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THE SHORT-TERM DYNAMICS OF CONFLICT-DRIVEN DISPLACEMENT: BAYESIAN MODELING OF DISAGGREGATED DATA FROM SOMALIA

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Understanding the short-run dynamics of conflict and forced displacement is crucial for the design of effective policy responses, yet quantitative analyses in this realm are sparse. This is primarily due to the scarcity of high-frequency displacement data and methodological challenges arising when modeling imperfect data collected in conflict zones. Addressing both issues, we develop a Bayesian panel regression model to assess the short-term impact of conflict on displacement in Somalia, utilizing weekly panel data that encompasses eight million displacements and 19,000 conflict events from 2017 to 2023. Results suggest a rapid and nonlinear displacement response postconflict, with significant heterogeneity in effects dependent on the nature of conflict events. In a displacement forecasting exercise, our model outperforms standard benchmarks, underscoring its potential for informing decision-makers in crisis scenarios.

1. Introduction. In 2022, the United Nations High Commissioner for Refugees (UNHCR) reported 108 million forcibly displaced persons worldwide, surpassing 1% of the global population.[1] This displacement crisis is primarily attributed to conflict and generalized violence (Schmeidl (1997, 2001), Davenport, Moore and Poe (2003), Hatton (2009), Conte and Migali (2019), Abel et al. (2019)). A detailed understanding of the dynamics of conflict and displacement is crucial for policymakers, NGOs, and other stakeholders involved in humanitarian assistance. This paper contributes to this understanding by focusing on the immediate effects of conflict events on forced displacement with a specific focus on Somalia. The situation in Somalia is especially severe, with an estimated 3.8 million people, or about 20% of the population, internally displaced in 2022 (DRC (2022)).

According to theoretical models of displacement and qualitative evidence, the impact of conflict on displacement materializes rapidly and in the immediate spatial proximity of the conflict event.[2] This suggests that empirical models examining conflict and displacement should ideally focus on small-scale geographical areas and short-term effects. However, this presents quantitative research in this field with two serious challenges. First, granular data on displacement is only rarely available. This is largely due to inadequate data infrastructure in areas where this issue is most relevant. As a result, most quantitative literature on the topic focuses on aggregate data, for instance, on the country-year level.[3] Although such data can reveal broad patterns, it fails to capture the immediate impact of conflict, thereby limiting the direct applicability of these studies to policy formulation. Second, the task of modeling

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[1]https://www.unhcr.org/global-trends-report-2022.

[2]A review of empirical and theoretical literature on conflict and displacement is provided in the Supplementary Material (Zens and Thalheimer (2025)).

[3]Exceptions include studies using mobile phone tracking (Lu, Bengtsson and Holme (2012), Tai, Mehra and Blumenstock (2022)) or analysis of refugee flows from Ukraine in 2022 (Wycoff et al. (2023)), which underscore the rapid impact of conflict on displacement.

disaggregated data on conflict-related displacement presents significant challenges in itself. Such data usually stems from volatile conflict environments, leading to issues such as aggravated sampling noise and partially missing data (Sarzin (2017)). Moreover, the generally limited availability of data in conflict-affected areas makes it difficult to statistically account for spatial and temporal dependencies that may characterize fine-grained displacement data.

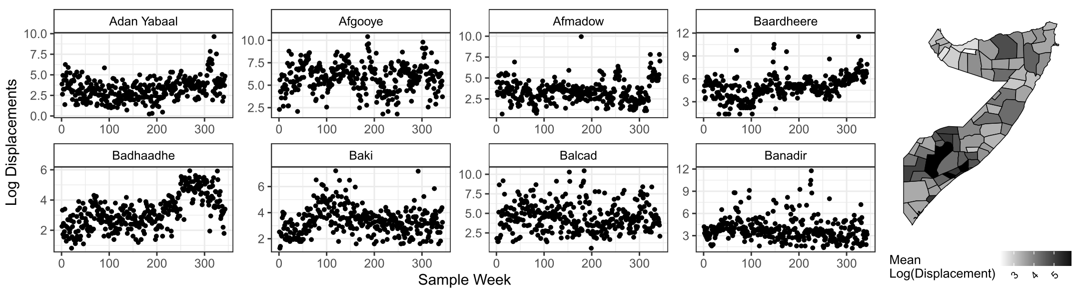
In this article we aim to overcome both of these challenges. We analyze weekly panel data covering more than eight million internal displacements and 19,000 conflict events in 74 districts of Somalia between 2017 and 2023. We highlight several empirical issues that potentially arise when working with disaggregated data from conflict zones. To address these issues, we propose a specialized Bayesian statistical framework. This framework is grounded in both theoretical considerations on the dynamics of human displacement in Somalia and in stylized empirical facts derived from the data. The model integrates Bayesian factor models (Conti et al. (2014)), dynamic linear models (West and Harrison (1997)), distributed lag models (Schwartz (2000)) as well as Bayesian shrinkage and smoothing priors (Lang and Brezger (2004), Piironen and Vehtari (2017)). Combining these components in a single panel regression framework allows us to flexibly account for latent spatiotemporal dependencies while ensuring a certain robustness against overfitting noisy data.

We apply the model to displacement data from Somalia to provide an in-depth analysis of the short-run impact of different types of conflict events on displacement. Our findings suggest a rapid and nonlinear displacement response postconflict, with significant heterogeneity in effects dependent on the nature of conflict events. In addition, we demonstrate the utility of the approach in the context of displacement forecasting, where our framework outperforms several benchmark models in producing short-run displacement predictions.

This article hence makes three key contributions. First, we introduce a statistical framework that can be used to explore and analyze the underlying drivers of forced displacement and has a broader application in Bayesian regression analysis of high-resolution panel data. The model can be used to evaluate predictions obtained from theoretical models on forced displacement. In addition, models that can credibly attribute displacement to conflict have applications in the human rights context and have, for instance, been used in war crime trials in The Hague (Ball and Asher (2002)). Second, we provide policy-relevant evidence on the impact of conflict on internal displacement in Somalia, contributing directly to the literature on short-run drivers of displacement. Given the challenges in data collection and modeling, previous research in this area has partially yielded inconsistent results; see the literature review in the Supplementary Material. The obtained impact estimates can further be used to inform policymakers, NGOs, and complementary theoretical and simulation-based approaches, relying, for instance, on agent-based models. Third, our evaluation of the predictive power of the model contributes to the displacement forecasting literature. This evaluation is particularly relevant given the previously demonstrated limited gains of black-box machine learning tools over simple benchmarks in predicting displacement in Somalia (Pham and Luengo-Oroz (2023)).

