Conflicts in Spatial Networks*

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Abstract

This paper studies how conflict spreads within a spatial network. We first construct a novel panel data set that combines geo-referenced information about battle events and natural disasters, at the monthly level, for 5,944 districts in 53 African countries, over the period from 1989 to 2015. At this fine temporal and spatial resolution, natural disasters are formidable exogenous shocks that affect the costs and benefits of fighting in a locality. We find that natural disasters decrease battle incidence in the affected locality and that this effect persists over time and space. This mitigating effect appears to be more pronounced in more developed localities. We then provide a simple theoretical framework that shows that these results may be explained by the fact that natural disasters divert fighting activity to surrounding localities, particularly those that are connected via geographic and road networks.

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1 Introduction

In 2014, over half of the world's conflict incidents took place in Africa, despite it having only 16% of the global population (Cilliers, 2015). One feature of African conflicts is that they often start off as relatively small, localized events but then spread quickly to neighboring regions as well as across borders, sometimes resulting in long lasting intra and interstate wars.

This study aims to explore the spatial aspects of the nexus between local economic shocks and violent conflicts. We analyze the consequences of a negative exogenous shock on the incidence of conflict in a locality as well as its spillover effects in a spatial network.

To empirically test these ideas, our identification strategy exploits the exogenous variation in local natural disasters as negative economic shocks, that locally increase the costs and decrease the benefits of fighting. We construct a novel panel dataset at the district-month level for 5,944 African ADM2 (second subnational) units, over the period from 1989 to 2015, that combines geo-referenced data on battle events and disaster occurrences. The dataset's fine degree of spatial and temporal resolution allows us to include a large set of district $\times$ year fixed effects and thereby control, in the most flexible way, for a wide range of unobservable variables that might simultaneously drive battle and disaster incidents. Our estimates enable us to identify the within district-year variation in local battle events that is due to disaster shocks in each month.

In a first step, we use our empirical approach to identify the short-term effects in each month and the following month as well as the cumulative effects in the following 12-months in the directly affected district. We find that local disaster events systematically decrease the likelihood of a local battle. This effect is economically and statistically significant and persistent over time. We then present evidence that supports our claim that disaster events decrease battle incidence by increasing the cost of fighting and decreasing the benefits of fighting locally.

In the second step, we estimate a spatial econometric model to analyze the spatial spillover effects of local natural disasters on battle incidence in other districts. Our results show that, in contrast with the direct local effects which materialize in the very short run (as represented by the fine *monthly* level of temporal granularity), spatial spillovers of battle activities become prominent in the medium to long run. Indeed, we observe that local disasters divert battle activity to surrounding districts only at the *yearly* level of temporal aggregation. Moreover, we observe that battle spillovers occur in the same year if districts are linked by a *road network* and in the following year if districts are linked by *geographic proximity*. These results seem quite intuitive as roads provide an accessible means through which the spillovers can spread. When the connection is not through roads, it takes extra effort and planning for battles to be relocated, suggesting a longer time lag for spillovers to happen.

We then examine the importance of a locality's characteristics in the diffusion process. In particular, we consider three key characteristics of a locality, i.e., economic activity (as proxied by nighttime light), mining, and agricultural activities, to explore the mechanisms driving the diffusion of violence. Our results highlight, in particular, the role of mining activity on the spatial dynamics of conflict spillovers. Indeed, we find that, first, mining activity in the disaster-affected locality tends to decrease the probability that the combat activity will shift to neighboring localities. Second, natural disasters tend to increase the likelihood of conflict in those neighboring localities that are home to mining activities. We further find that a locality with mining activity will experience positive battle spillovers from the neighboring localities only if they are linked by roads.

To provide a possible mechanism of these results, we develop a very simple model in which a set of players are involved in different battles. These battles are connected through a network[1] and each player has to decide how much effort to exert in each battle. The probability of winning a battle is determined by the standard Tullock contest success function (CSF) so that the higher the effort, the higher the chance of winning the battle. Because the model is quite general and the best response functions are not linear, we focus on two specific networks structure (a star and a line network) to derive some comparative statics results. Since, in the data, we only have information at the district level, in the model, we aggregate the agents' efforts to obtain a prediction at the district level. In particular, we identify a district with a battle and the agents who are involved in this battle. We show that a negative shock in one district reduces the battle intensity in this district but increases it in path-connected districts depending on the location of the battle in the network and the strength of each agent involved in each battle. The mechanism behind this result is that the central agent (i.e., the agent involved in two battles) must re-allocate efforts in both battles in order to maximize total payoff; whereas, the other two agents must respond optimally to the re-allocation. This may explain why a local shock in a given district propagates to other path-connected districts. We show that this result continues to hold in a line network in which a shock on the district on the left of the line affects the battle of the district on the right of the line, even though these two districts are not connected.

Taken together, our results put forward an important characteristic of the spatial diffusion of conflict, which we label the "donut effect". In essence, we show that a negative economic shock in a given district decreases its own conflict probability, while increasing the conflict probability of other districts connected via spatial networks. Through the detailed examination of granular level data, we further show the heterogeneity in the diffusion process along temporal (i.e., short run versus long run) and spatial (i.e., direct and spillover effect) dimensions.

In the short term, a negative shock might alter the costs and benefits of fighting in such

[1] For overviews on the economics of networks, see Jackson (2008) and Jackson et al. (2017).

a way that incapacitates rebels from fighting in a given locality. Increased costs, such as limited maneuverability or access to financial and military resources, are likely to outweigh the benefits of fighting in a locality affected by a natural disaster. The negative direct effect of battles in a locality in both the contemporary period and the period immediately following a natural disaster represent such an incapacitation effect. However, in the longer term, rebels are likely to consider a broader range of strategic elements, which are not limited to incapacitation *per se*. Accordingly, we observe that fighting activity relocates to well-connected neighboring districts with distinct wealth characteristics, where the net benefit from a battle is likely to be higher than that of fighting in a natural disaster-ridden district.

Our evidence of a *donut-shaped* model of conflict diffusion is highly relevant to policy-makers. Indeed, to reduce the risk of escalation, national governments and international organizations often try to contain the initial local conflict through military interventions that either increase the costs of or decrease the benefits from fighting in a specific locality. However, once larger forces move into an area and clear it from insurgents, fighting often flares up in other areas. These types of interventions can have the unintended effect of spreading conflict to previously unaffected areas and potentially dragging new parties into the violent conflict. As such, a more structured and deeper understanding of these spatial interactions can potentially help to build more informed policy strategies in the context of localized violence in Africa.

Our study contributes to various strands of literature. Firstly, we relate to the literature that analyzes the causes and spread of violent conflicts, which has been the subject of a vast body of literature in economics and other social sciences (e.g. Buhaug and Gleditsch 2008; Rigterink, 2010; Novta, 2016; Ray and Esteban, 2017). There is, first, an important body of literature using *national data* that follows the *grievance* or *opportunity cost* model (Collier and Hoeffler, 2004), which predicts a negative relationship between income shocks and the probability of a battle. Accordingly, higher incomes lead to fewer battles, because the opportunity cost of battle is high (e.g. Blattman and Miguel, 2010; Besley and Persson 2011). By the same argument, lower incomes lead to a higher probability of battles occurring, as people have "nothing to lose" following a battle (Miguel et al., 2004; Chassang and Padró i Miquel, 2009; Ciccone, 2011; Couttenier and Soubeyran, 2014). Some country-level studies, such as Bosker and de Ree (2014), also look at the spillover effects of civil wars. They provide empirical evidence that cross-border battle spillovers are an important factor in explaining the pattern of battle clusters.

In particular, our paper relates to the more recent generation of economic studies that has focused on the *localized* nature of conflict events. These studies contain theoretical and empirical analyses of how local positive (e.g. Dube and Vargas, 2013; Berman and Couttenier, 2015; Fjelde, 2015; Berman et al., 2021; McGuirk and Burke, 2020) and negative (e.g. Hodler and Raschky 2014b; Harari and La Ferrara, 2018; Berman et al., 2021) economic shocks influence the likelihood of local conflict. Although the focus of the theoretical models and empirical analyses in these studies is on the local effects of shocks on conflict, most of them include an empirical section that investigates whether these local shocks trigger violence in neighboring localities.

Our study is more closely related to the latter literature. For example, Harari and La Ferrara (2018) find that negative weather shocks in agricultural growing seasons increase the likelihood of battles and show that the most likely mechanism is the opportunity cost channel. By contrast, Berman et al. (2017) use the exogenous variation in world mineral prices to identify the causal effect of positive shocks to local mining wealth on battles. Both studies find that these exogenous shocks not only increase battle incidence in the directly affected area but also create spatial battle spillovers to neighboring regions. McGuirk and Burke (2020) study the effect of plausibly exogenous global food price shocks on local violence across the African continent. They find that in food-producing areas, higher food prices reduce battles over the control of territory ("factor conflict") and increase battles over the appropriation of surplus ("output conflict"). They argue that this difference arises because higher prices raise the opportunity cost of soldiering for producers, while simultaneously inducing net consumers to appropriate increasingly valuable surplus as their real wages fall.

Secondly, there is a recent body of theoretical and empirical literature on networks and conflicts (Dell, 2015; König, et al., 2017; Brangewitz et al., 2019; Eubank, 2019; Mueller et al., 2021). First, we contribute to the large body of theoretical literature on conflicts (for an overview, see Kovenock and Roberson, 2012), which, more recently, has been using network theory (Goyal and Vigier, 2014; Jackson and Nei, 2015; Franke and Öztük, 2015; Hiller, 2017; König, et al., 2017; Kovenock and Roberson, 2018; Xu et al., 2019; Bocher et al., 2020; Mueller et al., 2021). Our theoretical model is different because agents are involved in multiple battles and we focus on the spillover effects of a negative shock in the network of conflicts. Even though our comparative statics results are shown for very specific networks, we believe that the general mechanism of spillovers across battlefields should hold for more general network structure. Second, from an empirical perspective, we complement this literature by showing the existence of a "donut" pattern in conflict diffusion. Specifically, we show that exogenous events that *decrease* the likelihood of a battle 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 battle locally. Moreover, our empirical analysis amalgamates large amounts of spatially and temporally granular data, as well as on multiple dimensions of network connectivity, which provides us with a greater degree of flexibility; compared to the existing literature, we are able to provide insights on the mechanisms behind the local and spillover effects of conflict in the short and the long run.

Thirdly, we contribute to the largely empirical literature on the relationship between natural disasters and conflicts. This body of literature considers the economic effects of natural disasters, both at the micro (Mottalebab et al., 2015) and macro (Deryugina and Hsiang 2014; Hsiang et al. 2017; Hsiang and Jina 2014) levels. Yet others consider the effect of climate shocks on battles (Miguel et al., 2004; Hsiang et al., 2013; Hodler and Raschky, 2014b; Couttenier and Soubeyran, 2014; Mach et al. 2019). Most of these studies, however, focus on temperature and precipitation shocks and are implemented at a more aggregate level in both temporal (i.e. yearly or growing season) and spatial (i.e. country) dimensions. Our study contributes to this literature by introducing a novel geo-referenced data set of natural disasters of all types, at a very fine spatial and temporal resolution (i.e. district-month level), which allows us to better investigate the mechanisms at play in determining the relationship between natural disasters and battles.

The remainder of the paper is organized as follows. Section 2 describes the data and provides some descriptive statistics. Sections 3 presents the empirical analysis of the direct effect of a natural disaster on battles. Section 4 empirically analyzes spillover effects. Section 5 develops a simple theoretical framework that provides a possible mechanism for our results. Finally, Section 6 concludes. We provide additional figures in the Online Appendix A. Online Appendix B reports on several robustness checks. All proofs of the theoretical model can be found in the Online Appendix C.

2 Data

We use observations at the second, subnational administrative unit (ADM2, henceforth "districts") level, and the final dataset consists of 5,944 districts from 53 African countries over the period from 1989 to 2015.[2] We use two main units of observation, that is, *district-year* and *district-month*.

[2]This is available for most countries, except Egypt and Libya, where boundaries were only available at the ADM1 level. We address any concern about differences in the size of administrative units by using district-year fixed effects.

2.1 Battles

Data on battles is obtained from the Uppsala Conflict Data Program's (UCDP) Georeferenced Event Dataset (Croicu and Sundberg, 2017). This data set provides information on violent events across the world from 1989 to 2016, covering individual events of organized violence, which are geo-coded down to the level of individual villages, with temporal durations disaggregated to the daily level. Violent events are categorized based on whether they were "state-based violence", "non-state violence" or "one-sided violence". Accordingly, for each individual violent event, there is information on the place and date of the event, actors participating in the event, and estimates of fatalities.

Using the information on the precise location (i.e., latitude, longitude) of the violent event in the dataset, we first conduct a spatial analysis[3] where we geolocate each battle in the ADM2 districts. We then aggregate all such battle events at the district-year and district-month levels.

Our main indicator of a battle takes the form of a binary variable, which assumes a score of one if a battle leading to at least one death occurred in district i in the given time period, and zero otherwise.[4] Figure B.1 in Appendix A displays the distribution of battles in Africa over our sample period.

There are two alternative datasets of localised events that are used in the literature. The first one is the Armed Conflict Location and Event Data (ACLED) dataset. The challenge with using ACLED in our setting is that ACLED only starts in 1997, thereby vastly reducing the number of natural disasters, and therefore treatment events, in our sample.[5] The second

[3]This procedure was implemented in ArcMap 10.5

[4]Much of the existing work (see Blattman and Miguel, 2010) uses two (annual) death-based indicators of battle, i.e., battles leading to at least one death, and battles leading to at least 25 deaths. Because our paper uses spatially and temporally disaggregated data, we prefer the former than the latter.

[5]In a robustness test, we use ACLED battles as outcome variables. The estimated coefficients have the same sign and a similar direction but are not precisely estimated.

one is the Global Database of Events, Language, and Tone (GDELT) dataset. There are two caveats in applying GDELT to our analysis. Firstly, compared to UDCP, GDELT also has very limited temporal coverage. Most relevant events in Africa recorded in GDELT start around 2000. Secondly, GDELT does not have a specific category for violent conflict or battles. The closest category is labelled "Fight". A closer look at the actual events, which are based on media reports, reveals that this variable defines "fighting" very broadly and therefore not suited for our application.[6]

2.2 Natural Disasters

We capture a negative shock in a district through the occurrence of a natural disaster in that district. Data on natural disasters are drawn from the Emergency Events Database (EM-DAT) (see Guha-Sapir et al., 2016), which is a global database on natural and technological disasters, containing data on the occurrence and effects of over 22,000 global mass disasters from 1900 to date. Any natural or man-made disaster where either (*i*) 10 or more people died, or (*ii*) 100 or more people were affected, or (*iii*) a state of emergency was declared, or (*iv*) a call for international assistance was made, is included in the dataset. For each natural disaster, there is information on, among others, location, disaster type, date, number of deaths, number of people affected, the estimated damage, as well as on whether aid from the Office of US Foreign Disaster Assistance (OFDA) was received following a disaster.[7]

The natural disaster category in EM-DAT is divided into 6 sub-groups, which, in turn, cover 15 disaster types and more than 30 sub-types. For our study's purpose, we consider natural disasters classified as geophysical (e.g., earthquake, volcanic activity), meteorological

[6]For example, this category includes events related to criminal activity, physical alterations between individuals such as assault and battery, and even movie reviews.

[7] OFDA is an organizational unit within the United States Agency for International Development (USAID) that is charged by the President of the United States with directing and coordinating international US government disaster assistance.

(e.g., extreme temperature, storm), hydrological (e.g., flood, landslide), climatological (e.g., wildfire), or extraterrestrial (space weather). For the purpose of our study, we exclude droughts from the set of natural disasters for the followings reasons. First, droughts are typically spread across multiple ADM2 districts. Therefore, the effects of a drought are not strictly "local" with respect to the fine spatial granularity pursued in this analysis. Second, the spatial extent of the affected area is often not clearly defined, making it difficult to precisely assign the treatment. Third, droughts are slow onset disasters and their effects last over prolonged time periods, transcending the fine temporal resolution of our data. Fourth, droughts are potentially endogenous in the context of this analysis as the probability of occurrence can, partially, be the result of a conflict itself.

The availability of EM-DAT data at the country level, however, is a challenge when conducting a district-level analysis. We overcome this challenge by manually geocoding 1,016 natural disasters that occurred in Africa over the period from 1989 to 2015. Natural disasters where the exact individual village or subnational district was identified were precisely geocoded; whereas, 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 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. Figure B.2 in Appendix A 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 other indicators to reflect different disaster categories. 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.[8]

2.3 Other covariates

We use three additional data sets to explore the mechanisms through which natural disasters affect battle incidence.

First, we identify districts with high and low economic activity levels, using satellite data on the intensity of *nighttime lights*, sourced from the National Oceanic and Atmospheric Administration (NOAA). Nighttime luminosity has been identified as an indicator of the level of economic activity, both at the national level (Henderson et al., 2012) and the subnational level (Hodler and Raschky, 2014). NOAA provides annual data for the time period from 1992 onwards for output pixels that correspond to less than one square kilometer. The data are presented on a scale from 0 to 63, with higher values implying more intense nighttime lights.

