

ARTICLE TYPE

Subject to Change: Quantifying Transformation in Armed Conflict Actors At Scale Using Text

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Abstract

An extensive theoretical and practitioner literature addresses the drivers and consequences of change and transformation of violent rebel actors during conflicts. However, measurement challenges constrain large-N empirical study of the effects and consequences of such transformations. This Research Note introduces a strategy to identify periods of transformation and change in the operation of non-state armed militant groups via computational text analysis of trends in reporting on activities. It presents the measurement approach and demonstrates scalability to a corpus of more than 200 militant groups operating from 1989 to 2020. The study concludes by extending a recent analysis of the impacts of uncertainty on conflict termination. An online appendix demonstrates the advantages and drawbacks of the measurement through a series of case studies.

Keywords: text analysis, topic modeling, civil wars

Transformation and uncertainty are central to a wide range of scholarship on the operation of armed groups and the outcomes of civil wars, yet capturing dynamism and evolution in violent non-state actors remains difficult. Modeling change is an important link in quantitatively testing theoretical expectations about conflict. Many theorized effects of opaque-but-important internal shifts during conflict remain understudied because the literature lacks a way to measure and identify

periods of uncertainty across time and space (Nilsson and Svensson 2021).

Measuring changes within substate armed groups is challenging for several reasons. First, their internal processes are typically opaque, if not actively hidden. Second, data availability is inconsistent: some conflicts produce dense information while others remain hard to access. Likewise, the data availability of previous information eras limits the scope of historical work. Third, event data provides what is recorded to have happened and to whom it was attributed, but rarely the processes, negotiations, compromises, and opportunities that lead to tactical and strategic decisions. Fourth, the amorphous nature of organizational transformations makes it challenging to identify change points according to a consistent metric.

These challenges have led scholars interested in the evolution of militant groups to model change indirectly, such as through the emergence of new militant groups within a conflict setting (Lounsbury and Cook 2011) or from one form of mobilization into another, including between violence and non-violence (Dudouet 2013), violence and political engagement (Acosta 2014; Mampilly 2012), and insurgency and terrorism (Cronin 2009; Findley and Young 2012; Fortna, Lotito, and Rubin 2018). Other researchers have developed rich theoretical and qualitative scholarship on the dynamics and trajectories of specific organizations, an approach that is invaluable for “why” questions and for insight into dynamics of specific movements and their larger political and cultural contexts (Giustozzi 2019; Morrison 2013; Mosinger 2019; Sinno 2011; South and Joll 2016; Stange and Patock 2010; Woldemariam 2018; Wood 2008).

This Research Note contributes to filling the the gap between theory and measurement tools by proposing a strategy that can identify change points rapidly and at scale by computationally modeling reporting on group activities. A text-as-data strategy has several advantages. First, it allows the results to vary by location and context. Secondly, researchers can customize transition thresholds and temporal granularity while also retaining transparency. Third, because the approach models texts sourced from a widely used database of conflict events, potential transition periods can be cross-checked with vetted documentation. Finally, it can be implemented at scale.

This Note proceeds in three parts. First, I describe the measurement strategy. Second, I produce yearly estimates and a summary change indicator for 258 unique rebel groups in armed conflicts. To highlight the utility of this measure for scholars interested in conflict processes and dynamics, I use the output of the measurement to extend the analysis by Nilsson and Svensson 2021, which uses

Islamist motivation as a proxy for the effects of uncertainty on the length of civil conflicts. I reinforce and complement their study by operationalizing “uncertainty” as the existence of years in which reporting on the activities of the non-state actor in a conflict dyad underwent large thematic shifts. The measure is uncorrelated with their Islamist proxy but operates according to their theoretical expectations. An accompanying Appendix explores the face validity of the measurement strategy for four violent conflict actors whose operation covers a range of expected behavioral trajectories. As well, the Appendix presents additional robustness checks and a discussion of the limitations of this measurement strategy, and an extension of the replication that leverages additional information that the measurement strategy can provide.