The remainder of this article is structured as follows. Section 2 introduces the data we use and highlights challenges when modeling detailed displacement data. In Section 3 we propose a specialized Bayesian statistical framework for modeling conflict and displacement. Section 4 presents our results on the short-term dynamics of conflict-driven displacement and the results of the displacement forecasting exercise. Section 5 concludes with key insights for empirical studies on conflict and displacement, strategic considerations for policy development, and pathways for future research.

2. Data description. In this section we describe the two main data sets from which we source the variables used for the empirical analysis in detail, highlighting potential methodological challenges. Limitations and potential shortcomings of the data are discussed in a dedicated section in the Supplementary Material.



(a) (b)

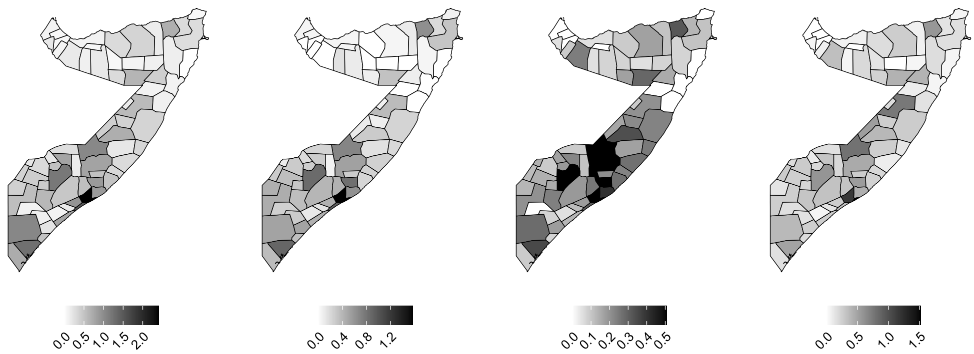
FIG. 1. *Patterns of observed internal displacements*: (*a*) *shows weekly time series for eight example districts across the sample period from January* 2017 *to July* 2022. *y-axis is on a log scale. x-axis indicates weeks in the sample period.* (*b*) *shows average log displacements in each of the* 74 *districts of Somalia.*

2.1. *Data on internal displacement.* The dependent variable of interest is the logarithm of the number of internal displacements reported in the 74 districts of Somalia for each week from January 2017 to July 2023, a period of $T = 343$ weeks. The data is obtained from the *Protection and Return Monitoring Network (PRMN) Somalia* led by the UNHCR. This monitoring network aims to document the number of internally displaced persons (IDPs) per district every week (UNHCR (2017)). The data is collected by the Norwegian Refugee Council (NRC) and local partners on behalf of the UNHCR. Specifically trained monitors measure the movements of displaced populations at strategic points, including transit sites and IDP settlements. The data are obtained based on individual or group interviews of displaced persons and make use of standardized forms to collect information. Quality control procedures are in place to ensure a reasonable level of data quality after the partners upload the results of these interviews onto an online platform.

Figure 1 visualizes the average log displacement in each district as well as eight example time series of observed log displacements. A preliminary investigation of these series makes some stylized facts of the data apparent. First, the unconditional means of the time series vary strongly across districts, reflecting both differences in population size and resilience to factors leading to displacement. Furthermore, the displacement series often follow district-specific and complex trending patterns. These slow-moving trends potentially reflect slow-onset hazards such as droughts or changing economic conditions. While the variance around these trends is relatively small in some districts, the behavior of the displacement flow series in other districts is much more volatile.

In addition to these within-district temporal dependency patterns, cross-district spatial dependencies are to be expected as well. For instance, several districts in Southern Somalia are connected via the major rivers *Juba* and *Shebelle*. Flash floods caused by rising river levels can lead to simultaneous displacement fluctuations in these districts. Similarly, droughts or economic crises are likely to affect displacement in multiple districts jointly. A major modeling challenge in this context is that no explicit measurements of river levels, flood depth, and economic or drought developments are available. Additionally, 30.4% of week-district cells are treated as missing observations due to the absence of reported displacement counts. We aim to address all of these stylized facts and modeling issues explicitly in the statistical framework and estimation algorithm outlined in Section 3.

2.2. *Data on conflict and conflict-related events.* The main independent variable of interest is the occurrence of conflict and conflict-related events, which we measure using data obtained from the *Armed Conflict Location & Event Data Project* (ACLED). This event-based data set collects occurrences of political violence and protest including, for instance,



(a) Battles (b) Explosive / Remote (c) Strat. Dev. (d) Against Civilians

FIG. 2. *Average weekly occurrence of various types of conflict and conflict-related events from January* 2017 *to July* 2023. *Data is presented on a square root scale, and scales differ across panels.*

military battles, suicide bombings, and riots (Raleigh et al. (2010)). ACLED includes information on events by date, location, actor, and event type. It is one of the highest-quality data sets on violent events on a disaggregated scale and is widely used in research analyzing the causes and effects of conflict (Eck (2012), Thalheimer, Schwarz and Pretis (2023), Oh et al. (2024)). Data is collected via traditional media, reports of international institutions and NGOs, local partners, and social media channels such as Twitter or Telegram. The reliability of the data is ensured via several layers of quality control, including source control and peer review mechanisms, involving academic researchers, policy and practitioner communities as well as country experts.

