How Natural Disasters Spread Conflict*

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Abstract

This paper studies how natural disasters spread conflicts within a network. We first construct a new panel data set that combines geo-referenced information about conflict events and natural disasters, for 5,944 districts in 53 African countries, over the period 1989–2020. Considering natural disasters as exogenous shocks that affect the combatants' activity in a locality, we find that natural disasters decrease conflict incidence in the affected locality, increase conflict incidence in neighboring localities, and lead to an overall net increase in conflict incidence. The spatial dispersion of conflict varies by the level of local rent-seeking opportunities and the level of international, post-disaster aid. We then provide a simple theoretical framework that may explain this conflict dispersion pattern. Findings provide important implications for implementing local and aggregate level conflict mitigation policies.

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1 Introduction

Climate change ranks among humanity's most pressing threats, not least because mounting evidence links it to rising violence and conflict (Hsiang et al. 2013; Burke et al. 2015; Mach et al. 2019). Africa sits at the center of this risk: its food-producing ecosystems, coastlines, and fast-growing urban settlements are highly exposed to warming-driven stresses, while governance and fiscal buffers remain limited (Trisos et al. 2022). These climatic pressures intersect with a distinctive conflict landscape. In 2014, more than half of the world's documented violent events took place on the continent, even though it is home to only 16 percent of the global population (Cilliers 2015). Conflicts in Africa often ignite as localised skirmishes and then cascade across districts and national borders.[1]

A large empirical literature in economics has focused on droughts, emphasizing their effects on agricultural incomes, food insecurity, and the opportunity costs of mobilization (e.g. (Miguel, Satyanath & Sergenti 2004, Harari and La Ferrara 2018, McGuirk and Nunn 2025). However, recent assessments underscore that droughts are neither the only nor necessarily the most acute natural disasters facing African societies (GCA 2022). While droughts have affected more people in Africa overall in the longer term, during the last decade (2010–2020) more people across Africa have been impacted by floods alone compared to droughts (Lumbroso, 2020). Droughts largely affect North and Southern Africa. In contrast, floods and storms affect almost all regions of the continent, and increasingly strike areas that are both more densely populated and exhibit higher levels of economic activity.[2] The frequency and

[1] One example is the Boko Haram insurgency in Nigeria, which began as small skirmishes with security forces in 2009—mainly in Bauchi, Borno, Yobe, and Kano states (Thurston 2018). By 2014 the insurgency had intensified and spread to Cameroon, Chad, Mali, and Niger (Dowd 2015). A second example is the Lord's Resistance Army, which started in 1987 in northern Uganda and later spilled into Sudan, the Central African Republic, and the Democratic Republic of Congo, where it remains active.

[2] Based on the disaster data used in this study (Section 2.2), 174 subnational areas were hit by major droughts compared to 1,079 subnational areas who were affected by any other natural disaster type over the period 1989–2020. In addition, non-drought disasters also impact areas with more economic activity, as proxied by nighttime light (NTL) intensity. The average NTL intensity in flood affected areas is 3.23 compared to 0.11 in drought affect areas.

severity of these types of natural hazards are projected to rise in Africa under most warming scenarios (World Meteorological Organization 2024).

Sudden-onset disasters—such as floods, storms, and earthquakes—differ fundamentally from *slow-onset* disasters like droughts in their nature, immediacy, and spatial footprint of destruction. While slow-onset disasters primarily affect agricultural output by gradually reducing crop yields and depleting water resources over extended periods, sudden-onset disasters typically devastate physical infrastructure, housing, and other durable assets within hours or days. These distinct destructive mechanisms are crucial because they shape both the immediate human and economic toll of disasters and the subsequent responses of affected populations. For instance, Deryugina et al. (2018) show that Hurricane Katrina—a sudden-onset disaster—triggered widespread displacement, sharp but temporary income losses, and large-scale geographic reshuffling of human capital, with recovery facilitated by substantial external aid. In contrast, Hornbeck (2012) finds that slow-onset disasters, such as the Dust Bowl, induced persistent economic decline through gradual environmental degradation, with adaptation occurring via long-term out-migration and land abandonment rather than recovery.

These contrasting dynamics have direct implications for the spatial distribution of conflict. Sudden-onset disasters can produce short-term destruction of contested resources, hinder the maneuverability of conflict actors, and promote conflict diffusion. Droughts, by contrast, may locally lower the opportunity cost of participating in violence, but their slower progression and wider spatial reach imply more diffuse and potentially delayed effects on conflict. Understanding these distinctions is central to explaining why different disaster types generate distinct spatial conflict dynamics—a key focus of this study—and, in turn, to informing the design of effective policy responses.

This paper provides a theoretical and empirical analysis of how such disasters reshape the geography of conflict in Africa. We analyse how a negative, exogenous shock to one district alters violence locally and how that effect spills over to neighbouring districts through the network that links combatants.

To examine both the direct and the spillover effects of natural disasters on conflict, we assemble a district–year panel that covers 5,944 African ADM2 units (second-level administrative areas) from 1989 to 2020. The data set links geo-referenced conflict events—our outcome variable—to geo-referenced natural disasters—our treatment variable.[3] Next, we construct an altitude-adjusted inverse-geodesic distance matrix to measure connectivity between districts. Merging this spatial network with the panel allows us to trace how a disaster in one location alters conflict risk in neighbouring areas. Our identification rests on the quasi-random timing and location of disasters, which we treat as exogenous shocks to the local probability of conflict.

Our results reveal that the spatial dynamics of disaster-induced conflict differ markedly by disaster type. We find that sudden-onset disasters, such as floods and storms, decrease conflict incidence within the directly affected district but generate systematic and positive spillovers to geographically connected areas. In contrast, droughts increase the likelihood of conflict within the affected district and produce additional, persistent spillovers into neighboring regions.

The second part of the paper investigates the mechanisms underlying these spatial patterns. We construct district-level proxies for rent-seeking potential—economic activity measured by night-time lights, agro-climatic suitability for high-value crops, and the value of mineral deposits. Following Nunn and Qian (2014), we also track international emergency aid from the Office of Foreign Disaster Assistance (OFDA), which can ease liquidity and logistical constraints for both rebel groups and government forces. After a disaster, vio-

[3] We rely on EM-DAT, which records a natural disaster when at least one of the following criteria is met: (i) ten or more deaths, (ii) one hundred or more people affected, (iii) a state of emergency, or (iv) a call for international assistance.

lence is particularly likely to spill over into neighboring districts characterized by greater economic development, higher crop suitability, and the presence of mineral resources, consistent with combatants reallocating efforts toward still-lucrative targets. In contrast, large inflows of emergency aid dampen the outward diffusion of conflict but increase the likelihood that fighting persists within the disaster-affected area. Taken together, these results suggest that, relative to droughts, distinct mechanisms drive the spatial conflict dynamics following sudden-onset disasters, underscoring the need for more nuanced policy responses.

To explain these findings, we build a simple model in which several players contest rents in a set of interconnected "battles."[4] Each player chooses how much effort to devote to each battle, and success probabilities follow the standard Tullock contest success function (CSF): greater effort raises the chance of winning and thus securing the prize. Because the general model yields nonlinear best-response functions, we study two tractable network structures, a star and a line, to derive clear comparative-statics results.

The empirical data are available only at the district level, so we aggregate individual efforts accordingly: each district corresponds to one battle and its combatants. A negative shock to one district lowers battle intensity there but raises it in path-connected districts; the magnitude depends on the battle's position in the network and on combatant strength. The logic is intuitive: the central agent (the one engaged in two battles) reallocates effort across contests to maximize total pay-off, and the remaining agents respond optimally. This mechanism explains how a local shock propagates through the network. The same pattern emerges in the line network: a shock to the left-hand district affects the battle in the right-hand district, even though the two districts are not directly connected.

Using geo-referenced data on conflict and natural disasters at the district level helps identify patterns, but it also limits our ability to uncover the deeper mechanisms that motivate armed actors. Both the outcome and treatment variables are imperfect proxies that combine

[4]For surveys of network economics, see Jackson (2008) and Jackson et al. (2017).

several distinct processes. As a result, we confront the same questions that challenge much of the literature. Natural disasters can raise armed groups' costs of manoeuvring—or even render an area inoperable—while simultaneously lowering the expected returns from controlling local resources. They may increase grievances or reduce opportunity costs for civilians, thereby encouraging recruitment into belligerent factions (Collier and Hoeffler 2004). Disasters can also weaken state capacity to maintain order (Fearon and Laitin 2003). In addition, refugees who flee to neighbouring districts may become more susceptible to recruitment by armed groups, creating another channel for conflict spillovers (Humphreys and Weinstein 2008). It is therefore likely that the mechanisms behind our findings represent an intertwined mix of these explanations (Cedermann and Vogt 2017).

As stated above, our model only offers one possible mechanism; other forces are likely at work.[5] Because the data are aggregated at the district level, our empirical analysis remains agnostic about the micro-level channels that link natural disasters to conflict. Even so, the findings have clear policy relevance: local shocks propagate to neighbouring districts and can raise overall levels of violence, as illustrated by Boko Haram in Nigeria and the Lord's Resistance Army in Uganda.

Understanding the dynamics of conflict diffusion after natural disasters is particularly important for policymakers. To curb escalation, governments and international organisations often deploy troops to contain an initial outbreak, thereby raising the costs or lowering the benefits of fighting in the affected locality. Yet once these forces clear an area, violence frequently re-emerges elsewhere. Such interventions can therefore spread conflict to previously untouched districts and draw in new actors. Post-disaster aid presents a similar trade-off: while it dampens outward diffusion, it also increases the likelihood that hostilities persist within the stricken district. A more systematic understanding of these spatial interactions

[5] For instance, a negative shock can prompt population movements. A natural disaster may generate a wave of refugees whose arrival heightens frictions and escalates violence in adjacent areas.

can help decision-makers design more effective strategies for managing localised violence in Africa.

Our study contributes to several strands of the literature. First, we draw attention to conflict displacement, an aspect that has received relatively little coverage in the economics of conflict. Most existing work focuses on the causes and diffusion of violence (e.g., Buhaug and Gleditsch 2008; Rigterink 2010; Novta 2016; Ray and Esteban 2017).

A large body of research employs national data within the *grievance–opportunity-cost* framework of Collier and Hoeffler (2004), which predicts a negative relationship between income shocks and the likelihood of battle (Miguel et al. 2004; Chassang and Padró i Miquel 2009; Blattman and Miguel 2010; Besley and Persson 2011; Ciccone 2011; Couttenier and Soubeyran 2014). Some country-level studies extend the analysis to spillovers. Bosker and de Ree (2014) show that cross-border conflict diffusion helps explain clusters of violence, while Yesilyurt and Elhorst (2017) find that one country's military spending affects that of its spatial neighbours.

Much of this work takes the economic model of crime as a reference point (Corchón 2007); accordingly, the crime literature has long recognised the importance of displacement (Freeman 1999; Chalfin and McCrary 2017). Our paper brings this insight explicitly into the study of armed conflict.

Our paper builds on a recent generation of studies that emphasise the localised nature of conflict. This literature combines theory and evidence to show how positive (e.g., Dube and Vargas 2013; Berman and Couttenier 2015; Fjelde 2015; Berman et al. 2017; McGuirk and Burke 2020) and negative (e.g., Hodler and Raschky 2014b; Harari and La Ferrara 2018; Berman et al. 2021; Cervellati et al. 2022) economic shocks affect the incidence of violence. Although these papers focus on local effects, most also test whether shocks spill over into neighbouring areas.

Our study is closest to this latter strand. Harari and La Ferrara (2018) show that adverse weather during the growing season raises conflict, primarily through the opportunity-cost channel. Berman et al. (2017) exploit exogenous changes in world mineral prices and find that positive shocks to local mining wealth heighten conflict both locally and in adjacent districts. McGuirk and Burke (2020) examine global food-price spikes and document that, in food-producing areas, higher prices reduce “factor conflict” over land but increase “output conflict” over surplus; the authors argue that rising prices raise producers’ opportunity cost of soldiering while eroding consumers’ real wages. Cervellati et al. (2022) link malaria outbreaks to surges in civil violence.

We extend this literature by analysing natural disasters as negative shocks that reshape conflict dynamics across Africa. To our knowledge, this is the first study to estimate both the local and the spillover effects of disaster-induced shocks on armed conflict across the continent.

Second, a growing theoretical and empirical literature examines conflict through the lens of networks (Dell 2015; König et al. 2017; Brangewitz et al. 2019; Eubank 2019; Mueller et al. 2022). We contribute to this body of work, and to the broader theoretical literature on conflict (for a survey, see Kovenock and Roberson 2012), by incorporating network theory more explicitly (Goyal and Vigier 2014; Jackson and Nei 2015; Franke and Öztürk 2015; Hiller 2017; König et al. 2017; Kovenock and Roberson 2018; Bocher et al. 2020; Mueller et al. 2022; Xu et al. 2022).

Our model departs from earlier studies in two ways. First, agents participate in multiple battles rather than a single contest. Second, we focus on how a negative shock in one location propagates through the conflict network. Although we present comparative-statics results for two specific network topologies, the underlying spillover mechanism should extend to more general structures.

Moreover, from an empirical perspective, we complement this literature by showing that exogenous events which *decrease* the likelihood of a conflict locally can increase the probability of a conflict in neighboring localities connected via a spatial network. We thereby complement the existing work on conflict spillovers that exclusively focuses on spillover effects of factors that *increase* the likelihood of a conflict locally.

Third, we add to the predominantly empirical literature on natural disasters and conflict. Existing work measures the economic consequences of disasters at both the micro (Mottalebab et al. 2015) and macro levels (Deryugina and Hsiang 2014; Hsiang et al. 2017; Hsiang and Jina 2014). Other studies examine how climate shocks affect violence (Miguel et al. 2004; Hsiang et al. 2013; Hodler and Raschky 2014b; Couttenier and Soubeyran 2014; Mach et al. 2019). Most of this research focuses on temperature or precipitation shocks and relies on aggregated data—annual or growing-season observations at the country level. We advance the literature by introducing a geo-referenced, district-level data set that covers all types of natural disasters, allowing a more granular analysis of the mechanisms linking disasters to conflict.

The remainder of the paper is organized as follows. Section 2 describes the data and provides descriptive statistics. Sections 3 presents the baseline empirical framework, while Section 4 discusses diagnostics and robustness checks. We examine potential mechanisms in Section 5. Finally, Section 6 concludes. We provide additional descriptions of the data, robustness checks, and the theoretical model in the Online Appendix.

2 Data

We work at the second administrative level (ADM2, hereafter "districts") and assemble a panel of 5,944 districts from fifty-three African countries for 1989–2020.[6] The unit of observation is the *district–year*.

2.1 Conflict data

We obtain conflict events from the Uppsala Conflict Data Program's Georeferenced Event Dataset (GED; Croicu and Sundberg 2017). UCDP defines an armed conflict as "a contested incompatibility concerning government and/or territory in which the use of armed force between the military forces of two parties—of which at least one is the government of a state—results in at least twenty-five battle-related deaths in a calendar year." GED reports each violent event's date, actors, coordinates, and fatalities.

Using the reported latitude and longitude, we assign every event to an ADM2 district in ArcMap 10.5 and aggregate events to the district–year level. Our main indicator, *conflict*, equals one if at least one fatal event occurs in district i during year t and zero otherwise. On the basis of the actors involved, we also create binary indicators for the three subtypes of violence: "state-based," "non-state," and "one-sided." Panel (a) of Figure A.2 in the online appendix maps the spatial distribution of events.

UCDP records only events that (i) belong to a dyad responsible for at least twenty-five battle deaths in a given year and (ii) themselves cause at least one fatality. Initial skirmishes or very low-intensity clashes, precisely those that have *not yet* spilled over, are therefore excluded. As a result, some conflicts enter the database only after they have escalated beyond the purely local stage; our baseline estimates thus pertain to conflicts that have

[6] ADM2 boundaries are unavailable for Egypt and Libya, where only ADM1 units exist. The average district in our sample covers 39 km^2 and has a population of about 45,000.

already passed an initial escalation threshold and may understate true diffusion.

To check the sensitivity of our findings, we replicate the analysis with the Armed Conflict Location and Event Data (ACLED) set, which records non-fatal incidents, demonstrations, and lower-threshold violence. Although ACLED captures a broader spectrum of political disorder, its event-coding rules are less tightly aligned with our theoretical framework, which assumes clearly defined conflict parties that decide whether to engage in a given location.[7]

2.2 Natural disasters

Our key treatment variable is the occurrence of a natural disaster, which we use as an exogenous negative shock to a district.

Natural disasters differ from the economic shocks commonly examined in the conflict literature in several ways that shape both local and spillover effects. First, they are typically *rapid-onset* events that destroy built and transport infrastructure, depress agricultural production, and undermine household welfare far more abruptly than price fluctuations or cyclical slowdowns. Floods, earthquakes, and storms generate immediate physical damage, displace residents and combatants, and can redirect violence into neighbouring districts. By contrast, commodity-price shocks unfold more gradually and mainly alter economic incentives without comparable physical displacement.

Second, disasters can amplify pre-existing vulnerabilities related to resource scarcity and weak governance. Slow-onset droughts, for example, reduce agricultural output over time and can spark protracted resource conflicts as communities compete for dwindling supplies. Unlike trade disruptions or financial crises, such climate-related shocks simultaneously intensify grievances and lower the opportunity cost of mobilisation, especially in agriculture-

[7] See Keck 2012 and Raleigh et al. 2023 for detailed comparisons of UCDP and ACLED. Keck reports that up to 29 percent of ACLED events may be incorrectly geolocated for certain African conflicts.

dependent regions. These characteristics—exogenous, localised, and destructive of both assets and livelihoods—distinguish natural disasters from the shocks most often studied in the existing literature.

We obtain disaster data from the Emergency Events Database (EM-DAT; Guha-Sapir et al. 2016), which records more than 22,000 mass disasters worldwide since 1900. An event enters EM-DAT when at least one of the following criteria is met: *(i)* ten or more deaths, *(ii)* one hundred or more people affected, *(iii)* a state of emergency declared, or *(iv)* a call for international assistance. For each disaster, the database reports location, type, date, deaths, people affected, estimated damage, and whether post-event aid from the Office of U.S. Foreign Disaster Assistance was received.

EM-DAT lists 4,525 disasters in Africa for 1989–2020, of which 2,229 are natural and the remainder technological (man-made). We retain only natural events, omitting biological disasters (epidemics and insect infestations) and keeping those classified as geophysical (e.g., earthquakes, volcanic activity), meteorological (e.g., extreme temperatures, storms), hydrological (e.g., floods, landslides), or climatological (e.g., wildfires). This yields 1,534 natural disasters, none of which are "extraterrestrial" events, which EM-DAT also codes but did not record for Africa during our period. After filtering for events with valid subnational coordinates, our final data set contains 1,326 district-level disasters. Table A.1 summarises the distribution by disaster type; floods are by far the most common.

The key challenge when conducting a district-level analysis using EM-DAT data is the unstructured nature of the subnational location information.[8] We overcome this challenge by manually geocoding each of these 1,326 natural disasters. Natural disasters where the exact individual village or subnational district was identified were precisely geocoded, while those recorded as having occurred in larger geographic units were assigned to all districts within that geographic unit. For each geocoded natural disaster, we allocate a precision

[8]See Figure A.1 for a sample data extract.

score, which assigns a value of 4 for precision at the district level (i.e., the highest level of precision), a value of 3 for precision at the provincial level, 2 at the state level, and 1 at the country level (the lowest level of precision). We restrict our analysis to natural disasters geocoded with a precision score of 3 or 4, which accounts for over 96% of the total number of the geocoded natural disaster locations. Panel (b) in Figure A.2 displays the distribution of natural disasters in Africa.

