction faces inherent constraints due to the idiosyncrasies of cases (Cederman and Weidmann 2017).

6.2 Limitations

Despite these contributions, the presented work likewise has limitations, which can be classified as theoretical or methodological. In terms of theoretical limitations, the central argument contends that more substantial armed violence originates from preceding collective action.[1] This reveals two pathways to civil war onset: The protest and the clandestine pathway.[2] Protesters may gradually transition to more violent tactics (Rød and Weidmann 2023). Alternatively, civil conflict breaks out after the non-state actor completes mobilizing for armed action (Malone 2021).

While these pathways likely cover a large share of cases, they ignore the possibility

[1]This dissertation follows the tradition of understanding civil war as inherent in previous political contention (Lichbach et al. 2003).

[2]These terms are derived from Lewis (2017), stating that civil wars begin like social movements (protest pathway) or through a process of remote mobilization (clandestine pathway).

that civil war may *indeed* be a surprise. For instance, it seems entirely plausible that civil war is prompted by triggering events, leading to an explosive surge in hostilities, or a swift spillover of armed action from a neighboring country. Moreover, the non-state actor might rely exclusively on non-violent recruitment strategies, which have no direct empirical implications, as they do not produce initial fatalities from low-intensity armed conflict. Consequently, there will be no preceding protest nor violent mobilization. While assumed to be empirically rare, such onsets fall outside the scope of the theoretical argument.

Taking a closer look at the proposed theoretical argument itself, the causal mechanism excludes relevant heterogeneity in the government and the non-state groups. While these factors are omitted for necessity, keeping the theoretical complexity manageable, the corresponding aspects are certainly not irrelevant. Applying the 'law of cohesive responsiveness', the government is assumed to counter opposing collective action with repression (Davenport 2007). While the proposed theoretical mechanism allows for protest to exhaust or for a resolution of the incompatibility, it does not account for the strategic decision-making of the government. Another generalization is made concerning the characteristics of the non-state group, treating them as unitary actors. However, rebel strength, internal organization, access to social networks, and engagement with civilians are known to impact conflict dynamics (Braithwaite and K. G. Cunningham 2020; D. E. Cunningham et al. 2013).

Existing data on the characteristics of non-state actors, specifically the Non-State Actors in Armed Conflict Dataset (D. E. Cunningham et al. 2013) and the Foundations of Rebel Group Emergence Dataset (Braithwaite and K. G. Cunningham 2020), are time-invariant and documented on the dyad-level, making them challenging to include in the country-year or country-month setting. Gradually shifting from theoretical to methodological shortcomings, another limitation is the selection bias prevalent in the UCDP data, given that only conflict actors with a certain intensity (i.e., at least 25 fatalities per year) are considered, excluding early failed non-state actors (Lewis 2017). When investigating how civil war originates from clandestine mobilization, early failed groups are particularly insightful. Existing data collection efforts on organized actors that remain below the conventional levels of civil conflict (Malone 2022) have too little overlap with this dissertation's temporal coverage (1970—2012 versus 1989—2023 and shorter).

The lack of up-to-date information on rebel characteristics points towards another key limitation of this work: Poor data quality. The underlying issues with the data have long been stressed (e.g., Dixon 2009) and likewise apply here. For example, the extent of missing values in the World Bank indicators is concerning, which requires imputing data for countries completely missing, accepting the possibility of bias (Gorelick 2006). There is not much that can be done beyond what is implemented here (i.e., careful development of an imputation strategy, and including dummy indicators for denoting which observations were filled in), other than acknowledging the shaky data basis.

The poor data quality is particularly concerning against the background of machine learning being described as data-driven, which dictates a need for ample observations. While machine learning is situated as one of the main contributions, this approach likewise has limitations. Social scientists are most concerned about omitted variables bias, which occurs when the effect of a third variable Z is erroneously assigned to X, and can distort the causal effect in either direction by increasing or decreasing the slope (Kellstedt and Whitten 2018). When studying complex phenomena, navigating between omitted-variable bias and multicollinearity almost naturally produces 'garbage can' models, which are inherently unstable due to the weak data basis for estimating causal effects (Kellstedt and Whitten 2018; Schrodt 2014).

Machine learning has better chances at accurately capturing the underlying data-generating process by identifying the ideal cutoff between underfitting and overfitting (Colaresi and Mahmood 2017). Yet, this strength comes at the cost of causality. Machine learning returns correlations instead of isolating causal effects. The presented findings provide indications on which structural risk factors might be associated with which type of collective action, including the sign of the correlation, but cannot be interpreted in a causal sense. The approach in this thesis diverges from attempts to use machine learning for causal inference (e.g., Basuchoudhary et al. 2021).

The difference between causation and correlation leads to a bigger discussion on the overall research design, borrowing from both the deductive and the inductive traditions. While this thesis sets out to validate civil conflict theory with machine learning tools, thereby following the deductive tradition, the deployed empirical strategies likewise align with the idea of induction, deriving novel theoretical conclusions from the evidence uncovered. The machine learning approach has the advantage of testing a vast range of theories without being constrained by prior assumptions and instead allows patterns and correlations to emerge naturally from the data, which can reveal previously untheorized mechanisms.

Simultaneously, integrating the deductive and inductive traditions risks not being able to sufficiently implement either. This corresponds to a final limitation: Adopting an approach that could be criticized as a kitchen sink strategy (i.e., throwing in large numbers of indicators and only investigating relevant ones), which leaves little space to fully unpack the novel empirical insights that originate from the data.

6.3 Avenues for Future Research

This project borrows from the deductive and inductive traditions. As established in the previous paragraph, the machine learning approach enables validating a vast range of theoretical arguments, while allowing correlations to emerge naturally from the data. This helps to identify previously untheorized mechanisms, thereby offering evidence for induction. However, novel findings remain underdeveloped at times due to the limited scope. The duality between deduction and induction hints at avenues for future research, corresponding to the four stand-alone papers.

Paper i: The first paper uncovers certain combinations of structural risk factors, which are associated with an increased probability of civil war onset. The identified pathways are interpreted using anecdotal evidence from some selected cases in the sample. Future research might build on these initial investigations by systematizing the profiles of the stereotypical pathways that transpire. For instance, a larger pool of onset cases could be included in the analysis by lowering the threshold for denoting civil war onset from 1,000 to 25 fatalities. Instead of unpacking each case individually, the cluster analysis suggests a greater reliance on centroids. The centroid covariate combinations could be interpreted as actual stereotypes, being a fictional average of risk factors that apply to each onset in the cluster.

The first paper's main argument is derived from rationalist explanations of war. In this context, Gartzke (1999) claims that there are no systematic conditions that explain why uncertainty prompts armed conflict in some situations only. This suggests that there is a systematic component of civil war and a random aspect, unique to each background. While game theoretical hypotheses, as developed by rationalist explanations (e.g., Fearon 1995; Gartzke 1999), are rarely validated empirically, this could be another avenue for future research. Based on in-depth case study analyses, it might be possible to quantify the systematic drivers of civil war and filter out the random, context-specific components. The corresponding insights relate to the broader discussion on the temporal complexity of civil war, contending that outbreaks of armed violence require both a high-risk situation—a powder keg—and a triggering event—a spark (Chadefaux 2014). The powder keg is the systemic component of civil war, while the spark is unique to each case.

Paper ii: The second paper reveals interesting differences in the causes of collective action, contrasting protests with low-intensity armed conflict. In this context, protest is a regular form of political participation in democracies and thereby has a fundamentally diverging meaning. Future research should theorize about the conditions under which protest constitutes an early warning signal for armed action, and when the risk of violent escalation approaches zero. First indications can be derived from Rød and Weidmann (2023), suggesting that protest-to-civil conflict transitions are more likely in autocratic regimes, given the severity of state repression, the resolve of protesters, and the widespread discontent with the regime.

Concerning the specific patterns in correlations, while plausible, the corresponding theoretical mechanisms remain somewhat underexplored, pointing towards another avenue for future research. Mobile phones enhance protest activity but seem to have no effect on more violent forms of contention, such as battle events and one-sided violence. *Paper ii* suggests that non-state actors rely on more covert ways of communication when implementing armed action, due to the high risk of being discovered (Shapiro and Weidmann 2015). Future research could further probe the emerging associations by exploring under which conditions non-state actors might use digital communication or more secretive tools to coordinate for armed attacks. This is particularly relevant, given that systematic research on the formation of rebel groups is still in its early stages (Larson and Lewis 2018; Malone 2019).

Paper iii: The third paper uncovers three dangerous protest patterns that precede high fatalities in civil conflict: A gradual escalation of protest intensity, high protest activity followed by a sudden drop, and a pattern of high-low-high (U-shape). The former two are consistent with existing theoretical mechanisms: Protest escalation and protest capture (Rød and Weidmann 2023). The third trajectory is novel, potentially being indicative of group splintering or deploying protest as a diversion. While these theoretical arguments seem plausible, they could be further specified in future research by theorizing on the strategic decision-making of the non-state actor and drawing on existing arguments on group radicalization and splintering (e.g., Tarrow 2011). The derived theoretical model could be validated on new data, taking a qualitative approach to accurately trace the causal mechanism.

The developed methodological approach, using time series clustering to extract recurring patterns in sequences of events, is versatile and can be applied to a wider range of phenomena. The underlying assumption of *paper iii* is that the continued interactions between the government and the non-state actor produce patterns in sequences of protest events. Similar arguments might apply to a larger set of outcomes, where interactions between the state and the opposition are at the center of the theoretical mechanism, such as tactical changes in battle strategies. For example, a non-state actor might shift from fighting the government to civilian targeting as a last resort, when the group has suffered intensive losses on the battlefield (Hultman 2007). Instead of using the $t-1$ of rebel deaths, there might be recurring patterns in battle events that indicate an immediate shift in strategies.

Paper iv: The fourth paper's main goal is to validate the theoretical argument that collective action mediates between structural risk factors and civil conflict. In validating this claim, the paper develops a novel conflict prediction model—the Onset catcher—tailored towards anticipating new outbreaks of armed violence. While this exercise is certainly valuable for theory validation, deploying the Onset catcher for practical early warning requires a simplification of the algorithm. Specifically, the advantage of using a long list of structural risk factors, as opposed to a few selected but strong correlates such as conflict history, population size, and economic performance, might be questioned. Future research should explore how the underlying idea of the Onset catcher can be incorporated in existing modelling approaches, in particular the Shape finder (Schincariol et al. 2025), thereby adopting a more simplified yet powerful risk-taking framework.

The Shape finder is an autoregressive model that assigns each input sequence to the most similar past cases (Schincariol et al. 2025). Predictions are returned as the aggregated future fatality series of the specific closest matches. This methodology can easily be adopted to include covariates, predicting a certain outcome with another type of input.[3] Instead of matching on past fatality sequences, the closest historical analogs in collective action, considering protest, riots, battles, remote violence, non-state conflict, and one-sided violence, could be used to anticipate new outbreaks of armed conflict. Maintaining a similar hurdle approach to the Onset catcher allows discarding cases with ongoing armed action, making an onset conceptually impossible, and directs attention towards countries with a high baseline risk of armed violence by filtering out low-risk settings.

[3]See Schincariol and Chadefaux (2025) for an application to migration flows, using food prices and conflict dynamics as covariates.

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A Appendix—Introduction

Name: Description	**Source**
Number of fatalities (outcome): The number of battle-related deaths in civil conflict (excluding events between states). This variable is log-transformed ($log+1$) in the models, and a lagged dependent variable ($t-1$) is included.	Sundberg and Melander 2013[1]
Time since last civil conflict: The exponential time since the last civil conflict. Civil conflict occurs if armed violence between the government and at least one non-state group causes a minimum of 25 fatalities (N. P. Gleditsch et al. 2002). Here, the 25-fatality threshold is understood as a cutoff, coding country-months as *one* if the number of fatalities surpasses 25. The exponential function is defined as $2^{time/12}$ (adapted from Hegre et al. 2019). For easier interpretation, the function returns the exponential growth instead of the decay. The function is applied to the $t-1$ lag of the cumulative count of zeros ($time$), which resets when civil conflict occurs. Left-censored observations are likewise set to zero, which is according to common practice (Beck et al. 1998).	Sundberg and Melander 2013
Time since last civil war: The exponential time since the last civil war. Civil war occurs if armed violence between the government and at least one non-state group causes a minimum of 1,000 fatalities (N. P. Gleditsch et al. 2002). The 1,000-fatality threshold is understood as a cutoff, coding country-months as *one* if the number of fatalities surpasses 1,000. The decay function is defined as $2^{time/12}$ (adapted from Hegre et al. 2019). For easier interpretation, the function returns the exponential growth instead of the decay. The function is applied to the $t-1$ lag of the cumulative count of zeros ($time$), which resets when civil war occurs. Left-censored observations are likewise set to zero, which is according to common practice (Beck et al. 1998).	Sundberg and Melander 2013
Fatality in neighborhood: Dummy variable signifying whether there was at least one fatality from civil conflict in any neighboring country in the previous year ($t-1$). The neighbors are manually coded, taking geodatasource 2024 as the point of departure and by consulting `https://geacron.com/home-en/` and K. S. Gleditsch and Ward (1999) to account for changes in the borders over time.	Sundberg and Melander 2013
Infant mortality: The number of infants who die before turning one year old per 1,000 births.	World-Bank 2025[2]
GDP per capita: The GDP per capita in current US dollars. The end-of-year GDP is divided by the mid-year population to obtain the per capita value. The variable is log-transformed ($log+1$) in the models.	World-Bank 2025

[1]The UCDP GED version 24 was downloaded from `https://ucdp.uu.se/downloads/ged/ged241-csv.zip` on the 9^{th} of August 2025.

[2]The World Bank data (World-Bank 2025) were accessed via the World Bank API, using the `wbgapi` package in Python (`https://pypi.org/project/wbgapi/`). The data for this paper were retrieved on the 22^{th} of August 2025.

GDP growth: The GDP growth rate in percentage, taking the average growth per year. Values can be positive or negative.	World-Bank 2025
Oil rents: The percentage of the GDP that is obtained from oil rents. The variable is log-transformed ($log + 1$) in the models.	World-Bank 2025
Population size: The mid-year number of residents in a country. The variable is log-transformed ($log + 1$) in the models.	World-Bank 2025
Male population (15-19): The percentage of males aged between 15-19 compared to the male population as a whole.	World-Bank 2025
Ethnic fractionalization: Ethnolinguistic fractionalization (ELF) index, calculated as $1 - \sum(Proportion\, group\, i)^2$ (Alesina et al. 2003), where groups refer to politically relevant ethnic groups. The variable ranges from zero to one. Higher values mean higher fractionalization.	Vogt et al. 2015[3]
Male schooling: Expected years of schooling for men.	UNDP 2024
Temperature: The average surface temperature per year (in °C).	CCKP 2024
Freshwater withdrawals: The annual freshwater withdrawals as a percentage of the available internal freshwater deposits. The variable is log-transformed ($log + 1$) in the models.	World-Bank 2025
Electoral democracy: The extent to which the principles of electoral democracy are implemented (V-Dem 2024a). The index ranges from zero to one. Higher values imply a higher level of implementation.	V-Dem 2024b
Liberal democracy: The level to which the principles of liberal democracy are implemented (V-Dem 2024a). The index ranges from zero to one, with higher values implying a higher level of implementation.	V-Dem 2024b
Egalitarian democracy: The level to which the principles of egalitarian democracy are implemented (V-Dem 2024a). The index ranges from zero to one, with higher values implying a higher level of implementation.	V-Dem 2024b
Civil liberties: The extent to which civil liberties are protected (V-Dem 2024a). The index ranges between zero and one. Higher values imply a higher level of protection.	V-Dem 2024b
Exclusion by social group: The level to which there is exclusion based on social group (V-Dem 2024a). The index ranges from zero to one, with higher values implying a higher level of exclusion.	V-Dem 2024b

Table A1. Operationalization table for the variables in the *simple* civil war model.

