Conflicts in Networks*

Ashani Amarasinghe† Paul A. Raschky‡ Yves Zenou§ Junjie Zhou¶

December 2023

Abstract

This paper studies how conflicts spread within a network. We first construct a new panel data set that combines geo-referenced information about conflict events and natural disasters for 5,944 districts in 53 African countries over the period 1989–2020. Considering natural disasters as exogenous shocks that affect the combatants' activity in a locality, we find that natural disasters decrease conflict incidence in the affected locality, increase conflict incidence in neighboring localities, and lead to an overall net increase in conflict incidence. The effects differ based on district-level characteristics and are not driven by economic spillover effects. We then provide a simple theoretical framework that may explain this donut-shaped conflict dispersion pattern. Findings provide important implications for implementing local and aggregate level conflict mitigation policies.

JEL classification numbers: D74, D85, O55.
Key words: Natural disasters, conflict, Africa, spillovers, networks.

*We thank Eik Swee as well as conference and seminar participants at the Australasian Development Economics Workshop, Australian Conference of Economists, Deakin University and Monash University for their helpful comments. We also thank Shaun Astbury for excellent research assistance. Ashani Amarasinghe gratefully acknowledges support of the Australian Government through its Research Training Program Scholarship. Paul Raschky gratefully acknowledges financial support from the Australian Research Council (ARC Discovery Grant DP150100061). Yves Zenou gratefully acknowledges financial support from the Australian Research Council (ARC Discovery Grant DP200102547). This research was supported in part by the Monash eResearch Centre and eSolutions-Research Support Services through the use of the Monash Campus HPC Cluster.

†School of Economics, University of Sydney, and SoDa Laboratories, Monash University. Email: ashani.amarasinghe@sydney.edu.au.

‡Department of Economics and SoDa Laboratories, Monash University. Email: paul.raschky@monash.edu.

§Department of Economics, Monash University. Email: yves.zenou@monash.edu.

¶School of Economics and Management, Tsinghua University. Email: zhoujunjie@sem.tsinghua.edu.cn.

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. One example is the Boko Haram insurgency in Nigeria, which started initially as small, localised skirmishes between Nigerian security forces and Bokom Haram militants in 2009, mainly in the north-eastern states of Bauchi, Borno, Yobe and Kano states (Thurston, 2018). However, by 2014, the conflict increased in intensity and Boko Haram started expanding its territory not only within Nigeria but also spread the insurgency to neighboring Cameroon, Chad, Mali, and Niger (Dowd, 2015). Another example is the guerilla campaign by the Lord's Resistance Army (LRA), which started in 1987 in Northern Uganda and spilled over into neighboring Sudan, the Central African Republic and the Democratic Republic of Congo; in the latter two, the LRA is still active today.

This paper examines the spread of conflicts following a natural disaster. In particular, we analyze the consequences of a negative exogenous shock on the incidence of conflict in one locality and its spillover effects to other localities linked through a network.

To empirically investigate the direct and spillover effects of natural disasters, we construct a new panel data set at the district-year level for 5,944 African ADM2 (second subnational) units, over the period from 1989 to 2020, that combines geo-referenced data on conflict events, which is the outcome variable of our study, and disaster events, which is our treatment variable. We then generate two connectivity networks between the set of districts in Africa: an altitude-adjusted inverse geodesic distance network and an inverse major road network. By combining our panel data set with these connectivity networks, we are able to examine the spillover effects of natural disasters on conflict incidence within these networks. As such, our identification strategy exploits the exogenous variation in the timing and location of natural disasters as shocks that locally affect the likelihood of a conflict event.

We find that the occurrence of a natural disaster decreases conflict in the locality where the disaster occurred, but generates positive spatial spillovers of conflict in connected districts. Positive spatial spillover effects occur under both forms of connectivity networks, although the spatial spillovers in the inverse geodesic network dominate the ones in the major road network . In total, a local natural disaster leads to a net increase in the likelihood of violent conflict in the spatial system. Our estimates are robust to a number of alternative specifications.

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 local conflict probability, while increasing the conflict probability of other districts connected via spatial networks.

We then examine the heterogeneity of these effects. Using nighttime luminosity as a proxy for district-level economic activity, we find that disaster-driven spatial spillovers of conflicts are not the results of any potential disaster-driven spatial *economic* spillovers. Next, we consider how district-specific characteristics, that is, economic activity (as proxied by nighttime light), mining, and agricultural suitability, drive the diffusion of conflicts. We find that combat activity is less likely to spill outwards to neighboring districts if the disaster occurred in a mining district. Moreover, when disasters drive out conflict, conflict activity is more likely to spread to neighboring districts with active mining. We also find that violence tends to spread more towards neighboring districts with more land suitable for agriculture.

To provide a possible theoretical explanation of these results, we develop a 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.

There are limitations of using geo-referenced conflict and natural disaster events at a local level to understand the deeper, underlying mechanisms behind the actors' motivation to fight. Both our outcome and treatment variable are imperfect proxies that bundle a number of variables. Given such aggregated variables, we face similar challenges to the existing literature in providing answers to questions such as: "Who is fighting?" "Why do they fight?" and "How do they fight?" (see e.g., Blattmann and Miguel, 2010). Natural disasters might increase the armed groups' costs to maneuver or make it completely impossible to operate in an area. They might also decrease the benefits of fighting over local resources, increase

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

grievances or decrease opportunity costs for the local population and therefore increase the motivation to join one of the belligerent groups (e.g. Collier and Hoeffler, 2004). Natural disasters might weaken the state's capacity to ensure local stability (e.g. Fearon and Laitin, 2003) and disaster refugees who migrated to neighboring districts might be more vulnerable to the recruitment efforts of armed groups (e.g. Humphreys and Weinstein, 2008), which could be another explanation for conflict spillovers following a natural disaster. It is very likely that the mechanisms behind our results are an intertwined bundle of all of these explanations (Cedermann and Vogt, 2017).

As stated above, our model only offers one possible mechanism; other forces may be at work.[2] Because we have aggregate data at the district level, in our empirical analysis, we are agnostic about the forces that explain the conflicts and the consequences of a negative shock at the micro level. Our results are still useful for policy reasons because it indicates that local negative shocks propagate to neighboring districts and thus may increase violence and conflicts in the country, as highlighted in the case of Boko Haram in Nigeria or the Lord's Resistance Army in Uganda. Our evidence of a *donut-shaped* model of conflict diffusion is particularly relevant to policy-makers because, to reduce the risk of escalation, national governments and international organizations often try to contain the initial local conflict through military interventions, which 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 build more informed policy strategies in the context of localized violence in Africa.

[2] For example, it is also possible that, following a negative shock, populations may migrate in response to these shocks. Indeed, a natural disaster that afflicts an area may produce a wave of refugees and movement of people who subsequently heighten frictions and escalate violence in another adjacent areas.

Our study contributes to various strands of the literature. Firstly, we specifically turn the spotlight on conflict displacement, a feature that has so far received relatively little attention in the literature on conflicts in economics. So far, the literature has analyzed 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 (e.g. Miguel et al., 2004; Chassang and Padró i Miquel, 2009; Blattman and Miguel, 2010; Besley and Persson 2011; Ciccone, 2011; Couttenier and Soubeyran, 2014). Some country-level studies, 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. Yesilyurt and Elhorst (2017) show that military expenditure of one country effects the military expenditure of other, spatially closer countries. This literature often uses the economic model of crime as a reference model to explain conflict (see e.g., Corchón, 2007) and the literature on the economics of crime has regarded the importance of crime displacement for a long time (see e.g., the overviews by Freeman, 1999, and Chalfin and McCrary, 2019).

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; Cervellati et al. 2022) 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 conflict 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 conflicts. Both studies find that these exogenous shocks not only increase conflict incidence in the directly affected area but also create spatial conflict 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 conflicts over the control of territory ("factor conflict") and increase conflicts 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. A very recent study by Cervellati et al. (2022) examines the effect of malaria outbreaks on civil conflict in Africa. We contribute to this literature by focusing on natural disasters as a negative economic shock that affects the broader conflict behaviours in Africa. To the best of our knowledge, we are the first to examine the local and spillover effects of conflict in Africa due to natural disasters.

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; Guarnieri, 2023). 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; Bocher et al., 2020; Mueller et al., 2021; Xu et al., 2022). 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 structures. Moroever, 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 conflict locally can increase the probability of a conflict in neighboring localities connected via a spatial network. We thereby complement the existing work on conflict spillovers that exclusively focuses on spillover effects of factors that *increase* the likelihood of a conflict locally.

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 conflict (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 new geo-referenced data set of natural disasters of all types, at a very fine spatial resolution (i.e. district-level), which allows us to better investigate the mechanisms at play in determining the relationship between natural disasters and conflict.

The remainder of the paper is organized as follows. Section 2 describes the data and provides descriptive statistics. Sections 3 presents the baseline empirical framework, while Section 4 discusses diagnostics and robustness checks. We examine potential mechanisms in Section 5. Section 6 develops a simple theoretical framework that provides a possible explanation for our results. Finally, Section 7 concludes. We provide additional descriptions of the data, robustness checks, and the proofs of the theoretical model in the Online Appendix.

2 Data

We use observations at the second, subnational administrative unit (ADM2, henceforth "districts") level, and the final data set consists of 5,944 districts from 53 African countries over the period from 1989 to 2020.[3] The unit of observation is a *district-year*. In a robustness check, we also conduct the analysis at the *grid cell-year* level.[4]

2.1 Conflict Data

Data on conflict is obtained from the Uppsala Conflict Data Program's (UCDP) Georeferenced Event data set (Croicu and Sundberg, 2017). According to UCDP, an armed conflict is defined as a "contested incompatibility that concerns government and/or territory over which the use of armed force between the military forces of two parties, of which at least one is the government of a state, has resulted in at least 25 conflict-related deaths each year". UCDP contains data on individual violent events which are organized under each such armed conflict. Within the scope of our study, we use the term "conflict" to refer to such individual violent events. For each such conflict event, UCDP provides detailed data on, for example, the dates, actors involved, the geo-coordinates and the number of deaths, among many others.

Using information on the precise location (i.e., latitude, longitude) of the violent event, we first geolocate each conflict event in to ADM2 districts.[5] We then aggregate all local

[3]ADM2 subnational district boundaries are available for most countries, except Egypt and Libya, where boundaries were only available at the ADM1 level.

[4]See Table B.9.

[5]This procedure was implemented in ArcMap 10.5.

conflict events at the district-year level. Our main indicator of a *conflict* takes the form of a binary variable, which assumes a score of one if a conflict event leading to at least one death occurred in district i in year t, and zero otherwise. Using information on the actors involved, we also generate indicators on the subcategories of local conflict, that is, "state-based violence", "non-state violence" and "one-sided violence". Panel (a) in Figure A.1 in the Online Appendix displays the distribution of battles in Africa over our sample period.

We also supplement the UCDP data set with data on violent events sourced from the Armed Conflict Location and Event Data (ACLED) data set. Using the same procedure as with the UDCP data, we generate binary indicators that represent whether or not a conflict event occurred in a given district-year. The challenge with using ACLED in our setting is that ACLED data only starts in 1997, thereby reducing the number of years in our sample. Nevertheless, in a series of robustness checks, we replicate our baseline results for this shorter time period, using ACLED by itself as well as a pooled data set that combines UCDP and ACLED.

2.2 Natural Disasters

The key treatment variable in our study is a natural disaster, which we use as a proxy for a negative economic shock in a district. Data on natural disasters are drawn from the Emergency Events Database (EM-DAT) (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 data set. 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.