1. Quantifying Change Points at Scale

I produce a high-level encapsulation of the behavior associated with reported activities of rebel groups in a given year by using a computational text model to assign news articles to one of two group-specific topics. I then aggregate these into a yearly summary of reported activity patterns. In the sections that follow, use the term “frame” to describe the high-level summary produced by the content of, and proportion of articles ascribed to, these topics. Concrete examples of the output can be seen in the Illustration and Proof of Concept section of the Online Appendix. The approach conceptualizes “change” via revealed preferences, which capture actions and thus incorporates strategic decisions as well opportunism, disobedience, shirking, or misjudgment (Beshears et al. 2008).¹

In general, text methods can be classified as *supervised* or *unsupervised*, depending on whether the researcher provides a coding scheme before the analysis (Benoit 2020; Wilkerson and Casas 2017). An unsupervised model is appropriate for the goal of this project because it can discover actor-specific patterns of representation at scale.² To identify group themes, I use the Structural Topic Model (STM), an unsupervised topic model that classifies documents based on patterns of co-occurrence of features (words) in the texts without guidance and direction from the researcher (Roberts et al. 2014). STM is well suited to modeling dynamic changes because the algorithm permits researchers to

1. *Ceteris paribus*, capturing normative, or true, preferences would provide a closer fit with theoretical expectations. However, this route is complicated by access and by strategic incentives to misrepresent true objectives at an organizational, factional, or personal level. For these reasons, quantifying normative preferences is daunting for any specific group and intractable at scale.

2. A supervised model would require the researcher to identify dictionary terms for each of the candidate actors. This type of approach could model specific theoretical changes, such as threat perception over time or shifts between insurgent and terror tactics. However, using a supervised approach to identify group-specific theoretical shifts requires specifying the dimensions to find for each candidate group or restricting the potential dimensions to only those that fit a general trajectory.

incorporate document-level covariates, such as time or author assignment (Roberts, Stewart, and Airoidi 2016). Moreover, structural topic models are appropriate for short texts on a narrow range of issues, as one would expect to find in a corpus of brief reports on violent events (Roberts et al. 2014). Although rarely applied in the conflict literature, the STM has been used by scholars of comparative politics to identify and quantify trends in opaque processes such as corruption (Pan and Chen 2018); individual preferences in consensus-based institutions (Baerg and Lowe 2020), and institutional support for human rights abuses (Bagozzi and Berliner 2018; Magaloni and Rodriguez 2020).

A two-topic topic model, such as the one used here, is essentially a unidimensional text scaling model with the discovered topics serving as scale anchor points. Although scholars have, with reason, critiqued unidimensional scaling models as an oversimplification of complex dynamics (*e.g.* Klar 2014), such scales are widely used to produce high-level summaries of political actors and estimates of how their goals change over time (*e.g.* Becker and Malesky 2017; Egerod and Klemmensen 2020; Grimmer 2010; Lauderdale and Clark 2014; Slapin and Proksch 2008). The parsimony of the two-topic model allows the algorithm to efficiently highlight change points without the need for researchers to tune more than two hundred separate models, as they would if they customized the number of topics to each group.

Data and Output

For data on non-state armed conflict actors, I use the source articles collected in the UCDP's disaggregated Georeferenced Event Dataset (GED) version 21.1 (Pettersson et al. 2021).³ Using the UCDP's database of non-state actors and events allows the project to benefit from their systematic selection, vetting, and deduplication processes (see Sundberg and Melander 2013). I subset the GED to conflicts classified as intrastate, extrasystemic, or internationalized intrastate conflict. I then derived a list of the non-state organized armed groups using version 21.1 of the UCDP Actor Dataset (Pettersson et al. 2021). This produced articles associated with 191,252 violent events from 1989–2020, representing the activity of 352 nonstate organized armed groups (actors) across 393 unique conflict dyads. The text model requires sufficient group-level data to identify patterns in descriptions of group activity. Thus, I removed actors associated with fewer than 10 events and those

3. A discussion of the advantages and drawbacks can be found in the Online Appendix.

for which there were fewer than 10 words remaining after stemming and stopword processing.⁴

I use source articles rather than extracted features of events based on the rationale that even short articles embed both specific activities and a summary representation. For example, a group may be described as rebels (representation) who engage in clashes with government forces (activity) or as local militants (representation) who kill civilians and regional policemen (activity). Modeling articles thus allows the algorithm to pick up changes in activity patterns (via verbs) as well as changes in how local observers perceive and describe the organization (via adjectives and nouns).

The 10-event threshold produced 2180 group years for 258 unique armed [non-state] conflict actors, representing 190,688 recorded events from 151 uniquely named conflicts. I created an actor-specific corpus of news articles from the GED for each of these actors and estimated a two-topic Structural Topic Model with splined year covariates. This generated 258 separate models, one for each non-state armed actor with enough content to model. Within each actor corpus, I assigned an expected thematic proportion from that actor's Topic One and Topic Two to each source article. To identify and summarize trends, I assigned each actor-specific Topic One the value of -1 and Topic Two the value of $+1$. I then used the topic ratio assigned to each article to position each on the $[-1, 1]$ two-dimensional scale.