We generate a time-invariant binary indicator $Light_i$as a proxy for the level of economic activity in a district. This indicator is based on *initial nighttime light*, which is the nighttime light value for the year 1992, the starting point of this data. Districts with a nighttime light value of 10 and above in 1992 receive a score of 1 (high level of economic activity), and those with a value of less than 10 in 1992 receive a score of 0 (low level of economic activity).[9] Because of its time-invariant nature, this variable filters out short-term negative shocks on

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

[9] As indicated in Table C.2.7, our empirical results are robust to alternative thresholds of initial nighttime light.

economic activity due to the occurrence of natural disasters, thereby addressing potential endogeneity concerns. We identify 8% of the districts as displaying a high level of economic activity.

Second, we use data on mining activity in subnational districts in Africa, obtained from the SNL Mining & Metals database. This database covers mining projects across Africa that were active during our sample period. For each project, it contains information about the point location, that is, the geographic coordinates, and the (potentially multiple) resources extracted at this location. For this study's purpose, we use the point locations of the mining projects to assign them to districts and identify all districts where a mine was active for at least one year during our sample period. We use this information to construct a time-invariant indicator of mining activity, which is a binary variable that equals 1 if at least one active mining project operated in the district over the period, and zero otherwise.[10]

Finally, we classify districts as agricultural and non-agricultural using the raw raster data obtained from the Global Land Cover Characteristics Data Base Version 2.0.[11] For each district, we calculate the fraction of agriculturally suitable land and we classify districts with over 50% agriculturally suitable land as agricultural. In our data, 29% of the districts qualify as agricultural.

Table 1 provides descriptive statistics of the key variables, at the district, district-year, and district-month levels.

[Table 1 about here]

[10]Based on this definition, approximately 4% of African districts are considered mining districts in our sample.

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

2.4 Connectivity matrices

We follow Amarasinghe et al. (2020)[12] and construct two[13] spatial weighting matrices based on geographic and road connectivity.

2.4.1 Geographic connectivity

The first form of connectivity we explore is based on the geography. We use the geographic distance between districts to construct the *weighted connectivity matrix*, using the following steps. We start by identifying the centroid of each district, and then proceed by calculating the geodesic distance $d_{ic,jc}$ connecting the centroids of districts i and j in country c. Next, we use elevation data from GTOPO30 to measure the variability of altitude, $e_{ic,jc}$, along the geodesic connecting the centroids of districts i and j, as per Acemoglu et al. (2015). In the final step we calculate the inverse of the altitude-adjusted geodesic distance as $\tilde{d}_{ic,jc} = \frac{1}{d_{ic,jc}}(1 + e_{ic,jc})$.

In using the inverse of the altitude-adjusted geodesic distance, we weight the geographic connectivity between two districts along two dimensions. Accounting for variability in altitude, $e_{ic,jc}$, means we take into consideration the topology of the landscape. Accordingly, districts connected through a level surface receive a higher connectivity score as opposed to districts separated by a mountainous terrain. Additionally, by using the inverse of the altitude-adjusted geodesic distance, we assign a higher weight to the connectivity between districts located in close geographic proximity, as opposed to those located further away

[12] Observe that the analysis in Amarasinghe et al. (2020) is very different to that of the current paper since, in the former, there is no "conflict" and "battles" between districts and the focus is on which districts diffuse local economic activity (as measured by nighttime light intensity) the most to neighboring districts whereas, in this paper, we analyze the effect of disasters on local and distant battles.

[13] In consideration of the rich ethnic diversity in Africa, we also analyzed the effects of ethnic connectivity using data on the spatial distribution of ethnic homelands based on the work by Murdock (1959). However, we did not find any systematic effects of ethnic connectivity on spatial conflict spillovers in our setting and therefore we excluded this type of connectivity in the analysis.

from each other. This approach accounts for the accessibility from one location to another by taking into account the differences in the underlying terrain (mountainous vs. flat).

In our empirical estimates, we construct multiple connectivity matrices truncated at different cut-off distances from a district's centroid. This implies that we can identify the neighbors of district i lying within different radii from its centroid and, thereby, determine the exact extent of the spatial spillovers.

2.4.2 Road connectivity

Given the importance of roads in maintaining links between districts in general, and in potentially spreading conflict (e.g. Rogall 2014), we construct a *road-based connectivity matrix*. For this purpose, we use data on the primary and secondary road network in Africa from OpenStreetMap (OSM).[14] To generate a network graph of the road network, we intersect these roads with district boundary polygons using the following steps.[15] First, we split the road polylines into segments whenever they intersect with a district boundary. For each segment (edge) we calculate the road travel distance in km between each intersection (node).[16] Next, we identify the shortest path on the road segments between each district and calculate the distance on that path. If districts A and B are adjacent and connected via a major road, we assign a distance value of 1km. If districts A and B are not adjacent, but connected via the road network, they are assigned the road distance between the closest road

[14] OSM is an open-source mapping project where information about roads (and other objects) is crowd-sourced by over two million volunteers worldwide, who can collect data using manual surveys, handheld GPS devices, aerial photography, and other commercial and government sources. See https://openstreetmap.org for more information and https://geofabrik.de for the shapefiles. We opted for the OSM instead of the World Bank's African Infrastructure Country Diagnostic (AICD) database because the AICD data does not contain information for countries with Mediterranean coastline as well as Djibouti, Equatorial Guinea, Guinea-Bissau, and Somalia. We accessed the OSM data in early 2016 and extracted information about major roads (e.g., highways and motorways) for the African continent. Figure B.3 provides a visualisation of the road network.

[15] The road connectivity analysis between ADM2 polygons was conducted in ArcMap 10.2 using arcpy. The python scripts are available upon request.

[16] If the road starts/ends in a district, we calculate the distance between the start/end point and the intersection.

and district boundary node of A and the closest road and district boundary node of B (i.e., the road travel distance through the whole district that one has to cross to get from district A to district B). The final road connectivity matrix assigns a value equal to the inverse of the road distance in km between districts i and j if they are connected via a major road, and 0 if they are not connected. As with the altitude-adjusted inverse distance matrix, we again construct different weighting matrices by truncating at different cutoff distances. It is important to note, that this matrix is based on road connection and not road quality.[17]

3 Direct effects of natural disasters on battles

In the first part of the empirical analysis, we estimate the direct effect of natural disasters on battles in a district. We conduct this estimation at two different levels of *temporal* aggregation, that is, district-year level and district-month level.[18]

3.1 Direct effects - district-year level analysis

For the district-year level analysis, we use the following econometric specification:

$$Battle_{iy} = \beta_0 DIS_{iy} + \beta_1 DIS_{i,y-1} + \gamma Battle_{i,y-1} + \mathbf{FE_i} + \mathbf{FE_{cy}} + \epsilon_{iy} \tag{1}$$

Panel unit i is districts in a given country c in year y. Our dependent variable $Battle_{iy}$ is a binary variable that switches to one if there was at least one battle, resulting in at least one death, in district i in year y, and zero otherwise. Our empirical proxy for the negative shock

[17] One concern could be that road infrastructure and thereby road-connectivity could be negatively correlated with fighting activity due to long-lasting destruction of the infrastructure. In a robustness check, we compile cross-sectional data at the ADM2 level and per capita road infrastructure on conflict variables as well as a set of controls. The results in the Appendix, Table C.3.9 show that estimated coefficients of the conflict variables are basically zero and statistically not significant.

[18] We also explore the direct effects of natural disasters on battles at a more *spatially* aggregated level, i.e., at the country level. These estimates are provided in Table C.1.1.

is DIS_{iy}, which is a binary indicator that equals one if a natural disaster event occurred in district i in year y, and zero otherwise. We also include the temporal lag of this independent variable, that is, $DIS_{i,y-1}$, to evaluate the effect of a disaster on a battle after the time lag.

To separate the effect of autocorrelation of battles in the temporal dimension, we include the temporal lag of the dependent variable, that is, $Battle_{i,y-1}$ as a control in equation (1).[19] In our preferred specification, we include district ($\mathbf{FE_i}$) and country× year ($\mathbf{FE_{cy}}$) fixed effects, which absorb time-invariant district-specific characteristics and time-variant country-specific shocks,[20] respectively. This relatively conservative set of fixed effects also addresses the concern of non-random underreporting of natural disasters. Finally, ϵ_{iy} is an error term.

The construction of a new data set of natural disasters incorporating their fine spatial and temporal distribution provides us with a neat localized economic shock. Moreover, being *natural*, they are by definition *exogenous* shocks, which minimizes any concern on potential simultaneity. The exogeneity of the negative income shock, coupled with the comprehensive set of fixed effects, allows us to causally interpret β_0 and β_1, the coefficients of interest.

Table 2 displays our main results using data at the *district-year level*. Columns (1) to (4) control for district and year fixed effects. We observe that the coefficient of interest is negative and statistically significant at the 10% level, for both the contemporary period and the first lag. More specifically, the results in column (4) suggest that the occurrence of a natural disaster in district i in year y reduces its battle probability in the same year by 0.79 percentage points and in the following year by 0.65 percentage points.

[19] Including a lagged dependent variable in a fixed effects specification can result in the well-known Nickell bias. Panel A in Table C.3.8 presents results of specifications without the lagged dependent variable as well as results of an LDV model. The results show that the coefficients of our key explanatory variables remain very similar. Moreover, In Figure C.2.2, we show that the results remain robust to the inclusion of a number of alternative sets of fixed effects, and with/without the inclusion of thee LDV.

[20] This includes, among others, macroeconomic and trade shocks (e.g. Jackson and Nei, 2015; Martin et al., 2008) that affect all districts in a country and year.

[Table 2 about here]

However, region and year fixed effects *per se* may be insufficient to claim a causal relationship between natural disasters and battles, as they do not adequately account for country-wide time-varying events that affect battle probability. In columns (5) to (8) we control for such unobservable variables using country-year fixed effects. We observe that when controlling for country-year fixed effects, the negative effect of natural disasters on battles is no longer statistically significant.[21]

These results indicate that aggregation of variables of interest at the yearly level does not provide us with a comprehensive understanding of what happens at the finer temporal resolutions.[22] Given the high frequency of natural disasters and battles in Africa, it is important to explore the effects that materialize within the short run. In the ensuing sections, our study addresses this shortcoming in the existing literature by conducting an analysis at this fine temporal resolution (i.e. monthly aggregation).

3.2 Direct effects - district-month level analysis

Therefore, to exploit the fine temporal granularity of our data, we use the following econometric specification, where the time unit is month m in year y.

$$Battle_{iym} = \sum_{\tau=0}^{\tau=1} \beta_\tau DIS_{iy,m-\tau} + \gamma Battle_{iy,m-1} + \mathbf{FE_m} + \mathbf{FE_{iy}} + \epsilon_{iy,m} \tag{2}$$

The coefficients of interest are again β_τ, which capture the effect of a natural disaster in district i on the probability of a battle in i, in the current month and the next month, respectively. We control for the potential temporal autocorrelation of battles by including

[21] In Tables C.3.1 to C.3.3, we conduct a number of robustness checks using alternative definitions of the dependent and independent variables.

[22] Almost all existing work on battles and their causes use annual data.

the lagged dependent variable $Battle_{iy,m-1}$.[23]

In addition to these key variables, we use two sets of fixed effects at this monthly level. First, we include month of the year fixed effects ($\mathbf{FE_m}$), which account for season specific shocks that can simultaneously influence the occurrence of natural disasters as well as battles. Second, we also include a vector of district × year fixed effects, $\mathbf{FE_{iy}}$. This vector absorbs two main sources of unobserved variation. First, it captures all district specific, time-invariant characteristics that could explain between-district differences in battle prevalence as well as exposure to natural disasters (i.e., topography). Second, it absorbs any unobserved shocks to the district (and country) that could simultaneously drive battles and the disaster risk (i.e., changes to economic development at the national and subnational level; climatic phenomena such as the El Nino/La Nina cycles).

Table 3 presents the empirical results at the *district-month* level. Observe that even at this fine temporal resolution, the effect of a natural disaster in month m of year y on the battle incidence of district i is always negative. This effect is statistically significant at the 1% level when including district, year, and month fixed effects separately (Columns (1) to (4)). It remains statistically significant at the 5% level, when we include the stringent set of district × year fixed effects (Column (8)), which is our preferred specification.[24]

[Table 3 about here]

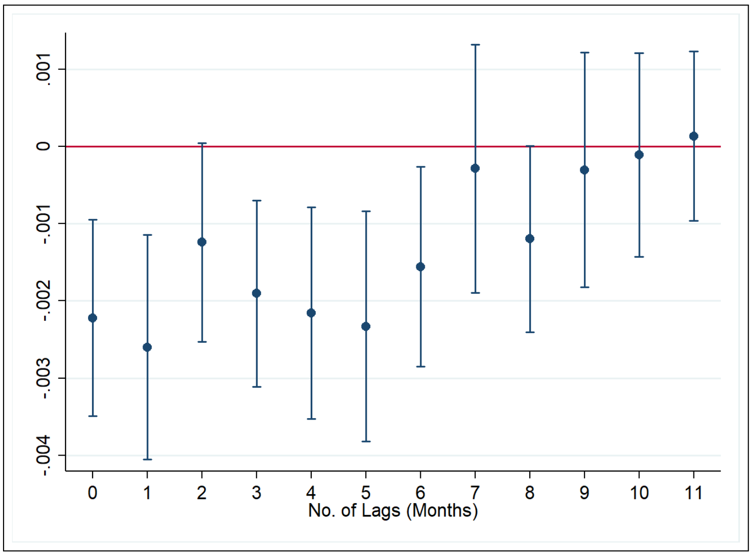
Temporal disaggregation not only enables us to measure the negative effect of natural disasters on battles with greater precision, but also gives us the opportunity of examining the

[23]Panel B in Table C.3.8 presents the results of district-month specifications without the lagged dependent variable as well as the results of the LDV model. Moreover, In Figure C.2.2, we show that the results remain robust to the inclusion of a number of alternative sets of fixed effects, and with/without the inclusion of the LDV.

[24]In Figure C.2.2 and Tables C.2.1 to C.2.5 , we conduct a number of robustness checks at the district-month level, using alternative definitions of the dependent and independent variables. Particularly, in Table C.2.1 we show that the baseline estimates remain robust when using spatial HAC standard errors, allowing for spatial correlation up to 100km and for infinite serial correlation.

persistence of this effect over the following months. We do this by extending the specification in equation (2) to include up to 11 additional lags of the independent variable $DIS_{iy,m}$. Figure 1 plots the point estimates and 90% confidence intervals for each monthly lag starting with the effect in the current month. We observe that there is a persistent negative effect of natural disasters on battles, spreading up to a 6 month lag.[25]

Figure 1: The Effect of Natural Disasters on Battles Over Time—District-Month Level



Notes: Dots on show the regression results using Eq. (2) and including up to 11 temporal lags of the independent variable $Disaster_{iym}$. Vertical lines show the 90% confidence interval based on standard errors clustered at the country×year level.

The results in Table 3 and Figure 1 show that, following a negative economic shock, battle probability in the affected district reduces, due to the decreased efforts of involved players. Almost all existing work on the diffusion of violent events observe an increase of violence in a locality affected by an exogenous economic shock, which then propagates to neighboring districts. By contrast, in our setting, we establish that the battle probability of the locality affected by the negative economic shock decreases, and we explore the mechanism

[25]In Figure C.2.1, we conduct the same exercise but also include the period up to 11 months *before* the occurrence of the natural disaster, in the spirit of an event study exercise. We re-establish that the effects of natural disasters persist temporally, while also confirming the absence of pre-trends.

behind such decline, as well as the consequent spillover effects in the following sections.

Moreover, Tables 2, 3 and Figure 1 taken together also highlight a key empirical contribution of this study. Existing studies on conflicts have so far relied on data at the yearly level. We show, in Table 2, that there is no statistically significant relationship between natural disasters and battles at the yearly level. The statistically significant negative relationship is only observed at the disaggregated monthly level, as demonstrated in Table 3. Interestingly, we are able to exploit the fine temporal granularity of our data to show that the direct effect of a natural disaster on battle probability in given district persists up to approximately 6 months following a natural disaster, and gradually disappears thereon. These results suggest that some dynamics associated with local conflict might not be adequately captured by aggregated, annual data.

3.3 Direct effects - mechanisms

Identifying that natural disasters decrease battle probability *per se* provides limited insights as to the mechanisms driving this relationship. If, for example, policies are to be drafted based on this relationship, more information on the mechanisms would be needed. Therefore, in this next part of our analysis, we provide some insight as to what drives the relationship between natural disasters and battles.

For this purpose, we test the following equation:

$$\begin{aligned} Battle_{iym} = \sum_{\tau=0}^{\tau=2} \beta_{\tau} DIS_{iy,m-\tau} + \sum_{\tau=0}^{\tau=2} \theta_{\tau} (DIS_{iy,m-\tau} \times \mathbf{Z_i}) \\ + \gamma Battle_{iy,m-1} + \mathbf{FE_{iy}} + \mathbf{FE_m} + \epsilon_{iy,m} \end{aligned} \tag{3}$$

Here, $\mathbf{Z_i}$ is a vector of time-invariant variables that contains information about different characteristics of district i that can help us identify the mechanism through which the disaster affects the costs and benefits of a battle. We examine three such channels. First, $Light_i$, a binary variable that switches to 1 if the average nighttime light intensity in district i in 1992 is above 10, and 0 otherwise, as a proxy for the level of local economic activity. [26] Second, $Mine_i$, a binary variable that switches to 1 if district i is home to a mineral mine, and 0 otherwise. Third, $Agri_i$, a binary variable that switches to 1 if district i has over 50% agriculturally suitable land, and 0 otherwise.