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, which could be geophysical (e.g., earthquake, volcanic activity), meteorological (e.g., extreme temperature, storm), hydrological (e.g., flood, landslide), or climatological (e.g., wildfire).[6] Table A.1 provides the breakdown of the different natural disaster categories during the sample period. We observe that floods are the most common natural disasters during our period of time.

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 1,326 natural disasters that occurred in Africa over the period from 1989 to 2020. Natural disasters where the exact individual village or subnational district was identified were precisely geocoded, while those recorded as having occurred in larger geographic units were assigned to all districts within that geographic unit. For each geocoded natural disaster, we allocate a precision score, which assigns a value of 4 for precision at the district level (i.e., the highest level of precision), a value of 3 for precision at the provincial level, 2 at the state level, and 1 at the country level (the lowest level of precision). We restrict our analysis to natural disasters geocoded with a precision score of 3 or 4, which accounts for over 96% of the total number of the geocoded natural disaster locations. Panel (b) in Figure A.1 displays the distribution of natural disasters in Africa.

Our preferred indicator for natural disasters is a binary variable that assumes a value of 1 if a natural disaster occurred in district i in a time period, and zero otherwise. We also generate two indicators on natural disaster subcategories, which we use in our robustness

[6]Note that EM-DAT also contains information about "extraterrestrial" events such as asteroid impacts on earth. However, during our sample period no such events were reported in Africa.

checks. First, following Gassebner et al. (2010) and puzzelloo 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.[7]

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

So far, we have focused on subnational, ADM2 districts. The choice of the spatial unit of analysis, districts at the second subnational level, is determined by the available location information of natural disaster events in the raw data. The EM-DAT data set only contains location names of subnational units rather than precise coordinates of the affected areas. As such, we do not have the information to conduct a spatial join based on precise lon/lat coordinates which, together with geocoded data on conflict events, would enable us to conduct the study at a more granular grid cell level.

Nevertheless, in a robustness check we replicate our main specifications using *grid cells* by overlaying the district boundary polygons with 0.5×0.5 grid cell boundary polygons. This allows us to assign natural disaster events that were geolocated based on the name of the ADM2 district they occurred in, to grid cells that fall within a the affected ADM2

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

district. In the case of multiple district overlays, we assign the natural disaster to the grid cell only if it occurred in the district with the largest share of the grid cell area. This highlights the main caveat of using grid cells instead of administrative regions in our setting. By assigning natural disasters that occurred in specific administrative regions to grid cells with arbitrarily drawn borders we add further noise to our treatment variable. The disaster location information based on administrative units is already measured with some degree of error. By assigning a disaster event to grid cell/ADM2 border overlays, we might assign the treatment variable to units that are in reality not directly hit by the event.

Estimates presented in Table B.9 confirm that overall our findings are robust to using grid cells instead of districts as our spatial unit. The sign and magnitude of the direct effect is very similar to our baseline estimates. However, the coefficients for the direct effect are less precisely estimated which is likely a result of the increased noise that was introduced by assigning disaster events to grid-cells with arbitrary, rectangular borders.

2.3 Other covariates

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

To identify a district's level of economic activity, we using satellite data on the intensity of *nighttime lights*. 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). Within our study we use nighttime lights in two ways. First, we use the relatively recent harmonized nighttime light dataset by Li et al. (2020), which combines data from the origianl DMSP satellites (1992–2012) and the more recent VIIRS satellites (2013–2020) to create a harmonised luminosity product for the period 1992–2020. By matching this data set to the district units used in our study, we can calculate the annual average nighttime luminosity for each district. Since the nighttime luminosity data is only available from 1992, our empirical examinations using this data set are for the period 1992-2020. We use this indicator in our examinations of economic spillover effects following natural disasters.

Next, we use nighttime light values in the first year of the sample to classify districts in to those with high and low levels of economic activity. We generate a time-invariant binary indicator $LightDum_i$ 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 set. 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). We identify 8% of the districts as displaying a high level of economic activity.

To identify mining activity in subnational districts in Africa, we obtain data 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. 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.[8]

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.[9] 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

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

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

as agricultural.

2.4 Connectivity matrices

We follow Amarasinghe et al. (2020)[10] and construct two[11] spatial weighting matrices based on geographic and major 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 distance-weighted connectivity matrix using the following steps. We identify the centroid of each district, and then calculate 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 that 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

[10]Observe that the analysis in Amarasinghe et al. (2020) is very different to that of the current paper since, in the former the focus is not on "conflicts" between districts, but rather on which districts diffuse local economic activity (as measured by nighttime light intensity) the most to neighboring districts. By contrast, in this paper we analyze the effect of disasters on local and distant conflict events.

[11]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.

districts located in close geographic proximity, as opposed to those located further away from each other. As such, 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 Major road connectivity

Given the importance of major roads in maintaining links between districts in general, and in potentially spreading conflict (e.g. Rogall 2014), we next construct a road-based connectivity matrix. Reliable, time-variant data on the expansion of Africa's road network that covers the entire continent is not available.[12]

To obtain georeferenced information about the major road network for the entire continent, we use data on the primary and secondary road network in Africa from OpenStreetMap (OSM).[13] This data is of cross-sectional nature and provides a snap-shot of the major road network in Africa at the time of collection, 2016.

To generate a network graph of the major road network, we intersect these major roads

[12] A few recent studies (e.g. Storeygard 2016, Bonfatti et al. 2020) have digitized yearly maps from road atlases but only for a small subset of African countries.

[13] 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 A.2 provides a visualisation of the road network.

with district boundary polygons using the following steps.[14] First, we split the major road polylines into segments whenever they intersect with a district boundary. For each segment (edge) we calculate the major road travel distance in km between each intersection (node).[15] 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 value of 1, which represents the highest level of major road connectivity. If districts A and B are not adjacent, but connected via the major road network, they are assigned the inverse of the major road distance between the closest major road and district boundary node of A and the closest major road and district boundary node of B (i.e., the major road travel distance through the whole district that one has to cross to get from district A to district B). As such, the final major road connectivity matrix assigns a value equal to the inverse of the major 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 major road connection and not road quality.

One concern related to the major road network is that major road infrastructure and thereby major road-connectivity could be negatively correlated with fighting activity due to long-lasting destruction of the infrastructure. For instance, it is possible that major roads are destroyed as a result of violent events which in turn could bias our estimates. To alleviate this concern, in a robustness check, we compile cross-sectional data on per capita major road infrastructure, conflict as well as a set of controls, at the ADM2 level. To flexibly address concerns on the lack of road investment in conflict-prone areas, we include ADM1 (first

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

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

subnational level) fixed effects. The results displayed in Table A.2 show that estimated effect of conflict on major road infrastructure is both economically and statistically insignificant.

Table 1 provides descriptive statistics of our key variables.

Table 1: Descriptive Statistics for our Key Variables

	Observations	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Conflict	190,208	0.0367	0.1880	0	1
DIS	190,208	0.0580	0.2337	0	1
Conflict if DIS >0	11,025	0.0309	0.1731	0	1
Conflict if DIS=0	179,183	0.0370	0.1888	0	1
Inverse Geodesic Network					
NDIS	190,208	0.4526	0.4978	0	1
Conflict if NDIS >0	86,094	0.0376	0.1902	0	1
Conflict if NDIS=0	104,114	0.0359	0.1861	0	1
Inverse Major Road Network					
NDIS	190,208	0.2111	0.4081	0	1
Conflict if NDIS >0	40,151	0.0444	0.2061	0	1
Conflict if NDIS=0	150,057	0.0346	0.1828	0	1
District Characteristics					
LightDum	190,208	0.0792	0.2701	0	1
MineDum	190,208	0.0436	0.2041	0	1
AgriDum	190,208	0.2917	0.4546	0	1

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

3 Empirical Framework

We now discuss the empirical framework. Our aim is to specify a model that captures both the direct effects of a natural disaster on conflict in district i as well as the spatial spill-over effects of natural disasters in district j on conflict in district i. Considering that natural disasters, both in i and j, are assumed to be exogenous explanatory variables, a spatial lag of X (SLX) model is a good starting point. SLX models have been used by recent studies in the spatial conflict literature to examine the spatial spillovers of regional conflict due to weather shocks (e.g. Eberele et al. 2020, McGuirk and Nunn 2021), exogenous food price shocks (McGuirk and Burke 2020) or soil productivity (Berman et al. 2021).

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

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

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

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 *major road connectivity.* $NDIS_{i,t}$ is 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 year t ($NDIS_{i,t} = 1$) or not ($NDIS_{i,t} = 0$).[16] The coefficients δ_0 and δ_1 therefore capture the spatial spillover effects attributable to the occurrence of a natural

[16] Both $\mathbf{\Omega_1}$ and $\mathbf{\Omega_2}$ are row-normalized stochastic matrices, so that the sum of each of its rows is equal to 1, that is, $\sum_j \omega_{ij} = 1$ for all i.

disaster in a neighboring district, in years t and $t-1$, respectively.

Additionally, the vectors $\mathbf{FE_i}$ and $\mathbf{FE_{ct}}$ capture district-specific time-invariant unobservables and country-specific time-variant unobservables, respectively. Given the nature of our key variables, the error term $\epsilon_{i,t}$ is assumed to be spatially and temporally correlated, and as such we present Conley (1999) clustered standard errors accounting for spatial correlation up to 500km and temporal correlation up to 1 period.[17] We estimate equation (1) using Ordinary Least Squares (OLS) with unit and time fixed effects.

While the SLX model is preferred because it is a less demanding specification compared to other spatial models, our choice relies on particular assumptions about the underlying data generating process. Relaxing some of the assumptions would result in a different set of specifications, each requiring a different set of econometric estimators which in turn come with their own set of caveats. While it is difficult to ascertain the true underlying data generating process, we briefly discuss alternative models (and their drawbacks) and check how sensitive our results are to different types of specifications.

To begin with, the SLX model assumes no spatial auto-correlation in conflict which in our setting is an assumption that is difficult to defend. Instead, we can specify a Spatial Durbin Model (SDM) that allows for spatial autoregressive processes in the dependent and explanatory variables (LeSage and Pace 2009). The challenge with the SDM model is that the spatial lag of the dependent variable, $NConflict_{i,t}$, is potentially endogenous. While there is a large literature[18] that has proposed a econometric tools to address this type of endogeneity across a wide set of specifications, none of the proposed estimators or the existing implementation in statistical software packages allows for a specification with a binary outcome variable and two spatial weighting matrices. Most importantly, the spatial

[17]The estimates were conducted in Stata 17 using the `reghdfespatial` command.

[18]These methods include quasi-maximum likelihood (e.g. Lee and Yu 2010), instrumental variables (e.g. Anselin 1988), generalized method of moments (e.g. Kelejian and Prucha 1998) or bias corrected estimator for spatial dynamic panels with both unit and time fixed effects (e.g. Yu et al. 2008)

lag is only a control variable in our setting and as we show in Tables 2 and B.1 our key parameters do not change when we exclude the spatial lag.

In addition, our baseline specification (1) could further be expanded by including the temporal lag of the dependent variable, $Conflict_{i,t-1}$. Including both spatial and temporal lags of our dependent variable as additional controls yields a general nesting spatial (GNS) econometric model (Elhorst 2014). In a robustness test in Table B.2 we present estimates including the temporal lag of the dependent variable, and our results remain very similar. However, including $Conflict_{i,t-1}$ in our fixed-effects specification creates an additional challenge because it can lead to biased estimates of the lagged dependent variable due to the "Nickell bias". Considering that our key parameters are not sensitive to the inclusion of the temporal lag, we refrain from including the temporal lag as an additional control.