This analysis produced a set of scaled UCDP source article texts for each conflict actor. To quantify evolution, I took the average yearly position of scaled articles. A yearly topic ratio of -1 indicates that all the articles for that year are associated with the actor's Topic One, and the inverse. At the other extreme, a topic ratio around 0 indicates that news coverage of the group was equally divided between the two topics.

Aggregating the topic proportions into a single metric for each group year allows analysis of temporal change via the difference between the current year's topic ratio and that of a lagged point. The magnitude of the difference between the topic ratio at year y_t and y_{t-n} serves to quantify the presence and expected magnitude of "change" between a given year, t , and n year(s) in the past. This produces a record of the descriptive evolution of 242 groups and 1818 group-years.⁵ This approach to measuring and summarizing changes in armed conflict actors is flexible and customizable.⁶ Given

4. Information about the stemming and stopword decisions can be found in the Online Appendix, along with analysis of more restrictive inclusion thresholds.

5. A few groups fall out of the analysis at this stage due to idiosyncrasies in their data that did not allow them to be modeled by the STM.

6. It is worth noting that cross-group comparisons can be done on magnitude and rates of change and by thematically clustering the discovered topics across groups, but that the substantive implications of each -1 and 1 point are unique to each

yearly and lagged topic proportion data, researchers can decide how to operationalize a “change” threshold tailored to their research design. As well, the design allows the model to identify topics that are specific to each actor, and for the proportion of the topics to change non-linearly over time.

In the analysis that follows, I operationalize “change” as occurring in a year during which an actor experienced a change in their topic ratio of $\geq |1|$ relative to the previous year. Substantively, this threshold suggests that in one year, reporting on the group’s behavior shifted from being predominantly associated with that group’s Topic One (or Topic Two) to the group-specific Topic Two (or Topic One).⁷ This is a high threshold, capturing rapid change in the descriptions of an organization’s behavior.

A group-level distribution of topic proportion changes based on a one-year lag can be seen in Figure 1. The figure shows the per-group distribution of yearly topic changes for each of the GED’s 174 armed conflict actors that have more than three active years and ten recorded activities. Militant groups with fewer changes have distributions that are concentrated around 0 and thus have a more peaked distribution. Conversely, groups with more framing instability have a flatter distribution, with more proportion changes near 2 and -2. The X-axis shows the distribution of one-year lagged topic proportion changes. Conflict actors are grouped by quartiles of activity levels. The first quartile contains actors with the least activity, while the fourth quartile represents the most active armed groups. Actors in the first quartile are associated with [10, 25] violent event records, actors in the second quartile are associated with (25, 75] violent events, those in the third are associated with (75, 219] events, and groups in the fourth quartile are associated with 219 or more violent events. As one would expect, for all groups, the distribution of year-on-year topic ratio changes is concentrated around zero. This indicates that most group years have very little change in the framing scale relative to the previous year. Nevertheless, across group activity levels there is within-group variation to analyze.

specific actor.

7. Conversely, a year-on-year change $\leq |1|$ could either represent a gradual change over several years or a group without a dominant thematic narrative in any given year. The two options can be adjudicated by looking at the specific case. For example, the longest-lasting organization without a “change” year is Hamas. However, between 2009–2011, description of their activities changed from a militancy stance to a political stance before reverting to a more militant depiction after 2019. This representation change happened across a few years, and thus no specific year reached the $|1|$ threshold. This case illustrates the importance of choosing a threshold that fits the substantive inquiry.