ACLED events are categorized into several event *types*, allowing us to investigate the impact of different classes of conflict and conflict-related events on displacement. Specifically, we will base our investigation on four ACLED categories. First, *battles* include events that are defined as a violent interaction between two organized armed groups at a particular time and location. For instance, this category includes clashes of armed government forces and rebel groups. Second, *explosions and remote violence* events are defined as "one-sided violent events in which the tool for engaging in conflict creates asymmetry by taking away the ability of the target to respond" and include suicide bombings or artillery shelling. Third, *violence against civilians* events capture any event "where an organized armed group deliberately inflicts violence upon unarmed noncombatants." such as shootings, sexual violence, or kidnapping of civilians. Fourth, the event type *strategic development* captures events "regarding the activities of violent groups that is not itself recorded as political violence, yet may trigger future events or contribute to political dynamics within and across states." Events that fall in this category include the formation of new rebel groups, the establishment of new headquarters, or nonviolent transfers of territory. All of the above definitions are taken from the ACLED codebook[4] and are repeated here for completeness. Figure 2 plots the average number of different types of conflict events across districts in Somalia. In total, in the sample period between January 2017 and July 2023, around 19,000 relevant events are recorded in the ACLED database, where 52.6% are coded as battles, 23.6% are coded as explosive and remote violence, 17.4% fall in the category violence against civilians, and the remaining 6.4% are strategic developments. More context on the civil war in Somalia is given in the Supplementary Material.

[4]ACLED Codebook Version 1 from January 2021, available online at the ACLED website https://acleddata.com/.

3. Statistical framework. Let y_{it} denote the logarithm of the number of displacements[5] in district i ($i = 1, \dots, N$) in week t ($t = 1, \dots, T$). We model y_{it} as the sum of a component C_{it}, representing conflict-driven displacement, and O_{it}, representing displacement due to nonconflict events,

$$y_{it} = C_{it} + O_{it}. \tag{1}$$

Conflict-driven displacement is further decomposed as $C_{it} = A_{it} + I_{it} + F_{it}$, where A_{it} are anticipation effects, I_{it} are immediate effects on impact, and F_{it} are aftermath effects of conflict events. We assume that these anticipation, impact, and aftermath components can be modeled using a distributed lead and lag structure

$$\begin{aligned} A_{it} &= \sum_{s \in \mathcal{C}} \sum_{j=1}^{4} c_{s,i,t+j} \beta_{sj}^{-}, \\ I_{it} &= \sum_{s \in \mathcal{C}} c_{s,i,t} \beta_s, \\ F_{it} &= \sum_{s \in \mathcal{C}} \sum_{j=1}^{8} c_{s,i,t-j} \beta_{sj}^{+}, \end{aligned} \tag{2}$$

where $\mathcal{C}$ is the set containing the four conflict event types and $c_{s,i,t}$ denotes the count of conflict events of type s in district i and week t. This specification allows us to investigate concurrent conflict impacts (via β_s), preemptive relocation efforts in the month before (via β_{sj}^{-}), and aftermath effects in the two months after conflict events (via β_{sj}^{+}).

The specification of O_{it} aims to capture latent spatiotemporal dependencies in displacement that are not captured by the conflict event indicators. We assume that displacement due to events other than conflict can be represented as

$$O_{it} = \mu_i + \alpha_{it} + \boldsymbol{\lambda}_i' \boldsymbol{f}_t + \boldsymbol{x}_{it}' \boldsymbol{\delta} + \varepsilon_{it}, \quad \varepsilon_{it} \sim \mathcal{N}(0, \sigma_i^2), \tag{3}$$

where μ_i are district-specific intercepts and α_{it} is a latent zero-mean trend component, responsible for capturing slow-moving within-district variables, such as droughts and economic factors. This dynamic component is modeled using a random walk structure $\alpha_{it} = \alpha_{it-1} + \eta_{it}$ where $\eta_{it} \sim \mathcal{N}(0, \theta_i)$. A factor structure with Q latent factors $\boldsymbol{f}_t = (f_{1t}, \dots, f_{Qt})'$ and corresponding loadings $\boldsymbol{\lambda}_i = (\lambda_{1i}, \dots, \lambda_{Qi})'$ accounts for latent cross-district spatial dependencies. The factors $\boldsymbol{f}_t$ represent unmeasured variables relevant to multiple districts, including, for example, river levels or supraregional drought developments. A similar combination of series-specific state space components and common latent factors as in (3) is utilized in Berry and West (2020) and Berry, Helman and West (2020). The linear component $\boldsymbol{x}_{it}' \boldsymbol{\delta}$ captures the impact of available control variables collected in $\boldsymbol{x}_{it}$. Here we include two variables measuring the UNHCR-reported share of displacements due to drought and floods in district i and week t, respectively. Broadly speaking, this allows us to control for average differences between conflict-related displacement and displacement due to droughts and floods. Finally, ε_{it} represents a heteroskedastic error term that captures potentially varying quality of measurement and heterogeneous error volatilities across districts. Importantly, the factor structure and the heteroskedastic error term marginally imply a full $N \times N$ cross-district error covariance matrix $\boldsymbol{\Lambda}\boldsymbol{\Lambda}' + \boldsymbol{\Sigma}$ where $\boldsymbol{\Lambda} = (\boldsymbol{\lambda}_1, \dots, \boldsymbol{\lambda}_N)'$ and $\boldsymbol{\Sigma} = \text{diag}(\sigma_i^2)$.

[5] While count data models offer greater theoretical rigor, we choose log displacement as the outcome variable to increase computational efficiency during model estimation while maintaining straightforward interpretation of the coefficients. For large counts this approach closely approximates a Poisson log-normal model (Steel and Zens (2024)).

3.1. *Prior elicitation.* We pursue a Bayesian approach to parameter estimation. The Bayesian paradigm allows for a probabilistic and intuitive interpretation of the obtained parameter estimates and forecasts, facilitating communication of results to potential stakeholders. Bayesian estimation requires soliciting suitable prior distributions on all relevant parameters. Weakly informative $N(0, 100)$ priors are chosen for β_s and $\boldsymbol{\delta}$, and we specify flat priors for μ_i. The variance parameters σ_i^2 are assumed to follow weakly informative inverse gamma distributions $\sigma_i^2 \sim \mathcal{IG}(2.5, 1.5)$. For the state equation variances, we choose $\theta_i \sim \mathcal{IG}(1, 0.005)$, which implies relatively smooth paths of the latent trend components α_{it}.