Our preferred indicator for natural disasters is a binary variable that assumes a value of 1 if a natural disaster occurred in district i in a time period, and zero otherwise. We also generate two indicators on natural disaster subcategories, which we use in our robustness checks. First, following Gassebner et al. (2010) and Puzzello and Raschky (2014), we classify disasters that either (*i*) kill at least 1000 people, or (*ii*) affect at least 100,000 people in total, or (*iii*) cause damages of at least one billion (real) dollars as *large* natural disasters, and all other disasters as *small* natural disasters. Next, following Skidmore and Toya (2002), we generate indicators of climatic and geologic disasters.[9]

For the purpose of the baseline estimates in our study, we exclude droughts from the set of natural disasters for the followings reasons. First, the spatial extent of the drought-affected area is often not clearly defined, making it difficult to precisely assign the treatment. Second, droughts are slow onset disasters and their effects last over prolonged time periods, transcending the fine temporal resolution of our data. Third, droughts are potentially endogenous in the context of this analysis as the probability of occurrence can, partially, be the result of a conflict itself. Nevertheless, in a robustness check we present estimates including droughts; our results remain qualitatively and quantitatively similar.

The choice of the spatial unit of analysis, i.e. districts at the second subnational level, is determined by the available location information of natural disaster events in the raw data.

[9]Geologic disasters include volcanic eruptions, natural explosions, avalanches, landslides, and earthquakes. Climatic disasters include floods, cyclones, hurricanes, ice storms, snowstorms, tornadoes, typhoons, and storms.

As displayed in Figure A.1, the EM-DAT data set only contains location names of subnational units rather than precise coordinates of the affected areas. As such, we do not have the information to conduct a spatial join based on precise longitude/lattitude coordinates which, together with geocoded data on conflict events, would enable us to conduct the study at a more granular grid cell level. Nevertheless, in Table B.10 we present two sets of tests that check the sensitivity of our results when accounting for differences in size of the geographic unit.

2.3 Other covariates

We draw on three additional data sets to investigate the mechanisms through which natural disasters influence conflict incidence.

Night-time lights. To proxy economic activity, we use satellite-based *night-time luminosity*. This measure tracks output at both national (Henderson et al. 2012) and subnational levels (Hodler and Raschky 2014). We rely on the harmonised series of Li et al. (2020), which combines the original DMSP imagery (1992–2012) with VIIRS data (2013–2020) to create a consistent record for 1992–2020. After matching the raster to our district polygons, we compute annual average luminosity for each district; analyses using this variable therefore cover 1992–2020. We also construct time-invariant indicators based on the *initial* (1992) luminosity distribution. *NoLight* equals one for districts that recorded zero luminosity in 1992. Among the remainder, *LowLight* and *HighLight* flag districts below and above the median initial value, respectively.

Agricultural suitability. Districts are classified by agricultural potential using raster data from the Global Land Cover Characteristics Database, version 2.0.[10] For each district

[10] https://lta.cr.usgs.gov/glcc/globdoc2_0

we calculate the share of land deemed agriculturally suitable. *NoAgri* identifies districts with no suitable land, while *LowAgri* and *HighAgri* separate the remainder at the median suitability share.

Mining wealth. Data on extractive activity come from the SNL Mining & Metals database, which reports the coordinates and mineral composition of projects active during our study period. Following Amarasinghe et al. (2024), we compute district-level *mining wealth* as the average value of all recorded minerals, weighted by contemporaneous world prices. *NoMine* marks districts without any project; the median splits the remainder into *LowMine* and *HighMine*.

2.4 Connectivity

Following Amarasinghe et al. (2024), we build a spatial weighting matrix that captures geographic connectivity. We first identify the centroid of each district and compute the great-circle (geodesic) distance, $d_{ic,jc}$, between the centroids of districts i and j in country c. We then incorporate terrain roughness using the altitude-variation index of Acemoglu et al. (2015), $e_{ic,jc}$, which measures changes in elevation along the straight line that connects the two centroids, based on GTOPO30 data. The resulting altitude-adjusted inverse distance is

$$\tilde{d}_{ic,jc} = \frac{1}{d_{ic,jc}\big(1 + e_{ic,jc}\big)}.$$

This metric assigns higher weights to pairs of districts that are both close together and separated by relatively flat terrain. Conversely, districts divided by mountainous topography or located farther apart receive lower weights.[11]

[11] As explained in Section 3, our results do not change if we use a connectivity matrix that just relies on simple geodesic distance.

For the baseline analysis, we truncate the matrix at a radius of 500 km: district i is connected to district j only if the centroid of j lies within 500 km of i's centroid. With this cut-off, only two districts—large ADM1 units in Libya and Mauritius, for which ADM2 boundaries are unavailable—have no neighbours. The average district has 518 neighbours, and the maximum is 1,478 for three small districts in Algeria. Sensitivity checks using alternative cut-offs yield similar results (Table B.12), confirming that 500 km is a practical upper bound for capturing meaningful spillovers.

We also construct alternative connectivity matrices based on contiguity, major road networks, and shared pre-colonial ethnic homelands. Appendix Table B.13 reports spillover estimates derived from these networks.

Table A.2 provides descriptive statistics of our key variables. Approximately 4% of the district-year observations in the sample experience a conflict over the sample period, while 6% experience a natural disaster. About 45% of the district-year observations report their neighbouring districts as having experienced a natural disaster.

3 Empirical Framework

We now present the empirical framework. Our goal is to estimate a model that captures (i) the direct effect of a natural disaster on conflict in district i and (ii) the spillover effect of a disaster in neighbouring district j on conflict in district i. We assume that disasters in both locations are exogenous and that the dependent variable, $Conflict$, exhibits spatial autocorrelation. Accordingly, we employ a Spatial Durbin Model (SDM), which includes spatial lags of both the dependent variable and the explanatory variables:

$$Conflict_{i,t} = \beta_0 DIS_{i,t} + \beta_1 DIS_{i,t-1} + \delta_0 NDIS_{i,t} + \delta_1 NDIS_{i,t-1} \\ + \gamma NConflict_{i,t} + \mathbf{FE_i} + \mathbf{FE_{ct}} + \epsilon_{i,t} \tag{1}$$

The variable $DIS_{i,t}$ is a binary indicator taking a value of 1 if a natural disaster occurred in district i in year t. As such, the coefficients β_0 and β_1 capture the direct effect of a natural disaster on battle probability in years t and $t-1$, respectively. The variable $NDIS_{i,t}$ captures the *spatial spillover* effect of a natural disaster that occurred in a neighboring district on battle probability in district i. We have:

$$NDIS_{i,t}{=}1 \text{ if } \textstyle\sum_{j=1}^{J} \omega_{ij} DIS_{jt} > 0$$
$$NDIS_{i,t}{=}0 \text{ if } \textstyle\sum_{j=1}^{J} \omega_{ij} DIS_{jt} = 0,$$

where the "neighbourhood" between districts is defined by the connectivity matrix $\mathbf{\Omega} = (\omega_{ij})$, with $\omega_{ij} \in [0, 1]$ when a link exists between districts i and j and $\omega_{ij} = 0$ otherwise. As noted above, $\mathbf{\Omega}$ measures *geographic connectivity* via the altitude-adjusted inverse geodesic distance. The variable $NDIS_{i,t}$ is the binary spatial lag of the disaster indicator; it equals one if at least one neighbouring district experiences a disaster in year t and zero otherwise.[12] The coefficients δ_0 and δ_1 therefore capture the spillover effects of a disaster in a neighbouring district in years t and $t-1$, respectively.[13]

The spatial lag of the dependent variable, $NConflict_{i,t}$, absorbs autocorrelation in local violence. District fixed effects, $\mathbf{FE}_i$, control for time-invariant unobservables, whereas country-year fixed effects, $\mathbf{FE}_{ct}$, net out time-varying national shocks. Because the residual

[12] $\mathbf{\Omega}$ is row-normalised, so $\sum_j \omega_{ij} = 1$ for every i.

[13] The altitude adjustment $e_{ic,jc}$ could be mechanically correlated with the probability of a disaster. This does not threaten identification because our spatial-exposure variable $NDIS_{ict}$ is a *binary* indicator that equals one whenever *any* disaster strikes a district connected to ii within the 500-km band. Since $e_{ic,jc} > 0$ for all pairs, the adjustment never determines whether a link is counted (only its weight) so the magnitude of $e_{ic,jc}$ cannot influence the switch from 0 to 1. Re-estimating the baseline using a matrix based solely on geodesic distance (i.e., setting $e_{ic,jc}$=0) yields coefficients that are virtually identical to Table 1, column (3)).

$\varepsilon_{i,t}$ is likely both spatially and temporally correlated, we report Conley (1999) standard errors that allow correlation within 500 km and across one period.[14] Equation (1) is estimated by ordinary least squares with the fixed effects described above.

A causal interpretation of the parameters β and δ requires that natural disasters—both in district i and in its neighbours—are as-good-as random conditional on the fixed effects. Disasters arise from exogenous geographic, climatic, and geological forces that are either time-invariant (e.g., topography, elevation) or time-varying (e.g., precipitation, wind speed, plate tectonics). Time-invariant confounders are captured by district effects, while country-year dummies absorb broader climatic patterns such as El Niño and La Niña. Note that these two sets of fixed effects not only capture confounding factors related to DIS but also $NDIS$. Section 4 further presents robustness checks, including tests for pre-trends and anticipation effects, that support these assumptions.

Table 1 reports the baseline estimates of both the direct and the spillover effects of natural disasters on conflict incidence. Column (1) presents the direct effect: a disaster lowers the probability of violence in the affected district, but the reduction materialises with a one-year lag.[15]

Columns (2) and (3) incorporate spillovers, defining neighbourhoods with the altitude-adjusted inverse-distance matrix truncated at 500 km. Column (2) adds disasters in neighbouring districts but omits the neighbours' own conflicts. Our preferred specification, Column (3), includes both variables, isolating the portion of conflict diffusion attributable solely to exogenous disaster shocks. In both specifications a disaster in a neighbouring district in year $t-1$ significantly increases the likelihood of conflict in district i.[16] The estimates yield

[14] Estimation is conducted in Stata 18 with the `reg2hdfespatial` command.

[15] Appendix A.3 explores the monthly dynamics of this effect with an alternative set of fixed effects.

[16] The definition of neighbouring districts in our main specification is agnostic of national borders. In Table B.14 in the appendix we present results where we explicitly account for national borders when defining neighbours. We split the baseline spillover treatment variable, $NDIS$, into disasters occurring in districts occurring in the same country in a different country from district i (within the 500km cut-off). The results

Table 1: Direct and spillover effects of natural disasters on conflict

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$	(4) $Conflict_{i,t}$
	Disasters excluding droughts			Droughts
$DIS_{i,t}$	-0.0026	-0.0028	-0.0027	0.0049
	{0.0021}	{0.0030}	{0.0030}	{0.0075}
	(0.0035)	(0.0035)	(0.0035)	(0.0094)
$DIS_{i,t-1}$	-0.0053**	-0.0056**	-0.0056**	0.0227**
	{0.0021}	{0.0028}	{0.0028}	{0.0102}
	(0.0030)	(0.0030)	(0.0030)	(0.0126)
$NDIS_{i,t}$		0.0055*	0.0057*	0.0116*
		{0.0033}	{0.0033}	{0.0070}
		(0.0035)	(0.0035)	(0.0093)
$NDIS_{i,t-1}$		0.0104***	0.0105***	0.0234***
		{0.0033}	{0.0033}	{0.0081}
		(0.0037)	(0.0037)	(0.0112)
$NConflict_{i,t}$			0.0049**	0.0024
			{0.0022}	{0.0031}
			(0.0025)	(0.0035)
$NConflict_{i,t-1}$			0.0080***	0.0045
			{0.0023}	{0.0031}
			(0.0025)	(0.0034)
Observations	184,264	184,264	184,264	107,325
Distance Cut-off	NA	500km	500km	500km
District FE	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. $NDIS$ ($NConflict$) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (battle), in any one of the district's neighbours, within the given time period. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, while () present country×year clustered standard errors. *** p<0.01, ** p<0.05, * p<0.1

two key insights. First, while a disaster suppresses violence where it strikes, it simultaneously pushes conflict into neighbouring districts. Second, the magnitudes are economically meaningful: according to Column (3), a disaster lowers the probability of conflict in the struck district by roughly 0.5 percentage points but raises it in neighbouring districts by about 0.5 percentage points contemporaneously and 1 percentage point the following year.[17]

In Column (4), we use droughts as the treatment.[18] Unlike the direct effects of rapid-onset disasters (such as floods, storms, or earthquakes), which are generally negative within the affected district, the estimates for droughts indicate a positive and statistically significant direct effect on conflict incidence in the subsequent year. Specifically, experiencing a drought in year $t-1$ increases the probability of conflict in the affected district by approximately 2.3 percentage points in year t. Moreover, the spatial spillover effects are substantial: droughts in neighboring districts increase conflict incidence both contemporaneously and with a lag. The magnitude of these spillover effects exceeds that of non-drought disasters, suggesting that droughts exert a more persistent and spatially diffuse influence on violence.

These contrasting spatial patterns are consistent with our theoretical argument regarding the underlying mechanisms. Sudden-onset disasters such as floods tend to destroy contestable assets—crops, infrastructure, or strategic locations—thereby reducing the immediate incentives for armed groups to engage in conflict within the affected district. The decline in local conflict following such events, combined with increased violence in neighboring areas,

show that the cross-border spillover effects are more pronounced that the within-country spillover effects. The direct, decreasing effect of disasters seems to be driven by state and onesided conflict events, while the spillover effects, both within and outside the country, are more pronounced for non-state conflict events.

[17] A notable feature is that the direct negative effect becomes significant only after one year. One plausible explanation is conflict persistence: combatants rarely cease hostilities the very moment a disaster occurs. Consistent with this interpretation, the heterogeneity analysis in Table B.6 shows that earthquakes generate an immediate and much larger drop in conflict probability than other hazards, suggesting that their destructive impact incapacitates armed groups more quickly. We also examine this effect further in Section A.3, exploiting the fine temporal granularity of the natural disaster data.

[18] We retain the same control group as in Columns (1)–(3) for cleaner interpretation of the estimates. Essentially, the comparison is between units that experienced a drought (treated units) and units that never experienced any other natural disaster (control units). We present estimates for other disaster types in Table B.6.

supports a displacement mechanism driven by resource loss. In contrast, droughts operate primarily through the opportunity cost channel. As shown by Harari and La Ferrara (2018), drought-induced agricultural shocks lower rural incomes and, consequently, the opportunity cost of participating in armed violence. This effect emerges with a temporal lag and extends beyond the affected area, consistent with local recruitment dynamics and the mobility of vulnerable populations. The persistence and spatial reach of the drought–conflict relationship highlight the importance of distinguishing among shock types when designing policy responses to disaster-induced conflict risks.

LeSage and Pace (2009) demonstrate that the point estimates from a spatial regression cannot, by themselves, quantify spillover effects.[19] Following LeSage and Pace (2009) and Debarsy et al. (2012), we compute the partial-derivative (marginal-effects) decomposition shown in Table 2. The results reveal a clear pattern: disasters reduce conflict in the district they strike (the direct effect) but increase conflict in connected districts (the indirect effect). These forces do not offset each other. Instead, the positive spillovers outweigh the local reduction, so the *total* effect of a disaster on the conflict network is positive. In other words, while violence abates where the disaster occurs, it spreads to neighbouring districts in sufficient measure to raise the overall incidence of conflict.

[19] In our setting, a disaster in district i has a direct effect on conflict within i and an indirect effect on every other district through the connectivity network. The magnitude of those effects varies with a district's location, its links via geography and major roads, and the parameters β, δ, and γ.

Table 2: Direct, indirect, and total Effects

	$Conflict_{i,t}$					
	Direct		Indirect		Total	
	Coeff.	*SE*	*Coeff.*	*SE*	*Coeff.*	*SE*
$DIS_{i,t}$	-0.0026	(0.0022)				
$DIS_{i,t-1}$	-0.0058***	(0.0022)				
$NDIS_{i,t}$			0.0899**	(0.0400)	0.0943**	(0.0417)
$NDIS_{i,t-1}$			0.1788***	(0.0494)	0.1877***	(0.0508)

Decomposition of he spatial effect into direct, indirect and total effects. Number of Obs. 184,264. $Conflict_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a battle resulting in at least one death in district i in year y. $DIS_{i,t}$ and $DIS_{i,t-1}$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in district i in years y and $t-1$, respectively. $NDIS_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in any one of district i's neighbours in year y. Neighbourhood is based on the altitude-adjusted inverse geodesic distance network. Disasters exclude droughts. The direct, indirect and total effects were calculated using the post-estimation command `impact` after the command `spxtregress` in Stata 19. *** p<0.01, ** p<0.05, * p<0.1

4 Diagnostic tests, alternative spatial econometric models, and robustness checks

4.1 Diagnostic tests

A central concern in difference-in-differences designs is the possibility of *negative weights*.[20] A TWFE coefficient is a weighted average of group- and period-specific average treatment effects (ATEs); if some weights are negative, the estimated coefficient can be negative even when all underlying ATEs are positive, and vice versa.

Most recent methodological work addresses this problem in *staggered-adoption* settings, in which units adopt the treatment once and remain treated (Borusyak, Jaravel, and Spiess 2024; Callaway and Sant'Anna 2021; Goodman-Bacon 2021). Our context differs: treatment—the occurrence of a natural disaster—lasts for only one period, and districts may be

[20]See Baker, Larcker, and Yang (2021) for a comprehensive discussion.

treated repeatedly. To our knowledge, no existing estimator directly tackles negative weights in such a repeated-treatment framework.

We follow De Chaisemartin and D'Haultfœuille (2020) and compute the weights attached to each treatment. Figure A.3 plots their distribution for both direct and spillover treatments. All direct-treatment weights are positive (panel A), and only a negligible share of spillover weights is negative (panel B), suggesting that bias from negative weights is unlikely to be a major concern. In addition, in Table B.1 we implement the estimator proposed by Chaisemartin and D'Haultfœuille (2024)[21] Overall, the pattern in our baseline estimates is replicated using this method too, i.e. we observe a negative direct effect and a positive spillover effect of natural disasters on conflict. This pattern holds when considering the contemporaneous and lagged periods separately as well as when considering the average effect for both periods. In terms of magnitude, the baseline estimates are slightly more conservative, on average, than the coefficients reported in Table B.1.

In Figure A.4 we conduct an event-study analysis traces the direct and spillover effects of a disaster from three years before to three years after the event. Panel A shows that the local negative effect becomes significant one year after the disaster, while panel B documents positive spillovers that persist for up to three years. Crucially, neither panel exhibits pre-trends, lending support to the parallel-trends assumption.[22]

In Tables A.3 and A.4 we examine the cross-sectional correlations for direct and spillover disaster occurrence indicators (i.e. DIS and $NDIS$), and a set of time-invariant district-level geographic, climatic, and socio-economic control variables, disaggregated by disaster type. While some district-specific characteristics can predict the occurrence of natural disasters, a

[21] Note that the corresponding Stata command `didmultiplegtdyn` does not allow for the simultaneous estimation of both direct and spillover effects. As a result, we estimate the direct and spillover effects as separate regressions.

[22] Because pre-tests may have low power, we follow Roth (2022) to compute the smallest linear trend that would be detected with 90 per cent power. With eleven pre-periods, the critical slope is 0.00021; using a more conservative specification, it is 0.00043. Both thresholds are small enough to rule out economically meaningful pre-trends.

large part of the variation gets absorbed by the comprehensive set of fixed effects we include in all our estimates.

Finally, in Table A.5 we examine serial and spatial correlation in disasters. Neither own-district (column 1) nor neighbouring-district (column 2) disasters are serially correlated, although a modest contemporaneous spatial correlation emerges (column 3)—expected when a single event spans more than one district. Our main specification absorbs this by including both DIS and $NDIS$.

