(Re)Emerging Disease and Conflict Risk in Africa, 1997 – 2019

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Abstract

While the number of infectious zoonotic disease outbreaks has been rising, their impact on civil war and social conflict is poorly understood. This study addresses this fundamental limitation using a geolocated monthly dataset on 22 zoonotic diseases in Africa. Zoonotic disease is a key driver of new epidemics, making such pathogens a useful test case. Results suggest that over the January 1997 – December 2019 period, zoonotic disease was negatively associated with state initiation of civil conflict, and positively associated with social conflict involving identity militias. Additional analyses find that the effect for identity militias is consistent with a causal interpretation. Rebel violence is not significantly associated with outbreaks. The results are robust to endogeneity concerns and additional sensitivity analyses.

Keywords: *Civil war; Georeferenced data; Infectious disease; Social conflict; Zoonotic pathogens*

Main

When an Ebola outbreak occurred in North Kivu province of the Democratic Republic of the Congo (DRC) in 2018–2019, local health workers found themselves engulfed in a wave of intensified violence. As the state retracted from the region, "[o]rganizational imperatives produced an inwards-oriented focus that contributed to misunderstanding and mistrust in their engagement with populations…including [relying on] militia and armed groups for protection… and the use of force to disperse protesters, transport suspected cases to treatment centers, and to impose virus-proof burial techniques" [1].

This case illustrates the potential dynamics that might arise in the wake of an emerging disease outbreak, and, we argue, is hardly unique. In recent years, the media has been inundated with stories about the outbreaks of deadly diseases such as Ebola, swine flu, and COVID-19. One important, yet poorly understood implication of such outbreaks relates to their destabilizing impact on political stability [2-3]. Although several studies explored the impact of some protracted epidemics like malaria, HIV/AIDS, and COVID-19 on civil war [4-10], the effects of new and remerging disease outbreaks, broadly, on armed conflict deserve further consideration. Furthermore, we know very little about the local-level impact of disease outbreaks on conflict, even though environmental drivers of violence operate primarily at this level [11].

This study fills this gap by exploring the impact of infectious zoonotic disease outbreaks on conflict in Africa, a continent that has produced many emerging pathogens in recent decades. By "zoonotic," we refer to diseases whose reservoir is in animal hosts, and who can infect humans directly or via an intermediary [12]. Zoonotic pathogens are crucial drivers of emergent and reemergent diseases, with outbreaks posing a grave threat of becoming deadly regional and even global epidemics [13]. Considering this risk, such outbreaks are often immediately and

significantly impactful, requiring swift and decisive action and, given the potential danger they pose to regional and global health, are highly likely to be reported, allowing for comprehensive data collection and analysis. Additionally, due to their vector-borne nature, zoonotic outbreaks are more likely to be affected by conflict-unrelated factors such as animal migration and agriculturally-driven changes in land use, rather than be directly driven by conflict-related issues, possibly making endogeneity less of a concern in the data, although considering the risk is viable, we still ensure our results are robust to such simultaneity concerns.

Results

Considering the dearth in data on localized zoonotic disease outbreak events required for assessing these issues, a new geolocated monthly outbreak event dataset on 22 zoonotic pathogens, identified by the World Health Organization (WHO) as outbreaks of concern [14], including diseases such as Ebola, bubonic plague, anthrax, and Lassa virus, was created (see Methods and the SI file for detailed discussions of the data and collection procedures). Leveraging these data, we estimate the influence of outbreak events on conflict in Africa between Jan. 1997 and Dec. 2019 using a 0.5 degree (~55km^2 cells at the equator) gridded analysis (10,674 grids observed over 288 consecutive months without adjusting for missing information). We use the Armed Conflict Location and Event Dataset (ACLED) [15], which starts coding violence in Africa beginning in Jan. 1997, to create actor-oriented operationalizations that capture multiple nuances of conflict, including not only *civil war* involving state and rebel forces, that focus of many studies, but also *social conflicts*, defined here as initiated by civil defense forces, mercenaries, vigilantes, and repressive other nonstate actors often referred to as "militias" (see Methods) [16]. For illustration, Supplementary Figure 1 reports total outbreak frequencies for the zoonotic disease outbreak (ZDO) explanatory

variable, and Supplementary Figure 2 reports total conflict frequencies for each of the four dependent variables.

[Table 1 about here]

[Figure 1 about here]

Figure 1: Percent change in expected conflict rates for a one outbreak change across four actor types (top: baseline models; bottom: country-fragility adjusted models). *n*=1,779,790 for the baseline models and *n*=1,473,765 for the country-feature adjusted models. Y axis ranges vary between panels.