The factors are assumed to arise from independent Gaussian densities with unit variances, that is, $\boldsymbol{f}_t \sim \mathcal{N}(0, \boldsymbol{I}_Q)$ where $\boldsymbol{I}_Q$ is the Q-dimensional identity matrix. This allows for scale identification and implies that all the information regarding the error correlations across districts is summarized in the factor loadings $\boldsymbol{\lambda}_i$. For these loadings we choose an informative prior distribution that reflects the idea that the error correlation matrix across districts is potentially sparse and that the latent shocks to displacement may be uncorrelated for certain district pairs. Specifically, we utilize the horseshoe prior of Carvalho, Polson and Scott (2009) due to its well-documented ability to regularize noisy signals and the ease of implementation due to the algorithm proposed in Makalic and Schmidt (2016). This prior places most probability mass on zero. Estimates of $\boldsymbol{\lambda}_i$ will, therefore, only deviate significantly from zero in case the data is informative enough, encouraging in turn sparse estimates of $\boldsymbol{\Lambda}\boldsymbol{\Lambda}'$. Importantly, this prior mitigates the issue of overfitting when attempting to estimate an $N \times N$ covariance matrix of $\boldsymbol{\varepsilon}_i$ from potentially noisy and incomplete time series.

Finally, a prior on the distributed lead and lag coefficients $\boldsymbol{\beta}^+$ and $\boldsymbol{\beta}^-$ needs to be chosen. Here we superimpose the a priori assumption that the impact of conflict on displacement plays out relatively smoothly over time. In a setting with noisy data from conflict zones, this assumption provides further structure and mitigates overfitting. To enforce smooth-distributed lag functions for the anticipation and aftermath effects, we assume a second-order random walk on the distributed lag coefficients

$$
\begin{aligned}
&\beta_{s,j}^+ = 2\beta_{s,j-1}^+ - \beta_{s,j-2}^+ + \zeta_{s,j}^+, \quad \zeta_{s,j}^+ \sim \mathcal{N}\left(0, \frac{\tau_s^+}{\kappa_{s,j}^+}\right), \tau_s^+ \sim \mathcal{IG}(c_0^+, d_0^+), \\
&\beta_{s,j}^- = 2\beta_{s,j-1}^- - \beta_{s,j-2}^- + \zeta_{s,j}^-, \quad \zeta_{s,j}^- \sim \mathcal{N}\left(0, \frac{\tau_s^-}{\kappa_{s,j}^-}\right), \tau_s^- \sim \mathcal{IG}(c_0^-, d_0^-),
\end{aligned}
\tag{4}
$$

with diffuse priors on initial values. Further assuming $\kappa_{s,j}^+, \kappa_{s,j}^- \sim \mathcal{G}(\frac{1}{2}, \frac{1}{2})$ marginally implies Cauchy priors on $\zeta_{s,j}^+$ and $\zeta_{s,j}^-$ to induce smoothing, and we set $c_0^+ = c_0^- = 1$ and $d_0^+ = d_0^- = 0.005$, as suggested in Lang and Brezger (2004).

3.2. *Parameter estimation and model identification.* The proposed model can be estimated efficiently using Markov chain Monte Carlo (MCMC) methods. In particular, the static factor structure enables the parallelization of otherwise computationally costly sampling steps, such as updating the latent state space components α_{it}. Parallel updates of factors and loadings further reduce the computational workload. Estimation of the model via MCMC is especially convenient, as this facilitates the handling of missing data points via imputation during estimation.

A sketch of the Gibbs sampling algorithm we use to sample iteratively from the conditional posterior distributions of the parameters is as follows. First, missing data points are imputed from $y_{it} \sim \mathcal{N}(C_{it} + O_{it}, \sigma_i^2)$.[6] Second, the latent states α_{it} are updated for all i in parallel.

[6]We assume that missing observations are missing at random (MAR). Future research could explore a missing not at random (MNAR) setting and develop a sample selection framework including an explicit model for the

These updates can be conducted highly efficiently using simulation smoothing techniques, as per Chan and Jeliazkov (2009) or McCausland, Miller and Pelletier (2011). The regression coefficients $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ are then jointly simulated with the intercepts μ_i via a single Bayesian regression update. The prior precision matrix for $\boldsymbol{\beta}$, implied by (4), can be constructed using the ideas outlined in Chan and Jeliazkov (2009). Factors $\boldsymbol{f}_t$ for all t can be updated in parallel, followed by parallel Bayesian regression updates to obtain samples for the loadings $\boldsymbol{\lambda}_i$ for all i. Finally, the variance parameters are updated using data augmentation for the horseshoe parameters as in Makalic and Schmidt (2016), conditional updates for the Cauchy prior parameters as given in Lang and Brezger (2004), and relying on standard conjugate updates for the remaining variance parameters σ_i^2 and θ_i. All posterior samples are simulated from posterior distributions that are conditional on all of the other parameters. In the Supplementary Material, a Monte Carlo simulation study is presented that demonstrates that this algorithm accurately recovers the parameters of the data-generating process.

Rotational identification of the factors $\boldsymbol{f}_t$ and the corresponding loadings collected in $\boldsymbol{\Lambda}$ typically requires a set of restrictions on the loadings matrix $\boldsymbol{\Lambda}$ (Frühwirth-Schnatter, Hosszejni and Lopes (2024)). However, the cross-district covariances encoded in $\boldsymbol{\Sigma} + \boldsymbol{\Lambda}\boldsymbol{\Lambda}'$ are identified under mild conditions. As inference on $\boldsymbol{f}_t$ is not the primary goal of our analysis, we do not restrict the loadings and factors beyond the a priori assumptions of independence across factors and unit variances for all factors. A second identification issue is that the intercepts μ_i and the level of the latent trends α_{it} are not separately identifiable. To resolve this, we impose a sum-to-zero constraint on $\boldsymbol{\alpha}_i = (\alpha_{i1}, \dots, \alpha_{iT})'$ during posterior simulation.

4. Results. The presented results are based on 12,000 posterior iterations, where the first 2500 draws are discarded, and every fourth draw is saved to reduce the storage demand of the results. One estimation run using `R` takes roughly 30 minutes on a single core of an AMD Ryzen 5 5500U CPU. In general, convergence of the Markov chains is rapid, and the Gibbs sampler is mixing well. Trace plots and effective sample sizes are provided in the Supplementary Material.

To select an appropriate number of factors Q, we evaluate models with Q ranging from 1 to 10 in the course of the forecasting exercise detailed in Section 4.3. We proceed to discuss results based on a model with $Q = 2$ latent factors, which maximizes out-of-sample prediction accuracy across several criteria. However, the results remain similar as the number of factors increases. An alternative, more computationally intensive approach to model selection that treats the number of factors Q as a random quantity to be estimated is discussed in Frühwirth-Schnatter, Hosszejni and Lopes (2024).