4.2 Alternative spatial econometric models

Our preference for the SDM relies on specific assumptions about the data-generating process. Because the true process is unknown, we gauge the sensitivity of our findings to alternative spatial specifications. A natural starting point is the *general nesting spatial* (GNS) model with common factors, described by Elhorst (2022, 264) as "the most general spatial econometric model currently available." The GNS not only includes spatial lags of the key variables but also captures dynamics through the temporal lag of the dependent variable, $Conflict_{i,t-1}$.[23] This can also capture conflict persistence: violence in previous years may influence current violence. Adding this lag to equation (1) therefore produces a restricted form of the GNS. Column (1) of Table B.2 shows that the results remain largely unchanged. That said, introducing $Conflict_{i,t-1}$ in a fixed-effects setting risks "Nickell bias," and the GNS is often over-parameterised, which can inflate standard errors (Elhorst 2014).

A simpler alternative is the *spatial lag of X* (SLX) model, which omits spatial autocorrelation in the dependent variable. Recent studies have used SLX specifications to analyse conflict spillovers from weather shocks (Eberle et al. 2020; McGuirk and Nunn 2021), food-price shocks (McGuirk and Burke 2020), and soil productivity (Berman et al. 2021). We

[23] A full GNS would also contain spatially autocorrelated errors (Elhorst 2022).

estimate an SLX variant by dropping the spatial lag of the dependent variable from equation (1); results appear in column (2) of Table B.2. However, the SLX assumption of zero spatial dependence in conflict is difficult to defend here; if violated, the model suffers omitted-variable bias. For that reason, we retain the SDM—augmented with a range of robustness checks—as our preferred specification.

The spatial-econometric literature offers several estimators that address the endogeneity of the spatial lag in SDM settings, including maximum likelihood (Ord 1975), quasi-maximum likelihood (Lee 2004), instrumental variables (Anselin 1988), GMM (Kelejian and Prucha 1998, 1999, 2010; Kapoor et al. 2007), and Bayesian MCMC (LeSage 1997). Yu et al. (2008) and Lee and Yu (2010b) propose bias-corrected estimators for dynamic spatial panels with two-way fixed effects. None of these methods, however, is currently implemented for binary outcomes with spatial weights. We therefore estimate a linear probability model with district and year fixed effects and report robustness checks that exclude the potentially endogenous spatial and temporal lags.

4.3 Robustness Checks

In this section we present additional robustness checks. We first reconsider the definition of a disaster. The baseline excludes droughts for two reasons: droughts are spatially diffused, making precise localisation difficult, and they unfold over multiple years, complicating attribution to a single period. Table B.3 re-estimates the model with droughts included. The spillover effect becomes even larger and appears contemporaneously, while the sign of the direct effect remains unchanged.

EM-DAT reporting improved markedly after 2000, raising the possibility of measurement error in the early years. Restricting the sample to 2000–2020 (Table B.4) leaves the spillover estimates intact. The direct effect stays negative but is estimated less precisely, consistent with the loss of observations.

Table B.5 investigates whether the conflict effects vary by disaster category. In each column we keep the same control group as in the baseline and redefine the treated group according to the relevant disaster type. Columns (1) and (2) split events into *large* and *small* disasters.[24] Although the direct coefficients are negative for both size classes, neither is statistically significant. Interestingly, the immediate positive spillover stems from small disasters, whereas the lagged positive spillover is driven by large disasters. Next, we contrast *climatic* with *geologic* events.[25] Both the negative direct effect and the positive spillovers are concentrated in the climatic category. Table B.6 drills down to individual hazards and shows that floods generate the strongest pattern.[26]

Most disaster types reduce conflict where they strike and raise it in connected districts; droughts are the exception, increasing conflict risk in both the affected and neighbouring areas. This finding mirrors Harari and La Ferrara (2018), who document higher violence following droughts during the growing season. Table B.7 corroborates this result with the Standardised Precipitation–Evapotranspiration Index (SPEI). Column (1) reproduces the familiar positive direct effect of drought on conflict. When spatial spillovers are included (column (2)), the spillover term remains positive and significant, whereas the direct coefficient becomes imprecise. The difference likely reflects Harari and La Ferrara's practice of interacting SPEI with the local growing season, making their measure more tightly linked to agricultural stress.

Taken together, the evidence suggests a useful distinction. Disasters that are more likely to destroy physical—and especially public—infrastructure (e.g., floods, earthquakes,

[24]Following Gassebner et al. (2010) and Puzzello and Raschky (2014), we classify an event as large if it (i) causes at least 1,000 deaths, (ii) affects at least 100,000 people, or (iii) inflicts damages of at least one billion real U.S. dollars; all other events are deemed small.

[25]Geologic disasters include volcanic eruptions, natural explosions, avalanches, landslides, and earthquakes; climatic disasters comprise floods, cyclones, hurricanes, ice storms, snowstorms, tornadoes, typhoons, and storms (Skidmore and Toya 2002).

[26]Floods account for roughly 67 per cent of the disasters in our sample; see Table A.1 for details.

landslides) tend to *lower* conflict in the struck district but diffuse violence outward. By contrast, disasters that primarily harm agricultural output or human health (e.g., droughts) tend to *raise* conflict both locally and in adjacent districts.

We next consider alternative definitions of the outcome variable. UCDP classifies violence into three actor-based categories—state-based, non-state, and one-sided conflict. Table B.8 estimates the disaster effects for each category separately and shows that the baseline pattern is driven primarily by state-based and non-state battles.

To test the robustness of our findings, we replicate the analysis with the Armed Conflict Location & Event Data set (ACLED). Because ACLED begins only in 1997, the number of observed disasters—and thus treatment events—falls sharply. Column (1) of Table B.9 reports estimates using an ACLED-based outcome that equals one if at least one violent event of any ACLED type occurs in a district–year. Column (2) re-estimates our preferred UCDP specification on the shorter 1997–2020 sample. Column (3) pools UCDP and ACLED events: the dependent variable equals one if either source records a violent event in the district–year. Across all three panels, the spatial spillover effects mirror the baseline. For the estimates using ACLED data, we even find spillover effects occurring in the concurrent year (columns (1) and (3). In contrast, we do not observe systematic, direct effects of disasters on ACLED events. While the sign is again negative, the size of the coefficient estimates is smaller compared to UDCP events and the estimates are not statistically significant. The large reduction in the number of observations is one reason; another is that the disaster-driven dispersion mechanism may apply more strongly to UCDP-type conflicts, which involve clearly defined actors, theatres, and fatality thresholds.

ADM2 districts across Africa vary in size and several recent studies of subnational conflict in Africa use *grid cells* rather than ADM2 units as the unit of analysis (Berman et al. 2017; Harari and La Ferrara 2018). Grid cells offer advantages—uniform size and stable boundaries—but they require precise geolocation for every variable so that events can be assigned to the correct cell. While exact coordinates are available for our outcome variable (conflict), they are often missing for natural disasters.[27] EM-DAT records disaster locations by the names of subnational units (villages, districts, provinces). Converting those names to grid cells introduces measurement error, which can attenuate coefficients.[28]

In Table B.10 we present the results of two sets of tests to check the sensitivity of our results when accounting for differences in size of the geographic unit. First, we replicate our analysis on a sub-sample of districts with an area of 55 km^2 and below.[29] The results in columns (1) and (2) show that the pattern of the main results are robust. Second, we accessed an alternative georeferenced dataset on flood disasters from the Dartmouth Flood Observatory (DFO, Brakenridge 2025). We combine the geographic centers of flood events from that dataset with grid cell polygons and re-estimate our main specification (columns (3) and (4)) Again we find a negative direct effect of floods on conflict, although it is not precisely estimated, and positive and statistically significant, conflict spillovers to neighboring regions.[30]

Although our main focus is conflict incidence, we also follow common practice in the literature (Harari and La Ferrara 2018) by examining battle onset and termination. Table B.11 defines two binary indicators—one for the first year of a battle in a cell (onset) and one for the last year (termination). We find no evidence that natural disasters significantly affect either onset or termination.

[27] Harari and La Ferrara (2018), for example, rely on the geo-referenced SPEI index to measure drought.

[28] Figure A.1 in the appendix illustrates this problem.

[29] This size cut-off is similar to the size of the PRIO grid cells (at the equator) that are commonly used and excludes very large districts.

[30] DFO's flood data does not offer any advantage over our manually-coded EM-DAT data. Its' point data mark only arbitrary geographic centres of a flood event, not the flood's footprint. Overlaying them on grids implies that only single cell will be treated and wrongly assigning neighbouring, affected cells to the control group. The accompanying rectangular "affected-area" polygons are ,to a large extent, not remote-sensing outputs but are based on media reports listing towns/provinces. More concerningly, some of these event polygons are unrealistically large, spanning over entire (or even multiple) countries.

We test the sensitivity of our results to different distance cut-offs and connectivity networks. Table B.12 varies the radius that defines the geographic network, while Table B.13 replaces the inverse-distance matrix with alternative links—contiguity (col. 1), shared pre-colonial ethnicity (col. 2), and primary/secondary roads (col. 3).[31] The direct, negative effect of a disaster is statistically significant in every specification. Contiguity and ethnic links show no significant diffusion of post-disaster conflict, whereas roads yield positive spillovers consistent with the baseline.[32] The insignificant findings for contiguity and ethnic homelands is not surprising. EM-DAT events usually strike clusters of adjacent districts, so a contiguity or ethnic-homeland matrix seldom isolates a neighbour that is exposed to a disaster while the focal district is not. Because there are so few of districts that are connected but not untreated themselves, the precision of the estimated δ is rather low. In Table B.14, we explore connectivity within and outside countries.

Our final robustness exercise asks whether the conflict spillovers are driven by *economic* spillovers induced by disasters. Because official, district-level GDP data are unavailable, we proxy economic activity with night-time lights, following Henderson et al. (2012) and Hodler and Raschky (2014). We use the harmonised DMSP–VIIRS series of Li et al. (2020), aggregated to districts for 1992–2020. In column (1) of Table B.15, we replace conflict with annual district-level night-time luminosity, $Light_{i,t}$, as the dependent variable in equation (1) and find no statistically significant effect of disasters on neighbouring districts' economic activity. Column (2) keeps $Conflict_{i,t}$ as the outcome but adds night-time lights for both districts i and j as controls; the disaster coefficients are virtually unchanged, indicating that the conflict spillovers we document are not mediated by economic spillovers.

[31] Road data (2016) come from OpenStreetMap; pre-colonial ethnic homelands from Murdock (1959).
[32] Unfortunately, the lack of time-varying road data prevents a deeper exploration.

5 Mechanisms of Disaster-Driven Conflict Diffusion

The relationship between natural disasters and spatial conflict dynamics is complex, driven by several overlapping mechanisms. The literature points to a variety of channels through which disasters may influence violence, including economic shocks, population displacement, and temporary losses of state capacity. Yet the aggregate nature of our data—and the absence of finer-grained information—limits our ability to test these channels directly. Any formal interpretation of the results must therefore remain cautious.

To maintain analytical tractability, we develop a theoretical framework that casts combatants as the central decision-makers. By narrowing the focus to this group, we can examine a single, tractable channel through which natural disasters redistribute conflict across space. Although the model is deliberately stylised, it offers a coherent first pass at how disasters may alter combatants' strategic behaviour—dampening violence where the shock occurs while pushing it into neighbouring districts.

In the model (Section C), several players compete in separate battles for contestable rents. These battles are linked by a network, and each player chooses how much effort to devote to each engagement. Victory follows a standard Tullock contest success function: greater effort raises the probability of winning. Because the best-response functions are nonlinear, we analyse a simple star network with two battles and three players, one of whom participates in both contests. A negative shock in one district lowers effort there but raises it in the connected district; the magnitude of each response depends on network position and player strength. The central player, who fights in both battles, reallocates effort across contests to maximise total pay-off, and the two peripheral players adjust optimally to this shift.

Following a negative shock in a locality, the resulting decrease in the benefits—and increase in the costs—of fighting produces heterogeneous effects across both time and space.

In the short run, a disaster reduces contestable rents and raises the costs of manoeuvring and of accessing financial or military resources, temporarily incapacitating rebels. This cost increase is likely to outweigh any residual benefits, generating the negative direct effect we observe in the struck district. Over a longer horizon, however, rebels expand their strategic calculus, shifting violence to well-connected neighbouring districts with higher prospective rents, where the expected pay-off exceeds that in the disaster-hit area.

Post-disaster emergency aid introduces a countervailing force. Relief programmes ease resource shortages and inject new, potentially lootable assets. By restoring local stakes and lowering operational costs, aid enables combatants to continue fighting in the affected district and reduces their incentive to relocate violence.

This section investigates the mechanisms behind these patterns. First, we examine how post-disaster conflict dispersion varies with local resource endowments, using geo-referenced measures of economic activity and natural-resource wealth. Second, we analyse how international emergency aid shapes the spatial diffusion of conflict after a disaster.

5.1 Conflict spillovers based on district-specific characteristics

We now investigate how the spatial dispersion of conflict in the aftermath of disasters varies by the expected returns from fighting in a particular locality. As described in Section 2.3, each district is classified, on the basis of pre-disaster averages, into *no*, *low*, or *high* categories for (i) night-time luminosity, (ii) agricultural suitability, and (iii) mining activity. We treat these time-invariant features as proxies for the local "prize" that combatants might seize once a neighbouring shock occurs.

To capture this, we define an interaction term $NDIS_{i,t} \times \mathbf{Z_i}$, where $\mathbf{Z_i}$ is a vector of time-invariant characteristic of district i, where district i is the recipient of conflict spillovers following the natural disaster shock experienced by its neighbour, district j. This interaction term would assume a value of 1 if $\sum_{j=1}^{J} \omega_{ij} DIS_{jt} > 0$ and Z_i=1. It would assume a value of 0 if $\sum_{j=1}^{J} \omega_{ij} DIS_{jt}$=0 or Z_i=0 or both.

We combine these interaction terms within the following specification, to explore the mechanisms underlying the spatial spillovers of conflict.

$$
\begin{aligned}
Conflict_{i,t} = \; & \beta_0 DIS_{i,t} + \beta_1 DIS_{i,t-1} + \delta_0 NDIS_{i,t} + \delta_1 NDIS_{i,t-1} \\
& + \lambda_0 (DIS_{i,t} \times \mathbf{Z_i}) + \lambda_1 (DIS_{i,t-1} \times \mathbf{Z_i}) \\
& + \mu_0 (NDIS_{i,t} \times \mathbf{Z_i}) + \mu_1 (NDIS_{i,t-1} \times \mathbf{Z_i}) \\
& + \gamma NConflict_{i,t} + \mathbf{FE_i} + \mathbf{FE_{cy}} + \epsilon_{i,t}
\end{aligned}
\tag{2}
$$

All variables remain the same as per Equation (1), with the only difference being the addition of the interaction terms, as discussed above. Consistent with baseline estimates, the "neighbourhood" is defined in terms of the inverse geographic distance. The error term $\epsilon_{i,t}$ is assumed to be spatially and temporally correlated and as such we present Conley (1999) clustered standard errors accounting for spatial correlation up to 500km and temporal correlation up to 1 period.

In Figure 1, panels (a)–(c) illustrate disaster-induced conflict diffusion through nighttime lights, agricultural activity, and mining activity, respectively. Dark-blue estimates capture the direct effect of a disaster in district i (DIS), conditional on district characteristics $\mathbf{Z}_i$; light-blue estimates show the spillover effect of disasters in neighboring districts ($NDIS$) conditional on the same characteristics.

Panel (a) shows that disasters reduce violent conflict mainly in districts with low yet positive nighttime-light intensity areas with some economic activity but neither the poorest regions nor urban hubs. The corresponding conflict spillovers likewise concentrates in low-light districts. This near-mirror pattern implies that combatants disengage from moderately lucrative districts and relocate to neighboring districts offering similar rent-seeking opportunities. Spillover estimates are positive but insignificant in high-light districts, perhaps because such areas enjoy stronger government protection and are less attractive to small rebel units.

These results are in line with the propositions in our theoretical framework in Section C. In our star-network set-up a disaster lowers the local prize; the central player therefore reallocates effort away from battle toward the adjacent battle, and peripheral opponents respond in kind, generating a mirror-image increase in neighbouring districts (Proposition 2). Urban or more developed districts face stronger state capacity, which raises contest costs and dampens both the direct and the displaced fighting, whereas zero-light districts offer little rent to compete for, leaving both coefficients close to zero.

Panel (b) reveals a similar pattern for agricultural suitability: disasters suppress fighting in districts with moderate or high suitability and, after a brief lag, displace violence into neighboring districts with comparable suitability. This echoes the comparative-statics result that higher (post-shock) relative prizes in connected nodes draw in relocated effort when the original battlefield becomes less profitable.

Panel (c) reports analogous results for mining activity. While the direct effect of disaster decreasing violence in mining districts is less pronounced, we again find that disaster lead to increases in fighting activity in neighboring districts with some or even high mining activity. For mining districts the direct negative effect is muted, indicating that combatants are reluctant to leave areas with extractive rents even after a shock. In cases where displacement occurs, however, conflicts preferentially jump into other mining districts, where similar rents can still be appropriated, in line with the model's prediction that effort is re-directed toward the next-best battle with comparable prize value.

Taken together, the three mechanisms support the idea that disaster-related conflict dispersion is driven, at least in part, by the presence of lootable resources and rent-seeking opportunities in a locality. By damaging physical and natural assets, disasters lower the pay-off to fighting in the affected locality, prompting combatants to shift operations to adjacent districts that offer comparable prizes.

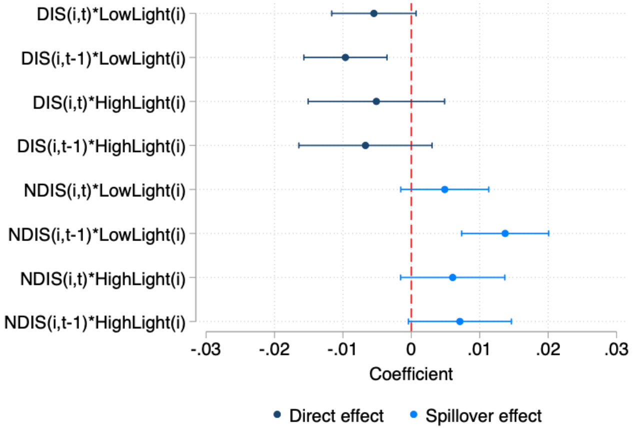
5.2 The role of foreign aid

The EM-DAT disaster database records whether an event received assistance from the Office of U.S. Foreign Disaster Assistance (OFDA). To examine whether the receipt of foreign assistance affects the dynamics of conflict spillovers, we convert this information into a binary aid indicator and re-estimate the model to test for heterogeneity. In doing so, we use an econometric specification similar to that of Equation 2. The distinction, however, is that within these estimates $\mathbf{Z_i}$ is replaced by a binary indicator on whether, following the natural disaster, the neighboring district received OFDA or not.

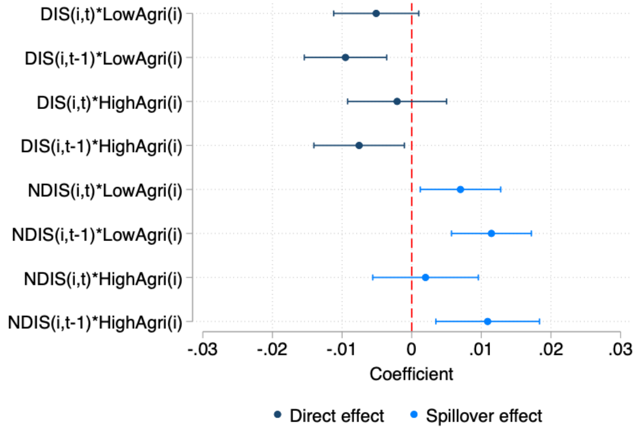
Figure 2 shows that the allocation of international emergency aid leads to reversal of the baseline conflict dispersion pattern.[33] In the baseline, a disaster lowers conflict in the struck district; with OFDA aid, conflict in that district *rises* significantly. Conversely, disasters without aid raise violence in neighbouring districts, whereas disasters followed by aid *reduce* it.

[33] Corresponding estimates, in tabular form, are in Table B.17.