Our empirical framework incorporates climate (precipitation, water deficits/droughts, temperature) and socioeconomic (nighttime light, population densities) indicators at the same resolution across the continent, reducing the risk that any identified relationships are the result of local-level confounders [17], in addition to adjusting our estimates to account for country level fragilities (GDP per capita, government efficiency, life expectancy at birth) and conflict history trends (conflict lags and time trends). Our multiple estimation procedures accommodate both local features and heterogeneities, ensure that only-within 0.5-degree grid-cell variations are isolated (in case of zoonotic disease and conflict clustering), and account for potential simultaneous relationships between and serial correlation in conflict and disease risk over time as well as average treatment effects in outbreak affected cells (see Methods).

Table 1 first reports estimates from eight baseline and country-fragility and conflict-history adjusted grid-month ordinary least squares (OLS) conflict models. $ZDO\ events_{it}$ has a negative and

statistically significant coefficient ($p<.05$, two-tailed test) in the state-initiated conflict models. Examining rebel-initiated conflict, ZDOs have no statistically meaningful coefficient, and the sign is ambiguous. Moving on to social conflict, there is evidence that zoonotic disease outbreaks have a positive coefficient in the political militias models, but this relationship is not statistically significant according to any meaningful threshold. Examining identity militias, ZDOs' coefficient is positive and statistically significant in the baseline model, and remains significant once the estimates are adjusted for country-level fragilities and conflict history trends, suggesting identity militia conflicts are positively associated with zoonotic disease outbreaks.

To provide a more substantive illustration, Figure 1 calculates the expected change (in percent) from each conflict type's mean for a one outbreak increase (see Methods). Statistically significant zoonotic outbreak coefficients from Table 1 are in black. A zoonotic disease outbreak is associated with an approximately 5% – 120% reduction in the number of state-initiated attacks. The relationship between disease outbreaks and rebel attacks is unclear (negative in the baseline models and positive in the country-adjusted ones), with zero being included in the confidence intervals in both models. For political militias, the predicted change is, on average, about 55% increase in the expected number of conflicts (from a sample mean of 0.005 political-militia-initiated conflicts), although the confidence intervals contain zero in both cases. Finally, a one-zoonotic disease outbreak change is associated with a 30% – 55% increase in the expected number of identity militia conflict (from a mean of 0.003 of identity-militia-initiated conflicts), and the confidence intervals do not contain zero. Overall, then, the results suggest zoonotic disease outbreaks are associated with a harm to the state's ability to initiate conflict, but an increase in social conflict rates. Importantly, these results are robust when the estimates are adjusted for key

local and nation-level confounders, including population, development, conflict history, environmental stressors, and time-constant local features (e.g., elevation, distance from capital).

Accounting for endogeneity and serial correlation

While the determinants of a zoonotic outbreak may not be directly influenced by conflict, it is possible that conflict might still impact zoonotic disease outbreaks, e.g., by inducing population movements. The direction of this endogenous risk can go both ways – for example, conflict may push people toward more contact with contagious wildlife, but it can also induce people to move away from such areas. To adjust the estimates to ensure plausibly exogenous associations, we use a two-way systems general methods of moments (GMM) approach, a well-established method designed to account for endogeneity and serial correlation (see Methods). These panel data methods are computationally intensive and are not recommended for very temporally long data series [18]. Accordingly, the country-fragility and conflict-history trends adjusted models from Table 1 are estimated on a series of 72 months for which information on all variables is available (Jan. 2013 – Dec. 2018) in Table 2. The associations with respect to zoonotic diseases' impact on conflict are robust, despite the loss of approximately two thirds of the sample due to temporal limitations. Sargan test estimates suggest the models are robust, although weakened by the many instruments (due to the large number of panels). Table 2 hence suggests the associations identified are plausibly exogenous and are robust to endogeneity and serial correlation.

[Table 2 about here]

To assess whether these associations are consistent with a causal interpretation, we provide a more penalizing assessment in Figure 2. Here, we report – for each conflict type – the average treatment effect in the treated (ATT), which is the average effect of outbreaks for those 0.5-degree

cell-months that experienced at least one outbreak (see Methods). To this end, we used key features of each cell-month to statistically match 836 0.5-degree cell-months that experienced at least one outbreak with 836 0.5-degree cell-months that have similar values on these key features but that did not experience an outbreak. By omitting, in effect, >99% of the sample, this approach strongly risks type-II error (i.e., falsely assuming no effect exists between the key variables) compared with a standard average treatment effect approach used in Table 2, but offers in return a causal interpretation of any associated effects. As Figure 2 illustrates, while we are unable to identify any clear ATT for zoonotic disease in three conflict types (state, rebel, and political militias), seeing that the 95% confidence intervals contain zero, we confirm that an outbreak event has a positive and different-from-zero ATT on conflict initiated by identify militias. We can therefore conclude that for identity militias, at least, zoonotic outbreaks the impact on increasing social conflict incidence is consistent with a causal interpretation.