4.1. *The short-run impact of conflict on displacement in Somalia.* The main results of the estimation exercise are summarized in Figure 3, which gives point estimates and estimated uncertainty bounds for $\boldsymbol{\beta}$, $\boldsymbol{\beta}^+$, and $\boldsymbol{\beta}^-$, the distributed lead and lag coefficients of the four conflict event indicators. These estimates indicate that, on average, a single battle event is associated with a 3% increase in displacements in the same week, with no detectable aftermath or anticipation effects. The effect of explosions and remote violence events is slightly stronger, with a 5% increase on average in the same week, and more pronounced aftermath effects. Significant anticipation, impact, and aftermath effects are observed for strategic developments, with a peak increase of between 15% and 20% within the same week and detectable effects up to more than a month after the event occurred. Strategic developments

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selection mechanism (i.e., observing any displacement). However, this approach is likely to significantly increase computational complexity and typically requires exclusion restrictions (Wagner, Frühwirth-Schnatter and Jacobi (2023)), which may be particularly difficult to identify in a data-sparse context.

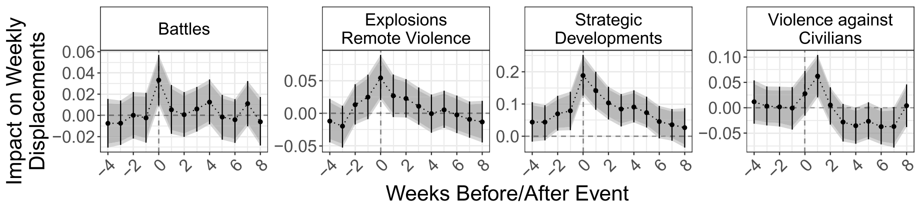


FIG. 3. *Posterior distributions of the estimated distributed lead, lag, and impact coefficients* $\boldsymbol{\beta}$, $\boldsymbol{\beta}^+$, *and* $\boldsymbol{\beta}^-$ *for the four considered types of conflict events. Shaded areas correspond to* 95% *credible intervals.*

typically correspond to high-visibility events with substantive information flow, such as land transfers or troop movements, signaling structural shifts in the balance of power and the potential for future violence.[7] These events appear to prompt both preemptive relocation efforts and strong aftermath effects, potentially in groups that are now exposed to new threats. Evidence for the important role of structural change in conflict-driven displacement patterns is also reported in Schon (2015). The pattern after events involving violence against civilians is more intricate, with a positive but insignificant point estimate in the week of the event, a stronger effect in the week after, and then some decreases in displacement occurrences in the following weeks. In general, the results in Figure 3 illustrate the complex and varied nature of displacement dynamics in the context of different types of conflict events. While we can speculate what drives these empirical patterns, these hypotheses cannot be conclusively evaluated using the data at hand, warranting further research.

In Figure 4 we present additional results from an alternative model specification that suggests the presence of nonlinear effects of the number of conflict events per week on displacement. The left column shows estimated coefficients of binary indicators representing weeks with any conflict event, while the right column shows estimated coefficients of the number of conflict events beyond the first in weeks with multiple events. Thus, the left column captures the effect of experiencing at least one conflict event compared to none, while the right column measures the incremental effect of each additional event beyond the first, distinguishing the effects of isolated vs. more intense periods of conflict on displacement.

The results suggest that, for battle events, the average displacement effects reported in Figure 3 are primarily driven by the presence of any battle event, highlighting the significant impact of experiencing a state of organized armed conflict compared to not being in one. In contrast, the average effects of explosive attacks and remote violence appear to be driven more strongly by weeks with multiple events. This suggests a cumulative and compounding psychological and physical toll of frequent explosions and remote attacks occurring within short periods. Similar evidence of nonlinear effects, where higher conflict intensity leads to greater displacement while this is not necessarily the case for lower conflict intensity, is reported in Bohra-Mishra and Massey (2011). For strategic developments and violence against civilians, we estimate patterns similar to their respective average effects for both the presence of any event and subsequent event counts.

To summarize, our estimates indicate that displacement as a response to conflict materializes very rapidly, particularly following battles and explosions, with the majority of the

[7]Within the considered sample period, the composition of strategic developments, according to the ACLED subevent categories, is as follows. "Agreement" accounts for 4%, "Arrests" for 7%, "Change to group/activity" for 14%, "Disrupted weapons use" for 22%, "Headquarters or base established" for 1%, "Looting/property destruction" for 12%, "Nonviolent transfer of territory" for 34%, and "Other" for 5% of the events. Developing methods that can robustly disentangle the effect of conflict by many, potentially very rare subevent types, is a promising avenue for future research.