In Table 4, we present the set of results that explain the heterogeneity of the disaster effect along these channels that might affect the benefits of fighting in a particular area. We find that the disaster effect is larger in districts with higher levels of economic activity, that is, those with more nighttime light activity. The effect of natural disasters is also more pronounced in districts with a large fraction of agricultural land. We do not find an indication that the location of mines affects the disaster shock effect on battles.

[Table 4 about here]

4 Natural disasters and battles: Spatial spillover effects

4.1 Spatial spillover effects - district-month level analysis

Considering the spatial distribution of both our dependent and independent variables, it is likely that spatial spillovers of these variables occur across districts. In this second part of the empirical analysis, we turn our attention to such spatial battle spillovers of natural disasters. For this purpose, we use the following specification, which takes the form of a spatial Durbin model that allows for spatial autoregressive processes in the dependent and

[26] Table C.2.7 provides estimates for alternative night time light thresholds.

explanatory variables.

$$
\begin{aligned}
Battle_{iym} = & \sum_{\tau=0}^{t} \beta_\tau DIS_{iy,m-\tau} + \sum_{\tau=0}^{t} \delta_\tau NDIS_{iy,m-\tau} \\
& + \gamma_1 Battle_{iy,m-1} + \gamma_2 NBattle_{iy,m} + \mathbf{FE_{iy}} + \mathbf{FE_m} + \epsilon_{iy,m}
\end{aligned}
\tag{4}
$$

The key variable of interest is $NDIS_{iy,m}$, which captures the direct *spatial spillover* effect of a natural disaster that occurred in a neighboring district on battle probability in district i. Here,

$$
\begin{aligned}
NDIS_{iy,m}{=}1 \text{ if } \textstyle\sum_{j=1}^{J} \omega_{ij} DIS_{jy,m} \geqslant 0 \\
NDIS_{iy,m}{=}0 \text{ if } \textstyle\sum_{j=1}^{J} \omega_{ij} DIS_{jy,m} = 0
\end{aligned}
$$

where the "neighborhood" between districts is defined by the connectivity matrix $\mathbf{\Omega} = (\omega_{ij})$ such that $\omega_{ij} \in [0,1]$ if a link exists between districts i and j and $\omega_{ij} = 0$ otherwise. We use two forms of connectivity: $\mathbf{\Omega_1}$ captures *geographic connectivity*; whereas, $\mathbf{\Omega_2}$ captures *road connectivity*. $NDIS_{iy,m}$ is therefore the binary transformation of the spatial lag of the natural disaster variable, which identifies whether at least one "neighboring" district experienced a natural disaster in month m of year y ($NDIS_{iy,m} = 1$) or not ($NDIS_{iy,m} = 0$).

We introduce enough flexibility in our empirical exercise to enable us to generate these matrices at different cutoff distances and to conduct separate estimates at these cutoffs. Both $\mathbf{\Omega_1}$ and $\mathbf{\Omega_2}$ are row-normalized so that the sum of each of its rows is equal to 1, that is, $\sum_j \omega_{ij} = 1$ for all i. We also include a temporal lag of this variable $NDIS_{iy,m-1}$ to identify if spatial spillovers occur with a time lag.

To account for potential spatial correlation of battles at the subnational level, we control for $NBattle_{iy,m}$ in our specification, where $NBattle_{iy,m}$ is a binary variable $= 1$ if $\sum_j \omega_{ij} Battle_{jy,m} > 0$, and $= 0$ otherwise. Additionally, as with previous estimations, we include $Battle_{iy,m-1}$ to control for the potential correlation of district i's battles along the temporal dimension.

Accordingly, the coefficients of interest δ_τ respectively capture the *spatial* and *spatial*$\times$*temporal* spillover effects of natural disasters occurring in neighboring districts on district i's own battle probability.

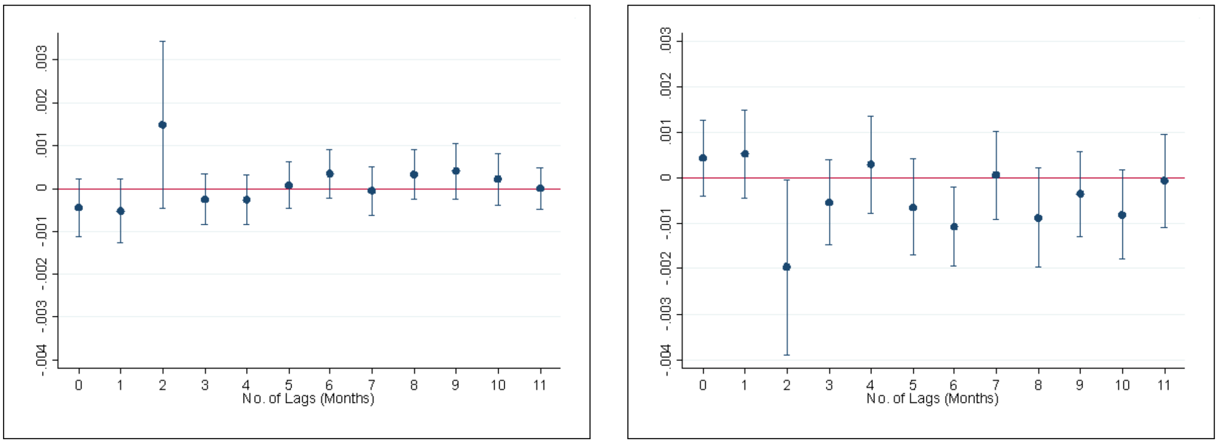
In Table 5, we examine the magnitude of spatial spillover effects at the district and month level, at a cutoff distance of 500km from each district.[27] Column (1) considers diffusion based purely on the altitude-adjusted inverse geodesic distance and Column (2) considers only the inverse road distance. In Column (3) we consider both types of connectivity together. In all three columns, the coefficients on the variables of interest, $NDIS_{iy,m}$ and $NDIS_{iy,m-1}$, are statistically insignificant.

[Table 5 about here]

Next, we look at whether the diffusion effect is present at the monthly level when using higher order temporal lags. Figure 2 shows the estimation of battle spillovers at the district-month level, when including up to 11 monthly lags. Panel (a) displays the coefficients on $NDIS_{iym}$ when the neighborhood is defined using the altitude-adjusted inverse geodesic distance matrix; whereas, in panel (b), the neighborhood is defined using the inverse road distance matrix.

[27] In Table C.2.8, we consider alternative cutoff distances as robustness checks.

Figure 2: Battle Diffusion at the District-Month Level



(a) Coefficient on $NDIS$ - Inverse Geodesic Distance (b) Coefficient on $NDIS$ - Inverse Road Distance

Notes: Dots show the estimated coefficients on $NDIS$ using Eq. 4, when including up to 11 temporal lags of the explanatory variables. Panel (a) displays the coefficient on $NDIS_{iym}$ when neighborhood is defined as per the altitude-adjusted inverse geodesic distance matrix; whereas, in Panel (b) neighborhood is defined using the inverse road distance matrix. Vertical lines show the 90% confidence interval based on standard errors clustered at the country×year level.

Accordingly, at this district-month level of disaggregation, we do not observe any evidence of spillover effects of neighbor's natural disasters on one's own battle incidence. Although no such effect is visible in the short run, it could be that spillover effects take longer to materialize. Moving troops from one district to another is unlikely to occur instantaneously. Indeed, after a natural disaster shock, it may take time to plan and execute new battle plans and move from one district to another.

4.2 Spatial spillover effects - district-year level analysis

To examine whether it indeed takes more time for spatial spillovers to materialize, we now explore whether any spatial and temporal spillovers occur at the aggregate district-year level, using the following specification.

$$
\begin{aligned}
Battle_{iy} = \beta_0 DIS_{iy} + \beta_1 DIS_{i,y-1} + \delta_0 NDIS_{iy} + \delta_1 NDIS_{i,y-1} \\
+ \gamma_1 Battle_{i,y-1} + \gamma_2 NBattle_{iy} + \mathbf{FE_i} + \mathbf{FE_{cy}} + \epsilon_{iy}
\end{aligned}
\tag{5}
$$

The coefficients of interest are δ_0 and δ_1, which capture the direct *spatial* battle spillover effects attributable to the occurrence of a natural disaster in a neighboring district in a given and the following year.

Table 6 presents the results for the specification with spatial spillover effects over the course of a year.

[Table 6 about here]

In column (1), we consider spillovers between neighbors as defined by the altitude-adjusted inverse geodesic distance matrix, truncated at a distance of 500km from the centroid of each district.[28] We do not observe any evidence of spillovers of battles attributable to natural disasters in the same period. However, we observe that, in the year following a natural disaster, battles do spillover to neighboring districts, and this result is statistically significant at the 1% level.

Next, in column (2), we consider spillovers between districts linked by the road network, where, again, this network is truncated at 500km. Here, too, we observe that battle spillovers do occur as a result of natural disasters, but, unlike column (1), these spillovers occur in the year when the natural disaster takes place.

To identify whether one form of connectivity dominates the spillover effects, in column (3) we consider "horse race" specifications using a combination of these connectivity networks. These results confirm those found in columns (1) and (2). Indeed, we observe that

[28] In Table C.3.7, we consider alternative distance cut-offs at the district-year level.

battle spillovers occur in the current year if districts are linked by road network, and in the following year if they are linked by geographic proximity. Intuitively, it seems reasonable that battle spillovers are observed rapidly in districts linked by roads, as roads provide an accessible means through which the spillovers can spread. When the connection is not through roads, it takes extra effort and planning for battles to be relocated, suggesting a longer time lag for spillovers to materialize.[29]

The results in Table 6 further confirm our results. Recall that, in Section 3.2, our empirical results showed that the probability of a battle reduces in a locality directly affected by a negative economic shock. In the current exercise, we build on this identified direct effect and show that battles do indeed spillover to connected neighboring districts. Taken together, these two key results suggest a "donut" shaped process of battle diffusion that can have important policy implications.

Moreover, comparing the results in Table 6 with those in Table 5, our empirical results further highlight the importance of temporal granularity in the battle diffusion process. We observe no evidence of battle spillovers attributable to natural disasters in the *short run*, but there is systematic evidence of natural disasters increasing the likelihood of a battle in neighboring districts in the *medium* to *long-run*. By contrast, in Section 3.2, we observe that the direct effects of a natural disaster on the affected locality materialize in the short run (Table 3). This ability to differentiate direct and spillover effects along the two distinct levels of temporal disaggregation yet again highlights the versatility of our analysis compared to the traditional studies that rely on annual data.

[29]Moreover, in Table C.3.6, we observe that these estimates remain robust when using spatial HAC standard errors, allowing for spatial correlation up to 500km and for infinite serial correlation.

4.3 Spatial spillover effects - mechanisms

Let us attempt to understand the mechanisms underlying the spatial spillover effects. As discussed in Section 2.3, our data enables us to categorize districts based on their levels of economic, mining, and agricultural activities. We use these time-invariant features of districts to explore whether any of these mechanisms play a role in battle diffusion following a natural disaster shock.

We approach this question in two ways. First, we consider the features of district i, which is the target/recipient of the battle spillovers following its neighbors' natural disaster shock. Here, we investigate whether the spillover of a battle is determined by the characteristics of the district to which the battles spill over. To capture this, we define an interaction term $NDIS_{iy} \times \mathbf{Z_i}$, where $\mathbf{Z_i}$ is defined as in Section 3.3 and is a vector of time-invariant variables that contains information about different characteristics of district i, that is, $Light_i$ (average nighttime light intensity), $Mine_i$ (mineral mine) and $Agri_i$ (over 50% agriculturally suitable land).

The second dimension we consider is whether the features of the neighboring district j where the natural disaster occurs (source district) play a role in determining whether the natural disasters lead to battle spillovers. We estimate this effect through the use of an interaction term $NDIS_{iy} \times \mathbf{Z_j}$ in our empirical specification.

We use the following specification to explore the mechanisms underlying the spatial spillovers of battles.

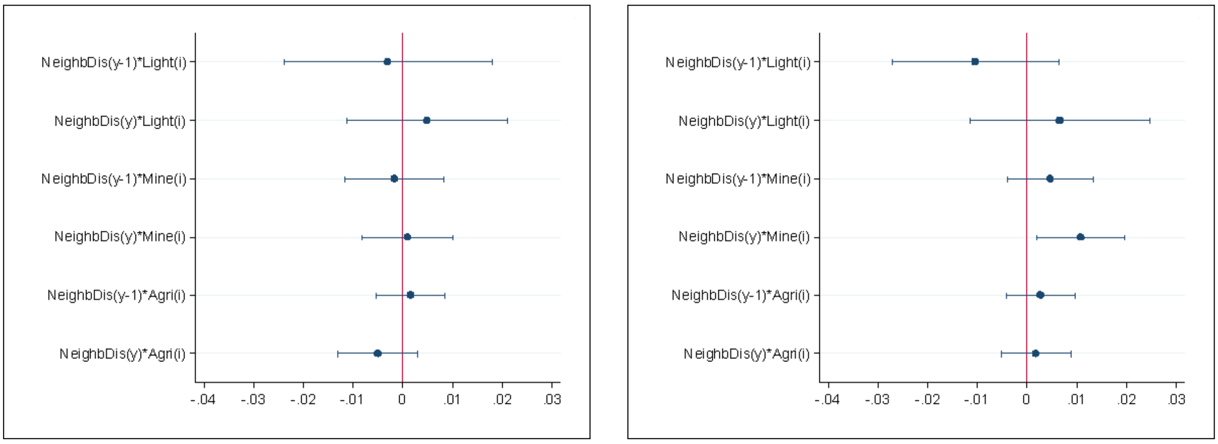
$$
\begin{aligned}
Battle_{iy} = {} & \beta_0 DIS_{iy} + \beta_1 DIS_{i,y-1} + \delta_0 NDIS_{iy} + \delta_1 NDIS_{i,y-1} \\
& + \lambda_0 (NDIS_{iy} \times \mathbf{Z_i}) + \lambda_1 (NDIS_{i,y-1} \times \mathbf{Z_i}) \\
& + \mu_0 (NDIS_{iy} \times \mathbf{Z_j}) + \mu_1 (NDIS_{i,y-1} \times \mathbf{Z_j}) \\
& + \gamma_1 Battle_{i,y-1} + \gamma_2 NBattle_{iy} + \mathbf{FE_i} + \mathbf{FE_{cy}} + \epsilon_{iy}
\end{aligned}
\tag{6}
$$

As before, the "neighborhood" is defined in terms of the inverse geographic distance and/or the inverse road distance.

Table 7 displays the results while Figure 3 plots them. Let us focus on Figure 3. In panel (a), neighbors are defined by the altitude-adjusted inverse distance matrix; whereas, in panel (b), they are defined by the inverse road distance matrix. We do not observe any evidence that the characteristics of district i affect the battle spillovers to itself, when natural disasters occur in districts within 500km of its centroid (panel (a)). However, in panel (b), we see that, if district i is a mining district, it will experience positive battle spillovers from its neighboring districts linked by roads up to 500km.

[Table 7 about here]

Figure 3: Mechanisms of Battle Diffusion - Local Features

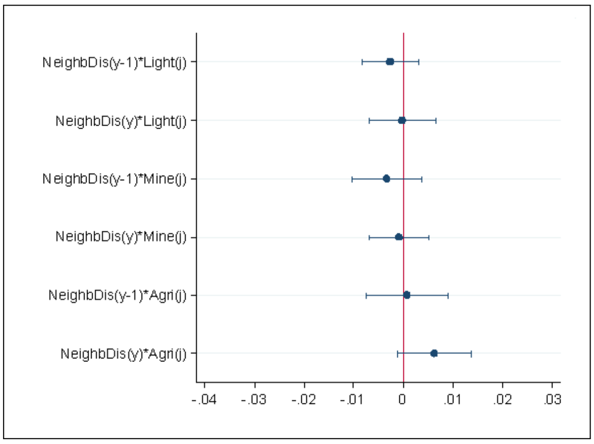


(a) Battle Diffusion in the Inverse geodesic Distance Network (b) Battle Diffusion in the Inverse Road Distance Network

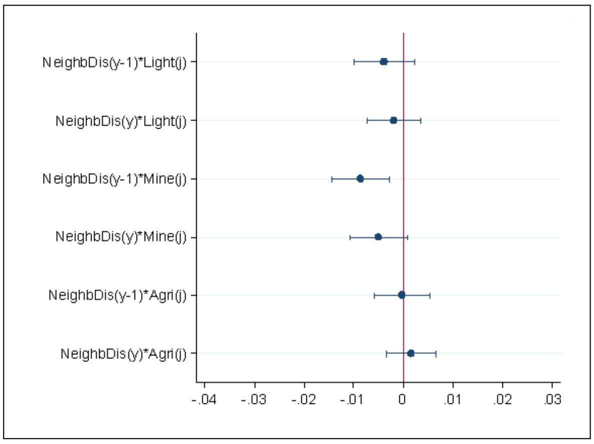
Notes: Dots show the estimated coefficients on $NeighbDisaster_{iy} \times \mathbf{Z_i}$ and $NeighbDisaster_{iy-1} \times \mathbf{Z_i}$ using Eq. (6), where $\mathbf{Z_i}$ refers to the time-invariant features of district i, as classified by the variables $Light_i$, $Mine_i$ and $Agri_i$. See Section 2.3 for more details on these variables. In Panel (a), neighborhood is defined as per the altitude-adjusted inverse geodesic distance matrix; whereas, in Panel (b) neighborhood is defined using the inverse road distance matrix. Horizontal lines show the 90% confidence interval based on standard errors clustered at the country×year level.