[3]The EPR data were downloaded from `https://icr.ethz.ch/data/epr/`on the 8^{th} of August 2025.

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B Appendix—Grievances and Opportunity

Name: Description	**Source**
Civil war onset (outcome): Dummy variable signifying if the country-year has experienced at least 1,000 fatalities from civil conflict (N. P. Gleditsch et al. 2002), with the two preceding years remaining below that threshold (adapted from Bara 2014). Civil conflict occurs between the government and at least one non-state actor (N. P. Gleditsch et al. 2002). Left-censored onsets, or rather, cases with at least 1,000 fatalities in 1989 or 1990, are not considered.	Sundberg and Melander 2013[1]
Fatalities in neighborhood: The $t-1$ lag of the total fatalities in the neighborhood. Only fatalities from civil conflict are counted. The geographic neighbors are obtained in manual coding, i.e., taking geodatasource 2024 as the point of departure and by consulting `https://geacron.com/home-en/`and K. S. Gleditsch and Ward (1999) to account for border changes. This variable is log-transformed ($log+1$) in the model.	Sundberg and Melander 2013
GDP per capita: The GDP per capita in current US dollars, obtained by dividing the annual GDP by the mid-year population. This variable is log-transformed ($log+1$) in the model.	World-Bank 2025a[2]
GDP growth: The average GDP growth rate in percentage. This variable takes negative and positive values.	World-Bank 2025a
Population size: The total number of residents in a country. The variable is log-transformed ($log+1$) in the model.	World-Bank 2025a
Oil rents: The income from oil rents as a percentage of the GDP.	World-Bank 2025a
Temperature: The mean surface temperature (in °C). This variable takes negative and positive values.	CCKP 2024
Ethnic exclusion: The proportion of the population with powerless status, summing across politically relevant ethnic groups. Powerless status implies that a group holds no power over executive decision-making (Vogt 2021).	Vogt et al. 2015[3]
Male education: The male secondary school enrollment rate (in percentage) compares the actual enrollment to the group of individuals that *should* be enrolled based on age and gender.	World-Bank 2025a

[1]The UCDP GED data version 24 was downloaded from `https://ucdp.uu.se/downloads/ged/ged241-csv.zip` on the 9^{th} of August 2025.

[2]The World Bank data (World-Bank 2025a; World-Bank 2025b) were accessed via the World Bank API, using `wbgapi` in Python (`https://pypi.org/project/wbgapi/`). The data for this paper were retrieved on the 22^{th} of August 2025.

[3]The EPR data were downloaded from `https://icr.ethz.ch/data/epr/` on the 8^{th} of August 2025.

Liberal democracy: The liberal democracy index measures the extent to which the principles of liberal democracy are fulfilled (V-Dem 2024a). The index ranges between zero and one, with higher values suggesting a higher level of democracy.	V-Dem 2024b
Regulatory quality: The regulatory quality index measures the extent to which the government can implement laws and regulations on the private sector (Kaufmann and Kraay 2024). The index is zero-centered, where negative values suggest low regulatory quality, and positive values suggest high regulatory quality.	World-Bank 2025b

Table B1. Operationalization table for the variables in the civil war model.

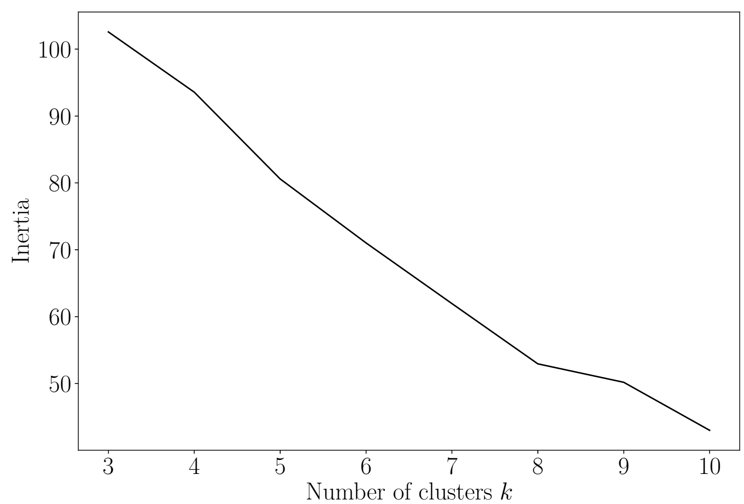

Figure B.1: Inertia for different numbers of clusters k, using the k-Means clustering algorithm on the SHAP values for onset cases. Applying the elbow method, the plot suggests selecting $k = 8$.

	Country	Year
1	Afghanistan	2005
2	Algeria	1994
3	Angola	1998
4	Burkina Faso	2022
5	Burundi	1997
6	Burundi	2000
7	Chad	2006
8	Colombia	1992
9	Colombia	1999
10	Congo	1997
11	DR Congo	1996
12	DR Congo	2009
13	DR Congo	2013
14	DR Congo	2017
15	DR Congo	2020
16	Ethiopia	2020
17	India	1999
18	Iraq	1991
19	Iraq	1997
20	Iraq	2004
21	Israel	2014
22	Israel	2023
23	Liberia	2003
24	Libya	2011
25	Libya	2016
26	Libya	2019
27	Mali	2022
28	Myanmar	1992
29	Myanmar	2021
30	Nepal	2002

	Country	Year
31	Nigeria	2013
32	Pakistan	2008
33	Pakistan	2023
34	Philippines	2000
35	Philippines	2017
36	Russia	1995
37	Russia	1999
38	Rwanda	1994
39	Rwanda	1998
40	Rwanda	2001
41	Sierra Leone	1995
42	Sierra Leone	1998
43	Somalia	2007
44	South Sudan	2014
45	Sri Lanka	2006
46	Sudan	1995
47	Sudan	2010
48	Sudan	2015
49	Sudan	2023
50	Syria	2011
51	Tajikistan	1996
52	Turkey	1992
53	Turkey	2016
54	Uganda	1996
55	Uganda	2004
56	Ukraine	2014
57	Yemen	1994
58	Yemen	2011

Table B2. List of civil war onsets. The indices are the same as in Figure 2.2. Civil war onset is coded as *one* if a country-year experiences at least 1,000 fatalities (N. P. Gleditsch et al. 2002) and the two previous years remain below this intensity level (adapted from Bara 2014). Left-censored, or rather, cases with at least 1,000 fatalities in 1989 or 1990, are excluded.

	24	18	38	Means
Fatalities in neighborhood ($log+1$)	7.17	6.36	1.95	3.25
GDP per capita ($log+1$)	8.94	3.18	4.72	8.11
GDP growth	-50.34	-64.05	-50.25	3.47
Population size ($log+1$)	15.66	16.69	15.73	16.08
Oil rents	36.33	23.34	0.00	3.92
Temperature	21.96	22.24	18.99	18.85
Ethnic exclusion	0.00	0.00	0.00	0.11
Male education	90.43	53.82	14.02	71.15
Liberal democracy	0.06	0.06	0.11	0.40
Regulatory quality	-1.43	-2.15	-1.34	-0.06

Table B3. Cluster 1: Economic crisis—The table presents value combinations on the independent variables for all cases included in the cluster. The last column shows the sample means for reference. The column names correspond to the case numbers in Table B2.

	43	19	25	26	Means
Fatalities in neighborhood ($log+1$)	3.93	8.24	7.96	7.10	3.25
GDP per capita ($log+1$)	6.18	6.84	8.93	9.21	8.11
GDP growth	6.69	21.24	-1.49	-11.20	3.47
Population size ($log+1$)	16.24	16.91	15.71	15.75	16.08
Oil rents	0.00	31.58	10.79	32.75	3.92
Temperature	26.83	21.96	23.20	22.70	18.85
Ethnic exclusion	0.00	0.00	0.16	0.16	0.11
Male education	8.20	45.56	96.89	96.89	71.15
Liberal democracy	0.10	0.07	0.17	0.15	0.40
Regulatory quality	-2.43	-2.18	-2.22	-2.30	-0.06

Table B4. Cluster 4: Weak state capacity—The table presents value combinations on the independent variables for all cases included in the cluster. The last column shows the sample means for reference. The column names correspond to the case numbers in Table B2.

	3	44	39	54	11	30	22	28	55	51	1	41	42	Means
Fatalities in neighborhood ($log+1$)	9.59	7.89	8.78	6.94	7.54	7.21	7.05	8.04	7.61	8.61	5.98	0.00	0.00	3.25
GDP per capita ($log+1$)	6.06	7.13	5.51	5.65	4.86	5.48	10.86	4.09	5.68	5.15	5.54	5.34	5.06	8.11
GDP growth	4.69	3.37	8.86	9.07	-1.02	0.12	1.83	9.66	6.81	-16.70	11.23	-8.00	1.79	3.47
Population size ($log+1$)	16.53	16.23	15.91	16.87	17.63	17.05	16.10	17.53	17.12	15.62	17.01	15.25	15.27	16.08
Oil rents	21.75	26.36	0.00	0.00	2.20	0.00	0.01	2.89	0.00	0.43	0.03	0.00	0.00	3.92
Temperature	22.63	27.86	19.57	22.68	23.65	12.44	20.66	22.73	23.22	-1.00	11.98	25.60	26.08	18.85
Ethnic exclusion	0.15	0.28	0.00	0.00	0.56	0.62	0.00	0.00	0.00	0.34	0.01	0.00	0.00	0.11
Male education	12.75	14.38	9.04	12.62	35.24	47.23	96.29	24.89	21.33	78.94	30.49	22.91	25.70	71.15
Liberal democracy	0.08	0.07	0.12	0.24	0.04	0.22	0.63	0.02	0.23	0.06	0.13	0.04	0.08	0.40
Regulatory quality	-1.45	-1.64	-1.35	-0.03	-1.76	-0.59	1.12	-1.68	-0.11	-1.52	-1.64	-1.53	-1.49	-0.06

Table B5. Cluster 2: Opportunity—The table presents value combinations on the independent variables for all cases included in the cluster. The last column shows the sample means for reference. The column names correspond to the case numbers in Table B2.

	5	6	40	14	15	12	13	47	48	46	50	Means
Fatalities in neighborhood ($log+1$)	7.30	8.10	8.12	6.74	5.50	6.75	5.40	7.90	7.76	6.29	7.26	3.25
GDP per capita ($log+1$)	5.08	4.91	5.47	6.08	6.23	5.64	6.07	7.18	7.17	6.14	7.99	8.11
GDP growth	-1.59	-0.86	8.48	3.73	1.74	2.86	8.48	3.86	1.91	6.00	2.85	3.47
Population size ($log+1$)	15.62	15.68	15.93	18.28	18.38	18.01	18.14	17.38	17.51	17.02	16.95	16.08
Oil rents	0.00	0.00	0.00	0.66	0.36	1.38	1.56	11.49	0.80	0.01	18.87	3.92
Temperature	20.34	20.40	18.86	24.61	24.81	24.17	24.37	28.26	27.64	26.63	18.39	18.85
Ethnic exclusion	0.85	0.85	0.84	0.39	0.47	0.54	0.54	0.70	0.63	0.82	0.78	0.11
Male education	9.35	10.59	11.36	58.95	66.98	49.33	49.30	46.13	48.02	33.64	75.71	71.15
Liberal democracy	0.15	0.15	0.10	0.12	0.15	0.16	0.13	0.07	0.07	0.02	0.04	0.40
Regulatory quality	-1.61	-1.14	-1.16	-1.48	-1.51	-1.51	-1.26	-1.34	-1.50	-1.36	-0.95	-0.06

Table B6. Cluster 3: Grievances—The table presents value combinations on the independent variables for all cases included in the cluster. The last column shows the sample means for reference. The column names correspond to the case numbers in Table B2.

	17	35	31	34	45	2	9	33	16	32	8	52	Means
Fatalities in neighborhood ($log+1$)	5.77	0.00	0.69	0.00	0.00	1.95	3.26	7.16	7.67	9.01	7.04	7.47	3.25
GDP per capita ($log+1$)	6.09	8.02	7.96	6.96	7.24	7.33	7.72	7.22	6.81	6.97	7.46	7.92	8.11
GDP growth	8.85	6.93	6.67	4.38	7.67	-0.90	-4.20	-0.04	6.06	2.12	4.04	5.04	3.47
Population size ($log+1$)	20.76	18.50	19.01	18.19	16.83	17.14	17.46	19.33	18.59	19.06	17.33	17.88	16.08
Oil rents	0.71	0.04	9.88	0.01	0.00	12.69	3.89	0.38	0.00	1.08	2.83	0.15	3.92
Temperature	24.10	26.12	27.26	25.56	26.57	23.18	23.09	21.38	23.79	20.57	23.61	9.30	18.85
Ethnic exclusion	0.01	0.13	0.03	0.13	0.14	0.28	0.29	0.08	0.04	0.14	0.29	0.00	0.11
Male education	50.93	80.59	57.45	73.50	90.88	65.04	70.40	45.33	35.39	33.46	55.92	64.81	71.15
Liberal democracy	0.58	0.35	0.39	0.44	0.25	0.10	0.42	0.21	0.15	0.23	0.43	0.38	0.40
Regulatory quality	-0.30	0.13	-0.68	0.02	-0.27	-0.91	-0.04	-0.90	-0.98	-0.60	-0.11	0.10	-0.06

Table B7. Cluster 8: Large population—The table presents value combinations on the independent variables for all cases included in the cluster. The last column shows the sample means for reference. The column names correspond to the case numbers in Table B2.

	20	57	7	10	29	23	56	58	Means
Fatalities in neighborhood ($log + 1$)	4.68	0.00	5.51	7.25	6.27	6.52	5.77	0.00	3.25
GDP per capita ($log + 1$)	7.19	7.46	6.81	6.69	7.13	5.48	8.02	7.08	8.11
GDP growth	53.39	6.72	-0.52	-0.62	-12.02	-30.15	-10.08	-12.71	3.47
Population size ($log + 1$)	17.13	16.60	16.19	14.88	17.79	14.95	17.64	17.13	16.08
Oil rents	64.66	38.27	30.85	38.84	0.06	0.00	0.54	23.42	3.92
Temperature	22.92	25.43	27.36	24.48	24.17	25.04	9.64	25.93	18.85
Ethnic exclusion	0.01	0.00	0.14	0.09	0.23	0.00	0.01	0.00	0.11
Male education	54.21	54.53	23.89	52.60	71.08	43.31	99.18	51.94	71.15
Liberal democracy	0.11	0.15	0.10	0.06	0.02	0.15	0.21	0.15	0.40
Regulatory quality	-1.65	-0.44	-1.08	-1.27	-1.12	-1.63	-0.59	-0.84	-0.06

Table B8. Cluster 5: Oil curse—The table presents value combinations on the independent variables for all cases included in the cluster. The last column shows the sample means for reference. The column names correspond to the case numbers in Table B2.