[Figure 2 about here]

Figure 2: Average treatment effect in treated cell months (ATT). n=836 matched observations. Z test values for each ATT comparison are p=0.968 (state), p=0.484 (rebel), p=0.981 (political militias), and p=0.021 (identity militias).

Additional sensitivity analyses

In addition to these endogeneity and causality robustness assessments, 58 additional sensitivity analyses are reported in the SI file. These assessments account for: (1) including only WHO/ISID confirmed outbreaks in our sample (Supplementary Table 3); (2) omitting all variables with missing information over the entire Jan. 1997 – Dec. 2019 period, which helps to also inferential biases due to multicollinearity [19] (Supplementary Table 4); (3) curtailing the analysis period to

Jan. 2003 – Dec. 2018, which corresponds to the period in Table 2 (Supplementary Table 5); (4) including only country fragility features and key controls (Supplementary Table 6); (5) using a binary outbreak indicator (corresponding to the ATT indicator) (Supplementary Table 7); (6) accounting for the intersection between floods and outbreaks (environmental pestilence) (Supplementary Table 8); (7) adding conflict types by other actors as controls (Supplementary Table 9); (8) repeating (7) with the addition of *t-1* conflict lags (Supplementary Table 10); (9) adding COVID-19 outbreaks over Jan. – Mar. 2020 to the sample (Supplementary Table 11); operationalizing $ZDO\ events_{it}$ as (10) only the most virulent strain outbreaks (Ebola, Marburg, plagues haemorrhagic fevers, rabies and anthrax) (Supplementary Table 12); (11) fevers and respiratory syndromes (Supplementary Table 13); and (12) all other outbreaks (Supplementary Table 14); estimating geospatially weighted grid-cell (13) pooled (Supplementary Table 15) and (14) random effect (Supplementary Table 16) regressions; (15) aggregating all conflict types to show null effect of outbreaks, which support disaggregation by actor and conflict type (Supplementary Table 17); (16) using linear and quadratic terms for rainfall (in mm) instead of precipitation anomalies (Supplementary Table 18); and (17) removing cities with at least 50,000 inhabitants from the sample (Supplementary Table 19). With respect to state-initiated conflict, our $ZDO\ event_{it}$ coefficient maintains its negative association in almost every case, but falls short of statistical significance in Supplementary Tables 6 (p=0.206) and 7 (p=0.116). For identity militias, the associations remain positive and statistically significant in every case excluding in Supplementary Table 4, where they do not reach the statistical significance threshold (p==0.069). In the disaggregated outbreak-type models we find that outbreaks other than fevers and respiratory syndromes and virulent strains are statistically and negatively associated with state-conflicts and

that fevers and respiratory syndromes are statistically and positively associated with increases in identity militia conflicts, as well as a reduction in rebel-initiated conflicts.

Discussion

This study provides evidence to show that in Africa between Jan. 1997 and Dec. 2019, zoonotic disease outbreaks are associated with a reduction of civil war activity by state forces by about half of its baseline rate but an intensification in social conflicts rates by identity militias by as much as a threefold. In the latter, we were able to confirm a relationship that is consistent with a causal interpretation. There is no clear evidence for the existence of a clear directional association between zoonotic disease outbreaks and conflict initiation by rebels engaged in civil war and political militias.

Past research on the impact of COVID-19, malaria, and HIV suggests several potential explanations for these observed associations. First, outbreaks can adversely affect the state and its administrative and security capacities. For instance, infectious disease outbreaks can constitute a governance shock. Outbreaks force the government to "shift its focus from other administrative functions to combating the disease, while simultaneously being forced to reduce its bureaucratic and even security operations to avoid infection and the spread of the pandemic to its employees and troops" [7], which can impact its ability and willingness to engage in armed conflict. Zoonotic disease outbreaks similarly constitute sudden shocks to governance – often, vaccines are not readily available, and containment of movements and activity is necessary. This compels state militaries to reduce conflict activity as the rate of zoonotic disease outbreak events increases. With respect to rebels, considering that null results do not imply conflict trends might shift in the in

future, future studies could assess, for example, the role resource endowments and group capacity play in governing rebel responses to spreading zoonotic disease.

Examining social conflict, if the government is temporarily weakened or incapacitated, a governance vacuum is created, which can increase the risk of violence involving nongovernmental militia actors. Such dynamics were evident in an interview conducted by one of the authors with a member of the Fulani in west Africa, who – when trying to escape the spread of COVID-19 – was subject to violence and extortion by local militias that were protecting local communities. During outbreaks, militias may even provide services the government cannot, such as aid, food, and healthcare [10]. For instance, the onset of the COVID-19 pandemic in some susceptible states has been "increasing stress on [their] precarious health-care system and exacerbating youth unemployment...This further undermines the fledgling government's legitimacy, as militias have stepped in to supply medical and humanitarian services" [20]. More likely, militias can leverage their comparative advantage and act more directly as defense providers, stepping in to provide security, both to react to rebel attacks, and to preempt any potential intensification of rebel violence [7]. Considering that service and security provision may not necessarily correlate, there are two explanations for the observed rise of conflict activity by militias in the lack of effective state protection and reduced government security activity.