Next, in Figure 4, we look at whether the battle diffusion depends on the characteristics of the neighboring districts ($\mathbf{Z_j}$). Again, in panel (a), we do not observe evidence of $\mathbf{Z_j}$ affecting battle spillovers when neighborhood is defined by the altitude adjusted inverse distance matrix. In panel (b), however, we observe a negative spillover effect in the road connectivity matrix, when district j is a mining district.

Figure 4: Mechanisms of Battle Diffusion - Neighbors' Features



(a) Battle Diffusion in the Inverse geodesic Distance Network



(b) Battle Diffusion in the Inverse Road Distance Network

Notes: Dots show the estimated coefficients on $NeighbDisaster_{iy} \times \mathbf{Z_j}$ and $NeighbDisaster_{iy-1} \times \mathbf{Z_j}$ using Eq. 6, where $\mathbf{Z_j}$ refers to the time-invariant features of district j (i.e. neighboring district), as classified by the variables $Light_i$, $Mine_i$ and $Agri_i$. See Section 2.3 for more details on these variables. In Panel (a), neighborhood is defined as per the altitude-adjusted inverse geodesic distance matrix; whereas, in Panel (b) neighborhood is defined using the inverse road distance matrix. Horizontal lines show the 90% confidence interval based on standard errors clustered at the country×year level.

Overall, these results can be summarized as follows: In general, differences in local characteristics such as the level of development or the fraction of agricultural land do not systematically affect the magnitude of spatial conflict spillovers as a result of negative economic shocks. The only exception is mining. On average, a disaster affecting a mining locality is less likely to lead to an outward shift of combat activity to other connected localities. By contrast, if belligerents are forced to shift combat activity to connected localities, they are more likely to shift activity to mining localities. Our results, once again, support the idea that mining activity is a key determinant of local violent conflict in Africa. Mines do not only increase the conflict prevalence in the mining locality (e.g. Berman et al. 2017) but they also systematically affect the likelihood and target location of spatial shifts in combat activity following negative economic shocks.

5 A possible 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 (Section 3) but also affects the neighboring districts (Section 4).

5.1 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:

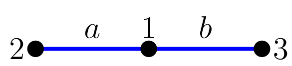


Figure 5: A star network

The matrix $\mathbf{\Gamma}$ representing the network depicted in Figure 5 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 5, 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:

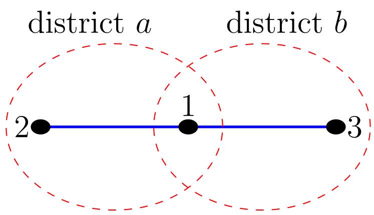


Figure 6: A star network

Of course, any other district representation can be made from Figure 5. 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 road between them and thus $\omega_{ab} > 0$.[30] For example, in Figure

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

6, there are two districts a and b and they are geographically adjacent to each other (i.e., there is a road between them). In that case, there are two layers of proximity, which involve different actors: (i) the *battle proximity* where, as in Figure 5, 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 6, 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 $\mathbf{x}^\alpha = \{x_i^\alpha\}_{i \in \mathcal{N}^\alpha} \in \mathbf{R}_+^{n^\alpha}$ 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:

$$\Pi_i(\mathbf{x}_i, \mathbf{x}_{-i}) = \sum_{\alpha \in \mathcal{T}_i} v^\alpha p_i^\alpha(\mathbf{x}^\alpha) - C_i(\mathbf{x}_i), \tag{7}$$

which is just the net expected value of winning the battle(s). Indeed, in (7), $p_i^\alpha(\mathbf{x}^\alpha)$ is the probability of winning battle α for player i. It is given by the following Tullock CSF:

$$p_i^\alpha(\mathbf{x}^\alpha) = \frac{x_i^\alpha}{\sum_{j \in \mathcal{N}^\alpha} x_j^\alpha}. \tag{8}$$

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 6. 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 $i \in \mathcal{N}$,

$$\Pi_i(\mathbf{x}_i^*, \mathbf{x}_{-i}^*) \geq \Pi_i(\mathbf{x}_i, \mathbf{x}_{-i}^*), \quad \forall \mathbf{x}_i. \tag{9}$$

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 5 or Figure 6 because it is tractable and still provides all the intuition we need for our empirical analysis.[31]

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.

[31] In Section 5.3, we provide similar results for a line network with more agents and more battles.

5.2 Star network

5.2.1 The model

Consider the star network depicted in Figure 5 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:

$$
\begin{aligned}
\Pi_1(\mathbf{x}_1, \mathbf{x}_{-1}) =& v^a \frac{x_1^a}{x_1^a + x_2^a} + v^b \frac{x_1^b}{x_1^b + x_3^b} - \frac{s_1}{2}(x_1^a + x_1^b)^2, \\
\Pi_2(\mathbf{x}_2, \mathbf{x}_{-2}) =& v^a \frac{x_2^a}{x_1^a + x_2^a} - \frac{s_2}{2}(x_2^a)^2, \\
\Pi_3(\mathbf{x}_3, \mathbf{x}_{-3}) =& v^b \frac{x_3^b}{x_1^b + x_3^b} - \frac{s_3}{2}(x_3^b)^2.
\end{aligned} \tag{10}
$$

5.2.2 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

$$F_1(x_1^a, x_1^b, x_2^a) := \frac{\partial \Pi_1}{\partial x_1^a} = \frac{v^a x_2^a}{(x_1^a + x_2^a)^2} - s_1(x_1^a + x_1^b), \tag{11}$$

$$F_2(x_1^a, x_1^b, x_3^b) := \frac{\partial \Pi_1}{\partial x_1^b} = \frac{v^b x_3^b}{(x_1^b + x_3^b)^2} - s_1(x_1^a + x_1^b), \tag{12}$$

$$F_3(x_1^a, x_2^a) := \frac{\partial \Pi_2}{\partial x_2^a} = \frac{v^a x_1^a}{(x_1^a + x_2^a)^2} - s_2 x_2^a, \tag{13}$$

$$F_4(x_1^b, x_3^b) = \frac{\partial \Pi_3}{\partial x_3^b} = \frac{v^b x_1^b}{(x_1^b + x_3^b)^2} - s_3 x_3^b. \tag{14}$$

We have the following results:[32]

Proposition 1. *Consider the star network depicted in Figure 5 and the payoff functions given by (10). Then, there exists a unique interior Nash equilibrium $(x_1^{a*}, x_1^{b*}, x_2^{a*}, x_3^{a*})$ that simultaneously solves:*

$$\begin{cases} F_1(x_1^{a*}, x_1^{b*}, x_2^{a*}) = 0 \\ F_2(x_1^{a*}, x_1^{b*}, x_3^{b*}) = 0 \\ F_3(x_1^{a*}, x_2^{a*}) = 0 \\ F_4(x_1^{b*}, x_3^{b*}) = 0 \end{cases} \tag{15}$$

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 (15) is highly non-linear and, therefore, there are no explicit expressions for the equilibrium. Instead, we apply the implicit function theorem to the system (15) 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*

$$z(x, y) = \frac{vx}{x + y} - \frac{s}{2}x^2. \tag{16}$$

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 (11)–(14) 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*

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

relationship between the efforts of two players involved in the same battle. Figure 7 depicts this relationship.

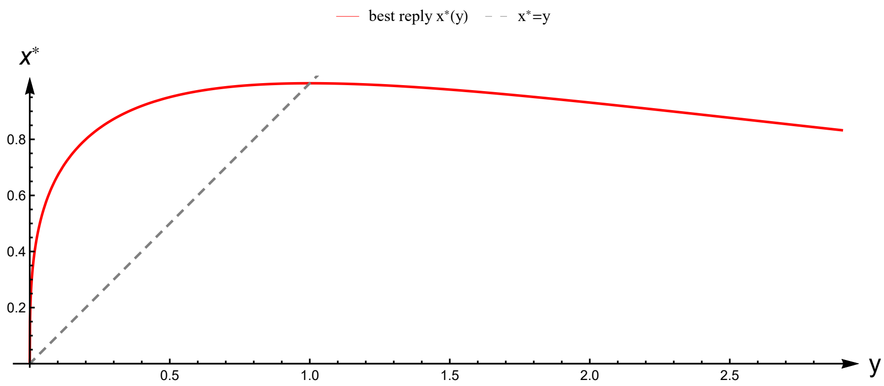


Figure 7: Best response function $x^*(y)$

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.

5.2.3 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 6. 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.[33] 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 5 and 6 and the payoff functions given by (10). 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, $\frac{\partial (x_1^{b*} + x_3^{b*})}{\partial v^a} < 0$.*

[33] 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

$$\frac{\partial^2 \Pi_1}{\partial x_1^a \partial x_1^b} = -\frac{\partial^2 C_1}{\partial x_1^a \partial x_1^b} = -s_1 < 0. \tag{17}$$

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 8, we illustrate our results by plotting the four efforts of the different players when v^a increases.[34] 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.

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

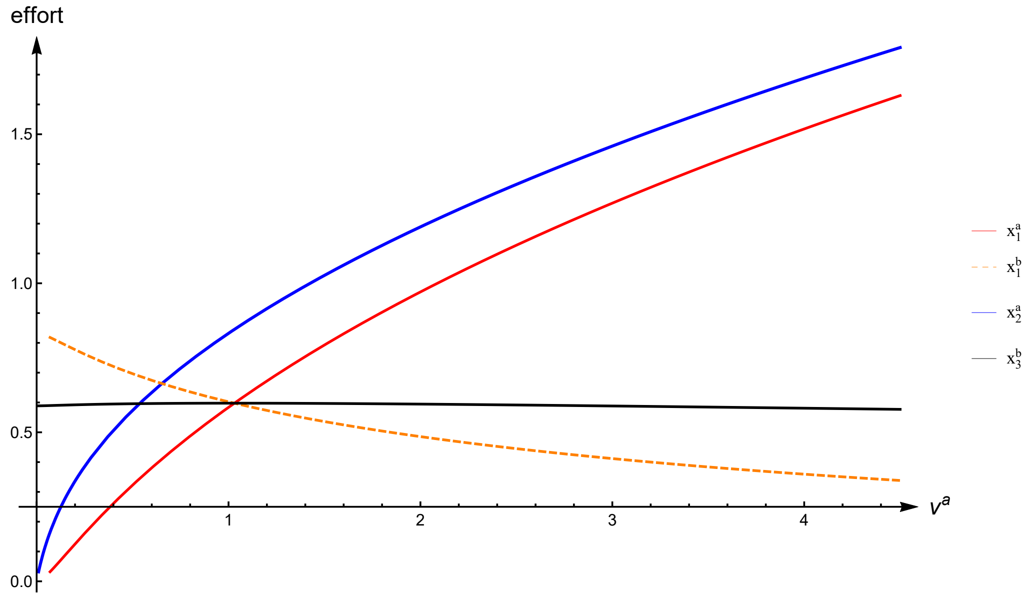


Figure 8: The effect of an increase of v^a on the effort of each agent involved in battles in the network described in Figure 5

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.

5.3 More complex network structure: A line network

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

Figure 9: A line network with four players and three battles

Observe that this network is similar to the one depicted in Figure 5; however, we added a link between players 2 and 4 and battle c.

The matrix $\mathbf{\Gamma}$ representing the network depicted in Figure 9 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 9, there can be four districts, each corresponding to a battle: districts a, b, c, d. This network with districts can be represented as follows:

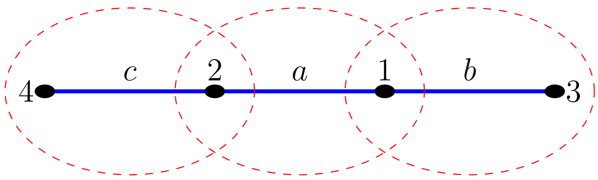


Figure 10: A line network with three districts

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:

$$
\begin{aligned}
\Pi_1(\mathbf{x}_1, \mathbf{x}_{-1}) =& v^a \frac{x_1^a}{x_1^a + x_2^a} + v^b \frac{x_1^b}{x_1^b + x_3^b} - \frac{s_1}{2}(x_1^a + x_1^b)^2, \\
\Pi_2(\mathbf{x}_2, \mathbf{x}_{-2}) =& v^a \frac{x_2^a}{x_1^a + x_2^a} + v^c \frac{x_2^c}{x_2^c + x_4^c} - \frac{s_2}{2}(x_2^a + x_2^c)^2, \\
\Pi_3(\mathbf{x}_3, \mathbf{x}_{-3}) =& v^b \frac{x_3^b}{x_1^b + x_3^b} - \frac{s_3}{2}(x_3^b)^2, \\
\Pi_4(\mathbf{x}_4, \mathbf{x}_{-4}) =& v^c \frac{x_4^c}{x_2^c + x_4^c} - \frac{s_4}{2}(x_4^c)^2.
\end{aligned}
\tag{18}
$$

We have the following result:[35]

Proposition 3. *Consider the line network depicted in Figures 9 and 10 and the payoff functions given by (18). 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 $sign \frac{\partial (x_2^{c*} + x_4^{c*})}{\partial v^b} = sign(x_2^{a^*} - x_1^{a*})$.*

[35] 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 9 is longer than the one in Figure 5, 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.

5.4 Discussion

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) in Section 3, we show in Table 2, Table 3 and Figure 1 that the occurrence of a natural disaster in a district reduces the battle probability in this district. Moreover, in Table 4, we show that the disaster effect is larger in districts with more economic activity (more nighttime light activity) and in districts with a large fraction of agricultural land. Second, (ii) in Table 6, 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 road network and geographic proximity. Finally, in Table 7 and Figure 3, we show that if the district affected by the disaster is a mining district, then this district affects the battle spillovers to itself. In Figure 4, we show that the battle diffusion occurs if the neighboring district is a mining district.

6 Conclusion

This paper examines the direct and spillover effects of battle diffusion in response to a negative economic shock, through a novel network perspective. We analyze the effect of natural disasters on battles in Africa, using a novel panel-dataset that combines geo-referenced information about battle events and natural disasters at the monthly level for 5,944 districts in 53 African countries over the period from 1989 to 2015. Empirical results reveal that natural disasters do indeed decrease battle incidence in the affected district and that they divert fighting activity to surrounding districts, particularly those that are better connected via the geographic and road networks. This shift in combat activity occurs with some significant time lag.

Our fine-grained data helps shed light on the logistics and mechanics underlying broader patterns in the literature, thereby providing some novel insights on the dynamics of local conflicts and spatial-conflict spillovers. In particular, we show that some patterns of local conflicts are not necessarily picked up by aggregate, annual data, while spatial-spillover effects only materialize itself in a longer, more aggregated data. We also show that the diffusion effects differ by the nature of connectivity between districts; roads and geographic districts have a distinct effect both in magnitude and time horizons associated to battle spillovers. In terms of the mechanisms, our results highlight that mining activity plays a crucial role in determining the spatial dynamics of conflict in Africa. Outward shifts in conflict, caused by negative economic shocks, are less likely to occur in mining localities. If a shift occurs, however, mining localities are more likely to be the target of a new combat activity.

To provide a theoretical mechanism for these results, we develop a simple network model in which players are involved in multiple battles. We show that, when a negative shock hits a district, the total battle in this district decreases, while the total battle in neighboring districts increases. We show that a negative shock in a district propagates to path-connected districts because agents shift their effort to other battles in which they are involved, which, in turn, affects the conflict in these battles; and so on. More generally, our model shows that a local shock 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.

More generally, our findings provide a novel perspective on how conflict spreads across space and time. While the existing work in this broad literature focuses on the battle spillovers triggered by events that increase battle probability in the affected locality, our work extends this literature by modeling the spillover effects of violence following a reduction in the battle probability in the affected locality. This "donut" effect of battle diffusion is important not only in the academic discourse, but also for policy makers, as it provides insights on how strategies that mitigate the spread of conflicts should consider the network of connected localities.

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Tables

Table 1: Descriptive Statistics for Key Variables

Variable	**Observations**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
		District Characteristics			
Light	5,944	0.0792	0.2701	0	1
Mine	5,944	0.0436	0.2042	0	1
Agri	5,944	0.2917	0.4546	0	1
		District-Year Aggregation			
$Pr(Battle > 0)$					
All Districts	160,488	0.0344	0.1821	0	1
if DIS >0	10,748	0.0296	0.1695	0	1
if DIS=0	149,740	0.0347	0.1830	0	1
$Pr(DIS > 0)$					
All Disasters	160,488	0.0670	0.2500	0	1
		District-Month Aggregation			
$Pr(Battle > 0)$					
All Districts	1,925,856	0.0056	0.0746	0	1
if DIS>0	11,400	0.0044	0.0661	0	1
if DIS =0	1,914,456	0.0056	0.0746	0	1
$Pr(\text{DIS} > 0)$					
All Disasters	1,925,856	0.0059	0.0767	0	1

Battle 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. Disasters exclude droughts. *Light* = 1 if *Initial Light* in district $i \geqslant 10$ (on a scale of 0-63) and = 0 otherwise. *Mine* = 1 if at least one active mine was present in district i over the sample period, and = 0 otherwise. *Agri* = 1 if more than 50% of the land area of district i was agriculturally suitable, and = 0 otherwise.