	49	21	53	Means
Fatalities in neighborhood ($log + 1$)	12.01	11.18	11.02	3.25
GDP per capita ($log + 1$)	6.68	10.55	9.30	8.11
GDP growth	-29.43	3.78	3.32	3.47
Population size ($log + 1$)	17.73	15.92	18.19	16.08
Oil rents	3.30	0.01	0.03	3.92
Temperature	27.19	20.63	12.25	18.85
Ethnic exclusion	0.63	0.12	0.00	0.11
Male education	47.98	95.82	109.02	71.15
Liberal democracy	0.05	0.66	0.15	0.40
Regulatory quality	-1.60	1.21	0.19	-0.06

Table B9. Cluster 6: Bad neighborhood—The table presents value combinations on the independent variables for all cases included in the cluster. The last column shows the sample means for reference. The column names correspond to the case numbers in Table B2.

	37	36	4	27	Means
Fatalities in neighborhood ($log + 1$)	3.56	7.31	7.09	7.29	3.25
GDP per capita ($log + 1$)	7.19	7.89	6.73	6.88	8.11
GDP growth	6.40	-4.14	1.50	3.51	3.47
Population size ($log + 1$)	18.81	18.82	16.93	16.95	16.08
Oil rents	8.76	4.55	0.00	0.00	3.92
Temperature	-4.33	-2.65	28.59	28.92	18.85
Ethnic exclusion	0.17	0.17	0.00	0.00	0.11
Male education	91.93	89.08	31.27	41.87	71.15
Liberal democracy	0.28	0.30	0.24	0.15	0.40
Regulatory quality	-0.52	-0.43	-0.47	-0.63	-0.06

Table B10. Cluster 7: Climate—The table presents value combinations on the independent variables for all cases included in the cluster. The last column shows the sample means for reference. The column names correspond to the case numbers in Table B2.

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C Appendix—To Demonstrate or Fight

Name: Description	Source
year: The sample covers years 1989—2023. Only the years that a country was independent are included. The years of independence are adapted from K. S. Gleditsch and Ward (1999).	K. S. Gleditsch and Ward 1999[1]
country: Countries in K. S. Gleditsch and Ward (1999) comprise the sample. Four sets of countries are excluded: (1) Microstates, including Dominica, Grenada, Saint Lucia, Saint Vincent and the Grenadines, Antigua & Barbuda, Saint Kitts and Nevis, Monaco, Liechtenstein, San Marino, Andorra, Abkhazia, South Ossetia, São Tomé and Principe, Seychelles, Vanuatu, Kiribati, Nauru, Tonga, Tuvalu, Marshall Islands, Palau, Micronesia, and Samoa, (2) states that no longer exist, including German Democratic Republic, Czechoslovakia, Yugoslavia, and People's Republic of Yemen, (3) states that are not available or have extensive missingness in the World Bank data, including Taiwan, Kosovo, and Democratic People's Republic of Korea, and (4) states not available in the V-Dem data, including Bahamas, Belize, and Brunei Darussalam.	K. S. Gleditsch and Ward 1999
Outcomes	
d_civil_war: A dummy variable indicating whether there were more than 1,000 fatalities in civil conflict per country-year (adapted from N. P. Gleditsch et al. 2002). Events between states are excluded. This variable is not available on the country-month.	Sundberg and Melander 2013[2]
d_civil_conflict: A dummy variable indicating whether there were more than 25 fatalities in civil conflict per country-year (adapted from N. P. Gleditsch et al. 2002). Events between states are excluded. This variable is not available on the country-month.	Sundberg and Melander 2013
d_protest: A dummy variable indicating whether there were more than 25 protest events per country-year (adapted from N. P. Gleditsch et al. 2002) or at least one protest event on the country-month.	Raleigh et al. 2010[3]
d_riot: A dummy variable indicating whether there were more than 25 riot events per country-year (adapted from N. P. Gleditsch et al. 2002) or at least one riot event on the country-month.	Raleigh et al. 2010

[1] The country list is obtained from `http://ksgleditsch.com/data-4.html`. For the dissolution of the Soviet Union, the start dates in K. S. Gleditsch and Ward (1999) were verified against the dates of recognition (`https://en.wikipedia.org/wiki/Dissolution_of_the_Soviet_Union#Chronology_of_declarations`). Estonia, Latvia, and Lithuania have observations dating back to 1991, while the remaining post-Soviet states have observations starting from 1992 onward.

[2] UCDP GED version 24 was downloaded from `https://ucdp.uu.se/downloads/ged/ged241-csv.zip` on the 9^{th} of August on 2025.

[3] The ACLED data were downloaded from `https://acleddata.com/conflict-data/data-export-tool` (the old data export tool) on the 23^{rd} of April 2024.

d_terror/d_remote: A dummy variable indicating whether there was at least one fatality from terrorism per country-year or at least one remote violence event on the country-month. Terrorist events with high uncertainty are excluded (i.e., where the month of the event is unknown and when the terrorist nature is doubted).	LaFree 2010[4]; Raleigh et al. 2010
d_sb: A dummy variable indicating whether there was at least one fatality from civil conflict per country-year or the country-month. Events between states are excluded. On the country-month, events that cannot be uniquely assigned to one month are removed.	Sundberg and Melander 2013
d_osv: A dummy variable indicating whether there was at least one fatality from one-sided violence per country-year or the country-month. On the country-month, events that cannot be uniquely assigned to one month are removed.	Sundberg and Melander 2013
d_ns: A dummy variable indicating whether there was at least one fatality from non-state conflict per country-year or the country-month. On the country-month, events that cannot be uniquely assigned to one month are removed.	Sundberg and Melander 2013
Conflict History Theme	
d_civil_war_lag1: The $t-1$ lag of more than 1,000 fatalities in civil conflict. This variable is not available on the country-month.	Sundberg and Melander 2013
d_civil_conflict_lag1: The $t-1$ lag of more than 25 fatalities in civil conflict. This variable is not available on the country-month.	Sundberg and Melander 2013
d_protest_lag1: The $t-1$ lag of more than 25 protest events on the country-year or at least one protest event on the country-month.	Raleigh et al. 2010
d_riot_lag1: The $t-1$ lag of more than 25 riot events on the country-year or at least one riot event on the country-month.	Raleigh et al. 2010
d_terror_lag1/d_remote_lag1: The $t-1$ lag of at least one fatality from terrorism on the country-year or at least one remote violence event on the country-month.	LaFree 2010; Raleigh et al. 2010
d_sb_lag1: The $t-1$ lag of at least one fatality from civil conflict on the country-year or the country-month.	Sundberg and Melander 2013
d_osv_lag1: The $t-1$ lag of at least one fatality from one-sided violence on the country-year or the country-month.	Sundberg and Melander 2013
d_ns_lag1: The $t-1$ lag of at least one fatality from non-state conflict on the country-year or the country-month.	Sundberg and Melander 2013

[4] The GTD data were downloaded from `https://www.start.umd.edu/data-tools/GTD` on the 26^{th} of January 2024.

d_civil_war_zeros_growth: The exponential time since more than 1,000 fatalities from civil conflict. The function is defined as $2^{time/12}$ (adapted from Hegre et al. 2019). Instead of calculating the decay, the exponential growth is considered for a more intuitive interpretation. The function is applied to the $t-1$ lag of the cumulative count of zeros ($time$). If there is an event, the counter resets to zero. Left-censored observations (e.g., 1989) are likewise set to zero, which is in line with common practice (Beck et al. 1998). This variable is not available on the country-month.	Sundberg and Melander 2013
d_civil_conflict_zeros_growth: The exponential time since more than 25 fatalities from civil conflict (further explanations above). This variable is not available on the country-month.	Sundberg and Melander 2013
d_protest_zeros_growth/d_protest_zeros_decay: The exponential time since more than 25 protest events on the country-year (further explanation above). On the country-month, the decay function is used in its original state $2^{-time/12}$ (Hegre et al. 2019), considering at least one protest event per country-month.	Raleigh et al. 2010
d_riot_zeros_growth/d_riot_zeros_decay: The exponential time since more than 25 riot events on the country-year (further explanations above). On the country-month, the decay function is used in its original state $2^{-time/12}$ (Hegre et al. 2019), considering at least one riot event per country-month.	Raleigh et al. 2010
d_terror_zeros_growth/d_remote_zeros_decay: The exponential time since at least one fatality from terrorism on the country-year (further explanations above). On the country-month, the decay function is used in its original state $2^{-time/12}$ (Hegre et al. 2019), considering at least one remote violence event per country-month.	LaFree 2010; Raleigh et al. 2010
d_sb_zeros_growth/d_sb_zeros_decay: The exponential time since at least one fatality from civil conflict on the country-year (further explanations above). On the country-month, the decay function is used in its original state $2^{-time/12}$ (Hegre et al. 2019), considering at least one fatality from civil conflict per country-month.	Sundberg and Melander 2013
d_osv_zeros_growth/d_osv_zeros_decay: The exponential time since at least one fatality from one-sided violence on the country-year (further explanations above). On the country-month, the decay function is used in its original state $2^{-time/12}$ (Hegre et al. 2019), considering at least one fatality from one-sided violence per country-month.	Sundberg and Melander 2013
d_ns_zeros_growth/d_ns_zeros_decay: The exponential time since at least one fatality from non-state conflict on the country-year (see further explanations above). On the country-month, the decay function is used in its original state $2^{-time/12}$ (Hegre et al. 2019), considering at least one fatality from non-state conflict per country-month.	Sundberg and Melander 2013

d_neighbors_civil_war_lag1: Dummy variable indicating whether at least one neighbor had more than 1,000 fatalities from civil conflict in the previous year ($t-1$). The neighbors are obtained in manual coding, i.e., by taking geodatasource (2024) as point of departure and by consulting `https://geacron.com/home-en/` and K. S. Gleditsch and Ward (1999) to document border changes over time. This variable is not available on the country-month.	Sundberg and Melander 2013
d_neighbors_civil_conflict_lag1: Dummy variable indicating whether at least one neighbor had more than 25 fatalities from civil conflict in the previous year ($t-1$) (further explanations above). This variable is not available on the country-month.	Sundberg and Melander 2013
d_neighbors_protest_lag1: Dummy variable indicating whether at least one neighbor had more than 25 protest events in the previous year ($t-1$) (further explanations above). This variable is not available on the country-month.	Raleigh et al. 2010
d_neighbors_riot_lag1: Dummy variable indicating whether at least one neighbor had more than 25 riot events in the previous year ($t-1$) (further explanations above). This variable is not available on the country-month.	Raleigh et al. 2010
d_neighbors_terror_lag1: Dummy variable indicating whether at least one neighbor had at least one fatality from terrorism in the previous year ($t-1$) (further explanations above). This variable is not available on the country-month.	LaFree 2010
d_neighbors_sb_lag1: Dummy variable indicating whether at least one neighbor had at least one fatality from civil conflict in the previous year ($t-1$) (further explanations above). This variable is not available on the country-month.	Sundberg and Melander 2013
d_neighbors_osv_lag1: Dummy variable indicating whether at least one neighbor had at least one fatality from one-sided violence in the previous year ($t-1$) (further explanations above). This variable is not available on the country-month.	Sundberg and Melander 2013
d_neighbors_ns_lag1: Dummy variable indicating whether at least one neighbor had at least one fatality from non-state conflict in the previous year ($t-1$) (further explanations above). This variable is not available on the country-month.	Sundberg and Melander 2013
regime_duration: The number of years since the country became independent, using the start dates in K. S. Gleditsch and Ward (1999).	K. S. Gleditsch and Ward 1999
Demography Theme	
pop: The total number of residents in a country. This variable is log-transformed ($log+1$) in the models.	World-Bank 2025a[5]

[5] The World Bank data (World-Bank 2025a; World-Bank 2025b) were accessed via the World Bank data API, using the `wbgapi` library in Python (`https://pypi.org/project/wbgapi/`). The

pop_density*: Population density denotes the mid-year number of residents as a proportion of the country's size in square kilometers.	World-Bank 2025a
urb_share: The number of people living in an urban setting as a proportion of the total population.	World-Bank 2025a
rural_share: The number of people living in a rural setting as a proportion of the total population.	World-Bank 2025a
pop_male_share: The male population as a proportion of the total population.	World-Bank 2025a
pop_male_share_0_14: The male population aged between zero and 14 years as a proportion of the total male population.	World-Bank 2025a
pop_male_share_15_19: The male population aged between 15 and 19 years as a proportion of the total male population.	World-Bank 2025a
pop_male_share_20_24: The male population aged between 20 and 24 years as a proportion of the total male population.	World-Bank 2025a
pop_male_share_25_29: The male population aged between 25 and 29 years as a proportion of the total male population.	World-Bank 2025a
pop_male_share_30_34: The male population aged between 30 and 34 years as a proportion of the total male population.	World-Bank 2025a
group_counts*: The number of politically relevant ethnic groups. The EPR data are coded on the ethnic group level and are converted to the ethnic group-country-year by duplicating the ethnic groups based on the values in $from$ and *to*. The final variables are obtained by summarizing ethnic groups for each country-year.	Vogt et al. 2015[6]
monopoly_share*: The proportion of the population with monopoly status, summing across ethnic groups. Monopoly status implies that a group has the monopoly over executive decision-making (Vogt 2021).	Vogt et al. 2015
discriminated_share*: The proportion of the population with discriminated status, summing across ethnic groups. Discriminated status means that a group is discriminated against in the political arena, denying them access to political power (Vogt 2021).	Vogt et al. 2015
powerless_share*: The proportion of the population with powerless status, summing across ethnic groups. Powerless status means that a group is systematically excluded from executive decision-making (Vogt 2021).	Vogt et al. 2015
dominant_share*: The proportion of the population with dominant status, summing across ethnic groups. Dominant status implies that the group dominates the political arena, while other groups are included but have no real power (Vogt 2021).	Vogt et al. 2015
ethnic_frac*: Ethnolinguistic fractionalization (ELF) index, calculated as $1 - \sum_{i=1}^{N}(Proportion\ group\ i)^2$ (Alesina et al. 2003), where groups refer to ethnicity. Fractionalization is calculated across ethnic groups.	Vogt et al. 2015

data for this paper were retrieved on the 22^{th} of August 2025.