First, governments or local nongovernmental organizations may "contract" such groups to engage in conflict or provide security when and where the government is unable or willing [16], such as in the wake of the outbreak of a deadly disease. For instance, during the 2018-2019 wave of Ebola outbreaks in eastern DRC, the actions of local health organization contributed to intensification of militia activity. By being forced to bribe rebels and state forces to protect workers and prevent the spread of disease, the actions of these organizations created mistrust in local health

personnel, opening the door to local defense militias to move in and engage – often violently – with the implementation of health measures due to the governance vacuum created by the rebels and state forces who were paid to stay away from these zones [1]. Second, civil defense militias might be organized independently or semi independently by local communities in affected regions to provide security [21], or get recruited to protect, e.g., areas where natural resources are extracted or pastoralist zones [22]. Such militias are impacted by the constraints faced by government forces to a lesser extent, and – unlike rebel groups – do not face similar pressures to advance state or regional takeover goals, thereby using the opportunity provided by the outbreak to expand operations and security relevance [7]. The finding that identity militias – groups that include civil and community defense forces – rather than organizations tied to political parties and leaders (political militias) intensify their security activity during zoonotic disease outbreaks is in line with the second (community mobilization) explanation. For example, in the height of the COVID-19 pandemic in Nigeria, abduction rates by armed groups increased by 169% [22]. Due to the poor performance of the state's security forces, vigilante militias emerged as the key alternative security force across all states to protect people against rebel groups and kidnappings [22]. Similarly, after the imposition of lockdown following the spread of the COVID-19 pandemic, locals in southwestern Nigeria turned to community defense forces to help provide security against the rise of crime [23]. The vigilantes were able to provide security where official police forces could not.

Considering the risk of emerging zoonotic pathogen outbreaks is poised to increase in the coming decades due to population growth, deforestation trends, and climate change [13], this study's findings provide a template for assessing impacts and suggest mitigation strategies. The results underscore the importance of studying the entire spectrum of actors involved in conflict rather than focusing only on civil wars and the often-used government vs. rebel conflict dichotomy.

If disease outbreaks create incentives for civilians to turn to militias for protection, this can lead to loss of state power and legitimacy over the longer term, even if over the short term, identity militias provide security and protection. Therefore, considering (re)emerging disease outbreaks can pose threats to the state sovereignty, interventions designed to bolster the state and its capacities (assuming such bolstering does not cause more harm to its citizens, as in the case of repressive states) can assist in preventing protracted conflict and improving political stability over the short term. Moreover, as our findings in Supplementary Tables 12-14 show, outbreaks involving pathogens other than the most virulent ones and fevers or respiratory syndrome diseases might necessitate interventions that are specifically designed to address decline in state activity, while addressing the potential impacts fevers and respiratory syndrome outbreaks (including COVID-19) on conflict may require strategies that seek to directly address intensification in identity militias activity, as was also supported by some of the qualitative evidence [22-23].

Finally, it is important to highlight some limitations of this study. Most importantly, our data focused only on African states, and only on a subset of potential zoonotic pathogens. This means that the findings might not be viable on a global scale, or for other pathogens, zoonotic or not. Second, this study focused on armed and social conflicts between different combatant parties. As such, the results may not be applicable for other dynamics of violence, including attacks on civilian or authoritarian repression, which might still be viable pathways of risk [24-25]. Finally, due to the macro-level nature of our sub-national analysis, we were unable to assess some specific determinants that might lead some groups to choose a path of violence, including, for instance, service endowments, ideology, and political allegiances [10].

Methods

Sample

The sample is constructed using the 0.5-degree grid cell – approximately 55km x 55km at the equator, which decreases in size toward the poles – measured for each month between Jan. 1997 and Dec. 2019, although due to lack of available information on some of the controls, a more constrained period (Jan. 2000 – Dec. 2018) is analyzed in most models. This framework includes climate and socioeconomic indicators at the same resolution across the continent, reducing the risk that any identified relationships are the result of local-level confounders. The empirical construction uses AfroGrid, a recently released data framework specifically designed to study environmental conflict in Africa [17]. Its subnational/localized geospatial resolution combined with subannual (monthly) temporal disaggregation make AfroGrid an especially useful tool for assessing local level zoonotic outbreak events' impact on conflict as unanticipated shocks [11].

Dependent variables

The dependent variables are actor-oriented operationalization using data from ACLED [15] and the actor-specific interaction codes therein. The first two dependent variables capture the government vs. rebel conceptualizations of civil war based on the number of conflict incidents initiated by (i) state and (ii) rebel forces. The next two dependent variables operationalize social conflict based on a wide spectrum of nongovernmental actors (mentioned in Main) often referred to as “militias” [16] and classified as to whether these groups were (iii) politically-, or (iv) self-defense (identity) oriented.