Table 2: Natural Disasters and Battles at the District-Year Level

VARIABLES	(1) $Battle_{iy}$	(2) $Battle_{iy}$	(3) $Battle_{iy}$	(4) $Battle_{iy}$	(5) $Battle_{iy}$	(6) $Battle_{iy}$	(7) $Battle_{iy}$	(8) $Battle_{iy}$
DIS_{iy}	-0.0101**	-0.0099*	-0.0080*	-0.0079*	-0.0024	-0.0028	-0.0021	-0.0021
	(0.0050)	(0.0051)	(0.0042)	(0.0042)	(0.0033)	(0.0033)	(0.0030)	(0.0030)
DIS_{iy-1}		-0.0086*		-0.0065*		-0.0050		-0.0045
		(0.0046)		(0.0038)		(0.0032)		(0.0028)
Observations	160,488	154,544	154,544	154,544	160,488	154,544	154,544	154,544
Number of Districts	5,944	5,944	5,944	5,944	5,944	5,944	5,944	5,944
District FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	NO	NO	NO	NO
Country × Year	NO	NO	NO	NO	YES	YES	YES	YES
Other Controls	NO	NO	YES	YES	NO	NO	YES	YES

Battle 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 year y. Disasters exclude droughts. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 3: Natural Disasters and Battles at the District-Month Level

VARIABLES	(1) $Battle_{iym}$	(2) $Battle_{iym}$	(3) $Battle_{iym}$	(4) $Battle_{iym}$	(5) $Battle_{iym}$	(6) $Battle_{iym}$	(7) $Battle_{iym}$	(8) $Battle_{iym}$
DIS_{iym}	-0.0025***	-0.0025***	-0.0026***	-0.0026***	-0.0015**	-0.0015**	-0.0014**	-0.0015**
	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0007)
$DIS_{iy,m-1}$		-0.0027***		-0.0021***		-0.0017**		-0.0018**
		(0.0008)		(0.0007)		(0.0007)		(0.0007)
Observations	1,925,856	1,919,912	1,919,912	1,919,912	1,925,856	1,919,912	1,919,912	1,919,912
Number of Districts	5,944	5,944	5,944	5,944	5,944	5,944	5,944	5,944
District-FE	YES	YES	YES	YES	NO	NO	NO	NO
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	NO	NO	NO	NO
District × Year FE	NO	NO	NO	NO	YES	YES	YES	YES
Other Controls	NO	NO	YES	YES	NO	NO	YES	YES

Battle 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 month m of year y. Disasters exclude droughts. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the *country* × *year* level in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

Table 4: Natural Disasters and Battles at the District-Month Level: Channels

VARIABLES	(1) $Battle_{iym}$	(2) $Battle_{iym}$	(3) $Battle_{iym}$	(4) $Battle_{iym}$
$DIS_{iy,m}$	-0.0015**	-0.0012	-0.0014**	-0.0010
	(0.0006)	(0.0007)	(0.0007)	(0.0008)
$DIS_{iy,m-1}$	-0.0013*	-0.0013	-0.0018**	-0.0007
	(0.0007)	(0.0009)	(0.0007)	(0.0009)
$DIS_{iy,m} \times Light_i$	-0.0008			-0.0011
	(0.0025)			(0.0026)
$DIS_{iy,m-1} \times Light_i$	-0.0063***			-0.0069***
	(0.0024)			(0.0025)
$DIS_{iy,m} \times Agri_i$		-0.0012		-0.0013
		(0.0011)		(0.0012)
$DIS_{iy,m-1} \times Agri_i$		-0.0018		-0.0024*
		(0.0012)		(0.0013)
$DIS_{iy,m} \times Mine_i$			-0.0012	-0.0012
			(0.0020)	(0.0020)
$DIS_{iy,m-1} \times Mine_i$			0.0003	0.0003
			(0.0016)	(0.0017)
Observations	1,919,912	1,919,912	1,919,912	1,919,912
Number of Districts	5,944	5,944	5,944	5,944
Month FE	YES	YES	YES	YES
District × Year FE	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES

Battle 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 district i in month m of year y. Disasters exclude droughts. *Light*=1 if average nighttime light in 1992 (i.e. initial light) >10 (on a scale of 0-63), and 0 otherwise. *Agri*=1 if the fraction of land suitable for agriculture in district i is above 50%, and 0 otherwise. $Mine$ = 1 if the district hosted at least one active mining project over the sample period, and 0 otherwise. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Natural Disasters and Battle Diffusion at the District-Month Level

VARIABLES	(1) $Battle_{iym}$	(2) $Battle_{iym}$	(3) $Battle_{iym}$
Inverse Geodesic Distance			
$NDIS_{iym}$	-0.0002		-0.0005
	(0.0003)		(0.0004)
$NDIS_{iy,m-1}$	-0.0003		-0.0006
	(0.0003)		(0.0004)
$NBattle_{iym}$	0.0031***		0.0015***
	(0.0004)		(0.0003)
$NBattle_{iy,m-1}$	0.0006		-0.0001
	(0.0005)		(0.0005)
Inverse Road Distance			
$NDIS_{iym}$		0.0003	0.0007
		(0.0005)	(0.0005)
$NDIS_{iy,m-1}$		0.0003	0.0008
		(0.0005)	(0.0006)
$NBattle_{iym}$		0.0064***	0.0058***
		(0.0009)	(0.0008)
$NBattle_{iy,m-1}$		0.0022***	0.0022***
		(0.0006)	(0.0005)
DIS_{iym}	-0.0012	-0.0017**	-0.0016*
	(0.0008)	(0.0008)	(0.0008)
$DIS_{iy,m-1}$	-0.0014*	-0.0018**	-0.0017**
	(0.0008)	(0.0009)	(0.0009)
Observations	1,919,912	1,919,912	1,919,912
Number of Districts	5,944	5,944	5,944
Distance Cut-off	500km	500km	500km
Month FE	YES	YES	YES
District × Year FE	YES	YES	YES
Other Controls	YES	YES	YES

Battle 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* (*NBattle*) 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 and the inverse road distance matrix, truncated at the indicated distance cut-off. Disasters exclude droughts. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Natural Disasters and Battle Diffusion at the District-Year Level

VARIABLES	(1) $Battle_{iy}$	(2) $Battle_{iy}$	(3) $Battle_{iy}$
Inverse Geodesic Distance			
$NDIS_{iy}$	0.0042		0.0034
	(0.0030)		(0.0029)
$NDIS_{iy-1}$	0.0118***		0.0108***
	(0.0036)		(0.0033)
$NBattle_{iy}$	0.0015		-0.0023
	(0.0021)		(0.0020)
$NBattle_{iy-1}$	0.0057***		0.0032
	(0.0021)		(0.0020)
Inverse Road Distance			
$NDIS_{iy}$		0.0048**	0.0042*
		(0.0023)	(0.0023)
$NDIS_{iy-1}$		0.0037	0.0016
		(0.0023)	(0.0022)
$NBattle_{iy}$		0.0204***	0.0205***
		(0.0035)	(0.0034)
$NBattle_{iy-1}$		0.0106***	0.0102***
		(0.0027)	(0.0027)
DIS_{iy}	-0.0022	-0.0027	-0.0028
	(0.0030)	(0.0029)	(0.0029)
DIS_{iy-1}	-0.0048*	-0.0055**	-0.0053*
	(0.0028)	(0.0028)	(0.0028)
Observations	154,544	154,544	154,544
Number of Districts	5,944	5,944	5,944
Distance Cut-off	500km	500km	500km
District FE	YES	YES	YES
Country× Year FE	YES	YES	YES
Other Controls	YES	YES	YES

Battle 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* (*NBattle*) 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 and the inverse road distance matrix, truncated at the indicated distance cut-off. Disasters exclude droughts. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Natural Disasters and Battle Diffusion Mechanisms at the District-Year Level

VARIABLES	(1) $Battle_{iy}$	(2) $Battle_{iy}$	(3) $Battle_{iy}$
Inverse Geodesic Distance			
$NDIS_{iy}$	0.0015		0.0018
	(0.0034)		(0.0034)
$NDIS_{iy} \times Light_i$	0.0081		0.0049
	(0.0110)		(0.0098)
$NDIS_{iy} \times Mine_i$	0.0074		0.0010
	(0.0051)		(0.0055)
$NDIS_{iy} \times Agri_i$	-0.0044		-0.0049
	(0.0044)		(0.0049)
$NDIS_{iy} \times Light_j$	-0.0007		-0.0001
	(0.0043)		(0.0041)
$NDIS_{iy} \times Mine_j$	-0.0018		-0.0008
	(0.0037)		(0.0037)
$NDIS_{iy} \times Agri_j$	0.0077		0.0062
	(0.0048)		(0.0045)
$NBattle_{iy}$	0.0017		-0.0022
	(0.0021)		(0.0020)
$NDIS_{iy-1}$	0.0136***		0.0119***
	(0.0037)		(0.0034)
$NDIS_{iy-1} \times Light_i$	-0.0093		-0.0030
	(0.0136)		(0.0127)
$NDIS_{iy-1} \times Mine_i$	-0.0000		-0.0016
	(0.0054)		(0.0060)
$NDIS_{iy-1} \times Agri_i$	0.0031		0.0016
	(0.0038)		(0.0042)
$NDIS_{iy-1} \times Light_j$	-0.0036		-0.0025
	(0.0037)		(0.0035)
$NDIS_{iy-1} \times Mine_j$	-0.0050		-0.0033
	(0.0043)		(0.0043)
$NDIS_{iy-1} \times Agri_j$	0.0011		0.0008
	(0.0050)		(0.0050)
$NBattle_{iy-1}$	0.0055***		0.0030
	(0.0021)		(0.0020)
Inverse Road Distance			
$NDIS_{iy}$		0.0044	0.0033
		(0.0029)	(0.0029)
$NDIS_{iy} \times Light_i$		0.0093	0.0066
		(0.0115)	(0.0109)
$NDIS_{iy} \times Mine_i$		0.0115**	0.0108**
		(0.0050)	(0.0053)
$NDIS_{iy} \times Agri_i$		-0.0006	0.0018
		(0.0038)	(0.0042)
$NDIS_{iy} \times Light_j$		-0.0023	-0.0019
		(0.0034)	(0.0033)
$NDIS_{iy} \times Mine_j$		-0.0049	-0.0049
		(0.0036)	(0.0035)
$NDIS_{iy} \times Agri_j$		0.0025	0.0016
		(0.0031)	(0.0031)
$NBattle_{iy}$		0.0203***	0.0203***
		(0.0035)	(0.0034)
$NDIS_{iy-1}$		0.0067**	0.0046
		(0.0030)	(0.0029)
$NDIS_{iy-1} \times Light_i$		-0.0117	-0.0103
		(0.0117)	(0.0102)
$NDIS_{iy-1} \times Mine_i$		0.0045	0.0047
		(0.0048)	(0.0052)
$NDIS_{iy-1} \times Agri_i$		0.0028	0.0028
		(0.0036)	(0.0041)
$NDIS_{iy-1} \times Light_j$		-0.0045	-0.0038
		(0.0037)	(0.0037)
$NDIS_{iy-1} \times Mine_j$		-0.0091**	-0.0086**
		(0.0037)	(0.0035)
$NDIS_{iy-1} \times Agri_j$		-0.0007	-0.0002
		(0.0034)	(0.0034)
$NBattle_{iy-1}$		0.0105***	0.0100***
		(0.0027)	(0.0026)
DIS_{iy}	-0.0022	-0.0029	-0.0028
	(0.0030)	(0.0029)	(0.0029)
DIS_{iy-1}	-0.0044	-0.0047*	-0.0044*
	(0.0028)	(0.0026)	(0.0026)
Observations	154,544	154,544	154,544
Number of Districts	5,944	5,944	5,944
Distance Cut-off	500km	500km	500km
District FE	YES	YES	YES
Country× Year FE	YES	YES	YES
Other Controls	YES	YES	YES

Online Appendix

Conflicts in Spatial Networks

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A Additional figures

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Figure B.1: Distribution of battles in Africa