Table 2 presents the estimates for the direct and spillover effects of natural disasters on conflict incidence. For all estimates, we present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period. First, in Column (1), we consider the direct effects of natural disasters on violent conflict and we observe a negative effect with a time lag. Next, we examine the direct and spillover effects of natural disasters on conflict. In Column (2) we consider spillover effects when the neighborhood is defined by the inverse geodesic distance network. Interestingly, we observe a strong positive spillover effect of a natural disaster in i's neighboring districts (in year $t-1$) on the battle probability in district i. In Column (3), we define neighbourhood by the inverse major road distance network. Here too we observe similar patterns of a positive spillover effect of natural disasters, although with a less pronounced magnitude. Column (4) presents specifications that contain the spatial lags of natural disasters based on both definitions of neighbourhood, along with the direct effect. We consistently observe a negative direct effect from own district's natural disasters. We also observe a positive spillover effect arising from natural disasters in districts connected via the inverse geodesic network.

Table 2: Direct and spillover effects of natural disasters on conflict

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$	(4) $Conflict_{i,t}$	(5) $Conflict_{i,t}$	(6) $Conflict_{i,t}$	(7) $Conflict_{i,t}$
$DIS_{i,t}$	-0.0026	-0.0028	-0.0036	-0.0035	-0.0027	-0.0032	-0.0031
	{0.0030}	{0.0030}	{0.0031}	{0.0031}	{0.0030}	{0.0030}	{0.0030}
	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0034)	(0.0034)
$DIS_{i,t-1}$	-0.0053*	-0.0056**	-0.0062**	-0.0060**	-0.0056**	-0.0064**	-0.0061**
	{0.0028}	{0.0028}	{0.0029}	{0.0029}	{0.0028}	{0.0028}	{0.0028}
	(0.0030)	(0.0030)	(0.0029)	(0.0029)	(0.0030)	(0.0029)	(0.0028)
Inverse Geodesic Distance							
$NDIS_{i,t}$		0.0055*		0.0048	0.0057*		0.0054*
		{0.0033}		{0.0033}	{0.0033}		{0.0032}
		(0.0035)		(0.0035)	(0.0035)		(0.0034)
$NDIS_{i,t-1}$		0.0104***		0.0100***	0.0105***		0.0100***
		{0.0033}		{0.0033}	{0.0033}		{0.0032}
		(0.0037)		(0.0037)	(0.0037)		(0.0036)
$NConflict_{i,t}$					0.0049**		0.0003
					{0.0023}		{0.0022}
					(0.0025)		(0.0024)
$NConflict_{i,t-1}$					0.0080***		0.0043**
					{0.0023}		{0.0021}
					(0.0025)		(0.0023)
Inverse Major Road Distance							
$NDIS_{i,t}$			0.0036*	0.0027		0.0053**	0.0042**
			{0.0021}	{0.0020}		{0.0021}	{0.0020}
			(0.0024)	(0.0024)		(0.0024)	(0.0024)
$NDIS_{i,t-1}$			0.0035*	0.0014		0.0040*	0.0019
			{0.0021}	{0.0021}		{0.0021}	{0.0021}
			(0.0024)	(0.0023)		(0.0023)	(0.0023)
$NConflict_{i,t}$						0.0260***	0.0259***
						{0.0028}	{0.0028}
						(0.0035)	(0.0035)
$NConflict_{i,t-1}$						0.0169***	0.0166***
						{0.0024}	{0.0024}
						(0.0027)	(0.0027)
Observations	184,264	184,264	184,264	184,264	184,264	184,264	184,264
Number of Districts	5,944	5,944	5,944	5,944	5,944	5,944	5,944
Distance Cut-off	NA	500km	500km	500km	500km	500km	500km
District FE	YES	YES	YES	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES	YES	YES	YES

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

The specifications so far took the form of a SLX model. In Columns (5)–(7), we re-estimate the models from (2)–(4) and account for spatial and spatio-temporal correlation in neighborhood conflict. The estimated coefficient of the direct effect and the spill-over effects from inverse geodesic lags stay very similar, while the coefficient of the spill-over effects from road distance lags increases in magnitude and becomes more precisely estimated. Considering the sample means, the estimates in Column (7) suggest that a natural disaster reduces conflict in one's own district by approximately 9 percentage points, while increasing conflict in neighboring districts connected by the inverse geographic distance by approximately 2 percentage points.[19]

These estimates provide important insights on the effects of natural disasters on the battle probability. While the probability of a battle is reduced in a locality directly affected by a natural disaster, conflicts do spillover to neighboring districts, which suggests a "donut" shaped process of battle diffusion. Moreover, the stronger positive spillover effects of the inverse geodesic distance network, as compared to the effects of the inverse major road distance network, suggests that distance has a stronger role to play in the diffusion of conflicts in Africa than major roads.

LeSage and Pace (2009) show that one cannot simply use the point estimates from the spatial regression to quantify spatial spillovers. In our setting, the occurrence of a disaster in district i has a direct effect on conflict in i but also an indirect effect on all the other districts through geographic and road network connectivity. This implies that a disaster in one district has an impact on conflict in all other connected districts and vice versa. The size of these effects differs between districts and depends on the district's position in space, the degree of geographic and major road connectivity as well as the parameters β, δ, and γ. LeSage and Pace (2009) have proposed a partial derivative interpretation that

[19] In Table B.1, we present estimates when gradually adding control variables, including the full set of coefficients for all variables.

captures these dynamics and Debarsy et al. (2012) have provided a solution for a spatial panel framework. The results are presented in Table 3.[20] The decomposition of the spatial effect reveal an interesting pattern. Again, the negative direct and positive indirect effects of disasters confirm the donut shaped process of conflict diffusion. But these two effects do not cancel each other out. In contrast, the total effect of natural disasters on conflict events in the spatial system is positive. While conflict in districts directly hit by disasters is decreasing, it disperses violence to other, connected districts in the spatial system. These disaster induced increases in conflict in connected districts more than offset the decrease of conflict in the district directly hit by a disaster and leads to a net increase in conflict incidence in the spatial system.

Table 3: Direct, Indirect, and Total Effects

	$Conflict_{i,t}$					
	Direct		Indirect		Total	
	Coeff.	*SE*	*Coeff.*	*SE*	*Coeff.*	*SE*
$DIS_{i,t}$	-0.0029	(0.0023)				
$DIS_{i,t-1}$	-0.0061***	(0.0023)				
Inverse Geodesic Distance						
$NDIS_{i,t}$			0.0820**	(0.0385)	0.0863**	(0.0402)
$NDIS_{i,t-1}$			0.1644***	(0.0468)	0.1730***	(0.0482)
Inverse Major Road Distance						
$NDIS_{i,t}$			0.0599*	(0.0334)	0.0631*	(0.0350)
$NDIS_{i,t-1}$			0.0252	(0.0320)	0.0265	(0.0337)

Decomposition of he spatial effect into direct, indirect and total effects. Number of Obs. 184,264. $Conflict_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a battle resulting in at least one death in district i in year y. $DIS_{i,t}$ and $DIS_{i,t-1}$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in district i in years y and $t-1$, respectively. $NDIS_{i,t}$ ($NConflict_{i,t}$) are binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (battle), in any one of district i's neighbours in year y. Neighbourhood is based on the altitude-adjusted inverse geodesic distance network and the inverse major road distance network, truncated at 500km. Disasters exclude droughts. *** p<0.01, ** p<0.05, * p<0.1

[20] The direct, indirect and total effects were calculated using the post-estimation command `impact` after the command `spxtregress` in Stata 17.

4 Diagnostic tests and robustness exercises

4.1 Diagnostic tests

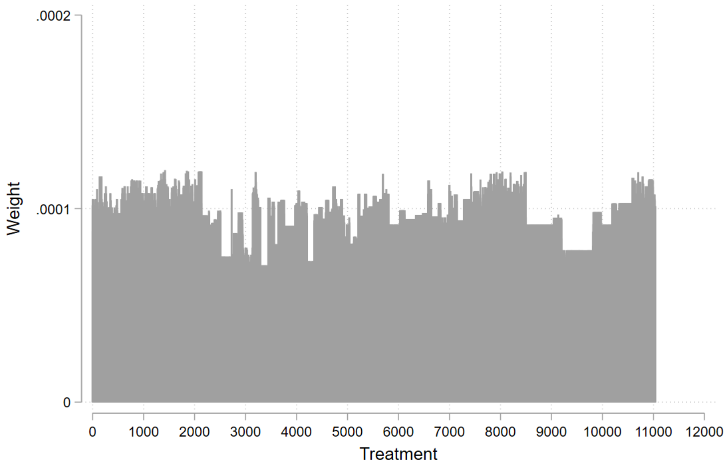
One key concern within this difference-in-difference framework, which has been highlighted in the recent literature on two-way fixed effects (TWFE) estimators, is the threat of negative weights.[21] The TWFE estimator is typically a weighted sum of the average treatment effects (ATE) in each group and period. However, when some weights are negative, the linear regression coefficient maybe negative while all the ATEs are positive, and vice versa.

The recent literature on difference-in-difference methods has developed applications to address the issue of negative weights, specifically in the case of staggered treatments where, although the treatment occurs at different times, once a unit is treated, it remains treated (for example, Borusyak, Jaravel and Spiess, 2022; Callaway and Sant'Anna, 2021, Goodman-Bacon, 2021). However, our context is different. The treatment (disaster) only switches on for one period and does not remain treated subsequently and units (districts) can be repeatedly treated. To the best of our knowledge, none of the existing diff-in-diff estimators address the concern of negative weights in a repeated treatment set up such as ours. Nevertheless, to examine the relevance of this issue in our setting, we follow the procedure suggested by De Chaisemartin and D'Haultfœuille (2020) to check if any weights attached to any of the treatments in this study are negative. Figure 1 displays the distribution of weights for each natural disaster event in our sample. We observe that all treatments are associated with positive weights, which improves our confidence that concerns on biases in relation to negative weights are minimal in our setting.

Next, we discuss the validity of our identifying assumption, that is, districts where natural disasters occurred are not statistically significantly different from districts where

[21] For a detailed discussion on this issue and the related literature, see Baker, Larcker and Yang (2021).

Figure 1: Diagnostic tests - Weights attached to each treatment as per De Chaisemartin and D'Haultfœuille (2020)



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

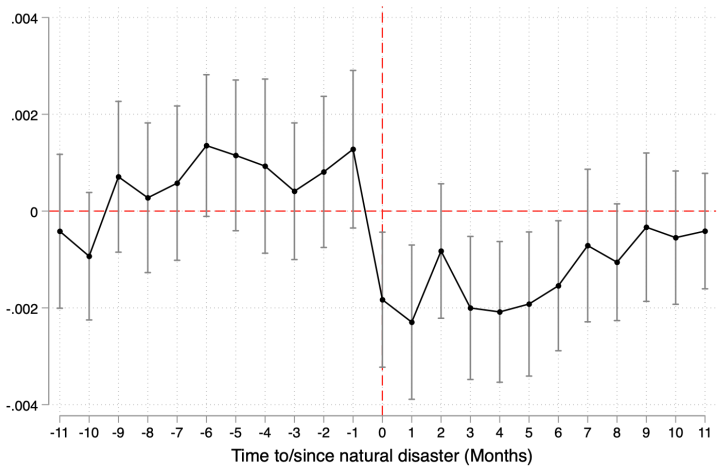
they did not occur. We confirm the validity of this assumption using two exercises.