Overview of Yearly Proportion Changes Grouped By Quartiles of Activity Level

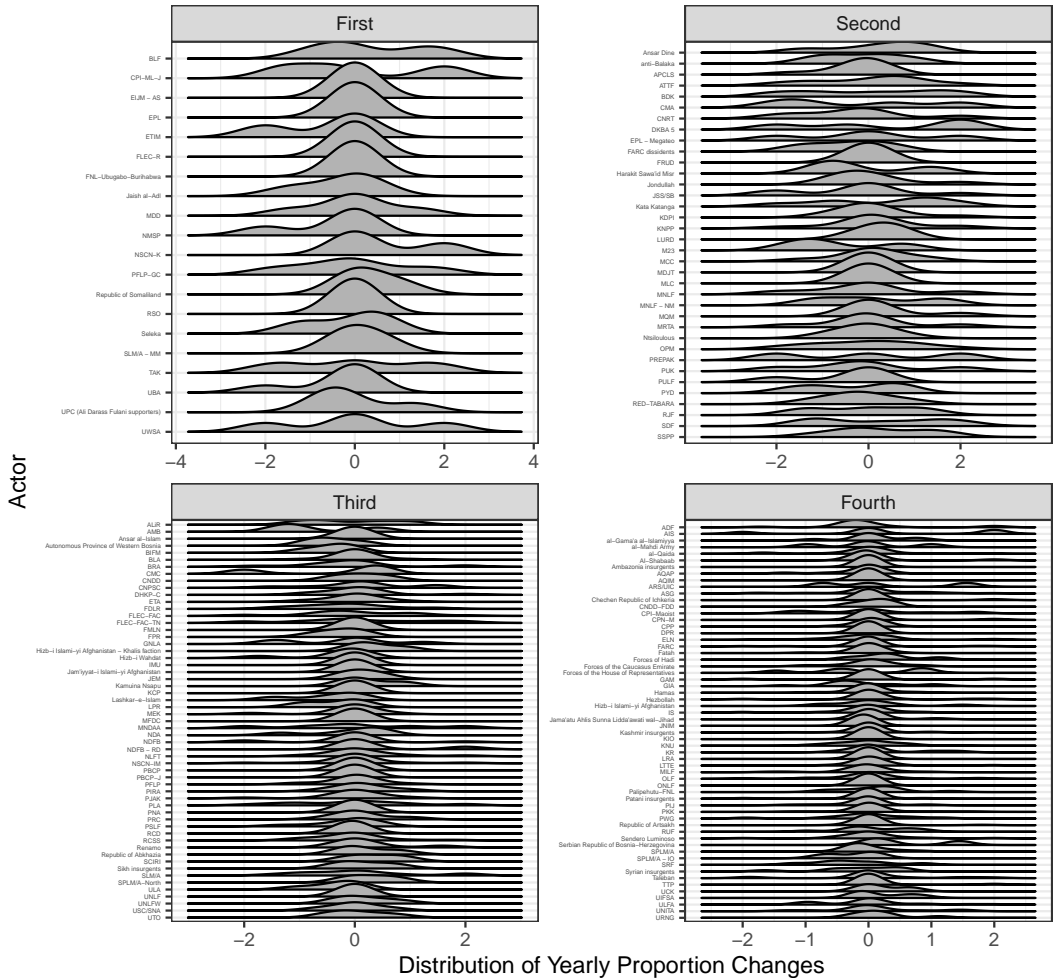


Figure 1. Group-level distributions of one-year topic changes.

The Supplemental Appendix provides a close analysis of the results for several groups, to illustrate the outcome and suggest face validity for using a text-based measurement strategy. The cases are chosen to cover a range of operational and situational environments. Additionally, the Appendix addresses four points of concern—selection effects, media access, model specification, and face validity—and describes in general how a researcher could analyze the results for specific groups of interest. The Appendix also discusses the opportunities (and limitations) for researchers to qualitatively interpret the meaning of the summary words in the group-specific scale. In the next section, I highlight how the measure can be used quantitatively, as part of a large-N statistical model.

2. Application and Replication

To demonstrate how the modeling strategy presented above can enhance existing research into the dynamics and consequences of armed conflict, I extend analysis from Nilsson and Svensson 2021. Their research design operationalized “uncertainty” via an indicator coding whether the non-state actor in a conflict dyad put forward Islamist claims or motivations in their first year of operation. Effectively, they used a theoretical argument about uncertainty to explain why Islamist conflicts are less likely to terminate in any given year. In addition to demonstrating the utility of my measurement approach, the extension fills an underlying measurement gap in the literature: they were unable to directly capture temporal variation in uncertainty as dynamic measures of group and conflict level uncertainty were previously unavailable to researchers of civil conflict.

I re-estimate their analysis using changes in the yearly topic ratio as an alternative operationalization of uncertainty. Rapid changes in the depiction of activities of the rebel group should reflect underlying instability in the conflict environment and be suggestive of observer uncertainty about the motivation and operational profile of the nonstate actor. Following Nilsson and Svensson’s logic that uncertainty prolongs conflict, such representational instability should be associated with conflicts that are more resistant to termination.⁸ The primary independent variable is an indicator that captures whether there have been any years with a rapid (as defined below) change in topic proportions. This is a time-invariant measure, intended to closely match the replicated model. The unit of analysis for the model is group-year.