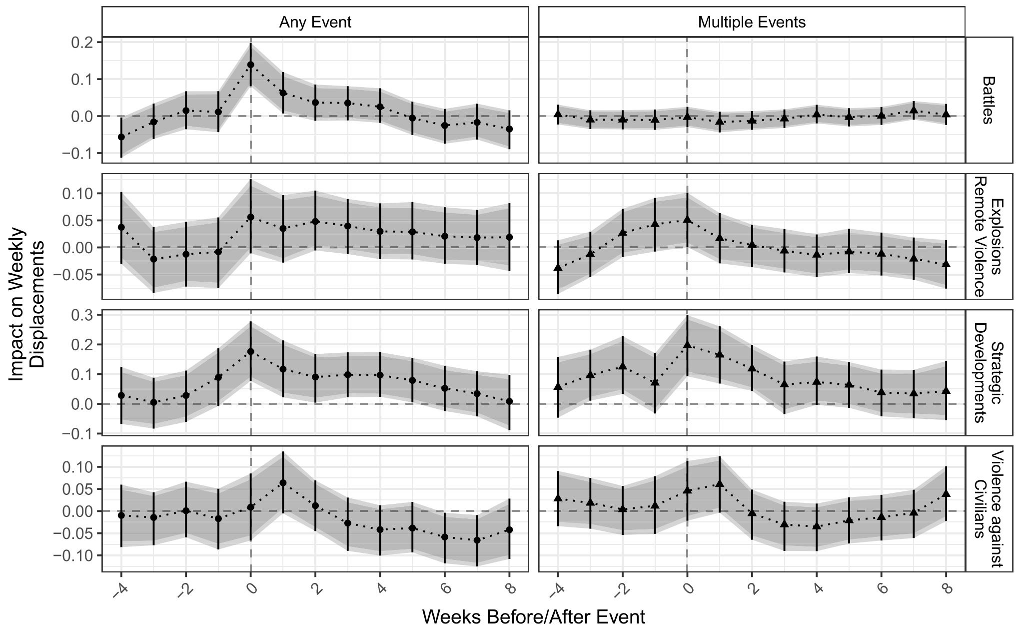


FIG. 4. *Posterior distributions of the estimated distributed lead, lag, and impact coefficients* $\boldsymbol{\beta}$, $\boldsymbol{\beta}^{+}$, *and* $\boldsymbol{\beta}^{-}$ *in the nonlinear specification. Shaded areas correspond to* 95% *credible intervals.*

impact typically observed within zero to two weeks after the event. However, both the magnitude and duration of the estimated effects vary significantly by type of conflict event. Displacement effects may last longer, up to several weeks, following strategic developments. Furthermore, the impact of conflict on displacement is characterized by intricate nonlinear patterns, especially in the context of organized armed battle events. A discussion on the internal and external validity of these results is provided in the Supplementary Material.

4.2. *Results on spatiotemporal dependencies*. In Figure 5 we provide the estimated posterior distributions of the district-specific, latent trend components α_{it} for eight example districts. The estimation results reveal several distinct patterns concerning the trending behavior of the displacement series. In certain districts the data is informative on highly intricate latent trends α_{it}. These trend components capture all sufficiently slow-moving, district-specific developments that correlate with displacement and are not accounted for by the cross-district factor structure, the included control variables, and the leads and lags of the conflict mea-

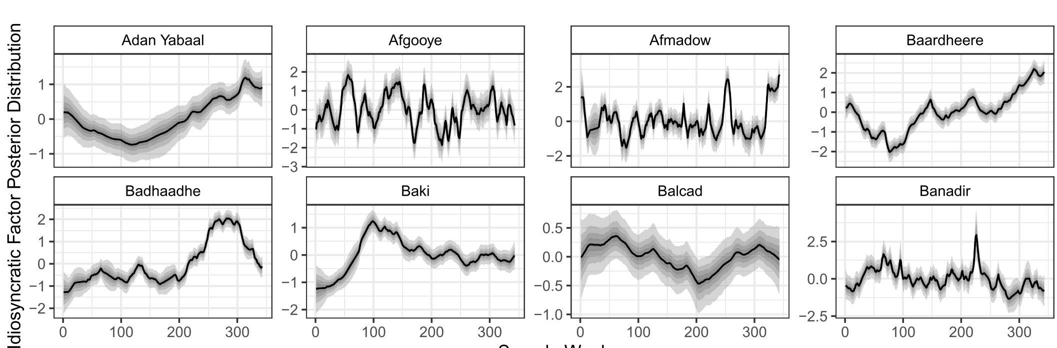
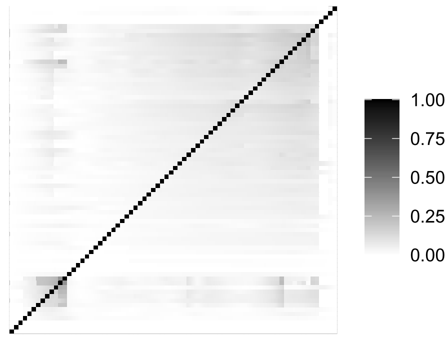
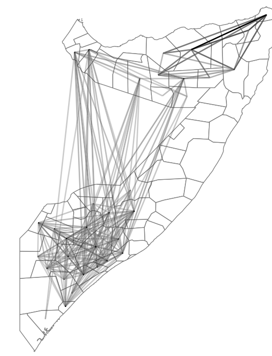


FIG. 5. *Posterior distributions of the estimated idiosyncratic trend components* α_{it} *for eight example districts across the sample period from January* 2017 *to July* 2023. *Shaded areas correspond to* 95% *credible intervals.*



(a) Error Correlation Estimates.



(b) Partial Correlation Network.

FIG. 6. *Estimated spatial dependency structure*: (*a*) *shows posterior mean estimates of error correlations across districts. Ordering of rows and columns of the matrices is based on clustering highly correlated districts for visualization purposes*. (*b*) *shows an estimated partial correlation network derived from the posterior distribution of* $\mathbf{\Sigma} + \mathbf{\Lambda}\mathbf{\Lambda}'$. *Stronger partial correlations correspond to less transparent edges.*

sures included in the model. The complex nature of the trend components α_{it} highlights the importance of such temporally correlated within-district factors (e.g., local droughts) when analyzing displacement patterns. The estimated paths of α_{it} further demonstrate that a conceptually simpler, classical panel specification based on district fixed effects—implying constant α_{it} for all i—is likely underspecified. Additional evidence for this claim is provided in Section 4.3.

Next, we focus on posterior mean estimates of the covariance structure across districts implied by the estimates of the idiosyncratic variances σ_i^2 and the factor loadings $\boldsymbol{\lambda}_i$. The implied correlation matrix is visualized in Figure 6. It shows a significant amount of cross-district correlation in the unobserved shocks to displacement. Blocks of correlated districts are visible in panel (a). Almost all nonzero correlations are estimated to be positive, implying predominantly positive co-movements in the latent shocks to displacement $\boldsymbol{\varepsilon}_i$. Suspected underlying, unmeasured factors, such as flash floods or political developments concerning more than one district, are in line with this finding. The correlation matrices are further estimated to be pronouncedly sparse, that is, including many zero elements, which is a consequence of the shrinkage prior specified on the elements of $\boldsymbol{\lambda}_i$. For completeness, estimates of the factors $\boldsymbol{f}_t$ based on a singular value decomposition are shown in the Supplementary Material.