First, exploiting the fine granularity of our data, we build a district×year×month level panel data set, which allows us to examine the persistent effect of natural disasters on battle probability. Figure 2 provides the estimates of the direct effect of natural disasters in district i on conflict in district i, at the district×year×month level. We find that there is an immediate and persistent negative local effect of natural disasters on battle probability. Interestingly, we observe no pre-trends leading up to the natural disaster, which confirms the validity of our identifying assumption that districts where natural disasters occurred are not statistically significantly different from districts where they did not occur.[22]

[22] Although Figure 2 shows no statistically significant difference in pre-trend coefficients between, Roth (2022) highlights that pre-tests may have low power and some pre-trends that could result in biases in the treatment effect may remain undetected. To better understand the size of a linear pre-trend for which at least of the pre-test coefficient is significant, we follow the approach by Roth (2022). For a number of pre-periods $\tau = 11$ as in Figure 2 the smallest absolute slope of a linear trend for which the probability of rejecting the pretest is 90% is 0.00021. Considering that the pretrend is more easily rejected for a larger pre-treatment

Second, in Figure 3 we conduct a prediction exercise. We use data on a series of district-specific characteristics and examine if these can predict the probability of a natural disaster in the given district. If the natural disaster can indeed be predicted, this would violate the validity of our identifying assumption. Interestingly, Figure 3 shows that none of the variables can statistically significantly predict the occurrence of natural disasters, thereby strengthening our identifying assumption.

Figure 2: Direct effect of natural disasters on conflict - District-year-month level event study



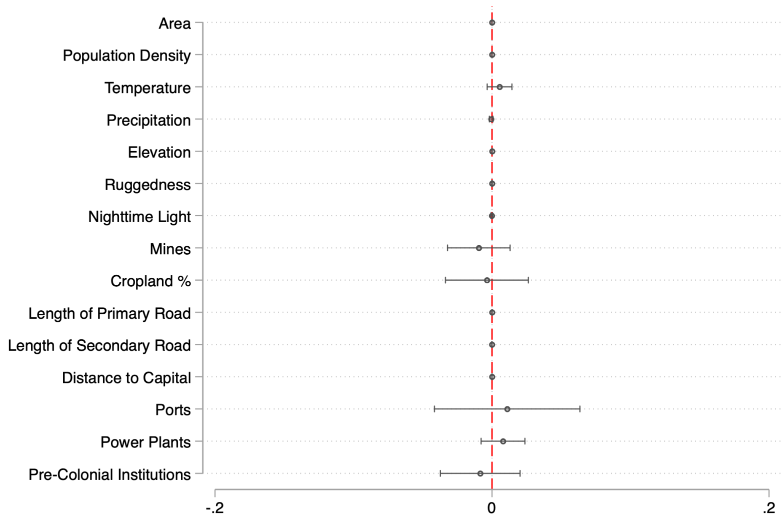
Note: Figure shows the direct effect of natural disasters in district i on conflict in district i, for the 11 months before and after the natural disaster occurs. The unit of observation is a district-year-month. Vertical lines depict the 90% level confidence intervals, based on standard errors clustered at the country-year level.

4.2 Robustness Checks

First, in Table B.1 we show the step-wise addition of control variables for the baseline specification. In Column (1) we only include the variables of interest, $NDIS_{i,t}$ and $NDIS_{i,t-1}$, as per the geographic and major road connectivity networks. In Column (2) we add the autoregressive lagged dependent variable. In Column (3) we include conflict in neighbouring

τ, we redo the test with a $\tau = 11$. Here the smallest absolute slope is 0.00043. Using this more conservative number, we are able to reject a pretrend with an absolute slope that is larger than 0.00043.

Figure 3: Correlation between natural disaster indicators and district level characteristics



Notes: Figure shows the cross-sectional correlation between the natural disaster indicators and a range of geographic and demographic variables in each district. The dependent variable is DIS, which is a binary variable =1 if the district recorded at least one natural disaster during the sample period, and 0 otherwise. Dots show the point estimates, while the vertical lines depict the 95% confidence intervals, based on standard errors clustered at the country level.

districts as a control variable, while in Column (4) we additionally include the LDV. In Columns (5) and (6) we include the direct effect of natural disasters in district i, along with the LDV. Finally, our preferred estimates are presented in Columns (7) and (8) where all the previously discussed control variables are included in the specification. Across the various specifications, the baseline results remain economically and statistically robust.

One concern with respect to conflicts is how persistent they are over time. It could be that conflicts in previous periods can affect conflict in the current period. The inclusion of district fixed effects can, to some degree, account for this persistent effect. Alternatively, we could include the lag of the dependent variable as a control variable. In our baseline specification, we do not include the lagged dependent variable as, in the presence of unit fixed effects, it could give rise to teh famous "Nickell bias". Nevertheless, in Table B.2 we provide estimates including the lagged dependent variable, and show that our results remain robust.

Next we move to alternative definitions of disasters. In the baseline specification, we exclude droughts as a disaster category for two key reasons. First, droughts are spatially dispersed and therefore, identifying the precise spatial location is difficult. Second, droughts are more temporally persistent natural disasters that spread across multiple years, in which case identifying the effect of a drought in a given year per se may be confusing. Nevertheless, in Table B.3 we re-estimate the baseline specification including droughts. Here, we observe a stronger spillover effect which materializes in the contemporary year as well.

In Table B.4, we examine the differential effects of disaster categories on battle probability. We observe that the negative effect of natural disasters on battle probability is attributable to those categorized as "large disasters".[23] Between climatic and geologic disasters, the negative effect is prominently observed in disasters classified as climatic.[24] In Table B.5, we further explore the effects if individual disaster categories, and note that the strongest effects are observed through floods.[25] Moreover, inspired by Harari and La Ferrara (2018), in Table B.6 we use the Standardised Precipitation-Evapotranspiration Index (SPEI), which is an indicator for drought conditions (low rainfall), as an alternative indicator for natural disasters. Here too we observe spillover effects on conflict, particularly along geographically connected districts.

Now we consider alternative definitions of the outcome variable. UCDP provides three classifications of conflict events, based on the actors involved i.e., state battles, non-state battles and onesided battles. In Table B.7, we examine the effects of natural disasters on

[23]Following Gassebner et al. (2010) and puzzelloo 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.

[24]Following Skidmore and Toya (2002), geologic disasters include volcanic eruptions, natural explosions, avalanches, landslides, and earthquakes. Climatic disasters include floods, cyclones, hurricanes, ice storms, snowstorms, tornadoes, typhoons, and storms.

[25]We observe here that approximately 67% of the natural disasters in our data set are classified as floods. Table A.1 provides the composition of disaster categories in our sample.

these conflict categories separately. We observe that the baseline effect is mainly driven by non-state battles.

To provide further evidence on the validity of our estimates, we replicate our baseline findings with an alternative conflict data set, that is, ACLED. It is important to note that ACLED only starts in 1997, thereby vastly reducing the number of natural disasters, and therefore treatment events, in our sample.

Column (1) of Table B.8 presents estimates, where the outcome variable is a dummy variable which equals to one if at least one violent event of any ACLED's event type occured in the district and year. For comparison, in column (2), we present estimates using our main outcome variable based on UDCP data but restricting the sample to the time period for which ACLED data is available (1997–2020). In column (3), we present results from an analysis that pools the event data from UDCP and ACLED for the shorter time period. Here the outcome variable is a dummy which equals 1 if either a UDCP or an ACLED event occurred in the district and year. The results in columns (10)–(3) show that we can replicate the pattern of our main results if we use ACLED data. However, the coefficients of interest are less precisely estimated due to the reduction of the number of observed natural disasters in the shorter sample.

In columns (4) and (5), we explore potential heterogeneity of the effect by the type of violence. In particular, we distinguish between event types around *Military* violence and event types around *Civilian Violence*. We find some differences by type of disasters. It seems that military violence is more likely to spill-over to neighbouring districts that are connected via major roads while civilian violence seems to spread more towards districts that are only connected geographically. The latter result is likely driven by riots which could be the result of refugees moving away from disaster affected areas to neighbouring districts leading to increased social tensions.

In Table B.9 we replicate the baseline estimate, but using grid cells as the unit of observation. Our baseline estimates remain robust to this alternative unit of analysis as well. We distinguish between battle onset and termination in Table B.10. For this purpose, 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). We do not find evidence of natural disasters having a statistically significant effect on the onset or termination of conflict *per se*. Finally, we examine the diffusion of conflict at different distance cutoffs along the geographic and major road networks in Table B.11.

5 Testing for heterogenous effects

5.1 Conflict spillovers vs economic spillovers

First, we examine whether the battle spillovers we observe as a result of natural disasters are driven by co-existent economic spillovers. It could be, for example, that a natural disaster leads to out-migration, which would then create economic spillovers to neighboring districts as well. These economic spillovers may aggravate or dampen the battle spillovers that arise as a result of natural disasters.

To examine this possibility, we first compile data on economic activity at the district level. In the absence of reliable, district-level GDP data from official accounts, we follow the common approach in the literature (e.g. Henderson et al., 2012; Hodler and Raschky, 2014) and use nighttime luminosity data as a proxy for district-level economic activity. In particular, we access the relatively novel harmonized nighttime light data set by Li et al. (2020), which combines data from the original DMSP satellites (1992–2012) and the more recent VIIRS satellites (2013–2020) to create a harmonised luminosity product for the period 1992–2020. We then match this data set to the district units used in our study, and calculate the annual average nighttime luminosity for each district. Since the nighttime luminosity data is only available from 1992, our empirical examinations below are for the period 1992-2020.

Using this indicator of district-level economic activity, we engage in two sets of empirical examinations to investigate the role of economic spillovers in the context of natural disasters and battle spillovers. First, to examine the effect of natural disasters on economic activity in neighboring districts, we substitute the district-level annual average nighttime luminosity ($Light_{i,t}$) as the outcome variable in Equation (1). Columns (1)-(3) of Table 4 present these estimates. Interestingly, we find no statistically significant effects of natural disasters on economic activity in neighboring districts. The weak positive spillover effect we observe under major road connectivity on Column (2) is no longer statistically significant when accounting for geographic connectivity in Column (3).

Next, we examine whether the battle spillovers we observe in our baseline estimates co-exist with any economic spillovers that may result from natural disasters. In Columns (4)-(6), we estimate Equation (1), where the outcome variable is $Conflict_{i,t}$, but now we additionally control for the level of nighttime luminosity in districts i and j. The idea here to examine whether the battle spillovers remain important when accounting for any economic spillovers. Reassuringly, we observe that the baseline estimates remain prominent even when these variables are included in the specification, confirming that the battle spillovers attributable to natural disaster events are not affected by any economic spillovers.