The key advantages of ACLED over other datasets for the specific purpose of this study is that it disaggregates all local conflict and violence incidents by the initiating actors, while coding a diverse actor typology. Using an actor-oriented operationalization helps to capture the direct impact of a zoonotic disease outbreak on their active engagement initiatives, which past research

suggests is key in the case of disease-conflict analysis [7-9]. Each dependent variable lags was created by using conflict values from the previous month.

Zoonotic disease outbreak events

The Geolocated Zoonotic Disease Outbreaks Dataset (G-ZOD) records monthly information on outbreak events involving 22 infectious, potentially lethal pathogens that were identified by the WHO [14] as posing potential or real epidemic risk in the African context over the Jan. 1996 – Dec. 2019 period (although due to the fact ACLED begins measuring conflict in 1997 we are forced to omit 1996 from analysis): Ebola-Zaire, Ebola-Sudan, Ebola-Täi forest, Ebola-Bundibugyo, Marburg, yellow fever, Rift Valley fever, H1N1 flu, H5N1 flu, SARS, MERS, chikungunya, Lassa, dengue, monkeypox, septicemic plague, bubonic plague, Crimean-Congo hemorrhagic fever, shigellosis, rabies, zika, and anthrax. The efforts focused on Africa to maximize the availability of time and resources, and because the continent experiences a high share of both global conflict events involving state, rebel and militia forces, and zoonotic disease outbreaks (including those involving emerging pathogens). The $ZDO\ events_{it}$ indicator was created by aggregating the total number of outbreaks occurring within each 0.5 grid to the monthly level, creating a framework that directly corresponds to AfroGrid's unit of analysis.

A detailed discussion of the data and multi-step approach used for coding the dataset is provided in the SI file. Considering these are event data, using the 0.5-degree month approach as used here is the lowest resolution, both geospatially and temporally, recommended in such analyses [26]. While a detailed discussion of this issue is also provided in the SI file, briefly, this level of resolution helps in reducing reporting issues that could affect event data, while still allowing for the most detailed subnational and subannual analysis possibly. To further avoid

inferential biases, we only retained subnational data (at the province level or below) and outbreak events that included, at the very least, information on the month and year of the outbreak.

Control variables

The controls used in the main and sensitivity analyses were aggregated from other databases into AfroGrid. Due to concerns related to inferential biases from including too many controls [18], only key confounders highlighted by past research at similar levels of resolution [11, 17] were included, while adding fixed effects for each grid cell to account for all constant (time invariant) features. The constant features covered by grid cell fixed effects include, for instance, mountainous coverage levels, travel distance to the nearest city, and the location of the national and province/state capitals, among others. To illustrate our findings are robust to this decision, we report models with additional controls in the SI File. NTL_{it} (accounting for local state capacity and development) measures the (natural log) total number of lighted pixels observed in a given 0.5-degree grid cell during a given year and was created by AfroGrid using VIIRS-adjusted DMSP data and a high sensitivity re-calibration method [27]. $Population_{it}$ measures the (natural log) number of people residing in a given 0.5-degree grid cell during a given year and was obtained from the Global spatio-temporally harmonised dataset [28]. Both variables were measured annually and aggregated into monthly using the last-value-carried-forward approach. Controls for drought and precipitation and temperature anomalies were created as normalized deviations (Z values) from long term trends of rainfall (in mm) and temperature (in Celsius) using CRU-TS data [29]. Research shows that it is important to account for the possibility a curvilinear relationship between rainfall and conflict [30-31]. In these regards, the use of anomalies rather than raw rainfall quantities effectively captures this curvilinear possibility, although it is important to note that the

results remain substantively and statistically unchanged when a logged variable of rainfall (in mm) and its quadratic terms are used in these models instead of the anomaly. Country level controls for (natural log) life expectancy in birth in years (a key indicator of development), government efficiency (a political capacity indicator with an index ranging from worst to best performance) and (natural log) GDP per capita in U.S. dollars (for measuring state capacity) were obtained from the World Bank [32]. All robustness models correspond to the country specifications unless stated otherwise. Summary statistics for all variables are in Supplementary Table 2, SI file.