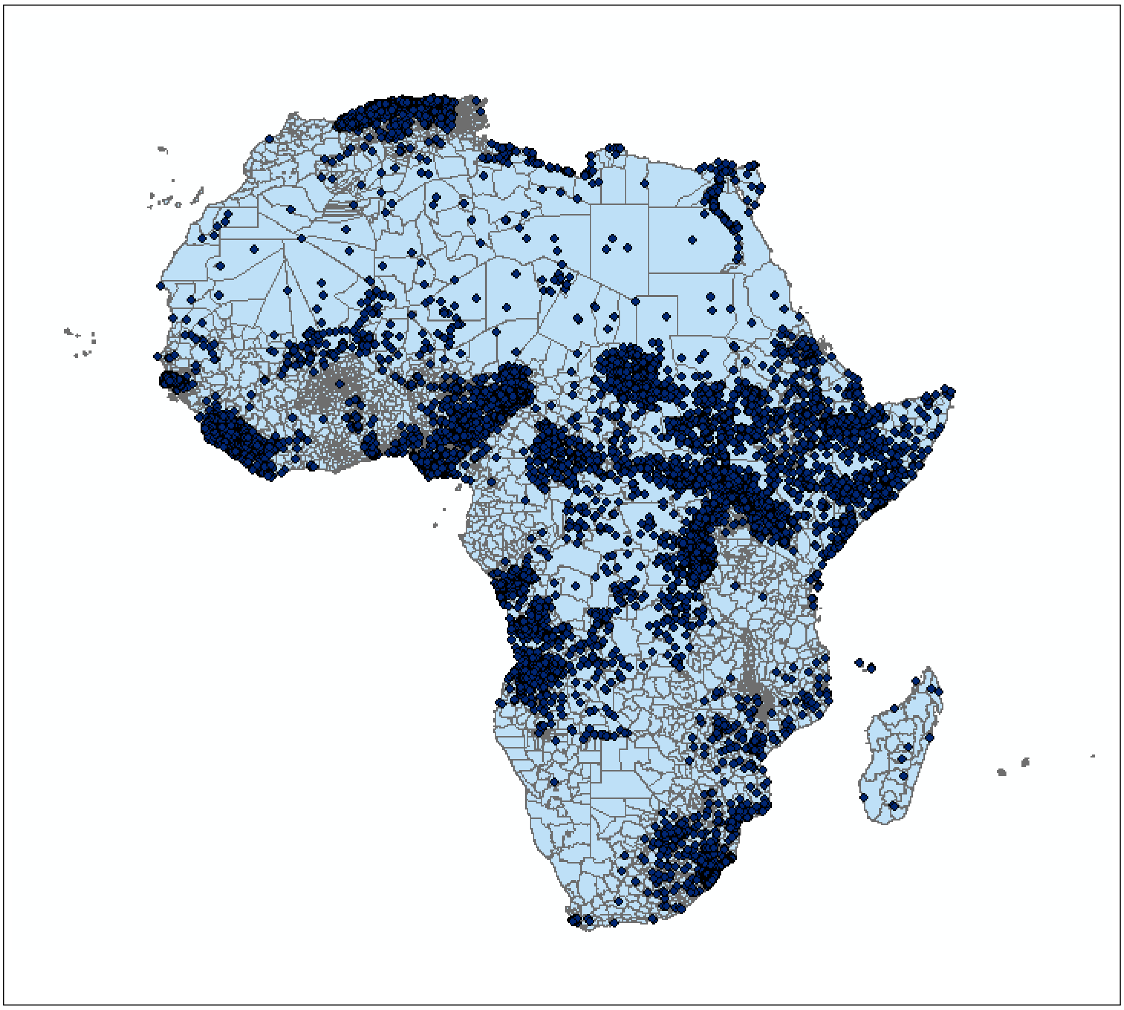


Figure B.2: Distribution of natural disasters in Africa

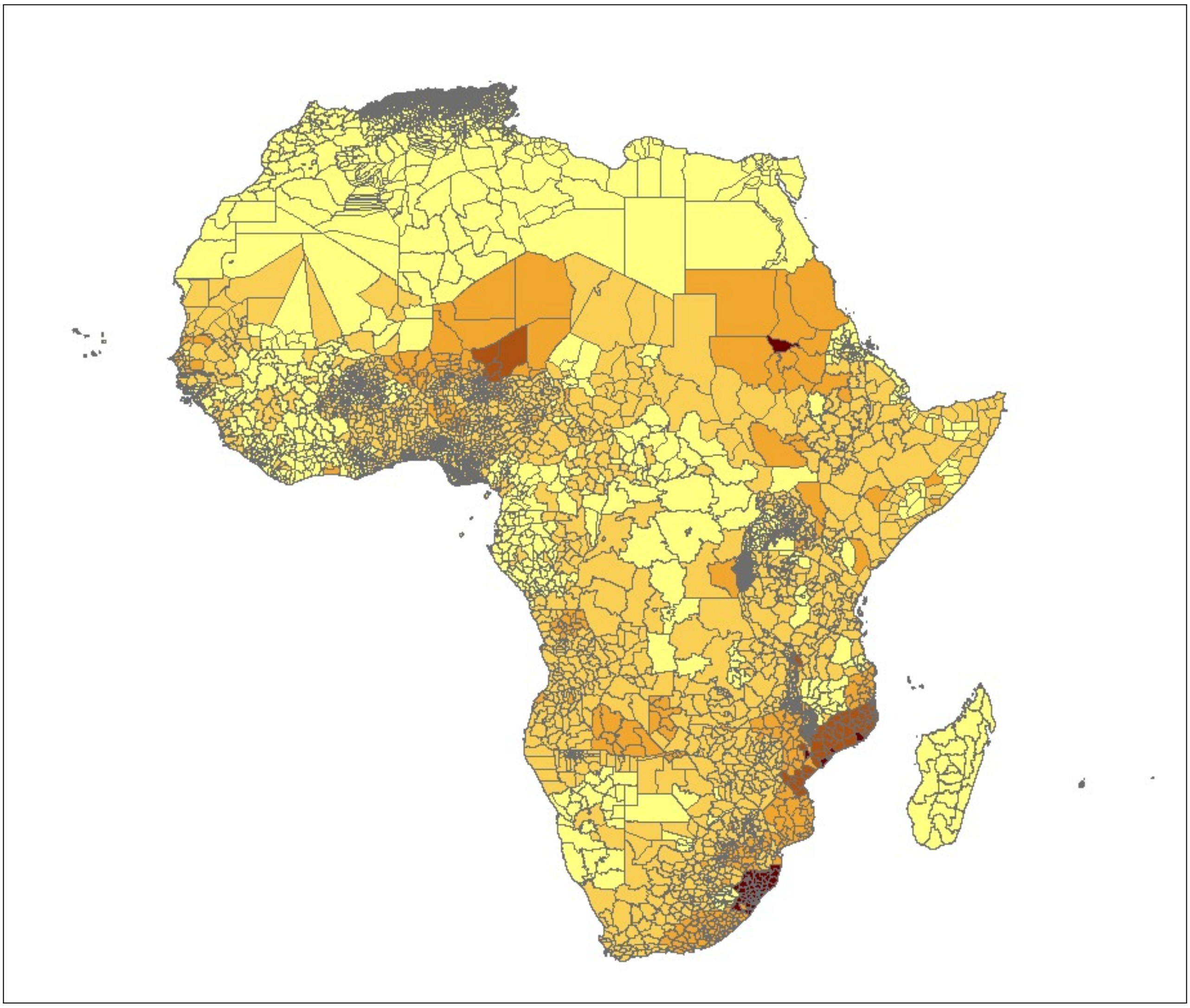
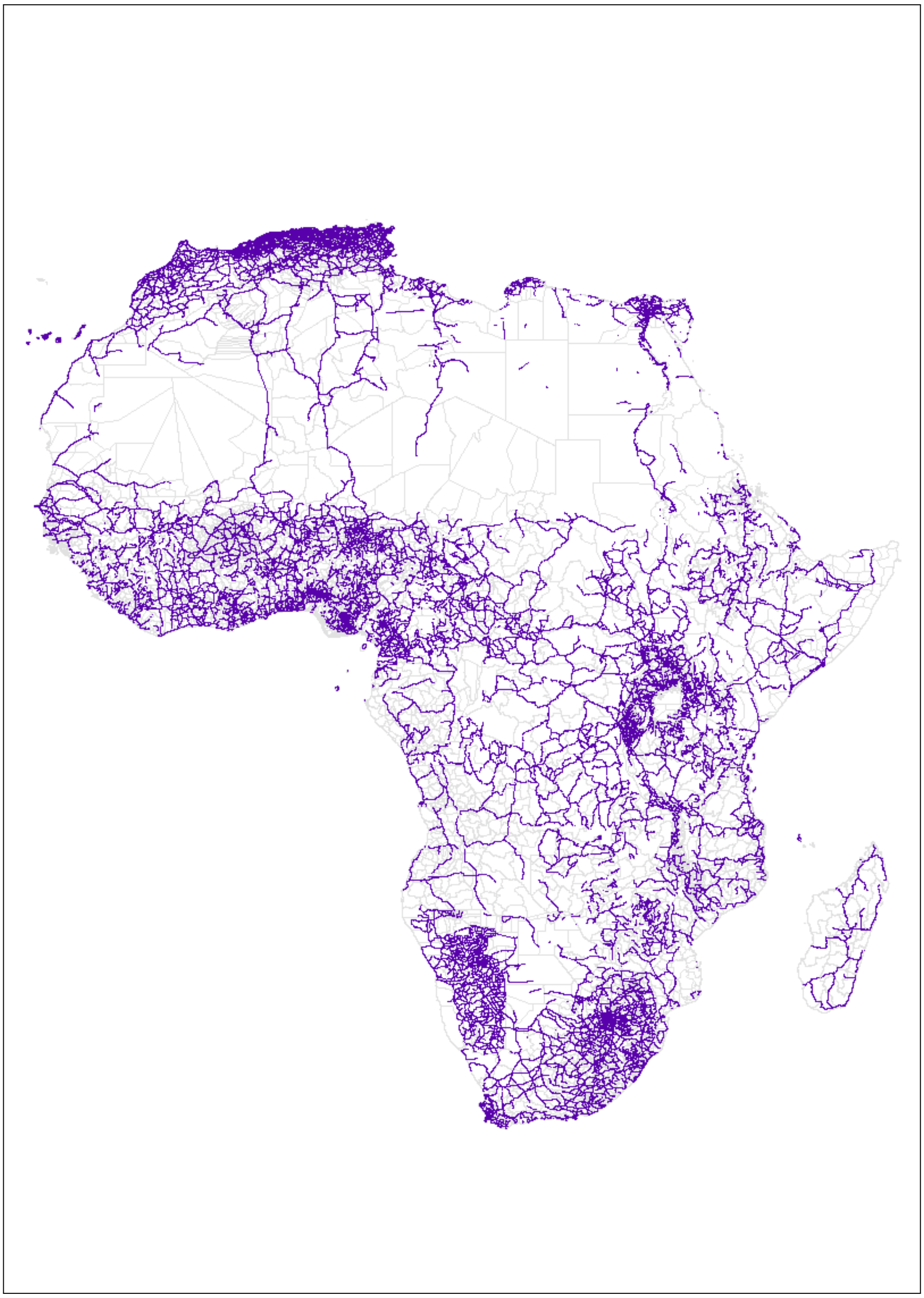


Figure B.3: Road connectivity in Africa



B Robustness checks

Appendix B presents the results from a number of robustness checks.

First, in Section B.1, we estimate the local effect of natural disasters on battles when aggregated at the *country* level (Table C.1.1). We observe that there is no statistically significant relationship at this coarse level of aggregation, and this, in turn, highlights the need for a more disaggregated analysis.

Second, in Section B.2, we perform some robustness checks at the *district-month* level. In Figure C.2.1, we conduct a robustness check where leads of the main explanatory variables are included in the specification, in addition to their lags, in the spirit of an event study specification. We observe that while the lags maintain their statistical significance (approximately up to 5 monthly lags), no statistically significant pre-trends are observed.

In Figure C.2.2 we display a number of robustness checks when including alternative sets of fixed effects. For each set of fixed effects, we present estimates including and excluding the LDV. We observe that the baseline estimates remain robust to these alternative sets of fixed effects as well.

In Table C.2.1, we replicate Table 2, but allow for spatial clustering of standard errors instead of clustering at the country×year level. Accordingly, here we present spatial heteroscedasticity and autocorrelation consistent (HAC) standard errors, allowing for spatial correlation up to 100km and for infinite serial correlation[5]. As these results indicate, our baseline estimates are quite robust to this alternative clustering approach.

In Table C.2.2, we replicate the specification in Eq (2), but additionally includes higher order autoregressive terms. We show that the magnitude and statistical significance of the variable of interest does not change drastically once these controls are included. In Table

[5]This procedure was implemented in Stata 14 using the “acreg” command by Colella et al. (2019).

C.2.3, we use the count of battles at the district-month level instead of a binary indicator. We observe that the negative effect of disasters is still there under this definition of battles as well. In Table C.2.4, we use alternative definitions of the dependent variable. We identify that the negative effect of natural disasters on battles stems mostly from battles involving state and non-state actors and not from one-sided battles.

In Table C.2.5, we use alternative definitions of the independent variable. Large disasters show a negative effect on battles in the period of occurrence, while the negative effect of small disasters occurs with a time lag. Climatic disasters lead to a reduction of battle incidence at the 1% level of statistical significance, while the effect of geologic disasters is statistically insignificant.

We distinguish between battle onset and termination in Table C.2.6. In order to do this, we first generate binary indicators to identify the first period of battle in a district (onset) and the last period of battle in a district (termination). Results indicate that natural disasters have a statistically significant effect on increasing the termination of battles, and no statistically significant effect on battle onset. This result further proves that natural disasters lead to a permanent appeasing effect in the context of Africa.

In Table C.2.7 we conduct a robustness check on the channels explored in the empirical analysis. In Table 4 we defined a district as one with high level of economic activity if it recorded an initial nighttime light value > 10 (on a scale of 0-63). In Table C.2.7, we check if these estimates are robust to alternative thresholds of the initial nighttime light value. Accordingly, we use 5 threshold scores from 10 to 50, in intervals of 10. As indicated, results remain qualitatively and quantitatively similar to those reported in Table 4.

Next, we look at the diffusion of battles along the geographic network at different distance cutoffs (Table C.2.8). As discussed before, in the short run, we do not see an effect of battle diffusion along the geographic network, even when truncated at shorter distances.

In Section B.3 we conduct the same robustness checks as in Section B.2, but at the *district-year* level of aggregation. We observe that the local effect (Tables C.3.1 to Table C.3.5) are less precisely defined at the district-year level than at the district-month level. By contrast, the diffusion effects (Table C.3.7) are more prominent in the medium to long run i.e. at the year level. Specifically, in Figure C.3.1, we show that the baseline spillover estimates are robust to the inclusion of alternative sets of fixed effects combining country, district and year levels. Moreover, these spillover results are robust to the exclusion of battles in neighbouring districts, as well as the direct effect of natural disasters in the affected district.

Finally, in Table C.3.8 we address concerns on the potential occurrence of the well-known Nickell bias when including a lagged dependent variable in a fixed effects specification. Panel A in Table C.3.8 presents results of specifications without the lagged dependent variable as well as results of a LDV model. The results show that the coefficients of our key explanatory variables remain very similar.

B.1 Robustness Checks at the Country-Year Level

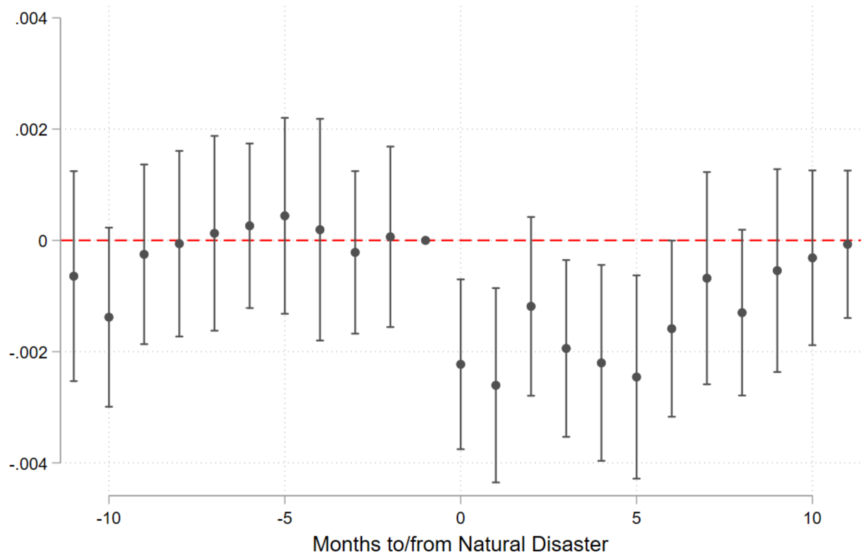
Table C.1.1: Natural Disasters and Battles at Country Level

VARIABLES	(1) Country-Year Level $Battle_{cy}$	(2) Country-Month Level $Battle_{cy,m}$
DIS_{cy}	-0.0043	
	(0.0277)	
DIS_{cy-1}	-0.0347	
	(0.0224)	
$DIS_{cy,m}$		0.1060
		(0.0117)
$DIS_{cy,m-1}$		0.0033
		(0.0128)
Observations	1,378	17,119
Number of Geographic Units	53	53
Month FE	NO	YES
Year FE	YES	YES
Country FE	YES	YES
Country × Year FE	NO	NO
Other Controls	YES	YES

Battle 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 geographic unit in the given time period. Disasters exclude droughts. Additional controls include $Battle_{it-1}$. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

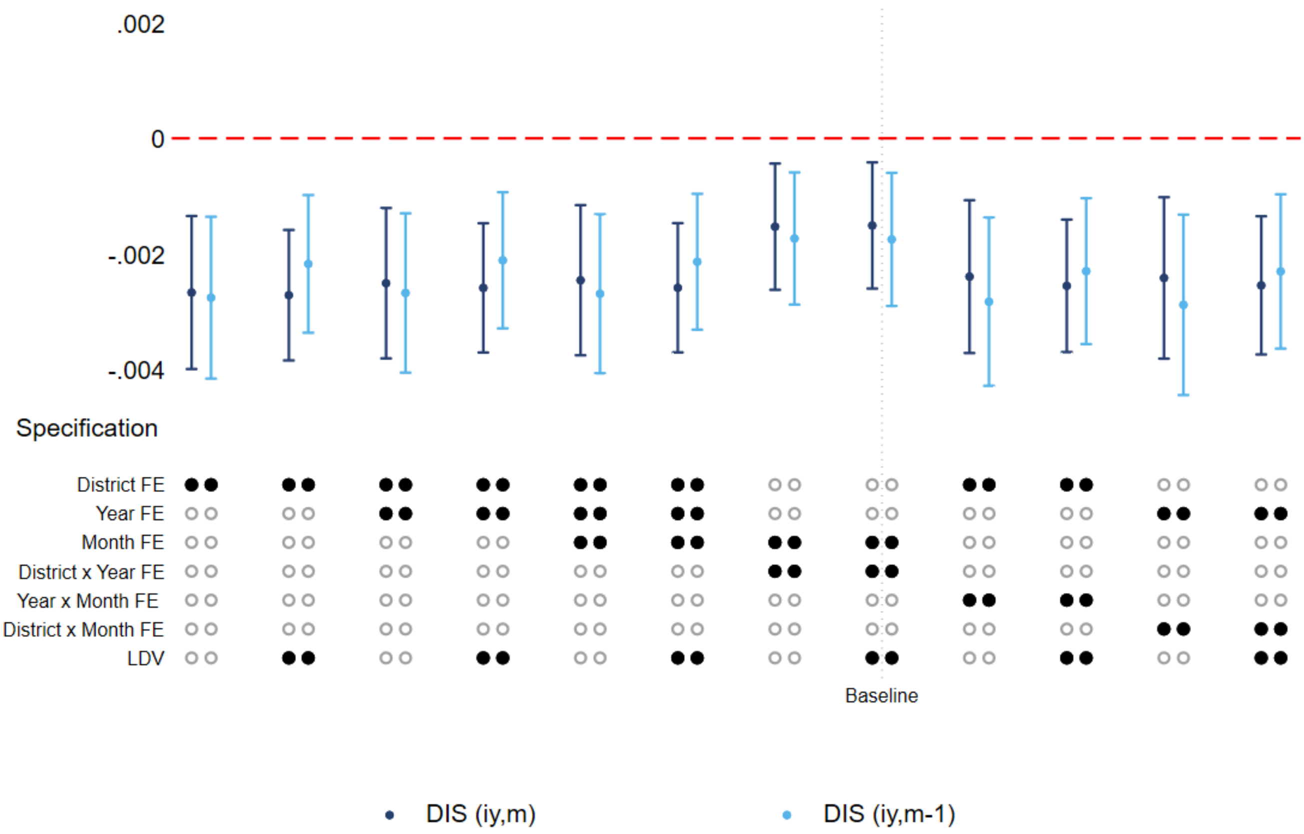
B.2 Robustness Checks at the District-Month Level

Figure C.2.1: Direct effect of natural disasters on battles: Event study estimates



Notes: Dots show the regression results using Eq. (2) and including up to 11 temporal lags and leads of the independent variable $Disaster_{iym}$. Country $\times$ year fixed effects and month fixed effects are included. Vertical lines show the 90% confidence interval based on standard errors clustered at the country$\times$year level.

Figure C.2.2: Direct effect of natural disasters on battles: Alternative specifications



Notes: Dots show the effects of the contemporary ($DIS_{iy,m}$) and one-period lagged ($DIS_{iy,m-1}$) direct effect of natural disasters on battle probability, as per Eq. (2). Each specification includes a set of fixed effects as specified in the grid. For each set of fixed effects, estimates with and without the LDV are displayed. Vertical lines show the 90% confidence interval based on standard errors clustered at the country×year level.