Panel (b) of Figure 6 shows a partial correlation network, based on the estimated error covariance matrix. Posterior mean estimates of the partial correlations are used, and partial correlations where zero is included in the 99% credible interval are dropped. More transparent lines correspond to smaller partial correlations. The resulting network structure is broadly clustered into two geographically distinct blocks of districts. The first cluster, in Southern Somalia, is characterized by districts close to the capital district, connected by rivers, and subject to flash flooding. In addition, these districts correspond to the main area of operations of Islamist militant group *Al Shabaab*, a key actor in the Somalia civil war. The second cluster, in the North of the country, corresponds to Somaliland and Puntland, two larger regions that pursue independence from the Southern parts of Somalia. Somaliland and Puntland are further characterized by repeated armed clashes over disputed districts and provinces in their bordering region. It is worth noting that our model does detect these geographic clusters and dependency structures without access to any explicit information on the spatial location of the districts.

Finally, in Figure 7 we visualize the fitted values of the model together with the raw data. Focusing on the previously considered eight example districts again, we find that the model is

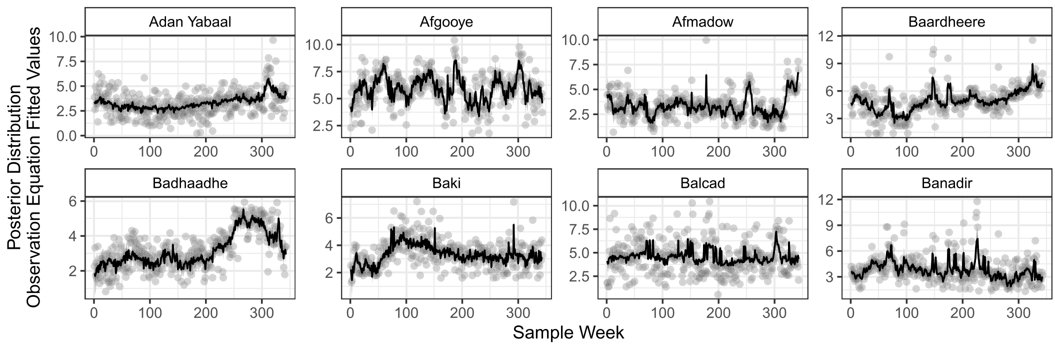


FIG. 7. *Observed log displacement y_{it} together with posterior means of fitted values $\hat{y}_{it}$ for eight example districts across the sample period from January* 2017 *to July* 2023.

able to follow the general trends in y_{it} relatively well. To give a sense of overall in-sample fit, the coefficient of determination of the Bayesian approach is $R^2 = 0.60$. The results nonetheless demonstrate the difficulty of designing empirical models that can consistently extract relevant information from potentially noisy and highly fluctuating time series in the context of displacement modeling, as also noted in Pham and Luengo-Oroz (2023). More generally, empirical modeling of human mobility patterns over time is well known to be highly challenging (Bijak et al. (2019)).

4.3. *Forecasting exercise*. Recent contributions have shown that the widely and traditionally used gravity models of migration are not well suited for forecasting migratory movements and that well-designed time series approaches can outperform gravity models by a significant margin (Welch and Raftery (2022), Beyer, Schewe and Lotze-Campen (2022)). Moreover, even highly flexible machine learning frameworks tend to perform only on par with simple benchmarks when forecasting displacement on a disaggregated level (Pham and Luengo-Oroz (2023)). At the same time, forecast-based humanitarian efforts are attracting growing attention (Thalheimer, Simperingham and Jjemba (2022)). In this context we conduct an out-of-sample forecasting exercise to evaluate the performance of the model relative to several benchmarks. In addition, the model specified in Section 3 is relatively flexible, warranting some evaluation of its out-of-sample performance to mitigate concerns about overfitting.

We focus on obtaining one-week ahead predictions for displacements for all 74 districts under consideration. For this we repeatedly split the data set into a training sample with a length of 291 weeks and a single one-step ahead hold-out week. The parameters of the competing modeling frameworks are estimated using the training sample and are subsequently used to predict displacement in the test week. This exercise is repeated 52 times, shifting the time window of the training sample by one week each time, until eventually all weeks in the last year of the full sample period have been used as holdout weeks once.

We compare 10 different forecasting methods. First, we consider several benchmarks, including a random walk model, rolling averages with varying window sizes, and an AR(1) model. Long-run average and long-run median displacement in each district, computed across the whole sample, are included as simplest benchmarks. Second, two fixed effects panel regression models leveraging a full set of week and district fixed effects are included in the exercise. The first panel model treats unobserved displacement as zero observations, while the second one drops unobserved displacement from the data set. Finally, the Bayesian model introduced in Section 3 is estimated. In terms of covariates, all panel models include lagged conflict indicators from $t-1$ to $t-8$.

TABLE 1
Results of Forecasting Exercise

Model	RMSE	DM p-val (RMSE)	MAE	DM p-val (MAE)	Corr.
Random Walk	1.673	4.67×10^{-15}	1.175	1.01×10^{-09}	0.593
AR(1)	1.473	3.00×10^{-03}	1.114	1.64×10^{-06}	0.636
Long Term Average	1.766	2.86×10^{-52}	1.376	1.52×10^{-70}	0.465
Long Term Median	1.829	3.05×10^{-60}	1.415	7.15×10^{-78}	0.434
Rolling Average (4 Weeks)	1.627	6.46×10^{-12}	1.152	2.07×10^{-07}	0.606
Rolling Average (8 Weeks)	1.623	1.52×10^{-11}	1.152	1.52×10^{-07}	0.605
Rolling Average (12 Weeks)	1.614	7.92×10^{-11}	1.148	4.44×10^{-07}	0.607
OLS 2FE DL (excl. zeros)	1.648	1.06×10^{-32}	1.308	1.37×10^{-52}	0.456
OLS 2FE DL (incl. zeros)	2.068	1.49×10^{-86}	1.597	7.93×10^{-114}	0.390
Bayesian DL	**1.429**	–	**1.058**	–	**0.643**

Note: "RMSE" is the root mean squared error. "MAE" is the mean average error. "Corr." is the correlation of the point predictions and the true values. "DL" indicates the distributed lag models. "DM p-val" refers to the p-value of a Diebold–Mariano test under the null hypothesis of equal predictive accuracy relative to the Bayesian DL model. Results are averaged across 52 one-step-ahead hold-out samples. **Bold values** indicate the best performance in each column.