Analysis

The associations in Table 1 and Supplementary Tables 3-14 and 17 were estimated using ordinary least squares (OLS) with cross-sectional/0.5-degree grid cell (*i*) and monthly (*t*) fixed effects and contemporaneous explanatory variables per econometric research recommendations [33-34]. The geospatially weighted associations in Supplementary Tables 15-16 were estimated using pooling and random-effects by grid cell instead of fixed effects. Identification was achieved using the following formulas:

Baseline:

$$\boldsymbol{y_{it}} = \beta_1 \boldsymbol{z_{it}} + \beta_2 \boldsymbol{n_{it}} + \beta_3 \boldsymbol{p_{it}} + \beta_{4-6} \boldsymbol{E_{it}} + \boldsymbol{\omega_i} + \boldsymbol{\phi_m} + \epsilon_i \quad (1)$$

Country-fragility and conflict-history trend adjusted:

$$\boldsymbol{y_{it}} = \beta_1 \boldsymbol{z_{it}} + \beta_2 \boldsymbol{n_{it}} + \beta_3 \boldsymbol{p_{it}} + \beta_{4-6} \boldsymbol{E_{it}} + \beta_{7-9} \boldsymbol{C_{it}} + \beta_{10} \boldsymbol{y_{it-1}} + \beta_{11} \boldsymbol{t_t} + \boldsymbol{\omega_i} + \boldsymbol{\phi_m} + \epsilon_i \quad (2)$$

Where $\mathbf{y_{it}}$ is a vector of each of the four conflict types; $\mathbf{z_{it}}$ is a grid-month vector of zoonotic disease outbreak events; $\mathbf{n_{it}}$ is a control for nighttime light emissions; $\mathbf{p_{it}}$ is a control for population densities; $\mathbf{E_{it}}$ is a matrix of climate controls (precipitation and temperature anomalies and drought); $\mathbf{C_{it}}$ is a matrix of country-level controls (life expectancy, government efficiency, and GDP per

capita); β is each respective independent variable's coefficient; $\boldsymbol{\omega_i}$ and $\boldsymbol{\phi_t}$ are fixed effects by grid cell and month, respectively; $\mathbf{y_{it-1}}$ is a one-month lag of each respective dependent variable and $\boldsymbol{t_t}$ is the time trend for each period in the sample; and ε_i are standard errors clustered by grid cell to account potential violations of homoskedasticity due to repeated measurement of similar values within each grid cell. Some specifications in the sensitivity analyses include additional controls for conflict, conflict lags, and spatial conflict lags added to equation (2). Statistical significance was assessed using two-tailed *Z* tests.

Figure 1 was estimated by using equations 1 and 2 for the baseline and country-adjusted model, respectively, for each dependent variable. The estimates, including the 95% confidence intervals, were bootstrapped as the effect of a one-ZDO outbreak change (i.e., from a case where $\mathbf{z_{it}}$ =0 to $\mathbf{z_{it}}$ =1) based 1,000 simulations, with the average, lowest 5% and highest 95% values reported.

Table 2 was estimated based on equation 2 using two-way system general methods of moments (GMM) estimators. The system GMM estimator is the more robust estimator, and uses past variations in each dependent variables to, in effect, 'exogenize' its variations at time *t* [18]. The two-way effects approach is akin to a unit fixed effects estimation, where the units are indexed according to the time series for each grid cell, removing – in effect – the need for grid cell fixed effects. Based on research recommendations, where only shallow dependent variable lags are preferred as instruments [35], two-to-four-month (*t*-2 to *t*-4) lags as our internal instruments. Considering the sheer size of the sample as well as the fact that GMM estimators are not recommended for very long time series [18], forcing us to limit the period of analysis to the Jan. 2013 – Dec. 2018 period (which correspond to the availability of information on some controls), leaving a total of 72 months for each grid cell for which information on all controls was available,

while providing estimates plausibly exogenous associations that are robust to endogeneity and serial correlation.

The average treatment effects in the treated (ATT) in Figure 2 were estimated based on the epidemiological causal estimation approach proposed by [36] in three steps. In the first step, we matched the treated units (i.e., 0.5-degree cell-months that experienced at least one ZDO outbreak) with untreated units with similar propensity scores (selected using the "nearest" method, where each unit is matched with the one most closely resembling it) on key features: nighttime light, population densities, conflict lags (for each respective conflict type), precipitation and temperature anomalies, drought severity, and month. In the second step, we regressed the binary ZDO treatment on each respective conflict variable using OLS in this matched sample, and included (as recommended) treatment-covariate interactions for each of the features of interest, to account for the possibility the sample was not fully balanced. In the third step, we estimated and plotted ATT in the treated sample, specifically, as the change in the number of conflicts for a case where ZDO=1. The reliance on matching-based methods provides estimates that are consistent with a causal interpretation in observational data such as the ones used here [37]. All analyses were conducted in R.

Data availability

All data required for replicating all tables and figures in this study and its SI file are openly available on the Harvard Dataverse at: https://doi.org/10.7910/DVN/TFYYDR.

Code availability

All code scripts required for replicating all tables and figures in this study and its SI file are openly available on the Harvard Dataverse at: https://doi.org/10.7910/DVN/TFYYDR.

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Author contributions

OK collected the data, conducted analysis, wrote the introduction, results, and methods sections, and assisted with writing the discussion section. KNG provided contextual evidence, and assisted with writing the framing and discussion section.