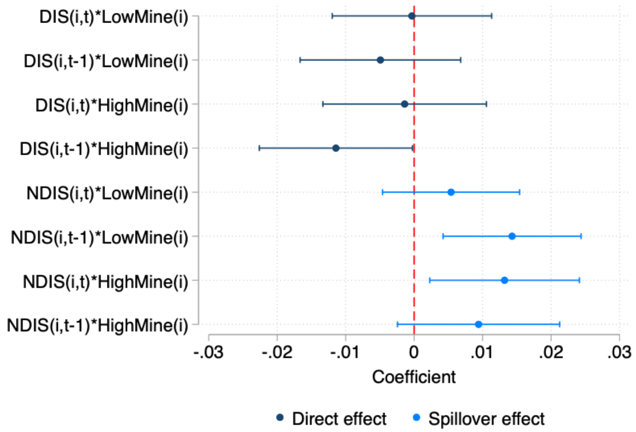
Figure 1: Heterogeneous effects of conflict diffusion



(a) Heterogeneity by level of nighttime light



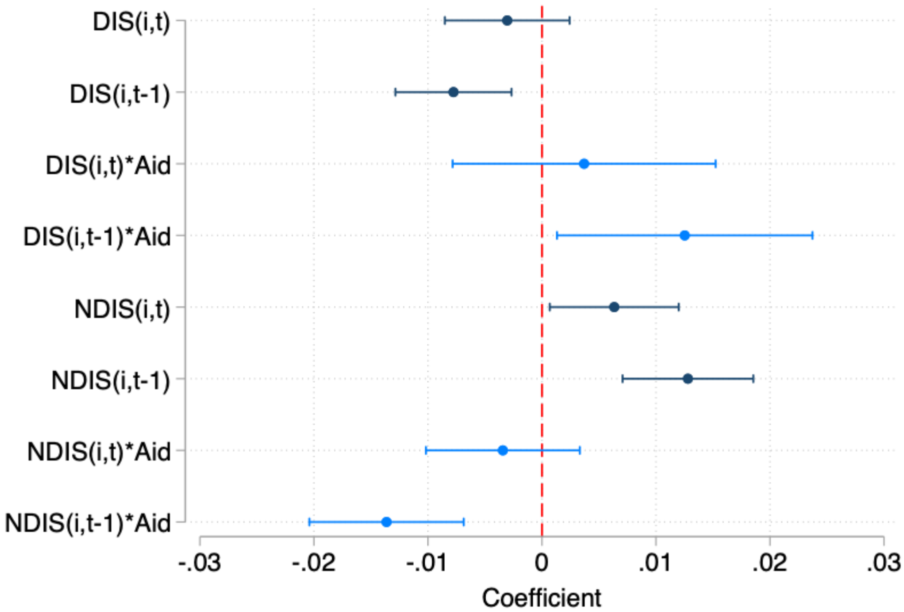
(b) Heterogeneity by level of agricultural activity



(c) Heterogeneity by level of mining wealth

Note: Dots show the estimated coefficients on $DIS_{i,t} \times \mathbf{Z_i}$ (in dark blue) and $NDIS_{i,t} \times \mathbf{Z_i}$ (in light blue) using Eq. (2). $\mathbf{Z_i}$ and $\mathbf{Z_j}$ are time-invariant binary indicators for nighttime light, mining wealth and agricultural suitability in district i. The "no–activity" category is the reference group. See Section 2.3 for variable definitions. Estimates correspond to Columns (2), (4) and (6) of Table B.16. Neighbourhood is defined based on the altitude-adjusted inverse geodesic distance matrix truncated at 500 km. Standard errors are based on Conley (1999) clustering, with 500 km spatial and one-period temporal correlation.

Figure 2: Effects by OFDA receipt status



Notes: DIS is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in the given district in the given time period. $NDIS$ is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in any one of the district's neighbours. Disasters exclude droughts. *Aid* is a binary indicator that identifies whether or not the natural disaster, whether in district i or in the neighbouring districts, received foreign aid from the OFDA. Dots show the estimated coefficients while horizontal lines show the 90% confidence intervals based on Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period. Neighbourhood is defined as per the altitude-adjusted inverse geodesic distance matrix truncated at 500km. Estimates include district and country×year fixed effects.

In the star–network contest of Section C an exogenous shock affects conflict through two channels: it destroys pre-existing rents in the epicentre but may simultaneously attract new, aid-related resources. Our comparative statics (Proposition 3) show that if the post-shock *net* prize in a district rises relative to surrounding districts, equilibrium effort is re-directed into the affected district, reducing the incentive to fight next door.

Emergency assistance therefore flips the spatial gradiant of prizes created by the disaster, transforming the outward displacement of violence into an inward pull. The empirical coefficients in Figure 2 map onto this prediction: aid restores (and even augments) the contestable surplus in the treated district, so combatants concentrate their effort there and abandon neighbouring battlefields.

Our findings reinforce the core mechanism of the model. Armed actors strategically reallocate effort toward the district with the highest relative post-shock prize and caution that well-intended relief can inadvertently stoke violence exactly where it is delivered. These results echo Nunn and Qian's (2014) conclusion that foreign aid can fuel violence by raising the returns to fighting or by supplying rebels with resources. Aid appears to concentrate armed activity in the recipient district, leaving less incentive or capacity for rebels to expand into surrounding areas, which helps explain the decline in neighbouring conflict when assistance is present.

6 Conclusion

This paper shows that natural disasters reshape the spatial patterns of violent conflict in Africa. Using a district–year panel for 5,944 ADM2 units across fifty-three countries from 1989 to 2020, we find that a disaster lowers the probability of conflict in the stricken district but raises it in neighboring districts that are connected through a geographic network. On net, disaster shocks increase the spatial system's overall likelihood of violence. Importantly, we show—both empirically and theoretically—that the spatial dynamics of conflict differ markedly between sudden-onset disasters and slow-onset disasters such as droughts. Their effects vary in nature, timing, and spatial extent, implying that each type of disaster warrants distinct analysis and tailored policy responses.

We highlight the roles of local resource wealth and international emergency aid in shaping the spatial dispersion of post-disaster conflict. First, conflict spillovers following disasters are larger when neighboring districts exhibit higher agricultural potential, greater mining wealth, or higher levels of economic development. This pattern is consistent with the notion that combatants reallocate their efforts toward areas offering more lootable resources and rent-seeking opportunities.

Second, emergency aid reverses the baseline pattern. When a disaster triggers assistance from the Office of U.S. Foreign Disaster Assistance, conflict increases in the disaster struck district but declines in neighbouring districts. Aid raises local stakes by injecting new, lootable resources and reduces the incentive to expand operations outward. This finding echoes Nunn and Qian's (2014) evidence that food aid can concentrate rather than diffuse violence.

A simple network model rationalises these results. Players allocate effort across multiple contests linked by a network. A negative shock reduces the prize in one district; the central combatant shifts effort to other contests, peripheral actors respond, and conflict migrates along the network.

This novel perspective on how conflict spreads after a disaster also provides some insights for policy-makers and international organisations. Because disasters displace rather than eliminate violence, security and peace-keeping forces should be positioned not only in high-risk districts but also in adjacent, economically attractive areas where conflict is likely to resurface. Emergency relief must be paired with transparent distribution, local monitoring, and, where feasible, cash-for-work schemes that limit the stock of lootable goods. Without such safeguards, aid can intensify fighting at the epicentre. Disaster-response protocols should incorporate network maps of district connectivity (roads, trade flows, ethnic links) to forecast where violence is most likely to spread and to allocate resources accordingly.

Taken together, our findings suggest that disaster management and conflict mitigation cannot be designed in isolation. Relief that stabilises one district may inadvertently ignite violence next door unless policymakers account for the underlying network of contests that links localities across space.

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(Not-for-Publication) Online Appendix

How Natural Disasters Spread Conflict

By Ashani Amarasinghe[1], Paul A. Raschky[2], Yves Zenou[3] and Junjie Zhou[4]

A Additional Data Description

A.1 Figures

Figure A.1: EM-DAT data extract

DisNo	Year	Disaster…	DisasterSubgroup	DisasterType	GeoLocations
2017-0306-GHA	2017	Natural	Hydrological	Flood	Birim Municipal, Ga South, Twifo Ati-Morkwa, Wassa Amenfi West (Adm2).
2019-0049-BDI	2019	Natural	Hydrological	Flood	Buterere, Kanyosha, Kinama, Musaga, Nyakabiga (Adm2).
2018-0008-MDG	2018	Natural	Meteorological	Storm	Analamanga (Adm1). Brickaville, Mahanoro, Mananjary, Nosy-Varika, Toamasina I, Toamasina II, Vatomandry (Adm2).
2017-0178-ZAF	2017	Natural	Meteorological	Storm	Cape Winelands District Municipality, City of Cape Town Metropolitan Municipality, Eden District Municipality (Adm2).
2019-0048-ZMB	2019	Natural	Hydrological	Flood	Chama, Chinsali, Isoka, Mpika, Nakonde (Adm2).

Source: EM-DAT

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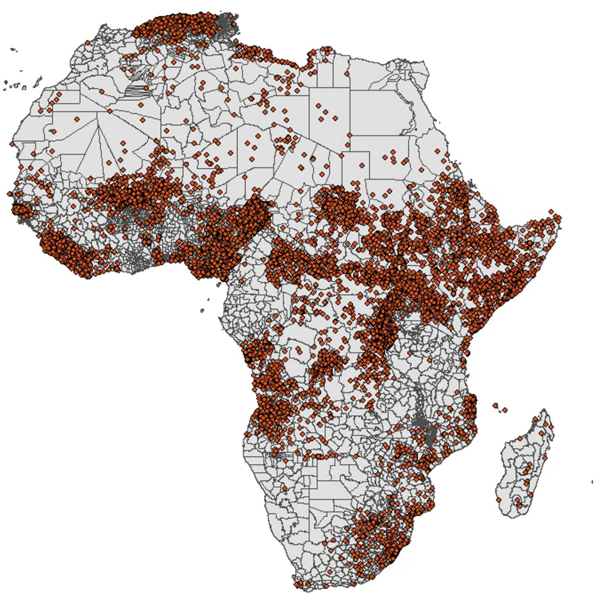
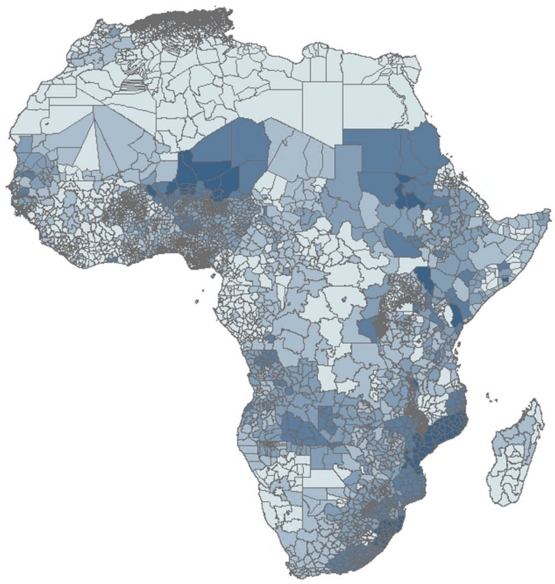
Figure A.2: Spatial distribution of conflicts and natural disasters in Africa



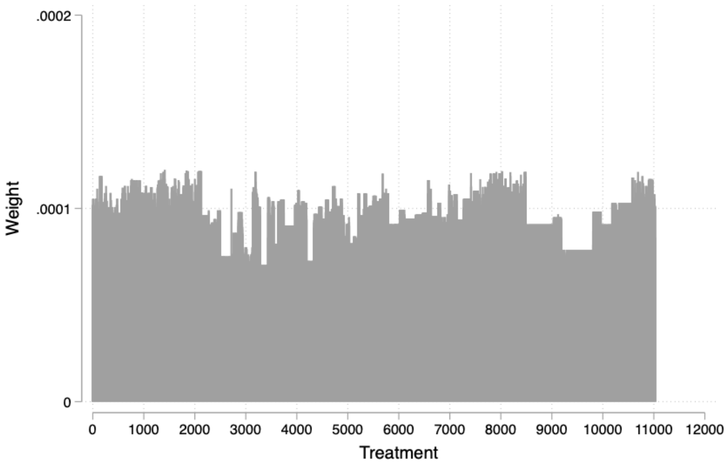
(a) Conflicts



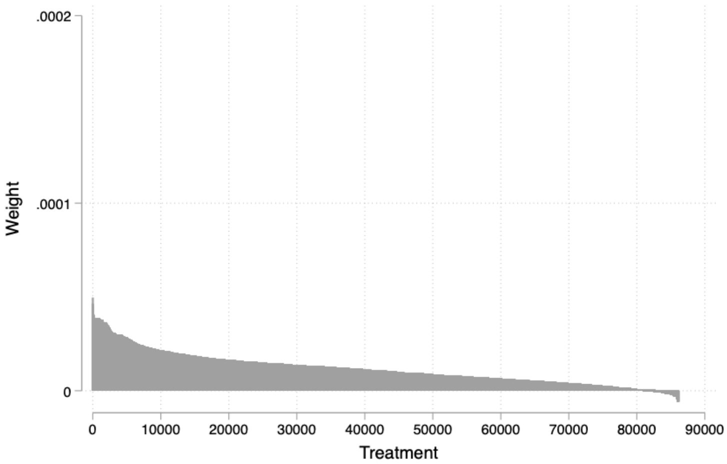
(b) Natural Disasters

Notes: Panel (a) shows the point locations of battle events in Africa, as per the UCDP data set. Panel (b) shows the district level dispersion of natural disasters in Africa, as per the EM-DAT data set. Darker colors indicate districts more prone to natural disasters over the sample period.

Figure A.3: Diagnostic tests - Weights attached to each treatment as per De Chaisemartin and D'Haultfœuille (2020)



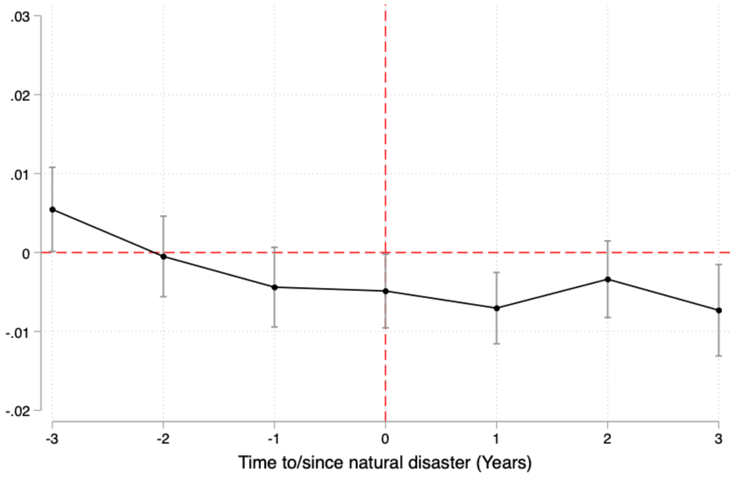
Panel A: Treatment DIS_{it}



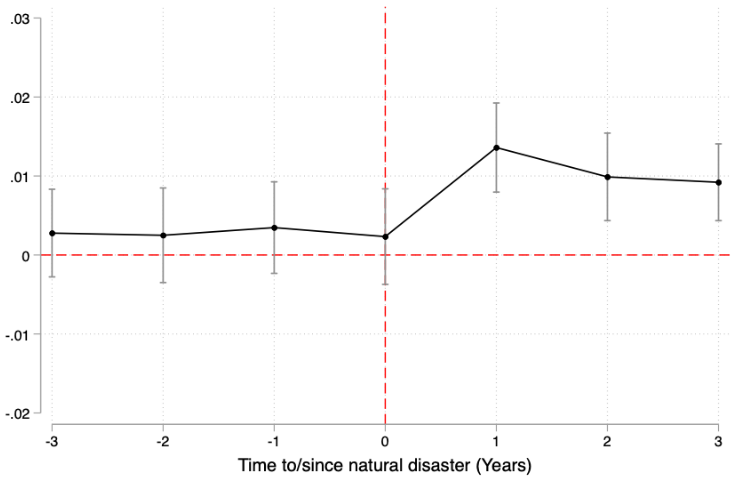
Panel B: Treatment $NDIS_{it}$ (based on inverse geographic distance)

Note: Figure shows the distribution of the weights attached to each ATE used in this study. This procedure was conducted using Stata's `twowayfeweights` estimator developed in line with De Chaisemartin and D'Haultfœuille (2020).

Figure A.4: Temporal dynamics



Panel A: Independent Variable DIS_{it}



Panel B: Independent Variable $NDIS_{it}$ (based on inverse geographic distance)

Note: Figure shows the direct and spillover effect of natural disasters in district i on conflict, for the 3 years before and after the natural disaster. The unit of observation is a district-year. Vertical lines depict the 95% level confidence intervals, based on Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 3 periods.

A.2 Tables

Table A.1: Disasters by type

Disaster Type	*Frequency*
Flood	886
Drought	174
Storm	141
Landslide	52
Earthquake	27
Wildfire	25
Extreme Temp	13
Volcano	5
Wave/Surge	3
Total	1,326

Table A.2: Descriptive statistics for key variables

	Observations	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Conflict	190,208	0.0367	0.1880	0	1
DIS	190,208	0.0580	0.2337	0	1
Conflict if DIS >0	11,025	0.0309	0.1731	0	1
Conflict if DIS=0	179,183	0.0370	0.1888	0	1
Spillover effects					
NDIS	190,208	0.4526	0.4978	0	1
Conflict if NDIS >0	86,094	0.0376	0.1902	0	1
Conflict if NDIS=0	104,114	0.0359	0.1861	0	1

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, and a natural disaster event, respectively, in district i in in the given time unit. $NDIS$ is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in at least one of the neighbouring districts, where neighbourhood is defined as per the altitude-adjusted inverse geodesic network.