5.2 Conflict spillovers based on district-specific characteristics

Now we move on to a more spatially detailed analysis where we examine whether the battle spillovers we observe in the baseline estimates are driven by any district-specific characteristics. As discussed in Section 2.3, our data enables us to categorize districts based on

Table 4: Natural Disasters and Economic Activity

	(1) $Light_{i,t}$	(2) $Light_{i,t}$	(3) $Light_{i,t}$	(4) $Conflict_{i,t}$	(5) $Conflict_{i,t}$	(6) $Conflict_{i,t}$
Inverse Geodesic Distance						
$NDIS_{i,t}$	0.0260		0.0082	0.0043		0.0042
	(0.0244)		(0.0096)	(0.0028)		(0.0028)
$NDIS_{i,t-1}$	-0.0083		0.0105	0.0096***		0.0091***
	(0.0256)		(0.0098)	(0.0029)		(0.0028)
Inverse Major Road Distance						
$NDIS_{i,t}$		0.0138*	0.0121		0.0029	0.0021
		(0.0083)	(0.0087)		(0.0019)	(0.0019)
$NDIS_{i,t-1}$		0.0029	0.0007		0.0027	0.0009
		(0.0086)	(0.0090)		(0.0020)	(0.0019)
$DIS_{i,t}$	-0.0215	-0.0100	-0.0099	-0.0024	-0.0025	-0.0024
	(0.0258)	(0.0124)	(0.0123)	(0.0027)	(0.0027)	(0.0027)
$DIS_{i,t-1}$	0.0066	0.0130	0.0133	-0.0057**	-0.0064**	-0.0062**
	(0.0198)	(0.0109)	(0.0109)	(0.0025)	(0.0025)	(0.0025)
Observations	166,432	166,432	166,432	166,432	166,432	166,432
Number of Districts	5,944	5,944	5,944	5,944	5,944	5,944
Distance Cutoff	500km	500km	500km	500km	500km	500km
District FE	YES	YES	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Disaster is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. *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 major road distance matrix, truncated at the indicated distance cut-off. *Light* represents the average value of nighttime lights in the given district for the given time period. Controls for Columns (1)-(3) are $NLight_{i,t}$, $NLight_{i,t-1}$ and $Light_{i,t-1}$. Controls for Columns (4)-(6) are $Light_{i,t}$, $Conflict_{i,t-1}$, $NConflict_{i,t}$ and $NConflict_{i,t-1}$. Conley (1999) clustered standard errors, accounting for spatial correlation of up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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 generate three time-invariant indicators on district-level characteristics. As such, $LightDum_i$ is a proxy for the level of economic activity in a district. Based on the value of nighttime light for the first year for which this data is available (i.e. 1992), $LightDum_i$ is a binary indicator=1 if the district recorded a light value of 10 and above in 1992 (high level of economic activity), and 0 (low level of economic activity) otherwise. $MineDum_i$ is a binary variable that equals 1 if at least one active mining project operated in the district over the period, and zero otherwise. $AgriDum_i$ is a binary indicator = 1 for districts with over 50% agriculturally suitable land, and 0 otherwise.

Using these indicators, we first consider whether the spillover of conflict is determined by the characteristics of the district to which the conflict spills over. To capture this, we define an interaction term $NDIS_{i,t} \times \mathbf{Z_i}$, where $\mathbf{Z_i}$ is a vector of time-invariant characteristic of district i, that is, $Light_i$, $Mine_i$ and $Agri_i$, where district i is the recipient of battle spillovers following the natural disaster shock experienced by its neighbour, district j.

Second, we consider whether the features of the neighboring district j where the natural disaster occurs (source district) play a role in determining battle spillovers. We estimate this effect through the use of an interaction term $NDIS_{i,t} \times \mathbf{Z_j}$, where $\mathbf{Z_j}$ is a vector of time-invariant characteristic of district j, that is, $Light_j$, $Mine_j$ and $Agri_j$.

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

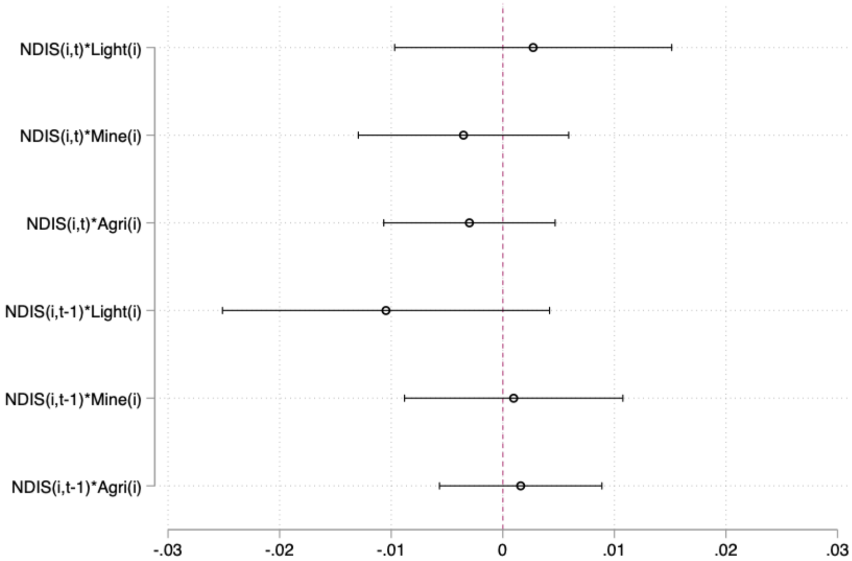
$$
\begin{aligned}
Conflict_{i,t} = {} & \beta_0 DIS_{i,t} + \beta_1 DIS_{i,t-1} + \delta_0 NDIS_{i,t} + \delta_1 NDIS_{i,t-1} \\
& + \lambda_0 (NDIS_{i,t} \times \mathbf{Z_i}) + \lambda_1 (NDIS_{i,t-1} \times \mathbf{Z_i}) \\
& + \mu_0 (NDIS_{i,t} \times \mathbf{Z_j}) + \mu_1 (NDIS_{i,t-1} \times \mathbf{Z_j})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

All variables remain the same as per Equation (2), with the only difference being the addition of the interaction terms as discussed above. As before, the "neighborhood" is defined in terms of the inverse geographic distance and/or the inverse major road distance. As with the baseline estimates, the error term $\epsilon_{i,t}$ is assumed to be spatially and temporally correlated and as such we present Conley (1999) clustered standard errors accounting for spatial correlation up to 500km and temporal correlation up to 1 period.

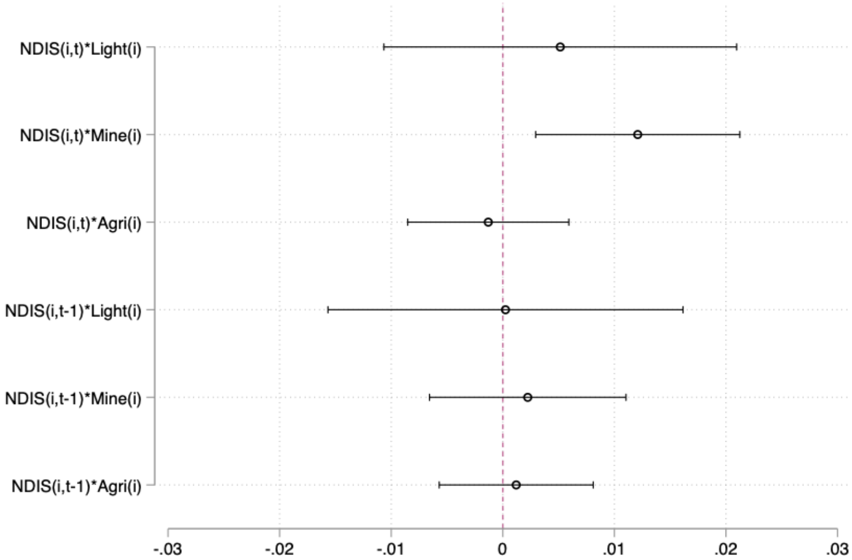
Table B.12 displays the results of this exercise, when considering the three potential mechanisms in isolation. Our preferred estimates appear in Table B.13, where we examine the relative importance of the mechanisms in a horserace specification.Moreover, in Table B.14 we provide the False Discovery Rate adjusted q-values for the same specification, and our coefficients of interest remain statistically significant. For ease of interpretation, we present the estimates in graphical format, in Figures 4 and 5 below.

First, Figure 4 provides the estimates based on the features of district i. In panel (a), neighbors are defined by the altitude-adjusted inverse distance matrix, while in panel (b), they are defined by the inverse major 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 observe that if district i is a mining district, it will experience positive battle spillovers from its neighboring districts linked by major roads.

Figure 4: Heterogenous Effects of Battle Diffusion - Local Features



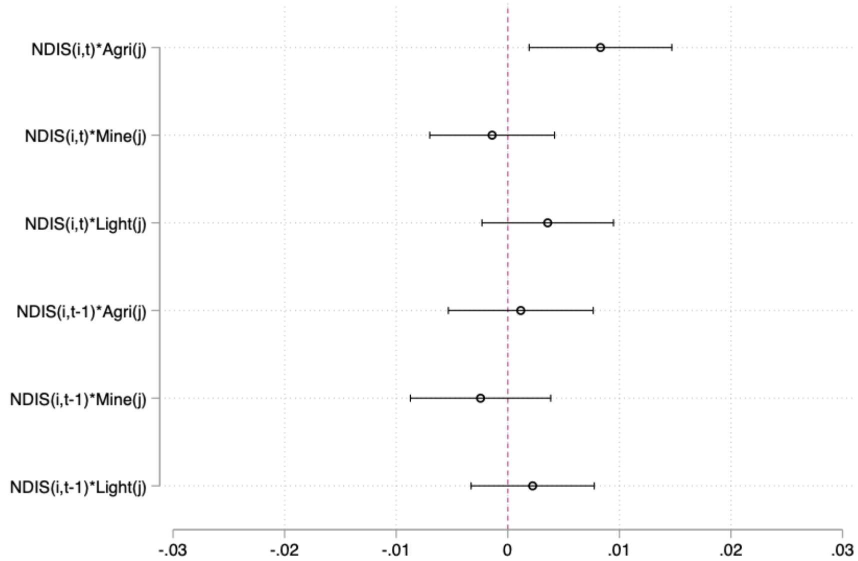
(a) Conflict Diffusion in the Inverse Geodesic Distance Network



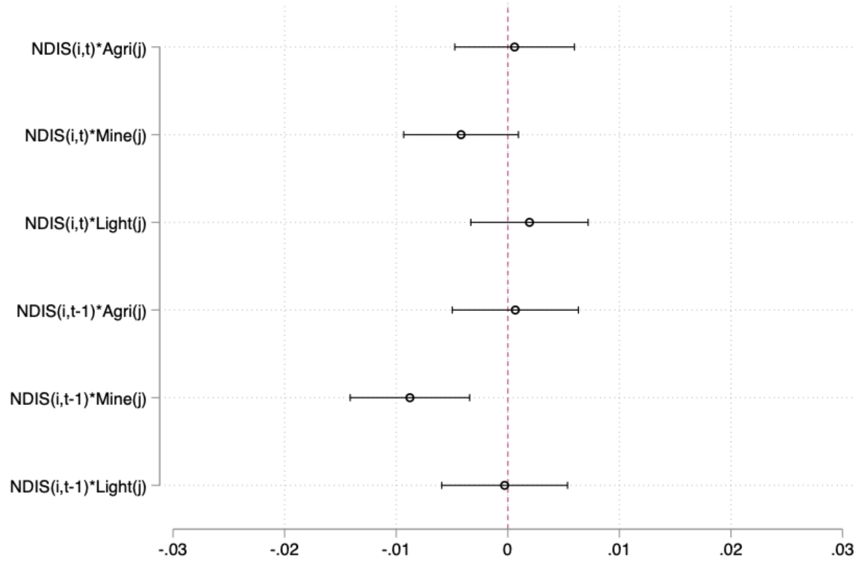
(b) Conflict Diffusion in the Inverse Major Road Distance Network

Notes: Dots show the estimated coefficients on $NDIS_{i,t} \times \mathbf{Z_i}$ and $NDIS_{i,t-1} \times \mathbf{Z_i}$ using Eq. (2), where $\mathbf{Z_i}$ refers to the time-invariant features of district i, as classified by the variables $Light_i$, $Mine_i$ and $Agri_i$. In Panel (a), neighborhood is defined as per the altitude-adjusted inverse geodesic distance matrix. In Panel (b) neighborhood is defined using the inverse major road distance matrix. Estimates include district and country×year fixed effects. Horizontal lines show the 95% confidence interval based on Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period.

Figure 5: Heterogenous Effects of Battle Diffusion - Neighbors' Features



(a) Conflict Diffusion in the Inverse Geodesic Distance Network



(b) Conflict Diffusion in the Inverse Major Road Distance Network

Notes: Dots show the estimated coefficients on $NDIS_{i,t} \times \mathbf{Z_j}$ and $NDIS_{i,t-1} \times \mathbf{Z_j}$ using Eq. 2, 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 $Agri_i$. In Panel (a), neighborhood is defined as per the altitude-adjusted inverse geodesic distance matrix. In Panel (b) neighborhood is defined using the inverse major road distance matrix. Estimates include district and country×year fixed effects. Horizontal lines show the 95% confidence interval based on Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period.