I replicate the central finding of Nilsson and Svensson: conflict dyads in which the armed non-state actor begins the conflict with an Islamist claim are less likely to terminate. I then introduce three measures of change: the first, and lowest, threshold is a binary indicator for whether the group had any one year changes in topic proportions of at least $|1|$ (*i.e.*, half of the range of the group-specific scale); the second is an indicator for whether the group had a shift of at least $|1.5|$ (*i.e.*, two-thirds of the scale’s range); and the third is an indicator whether the group experienced a single-year representational change of magnitude $|2|$ (*i.e.*, the entire possible range).⁹ Figure 2 summarizes the binary variables that capture whether a specific group was subject to a low (at least $|1|$ on the $[-1, 1]$ scale), medium (at least $|1.5|$ on the scale), or high (at least $|2|$ on the scale) change period across all

8. The index captures shifts in how external actors write about an organization, so one should expect some lag relative to the true process generating organizational or situational instability.

9. The $|1|$ and $|1.5|$ magnitude changes overlap closely with one and two standard deviations in the year-on-year change measure (0.74 and 1.48, respectively).

active years. The Appendix presents a time-varying specification of the model that uses the number of changes, whether there was a recent change, and the length of time between “change” years as independent variables. Additionally, the Appendix presents an analysis of whether the results are robust to more restrictive modeling thresholds.

Variable	No	Yes
Had Low Change	579	650
Had Med. Change	823	406
Had High Change	1028	201

Figure 2. Distribution of new binary variables

The original study and the extension have different temporal scope, which warrants discussion. Nilsson and Svensson’s dataset spans 1979–2013, whereas my measure of uncertainty is based on the UCDP GED, which spans 1989–2020. The results below cover 1989–2013, the intersection of the data.¹⁰ The data adaptation needed to incorporate my measure is described in detail in the Appendix.¹¹ I keep all other parameters the same as in Nilsson and Svensson’s analysis.

Figure 3 presents results for the replication and extension of the model of conflict termination. Adding the change measure strengthens the underlying finding that uncertainty prolongs conflict. Armed nonstate actors that underwent periods of rapid framing changes are associated with conflicts that are significantly more intractable than conflicts associated with groups that did not experience a representational change. The “Low Change” case of a one-year shift of at least magnitude |1| on the scale [1, 1] scale is associated with a conflict being 43 percent less likely to change. Likewise, armed groups with a one-year change of at least magnitude |1.5| (the “Medium Change” groups) are associated with a 50 percent decreased likelihood of termination. Conflicts in the “High Change” condition whereby the actor changed across the entire scale (and thus had a one-year change of magnitude of |2|) were 30 percent less likely to terminate, although estimated with lower precision than the original study. These findings are not driven by correlation between framing shocks and Islamist motivations: there is a very low correlation between Islamist motivation and having experienced rapid descriptive change.

Thus far, the analysis has used a binary measure of whether a militant group experienced a period

10. The difference in the data coverage produces a Termination dataset with 1,020 conflict-dyad years, versus Nilsson and Svensson’s 1,657 conflict-dyad years.

11. The extension to conflict recurrence is likewise featured in the Appendix because the differing temporal scope means that comparison to the original results is less informative.