Table A.3: Correlation between natural disaster indicators and district level characteristics - Direct effect)

	(1) *Dis*	(2) *LargeDis*	(3) *SmallDis*	(4) *ClimDis*	(5) *GeoDis*	(6) *Flood*	(7) *Storm*	(8) *Quake*	(9) *Slide*	(10) *Wildfire*	(11) *Drought*
$Area$	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$PopDensity$	0.0000**	0.0000***	0.0000	0.0000**	-0.0000	0.0000**	-0.0000	0.0000	-0.0000	-0.0000	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Temperature$	0.0578***	0.0442***	0.0419***	0.0581***	0.0016	0.0594***	-0.0144	0.0006	0.0013	-0.0112	0.0123
	(0.0104)	(0.0123)	(0.0100)	(0.0104)	(0.0013)	(0.0102)	(0.0102)	(0.0010)	(0.0011)	(0.0084)	(0.0115)
$Precipitation$	0.0016	0.0014	0.0007	0.0015	0.0003**	0.0013	0.0011*	0.0002*	0.0001*	0.0007	0.0001
	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0001)	(0.0010)	(0.0006)	(0.0001)	(0.0001)	(0.0005)	(0.0008)
$Elevation$	0.0003***	0.0002***	0.0003***	0.0003***	0.0001**	0.0003***	-0.0000	0.0000*	0.0000*	0.0000	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
$Ruggedness$	-0.0003	-0.0006	0.0004	-0.0003	-0.0000	-0.0004	0.0002	0.0000	-0.0000	0.0004	0.0004
	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0001)	(0.0006)	(0.0002)	(0.0001)	(0.0000)	(0.0003)	(0.0004)
NTL	0.0024	0.0023	0.0038*	0.0024	0.0001	0.0029	0.0017	-0.0000	0.0002	0.0027	-0.0007
	(0.0020)	(0.0021)	(0.0020)	(0.0020)	(0.0004)	(0.0019)	(0.0022)	(0.0003)	(0.0002)	(0.0023)	(0.0021)
$MineCount$	0.0164	0.0274	0.0274**	0.0159	0.0078*	0.0158	0.0978**	0.0065**	0.0016	0.0621***	0.0304
	(0.0215)	(0.0255)	(0.0133)	(0.0212)	(0.0043)	(0.0210)	(0.0407)	(0.0029)	(0.0039)	(0.0137)	(0.0266)
$CroplandShare$	0.1683*	0.1357	0.1608**	0.1600*	0.0154	0.1777*	-0.0306	0.0150	0.0004	-0.0586*	-0.0485
	(0.0872)	(0.1076)	(0.0775)	(0.0903)	(0.0167)	(0.0904)	(0.0653)	(0.0159)	(0.0086)	(0.0301)	(0.1201)
$PrimaryRoadKM$	0.0010***	0.0010**	0.0002	0.0010***	0.0001**	0.0010***	0.0004	0.0000	0.0001	0.0004**	0.0003
	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0006)
$SecondaryRoadKM$	0.0006***	0.0007***	0.0008***	0.0006***	-0.0001***	0.0006***	0.0006**	-0.0001**	-0.0000	0.0005***	0.0008**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0003)	(0.0000)	(0.0000)	(0.0001)	(0.0003)
$Distancetocapital$	0.0000**	0.0000**	0.0000**	0.0000**	0.0000	0.0000**	0.0000**	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Port$	-0.0402	-0.0406	-0.0111	-0.0383	0.0126	-0.0547	-0.0057	-0.0057	0.0122	-0.0278	0.0205
	(0.0406)	(0.0430)	(0.0399)	(0.0406)	(0.0125)	(0.0428)	(0.0287)	(0.0058)	(0.0107)	(0.0277)	(0.0348)
$PowerPlant$	0.0143	0.0130	0.0236*	0.0133	0.0110	0.0133	0.0069	0.0059	0.0034	0.0075	0.0010
	(0.0100)	(0.0114)	(0.0124)	(0.0101)	(0.0066)	(0.0100)	(0.0079)	(0.0052)	(0.0030)	(0.0085)	(0.0051)
$Pre-ColonialInst.$	-0.1064***	-0.1140**	-0.1101**	-0.1025**	-0.0108	-0.0986**	-0.0786*	-0.0070	-0.0037	-0.0168	-0.0399
	(0.0394)	(0.0431)	(0.0455)	(0.0392)	(0.0107)	(0.0387)	(0.0403)	(0.0085)	(0.0050)	(0.0114)	(0.0405)
Observations	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682
R-squared	0.3878	0.3044	0.2024	0.3831	0.0516	0.3885	0.2176	0.0259	0.0295	0.2055	0.1681

Outcome variables are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in the given district over the sample period. Standard errors are clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1

Table A.4: Correlation between natural disaster indicators and district level characteristics - Spillover effect)

	(1) $N(Dis)$	(2) $N(LargeDis)$	(3) $N(SmallDis)$	(4) $N(ClimDis)$	(5) $N(GeoDis)$	(6) $N(Flood)$	(7) $N(Storm)$	(8) $N(Quake)$	(9) $N(Slide)$	(10) $N(Wildfire)$	(11) $N(Drought)$
$Area$	-0.0000*	-0.0000**	-0.0000	-0.0000*	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$PopDensity$	0.0000	0.0000	0.0000	0.0000	0.0000***	-0.0000	0.0000	-0.0000	0.0000***	0.0000**	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Temperature$	0.0048	0.0048	0.0742***	0.0048	0.0064	0.0313***	0.0312*	0.0067	0.0073	-0.0480***	0.0829***
	(0.0041)	(0.0041)	(0.0084)	(0.0041)	(0.0139)	(0.0072)	(0.0175)	(0.0109)	(0.0131)	(0.0104)	(0.0101)
$Precipitation$	0.0010*	0.0010**	0.0034***	0.0010*	0.0061***	0.0023*	0.0036**	0.0015**	0.0059***	0.0019**	-0.0010
	(0.0005)	(0.0005)	(0.0009)	(0.0005)	(0.0008)	(0.0012)	(0.0016)	(0.0007)	(0.0008)	(0.0007)	(0.0017)
$Elevation$	0.0001***	0.0001***	0.0004***	0.0001***	0.0003***	0.0002***	0.0003***	0.0005***	0.0003***	-0.0002***	0.0006***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Ruggedness$	-0.0005*	-0.0005*	-0.0004	-0.0005*	-0.0011***	-0.0011**	-0.0007	-0.0008*	-0.0010***	0.0004	0.0002
	(0.0003)	(0.0003)	(0.0005)	(0.0003)	(0.0003)	(0.0005)	(0.0006)	(0.0005)	(0.0004)	(0.0006)	(0.0006)
NTL	-0.0001	-0.0001	0.0011	-0.0001	0.0003	0.0027	-0.0014	0.0019	0.0006	0.0024	0.0022
	(0.0013)	(0.0013)	(0.0022)	(0.0013)	(0.0017)	(0.0022)	(0.0031)	(0.0021)	(0.0018)	(0.0019)	(0.0027)
$MineCount$	0.0118	0.0070	0.0447	0.0118	0.0355	0.0219	0.0513	0.0795**	0.0090	0.0419	0.0418
	(0.0097)	(0.0073)	(0.0400)	(0.0097)	(0.0248)	(0.0229)	(0.0515)	(0.0379)	(0.0193)	(0.0363)	(0.0388)
$CroplandShare$	0.0741	0.0740	0.0343	0.0741	0.1134	0.1227	0.1982**	0.2004*	0.1197	-0.0836	0.1356
	(0.0552)	(0.0553)	(0.0757)	(0.0552)	(0.1170)	(0.1006)	(0.0979)	(0.1093)	(0.1134)	(0.1067)	(0.1029)
$PrimaryRoadKM$	0.0001**	0.0001**	0.0006*	0.0001**	0.0009	0.0003*	0.0008	0.0004	0.0008*	0.0010	0.0008**
	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0006)	(0.0002)	(0.0007)	(0.0006)	(0.0004)	(0.0006)	(0.0003)
$SecondaryRoadKM$	0.0001**	0.0001**	0.0005***	0.0001**	0.0003	0.0002**	0.0002	-0.0000	0.0004***	0.0004	0.0003*
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0002)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0003)	(0.0002)
$Distancetocapital$	0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000**	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Port$	-0.0298	-0.0281	-0.0332	-0.0298	-0.0615	-0.0010	-0.0076	-0.0069	-0.0473	-0.1286***	0.0467
	(0.0202)	(0.0200)	(0.0602)	(0.0202)	(0.0560)	(0.0285)	(0.0311)	(0.0244)	(0.0553)	(0.0400)	(0.0418)
$PowerPlant$	-0.0243*	-0.0247*	0.0036	-0.0243*	0.0240**	-0.0042	-0.0022	0.0071	0.0182	-0.0284**	-0.0046
	(0.0141)	(0.0140)	(0.0078)	(0.0141)	(0.0117)	(0.0168)	(0.0084)	(0.0063)	(0.0113)	(0.0137)	(0.0078)
$Pre-ColonialInst.$	-0.0140	-0.0149	-0.0325	-0.0140	0.0422	-0.0992	-0.1150**	0.0030	0.0865	-0.0632	-0.1129**
	(0.0148)	(0.0146)	(0.0292)	(0.0148)	(0.0553)	(0.0702)	(0.0490)	(0.0343)	(0.0519)	(0.0781)	(0.0552)
Observations	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682
R-squared	0.1187	0.1206	0.7658	0.1187	0.4685	0.3790	0.3320	0.3699	0.4547	0.1763	0.4924

Outcome variables are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in the given district over the sample period.
Standard errors are clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1

Table A.5: Temporal and spatial autocorrelation of natural disasters

	(1) $DIS_{i,t}$	(2) $NDIS_{i,t}$	(3) $DIS_{i,t}$
$DIS_{i,t-1}$	0.0021		0.0087
	(0.0133)		(0.0132)
$DIS_{i,t-2}$	-0.0203		
	(0.0150)		
$DIS_{i,t-3}$	-0.0085		
	(0.0133)		
$NDIS_{i,t}$			0.0176***
			(0.0040)
$NDIS_{i,t-1}$		0.0103	0.0048
		(0.0199)	(0.0066)
$NDIS_{i,t-2}$		-0.0011	
		(0.0213)	
$NDIS_{i,t-3}$		-0.0171	
		(0.0155)	
Observations	172,376	172,376	184,264
District FE	YES	YES	YES
Country× Year FE	YES	YES	YES

DIS is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. $NDIS$ is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in any one of the district's neighbours, within the given time period. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. Disasters exclude droughts. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

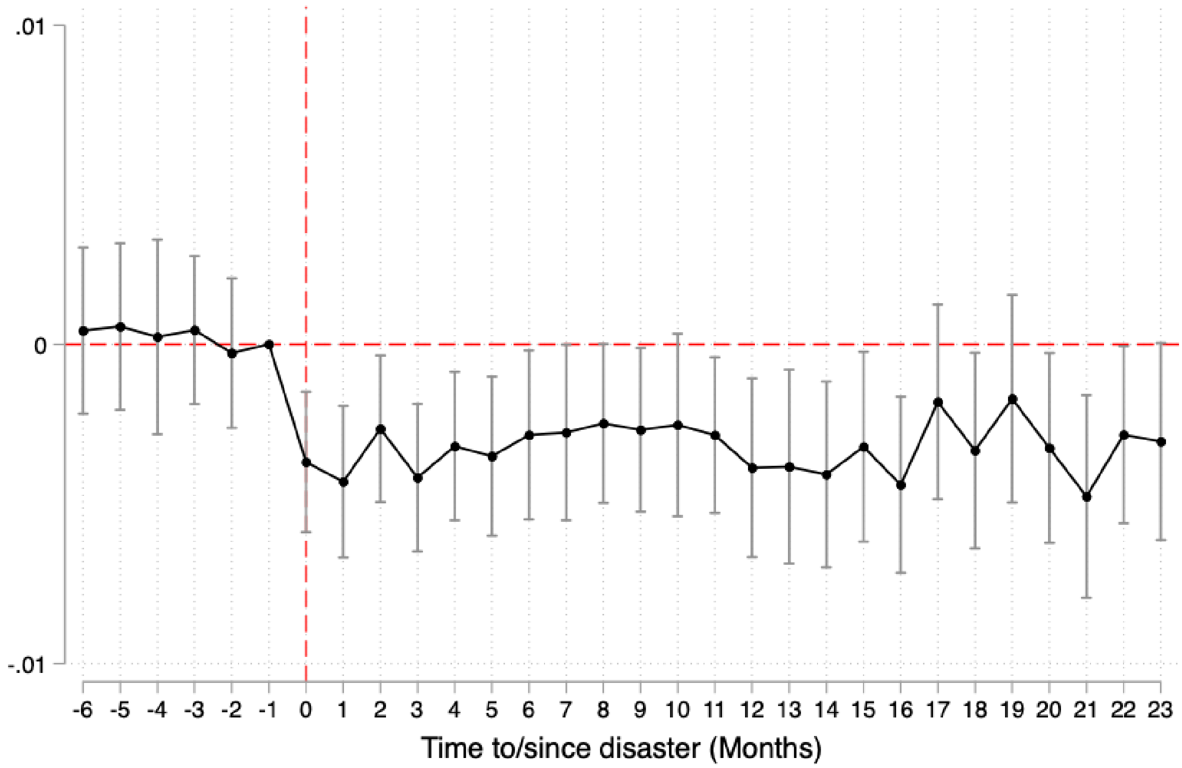
A.3 Direct effect of natural disasters on conflict at the district×month level

The EM-DAT data contains information about the date of the natural disaster event and we use this information to build a dataset at the district×month level. Figure A.5 presents the results of an event study analysis to estimate the direct effect of natural disasters on conflict using monthly data. We observe that the direct effect materialises in the contemporary month itself, and persists for up to two years.

At the district×year level estimates in Table 1, the direct effect is not statistically significant in the contemporary year, and only becomes statistically significant in $t + 1$. To examine this discrepancy, we conduct a test in Table A.6, where we re-estimate the direct effect of natural disasters on conflict at the district×year level, and add the different sets of fixed effects stepwise. In Column (1) we include district fixed effects only, and the effect is negative and statistically significant, indicating that the effect materialises contemporaneously. However, when we add country×year fixed effects in Column (2), the statistical significance disappears. In Column (2) we include both sets of fixed effects along with previous period's natural disaster indicator. Here, the negative effect is statistically significant at the 10% level.

These results suggest that the pattern of negative effect of natural disasters on conflict does exist in the contemporary time period, but the inclusion of a relatively conservative set of country×year fixed effects results in a p-value below the standard threshold of statistical significance.

Figure A.5: Event study of the effect of natural disasters on conflict - at the district×month level



Notes: Figure shows event study estimates of the effect of natural disasters on conflict, at the district×month level. Estimates include district and year×month fixed effects. Dots show the estimated coefficients while vertical lines show the 90% confidence intervals based on standard errors clustered at the country×year level.

Table A.6: Direct effects of natural disasters on conflict at the year level - Stepwise addition of controls

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$
$DIS_{i,t}$	-0.0129***	-0.0023	-0.0026
	(0.0046)	(0.0035)	(0.0035)
$DIS_{i,t-1}$			-0.0053*
			(0.0030)
Observations	190,208	190,208	184,264
District FE	YES	YES	YES
Country× Year FE	NO	YES	YES

Conflict and *DIS* are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. Disasters exclude droughts. () present country×year clustered standard errors. *** p<0.01, ** p<0.05, * p<0.1

B Robustness checks

Table B.1: Dynamic difference-in-differences estimates as per de Chaisemartin and D'Haultfœuille (2024)

	$Conflict_{i,t}$			
	Panel 1: Direct		Panel 2: Spillover	
	Coeff.	*SE*	*Coeff.*	*SE*
$DIS_{i,t}$	-0.0067**	(0.0033)		
$DIS_{i,t-1}$	-0.0070*	(0.0041)		
$Avg\ Direct\ Effect$	-0.0122**	(0.0061)		
$NDIS_{i,t}$			0.0082**	(0.0041)
$NDIS_{i,t-1}$			0.0089*	(0.0054)
$Avg\ Spillover\ Effect$			0.0120*	(0.0062)

This table presents dynamic difference-in-differences estimates as per de Chaisemartin and D'Haultfœuille (2024), estimated separately for direct and spillover treatments. Total number of observations considered is 184,264. $Conflict_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a battle resulting in at least one death in district i in year y. $DIS_{i,t}$ and $DIS_{i,t-1}$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in district i in years y and $t-1$, respectively. $NDIS_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in any one of district i's neighbours in year y. Neighbourhood is based on the altitude-adjusted inverse geodesic distance network truncated at 500km. For the direct effect estimation, $NDIS_{i,t}$ and $Conflict_{i,t-1}$ are included as controls. For the spillover effect estimation $DIS_{i,t}$ and $Conflict_{i,t-1}$ are included as controls. Estimates include district and year fixed effects. Disasters exclude droughts. The effects were calculated using the $did_multiplegt_dyn$ command in Stata 18. *** p<0.01, ** p<0.05, * p<0.1

Table B.2: Alternative spatial models

	(1) $Conflict_{i,t}$ GNS	(2) $Conflict_{i,t}$ SLX
$DIS_{i,t}$	-0.0019	-0.0028
	{0.0027}	{0.0030}
	(0.0031)	(0.0035)
$DIS_{i,t-1}$	-0.0049**	-0.0056**
	{0.0025}	{0.0028}
	(0.0025)	(0.0029)
$NDIS_{i,t}$	0.0044	0.0055*
	{0.0028}	{0.0033}
	(0.0029)	(0.0035)
$NDIS_{i,t-1}$	0.0097***	0.0104***
	{0.0028}	{0.0033}
	(0.0032)	(0.0037)
$Conflict_{i,t-1}$	0.2315***	
	{0.0105}	
	(0.0126)	
Observations	184,264	184,264
Distance Cut-off	500km	500km
District FE	YES	YES
Country× Year	YES	YES
$NConflict_{i,t}$	YES	NA
$NConflict_{i,t-1}$	YES	NA

$Conflict_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a battle resulting in at least one death in district i in year t. $DIS_{i,t}$ and $DIS_{i,t-1}$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in district i in years y and $t-1$, respectively. $NDIS_{i,t}$ ($NConflict_{i,t}$) are binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (battle), in any one of district i's neighbours in year t. Neighbourhood is based on the altitude-adjusted inverse geodesic distance network, truncated at 500km. Disasters exclude droughts. {} present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, while ( ) present standard errors clustered at the country×year level. *** p<0.01, ** p<0.05, * p<0.1

Table B.3: Effect of natural disasters including droughts

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$
$DIS_{i,t}$	-0.0018	-0.0018
	(0.0029)	(0.0029)
$DIS_{i,t-1}$	-0.0018	-0.0019
	(0.0029)	(0.0028)
$NDIS_{i,t}$		0.0081***
		(0.0031)
$NDIS_{i,t-1}$		0.0112***
		(0.0032)
Observations	184,264	184,264
Distance Cutoff	NA	500km
District FE	YES	YES
Country× Year FE	YES	YES
$NConflict_{i,t}$	NA	YES
$NConflict_{i,t-1}$	NA	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. $NDIS$ ($NConflict$) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of the district's neighbours, within the given time period. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.4: Restricting the sample from 2000-2020

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$
$DIS_{i,t}$	-0.0012	-0.0010
	(0.0037)	(0.0037)
$DIS_{i,t-1}$	-0.0051	-0.0053
	(0.0032)	(0.0032)
$NDIS_{i,t}$		0.0020
		(0.0038)
$NDIS_{i,t-1}$		0.0100***
		(0.0038)
Observations	118,880	118,880
Distance Cutoff	NA	500km
District FE	YES	YES
Country× Year FE	YES	YES
$NConflict_{i,t}$	NA	YES
$NConflict_{i,t-1}$	NA	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. $NDIS$ ($NConflict$) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of the district's neighbours, within the given time period. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. Disasters exclude droughts. Sample is restricted to years 2000-2020. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.5: Estimates by disaster category

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$	(4) $Conflict_{i,t}$
Disaster Category	*Large*	*Small*	*Climatic*	*Geologic*
$DIS_{i,t}$	-0.0014	-0.0021	-0.0023	-0.0123
	(0.0035)	(0.0043)	(0.0030)	(0.0233)
$DIS_{i,t-1}$	-0.0032	-0.0061	-0.0059**	0.0049
	(0.0034)	(0.0039)	(0.0028)	(0.0200)
$NDIS_{i,t}$	0.0044	0.0064**	0.0062*	0.0147
	(0.0042)	(0.0027)	(0.0033)	(0.0144)
$NDIS_{i,t-1}$	0.0172***	0.0013	0.0125***	0.0017
	(0.0040)	(0.0028)	(0.0033)	(0.0114)
Observations	155,494	139,480	182,576	97,752
Distance Cut-off	500km	500km	500km	500km
District FE	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES

$Conflict_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death in district i in year t. $DIS_{i,t}$ and $DIS_{i,t-1}$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in district i in years y and $t-1$, respectively. $NDIS_{i,t}$ ($NConflict_{i,t}$) are binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of district i's neighbours in year t. *Large* disasters are those that either (*i*) kills at least 1000 people, or (*ii*) affects at least 100,000 people in total, or (*iii*) causes damages of at least one billion (real) dollars, while remaining disasters are classified as *Small*. *Geologic* disasters include landslides, and earthquakes. *Climatic* disasters include floods, cyclones, hurricanes and storms. Neighbourhood is based on the altitude-adjusted inverse geodesic distance network, truncated at 500km. Disasters exclude droughts. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.6: Estimates by disaster type