Next, in Figure 5, we examine whether the battle diffusion depends on the characteristics of the neighboring districts ($\mathbf{Z_j}$). In Panel (a), we observe that battle spillovers are more likely to occur along the altitude adjusted inverse distance matrix when district j is an agriculturally suitable district. Interestingly, in Panel (b), we observe a negative spillover effect in the major road connectivity matrix, when district j is a mining district.

The evidence presented above suggest that the characteristics of both district i as well as j affect these spillovers. Specifically, on average, a disaster affecting a mining locality is less likely to lead to an outward shift of combat activity to other connected localities. Mines do not only increase 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. We observe a similar spillover if the neighboring district is agriculturally strong. Interestingly, we do not observe conflict spillovers being driven by high levels of economic activity, as proxied by nighttime light.

6 A possible theoretical mechanism

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

6.1 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:

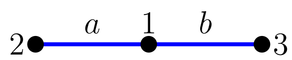


Figure 6: A star network

The matrix $\mathbf{\Gamma}$ representing the network depicted in Figure 6 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 6, 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:

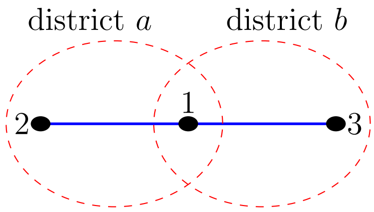


Figure 7: A star network

Of course, any other district representation can be made from Figure 6. In the empirical analysis, a district was defined by its *geographical* position and there will be a link between two districts if there is a major road between them and thus $\omega_{ab} > 0$.[26] For example, in Figure 7, there are two districts a and b and they are geographically adjacent to each other (i.e., there is a major road between them). In that case, there are two layers of proximity, which involve different actors: (i) the *Conflict proximity* where, as in Figure 6, 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 7, 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 $\mathbf{x}$.

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

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

$$\Pi_i(\mathbf{x}_i, \mathbf{x}_{-i}) = \sum_{\alpha \in \mathcal{T}_i} v^\alpha p_i^\alpha(\mathbf{x}^\alpha) - C_i(\mathbf{x}_i), \tag{3}$$

which is just the net expected value of winning the battle(s). Indeed, in (3), $p_i^\alpha(\mathbf{x}^\alpha)$ is the probability of winning battle α for player i. It is given by the following Tullock CSF:

$$p_i^\alpha(\mathbf{x}^\alpha) = \frac{x_i^\alpha}{\sum_{j \in \mathcal{N}^\alpha} x_j^\alpha}. \tag{4}$$

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

$$\Pi_i(\mathbf{x}_i^*, \mathbf{x}_{-i}^*) \geq \Pi_i(\mathbf{x}_i, \mathbf{x}_{-i}^*), \quad \forall \mathbf{x}_i. \tag{5}$$

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 6 or Figure 7 because it is tractable and still provides all the intuition we need for our empirical analysis.[27]

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

6.2 Star network

6.2.1 The model

Consider the star network depicted in Figure 6 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:

[27] In Section 6.3, we provide similar results for a line network with more agents and more battles.

$$
\begin{aligned}
\Pi_1(\mathbf{x}_1, \mathbf{x}_{-1}) =& v^a \frac{x_1^a}{x_1^a + x_2^a} + v^b \frac{x_1^b}{x_1^b + x_3^b} - \frac{s_1}{2}(x_1^a + x_1^b)^2, \\
\Pi_2(\mathbf{x}_2, \mathbf{x}_{-2}) =& v^a \frac{x_2^a}{x_1^a + x_2^a} - \frac{s_2}{2}(x_2^a)^2, \\
\Pi_3(\mathbf{x}_3, \mathbf{x}_{-3}) =& v^b \frac{x_3^b}{x_1^b + x_3^b} - \frac{s_3}{2}(x_3^b)^2.
\end{aligned} \tag{6}
$$

6.2.2 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

$$F_1(x_1^a, x_1^b, x_2^a) := \frac{\partial \Pi_1}{\partial x_1^a} = \frac{v^a x_2^a}{(x_1^a + x_2^a)^2} - s_1(x_1^a + x_1^b), \tag{7}$$

$$F_2(x_1^a, x_1^b, x_3^b) := \frac{\partial \Pi_1}{\partial x_1^b} = \frac{v^b x_3^b}{(x_1^b + x_3^b)^2} - s_1(x_1^a + x_1^b), \tag{8}$$

$$F_3(x_1^a, x_2^a) := \frac{\partial \Pi_2}{\partial x_2^a} = \frac{v^a x_1^a}{(x_1^a + x_2^a)^2} - s_2 x_2^a, \tag{9}$$

$$F_4(x_1^b, x_3^b) = \frac{\partial \Pi_3}{\partial x_3^b} = \frac{v^b x_1^b}{(x_1^b + x_3^b)^2} - s_3 x_3^b. \tag{10}$$

We have the following results:[28]

Proposition 1. *Consider the star network depicted in Figure 6 and the payoff functions given by (6). Then, there exists a unique interior Nash equilibrium* $(x_1^{a*}, x_1^{b*}, x_2^{a*}, x_3^{a*})$ *that simultaneously solves:*

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

$$\begin{cases} F_1(x_1^{a*}, x_1^{b*}, x_2^{a*}) = 0 \\ F_2(x_1^{a*}, x_1^{b*}, x_3^{b*}) = 0 \\ F_3(x_1^{a*}, x_2^{a*}) = 0 \\ F_4(x_1^{b*}, x_3^{b*}) = 0 \end{cases} \tag{11}$$

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 (11) is highly non-linear and, therefore, there are no explicit expressions for the equilibrium. Instead, we apply the implicit function theorem to the system (11) 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*

$$z(x, y) = \frac{vx}{x + y} - \frac{s}{2}x^2. \tag{12}$$

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 (7)–(10) 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* relationship between the efforts of two players involved in the same battle. Figure 8 depicts this relationship.

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

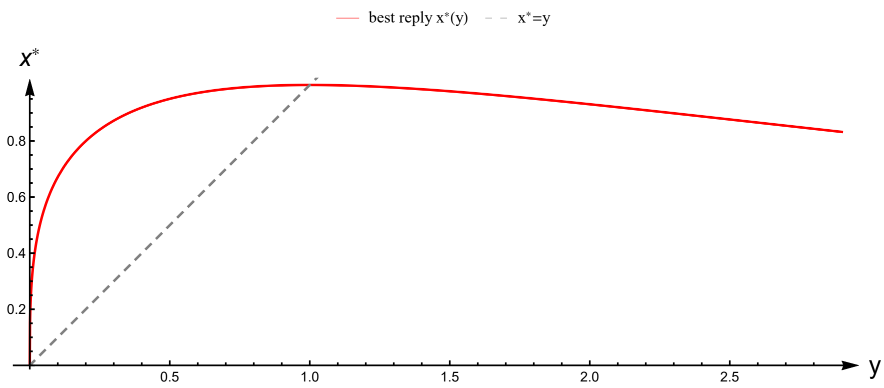


Figure 8: Best response function $x^*(y)$

$p_2^a(x_1^a, x_2^a) = x_2^a/(x_1^a + x_2^a)$, 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.

6.2.3 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 7. 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.[29] 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 6 and 7 and the payoff functions given by (6). 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, $\frac{\partial (x_1^{b*} + x_3^{b*})}{\partial v^a} < 0$.*

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

[29]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.

battle b. Indeed, efforts x_1^a and x_1^b are *strategic substitutes* because

$$\frac{\partial^2 \Pi_1}{\partial x_1^a \partial x_1^b} = -\frac{\partial^2 C_1}{\partial x_1^a \partial x_1^b} = -s_1 < 0. \tag{13}$$

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 9, we illustrate our results by plotting the four efforts of the different players when v^a increases.[30] 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.

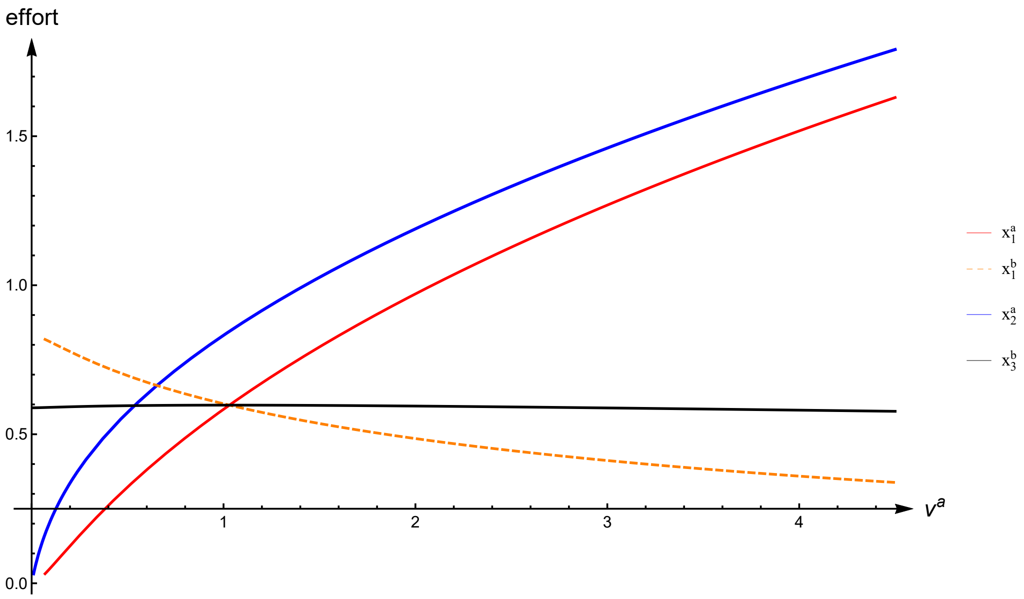


Figure 9: The effect of an increase of v^a on the effort of each agent involved in battles in the network described in Figure 6

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)

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

the relative position of a district within a given battle, and (*iii*) the non-monotonic best response function of each player.

6.3 More complex network structure: A line network

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

Figure 10: A line network with four players and three battles

Observe that this network is similar to the one depicted in Figure 6; however, we added a link between players 2 and 4 and battle c.

The matrix $\mathbf{\Gamma}$ representing the network depicted in Figure 10 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 10, there can be four districts, each corresponding to a battle: districts a, b, c, d. This network with districts can be represented as follows:

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

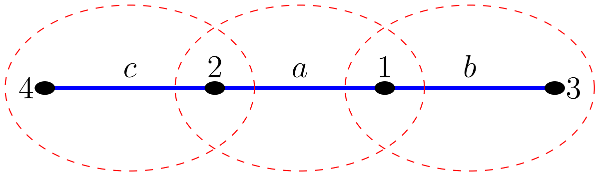


Figure 11: A line network with three districts

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:

$$\begin{aligned}
\Pi_1(\mathbf{x}_1, \mathbf{x}_{-1}) =& v^a \frac{x_1^a}{x_1^a + x_2^a} + v^b \frac{x_1^b}{x_1^b + x_3^b} - \frac{s_1}{2}(x_1^a + x_1^b)^2, \\
\Pi_2(\mathbf{x}_2, \mathbf{x}_{-2}) =& v^a \frac{x_2^a}{x_1^a + x_2^a} + v^c \frac{x_2^c}{x_2^c + x_4^c} - \frac{s_2}{2}(x_2^a + x_2^c)^2, \\
\Pi_3(\mathbf{x}_3, \mathbf{x}_{-3}) =& v^b \frac{x_3^b}{x_1^b + x_3^b} - \frac{s_3}{2}(x_3^b)^2, \\
\Pi_4(\mathbf{x}_4, \mathbf{x}_{-4}) =& v^c \frac{x_4^c}{x_2^c + x_4^c} - \frac{s_4}{2}(x_4^c)^2.
\end{aligned} \tag{14}$$

We have the following result:[31]

Proposition 3. *Consider the line network depicted in Figures 10 and 11 and the payoff functions given by (14). 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, $\frac{\partial (x_1^{b*} + x_3^{b*})}{\partial v^b} > 0$;*

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

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* $sign\frac{\partial (x_2^{c*}+x_4^{c*})}{\partial v^b} = sign(x_2^{a^*} - x_1^{a*})$.