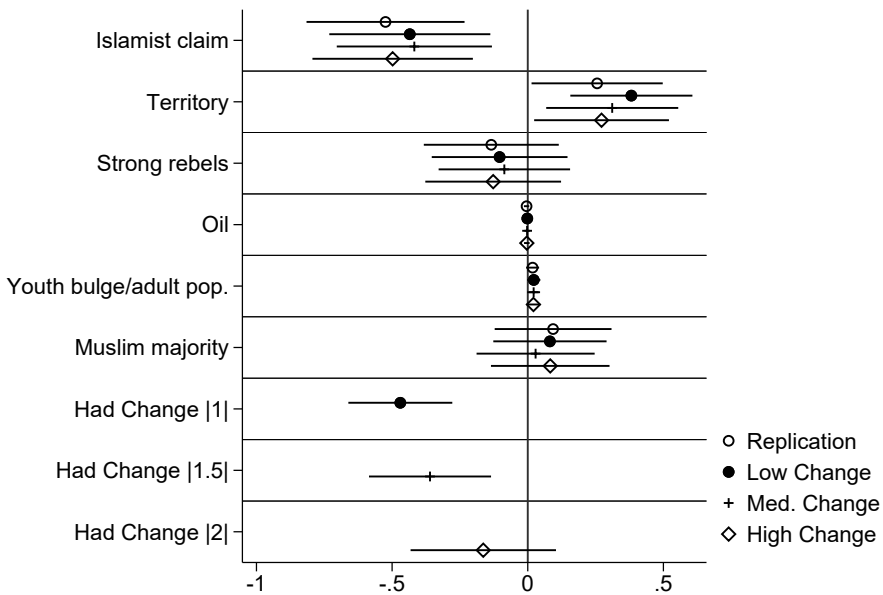


Figure 3. Replication of Termination Model With Change. Termination propensity is modeled via a Cox proportional hazard model to capture the effects of time. In these models, hazard ratios are interpreted relative to 1. A value above 1 indicates an increased likelihood of termination, whereas a value below 1 shows a reduced likelihood of termination. To account for the possibility of repeat events the specifications are stratified on termination episodes.

of framing change. This is the most conservative approach because it is agnostic to the precision with which the text-based measure identifies the date of the change. However, using more precise measurements may produce additional insights into the connection between group transformation and conflict termination. The Appendix extends the analysis by introducing variables that incorporate both time and frequency of group transformation.

This extension applied my original measurement of organizational change to recent scholarship on the consequences of uncertainty in civil conflict to highlight how the measure contributes a novel approach for external observers to identify and measure points at which the narrative around militant conflict actors change. In doing so, it reinforced the theoretical contribution of Nilsson and Svensson 2021, extended their analysis with a more conceptually-precise independent variable, and generalized their conclusions beyond the subset of conflicts that were Islamist from the outset.

3. Conclusion

This Note has made a methodological and substantive contribution to the scholarship of conflict dynamics and militant group operation. Methodologically, it demonstrates how scholars of conflict dynamics can apply new techniques to existing data— here, the UCDP GED—to generate a measurement of a process that has proven difficult to operationalize using more traditional methods. Substantively, this research closes an existing gap in the data on civil conflict by contributing a yearly summary of the framing and reporting on activities of armed non-state conflict actors. This measure provides a new avenue of inquiry into understanding which militant groups change their operating profile and under what conditions these changes tend to occur. Future work could extend this approach, for example, by applying the method to model the behavior of states.

The operationalization captures changes in third-party representation of rebel group operations. It differs from existing data on organizational attributes such as the Foundations of Rebel Group Emergence (FORGE) dataset, which focuses on lineage and organizational endowments (Braithwaite and Cunningham 2020), or REVMOD, which combs data sources to code group organizational traits (Acosta 2019). These and similar data sources such as Nonviolent and Violent Campaigns and Outcomes (NAVCO), All Minorities at Risk (AMAR), and Big Allied and Dangerous (BAAD) all build data from expert assessments of group attributes and structure (Asal and Rethemeyer 2008; Birnir et al. 2018; Chenoweth and Lewis 2013). This strategy produces data that is more specifically

about organizations, but requires that information be accessible to research team(s). Moreover, the level of dynamism varies for each dataset. Conversely, I model media coverage of activities and only indirectly capture organizational dynamics. Effectively, I exchange directness for coverage. Both data sources could be easily combined in future work, which would produce both depth from the existing organizational data and breadth from the media framing measure. A second extension could incorporate government behavior, which this analysis has largely elided.

Although focused on the application to a particular form of organizational data, that of violent rebel groups whose activities are collected in datasets of conflict events, the Note's underlying contribution of a method to measure difficult-to-quantify behavior via recorded activity patterns can be productively applied to other domains. Future extensions can apply the method to aggregate and model information about other political entities or to proxy challenging concepts such as stance (Bestvater and Monroe 2023). The strategy described in this Note may also be useful for scholars interested in dynamic processes more broadly, such as uncertainty in negotiations or bargaining (Fearon 1995).¹²

This Note has contributed a tool that can be paired with other organizational data to produce a dynamic window into the consequences and outcomes of organizational design and operations. It takes scholars of conflict a step closer to a dynamic measure of uncertainty and opens a new avenue of inquiry into understanding which militant groups change their operating profile and under what conditions these changes tend to occur.

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Notes

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12. The author thanks an anonymous Reviewer for this point

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