[6]The EPR data were downloaded from `https://icr.ethz.ch/data/epr/` on the 8^{th} of August 2025.

rel_frac*: Ethnolinguistic fractionalization (ELF) index, calculated as $1 - \sum_{i=1}^{N}(Proportion\, group\, i)^2$ (Alesina et al. 2003), where groups refer to religion. Fractionalization is calculated within ethnic groups, and the final value is the mean across groups. The EPR Ethnic Dimensions data documents internal characteristics of the ethnic groups in the core dataset, considering religion, language, and race (Bormann et al. 2017). Ethnic groups not included in the ethnic dimensions data take a value of zero for fractionalization, and the index is capped at zero if the sum of the squared proportions is larger than one.	Bormann et al. 2017
lang_frac*: Ethnolinguistic fractionalization (ELF) index, calculated as $1 - \sum_{i=1}^{N}(Proportion\, group\, i)^2$ (Alesina et al. 2003), where groups refer to language. Fractionalization is calculated within ethnic groups, and the final value is the mean across groups (further explanations above).	Bormann et al. 2017
race_frac*: Ethnolinguistic fractionalization (ELF) index, calculated as $1 - \sum_{i=1}^{N}(Proportion\, group\, i)^2$ (Alesina et al. 2003), where groups refer to race. Fractionalization is calculated within ethnic groups, and the final value is the mean across groups (further explanations above).[7]	Bormann et al. 2017
Geography Theme	
land*: The land area of a country in square kilometers. This variable is log-transformed ($log + 1$) in the models.	World-Bank 2025a
forest*: The proportion of land area covered by forest.	World-Bank 2025a
temp*: The average surface temperature (in °C) per year, which can be positive or negative.	CCKP 2024
co2*: The annual carbon dioxide (CO2) emissions (in Mega-tons of CO2 equivalent). This variable is log-transformed ($log + 1$) in the models.	World-Bank 2025a
percip*: The average precipitation per year (in millimeters).	World-Bank 2025a
waterstress*: Water stress refers to the proportion of annual freshwater withdrawals compared to all available water resources. This variable is log-transformed ($log + 1$) in the models.	World-Bank 2025a
agri_land*: The proportion of land area that can be used for agricultural production.	World-Bank 2025a
arable_land*: The proportion of land area that can be used for arable farming.	World-Bank 2025a

[7] There are two ethnic groups (43503000 and 81107000), which only take zeros for the proportions in the race category (although $phenotype1$ is not missing), which yields a fractionalization value of *one* based on the formula. The value of *one* is kept due to the lack of a better option.

rugged: Terrain ruggedness refers to the average difference in elevation (Nunn and Puga 2025). Missing values are imputed with the most similar match (e.g., South Sudan with Sudan). This variable is time-invariant.	Nunn and Puga 2012[8]
soil: The percentage of the total land area with fertile soil, understood as terrain without significant barriers to growing crops (Nunn and Puga 2025). Missing values are imputed with the closest match (e.g., South Sudan with Sudan). This variable is time-invariant.	Nunn and Puga 2012
desert: The percentage of the total land area covered with desert (Nunn and Puga 2025). Missing values are imputed with the closest match (e.g., South Sudan with Sudan). This variable is time-invariant.	Nunn and Puga 2012
tropical: The percentage of the land area with a tropical climate (Nunn and Puga 2025). Missing values are imputed with the most similar match (e.g., South Sudan with Sudan). This variable is time-invariant.	Nunn and Puga 2012
cont_africa: Dummy variable on whether the country is in Africa (Nunn and Puga 2025). Missing values are manually added.	Nunn and Puga 2012
cont_asia: Dummy variable on whether the country is in Asia (Nunn and Puga 2025). Missing values are manually added.	Nunn and Puga 2012
no_neigh: Dummy variable indicating whether a country has no direct neighbors (see further information above on how neighbors were coded). This variable is not available on the country-month.	geodatasource 2024
d_neighbors_non_dem*: Dummy variable indicating whether at least one neighbor is not democratic (see further information above on how neighbors were coded). A country-year is considered non-democratic if the liberal democracy index is ≤ 0.5. This variable is not available on the country-month.	V-Dem 2024b
Economy Theme	
natres_share*: Total natural resources rents as a proportion of the GDP. This variable is log-transformed $(log + 1)$ in the models.	World-Bank 2025a
oil_share*: Oil rents as a proportion of the GDP. This variable is log-transformed $(log + 1)$ in the models.	World-Bank 2025a
gas_share*: Natural gas rents as a proportion of the GDP. This variable is log-transformed $(log + 1)$ in the models.	World-Bank 2025a
coal_share*: Coal rents as a proportion of the GDP. This variable is log-transformed $(log + 1)$ in the models.	World-Bank 2025a
forest_share*: Forest rents as a proportion of the GDP. This variable is log-transformed $(log + 1)$ in the models.	World-Bank 2025a
mineral_share*: Mineral rents as a proportion of the GDP. This variable is log-transformed $(log + 1)$ in the models.	World-Bank 2025a

[8]The terrain ruggedness replication data were downloaded from `https://diegopuga.org/data/rugged/` on the 7^{th} of August 2025.

gdp*: The Gross Domestic Product (GDP) in current US dollars. The per capita value is obtained by dividing the GDP by the mid-year population. This variable is log-transformed ($log + 1$) in the models.	World-Bank 2025a
gni*: The Gross National Income (GNI) in current US dollars. The per capita value is obtained by dividing the GNI by the mid-year population.	World-Bank 2025a
gdp_growth*: The annual growth of the GDP. The growth rate is measured in percentage and can take positive and negative values.	World-Bank 2025a
unemploy*: The proportion of the labor force without employment.	World-Bank 2025a
unemploy_male*: The proportion of the male labor force without employment.	World-Bank 2025a
inflat*: A measure for inflation is the annual percentage change in the consumer price index, taking positive and negative values. This variable is log-modulus transformed ($log + 1$) in the models, which requires log-transforming the absolute value of X, and then multiplying it by the sign (John and Draper 1980).	World-Bank 2025a
conprice*: The consumer price index reflects the costs of obtaining a certain set of goods and services (in index units) if compared to a base period. The year 2010 is taken as a reference and is set to 100. This variable is log-transformed ($log + 1$) in the models.	World-Bank 2025a
undernour*: The proportion of the total population that is undernourished.	World-Bank 2025a
foodprod*: The annual food production index reflects the total production of all edible and nutritious food crops (in index units) if compared to a base period. Years 2014—2016 are the references and are set to 100.	World-Bank 2025a
water_rural*: The proportion of the rural population that has access to basic drinking water facilities.	World-Bank 2025a
water_urb*: The proportion of the urban population that has access to basic drinking water facilities.	World-Bank 2025a
agri_share*: The proportion of the total GDP that is obtained through agriculture, forestry, and fishing.	World-Bank 2025a
trade_share*: The proportion of the total GDP that is obtained through trade, considering both imports and exports.	World-Bank 2025a
fert: The fertility rate denotes the average number of children born per woman.	World-Bank 2025a
lifeexp_female: The female life expectancy at birth measured in years.	World-Bank 2025a
lifeexp_male: The male life expectancy at birth measured in years.	World-Bank 2025a
pop_growth*: The annual growth rate of the population. This variable can take positive and negative values.	World-Bank 2025a
inf_mort: The infant mortality rate is the number of infants who die before the age of one as a proportion of 1,000 births.	World-Bank 2025a

exports*: The proportion of the GDP that is obtained from the export of goods and services.	World-Bank 2025a
imports*: The proportion of the GDP that is obtained from the imports of goods and services.	World-Bank 2025a
primary_female*: The primary female school enrollment rate is the proportion of enrollment in comparison to everyone who *should* be enrolled.	World-Bank 2025a
primary_male*: The primary male school enrollment rate is the proportion of enrollment in comparison to everyone who *should* be enrolled.	World-Bank 2025a
second_female*: The secondary female school enrollment rate is the proportion of enrollment in comparison to everyone who *should* be enrolled.	World-Bank 2025a
second_male*: The secondary male school enrollment rate is the proportion of enrollment in comparison to everyone who *should* be enrolled.	World-Bank 2025a
tert_female*: The tertiary female school enrollment rate is the proportion of enrollment in comparison to everyone who *should* be enrolled.	World-Bank 2025a
tert_male*: The tertiary male school enrollment rate is the proportion of enrollment in comparison to everyone who *should* be enrolled.	World-Bank 2025a
eys*: The expected years of schooling.	UNDP 2024
eys_male*: The expected years of schooling for men.	UNDP 2024
eys_female*: The expected years of schooling for women.	UNDP 2024
mys*: The mean years of schooling.	UNDP 2024
mys_female*: The mean years of schooling for women.	UNDP 2024
mys_male*: The mean years of schooling for men.	UNDP 2024
Politics Theme	
armedforces_share*: The proportion of the armed forces personnel in comparison to the total labor force.	World-Bank 2025a
milex_share*: The military expenditure as a proportion of the GDP. This variable is log-transformed ($log + 1$) in the models.	World-Bank 2025a
corruption*: The control of corruption index measures perceptions on whether politics are free from personal gain (Kaufmann and Kraay 2024). The index is zero-centered. Negative values imply low control, and positive values suggest high control of corruption.	World-Bank 2025b
effectiveness*: The government effectiveness index measures perceptions on the quality of public services and the state's capability of implementing policies (Kaufmann and Kraay 2024). This variable is zero-centered, where negative values imply low quality, and positive values mean high quality.	World-Bank 2025b
polvio*: The political stability and absence of violence index measures perceptions on the danger to which a country might experience political instability and violence (Kaufmann and Kraay 2024). This index is zero-centered, where negative values imply a high risk of violence, and positive values mean a low risk.	World-Bank 2025b

regu*: The regulatory quality index measures perceptions on the extent to which the government can implement laws to effectively regulate the private sector (Kaufmann and Kraay 2024). This index is zero-centered. Negative values imply low regulatory quality, and positive values mean high regulatory quality.	World-Bank 2025b
law*: The rule of law index measures perceptions on the extent to which the judiciary upholds the rule of law (Kaufmann and Kraay 2024). This index is zero-centered, where negative values imply a low rule of law, and positive values mean a high rule of law.	World-Bank 2025b
account*: The voice and accountability index measures perceptions on the level to which political participation and civic freedoms are protected (Kaufmann and Kraay 2024). This variable is zero-centered, where negative values imply low accountability, and positive values suggest high accountability	World-Bank 2025b
tax*: The proportion of the GDP that is obtained by taxes. This variable is log-transformed ($log + 1$) in the models.	World-Bank 2025a
broadband*: The number of Internet broadband subscriptions per 100 people.	World-Bank 2025a
telephone*: The number of telephone subscriptions per 100 people.	World-Bank 2025a
internet_use*: The proportion of individuals with access to the Internet in comparison to the total population.	World-Bank 2025a
mobile*: The number of mobile phone subscriptions per 100 people.	World-Bank 2025a
polyarchy: Electoral democracy indicates if the principles of electoral democracies are implemented (V-Dem 2024a). The index ranges between zero and one, where higher values suggest stronger implementation.	V-Dem 2024b
libdem*: Liberal democracy indicates if the principles of liberal democracies are implemented (V-Dem 2024a). The index ranges from zero to one, where higher values suggest stronger implementation.	V-Dem 2024b
partipdem: Participatory democracy indicates if the principles of participatory democracies are implemented (V-Dem 2024a). The index ranges from zero to one, where higher values suggest stronger implementation.	V-Dem 2024b
delibdem: Deliberative democracy indicates the degree to which the principles of deliberative democracies are implemented (V-Dem 2024a). The index ranges between zero and one, where higher values suggest stronger democratic institutions.	V-Dem 2024b
egaldem: Egalitarian democracy indicates whether the principles of egalitarian democracies are implemented (V-Dem 2024a). The index ranges from zero to one, where higher values suggest stronger implementation.	V-Dem 2024b
civlib: Civil liberties indicate the degree to which civil liberties are protected (V-Dem 2024a). The index ranges from zero to one, where higher values suggest stronger protection.	V-Dem 2024b

phyvio: Physical violence measures if physical integrity is protected (V-Dem 2024a). The index takes values between zero and one, where higher scores suggest stronger protection.	V-Dem 2024b
pollib: Political civil liberties indicate whether political liberties are protected (V-Dem 2024a). The index ranges from zero to one, where higher values suggest stronger protection.	V-Dem 2024b
privlib: Private civil liberties indicate whether private civil liberties are protected (V-Dem 2024a). The index ranges between zero and one, where higher values suggest stronger protection.	V-Dem 2024b
execon*: Exclusion by socioeconomic group indicates if there is exclusion from services and politics based on status (V-Dem 2024a). The variable ranges from zero to one, where high values imply stronger exclusion.	V-Dem 2024b
exgender*: Exclusion by gender indicates if there is exclusion from services and politics based on gender (V-Dem 2024a). The variable ranges between zero and one, where high values imply stronger exclusion.	V-Dem 2024b
exgeo*: Exclusion by urban-rural divide indicates if there is exclusion from services and politics based on location (V-Dem 2024a). The variable ranges from zero to one, where high values imply stronger exclusion.	V-Dem 2024b
expol*: Exclusion by political group indicates if there is exclusion based on political affiliation (V-Dem 2024a). The variable ranges from zero to one, with high values implying stronger exclusion.	V-Dem 2024b
exsoc*: Exclusion by social group indicates if there is exclusion from services and politics based on social group (V-Dem 2024a). The variable ranges between zero and one, where high values imply stronger exclusion.	V-Dem 2024b
shutdown*: The frequency of Internet shutdowns by the government (V-Dem 2024a). This variable takes positive and negative values, where negative values imply that the government shuts down the Internet often, while positive values imply that shutdowns occur rarely.	V-Dem 2024b
filter*: The frequency to which the government filters the Internet (V-Dem 2024a). This variable takes positive and negative values. Negative values imply that the government filters the Internet often, while positive values mean that filtering occurs rarely.	V-Dem 2024b
tenure_months*: The number of months that the incumbent political leader has been in office (Besaw 2021), counting the months at the end of each year when the level of analysis is country-year. For the country-month, the original variable is used.	Curtis et al. 2021[9]
dem_duration*: The log-transformed number of months that a country has been democratic (Besaw 2021), counting the months at the end of each year for the country-year level of analysis. For the country-month, the original variable is used.	Curtis et al. 2021

[9]When a regime change occurs, REIGN codes duplicate entries: One country-month with the old and one with the new leader. In those cases, the observation with the old leader is kept.

elections*/election_recent*: Dummy variable measuring whether there was an election taking place that year (Besaw 2021) when the level of analysis is country-year. For the country-month, the variable denotes whether there was an election in any of the preceding six months (Besaw 2021). Imputed values are dichotomized post-hoc (coding > 0.5 as *one*).	Curtis et al. 2021
lastelection*: The inverted decay of the time since the last election (Besaw 2021), considering the end-of-year value when the level of analysis is country-year. For the country-month, the original variable is used.	Curtis et al. 2021

Table C1. Operationalization table for the variables included in the structural models. Variables marked with * have missing values, which are imputed based on the procedures explained in Section C.1. In that case, an additional dummy variable is included, indicating that the observation was filled in. Right-skewed variables are log-transformed ($log + 1$).

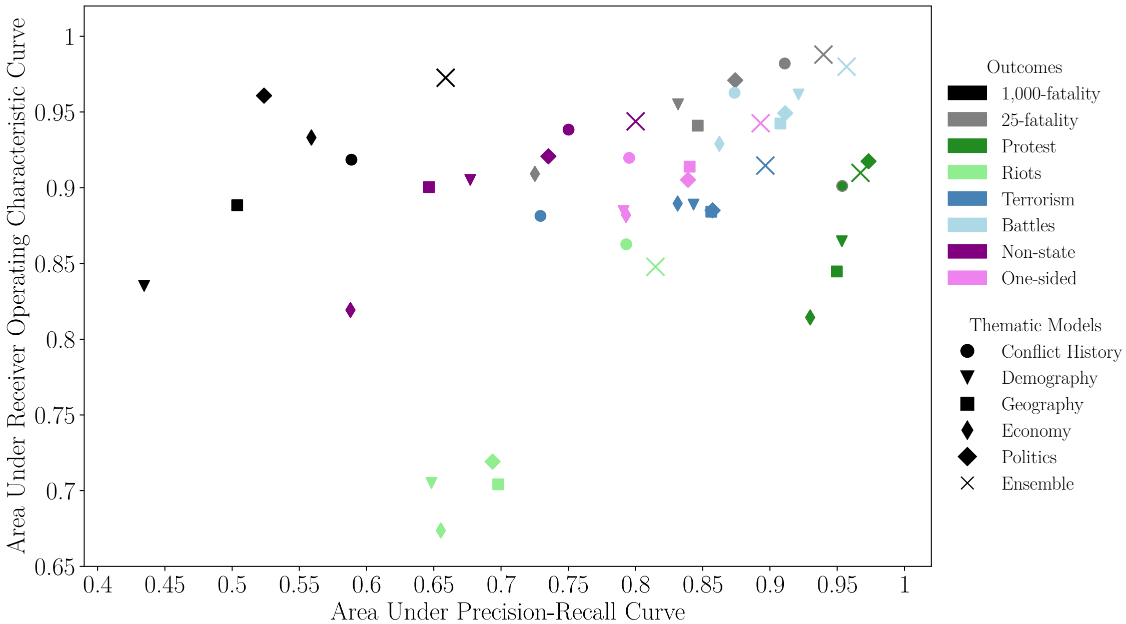


Figure C.1: Area Under the Precision-Recall Curve (x-axis), and the Area Under the Receiver Operating Characteristic Curve (y-axis), comparing the five thematic models across the six outcomes. Two theoretical baselines are included, indicating whether fatalities from civil conflict surpass 25 (gray) or 1,000 (black) deaths. The ensemble models are indicated by the X-marker.