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 10 is longer than the one in Figure 6, 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.

6.4 Discussion

6.4.1 Mechanism consistent with our model

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

Our empirical results are in accordance with the predictions of the model. First, (*i*) we show in Table 2 and Figure 2 that the occurrence of a natural disaster in a district reduces the battle probability in this district. Moreover, (*ii*) in Table 2, we show that the occurrence of a natural disaster in a given district leads to a positive and significant battle spillovers to districts that are linked by major road network and geographic proximity. Finally, in Table B.13 and Figure 4, 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 5, we show that the battle diffusion occurs if the neighboring district is a mining district.

6.4.2 Other possible mechanisms

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

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

7 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-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 2020. Empirical results reveal that natural disasters do indeed decrease conflict incidence in the affected district but increases fighting activity in surrounding districts, particularly those that are better connected via the geographic and major road networks. In total, local natural disasters result in a net increase in the likelihood of violent conflict in the spatial system. 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. As such, 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.

References

Acemoglu, D., C. Garcia-Gimeno, and J. A. Robinson. (2015), "State capacity and economic development: A network approach," *American Economic Review*, 105(8), 2364–2409.

Amarasinghe, A., R. Hodler, P. A. Raschky and Y. Zenou. (2020), "Key players in economic development," IZA Discussion Papers No. 13071.

Angrist, J. D. and J-S. Pischke (2009), *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton: Princeton University Press.

Anselin, L., J. Le Gallo and H. Jayet (2006), Spatial panel econometrics. In: Matyas L, P.

Sevestre (eds) *The Econometrics of Panel Data, Fundamentals and Recent Developments in Theory and Practice*, 3rd ed. Kluwer, Dordrecht, pp 901–969.

Baker, A. C., D. F. Larcker and C. CY Wang (2021), "How much should we trust staggered difference-in-differences estimates?," *Journal of Financial Economics*, 144(2), 370—395.

Berman, N. and M. Couttenier (2015), "External shocks, internal shots: The geography of civil conflicts," *Review of Economics and Statistics*, 97(4), 758–776.

Berman, Nicolas, Mathieu Couttenier, Dominic Rohner and Mathias Thoenig (2017), "This mine is mine! How minerals fuel conflicts in Africa," *American Economic Review*, 107(6), 1564–1610.

Berman, N., M. Couttenier and R. Soubeyran (2021), "Fertile ground for conflict," *Journal of the European Economic Association*, 19(1): 82–127.

Besley, T. J. and T. Persson (2011), "The logic of political violence," *Quarterly Journal of Economics*, 126(3): 1411–1446.

Blattman, C. and E. Miguel (2010), "Civil war," *Journal of Economic Literature*, 48(1), 3–57.

Bocher, O., M. Faure, Y. Long and Y. Zenou (2020), "Perceived competition in networks," CEPR Discussion Paper No. 15582.

Bonfatti, R., Y. Gu and S. Poelhekke (2020) "Priority Roads: The political economy of Africa's interior-to-coast roads," CEPR Discussion Paper No. DP15354.

Borusyak, K., X. Jaravel and J. Spiess (2022) "Revisiting event study designs: Robust and efficient estimation," arXiv Discussion Paper No. 2108.12419.

Bosker, M. and J. de Ree (2014), "Ethnicity and the spread of civil war," *Journal of Development Economics*, 108, 206—221.

Brangewitz, S., B. M. Djawadi, A. Endres and B. Hoyer (2018) "Network formation and disruption - an experiment. Are efficient networks too complex?" *Journal of Economic Behavior and Organization*, 157, 708–734.

Buhaug, H. and K. Gleditsch (2008), "Contagion or confusion? Why conflicts cluster in space, " *International Studies Quarterly*, 52(2), 215–233.

Callaway, B. and P. Sant'Anna (2021), "Difference-in-differences with multiple time periods." *Journal of Econometrics*, 225(2), 200–230.

Cederman L-E. and M. Vogt (2017), "Dynamics and logics of civil war." *Journal of Conflict Resolution*, 61(9), 1992–2016.

Cervellati, M., E. Esposito and U. Sunde (2022), "Epidemic shocks and civil violence: Evidence from malaria outbreaks in Africa." *Review of Economics and Statistics*, 104 (4), 780–796.

Chalfin, A. J. and McCrary, (2017), "Criminal Deterrence: A Review of the literature." *Journal of Economic Literature*, 55(1), 5–48.

Chassang, S. and G. Padró i Miquel (2009), "Economic shocks and civil war," *Quarterly Journal of Political Science*, 4(3), 211–228.

Ciccone, A. (2011), "Economic shocks and civil conflict: A comment," *American Economic Journal: Applied Economics*, 3(4), 215–227.

Cilliers, J. (2015), "Future (im)perfect? Mapping conflict, violence and extremism in Africa," ISS paper 287.

Colella, F., R. Lalive, S. O. Sakalli, and M. Theonig (2019), "Inference with arbitrary clustering, "IZA Working Paper 12584.

Collier, P. and A. Hoeffler (2004), "Greed and grievance in civil war," *Oxford Economic Papers*, 56, 563–595.

Conley, T. G. (1999), "GMM estimation with cross sectional dependence," *Journal of Econometrics*, 92(1), 1–45.

Corchón, L. C. (2007), "The theory of contests: A survey," *Review of Economic Design*, 11, 69–100.

Couttenier, M. and R. Soubeyran (2014), "Drought and civil war in Sub-Saharan Africa," *Economic Journal*, 124(575), 201–244.

Croicu, M. and R. Sundberg (2017), "UCDP GED codebook version 17.1," Department of Peace and battle Research, Uppsala University.

De Chaisemartin, C. and X. D'Haultfœuille (2020), "Two-way fixed effects estimators with heterogeneous treatment effects," *American Economic Review*, 110, 2964-2996.

Debarsy, N., C. Ertur and J. LeSage (2012), "Interpreting dynamic space-time panel data models," *Statistical Methodology*, 9, 158–171.

Dell, M. (2015), "Trafficking networks and the Mexican drug war," *American Economic Review*, 105(6), 1738–1779.

Deryugina, T. and S. M. Hsiang (2014), "Does the environment still matter? Daily temperature and income in the United States," *NBER Working Paper 20750.*

Dowd, C. (2015), "Grievances, governance and Islamist violence in Sub-Saharan Africa," *Journal of Modern African Studies*, 53(4), 505–531.

Dube, O. and J. F. Vargas (2013), "Commodity price shocks and civil conflict: Evidence from Colombia," *Review of Economic Studies*, 80(4) p. 1384—1421.

Eberle, U., D. Rohner and M. Thoening (2020), "Heat and hate, climate security and farmer-herder conflicts in Africa, " *ESOC Working Paper 22.*

Elhorst, J. P. (2014), *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*, Springer, Heidelberg.

Eubank, N. (2019), "Social networks and the political salience of ethnicity," *Quarterly Journal of Political Science*, 14(1), 1–39.

Fearon J. and D. Laitin (2003), "Ethnicity, insurgency, and civil war," *American Political Science Review*, 97(1), 75–90.

Fjelde, H. (2015), "Farming or fighting? Agricultural price shocks and civil war in Africa," *World Development*, 67, 525-–534.

Franke, J. and T. Öztük (2015), "Conflict networks," *Journal of Public Economics*, 126, 104–113.

Freeman, R. B. (1999), "The economics of crime," In: O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics, Vol. 3*, Amsterdam: Elsevier Science, pp. 3529–3571.

Gassebner, M., A. Keck and R. Teh (2010), "Shaken, not stirred: The impact of disasters on international trade," *Review of International Economics*, 18(2), 351–368.

Goodman-Bacon, A. (2021), "Difference-in-differences with variation in treatment timing, " *Journal of Econometrics*, 225(2), 254–277.

Goyal, S. and A. Vigier (2014), "Attack, defence and contagion in networks," *Review of Economics Studies*, 81(3), 1518–1542.

Guarnieri, E. (2023), "Cultural Distance and Ethnic Civil Conflict, " CESifo Working Paper 10609.

Guha-Sapir, D., R. Below and P. Hoyois (2016), "EM-DAT: The CRED/OFDA international disaster database," Université Catholique de Louvain, Brussels, Belgium.

Harari, M. and E. La Ferrara (2018), "Conflict, climate and cells: A disaggregated analysis," *Review of Economics and Statistics*, 100(4), 594–608.

Henderson, V.J., A. Storeygard and D.N. Weil (2012), "Measuring economic growth from outer space," *American Economic Review*, 102, 994–1028.

Hiller, T. (2017), "Friends and enemies: A model of signed network formation," *Theoretical Economics*, 12, 1057–1087.

Hodler, R. and P. A. Raschky (2014), "Regional favoritism," *Quarterly Journal of Economics*, 129, 995–1033.

Hodler, R. and P. A. Raschky (2014b), "Economic shocks and civil conflict at the regional level," *Economic Letters*, 124, 530-533.

Hsiang, S., M. Burke, and E. Miguel (2013), "Quantifying the influence of climate change on human conflict," *Science*, 341 (6151), 1212–1226.

Hsiang, S. and A. Jina (2014), "The Causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones," *NBER Working Paper 20352*.

Hsiang, S., R. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. J. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, K. Larsen and T. Houser (2017), "Estimating economic damage from climate change in the United States," *Science*, 356 (6345), 1362–1369.

Humphreys, M. and J. Weinstein(2008), "Who Fights? The determinants of participation in civil war. " *American Journal of Political Science*, 52, 436–455.

Jackson, M.O. (2008), *Social and Economic Networks*, Princeton: Princeton University Press.

Jackson, M. O., B. W. Rogers, and Y. Zenou (2017), "The economic consequences of social network structure," *Journal of Economic Literature*, 55(1), 49–95

Jackson, M. O. and S. Nei (2015), "Networks of military alliances, wars, and international trade," *Proceedings of the National Academy of Sciences of the USA*, 112(50), 15277–15284.

Kelejian, H. H. and I. R. Prucha (1998), "A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances." *Journal of Real Estate Finance and Economics*, 17(1), 99–121.

König, M. D., D. Rohner, M. Thoenig, and F. Zilibotti (2017), "Networks in conflict: theory and evidence from the Great War of Africa," *Econometrica*, 85, 1093–1132.

Kovenock, D. and B. Roberson (2012), "Conflicts with multiple battlefields," In: *Oxford Handbook of the Economics of Peace and Conflict*, Oxford: Oxford University Press.

Kovenock, D. and B. Roberson (2018), "The optimal defense of networks of targets," *Economic Inquiry*, 56, 2195–2211.

Lee, L. and J. Yu (2010), "Estimation of spatial autoregressive panel data models with fixed effects," *Journal of Econometrics*, 154(2), 165–185.

LeSage, J. and R. K. Pace (2009). *Introduction to Spatial Econometrics*, New York: Chapman and Hall.