The results of the forecasting exercise are summarized in Table 1, where we report the root mean squared error (RMSE) and the mean absolute error (MAE) of the point forecasts as well as the correlation of the point predictions and the true holdout values. All criteria are averaged across the 52 hold-out periods. We also report the p-values obtained from Diebold–Mariano tests (Diebold (2015)) with the null hypothesis of equivalent predictive performance relative to the Bayesian model.

We find that forecasts based on rolling averages already outperform the random walk model as well as the panel fixed effects regression considerably. This is in line with the findings in Pham and Luengo-Oroz (2023). The fixed effects panel models give considerably worse results than the simple AR(1) model. The Bayesian approach, introduced in Section 3, can improve over all benchmark models in all three forecast quality criteria.

In the Supplementary Material, we provide additional predictive results for varying values of the number of latent factors Q. Here $Q = 2$ outperforms the other specifications, but in general, the results are relatively similar. In addition, we evaluate an alternative prior setting based on independent horseshoe shrinkage priors for the conflict impact coefficients β_{sj}^{+} and β_{sj}^{-}. We find that, while the overall performance is similar to the smoothing prior introduced in Section 3, the independence prior performs slightly worse in terms of RMSE and correlations of predicted and true values. This provides some evidence that conflict effects tend to play out rather smoothly in the setting considered here.

It is important to note that the results of this small forecasting exercise are no conclusive evidence that the proposed model will show any kind of "optimal" forecasting performance in a given displacement forecasting setting. After all, the model is not explicitly designed with forecasting performance in mind. However, these results are a good indication that the additional complexity we introduce to capture latent spatiotemporal dependencies does not lead to severe overfitting concerns. Overall, the results in Table 1 are indicative of a certain strength of the proposed Bayesian framework when it comes to short-term displacement predictions. Further investigations and extensions toward fully-fledged early warning systems (Martin and Singh (2019)) or a forecasting tool for forced displacement flow matrices in the style of Welch and Raftery (2022) are promising future research avenues.

Finally, it is important to emphasize that this forecasting exercise does not fully reflect a *real-time* forecasting scenario for policy intervention in acute conflict situations. Emulating such an exercise requires taking into account the idiosyncrasies of real-time data flows and ex post data revisions, which are typically not documented in our setting. In addition, while ACLED conflict data are released frequently, UNHCR displacement data are released irregularly. Nevertheless, we believe that our findings are useful for future policy design by deepening the understanding of the relationship between conflict and displacement as well as by providing a starting point for developing specialized models in similar settings that allow for real-time data flows.

5. Discussion & concluding remarks. Drawing on unique and granular displacement data from Somalia, this paper empirically investigates the short-run dynamics of conflict and displacement. We highlight several challenges that are likely to complicate working with similar data sets and develop a Bayesian statistical approach aiming to overcome these challenges. We point out that our considerations apply more generally to the analysis of large N large T panel data sets. The utility of the approach is demonstrated in two empirical exercises focused on impact evaluation and humanitarian forecasting. We find that the response of displacement to conflict is rapid, nonlinear in the number of conflict events, and heterogeneous by conflict type. Finally, the model shows good forecasting performance relative to benchmark models. Besides potential use cases for empirical analyses and for humanitarian forecasting purposes, the modeling framework and derived impact estimates are of relevance for policymakers, nongovernmental organizations, and complementary theoretical and simulation-based literature.

In terms of policy insights, we acknowledge that any real and definite solution concerning the root causes of displacement in Somalia will require ending the ongoing state of civil war. However, this goal will remain unlikely for some time to come, not only in Somalia but in many other parts of the world that experience prolonged periods of conflict. As long as conflict situations are not fully resolved, a thorough understanding of the determinants of displacement is a necessary prerequisite to alleviate the manifold issues that displaced populations face and to design appropriate policies that focus on assistance, prevention, and relocation (Engel and Ibáñez (2007), Dirikgil (2023)). In this context our findings highlight the importance of rapid response teams, as displacement tends to occur swiftly following conflict. The relevance of daily and weekly time frames in the context of conflict-driven displacement cannot be overstated. Another notable observation is the apparent lack of anticipation effects in the case of battles, which suggests that civilians either lack adequate forewarning, choose not to relocate preemptively, or lack the resources to do so. Disseminating information on battle-related developments, if available, could facilitate preemptive relocation efforts. Our findings further underscore the importance of strategic developments. It appears that such events hold significant predictive power for displacement. In addition, local populations may be anticipating some of these events. Training and empowering local communities to report anticipated events could, therefore, support anticipatory action.

Concerning quantitative research on conflict-driven displacement, this study highlights the importance of a granular perspective. Our findings suggest that relying on aggregate displacement data may obscure important details, limiting the depth and accuracy of empirical analysis. In addition, a more nuanced approach to the broad concept of "conflict," for instance, based on disaggregations by conflict type, is likely to unveil patterns and dynamics that are otherwise overlooked. In general, there is a significant need for better and more granular data, not only on displacement and conflict but also on environmental drivers and modulating factors such as food insecurity.

In concluding the article, several pathways for future research and modeling approaches emerge. One key area is the exploration of differential vulnerabilities of populations, which could be explored potentially through hierarchical random effects models. Another avenue is the investigation of spatial spillovers, which can illuminate the broader regional impacts of conflict. Mixed-frequency models (Ghysels, Sinko and Valkanov (2007)) could be developed to overcome some of the issues of data availability on a granular level. Measurement error models (Carroll et al. (2006)) concerning both displacement measurements and conflict predictor variables could further improve the modeling framework. Finally, predictive modeling of inflowing IDPs, which focuses on where people move to, is another promising research direction with the potential to enhance the ability to anticipate and respond to crisis-induced displacement events.

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SUPPLEMENTARY MATERIAL

Additional results, replication code, study context and limitations (DOI: 10.1214/24-AOAS1959SUPP; .zip). The Supplementary Material provide additional results, replication code, a Monte Carlo simulation study, trace plots, and MCMC convergence diagnostics, a review of the theoretical and empirical literature on conflict and forced displacement, as well as a historical overview of the civil war in Somalia. In addition, potential shortcomings of the employed data are highlighted and a discussion of internal and external validity of the results is provided.

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