	Baseline	History	Demography	Geography	Economy	Politics	Ensemble
1,000-fatality	0.04762	0.02288	0.0368	0.03621	0.0325	0.02883	0.02498
25-fatality	0.19048	0.02829	0.06376	0.06655	0.09317	0.05683	0.03988
Protest	0.79093	0.08656	0.15752	0.1794	0.15273	0.1627	0.14085
Riots	0.43073	0.15104	0.21996	0.22324	0.22837	0.2135	0.16036
Terrorism	0.35714	0.12734	0.12464	0.11554	0.13698	0.12684	0.10706
Battles	0.26786	0.05256	0.0742	0.06842	0.10362	0.08052	0.05495
Non-state	0.1631	0.05944	0.083	0.08711	0.10114	0.07446	0.06556
One-sided	0.28095	0.08976	0.11593	0.1003	0.1262	0.10415	0.08881

Table C2. Brier scores for each thematic model across outcomes. The ensemble and a technical baseline (predicts most common class) are likewise included.

	Baseline	History	Demography	Geography	Economy	Politics	Ensemble
1,000-fatality	0.52381	0.58873	0.43457	0.50381	0.55897	0.52375	0.65881
25-fatality	0.59524	0.91102	0.83166	0.84627	0.7252	0.87421	0.9398
Protest	0.89547	0.95375	0.95349	0.94972	0.92992	0.97334	0.96733
Riots	0.71537	0.79314	0.64824	0.69791	0.65523	0.69372	0.81489
Terrorism	0.67857	0.72933	0.8432	0.85641	0.83137	0.85736	0.89657
Battles	0.63393	0.87368	0.92128	0.90782	0.86238	0.91137	0.95702
Non-state	0.58155	0.75023	0.67712	0.64647	0.58801	0.73525	0.80012
One-sided	0.64048	0.79532	0.79114	0.84028	0.793	0.83907	0.89312

Table C3. Area Under the Precision-Recall Curve (AUPR) for each thematic model across outcomes. The ensemble and a technical baseline (predicts most common class) are likewise included.

	Baseline	History	Demography	Geography	Economy	Politics	Ensemble
1,000-fatality	0.5	0.91852	0.83525	0.88845	0.93316	0.9608	0.97262
25-fatality	0.5	0.98204	0.95507	0.941	0.90919	0.97094	0.9879
Protest	0.5	0.90117	0.86464	0.84473	0.81439	0.91747	0.90982
Riots	0.5	0.86267	0.70503	0.70418	0.67374	0.71916	0.84779
Terrorism	0.5	0.8814	0.88889	0.88418	0.88958	0.88507	0.91464
Battles	0.5	0.9627	0.96154	0.94239	0.92899	0.94921	0.97992
Non-state	0.5	0.93837	0.90518	0.90044	0.81927	0.92077	0.94384
One-sided	0.5	0.91972	0.88468	0.91391	0.88198	0.90524	0.94263

Table C4. Area Under the Receiver Operating Characteristic Curve (AUROC) for each thematic model across outcomes. The ensemble and a technical baseline (predicts most common class) are likewise included.

C.1 Imputing Missing Values

To impute missing values, linear interpolation, mean imputation, and multivariate imputation techniques are applied. The combination of those imputation strategies was carefully developed by visually inspecting the original time series and the imputed ones (Figure C.2 shows examples). To further remedy potential biases, each variable with imputed values gets assigned a dummy (*_id), taking a value of one if the observation was imputed. These dummy variables are included in the models.

For one, the imputation of missing values is a challenging field, and filling in values can bias correlations in predictive modeling, especially the more extreme the level of missingness (Gorelick 2006).[10] For another, missingness in conflict data is hardly random. The likelihood of missingness is dependent on the statistical capacities of a country. Countries with weak statistical capacity, commonly weak states with poor economic performance, have a higher probability of missingness. Armed conflict is more frequent in those contexts as well, and therefore, the risk of armed conflict is correlated with the likelihood of missingness. This is concerning given that complete case analysis only offers unbiased estimates if missingness is 'completely at random' (Donders et al. 2006).

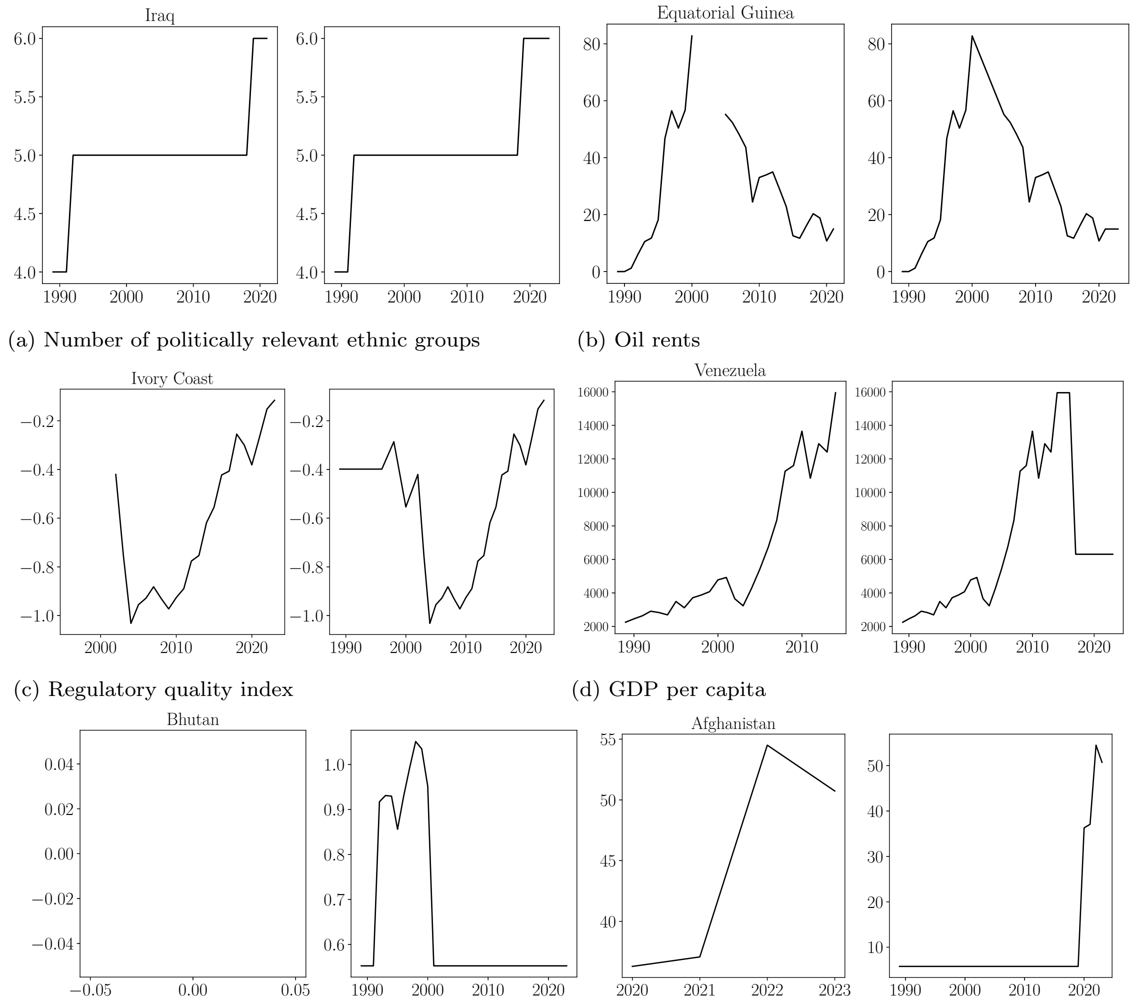
Since missingness in conflict data is not 'completely at random', missing values need to be imputed. This is further substantiated by the vast extent of missingness, which would require dropping a large number of observations in complete case analysis. The data used in this work are time series, and conventional imputation techniques (i.e., multivariate imputation) yield unrealistic results, where the imputed value falls outside of the trend (Honaker and King 2010). Linear interpolation and mean imputation are preferred. Multivariate imputation techniques are only applied when a country is completely missing, given that linear interpolation and mean imputation cannot be used.

Linear interpolation fills in missing values with a linear function and is often the default technique, because it works well for time series data (Noor et al. 2014). Missing values at the

[10] The imputation strategy likewise has an impact on model performance in conflict forecasting (Randahl 2022).

edges are extrapolated. Since the empirical strategy relies on forecasting, the imputation needs to adhere to a train-test split. For the test and validation data, linear interpolation is only implemented forward, while the training data allows for both directions. Cases where the test and validation data are completely missing are obtained with mean imputation. In mean imputation, the missing observation is replaced with the mean of existing cases (Noor et al. 2014). Only the training data are considered to avoid data leakage. While this can lead to unrealistic dents (see Figure C.2d), referring back to the training mean is the most conservative option.

For countries completely missing (whole dataset or training data), multivariate imputation techniques are applied, which fill missing values based on the values of other variables (scikit-learn 2025). Ridge Regression, a linear model with a penalty (λ) to control the size of the slopes (Hastie et al. 2017), is selected as the imputation model. λ is set to the default in the `scikit-learn` library. To predict missing observations, an input matrix for the `IterativeImputer` is constructed. The matrix includes the variable to be imputed, the $t-1$ until $t-5$ preceding values, and additional variables with a similar theme (e.g., other regime type indices for liberal democracy, etc.). The additional variables are set to zero in case of missingness. The imputation model is fitted in the training data, then used to fill in missing values in the test and validation data. While the multivariate imputation model seems to have a slight downward bias (see Figures C.2e and C.2f), more conservative values are less concerning than sudden surges in the time trend.



(a) Number of politically relevant ethnic groups (b) Oil rents (c) Regulatory quality index (d) GDP per capita (e) Military expenditure (f) Imports percentage of GDP

Figure C.2: Some examples are shown to validate the imputation strategies. For each panel, the original time series (left) and the time series after imputing missing values are presented (right). (a) linear interpolation forwards, (b) linear interpolation in between, (c) linear interpolation backward in the training data, (d) linear interpolation forward and mean imputation in the test data, (e) multivariate imputation for countries completely missing, and (f) multivariate imputation for countries completely missing in training data.

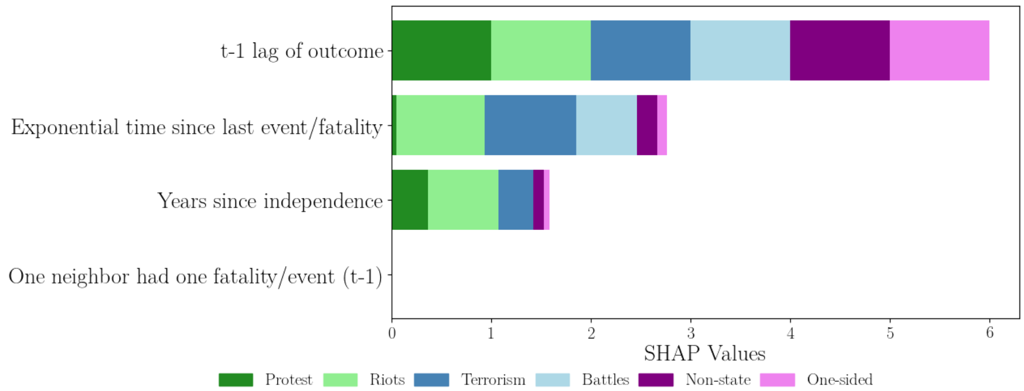
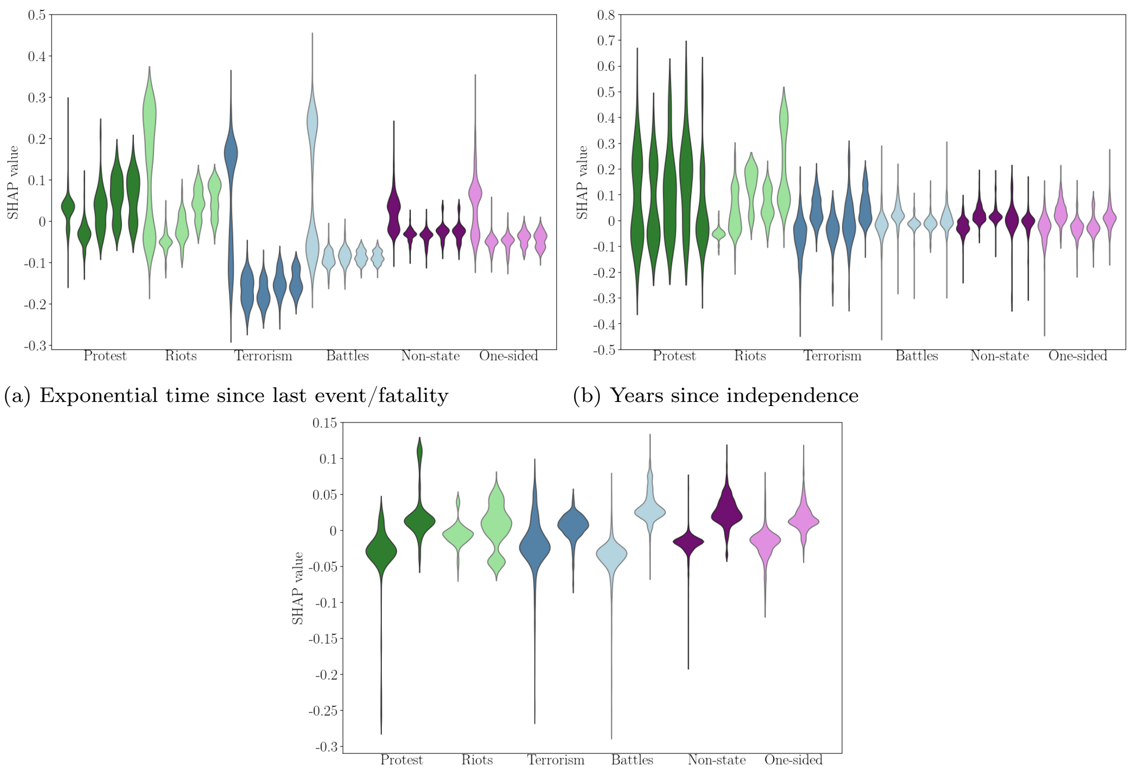


Figure C.3: SHAP scores (*min-max* normalized) for features in the conflict history theme.[a]

[a]For each variable, the mean of the absolute SHAP values across observations is calculated. To allow for an easier comparison, the means are *min-max* normalized, so that the variable with the highest absolute SHAP takes a value of one, and the variable with the lowest a value of zero.



(a) Exponential time since last event/fatality

(b) Years since independence

(c) One neighbor had one event/fatality ($t-1$)

Figure C.4: SHAP values for the conflict history theme. The continuous variables are binned into categories for better visibility. Protests are shown in dark green, riots in light green, terrorism in dark blue, battles in light blue, non-state conflict in purple, and one-sided violence in pink.