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$	(4) $Conflict_{i,t}$	(5) $Conflict_{i,t}$	(6) $Conflict_{i,t}$
$DisasterType$	$Flood$	$Landslide$	$Earthquake$	$Drought$	$Storm$	$Wildfire$
$DIS_{i,t}$	-0.0038	0.0130	-0.0231	0.0049	0.0165	-0.0055
	(0.0031)	(0.0344)	(0.0210)	(0.0075)	(0.0108)	(0.0160)
$DIS_{i,t-1}$	-0.0071**	-0.0137	-0.0061	0.0227**	0.0066	0.0008
	(0.0029)	(0.0252)	(0.0255)	(0.0102)	(0.0095)	(0.0183)
$NDIS_{i,t}$	0.0085**	-0.0015	0.0290**	0.0116*	-0.0046	0.0130*
	(0.0036)	(0.0235)	(0.0136)	(0.0070)	(0.0052)	(0.0073)
$NDIS_{i,t-1}$	0.0150***	-0.0042	0.0107	0.0234***	0.0027	0.0200**
	(0.0036)	(0.0158)	(0.0111)	(0.0081)	(0.0050)	(0.0082)
Observations	173,266	90,997	87,744	107,325	106,166	87,390
Distance Cut-off	500km	500km	500km	500km	500km	500km
District FE	YES	YES	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES	YES	YES

$Conflict_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death in district i in year t. $DIS_{i,t}$ and $DIS_{i,t-1}$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in district i in years y and $t-1$, respectively. $NDIS_{i,t}$ ($NConflict_{i,t}$) are binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of district i's neighbours in year t. Neighbourhood is based on the altitude-adjusted inverse geodesic distance network, truncated at 500km. Disasters exclude droughts. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.7: Direct and spillover effects of SPEI

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$
$SPEI_{i,t}$	0.0121***	0.0029
	(0.0041)	(0.0044)
$SPEI_{i,t-1}$	0.0042	-0.0045
	(0.0039)	(0.0042)
$NSPEI_{i,t}$		0.0236***
		(0.0082)
$NSPEI_{i,t-1}$		0.0219***
		(0.0081)
Observations	172,376	172,376
Distance Cut-off	NA	500km
District FE	YES	YES
Country× Year FE	YES	YES
$NConflict_{i,t}$	NA	YES
$NConflict_{i,t-1}$	NA	YES

$Conflict$ is a binary variable indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death in the given district in the given time period. $SPEI$ is the Standardised Precipitation-Evapotranspiration Index for the district, while $NSPEI$ is the spatial lag of the SPEI index for district's neighbours for the given year. $NConflict$ is a binary variable indicating the presence (=1) or absence (=0) of a conflict in any one of the district's neighbours. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.8: Estimates by conflict type

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$
$Conflict\ Type$	$State$	$Non-State$	$Onesided$
$DIS_{i,t}$	-0.0002	-0.0002	-0.0007
	(0.0022)	(0.0019)	(0.0019)
$DIS_{i,t-1}$	-0.0034*	-0.0005	-0.0036*
	(0.0020)	(0.0019)	(0.0019)
$NDIS_{i,t}$	0.0031	0.0024	-0.0002
	(0.0028)	(0.0016)	(0.0021)
$NDIS_{i,t-1}$	0.0049*	0.0041**	0.0032
	(0.0027)	(0.0016)	(0.0022)
Observations	184,264	184,264	184,264
Distance Cut-off	500km	500km	500km
District FE	YES	YES	YES
Country× Year FE	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES

$Conflict_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death in district i in year t. $DIS_{i,t}$ and $DIS_{i,t-1}$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in district i in years y and $t-1$, respectively. $NDIS_{i,t}$ ($NConflict_{i,t}$) are binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of district i's neighbours in year t. Neighbourhood is based on the altitude-adjusted inverse geodesic distance network, truncated at 500km. Disasters exclude droughts. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.9: ACLED vs UCDP comparison

	(1) ACLED $Violence_{i,t}$	(2) UCDP $Violence_{i,t}$	(3) Pooled $Violence_{i,t}$
$DIS_{i,t}$	-0.0014	-0.0019	-0.0008
	(0.0042)	(0.0033)	(0.0046)
$DIS_{i,t-1}$	-0.0013	-0.0058*	-0.0026
	(0.0042)	(0.0031)	(0.0045)
$NDIS_{i,t}$	0.0108**	0.0045	0.0118**
	(0.0042)	(0.0037)	(0.0046)
$NDIS_{i,t-1}$	0.0102**	0.0113***	0.0149***
	(0.0042)	(0.0036)	(0.0045)
Observations	136,712	136,712	136,712
Distance Cutoff	500km	500km	500km
District FE	YES	YES	YES
Country× Year FE	YES	YES	YES
$N(Outcome)_{i,t}$	YES	YES	YES
$N(Outcome)_{i,t-1}$	YES	YES	YES

DIS is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. The outcome variable in Column (1) is a binary variable indicating the presence (=1) or absence (=0) of a violent event as per the ACLED database. The outcome variable in Column (2) is a binary variable indicating the presence (=1) or absence (=0) of a violent event as per the UCDP database, for the same sample as in Column (1). The outcome variable in Column (3) is a binary variable indicating the presence (=1) or absence (=0) of a violent event as per either the ACLED or the UCDP database. $NDIS$ and $N(Outcome)$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event or the outcome variable of interest, respectively, in any one of the district's neighbours. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.10: Analysis for districts with area $\leq$ 55km^2 and using Dartmouth Flood Observatory (DFO) data at the Grid cell level

	Districts $\leq$ 55km^2 area		DFO data & Grid cells	
	(1)	(2)	(3)	(4)
	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$
$DIS_{i,t}$	0.0004	0.0005		
	(0.0034)	(0.0034)		
$DIS_{i,t-1}$	-0.0052*	-0.0051*		
	(0.0031)	(0.0031)		
$NDIS_{i,t}$	0.0038	0.0039		
	(0.0041)	(0.0041)		
$NDIS_{i,t-1}$	0.0101**	0.0102**		
	(0.0040)	(0.0040)		
$Flood_{i,t}$			-0.0075	-0.0075
			(0.0074)	(0.0074)
$Flood_{i,t-1}$			-0.0106	-0.0107
			(0.0079)	(0.0079)
$NFlood_{i,t}$			0.0035**	0.0033**
			(0.0014)	(0.0014)
$NFlood_{i,t-1}$			0.0039***	0.0038***
			(0.0014)	(0.0014)
Observations	156,922	156,922	320,385	320,385
Distance Cut-off	500km	500km	500km	500km
District/Grid cell FE	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES
$NConflict_{i,t}$	NO	YES	NO	YES
$NConflict_{i,t-1}$	NO	YES	NO	YES

Columns (1) and (2) replicate the baseline analysis for districts with area $\leq$ 55km^2. Columns (3) and (4) replicate the baseline analysis, at the grid cell level, using data on floods from the DFO. $Conflict$, DIS and $Flood$ are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, natural disaster event or flood, respectively, in the given district in the given time period. $NDIS$, $NConflict$ and $NFlood$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event, battle or flood, in any one of the district's neighbours. Disasters exclude droughts.() present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period. *** p<0.01, ** p<0.05, * p<0.1

Table B.11: Conflict onset and termination

	(1)	(2)
	$Onset_{i,t}$	$Termination_{i,t}$
$DIS_{i,t}$	-0.0018	-0.0007
	(0.0015)	(0.0014)
$DIS_{i,t-1}$	-0.0025	-0.0003
	(0.0016)	(0.0015)
Observations	146,805	161,534
District FE	YES	YES
Country × Year FE	YES	YES

Onset is a binary indicator = 0 in periods with no conflict events; = 1 in the first time period a district experiences a conflict; and missing in subsequent time periods. *Termination* is a binary indicator = 0 in periods of conflict; = 1 in the first period with no conflict; and missing in subsequent time periods. *DIS* is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. Disasters exclude droughts. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.12: Alternative distance cut-offs

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$	(4) $Conflict_{i,t}$	(5) $Conflict_{i,t}$
$DIS_{i,t}$	-0.0016	-0.0032	-0.0028	-0.0025	-0.0027
	(0.0026)	(0.0027)	(0.0028)	(0.0029)	(0.0030)
$DIS_{i,t-1}$	-0.0047*	-0.0057**	-0.0059**	-0.0058**	-0.0056**
	(0.0025)	(0.0026)	(0.0028)	(0.0028)	(0.0028)
$NDIS_{i,t}$	-0.0022	0.0045**	0.0053**	0.0045	0.0057*
	(0.0020)	(0.0022)	(0.0026)	(0.0029)	(0.0033)
$NDIS_{i,t-1}$	-0.0007	0.0027	0.0054**	0.0086***	0.0105***
	(0.0019)	(0.0022)	(0.0026)	(0.0029)	(0.0033)
Observations	184,264	184,264	184,264	184,264	184,264
Distance Cutoff	100km	200km	300km	400km	500km
District FE	YES	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. $NDIS$ ($NConflict$) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of the district's neighbours, within the given time period. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at the indicated distance cut-off. Disasters exclude droughts. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.13: Alternative connectivity networks

Connectivity	(1) Contiguity	(2) Ethnicity	(3) Roads	(4) Inverse Distance (no altitude adjusment)
	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$
$DIS_{i,t}$	-0.0007	-0.0024	-0.0032	-0.0027
	(0.0029)	(0.0030)	(0.0030)	(0.0030)
$DIS_{i,t-1}$	-0.0058**	-0.0058**	-0.0064**	-0.0056**
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
$NDIS_{i,t}$	-0.0017	-0.0006	0.0053**	0.0057*
	(0.0024)	(0.0024)	(0.0021)	(0.0033)
$NDIS_{i,t-1}$	0.0025	0.0019	0.0040*	0.0105***
	(0.0025)	(0.0025)	(0.0021)	(0.0033)
Observations	184,264	184,264	184,264	184,264
Distance Cut-off	NA	NA	500km	500km
District FE	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, an d natural disaster event, respectively, in the given district in the given time period. $NDIS$ ($NConflict$) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (battle), in any one of the district's neighbours, defined as per contiguity (Column 1), ethnicity (Column 2), inverse road distance (Column 3) and inverse geodesic distance with no altitude adjustment (Column 4). The contiguity network identifies neighbours with whom district i shares a common border. The ethnicity network identifies whether the majority ethnic group (as per Murdock (1959)) in districts i and j are the same. The inverse road distance network is based on the Open Street Map data on major roads in Africa as of 2016, and is truncated at 500km. Disasters exclude droughts. present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, while () present country×year clustered standard errors. *** p<0.01, ** p<0.05, * p<0.1

Table B.14: Incorporating country connectivity networks

	(1)	(2)	(3)	(4)	(5)
			$State$	$Non-State$	$Onesided$
	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$
$DIS_{i,t}$	-0.0019	-0.0016	-0.0001	0.0005	-0.0004
	(0.0030)	(0.0030)	(0.0022)	(0.0020)	(0.0019)
$DIS_{i,t-1}$	-0.0059**	-0.0059**	-0.0036*	-0.0008	-0.0043**
	(0.0028)	(0.0028)	(0.0020)	(0.0019)	(0.0019)
$NDIS_{i,t}$	-0.0004	-0.0002	-0.0003	-0.0022	0.0011
(within country)	(0.0035)	(0.0035)	(0.0028)	(0.0017)	(0.0021)
$NDIS_{i,t-1}$	0.0038	0.0042	0.0013	0.0026*	0.0006
(within country)	(0.0032)	(0.0032)	(0.0026)	(0.0016)	(0.0022)
$NDIS_{i,t}$		0.0039	0.0012	0.0024*	-0.0003
(Outside country)		(0.0028)	(0.0022)	(0.0015)	(0.0018)
$NDIS_{i,t-1}$		0.0055*	0.0016	0.0021	0.0024
(Outside country)		(0.0028)	(0.0022)	(0.0015)	(0.0019)
Observations	184,264	184,264	184,264	184,264	184,264
Distance Cut-off	500km	500km	500km	500km	500km
District FE	YES	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, an d natural disaster event, respectively, in the given district in the given time period. $NDIS$ (*within country*) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in any one of the district's neighbours, within 500km, and within country borders. $NDIS$ *outside country*) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in any one of the district's neighbours,within 500km but outside country borders. Disasters exclude droughts. () present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period. *** p<0.01, ** p<0.05, * p<0.1

Table B.15: Natural disasters and economic activity

	(1) $Light_{i,t}$	(2) $Conflict_{i,t}$
$DIS_{i,t}$	-0.0215	-0.0024
	(0.0258)	(0.0027)
$DIS_{i,t-1}$	0.0066	-0.0057**
	(0.0198)	(0.0025)
$NDIS_{i,t}$	0.0260	0.0043
	(0.0244)	(0.0028)
$NDIS_{i,t-1}$	-0.0083	0.0097***
	(0.0256)	(0.0029)
Observations	166,432	166,432
Distance Cutoff	500km	500km
District FE	YES	YES
Country× Year FE	YES	YES
Controls	YES	YES

Disaster is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. $NDIS$ is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in any one of the district's neighbours, within the given time period. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. *Light* represents the average value of night-time lights in the given district for the given time period. Controls for Column (1) are $NLight_{i,t}$, $NLight_{i,t-1}$ and $Light_{i,t-1}$. Controls for Column (2) are $Light_{i,t}$, $Conflict_{i,t-1}$, $NLight_{i,t}$, $NLight_{i,t-1}$, $NConflict_{i,t}$ and $NConflict_{i,t-1}$. Conley (1999) clustered standard errors, accounting for spatial correlation of up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.16: Heterogeneity by nighttime light, mining and agriculture

	(1) Z=Light $Conflict_{i,t}$	(2) Z=Light $Conflict_{i,t}$	(3) Z=Agri $Conflict_{i,t}$	(4) Z=Agri $Conflict_{i,t}$	(5) Z=Mine $Conflict_{i,t}$	(6) Z=Mine $Conflict_{i,t}$
$DIS_{i,t} \times No\ Z_i$	0.0067	0.0070	0.0003	-0.0008	-0.0032	-0.0025
	(0.0045)	(0.0047)	(0.0044)	(0.0044)	(0.0076)	(0.0073)
$DIS_{i,t} \times Low\ Z_i$	-0.0049	-0.0055	-0.0042	-0.0051	0.0006	-0.0003
	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0073)	(0.0071)
$DIS_{i,t} \times High\ Z_i$	-0.0053	-0.0051	-0.0027	-0.0021	0.0010	-0.0014
	(0.0062)	(0.0061)	(0.0043)	(0.0043)	(0.0071)	(0.0073)
$DIS_{i,t-1} \times No\ Z_i$	0.0071*	0.0088**	0.0027	0.0023	-0.0018	-0.0005
	(0.0042)	(0.0042)	(0.0042)	(0.0043)	(0.0076)	(0.0074)
$DIS_{i,t-1} \times Low\ Z_i$	-0.0080**	-0.0096***	-0.0087**	-0.0095***	-0.0033	-0.0049
	(0.0037)	(0.0037)	(0.0036)	(0.0036)	(0.0074)	(0.0071)
$DIS_{i,t-1} \times High\ Z_i$	-0.0081	-0.0067	-0.0074*	-0.0075*	-0.0113*	-0.0114*
	(0.0060)	(0.0059)	(0.0040)	(0.0039)	(0.0067)	(0.0068)
$NDIS_{i,t} \times No\ Z_i$		0.0016		0.0093***		0.0001
		(0.0033)		(0.0035)		(0.0062)
$NDIS_{i,t} \times Low\ Z_i$		0.0049		0.0070**		0.0054
		(0.0039)		(0.0035)		(0.0061)
$NDIS_{i,t} \times High\ Z_i$		0.0060		0.0020		0.0132**
		(0.0046)		(0.0046)		(0.0066)
$NDIS_{i,t-1} \times No\ Z_i$		-0.0045		0.0093***		-0.0039
		(0.0037)		(0.0036)		(0.0062)
$NDIS_{i,t-1} \times Low\ Z_i$		0.0137***		0.0115***		0.0143**
		(0.0039)		(0.0035)		(0.0061)
$NDIS_{i,t-1} \times High\ Z_i$		0.0071		0.0109**		0.0094
		(0.0046)		(0.0045)		(0.0072)
Observations	184,264	184,264	184,264	184,264	184,264	184,264
District FE	YES	YES	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES	YES	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. $NDIS$ ($NConflict$) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of the district's neighbours. Disasters exclude droughts. The set of districts is divided as no, low or high levels of activity based on binary indicators that capture the intensity of Nighttime Light, Mining and Agricultural activity. () present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period. *** p<0.01, ** p<0.05, * p<0.1

Table B.17: Estimates by OFDA receipt-status of natural disasters

	(1)
	$Conflict_{i,t}$
$DIS_{i,t}$	-0.0030
	(0.0033)
$DIS_{i,t} \times$ Aid	0.0037
	(0.0070)
$DIS_{i,t-1}$	-0.0078**
	(0.0031)
$DIS_{i,t-1} \times Aid$	0.0125*
	(0.0068)
$NDIS_{i,t}$	0.0063*
	(0.0034)
$NDIS_{i,t} \times Aid$	-0.0034
	(0.0041)
$NDIS_{i,t-1}$	0.0128***
	(0.0035)
$NDIS_{i,t-1} \times Aid$	-0.0136***
	(0.0041)
Observations	184,264
Distance Cut-off	500km
District FE	YES
Country× Year FE	YES
$NConflict_{i,t}$	YES
$NConflict_{i,t-1}$	YES

Conflict and *DIS* are binary variables indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. *NDIS* (*NConflict*) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of the district's neighbours. Disasters exclude droughts. *Aid* is a binary indicator that identifies whether or not the natural disaster, whether in district i or in the neighbouring districts, received foreign aid from the OFDA. () present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period. *** p<0.01, ** p<0.05, * p<0.1

C A possible theoretical mechanism

In this section, we provide a possible mechanism of our empirical results, which show how a negative shock on a district negatively affects the battle on this district, but also affects the neighbouring districts.

C.1 The general model

Players, districts, and battles Consider a set of players (which can be local military forces or militia) and different possible battles between them. The network represents the nodes (players) and the links (battles) between them. We use $n = 1, 2, 3, \cdots, i, j, \cdots$, to denote players and $\alpha = a, b, c, \cdots$, to denote battles. The set of players is denoted by $\mathcal{N}$, with $N = |\mathcal{N}| \geq 2$, and the set of battles by $\mathcal{T}$, with $T = |\mathcal{T}| \geq 1$.

Network We use an $N \times T$ matrix $\mathbf{\Gamma} = (\gamma_i^\alpha)$ to represent the battle structure. Specifically, we let $\gamma_i^\alpha = 1$ if player i is part of battle α; otherwise $\gamma_i^\alpha = 0$. Each player can be part of *multiple battles* and different battles may involve different subsets of players. Let $\mathcal{N}^\alpha = \{i \in \mathcal{N} : \gamma_i^\alpha = 1\} \subseteq \mathcal{N}$ denote the set of participants (players) in battle α. Let $n^\alpha = |\mathcal{N}^\alpha| \geq 2$ denote its cardinality. Similarly, let $\mathcal{T}_i = \{\alpha \in \mathcal{T} : \gamma_i^\alpha = 1\} \subseteq \mathcal{T}$ denote the set of battles that player i takes part in. Let $t_i = |\mathcal{T}_i| \geq 1$ denote the cardinality. Clearly, $i \in \mathcal{N}^\alpha$ if and only if $\alpha \in \mathcal{T}_i$.

Consider the following figure, which represents a star network:

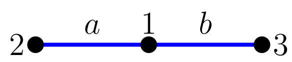


Figure C.1: A star network

The matrix $\mathbf{\Gamma}$ representing the network depicted in Figure C.1 is given by:

$$\mathbf{\Gamma} = \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$$

where rows correspond to players and columns to battles. We see that player 1 engages in a battle with players 2 and 3; whereas, player 2 engages in battle a with player 1 and player 3 engages in battle b with player 1. We have: $\mathcal{N} = \{1, 2, 3\}$, $\mathcal{T} = \{a, b\}$, $\mathcal{N}^a = \{1, 2\}$, $\mathcal{N}^b = \{1, 3\}$, $\mathcal{T}_1 = \{a, b\}$, $\mathcal{T}_2 = \{a\}$, $\mathcal{T}_3 = \{b\}$.