Competing interests

The authors declare no competing interests.

Tables

Table 1: Determinants of Armed Conflict in African Locations

	Civil War				*Social Conflict*			
	State		**Rebel**		**Political Militias**		**Identity Militias**	
	Baseline	**Country**	**Baseline**	**Country**	**Baseline**	**Country**	**Baseline**	**Country**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ZDO events$_{it}$	-0.019*	-0.013*	-0.002	0.002	0.013	0.010	0.009*	0.012*
	(-0.034,-0.004)	(-0.024,-0.001)	(-0.017,0.013)	(-0.009,0.013)	(-0.014,0.040)	(-0.017,0.036)	(0.00003,0.018)	(0.001,0.02
	[0.012]	[0.032]	[0.811]	[0.718]	[0.342]	[0.471]	[0.049]	[0.025]
NTL$_{it}^{l}$	0.001*	0.00002	0.00002	0.00004	0.001*	0.0002*	0.001*	0.0001*
	(0.001,0.002)	(-0.001,0.001)	(-0.0001,0.0005)	(-0.0001,0.0003)	(0.001,0.001)	(0.0001,0.001)	(0.001,0.001)	(0.00002,0.0
	[<0.001]	[0.853]	[0.222]	[0.320]	[<0.001]	[0.011]	[<0.001]	[0.033]
Population$_{it}$	0.014*	-0.001	0.0016	-0.0001	0.005*	0.001	0.003*	-0.0001
	(0.006,0.022)	(-0.003,0.002)	(-0.001,0.004)	(-0.001, 0.001)	(0.004,0.007)	(-0.00002,0.003)	(0.002,0.004)	(-0.001,0.0
	[<0.001]	[0.599]	[0.154]	[0.825]	[<0.001]	[0.054]	[<0.001]	[0.711]
Prec. anom.$_{it}$	0.00003	0.0001	-0.0005*	-0.0002*	-0.0002	-0.0002	-0.0001	-0.0002*
	(-0.0004,0.001)	(-0.0003,0.001)	(-0.001,-0.0003)	(-0.0004,-0.00004)	(-0.0004, 0.0001)	(-0.0004,0.00002)	(-0.0003,0.0001)	(-0.0004,-0.0
	[0.404]	[0.518]	[<0.001]	[0.018]	[0.190]	[0.074]	[0.235]	[0.031]
Drought$_{it}$	-0.0005	-0.0001	0.0006*	0.0003*	0.0001	0.0001	2.4e-05	0.0002*
	(-0.001,0.0002)	(-0.001,0.0003)	(0.0003,0.001)	(0.0001,0.0004)	(-0.0002,0.0004)	(-0.0001,0.0003)	(-0.0002,0.0002)	(0.00002,0.0
	[0.143]	[0.544]	[<0.001]	[0.0049]	[0.435]	[0.423]	[0.790]	[0.029]
Temp. anom.$_{it}$	-0.0003	-0.0003	0.0004*	0.00001	-0.0003*	-0.0001	1.4e-05	-0.00001
	(-0.001,0.0001)	(-0.001,0.0002)	(0.00001,0.001)	(0.0001,0.0002)	(-0.001,-0.00001)	(-0.0003,0.0001)	(-0.0002,0.0002)	(-0.0002,0.0
	[0.125]	[0.275]	[0.043]	[0.855]	[0.041]	[0.436]	[0.877]	[0.863]
Life exp.$_{it}$	.	-0.004*	.	-0.001*	.	-0.001	.	-0.0004
		(-0.007,-0.0003)		(-0.001,-0.0002)		(-0.003,0.0003)		(-0.001,0.0
		[0.032]		[0.007]		[0.115]		[0.368]
Gov. eff.$_{it}$	.	-0.001	.	0.0001*	.	0.0002	.	-0.0002
		(-0.001,0.0002)		(0.0004,0.002)		(-0.0001,0.001)		(-0.0005,0.0
		[0.132]		[0.003]		[0.133]		[0.248]
GDP pc$_{it}$	.	-0.061*	.	-0.011*	.	-0.016*	.	-0.026*
		(-0.079,-0.043)		(-0.019,-0.004)		(-0.025,-0.006)		(-0.034,-0.0
		[<0.001]		[0.004]		[0.002]		[<0.001]
DV$_{it-1}$	.	0.453*	.	0.323*	.	0.305*	.	0.092*
		(0.277,0.630)		(0.119,0.527)		(0.202,0.409)		(0 0.061,0.1
		[<0.001]		[0.002]		[<0.001]		[<0.001]
Trend	.	0.0001*	.	2e-05*	.	3e-05*	.	4e-05*