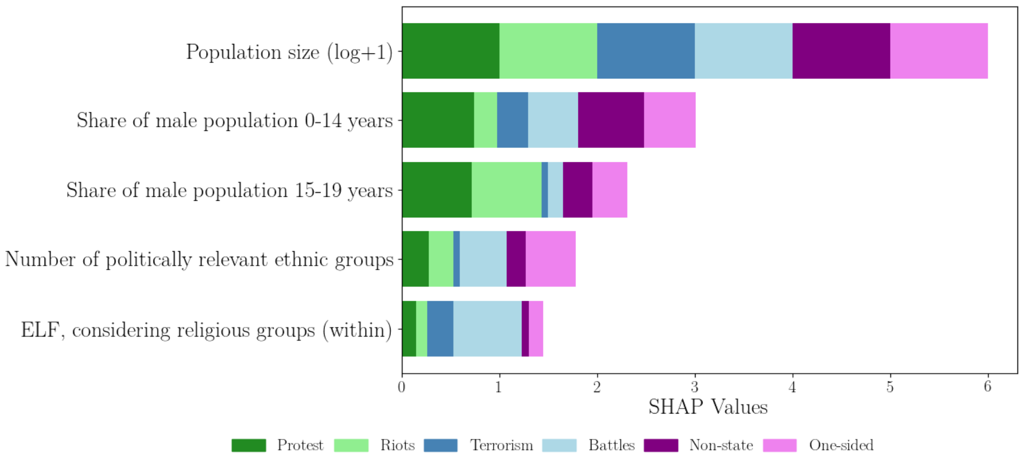
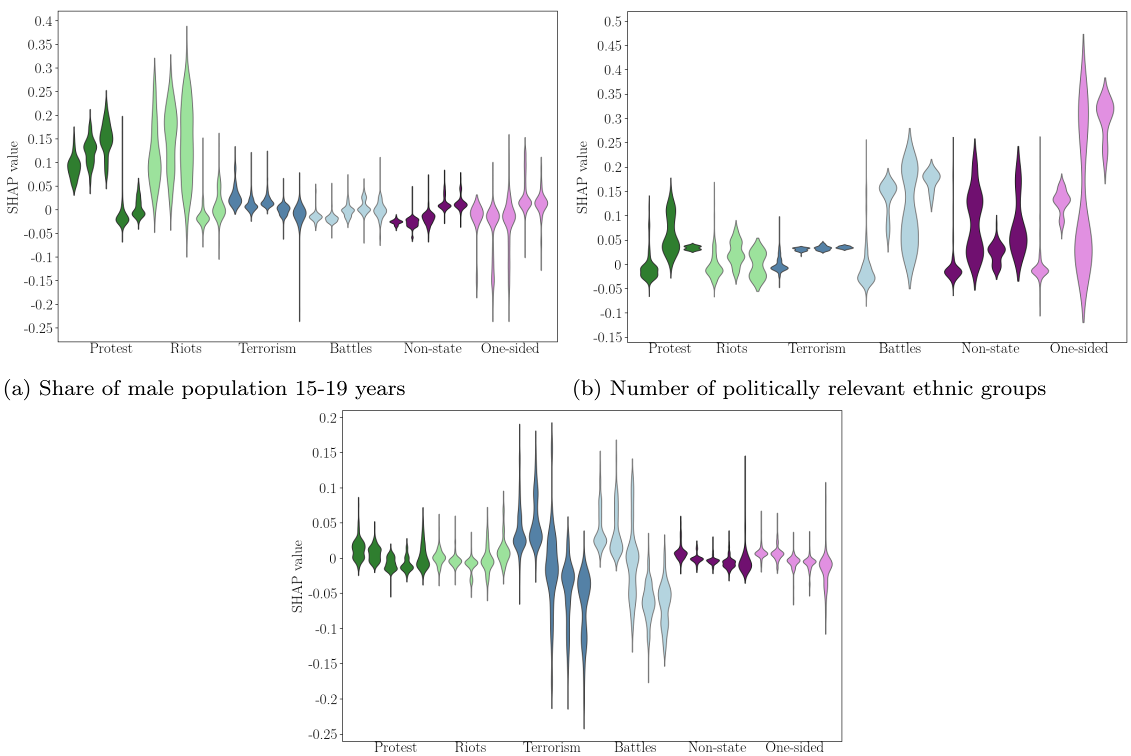


Figure C.5: SHAP scores (*min-max* normalized) for the most important features in the demography theme.



(a) Share of male population 15-19 years

(b) Number of politically relevant ethnic groups

(c) ELF, considering religious groups (within)

Figure C.6: SHAP values for the most important variables in the demography theme. The continuous variables are binned into categories for better visibility. Protests are shown in dark green, riots in light green, terrorism in dark blue, battles in light blue, non-state conflict in purple, and one-sided violence in pink.

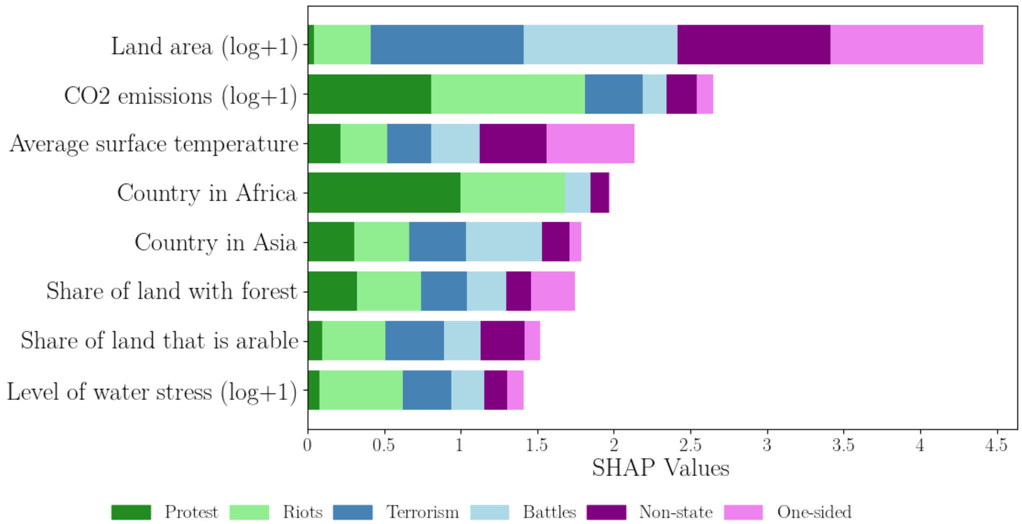
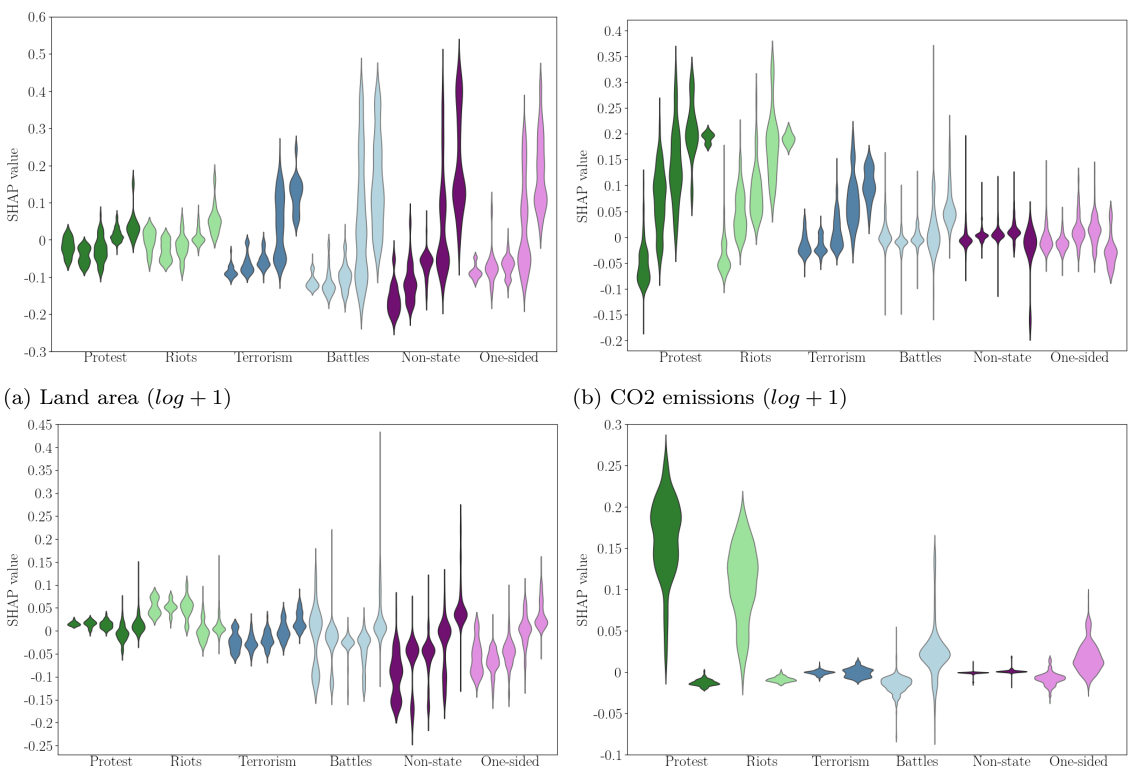


Figure C.7: SHAP scores (*min-max* normalized) for the most important features in the geography theme.



(a) Land area ($log + 1$)

(b) CO2 emissions ($log + 1$)

(c) Average surface temperature

(d) Country in Africa

Figure C.8: SHAP values for the most important variables in the geography theme. The continuous variables are binned into categories for better visibility. Protests are shown in dark green, riots in light green, terrorism in dark blue, battles in light blue, non-state conflict in purple, and one-sided violence in pink.

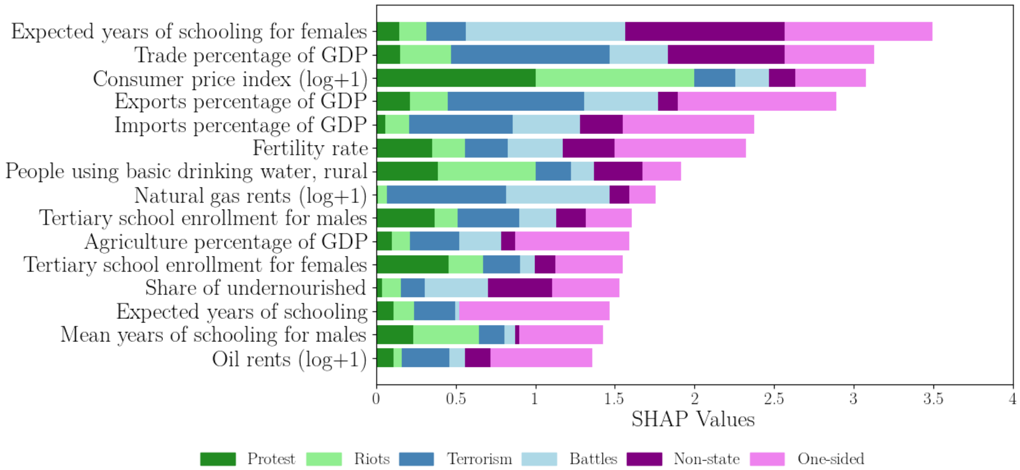


Figure C.9: SHAP scores (*min-max* normalized) for the most important features in the economy theme.

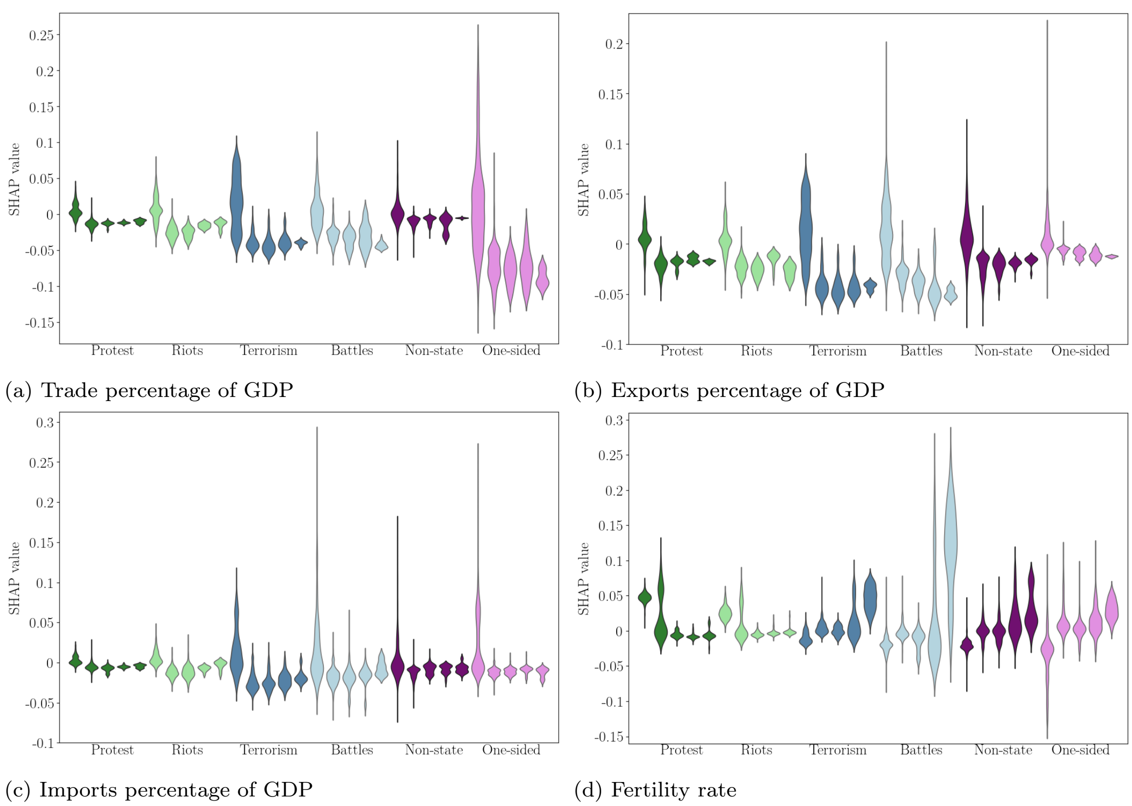


Figure C.10: SHAP values for the most important variables in the economy theme. The continuous variables are binned into categories for better visibility. Protests are shown in dark green, riots in light green, terrorism in dark blue, battles in light blue, non-state conflict in purple, and one-sided violence in pink.