Districts From the network, we can aggregate the players and the battles to obtain a *district*. Thus, a district corresponds to a battle and we assume that, in each district, only one battle can take place. We can define a connectivity matrix $\mathbf{\Omega} = (\omega_{ab})$ such that $\omega_{ab} \in [0, 1]$ if a link exists between two districts a and b and $\omega_{ab} = 0$ otherwise. For example, in the star network of Figure C.1, there are two districts: district a, which encompasses players 1 and 2 and where battle a takes place, and district b, which is made of players 1 and 3, and where battle b takes place, so that $\omega_{ab} > 0$. This can be represented as follows:

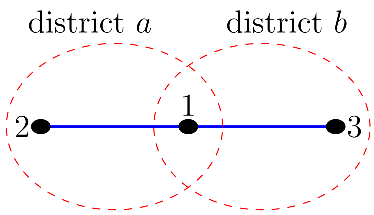


Figure C.2: A star network

Of course, any other district representation can be made from Figure C.1. In the empirical analysis, a district was defined by its *geographical* position and there will be a link between two districts if there is a major road between them and thus $\omega_{ab} > 0$.[5] For exam-

[5] In the empirical analysis, we also used the inverse distance between two districts to define a link between them.

ple, in Figure C.2, there are two districts a and b and they are geographically adjacent to each other (i.e., there is a major road between them). In that case, there are two layers of proximity, which involve different actors: (i) the *Conflict proximity* where, as in Figure C.1, a link is when two *players* have a battle with each other; this is captured by the matrix $\mathbf{\Gamma}$, (ii) the *geographical proximity* where, as in Figure C.2, there is a link between two *districts* when they are spatially adjacent to each other; this is captured by the matrix $\mathbf{\Omega}$.

Payoffs Taking the battle structure $\mathbf{\Gamma}$ as given, player i's strategy is to choose a nonnegative effort x_i^α for each battle $\alpha \in \mathcal{T}_i$ she is involved in. Thus, player i's strategy is a vector $\mathbf{x}_i = \{x_i^\alpha\}_{\alpha \in \mathcal{T}_i} \in \mathbf{R}_+^{t_i}$. Given player i's strategy $\mathbf{x}_i$, we denote $\mathbf{x} = (\mathbf{x}_1, \cdots, \mathbf{x}_n) \in \mathbf{R}_+^{\bar{n}}$ as the whole strategy profile, and $\mathbf{x}^\alpha = \{x_i^\alpha\}_{i \in \mathcal{N}^\alpha} \in \mathbf{R}_+^{n^a}$ as the effort vector in battle α. Here $\bar{n} = \sum_{\alpha \in \mathcal{T}} n^\alpha = \sum_{i \in \mathcal{N}} t_i = \sum_{i \in \mathcal{N}, \alpha \in \mathcal{T}} \gamma_i^\alpha$ denote the dimension of strategy profile $\mathbf{x}$.

The payoff function of player $i \in \mathcal{N}$ is equal to:

$$\Pi_i(\mathbf{x}_i, \mathbf{x}_{-i}) = \sum_{\alpha \in \mathcal{T}_i} v^\alpha p_i^\alpha(\mathbf{x}^\alpha) - C_i(\mathbf{x}_i), \tag{C.1}$$

which is just the net expected value of winning the battle(s). Indeed, in (C.1), $p_i^\alpha(\mathbf{x}^\alpha)$ is the probability of winning battle α for player i. It is given by the following Tullock CSF:

$$p_i^\alpha(\mathbf{x}^\alpha) = \frac{x_i^\alpha}{\sum_{j \in \mathcal{N}^\alpha} x_j^\alpha}. \tag{C.2}$$

Moreover, each battle α generates a benefit $v^\alpha > 0$ for the player who wins the battle. This value might vary across battles. Finally, there is a total cost of $C_i(\mathbf{x}_i)$, which depends on all the efforts player i exerts in each battle she is involved in.

Note that, in the data (Section 2), we only observe the total battle at the district level and the geographical link between districts and analyze how a negative shock (disaster) on a district affects the total battle in the different districts that are spatially connected. We do not, however, observe the players involved in battles in each district. Consider Figure C.2. In our model, this translates by studying how a decrease in v^a (the value of battle a) affects $x_1^a + x_2^a$, the total battle in district a, and $x_1^b + x_3^b$, the total battle in the (spatially) adjacent district b.

Nash equilibrium Let us solve the Nash equilibrium of this game for any network and any player. We are interested in the pure strategy Nash equilibrium of this battle game. A strategy profile $\mathbf{x}^* = (\mathbf{x}_1^*, \cdots, \mathbf{x}_n^*)$ is an equilibrium of the battle game if for every player $i \in \mathcal{N}$,

$$\Pi_i(\mathbf{x}_i^*, \mathbf{x}_{-i}^*) \geq \Pi_i(\mathbf{x}_i, \mathbf{x}_{-i}^*), \quad \forall \mathbf{x}_i. \tag{C.3}$$

This model is very general because it incorporates any network structure, the best response functions are non-linear but, more importantly, each agent is involved in many battles. We can still show that the equilibrium exists and is unique for any network structure and give conditions for which the equilibrium efforts are strictly positive. It is, however, difficult to explicitly characterize the Nash equilibrium of this game and to derive comparative statics results. Because we want to provide a mechanism of our empirical results, we would like to derive some properties of this equilibrium for specific networks that we could test empirically. We will mainly consider the star network of Figure C.1 or Figure C.2 because it is tractable and still provides all the intuition we need for our empirical analysis.[6]

The key aspect of our model is that agents are involved in *many battles*. This will explain why, after a negative shock, such as a disaster, agents shift their effort to other battles and can, thus, explain the propagation of shocks in path-connected districts. We can derive abstract comparative statics results for general network structures but, to understand how a shock propagates to other districts, we need to focus on specific networks.

[6] In Section C.3, we provide similar results for a line network with more agents and more battles.

C.2 Star network

C.2.1 The model

Consider the star network depicted in Figure C.1 where $\alpha = a, b$ (two battles and three players). Given the network structure, the strategies of the players are: $\mathbf{x}_1 = (x_1^a, x_1^b)$, $\mathbf{x}_2 = (x_2^a)$ and $\mathbf{x}_3 = (x_3^b)$. To keep the model tractable, we assume that the cost function is quadratic so that each player's payoff can be written as:

$$\begin{aligned}
\Pi_1(\mathbf{x}_1, \mathbf{x}_{-1}) =& v^a \frac{x_1^a}{x_1^a + x_2^a} + v^b \frac{x_1^b}{x_1^b + x_3^b} - \frac{s_1}{2}(x_1^a + x_1^b)^2, \\
\Pi_2(\mathbf{x}_2, \mathbf{x}_{-2}) =& v^a \frac{x_2^a}{x_1^a + x_2^a} - \frac{s_2}{2}(x_2^a)^2, \\
\Pi_3(\mathbf{x}_3, \mathbf{x}_{-3}) =& v^b \frac{x_3^b}{x_1^b + x_3^b} - \frac{s_3}{2}(x_3^b)^2.
\end{aligned} \tag{C.4}$$

C.2.2 Equilibrium analysis

Even in this simple network structure, closed-form expressions of the Nash equilibrium efforts are not possible, but we can use the first-order conditions (FOCs) of players to characterize the Nash equilibrium. Let

$$F_1(x_1^a, x_1^b, x_2^a) := \frac{\partial \Pi_1}{\partial x_1^a} = \frac{v^a x_2^a}{(x_1^a + x_2^a)^2} - s_1(x_1^a + x_1^b), \tag{C.5}$$

$$F_2(x_1^a, x_1^b, x_3^b) := \frac{\partial \Pi_1}{\partial x_1^b} = \frac{v^b x_3^b}{(x_1^b + x_3^b)^2} - s_1(x_1^a + x_1^b), \tag{C.6}$$

$$F_3(x_1^a, x_2^a) := \frac{\partial \Pi_2}{\partial x_2^a} = \frac{v^a x_1^a}{(x_1^a + x_2^a)^2} - s_2 x_2^a, \tag{C.7}$$

$$F_4(x_1^b, x_3^b) = \frac{\partial \Pi_3}{\partial x_3^b} = \frac{v^b x_1^b}{(x_1^b + x_3^b)^2} - s_3 x_3^b. \tag{C.8}$$

We have the following results:[7]

Proposition 1. *Consider the star network depicted in Figure C.1 and the payoff functions given by* (C.4)*. Then, there exists a unique interior Nash equilibrium* $(x_1^{a*}, x_1^{b*}, x_2^{a*}, x_3^{a*})$ *that simultaneously solves:*

$$\begin{cases} F_1(x_1^{a*}, x_1^{b*}, x_2^{a*}) = 0 \\ F_2(x_1^{a*}, x_1^{b*}, x_3^{b*}) = 0 \\ F_3(x_1^{a*}, x_2^{a*}) = 0 \\ F_4(x_1^{b*}, x_3^{b*}) = 0 \end{cases} \tag{C.9}$$

Given the existence, uniqueness, and interiority of the Nash equilibrium, we are interested in the effect on the shock of the valuations v^a and v^b on the battle levels of each district. Note that the system (C.9) is highly non-linear and, therefore, there are no explicit expressions for the equilibrium. Instead, we apply the implicit function theorem to the system (C.9) in order to derive the comparative statics results. Before performing these exercises, the following lemma will help us interpret our results.

Lemma 1. *For* $v > 0, s > 0$*, define*

$$z(x, y) = \frac{vx}{x+y} - \frac{s}{2}x^2. \tag{C.10}$$

For each $y > 0$*, there exists a unique maximizer* $x^*(y) = \arg\max_{x>0} z(x, y)$*. Moreover,* $x^*(y)$ *is first increasing, then decreasing in* y *with sign* $\left(\frac{\partial x^*}{\partial y}\right) = sign(x^* - y)$*.*

We can see from equations (C.5)–(C.8) that Lemma 1 describes the best response function $x^*(\cdot)$. In particular, Lemma 1 shows that $x^*(\cdot)$ first increases with y up to the maximum, which occurs at $x^* = y$, and then decreases. There is therefore a *non-monotonic bell shaped*

[7] All the proofs of the theoretical model can be found in Appendix C.5.

relationship between the efforts of two players involved in the same battle. Figure C.3 depicts this relationship.

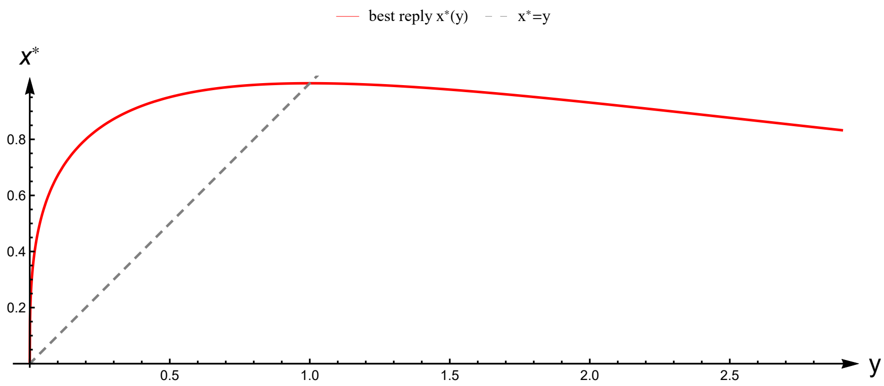


Figure C.3: Best response function $x^*(y)$

To see the implication of this Lemma, for example, consider the first-order condition of x_2^a, that is, $F_3(x_1^{a*}, x_2^{a*}) = 0$. Using Lemma 1, we know that the sign of $\frac{\partial x_2^{a*}}{\partial x_1^a}$ is the same as the sign of $(x_2^{a*} - x_1^{a*})$ and that the relationship is bell-shaped where the maximum occurs at $x_2^{a*} = x_1^{a*}$. Indeed, when $x_1^{a*} < x_2^{a*}$, which means that player 1 is "weak" because $p_2^a(x_1^a, x_2^a) = x_2^a/(x_1^a + x_2^a)$, the probability of winning battle a for player 2, is greater than 50%, then player 2's best response to an increase of x_1^{a*}, is to increase her effort x_2^a. By contrast, when $x_1^{a*} > x_2^{a*}$, we are on the decreasing part of the relationship because player 2 is now the "weak"player in battle a because she has a lower chance of winning the battle. Therefore, when player 1 increases her effort, player 2's best response is to decrease her effort. Indeed, player 2 knows that her marginal chance of winning the battle is lower and thus basically gives up by reducing her effort.

Observe that Lemma 1 provides the best response function of a player within an *isolated* battle and, hence, abstracts from the general equilibrium effects, that is, the link between battles through the cost function. In our model, a player may have multiple battles, For example, for player 1, who is involved in battles a and b, her cost function, $C_1(x_1^a, x_1^b) = \frac{s_1}{2}(x_1^a + x_1^b)^2$, is convex in her total effort $x_1^a + x_1^b$. This implies that increasing effort in one battle leads to higher marginal cost of effort in the other battle, that is, $\frac{\partial^2 C_1}{\partial x_1^a \partial x_1^b} = s_1 > 0$. This is not captured by Lemma 1, but we need to take this into account in the calculation of our comparative statics results.

C.2.3 Comparative statics: Negative shock on a district

As stated above, we do not observe the players involved in each battle in each district in the data. However, we observe the total battle in each district. Consider Figure C.2. In this section, we will study how a decrease in v^a, i.e., a negative shock on district a, affects $x_1^a + x_2^a$, the total battle in district a, and $x_1^b + x_3^b$, the total battle in the (spatially) adjacent district b.[8] To understand the mechanism behind the results, we will also study how a decrease in v^a affects the effort of each player involved in each battle.

Proposition 2. *Consider the star network depicted in Figures C.1 and C.2 and the payoff functions given by (C.4). When v^a, the value of battle a, decreases,*

1. *both players 1 and 2 decrease their efforts in battle a, that is, $\frac{\partial x_1^{a*}}{\partial v^a} > 0$ and $\frac{\partial x_2^{a*}}{\partial v^a} > 0$,*
2. *the total battle intensity in district a reduces, that is, $\frac{\partial (x_1^{a*} + x_2^{a*})}{\partial v^a} > 0$,*
3. *player 1 increases her effort in battle b, that is, $\frac{\partial x_1^{b*}}{\partial v^a} < 0$,*
4. *the total effort of players involved in battles a and b decreases, that is, $\frac{\partial (x_1^{a*} + x_1^{b*})}{\partial v^a} > 0$,*
5. *the effect on the effort of player 3 in battle b is ambiguous, that is, $\frac{\partial x_3^{b*}}{\partial v^a} \gtreqless 0$. Particularly, $sign \frac{\partial x_3^{b*}}{\partial v^a} = sign(x_1^{b*} - x_3^{b*})$.*
6. *the total battle intensity in district b increases, that is, $\frac{\partial (x_1^{b*} + x_3^{b*})}{\partial v^a} < 0$.*

[8] Without loss of generality, we focus on district a as the analysis for district b is similar because of the symmetry of the locations of these two districts.

The first result of this proposition is straightforward. When v^a, the value of battle a, decreases, both players involved in battle a spend less effort in that battle and, thus, x_1^a and x_2^a decrease. This leads to the fact that the total effort in battle a is reduced (result 2).

Moreover, because $C_1(x_1^a, x_2^a)$, player 1's cost, and v^b, the value of battle b, are fixed, player 1's incentive in battle b is higher because lower x_1^a decreases her marginal cost in battle b. Indeed, efforts x_1^a and x_1^b are *strategic substitutes* because

$$\frac{\partial^2 \Pi_1}{\partial x_1^a \partial x_1^b} = -\frac{\partial^2 C_1}{\partial x_1^a \partial x_1^b} = -s_1 < 0. \tag{C.11}$$

consequently, when v^a decreases, player 1 increases x_1^b, her effort in battle b (result 3). However, the aggregate effort of player 1 still goes down as the decrease in battle a dominates the increase in battle b (result 4).

The fifth result of this proposition is more complex and one needs to use Lemma 1 to understand this result. Indeed, when v^a decreases, player 1 decreases her effort in battle a and increases x_1^b, her effort in battle b. However, player 3's effort in battle b, depends on whether she is "weak"or "strong"in that battle. By the Chain rule,

$$\frac{\partial x_3^{b*}}{\partial v^a} = \frac{\partial x_3^{b*}}{\partial x_1^{b*}} \underbrace{\frac{\partial x_1^{b*}}{\partial v^a}}_{<0}$$

By Lemma 1, $sign \frac{\partial x_3^{b*}}{\partial x_1^{b*}} = sign(x_3^{b*} - x_1^{b*})$, therefore, $sign \frac{\partial x_3^{b*}}{\partial v^a} = sign(x_1^{b^*} - x_3^{b*})$. Intuitively, if player 3 is "weak", for example, because she has a very high marginal cost s_3, so that her effort x_3^{b*} is lower than $x_1^{b^*}$, then a decrease in v^a will increase player 1's effort in battle b x_1^{b*}. As a best response, player 3 lowers her effort x_3^{b*}. The opposite occurs if player 3 is "strong"in battle b.

The last result, where the intensity of the total battle in district b reduces, is because the direct effect of a decrease in v^a on battle a for player 1 is stronger than the indirect effect on battle b for player 3, even when the latter leads to more effort.

In summary, a negative shock to district a (i.e., a decrease in v^a) leads to a smaller battle in district a but a bigger battle in district b. Player 1's total effort decreases whereas player 3's effort can increase or decrease. The first result demonstrates that a negative local shock on district a has an effect on the adjacent district b through the general equilibrium effect. The mechanism behind this result is that the central player (or the player involved in many battles) must re-allocate efforts in both battles in order to maximize total payoff, whereas other players must respond optimally.

In Figure C.4, we illustrate our results by plotting the four efforts of the different players when v^a increases.[9] Consistent with Proposition 2, an increase in v^a leads to a big increase for the players in district a, that is both x_2^a, the effort of player 2 in battle a (blue curve) and x_1^a, the effort of player 1 in battle a (red curve) increase. We can also see that the effect of an increase of v^a is much smaller for the adjacent district b because x_1^b (dotted orange curve) slightly decreases, whereas x_3^b (solid black curve) is nearly unaffected. This is because, in this example, the effect of v^a does not spill over to player 3 involved in another battle.

[9]We use the following values for the parameters: $v^b = 1$, $s_1 = 0.35$, $s_2 = 0.35$, and $s_3 = 0.7$.

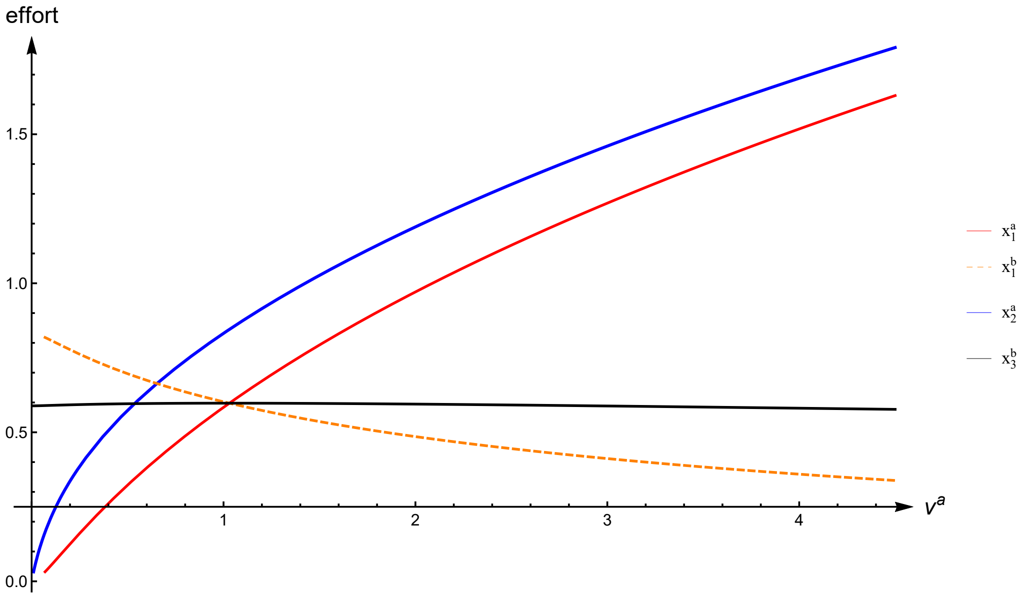


Figure C.4: The effect of an increase of v^a on the effort of each agent involved in battles in the network described in Figure C.1

More generally, our comparative statics results highlight the importance of three aspects of the model: (i) the cost linkage for a player/district participating in multiple battles, (ii) the relative position of a district within a given battle, and (iii) the non-monotonic best response function of each player.