		(0.0001,0.0001) [<0.001]		(0.00001,0.00003) [<0.001]		(0.00001,0.0001) [0.002]		(0.00003,0.0 [<0.001]
N	1,779,790	1,473,765	1,779,790	1,473,765	1,779,790	1,473,765	1,779,790	1,473,76
R^2	0.224	0.641	0.141	0.152	0.156	0.166	0.036	0.067
Adj. R^2	0.220	0.693	0.136	0.146	0.151	0.160	0.031	0.061
F-stat.	52.09*	267.4*	29.48*	26.73*	33.26*	29.68*	6.787*	10.75*
DF	1769966	1463970	1769966	1463970	1769966	1463970	1769966	1463970

Coefficients are reported with 97.5% confidence intervals clustered on grid cell in parentheses and p-values (based on two-tailed tests) in brackets; the unit of analysis is the cell-month; fixed effects by month and grid cell were included in each regression, but not reported here. * $p<0.05$; [1] Natural log; for some of the models, "." mean that this variable was not included in the model.

Table 2: Determinants of Armed Conflict in African Locations, Accounting for Endogeneity

	Civil War		***Social Conflict***	
	State	**Rebel**	**Pol. Mil.**	**Id. Mil.**
	(9)	**(10)**	**(11)**	**(12)**
ZDO events$_{it}$	-0.020*	0.003	0.029	0.026*
	(-0.0042,-0.0036)	(-0.013,0.019)	(-0.014,0.072)	(0.008,0.044)
	[0.017]	[0.682]	[0.173]	[0.005]
NTL$_{it}$[1]	-2e-06	-0.0001	0.001*	-0.00001
	(-0.0004,0.0004)	(-0.0003,0.0001)	(0.0008,0.0012)	(-0.0002,0.0002)
	[0.991]	[0.142]	[<0.001]	[0.926]
Population$_{it}$	0.002*	0.001*	0.002*	0.002*
	(0.00003,0.004)	(0.0006,0.0014)	(0.0012,0.0028)	(0.0016,0.0024)
	[0.0001]	[<0.001]	[<0.001]	[<0.001]
Prec. anom.$_{it}$	-0.0001	-0.0001	-0.0003	-0.0003
	(-0.0009,0.0007)	(-0.0005,0.0003)	(-0.0007,0.0001)	(-0.0007,0.0001)
	[0.775]	[0.719]	[0.172]	[0.213]
Drought$_{it}$	0.001	-0.00001	0.0001	0.001*
	(0.0002,0.0018)	(-0.0004,0.0004)	(-0.0003,0.0005)	(0.0008,0.0012)
	[0.194]	[0.975]	[0.749]	[0.005]
Temp. anom.$_{it}$	-0.0001	-0.0003	-0.0004*	0.00035
	(-0.0007,0.0005)	(-0.0007,0.0001)	(-0.0008,-0.00006)	(-0.00004,0.0007)
	[0.754]	[0.103]	[0.045]	[0.074]
Life exp.$_{it}$	-0.001*	-0.0002	-0.002*	-0.0002
	(-0.00002,0.002)	(-0.0008,0.0004)	(-0.0028,-0.0012)	(-0.001,0.0006)
	[0.012]	[0.515]	[<0.001]	[0.570]
Gov. eff.$_{it}$	0.0002	0.001*	-0.00004	0.0003*
	(-0.0002,0.0006)	(0.0006,0.0014)	(-0.0002,0.0002)	(0.0001,0.0005)
	[0.245]	[0.003]	[0.729]	[<0.001]
GDP pc$_{it}$	-0.002	-0.004*	-0.001	-0.011*
	(-0.001,0.006)	(-0.008,-0.0001)	(-0.009,0.007)	(-0.005,-0.017)
	[0.626]	[0.048]	[0.815]	[<0.001]

DV_{it-1}	0.818* (0.664,0.972) [<0.001]	0.478* (0.212,0.744) [<0.001]	0.408* (0.292,0.524) [<0.001]	0.169* (0.126,0.212) [<0.001]
N	547,691	547,691	547,691	547,691
Sargan χ^2	4,909.9*	3,903.3*	5,877.2*	5,859.6*
AR(1)	-3.770*	-4.817*	-5.622*	-8.804*

Coefficients are reported with 97.5% confidence intervals clustered on grid cell in parentheses and p-values (based on two-tailed tests) in brackets; the unit of analysis is the cell-month; the internal instruments for system GMM estimators are $t-2$ to $t-4$ lags. * p<0.05; [1] Natural log.

Figure captions

Figure 1: Percent change in expected conflict rates for a one outbreak change across four actor types (top: baseline models; bottom: country-fragility adjusted models). n=1,779,790 for the baseline models and n=1,473,765 for the country-feature adjusted models. Y axis ranges vary between panels.

Figure 2: Average treatment effect in treated cell months (ATT). n=836 matched observations. Z test values for each ATT comparison are p=0.968 (state), p=0.484 (rebel), p=0.981 (political militias), and p=0.021 (identity militias).

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