Table C.2.1: Natural Disasters and Battles at the District-Month Level - Spatial Clustering of Standard Errors

VARIABLES	(1) $Battle_{iy,m}$	(2) $Battle_{iy,m}$	(3) $Battle_{iy,m}$	(4) $Battle_{iy,m}$	(5) $Battle_{iy,m}$	(6) $Battle_{iy,m}$	(7) $Battle_{iy,m}$	(8) $Battle_{iy,m}$
$DIS_{iy,m}$	-0.0025***	-0.0025***	-0.0026***	-0.0026***	-0.0015**	-0.0015***	-0.0014**	-0.0015***
	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
$DIS_{iy,m-1}$		-0.0027***		-0.0021***		-0.0017***		-0.0018***
		(0.0007)		(0.0006)		(0.0005)		(0.0005)
Observations	1,925,856	1,919,912	1,919,912	1,919,912	1,925,856	1,919,912	1,919,912	1,919,912
Number of Districts	5,944	5,944	5,944	5,944	5,944	5,944	5,944	5,944
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
District-FE	YES	YES	YES	YES	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	NO	NO	NO	NO
District $\times$ Year FE	NO	NO	NO	NO	YES	YES	YES	YES
Other Controls	NO	NO	YES	YES	NO	NO	YES	YES

Battle 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 month m of year y. Disasters exclude droughts. Other controls include $Battle_{iy,m-1}$. Spatial HAC standard errors, allowing for spatial correlation up to 100km and for infinite serial correlation, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.2.2: Natural Disasters and Battles at the District-Month Level - With Higher Order Autoregressive Terms

	(1)	(2)
VARIABLES	$Battle_{iym}$	$Battle_{iym}$
DIS_{iym}	-0.0014**	-0.0015**
	(0.0006)	(0.0007)
$DIS_{iy,m-1}$		-0.0016**
		(0.0007)
$Battle_{iy,m-1}$	-0.0118**	-0.0121**
	(0.0055)	(0.0057)
$Battle_{iy,m-2}$		-0.0427***
		(0.0042)
Observations	1,919,912	1,913,968
Number of districts	5,944	5,944
Month FE	YES	YES
District × Year FE	YES	YES
Other Controls	YES	YES

This Table includes higher order autoregressive terms i.e. $Battle_{iy,m-1}$ $Battle_{iy,m-2}$ and $Battle_{iy,m-3}$ as additional controls. *Battle* 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 the given district in the given time period. Disasters exclude droughts. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the *country* × *year* level in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

Table C.2.3: Natural Disasters and Battles at the District-Month Level - Battle Intensity

VARIABLES	(1) $Battle_{iym}$	(2) $Battle_{iym}$
DIS_{iym}	-0.0023*	-0.0024*
	(0.0014)	(0.0007)
$DIS_{iy,m-1}$		-0.0024**
		(0.0011)
Observations	1,919,912	1,919,912
Number of districts	5,944	5,944
Month FE	YES	YES
District × Year FE	YES	YES
Other Controls	YES	YES

Battle is a count variable indicating the sum of all battle events resulting in at least one death in the given district in the given time period. 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. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the *country* × *year* level in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

Table C.2.4: Alternative Definition of the Dependent Variable

VARIABLES	(1) $State$ $Battle_{iym}$	(2) $Non-State$ $Battle_{iym}$	(3) $Onesided$ $Battle_{iym}$	(4) $State/Non-State$ $Battle_{iym}$
DIS_{iym}	-0.0009**	-0.0004	0.0003	-0.0015**
	(0.0004)	(0.0005)	(0.0004)	(0.0006)
$DIS_{iy,m-1}$	-0.0010**	-0.0004	-0.0004	-0.0015**
	(0.0005)	(0.0005)	(0.0004)	(0.0006)
Observations	1,919,912	1,919,912	1,919,912	1,919,912
Number of Districts	5,944	5,944	5,944	5,944
District FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
District × Year FE	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES

$Battle$ 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 the given district in the given time period. *State* ($NonState$) *Battle* is a binary variable indicating the presence (=1) or absence (=0) of a battle leading to at least one death, where at least one party was the state (both parties were nonstate), and both parties used force. *Onesided Battle* is a binary variable indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, where only one party used force and the other party did not retaliate. $State_/Non-State\ Battle$ is a binary variable indicating the presence (=1) or absence (=0) of a State or Non-State battle resulting in at least one death, and does not include Onesided battles. Disasters exclude droughts. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the $country \times year$ level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.2.5: Alternative Definition of the Independent Variable - District-Month Level

VARIABLES	(1) $Battle_{iym}$	(2) $Battle_{iym}$	(3) $Battle_{iym}$	(4) $Battle_{iym}$
$Large\ DIS_{iym}$	-0.0015**			
	(0.0008)			
$Large\ DIS_{iy,m-1}$	-0.0014			
	(0.0009)			
$Small\ DIS_{iym}$		-0.0015		
		(0.0013)		
$Small\ DIS_{iy,m-1}$		-0.0023*		
		(0.0012)		
$Climatic\ DIS_{iym}$			-0.0008	
			(0.0006)	
$Climatic\ DIS_{iy,m-1}$			-0.0018***	
			(0.0006)	
$Geologic\ DIS_{iym}$				-0.0175
				(0.0116)
$Geologic\ DIS_{iy,m-1}$				-0.0128
				(0.0106)
Observations	1,919,912	1,919,912	1,919,912	1,919,912
Number of Districts	5,944	5,944	5,944	5,944
District FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
District × Year FE	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES

Battle 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 the given district in the given time period. *Large DIS* is a binary variable indicating the presence (=1) or absence (=0) of a disasters 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. *Climatic* (*Geologic*) *DIS* is a binary variables indicating the presence (=1) or absence (=0) of a climatic (geologic) natural disaster event in the given district in the given time period. Disasters exclude droughts. Geologic disasters include volcanic eruptions, natural explosions, avalanches, landslides, and earthquakes. Climatic disasters include floods, cyclones, hurricanes, ice storms, snowstorms, tornadoes, typhoons, and storms. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.2.6: Natural Disasters, Battle Onset and Termination - District-Month level

VARIABLES	(1) $Onset_{iy,m}$	(2) $Termination_{iy,m}$
$DIS_{iy,m}$	0.0003	0.0009**
	(0.0002)	(0.0004)
$DIS_{iy,m-1}$	0.0000	0.0002
	(0.0002)	(0.0003)
Observations	1,563,293	1,675,017
Number of Districts	5,919	5,944
Month FE	YES	YES
District × Year FE	YES	YES
Other Controls	YES	YES

$Onset$ is a binary indicator = 0 in periods with no battle events; = 1 in the first time period a district experiences a battle; and missing in subsequent time periods. $Termination$ is a binary indicator = 0 in periods of battle; = 1 in the first period with no battle; 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. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.2.7: Natural Disasters and Battles at the District-Month Level: Channels - Sensitivity to Light Threshold

VARIABLES	(1) $Battle_{iym}$	(2) $Battle_{iym}$	(3) $Battle_{iym}$	(4) $Battle_{iym}$	(5) $Battle_{iym}$
DIS_{iym}	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$DIS_{iy,m-1}$	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$DIS_{iym} \times Light_i$	-0.001	0.000	0.002	0.003	0.003
	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
$DIS_{iy,m-1} \times Light_i$	-0.007***	-0.008***	-0.007**	-0.008**	-0.008
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
$DIS_{iym} \times Agri_i$	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$DIS_{iy,m-1} \times Agri_i$	-0.002*	-0.002*	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$DIS_{iym} \times Mine_i$	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$DIS_{iy,m-1} \times Mine_i$	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	1,919,912	1,919,912	1,919,912	1,919,912	1,919,912
Number of Districts	5,944	5,944	5,944	5,944	5,944
Month FE	YES	YES	YES	YES	YES
District × Year FE	YES	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES	YES
Initial Light >	10	20	30	40	50

Battle 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 district i in month m of year y. Disasters exclude droughts. *Light*=1 if average nighttime light in 1992 (i.e. initial light) > indicated value (on a scale of 0-63), and 0 otherwise. *Agri*=1 if the fraction of land suitable for agriculture in district i is above 50%, and 0 otherwise. $Mine = 1$ if the district hosted at least one active mining project over the sample period, and 0 otherwise. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the $country \times year$ level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

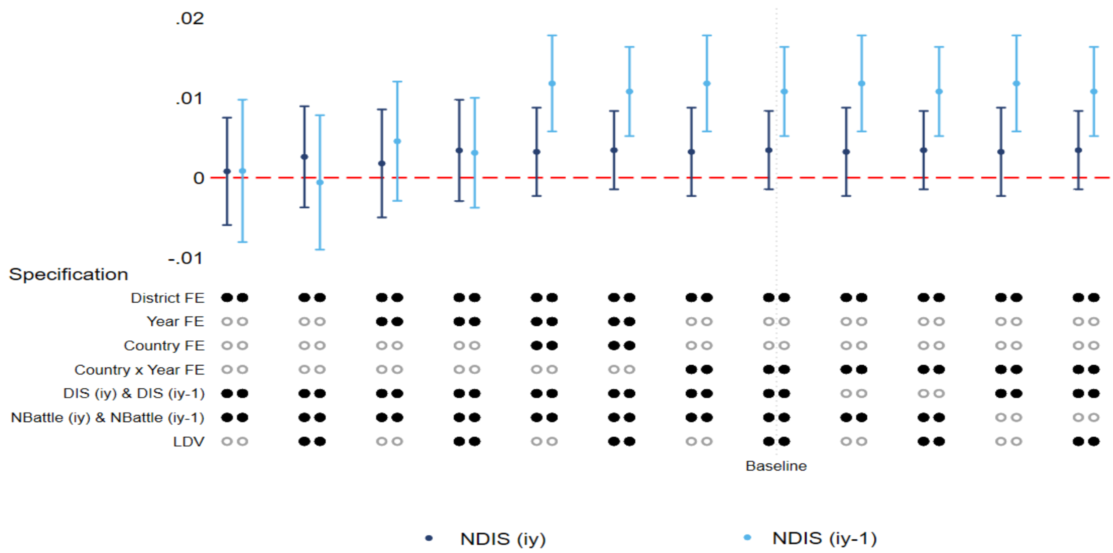
Table C.2.8: Natural Disasters and Battle Diffusion at the District-Month Level - Robustness to Alternative Distance Cut-offs

VARIABLES	(1) $Battle_{iym}$	(2) $Battle_{iym}$	(3) $Battle_{iym}$	(4) $Battle_{iym}$	(5) $Battle_{iym}$
Inverse Geodesic Distance					
$NDIS_{iym}$	0.0002	-0.0004	-0.0006	-0.0004	-0.0005
	(0.0006)	(0.0005)	(0.0006)	(0.0004)	(0.0004)
$NDIS_{iy,m-1}$	-0.0006	-0.0006	-0.0007	-0.0005	-0.0006
	(0.0006)	(0.0005)	(0.0005)	(0.0004)	(0.0004)
$NBattle_{iym}$	0.0051***	0.0031***	0.0026***	0.0020***	0.0015***
	(0.0008)	(0.0005)	(0.0004)	(0.0003)	(0.0003)
$NBattle_{iy,m-1}$	0.0015**	0.0004	0.0005	0.0003	-0.0001
	(0.0007)	(0.0007)	(0.0005)	(0.0005)	(0.0005)
Inverse Road Distance					
$NDIS_{iym}$	-0.0000	0.0003	0.0005	0.0006	0.0007
	(0.0009)	(0.0007)	(0.0007)	(0.0005)	(0.0005)
$NDIS_{iy,m-1}$	0.0003	0.0006	0.0007	0.0002	0.0008
	(0.0010)	(0.0008)	(0.0007)	(0.0006)	(0.0006)
$NBattle_{iym}$	0.0092***	0.0074***	0.0064***	0.0061***	0.0058***
	(0.0016)	(0.0012)	(0.0009)	(0.0009)	(0.0008)
$NBattle_{iy,m-1}$	0.0038***	0.0028***	0.0023***	0.0022***	0.0022***
	(0.0007)	(0.0005)	(0.0004)	(0.0004)	(0.0005)
DIS_{iym}	-0.0016*	-0.0013	-0.0013	-0.0015*	-0.0016*
	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
$DIS_{iy,m-1}$	-0.0014	-0.0014	-0.0015*	-0.0013	-0.0017**
	(0.0011)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Observations	1,919,912	1,919,912	1,919,912	1,919,912	1,919,912
Number of Districts	5,944	5,944	5,944	5,944	5,944
Distance Cutoff	100km	200km	300km	400km	500km
Month FE	YES	YES	YES	YES	YES
District × Year FE	YES	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES	YES

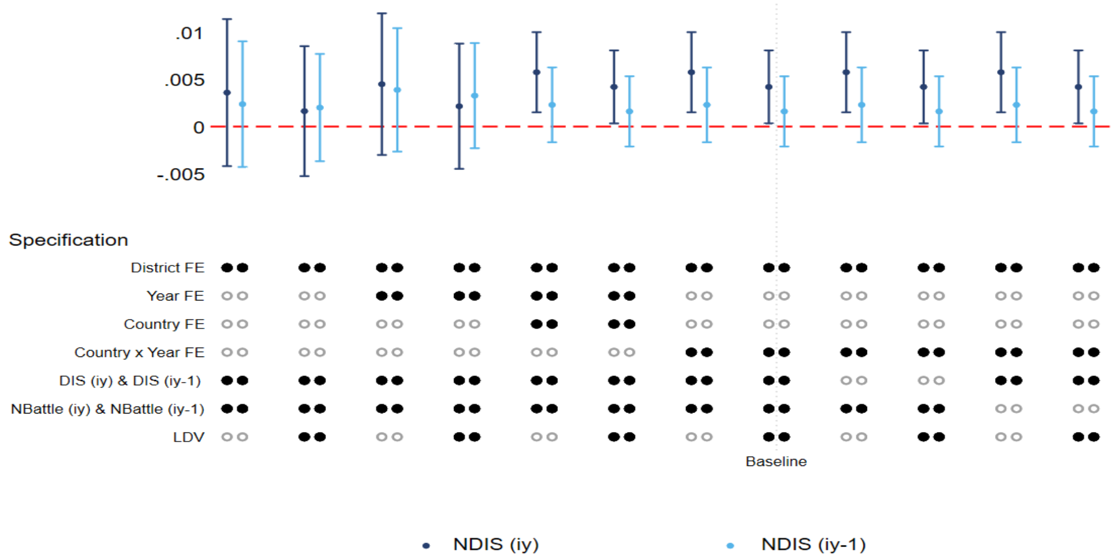
Battle and *DIS* are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death and natural disaster event, respectively, in the given district in the given time period. *NDIS* (*NBattle*) is a binary variable indicating the presence (=1) or absence (=0) 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 and the inverse road distance matrix, truncated at the indicated distance cut-off. Disasters exclude droughts. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the $country \times year$ level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

B.3 Robustness Checks at the District-Year Level

Figure C.3.1: Spillover effects of natural disasters on battles: Alternative specifications



(a) Inverse geodesic distance network



(b) Inverse road network

Notes: Dots show the spillover effects of $NDIS_{iy}$ and $NDIS_{iy-1}$ on battle probability, as per Eq. (6). Panel (a) and (b) display the estimates for the inverse geodesic distance network and the inverse road distance network, respectively. Each specification includes the specified set of fixed effects and control variables. Vertical lines show the 90% confidence interval based on standard errors clustered at the country×year level.