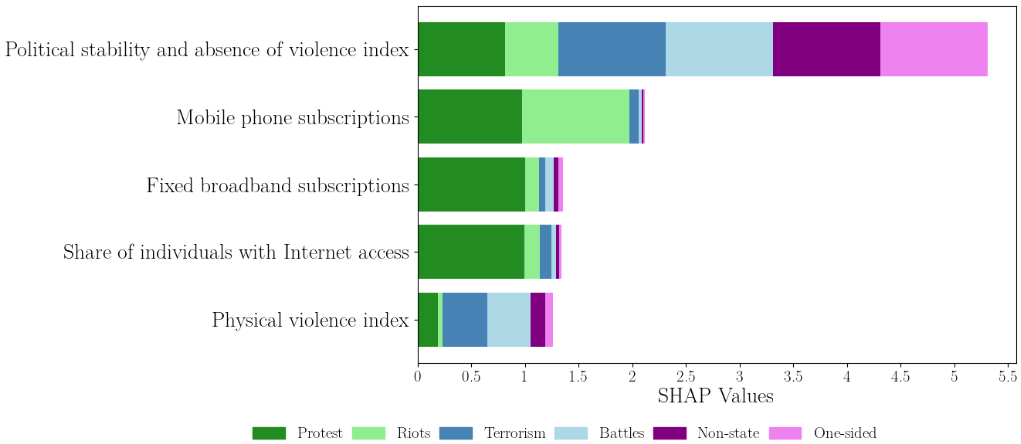
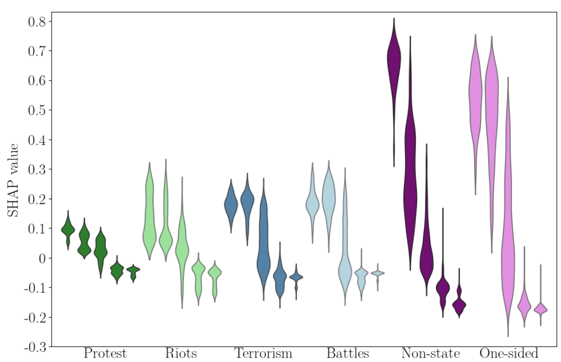
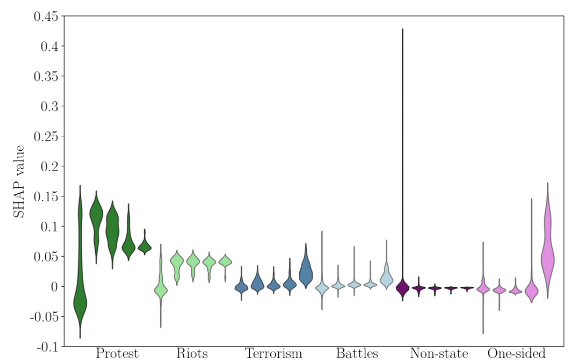


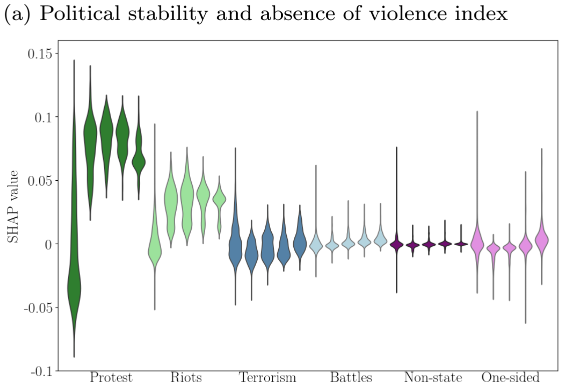
Figure C.11: SHAP scores (*min-max* normalized) for the most important features in the politics theme.



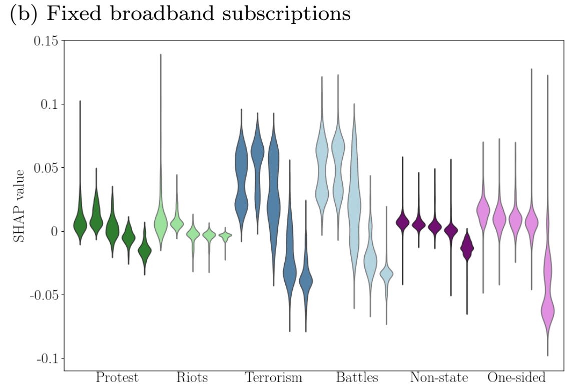
(a) Political stability and absence of violence index



(b) Fixed broadband subscriptions



(c) Share of individuals with Internet access



(d) Physical violence index

Figure C.12: SHAP values for the most important variables in the politics theme. The continuous variables are binned into categories for better visibility. Protests are shown in dark green, riots in light green, terrorism in dark blue, battles in light blue, non-state conflict in purple, and one-sided violence in pink.

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D Appendix—From Protests to Fatalities

Name: Description	**Source**
GDP per capita: The annual Gross Domestic Product (GDP) in current US Dollars. The per capita value is calculated by dividing the total GDP by the mid-year population. This variable is log-transformed in the models (*log*).	World-Bank 2025
Population size: The total number of mid-year residents in a country. This variable is log-transformed in the models (*log*).	World-Bank 2025
Liberal democracy index: This index denotes the degree to which the principles of liberal democracies are implemented, ranging between zero and one, where higher values mean a higher degree of implementation (V-Dem 2024a).	V-Dem 2024b
Physical violence index: This index denotes the degree to which physical integrity is respected, ranging between zero and one, where higher values mean a higher respect for physical integrity (V-Dem 2024a).	V-Dem 2024b
Political corruption index: This index denotes the level of corruption, ranging between zero and one, where higher values imply a higher level of corruption (V-Dem 2024a).	V-Dem 2024b
Rule of law index: This index denotes the degree to which laws are consistently and impartially applied, ranging between zero and one, where higher values imply a stronger rule of law (V-Dem 2024a).	V-Dem 2024b
Civil liberties index: This index denotes the degree to which civil liberties are respected, ranging from zero to one, where higher values imply a higher respect for civil liberties (V-Dem 2024a).	V-Dem 2024b
Neopatrimonial rule index: This index measures the degree to which political power is grounded in personal authority, ranging between zero and one, where higher values imply stronger neopatrimonial rule (V-Dem 2024a).	V-Dem 2024b

Table D1. Operationalization table for the control variables. Since the control variables are only available annually, values within years are constant.

Note: The World Bank data are accessed via the World Bank data API, using the `wbgapi` library in Python (`https://pypi.org/project/wbgapi/`). The data were retrieved on the 22^{th} of August 2025.

	Dependent Variable: Fatalities ($log+1$)				
	(1)	(2)	(3)	(4)	(5)
Number of Protest Events (*min-max*)	0.079* (0.033)	0.067* (0.032)	0.049 (0.037)		0.047 (0.036)
Lag 1: Number of Protest Events (*min-max*)	0.047 (0.044)	0.059 (0.053)	0.030 (0.043)		0.053 (0.053)
Lag 2: Number of Protest Events (*min-max*)	0.012 (0.033)	0.004 (0.035)	−0.004 (0.034)		−0.007 (0.036)
Lag 3: Number of Protest Events (*min-max*)	0.099* (0.046)	0.078^o (0.046)	0.079^o (0.048)		0.068 (0.049)
Cluster 1		0.081* (0.034)		0.056^o (0.033)	0.054 (0.033)
Cluster 2		0.032 (0.028)		0.024 (0.028)	0.011 (0.031)
Cluster 3		0.073* (0.037)		0.071^o (0.038)	0.061 (0.040)
Cluster 5		0.054* (0.025)		0.045^o (0.025)	0.040 (0.026)
Lag 1: Fatalities ($log+1$)	0.826*** (0.024)	0.824*** (0.024)	0.697*** (0.034)	0.697*** (0.034)	0.696*** (0.034)
GDP per Capita (log)	-0.023^o (0.012)	−0.027* (0.013)	−0.080 (0.050)	-0.083^o (0.050)	−0.078 (0.050)
Population Size (log)	0.046*** (0.012)	0.042*** (0.011)	0.342^o (0.206)	0.349^o (0.207)	0.299 (0.199)
Liberal Democracy	0.169 (0.210)	0.182 (0.210)	−0.439 (0.560)	−0.448 (0.561)	−0.426 (0.559)
Physical Violence	0.052 (0.159)	0.054 (0.160)	−0.077 (0.429)	−0.078 (0.426)	−0.068 (0.426)
Political Corruption	0.141 (0.134)	0.145 (0.135)	0.435 (0.447)	0.445 (0.446)	0.448 (0.444)
Rule of Law	−0.083 (0.225)	−0.041 (0.227)	0.208 (0.658)	0.193 (0.646)	0.229 (0.650)
Civil Liberties	−0.359 (0.246)	−0.389 (0.248)	−0.566 (0.833)	−0.573 (0.827)	−0.580 (0.828)
Neopatrimonial Rule	−0.109 (0.204)	−0.075 (0.207)	−0.976 (0.651)	−1.017 (0.641)	−0.951 (0.643)
Constant	−0.342 (0.277)	−0.311 (0.277)	−3.065 (3.711)	−3.166 (3.799)	−2.418 (3.633)
Country Fixed Effects	No	No	Yes	Yes	Yes
Clustered by Country	Yes	Yes	Yes	Yes	Yes
F-value (joint significance of clusters)		7.31***		3.56**	3.6**
R-squared	0.744	0.745	0.762	0.762	0.762
Number of Observations	23126	23126	23126	23126	23126

o p<0.1; * p<0.05; ** p<0.01; *** p<0.001. Country-clustered standard errors in parentheses.

Table D2. OLS regression on the log-transformed number of conflict-related fatalities (log +1), using static protest variables, dynamic protest variables, and a set of control variables.

	MSE
RR	0.02216 (0.103)
DRR	0.0191*** (0.09)
RRX	0.02107^{o} (0.105)
DRRX	0.01882*** (0.089)

o p<0.1; * p<0.05; ** p<0.01; *** p<0.001, *t* test for paired samples comparing model variants to the baseline RR or RRX. Standard errors are shown in parentheses.

Table D3. Mean squared error (MSE) for each model variant, baseline Ridge Regression (RR), dynamic RR (DRR), RR with additional static covariates (RRX), and RR including static and dynamic covariates (DRRX).

	MSE
RF	0.01971 (0.088)
DRF	0.01788*** (0.082)
RFX	0.01772*** (0.079)
DRFX	0.0159*** (0.074)

o p<0.1; * p<0.05; ** p<0.01; *** p<0.001, *t* test for paired samples comparing model variants to the baseline RF or RFX. Standard errors are shown in parentheses.

Table D4. Mean squared error (MSE) for each model variant, baseline Random Forest (RF), dynamic RF (DRF), RF with additional static covariates (RFX), and RF including static and dynamic covariates (DRFX).

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E Appendix—From Structure to Action

Name: Description	Source
Zero-inflation Process	
Fatalities in civil conflict ($t-1$): The $t-1$ lag for the number of fatalities in civil conflict. Events between states and events that occur over several months are excluded. This variable is log-transformed in the model ($log+1$).	Sundberg and Melander 2013
Fatalities in civil conflict ($t-2$): The $t-2$ lag for the number of fatalities in civil conflict. Events between states and events that occur over several months are excluded. This variable is log-transformed in the model ($log+1$).	Sundberg and Melander 2013
Fatalities in civil conflict ($t-3$): The $t-3$ lag for the number of fatalities in civil conflict. Events between states and events that occur over several months are excluded. This variable is log-transformed in the model ($log+1$).	Sundberg and Melander 2013
GDP per capita (log): The total Gross Domestic Product (GDP) in current US Dollars, divided by the mid-year population. This variable is log-transformed in the model (log).	World-Bank 2025
Count Process	
Fatalities in civil conflict ($t-1$): The $t-1$ lag for the number of fatalities in civil conflict. Events between states and events that occur over several months are excluded. This variable is log-transformed in the model ($log+1$).	Sundberg and Melander 2013
Fatalities in civil conflict ($t-2$): The $t-2$ lag for the number of fatalities in civil conflict. Events between states and events that occur over several months are excluded. This variable is log-transformed in the model ($log+1$).	Sundberg and Melander 2013
Fatalities in civil conflict ($t-3$): The $t-3$ lag for the number of fatalities in civil conflict. Events between states and events that occur over several months are excluded. This variable is log-transformed in the model ($log+1$).	Sundberg and Melander 2013
Population size (log): The total number of residents in a country. This variable is log-transformed in the model (log).	World-Bank 2025
GDP per capita (log): The total Gross Domestic Product (GDP) in current US Dollars, divided by the mid-year population. This variable is log-transformed in the model (log).	World-Bank 2025
GDP growth: The annual growth rate of the GDP, measured in percentage. The variable takes negative and positive values.	World-Bank 2025

Table E1. Operationalization table for variables in the Zero-inflated Negative Binomial (ZINB) regression model. The model specification is adapted from Bagozzi (2015).

Note: The UCDP GED version 24 was downloaded from `https://ucdp.uu.se/downloads/ged/ged241-csv.zip` on the 9^{th} of August 2025. The World Bank data were accessed via the API, using `wbgapi` in Python (`https://pypi.org/project/wbgapi/`). The data for this paper were retrieved on the 22^{th} of August 2025.

	$\epsilon_t = 0$	$\epsilon_t = 1$	$\epsilon_t = 2$	$\epsilon_t = 3$
-0.001	1	0.999	0.998	0.997
-0.005	1	0.995	0.99	0.9851
-0.01	1	0.99	0.9802	0.9704
-0.05	1	0.9512	0.9048	0.8607
-0.1	1	0.9048	0.8187	0.7408

Table E2. An exponential penalty with balancing factors $e^{-0.01}$ is applied to reward low temporal errors in the Onset score metric. The error tolerance is set to ± 3, which means that the temporal error (ϵ_t) has potential values of 0,1,2, or 3. A temporal error of 0 leads to no penalty, and the onset is counted in full. Balancing factor -0.01 leads to an *ideal* weighting, while larger values penalize the temporal error too severely, and lower values have too little impact.

$lags$	$thres$	Onset score	MSLE
$t-1$	0.35	0.076590	1.717122
$t-3$	0.35	0.069481	1.965817
$t-5$	0.35	0.069481	1.949781
$t-4$	0.35	0.069481	1.960915
$t-2$	0.35	0.069481	1.845167
$t-1$	0.3	0.056267	1.942005
$t-3$	0.3	0.052478	2.343054
$t-5$	0.3	0.052478	2.436285
$t-2$	0.3	0.052478	2.149989
$t-4$	0.3	0.052478	2.371904
$t-1$	0.4	0.038547	1.442652
$t-4$	0.4	0.034757	1.593484
$t-3$	0.4	0.034757	1.583674
$t-5$	0.4	0.034757	1.593644
$t-2$	0.4	0.034757	1.516395
$t-1$	0.25	0.032974	2.316984
$t-3$	0.25	0.021443	2.824542
$t-4$	0.25	0.021443	2.862112
$t-2$	0.25	0.021443	2.613100
$t-5$	0.25	0.021443	2.917348
$t-1$	0.2	0.018318	2.721961
$t-1$	0.15	0.017177	3.099381
$t-2$	0.15	0.012681	3.669601
$t-3$	0.15	0.007799	3.866819
$t-4$	0.15	0.007799	4.019963
$t-5$	0.15	0.007799	4.085066
$t-3$	0.2	0.000000	3.499956
$t-4$	0.2	0.000000	3.608992
$t-2$	0.2	0.000000	3.260086
$t-5$	0.2	0.000000	3.581996

Table E3. Onset score and Mean squared logarithmic error (MSLE) for different $lags$ and $thres$ values, considering out-of-sample predictions in the validation data (2020—2021). The best performing hyperparameters are $lags = t-1$ and $thres = 0.35$. Optimizing the threshold is more relevant than tuning the number of lags, and fewer lags lead to better performance.

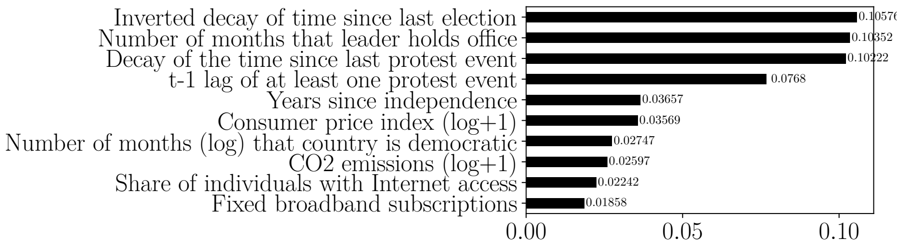


Figure E.1: Feature importance scores for the ten most important features in *stage i* (using data until 2019 during training), when predicting at least one protest event.