C.3 More complex network structure: A line network

Consider the following figure, which represents a line network with four players and three battles:

Figure C.5: A line network with four players and three battles

Observe that this network is similar to the one depicted in Figure C.1; however, we added a link between players 2 and 4 and battle c.

The matrix $\mathbf{\Gamma}$ representing the network depicted in Figure C.5 is given by:

$$\mathbf{\Gamma} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

where rows correspond to players and columns to battles. We have: $\mathcal{N} = \{1, 2, 3, 4\}$, $\mathcal{T} = \{a, b, c\}$, $\mathcal{N}^a = \{1, 2\}$, $\mathcal{N}^b = \{1, 3\}$, $\mathcal{N}^c = \{2, 4\}$, $\mathcal{T}_1 = \{a, b\}$, $\mathcal{T}_2 = \{a, c\}$, $\mathcal{T}_3 = \{b\}$, and $\mathcal{T}_4 = \{c\}$.

Districts From the network, we can aggregate the players and the battles to obtain a district. In the line network of Figure C.5, there can be four districts, each corresponding to a battle: districts a, b, c, d. This network with districts can be represented as follows:

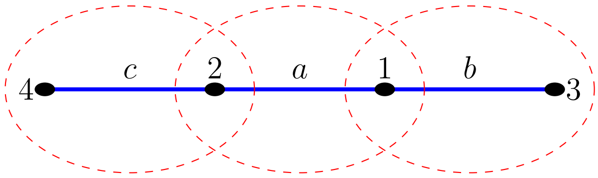


Figure C.6: A line network with three districts

As stated above, in the data, we only observe the total conflict at the district level and the geographical link between districts. In our model, let us study how a decrease in v^b, *a negative shock on district* b *(disaster)* affects the total conflict in the different districts a, b, c. In particular, we would like to show how a decreases in v^b (district located at the extreme right of the line network) affects the total conflict $x_2^c + x_4^c$ in district c (district located at the extreme left of the line network), even if districts b and c are *not* adjacent and involved different agents.

As above, to keep the model tractable, we assume that the cost function is quadratic; hence, each player's payoff can be written as:

$$
\begin{aligned}
\Pi_1(\mathbf{x}_1, \mathbf{x}_{-1}) =& v^a \frac{x_1^a}{x_1^a + x_2^a} + v^b \frac{x_1^b}{x_1^b + x_3^b} - \frac{s_1}{2}(x_1^a + x_1^b)^2, \\
\Pi_2(\mathbf{x}_2, \mathbf{x}_{-2}) =& v^a \frac{x_2^a}{x_1^a + x_2^a} + v^c \frac{x_2^c}{x_2^c + x_4^c} - \frac{s_2}{2}(x_2^a + x_2^c)^2, \\
\Pi_3(\mathbf{x}_3, \mathbf{x}_{-3}) =& v^b \frac{x_3^b}{x_1^b + x_3^b} - \frac{s_3}{2}(x_3^b)^2, \\
\Pi_4(\mathbf{x}_4, \mathbf{x}_{-4}) =& v^c \frac{x_4^c}{x_2^c + x_4^c} - \frac{s_4}{2}(x_4^c)^2.
\end{aligned}
\tag{C.12}
$$

We have the following result:[10]

Proposition 3. *Consider the line network depicted in Figures C.5 and C.6 and the payoff functions given by (C.12). When v^b, the value of battle b, decreases,*

1. *both players 1 and 3 decrease their efforts in battle b, that is, $\frac{\partial x_1^{b*}}{\partial v^b} > 0$ and $\frac{\partial x_3^{b*}}{\partial v^b} > 0$, and the total battle intensity in district b is reduced, that is, $\frac{\partial (x_1^{b*}+x_3^{b*})}{\partial v^b} > 0$;*

2. *player 1 increases her effort in battle a, that is, $\frac{\partial x_1^{a*}}{\partial v^b} < 0$, but her total effort decreases, that is, $\frac{\partial (x_1^{a*}+x_1^{b*})}{\partial v^a} > 0$;*

3. *the effect on the effort of player 2 in battle a and in battle c as well as on her total effort is ambiguous. Particularly, $sign\frac{\partial x_2^{a*}}{\partial v^b} = sign(x_1^{a^*} - x_2^{a*})$, $sign\frac{\partial x_2^{c*}}{\partial v^b} = sign(x_2^{a^*} - x_1^{a*})$, and $sign\frac{\partial (x_2^{a*}+x_2^{c*})}{\partial v^b} = sign(x_1^{a^*} - x_2^{a*})$;*

4. *the total battle intensity in district a increases, that is, $\frac{\partial (x_1^{a*}+x_2^{a*})}{\partial v^b} < 0$.*

5. *the effect on the effort of player 4 in battle c as well as the total effect on battle c is ambiguous. Particularly, $sign\frac{\partial x_4^{c*}}{\partial v^b} = sign(x_1^{a^*} - x_2^{a*})(x_2^{c^*} - x_4^{c*})$ and $sign\frac{\partial (x_2^{c*}+x_4^{c*})}{\partial v^b} = sign(x_2^{a^*} - x_1^{a*})$.*

[10] Even though it is more cumbersome, the proof of Proposition 3 is similar to that of Proposition 2 and is thus omitted.

The results of this proposition are similar to that of Proposition 2 since the effect of a negative shock on the district negatively affects the efforts of the agents involved in this district and, thus, the total conflict in this district (part 1), but it also propagates to other districts, depending on the origin of the shock (i.e., how far a district is located from the district that experiences the shock) and whether a player is "weak" or "strong" in the battle she is involved in. This is a general pattern that holds whenever the network does not have a cycle; for example, a tree network.

Interestingly, because the network depicted in Figure C.5 is longer than the one in Figure C.1, Proposition 3 shows that a negative shock (such as a natural disaster) in district b, located at the extreme right of the network, affects the effort of agent 4, located at the extreme left of the network, and thus the conflict in district c, which is not adjacent to district b. Indeed, some agents are involved in two battles. Thus, when deciding how much effort to devote to each battle/district, they evaluate their relative strength and their relative chances of winning a battle and decide to exert more effort in battles they have the highest chances of winning. However, when there is a negative shock in a given district, the value of winning a battle goes down and thus agents shift their effort to the other battle they are involved in. For example, when v^b decreases, agent 1 decreases her effort in battle b but increases it in battle a. This negative shock propagates to other agents and battles who are path-connected in the network but has a lower effect on them. This is why a decrease of v^b affects the effort of agent 4 but the agent 4's effort will increase or decrease depending her relative strength compared to agent 2, who is involved in the same battle as agent 4 (battle c), but also on the relative strength of agent 2 compared to agent 1 in battle a (part 5 of Proposition 3). This is the propagation of the shock on district b, which first *directly* affects the agents involved in district b, that is, agents 1 and 3, and then *indirectly* affects the other path-connected agents, that is, first, agent 2, who is in conflict with agent 1 in battle a and, then, agent 4, who is in conflict with agent 2 in battle c.

C.4 Discussion

C.4.1 Mechanism consistent with our model

Even though our model is based on a very specific network structure (the star and the line network), we believe that the intuition and the prediction of the model carry over qualitatively to more complex network structures. Thus, our model is able to provide a simple mechanism that explains (*i*) how a negative shock (a natural disaster in the data) on a given district negatively affects the total battle in this district and (*ii*) how this negative shock affects the total battle in the (spatially) adjacent districts. Our model shows that (*i*) when a natural disaster occurs in a district, the agents involved in a conflict in this district will decrease their effort because there are less resources to grab. Consequently, (*ii*) these agents will shift their effort to spatially adjacent districts, thereby increasing the conflict in these districts; the effect will fade away for districts located further away from the district directly affected by the disaster. Our model also predicts that the intensity of the conflict in spatially adjacent districts will depend on the relatively strength of the agents involved in the conflicts in these districts. Another prediction of our model is that more "valuable" districts (higher v^{α}), that is, districts with more economic activity, agricultural land, or mineral mines are more likely to be worth fighting over, to capture local rents from economic activity or mineral resources or for strategic reasons. If a disaster hits those districts, the damages are likely to be higher and therefore the benefits of fighting might be lower as well.

Our empirical results are in accordance with the predictions of the model. First, (*i*) we show in Table 1 and Figure A.4 that the occurrence of a natural disaster in a district reduces the battle probability in this district. Moreover, (*ii*) in Table 1, we show that the occurrence of a natural disaster in a given district leads to a positive and significant battle spillovers to districts that are linked by major road network and geographic proximity. Finally, in Figure 1(b), we show that the battle diffusion occurs if the neighboring district is an agricultural district.

C.4.2 Other possible mechanisms

First, when interpreting the negative effect of a natural disaster in a district on fighting in that district, two interpretations are possible: "incapacitation" or an "economic loss" channel. Incapacitation means that if there is a flood, then nobody can fight. Economic loss would mean that the shock decreases the value of production in that district. In our empirical analysis, we showed the floods are the most prominent type of natural disaster in our sample (see Table A.1). This means that we have an incapacitation effect (at least in the short run), because it makes it impossible for conflicts to operate.

Our model only offers one possible mechanism, that is, when there is a negative shock (e.g., floods) in a district, central players relocate their forces and thus spread the conflicts to path-connected districts. From our empirical analysis, it is hard to infer whether rebels relocate because fighting has become complicated or simply because their targets have moved. Other mechanisms may be at work. For example, it is possible that, following a negative shock, populations may migrate in response to these shocks. Indeed, a natural disaster that afflicts an area may produce a wave of refugees and movement of people who subsequently heighten frictions and escalate violence in another adjacent areas. Given that we have aggregate data, we cannot test whether this mechanism or the one proposed by our model is at work.

C.5 Proofs of the Theoretical Model

Proof of Proposition 1: The existence and uniqueness result of the Nash equilibrium result of this proposition follows directly from Theorems 1 and 2 in Xu et al. (2022). Indeed, the cost function is quadratic, and therefore convex and strongly monotone, and the Tullock contest success function (CSF), given by (C.2), satisfies the assumption on the CSF assumption in Xu et al. (2022). This shows the existence and uniqueness of the Nash equilibrium. Moreover, Xu et al. (2022) also show the unique equilibrium satisfies the property that every conflict contains at least two contestants with positive efforts. Since, in the star depicted in Figure C.1, each conflict only has two contestants, this unique equilibrium is interior. □

Proof of Lemma 1: It is easily verified that $\frac{\partial^2 z(x,y)}{\partial x^2} < 0$ so that z is strictly concave in x. Moreover,

$$\frac{\partial z}{\partial x}(0, y) = v/y > 0,$$

and

$$\lim_{x\to\infty} \frac{\partial z}{\partial x}(0, y) = -\infty,$$

so there exists a unique $x^*(y)$ such that $\frac{\partial z}{\partial x}(x^*(y), y) = 0$. Clearly such x^* is the maximizer by the concavity of z.

Moreover, by the implicit function theorem,

$$\frac{\partial x^*}{\partial y} = -\left(\frac{\partial^2 z}{\partial x^2}\right)^{-1} \frac{\partial^2 z}{\partial x \partial y}|_{x=x^*}.$$

Since

$$\frac{\partial^2 z}{\partial x^2} < 0, \frac{\partial^2 z}{\partial x \partial y} = \frac{v(x-y)}{(x+y)^3},$$

so

$$sign\frac{\partial x^*}{\partial y} = sign(x^* - y).$$

This completes the proof of the lemma. □

Proof of Proposition 2: By applying the implicit function theorem to system (C.9) for the parameter v^a, we obtain:

$$\begin{pmatrix} \frac{\partial x_1^a}{\partial v^a} \\ \\ \frac{\partial x_1^b}{\partial v^a} \\ \\ \frac{\partial x_2^a}{\partial v^a} \\ \\ \frac{\partial x_3^b}{\partial v^a} \end{pmatrix} = -\mathbf{M}^{-1} \begin{pmatrix} \frac{\partial F_1}{\partial v^a} \\ \\ \frac{\partial F_2}{\partial v^a} \\ \\ \frac{\partial F_3}{\partial v^a} \\ \\ \frac{\partial F_4}{\partial v^a} \end{pmatrix} \tag{C.13}$$

where

$$\mathbf{M} := \begin{pmatrix} \frac{\partial F_1}{\partial x_1^a} & \frac{\partial F_1}{\partial x_1^b} & \frac{\partial F_1}{\partial x_2^a} & \frac{\partial F_1}{\partial x_3^b} \\ \\ \frac{\partial F_2}{\partial x_1^a} & \frac{\partial F_2}{\partial x_1^b} & \frac{\partial F_2}{\partial x_2^a} & \frac{\partial F_2}{\partial x_3^b} \\ \\ \frac{\partial F_3}{\partial x_1^a} & \frac{\partial F_3}{\partial x_1^b} & \frac{\partial F_3}{\partial x_2^a} & \frac{\partial F_3}{\partial x_3^b} \\ \\ \frac{\partial F_4}{\partial x_1^a} & \frac{\partial F_4}{\partial x_1^b} & \frac{\partial F_4}{\partial x_2^a} & \frac{\partial F_4}{\partial x_3^b} \end{pmatrix} \quad \textit{and} \quad \begin{pmatrix} \frac{\partial F_1}{\partial v^a} \\ \\ \frac{\partial F_2}{\partial v^a} \\ \\ \frac{\partial F_3}{\partial v^a} \\ \\ \frac{\partial F_4}{\partial v^a} \end{pmatrix} = \begin{pmatrix} \frac{x_2^a}{(x_1^a+x_2^a)^2} \\ \\ 0 \\ \\ \frac{x_1^a}{(x_1^a+x_2^a)^2} \\ \\ 0 \end{pmatrix} \tag{C.14}$$

with

$$\frac{\partial F_1}{\partial x_3^b} = \frac{\partial F_2}{\partial x_2^a} = \frac{\partial F_3}{\partial x_1^b} = \frac{\partial F_3}{\partial x_3^b} = \frac{\partial F_4}{\partial x_1^a} = \frac{\partial F_4}{\partial x_2^a} = 0 \tag{C.15}$$

$$\begin{aligned} \frac{\partial F_1}{\partial x_1^a} = -s_1 - \frac{2v^a x_2^a}{(x_1^a+x_2^a)^3}, \frac{\partial F_1}{\partial x_1^b} = -s_1, \frac{\partial F_1}{\partial x_2^a} &= \frac{v^a}{(x_1^a+x_2^a)^2} - \frac{2v^a x_2^a}{(x_1^a+x_2^a)^3}, \\ \frac{\partial F_2}{\partial x_1^a} = -s_1, \frac{\partial F_2}{\partial x_1^b} = -s_1 - \frac{2v^b x_3^b}{(x_1^b+x_3^b)^3}, \frac{\partial F_2}{\partial x_3^b} &= \frac{v^b}{(x_1^b+x_3^b)^2} - \frac{2v^b x_3^b}{(x_1^b+x_3^b)^3}, \\ \frac{\partial F_3}{\partial x_1^a} = \frac{v^a}{(x_1^a+x_2^a)^2} - \frac{2v^a x_1^a}{(x_1^a+x_2^a)^3}, \frac{\partial F_3}{\partial x_2^a} &= -s_2 - \frac{2v^a x_1^a}{(x_1^a+x_2^a)^3}, \\ \frac{\partial F_4}{\partial x_1^b} = \frac{v^b}{(x_1^b+x_3^b)^2} - \frac{2v^b x_1^b}{(x_1^b+x_3^b)^3}, \frac{\partial F_4}{\partial x_3^b} &= -s_3 - \frac{2v^b x_1^b}{(x_1^b+x_3^b)^3}. \end{aligned} \tag{C.16}$$

Note that $\mathbf{M}$ is just the Jacobian matrix of system (C.9) with respect to $(x_1^a, x_1^b, x_2^a, x_3^b)$.

We can easily verify that the sign of the determinant of $\mathbf{M}$ is given by:

$$det(\mathbf{M}) := J = \begin{vmatrix} \frac{\partial F_1}{\partial x_1^a} & \frac{\partial F_1}{\partial x_1^b} & \frac{\partial F_1}{\partial x_2^a} & \frac{\partial F_1}{\partial x_3^b} \\ \frac{\partial F_2}{\partial x_1^a} & \frac{\partial F_2}{\partial x_1^b} & \frac{\partial F_2}{\partial x_2^a} & \frac{\partial F_2}{\partial x_3^b} \\ \frac{\partial F_3}{\partial x_1^a} & \frac{\partial F_3}{\partial x_1^b} & \frac{\partial F_3}{\partial x_2^a} & \frac{\partial F_3}{\partial x_3^b} \\ \frac{\partial F_4}{\partial x_1^a} & \frac{\partial F_4}{\partial x_1^b} & \frac{\partial F_4}{\partial x_2^a} & \frac{\partial F_4}{\partial x_3^b} \end{vmatrix} > 0. \tag{C.17}$$

We apply the Cramer's rule to compute each component of the left-hand side (LHS) of (C.13). After some simplifications, we obtain:

$$\frac{\partial x_1^a}{\partial v^a} = \frac{(v^a x_1^a + s_2 x_2^a (x_1^a + x_2^a)^2)((v^b)^2 + s_1 s_3 (x_3^b + x_1^b)^4 + 2v^b (x_3^b + x_1^b)(s_3 x_3^b + s_1 x_1^b))}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^4} > 0 \tag{C.18}$$

$$\frac{\partial x_1^b}{\partial v^a} = -\frac{s_1 (v^a x_1^a + s_2 x_2^a (x_1^a + x_2^a)^2)(2v^b x_1^b + s_3 (x_3^b + x_1^b)^3)}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^3} < 0 \tag{C.19}$$

$$\frac{\partial x_1^a}{\partial v^a} + \frac{\partial x_1^b}{\partial v^a} = \frac{v^b (v^a x_1^a + s_2 x_2^a (x_1^a + x_2^a)^2)(v^b + 2s_3 x_3^b (x_3^b + x_1^b))}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^4} > 0 \tag{C.20}$$

$$\begin{aligned} \frac{\partial x_2^a}{\partial v^a} =& \frac{s_1 \left[(v^b)^2 x_1^a (x_1^a + x_2^a)^2 + s_3 v^a x_2^a (x_3^b + x_1^b)^4 + 2v^b (x_3^b + x_1^b)(s_3 x_1^a x_3^b (x_1^a + x_2^a)^2 + v^a x_2^a x_1^b) \right]}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^4} \\ &+ \frac{v^a v^b x_2^a (v^b + 2s_3 x_3^b (x_3^b + x_1^b))}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^4} > 0 \end{aligned} \tag{C.21}$$

$$\frac{\partial x_3^b}{\partial v^a} = \frac{s_1 v^b (x_1^b - x_3^b)(v^a x_1^a + s_2 x_2^a (x_1^a + x_2^a)^2)}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^3} \tag{C.22}$$

$$\frac{\partial x_1^b}{\partial v^a} + \frac{\partial x_3^b}{\partial v^a} = -\frac{s_1 (v^a x_1^a + s_2 x_2^a (x_1^a + x_2^a)^2)(v^b + s_3 (x_3^b + x_1^b)^2)}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^2} < 0 \tag{C.23}$$

This completes the proof of the proposition. □