Table C.3.1: Alternative Definitions of the Dependent Variable - District-Year Level

VARIABLES	(1) $State$ $Battle_{iy}$	(2) $Non-State$ $Battle_{iy}$	(3) $Onesided$ $Battle_{iy}$	(4) $State/Non-State$ $Battle_{iy}$
DIS_{iy}	-0.0002	-0.0010	-0.0009	-0.0015
	(0.0021)	(0.0022)	(0.0018)	(0.0023)
DIS_{iy-1}	-0.0034*	-0.0003	-0.0036**	-0.0011
	(0.0019)	(0.0022)	(0.0017)	(0.0025)
Observations	154,544	154,544	154,544	154,544
Number of Districts	5,944	5,944	5,944	5,944
District FE	YES	YES	YES	YES
Country × Year	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES

Battle 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 the given district in the given time period. *State* (*NonState*) *Battle* is a binary variable indicating the presence (=1) or absence (=0) of a battle leading to at least one death, where at least one party was the state (both parties were nonstate), and both parties used force. *Onesided Battle* is a binary variable indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, where only one party used force and the other party did not retaliate. $State/Non-State$ *Battle* is a binary variable indicating the presence (=1) or absence (=0) of a State or Non-State battle resulting in at least one death, and does not include Onesided battles. Disasters exclude droughts. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.3.2: Natural Disasters and Battles at the District-Year Level - Battle Intensity

VARIABLES	(1) $Battle_{iy}$	(2) $Battle_{iy}$
DIS_{iy}	0.0134	0.0134
	(0.0139)	(0.0139)
DIS_{iy-1}		-0.0064
		(0.0196)
Observations	154,544	154,544
Number of Districts	5,944	5,944
District FE	YES	YES
Country × Year	YES	YES
Other Controls	YES	YES

Battle is a count variable indicating the sum of battles that occurred in the given district in the given year. 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. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the $country \times year$ level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.3.3: Alternative Definitions of the Independent Variable - District-Year Level

VARIABLES	(1) $Battle_{iy}$	(2) $Battle_{iy}$	(3) $Battle_{iy}$	(4) $Battle_{iy}$
$Large\ DIS_{iy}$	-0.0042			
	(0.0033)			
$Large\ DIS_{iy-1}$	-0.0051*			
	(0.0029)			
$Small\ DIS_{iy}$		-0.0010		
		(0.0051)		
$Small\ DIS_{iy}$		-0.0042		
		(0.0047)		
$Climatic\ DIS_{iy}$			-0.0011	
			(0.0030)	
$Climatic\ DIS_{iy}$			-0.0019	
			(0.0029)	
$Geologic\ DIS_{iy}$				-0.0310*
				(0.0181)
$Geologic\ DIS_{iy}$				0.0210
				(0.0309)
Observations	154,544	154,544	154,544	154,544
Number of Districts	5,944	5,944	5,944	5,944
District FE	YES	YES	YES	YES
Country × Year	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES

Battle 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 the given district in the given time period. *Large* DIS is a binary variable indicating the presence (=1) or absence (=0) of a disasters 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. *Climatic* (*Geologic*) DIS is a binary variables indicating the presence (=1) or absence (=0) of a climatic (geologic) natural disaster event in the given district in the given time period. Disasters exclude droughts. Geologic disasters include volcanic eruptions, natural explosions, avalanches, landslides, and earthquakes. Climatic disasters include floods, cyclones, hurricanes, ice storms, snowstorms, tornadoes, typhoons, and storms. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.3.4: Natural Disasters and Battles at the District-Year Level: Channels

VARIABLES	(1) $Battle_{iy}$	(2) $Battle_{iy}$	(3) $Battle_{iy}$	(4) $Battle_{iy}$
DIS_{iy}	-0.0014	-0.0012	-0.0023	-0.0003
	(0.0030)	(0.0030)	(0.0031)	(0.0031)
DIS_{iy-1}	-0.0039	-0.0032	-0.0046	-0.0023
	(0.0028)	(0.0031)	(0.0029)	(0.0030)
$DIS_{iy} \times Light_i$	-0.0103			-0.0115
	(0.0102)			(0.0105)
$DIS_{iy-1} \times Light_i$	-0.0089			-0.0105
	(0.0111)			(0.0114)
$DIS_{iy} \times Agri_i$		-0.0032		-0.0042
		(0.0036)		(0.0038)
$DIS_{iy-1} \times Agri_i$		-0.0051		-0.0060
		(0.0040)		(0.0042)
$DIS_{iy} \times Mine_i$			0.0035	0.0036
			(0.0059)	(0.0059)
$DIS_{iy-1} \times Mine_i$			0.0022	0.0021
			(0.0052)	(0.0052)
Observations	154,544	154,544	154,544	154,544
Number of Districts	5,944	5,944	5,944	5,944
District FE	YES	YES	YES	YES
Country × Year FE	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES

Battle 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. $Light_i$=1 if average nighttime light in 1992 (i.e. initial light) >10 (on a scale of 0-63), and 0 otherwise. $Agri_i$=1 if the fraction of land suitable for agriculture in district i is above 50%, and 0 otherwise. $Mine = 1$ if the district hosted at least one active mining project over the sample period, and 0 otherwise. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the $country \times year$ level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.3.5: Natural Disasters, Battle Onset and Termination - District-Year level

VARIABLES	(1) $Onset_{iy}$	(2) $Termination_{iy}$
DIS_{iy}	-0.0018	0.0009
	(0.0015)	(0.0018)
DIS_{iy-1}	-0.0025*	0.0004
	(0.0015)	(0.0020)
Observations	125,723	136,370
Number of Districts	5807	5,944
District FE	YES	YES
Country × Year FE	YES	YES
Other Controls	YES	YES

Onset is a binary indicator = 0 in periods with no battle events; = 1 in the first time period a district experiences a battle; and missing in subsequent time periods. *Termination* is a binary indicator = 0 in periods of battle; = 1 in the first period with no battle; 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. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.3.6: Natural Disasters and Battle Diffusion at the District-Year Level - Spatial Clustering of Standard Errors

VARIABLES	(1) $Battle_{iy}$	(2) $Battle_{iy}$	(3) $Battle_{iy}$
Inverse Geodesic Distance			
$NDIS_{iy}$	0.0042		0.0034
	(0.0033)		(0.0033)
$NDIS_{iy-1}$	0.0118***		0.0108***
	(0.0032)		(0.0030)
$NBattle_{iy}$	0.0015		-0.0023
	(0.0021)		(0.0021)
$NBattle_{iy-1}$	0.0057***		0.0032*
	(0.0020)		(0.0019)
Inverse Road Distance			
$NDIS_{iy}$		0.0048**	0.0042**
		(0.0021)	(0.0021)
$NDIS_{iy-1}$		0.0037*	0.0016
		(0.0021)	(0.0020)
$NBattle_{iy}$		0.0204***	0.0205***
		(0.0033)	(0.0033)
$NBattle_{iy-1}$		0.0106***	0.0102***
		(0.0026)	(0.0026)
DIS_{iy}	-0.0022	-0.0027	-0.0028
	(0.0030)	(0.0030)	(0.0030)
DIS_{iy-1}	-0.0048*	-0.0055*	-0.0053*
	(0.0028)	(0.0028)	(0.0028)
Observations	154,544	154,544	154,544
Number of Districts	5,944	5,944	5,944
Distance Cutoff	500km	500km	500km
District FE	YES	YES	YES
Country× Year FE	YES	YES	YES
Other Controls	YES	YES	YES

Battle and *Disaster* 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. *NeighbDisaster* (*NeighbBattle*) 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 and the inverse road distance matrix, truncated at the indicated distance cut-off. Other controls include $Battle_{iy-1}$. Disasters exclude droughts. Spatial HAC standard errors, allowing for spatial correlation up to 100km and for infinite serial correlation, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.3.7: Natural Disasters and Battle Diffusion at the District-Year Level - Robustness to Alternative Distance Cut-offs

VARIABLES	(1) $Battle_{iy}$	(2) $Battle_{iy}$	(3) $Battle_{iy}$	(4) $Battle_{iy}$	(5) $Battle_{iy}$
Inverse Geodesic Distance					
$NDIS_{iy}$	-0.0027	0.0046*	0.0041	0.0040	0.0034
	(0.0030)	(0.0026)	(0.0028)	(0.0027)	(0.0029)
$NDIS_{iy-1}$	-0.0026	0.0010	0.0052*	0.0083***	0.0108***
	(0.0024)	(0.0027)	(0.0031)	(0.0028)	(0.0033)
$NBattle_{iy}$	0.0154***	0.0036	-0.0017	-0.0019	-0.0023
	(0.0032)	(0.0025)	(0.0021)	(0.0020)	(0.0020)
$NBattle_{iy-1}$	0.0099***	0.0062***	0.0030	0.0042**	0.0032
	(0.0026)	(0.0023)	(0.0020)	(0.0020)	(0.0020)
Inverse Road Distance					
$NDIS_{iy}$	0.0047	0.0020	0.0033	0.0047**	0.0042*
	(0.0034)	(0.0026)	(0.0025)	(0.0024)	(0.0023)
$NDIS_{iy-1}$	0.0028	0.0028	0.0008	0.0011	0.0016
	(0.0030)	(0.0026)	(0.0024)	(0.0023)	(0.0022)
$NBattle_{iy}$	0.0277***	0.0265***	0.0235***	0.0218***	0.0205***
	(0.0037)	(0.0032)	(0.0032)	(0.0033)	(0.0034)
$NBattle_{iy-1}$	0.0137***	0.0118***	0.0122***	(0.0023)	0.0102***
	(0.0027)	(0.0026)	(0.0025)	(0.0026)	(0.0027)
DIS_{iy}	-0.0032	-0.0038	-0.0032	-0.0031	-0.0028
	(0.0028)	(0.0028)	(0.0028)	(0.0029)	(0.0029)
DIS_{iy-1}	-0.0046	-0.0058**	-0.0052*	-0.0053*	-0.0053*
	(0.0029)	(0.0027)	(0.0027)	(0.0028)	(0.0028)
Observations	154,544	154,544	154,544	154,544	154,544
Number of Districts	5,944	5,944	5,944	5,944	5,944
Distance Cutoff	100km	200km	300km	400km	500km
District FE	YES	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES	YES

Battle 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* (*NBattle*) 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 and the inverse road distance matrix, truncated at the indicated distance cut-off. Disasters exclude droughts. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.3.8: Fixed Effects and Lagged Dependent Variable Specifications

	(1) *Baseline*	(2) *FE Only*	(3) *LDV Only*
		$Panel\ A: District-Year\ Level$	
VARIABLES	$Battle_{iy}$	$Battle_{iy}$	$Battle_{iy}$
DIS_{iy}	-0.0021	-0.0028	-0.0041
	(0.0030)	(0.0033)	(0.0032)
$Battle_{iy-1}$	0.1856***		0.4015
	(0.0145)		(0.0161)
Observations	154,544	154,544	154,544
Number of Districts	5,944	5,944	5,944
District FE	YES	YES	NO
Country × Year	YES	YES	NO
		$Panel\ B: District-Month\ Level$	
VARIABLES	$Battle_{iym}$	$Battle_{iym}$	$Battle_{iym}$
DIS_{iym}	-0.0014**	-0.0015**	-0.0017***
	(0.0006)	(0.0006)	(0.0006)
$Battle_{iy,m-1}$	-0.0118**		0.2770***
	(0.0055)		(0.0127)
Observations	1,919,912	1,919,912	1,919,912
Number of Districts	5,944	5,944	5,944
Month FE	YES	YES	NO
District × Year	YES	YES	NO

This Table follows the recommendation of Angrist and Pischke (2009) on addressing Nickell bias in estimates with lagged dependent variables (LDV). Columns 1 provides our baseline specification. In Column 2 we include only the fixed effects in our estimate, and omit the LDV. In Column 3 we omit the fixed effects but include only the LDV. *Battle* and *DIS* are binary variables indicating the presence (=1) or the absence (=0) of a battle resulting in at least one death and natural disaster event, respectively, in the given time period. Disasters exclude droughts. Standard errors, clustered at the *country* × *year* level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.3.9: Correlation Between Battle Events and Road Connectivity

VARIABLES	(1) $Road\ Length_i$	(2) $Road\ Length_i$	(3) $Road\ Length_i$
$Battle_i$	-0.0010	-0.0011	-0.0007
	(0.0008)	(0.0009)	(0.0008)
$Light_i$		0.1006***	0.0668***
		(0.0322)	(0.0186)
$Temperature_i$			0.3513***
			(0.0565)
$Precipitation_i$			-0.2467***
			(0.0531)
Observations	3,739	3,739	3,739
Number of Districts	3,739	3,739	3,739
Number of Countries	47	47	47
Country FE	YES	YES	YES

This Table presents the cross-sectional regression estimates on the correlation between a district's battle incidence and road connectivity. $Road\ Length_i$ is the log of the per capita total road length of a district. $Battle_i$ is the total number of battles resulting in at least one death in the sample period. $Light_i$ is the log of the per capita average nighttime light over the sample period. $Temperature$ and $Precipitation$ are the log of the dictrict's average temperature and precipitation over the sample period. Sample size limited by data availability. Standard errors, clustered at the country level, in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

C 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 3 in Xu et al. (2019). Indeed, the cost function is quadratic, and therefore convex and strongly monotone, and the Tullock contest success function (CSF), given by (8), satisfies the assumption on the CSF assumption in Xu et al. (2019). This shows the existence and uniqueness of the Nash equilibrium. Moreover, Xu et al. (2019) also show the unique equilibirum satisfies the property that every battle contains at least two contestants with positive efforts. Since, in the star depicted in Figure 5, each battle 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 (15) for the parameter v^a, we obtain:

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

where

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

with

$$\frac{\partial F_1}{\partial x_3^b} = \frac{\partial F_2}{\partial x_2^a} = \frac{\partial F_3}{\partial x_1^b} = \frac{\partial F_3}{\partial x_3^b} = \frac{\partial F_4}{\partial x_1^a} = \frac{\partial F_4}{\partial x_2^a} = 0 \tag{C.3}$$

$$\begin{aligned}
\frac{\partial F_1}{\partial x_1^a} = -s_1 - \frac{2v^a x_2^a}{(x_1^a+x_2^a)^3}, \frac{\partial F_1}{\partial x_1^b} = -s_1, \frac{\partial F_1}{\partial x_2^a} = \frac{v^a}{(x_1^a+x_2^a)^2} - \frac{2v^a x_2^a}{(x_1^a+x_2^a)^3}, \\
\frac{\partial F_2}{\partial x_1^a} = -s_1, \frac{\partial F_2}{\partial x_1^b} = -s_1 - \frac{2v^b x_3^b}{(x_1^b+x_3^b)^3}, \frac{\partial F_2}{\partial x_3^b} = \frac{v^b}{(x_1^b+x_3^b)^2} - \frac{2v^b x_3^b}{(x_1^b+x_3^b)^3}, \\
\frac{\partial F_3}{\partial x_1^a} = \frac{v^a}{(x_1^a+x_2^a)^2} - \frac{2v^a x_1^a}{(x_1^a+x_2^a)^3}, \frac{\partial F_3}{\partial x_2^a} = -s_2 - \frac{2v^a x_1^a}{(x_1^a+x_2^a)^3}, \\
\frac{\partial F_4}{\partial x_1^b} = \frac{v^b}{(x_1^b+x_3^b)^2} - \frac{2v^b x_1^b}{(x_1^b+x_3^b)^3}, \frac{\partial F_4}{\partial x_3^b} = -s_3 - \frac{2v^b x_1^b}{(x_1^b+x_3^b)^3}.
\end{aligned} \tag{C.4}$$

Note that $\mathbf{M}$ is just the Jacobian matrix of system (15) 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:

$$det(\mathbf{M}) := J = \begin{vmatrix}
\frac{\partial F_1}{\partial x_1^a} & \frac{\partial F_1}{\partial x_1^b} & \frac{\partial F_1}{\partial x_2^a} & \frac{\partial F_1}{\partial x_3^b} \\
\frac{\partial F_2}{\partial x_1^a} & \frac{\partial F_2}{\partial x_1^b} & \frac{\partial F_2}{\partial x_2^a} & \frac{\partial F_2}{\partial x_3^b} \\
\frac{\partial F_3}{\partial x_1^a} & \frac{\partial F_3}{\partial x_1^b} & \frac{\partial F_3}{\partial x_2^a} & \frac{\partial F_3}{\partial x_3^b} \\
\frac{\partial F_4}{\partial x_1^a} & \frac{\partial F_4}{\partial x_1^b} & \frac{\partial F_4}{\partial x_2^a} & \frac{\partial F_4}{\partial x_3^b}
\end{vmatrix} > 0. \tag{C.5}$$

We apply the Cramer's rule to compute each component of the left-hand side (LHS) of (C.1). After some simplifications, we obtain:

$$\frac{\partial x_1^a}{\partial v^a} = \frac{(v^a x_1^a + s_2 x_2^a (x_1^a+x_2^a)^2)((v^b)^2 + s_1 s_3 (x_3^b+x_1^b)^4 + 2v^b(x_3^b+x_1^b)(s_3 x_3^b + s_1 x_1^b))}{J(x_1^a+x_2^a)^4 (x_3^b+x_1^b)^4} > 0 \tag{C.6}$$

$$\frac{\partial x_1^b}{\partial v^a} = -\frac{s_1(v^a x_1^a + s_2 x_2^a (x_1^a+x_2^a)^2)(2v^b x_1^b + s_3(x_3^b+x_1^b)^3)}{J(x_1^a+x_2^a)^4 (x_3^b+x_1^b)^3} < 0 \tag{C.7}$$

$$\frac{\partial x_1^a}{\partial v^a} + \frac{\partial x_1^b}{\partial v^a} = \frac{v^b(v^a x_1^a + s_2 x_2^a (x_1^a+x_2^a)^2)(v^b + 2 s_3 x_3^b (x_3^b+x_1^b))}{J(x_1^a+x_2^a)^4 (x_3^b+x_1^b)^4} > 0 \tag{C.8}$$

$$\frac{\partial x_2^a}{\partial v^a} = \frac{s_1\left[(v^b)^2 x_1^a (x_1^a + x_2^a)^2 + s_3 v^a x_2^a (x_3^b + x_1^b)^4 + 2v^b (x_3^b + x_1^b)(s_3 x_1^a x_3^b (x_1^a + x_2^a)^2 + v^a x_2^a x_1^b)\right]}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^4} + \frac{v^a v^b x_2^a (v^b + 2s_3 x_3^b (x_3^b + x_1^b))}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^4} > 0 \tag{C.9}$$

$$\frac{\partial x_3^b}{\partial v^a} = \frac{s_1 v^b (x_1^b - x_3^b)(v^a x_1^a + s_2 x_2^a (x_1^a + x_2^a)^2)}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^3} \tag{C.10}$$

$$\frac{\partial x_1^b}{\partial v^a} + \frac{\partial x_3^b}{\partial v^a} = -\frac{s_1 (v^a x_1^a + s_2 x_2^a (x_1^a + x_2^a)^2)(v^b + s_3 (x_3^b + x_1^b)^2)}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^2} < 0 \tag{C.11}$$

This completes the proof of the proposition. □