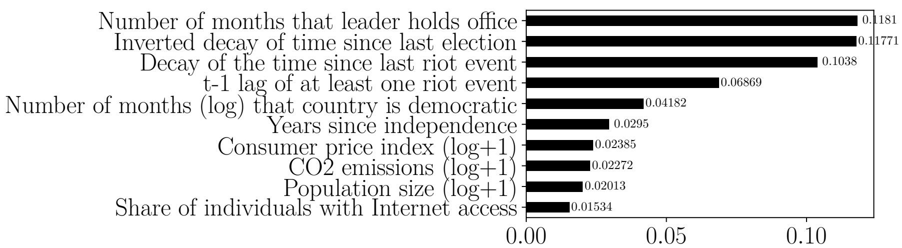


Figure E.2: Feature importance scores for the ten most important features in *stage i* (using data until 2019 during training), when predicting at least one riot event.

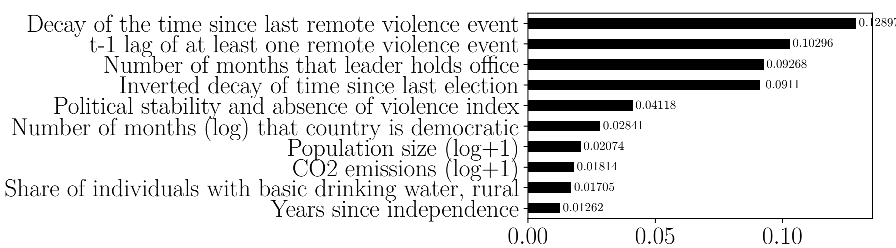


Figure E.3: Feature importance scores for the ten most important features in *stage i* (using data until 2019 during training), when predicting at least one remote violence event.

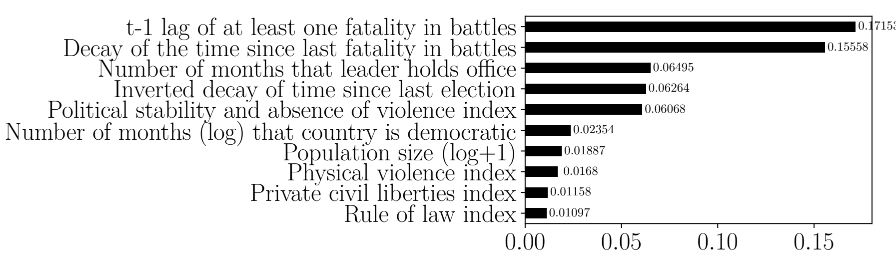


Figure E.4: Feature importance scores for the ten most important features in *stage i* (using data until 2019 during training), when predicting at least one fatality in battles.

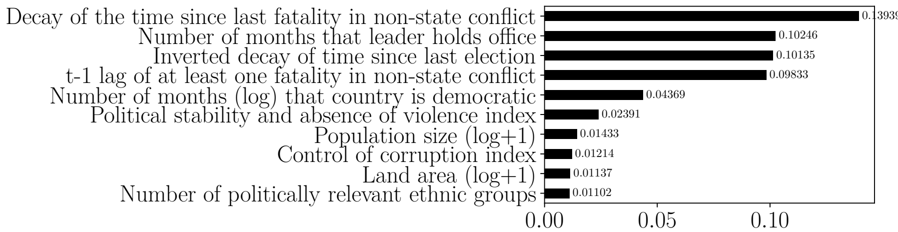


Figure E.5: Feature importance scores for the ten most important features in *stage i* (using data until 2019 during training), when predicting at least one fatality in non-state conflict.

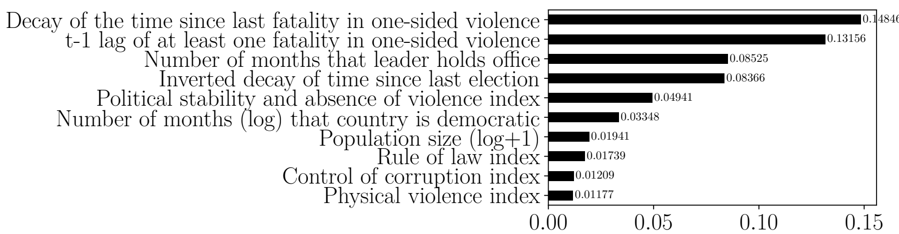


Figure E.6: Feature importance scores for the ten most important features in *stage i* (using data until 2019 during training), when predicting at least one fatality in one-sided violence.

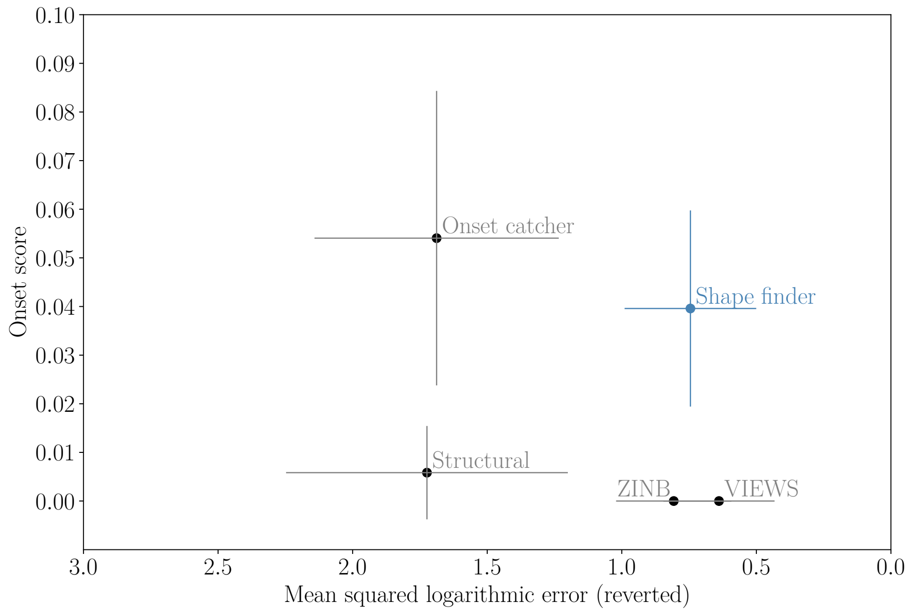


Figure E.7: The performance of the Onset catcher is validated against the Shape finder (Schincariol et al. 2025). The Onset catcher outperforms the Shape finder at anticipating onsets, as indicated by the higher Onset score. However, the Shape finder (blue) shows a surprisingly high value on the Onset score, despite having hard-coded onset cases by always predicting zero for $flat$ inputs. This unexpected finding is further unpacked in Figures E.8 and E.9.

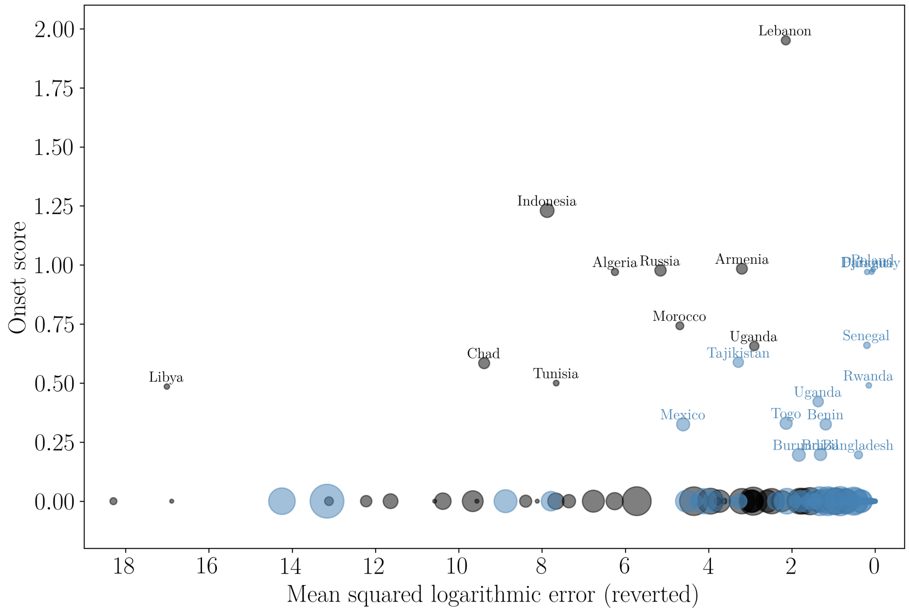
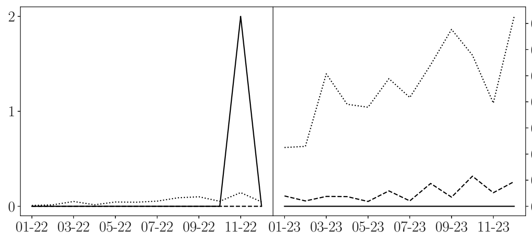
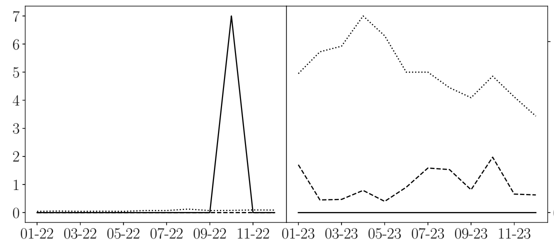


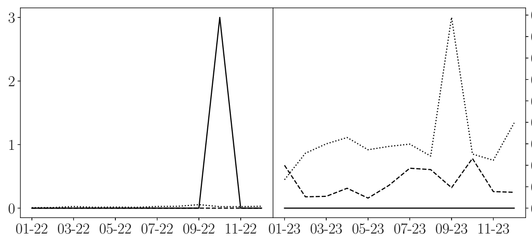
Figure E.8: The Mean squared logarithmic error (reverted) and the Onset score are shown for each country. The black markers refer to the Onset catcher, and blue to the Shape finder. The size of the marker indicates the sum of observed fatalities in the prediction window ($log + 1$). The Shape finder has a comparatively high Onset score for some countries while maintaining a low prediction error. Figure E.9 discusses some selected cases.



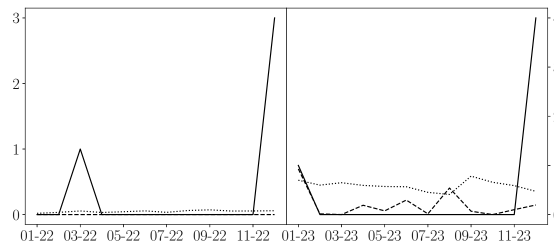
(a) Poland



(b) Djibouti

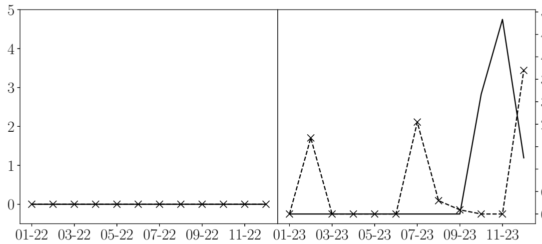


(c) Paraguay

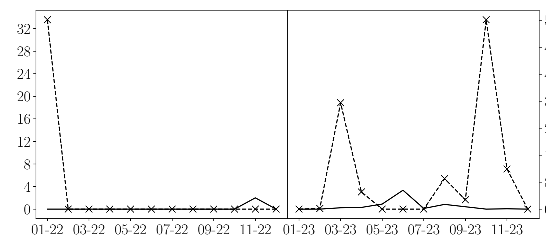


(d) Senegal

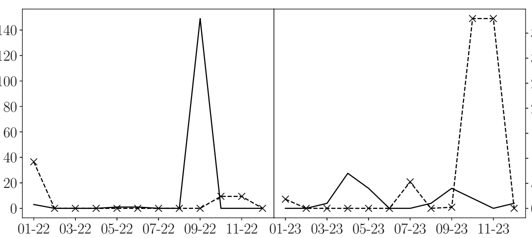
Figure E.9: The Shape finder can predict onset cases when the algorithm returns non-zero predictions in 2023 and a flat forecast for 2022. The solid line refers to the actual number of fatalities in state-based conflict, the dashed lines are the Shape finder predictions, and the dotted lines indicate the VIEWS forecasts. This means that the Shape finder's performance on onset cases originates from the peculiarities of the algorithm, by passing on flat input sequences (Schincariol et al. 2025), rather than showing a systematic ability to anticipate conflict onsets.



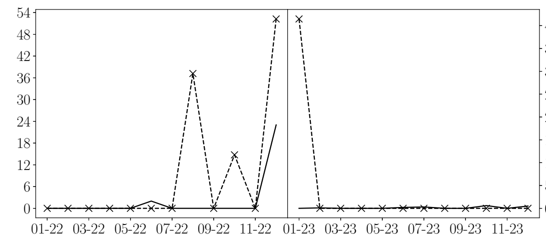
(a) Lebanon



(b) Russia

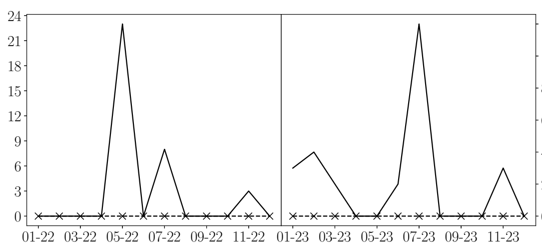


(c) Armenia

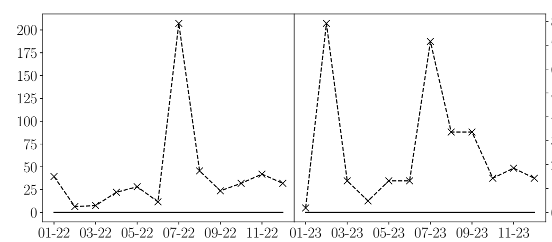


(d) Uganda

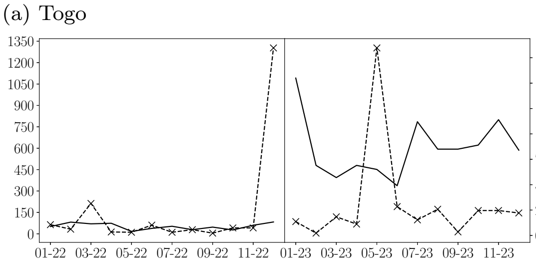
Figure E.10: Some selected examples for well-performing cases, which are countries where the Onset catcher produces a non-zero value on the Onset score. The actual number of fatalities is shown in solid black, and the Onset catcher predictions are shown as a dashed line.



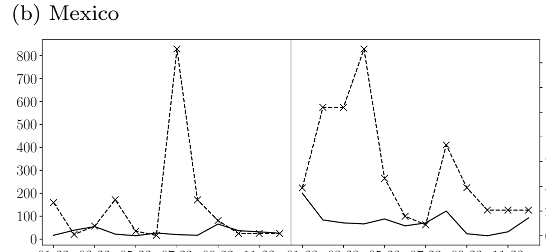
(a) Togo



(b) Mexico



(c) Pakistan



(d) Mozambique

Figure E.11: Some selected examples for poorly-performing cases. The Onset catcher completely misses the new outbreaks (i.e., Togo) or overpredicts the number of fatalities markedly. The actual deaths are shown in solid black, and the Onset catcher predictions are shown as a dashed line.

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