Mach, K.J., C.M. Kraan, W.N. Adger ,H. Buhaug, M. Burke, J. D. Fearon, C. B. Field, C. S. Hendrix, J.-F. Maystadt, J. O'Loughlin, P. Roessler, J. Scheffran, K. A. Schultz, and N. von Uexkull (2019), "Climate as a risk factor for armed conflict," *Nature*, 571, 193–197.

Martin, P., T. Mayer and M. Thoenig(2008), "Make trade not war?," *Review of Economic Studies*, 75(3), 865–900.

McGuirk, E. and M. Burke (2020), "The economic origins of conflict in Africa, " *Journal of Political Economy*, 128(10), 3940–3997.

McGuirk, E. and N. Nunn (2021), "Transhumant pastoralism, climate change, and conflict in Africa,"NBER Working Paper No. 28243.

Miguel, E., Satyanath, S. and E. Sergenti (2004), "Economic shocks and civil conflict: An instrumental variables approach," *Journal of Political Economy*, 112(4), 725–753.

Mottalebab, K.A., S. Mohanty and A. K. Mishra (2015), “Intra-household resource allocation under negative income shock: A natural experiment,” *World Development*, 66, 557–571.

Mueller, H., D. Rohner and D. Schoenholzer (2022), “Ethnic violence across space,” *Economic Journal*, 132(642), 709–740.

Müller-Crepon, C., P. Hunziker and L.-E. Cederman, (2021), “Roads to rule, roads to rebel: Relational state capacity and conflict in Africa. ” *Journal of Conflict Resolution*, 65(2–3), 563–590.

Murdock, G. P. (1959), *Africa: Its Peoples and Their Culture History*, New York: McGraw-Hill Book Company.

Novta, N. (2016), “Ethnic diversity and the spread of civil war,” *Journal of the European Economic Association*, 14(5), 1074–1100.

Prunier, G. (2004), “Rebel movements and proxy warfare: Uganda, Sudan and the Congo (1986-99),” *African Affairs*, 103(412), 359–383.

Puzzello, L. and P. A. Raschky (2014), “Global supply chains and natural disasters: Implications for international trade,” In: B. Ferrarini and D. Hummels (Eds.), *Asia and Global Production Networks: Implications for Trade, Incomes and Economic Vulnerability*, Cheltenham: Edward Elgar Publishing, pp. 112–147.

Ray, D. and J. Esteban (2017), “Conflict and development,” *Annual Review of Economics*, 9, 263–293.

Roth, J. (2022), “Pretest with Caution: Event-Study Estimates after Testing for Parallel Trends,” *American Economic Review: Insights*, 4(3), 305–22.

Rigterink, A. S. (2010), “Natural resources and civil conflict: An overview of controversies, consensus, and channels,” *The Economics of Peace and Security Journal*, 5(2), 17–22.

Roberson, B. (2006), “The colonel Blotto game,” *Economic Theory*, 29, 1–24.

Rogall, T. (2014), "Mobilizing the masses for genocide," Stockholm University, mimeo.

Skidmore, M. and H. Toya (2002), "Do natural disasters promote long-run growth?" *Economic Inquiry*, 40, 664–687.

Storeygard, A. (2016) "Farther on down the road: transport costs, trade and urban growth in Sub-Saharan Africa," *Review of Economic Studies*, 83(3), 1263–1295,

Thurston, A. (2018). *Boko Haram: The history of an African jihadist movement*, Princeton: Princeton University Press.

Xu, J., Y., Zenou and J. Zhou (2022), "Equilibrium characterization and shock propagation in conflict networks," *Journal of Economic Theory*, 206, 105571.

Yesilyurt, M. E. and J. P. Elhorst (2017), "Impacts of neighboring countries on military expenditures: A dynamic spatial panel approach," *Journal of Peace Research*, 54(6), 777–790.

Yu, J., R. de Jong and L. F. Lee (2008), "Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large ," *Journal of Econometrics*, 146(1), 118–134,

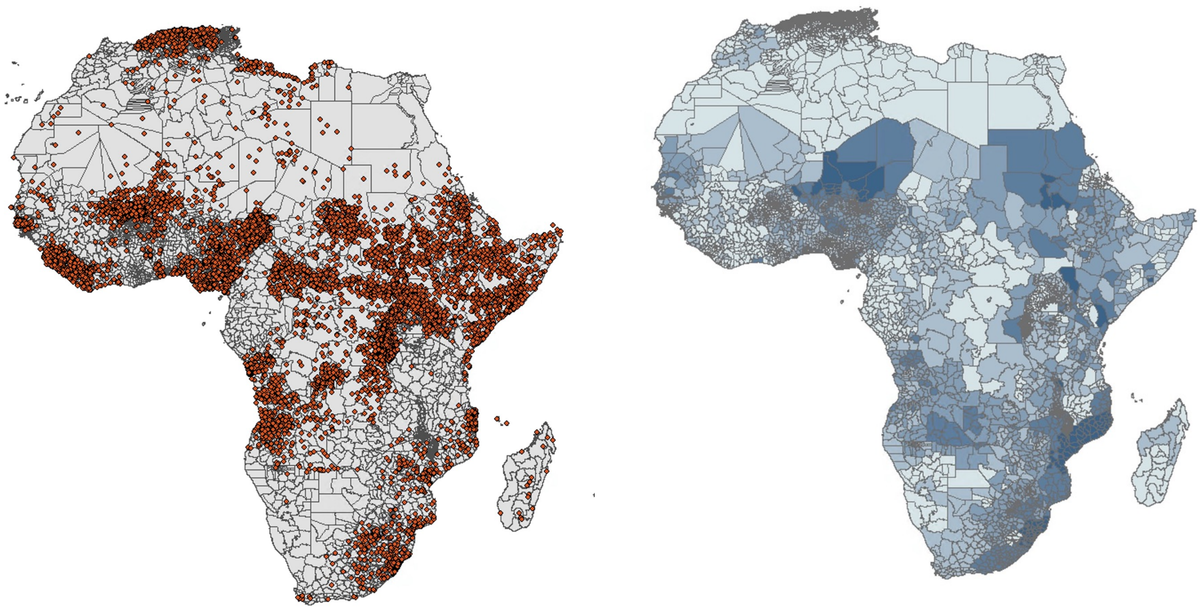
(Not-for-Publication) Online Appendix

Conflicts in Spatial Networks

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

A Additional Data Description

Figure A.1: Conflicts and Natural Disasters in Africa



(a) Conflicts

(b) Natural Disasters

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

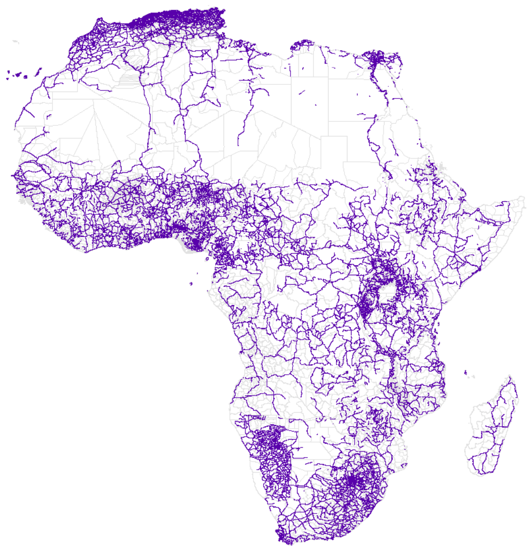
[1]School of Economics, University of Sydney and SoDa Laboratories, Monash University. Email: ashani.amarasinghe@sydney.edu.au.

[2]Department of Economics and SoDa Laboratories, Monash University. Email: paul.raschky@monash.edu.

[3]Department of Economics, Monash University. Email: yves.zenou@monash.edu.

[4]School of Economics and Management, Tsinghua University. Email: zhoujunjie@sem.tsinghua.edu.cn.

Figure A.2: Primary and Secondary Roads in Africa



Source: OpenStreetMap

Table A.1: Disasters by type

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

Table A.2: Correlation Between Conflict and Major Road Connectivity

	(1) $Road\ Length_i$ $(Total)$	(2) $Road\ Length_i$ $(Total)$	(3) $Road\ Length_i$ $(PerCapita)$	(4) $Road\ Length_i$ $(PerCapita)$
$Conflict_i$	2.0936	2.1202	-0.0000	-0.0000
	(1.2983)	(1.3217)	(0.0000)	(0.0000)
$Light_i$		-0.2610		-0.0002
		(8.1773)		(0.0002)
$Temperature_i$		156.2588		-0.0122
		(157.6420)		(0.0121)
$Precipitation_i$		-154.7041**		-0.0084**
		(69.3215)		(0.0036)
Observations	5,944	5,837	5,880	5,778
Country FE	YES	YES	YES	YES

This Table presents the cross-sectional regression estimates on the correlation between a district's battle incidence and major road connectivity. The outcome variable in Columns (1) and (2) is the total major road length of district i, while the outcome variable in Columns (3) and (4) is the per capita major road length of district i. $Conflict_i$ is the total number of battles resulting in at least one death in the sample period. $Light_i$ is the log of the total nighttime light over the sample period. $Temperature$ and $Precipitation$ are the log of the district'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

B Robustness checks

Table B.1: Natural Disasters and Battle Diffusion at the District-Year Level - Step-by-Step Addition of Controls

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$	(4) $Conflict_{i,t}$
Inverse Geodesic Distance				
$NDIS_{i,t}$	0.0048	0.0054*	0.0048	0.0054*
	{0.0033}	{0.0032}	{0.0033}	{0.0032}
	(0.0035)	(0.0034)	(0.0035)	(0.0034)
$NDIS_{i,t-1}$	0.0101***	0.0101***	0.0100***	0.0100***
	{0.0033}	{0.0032}	{0.0033}	{0.0032}
	(0.0038)	(0.0036)	(0.0037)	(0.0036)
$NConflict_{i,t}$		0.0003		0.0003
		{0.0022}		{0.0022}
		(0.0024)		(0.0024)
$NConflict_{i,t-1}$		0.0043**		0.0043**
		{0.0021}		{0.0021}
		(0.0023)		(0.0023)
Inverse Major Road Distance				
$NDIS_{i,t}$	0.0022	0.0039**	0.0027	0.0042**
	{0.0020}	{0.0020}	{0.0020}	{(0.0020}
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
$NDIS_{i,t-1}$	0.0006	0.0011	0.0014	0.0019
	{0.0020}	{0.0020}	{0.0021}	{0.0021}
	(0.0024)	(0.0023)	(0.0023)	(0.0023)
$NConflict_{i,t}$		0.0259***		0.0259***
		{0.0028}		{0.0028}
		(0.0035)		(0.0035)
$NConflict_{i,t-1}$		0.0166***		0.0166***
		{0.0024}		{0.0024}
		(0.0027)		(0.0027)
$DIS_{i,t}$			-0.0035	-0.0031
			{0.0031}	{0.0030}
			(0.0035)	(0.0034)
$DIS_{i,t-1}$			-0.0060**	-0.0061**
			{0.0029}	{0.0028}
			(0.0029)	(0.0028)
Observations	184,264	184,264	184,264	184,264
Number of Districts	5,944	5,944	5,944	5,944
Distance Cut-off	500km	500km	500km	500km
District FE	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES

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

Table B.2: Direct and spillover effects of natural disasters on conflict - Including the Lagged Dependent Variable

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$
Inverse Geodesic Distance			
$NDIS_{i,t}$	0.0044		0.0042
	{0.0028}		{0.0027}
	(0.0029)		(0.0028)
$NDIS_{i,t-1}$	0.0097***		0.0092***
	{0.0028}		{0.0028}
	(0.0032)		(0.0031)
Inverse Major Road Distance			
$NDIS_{i,t}$		0.0037**	0.0029
		{0.0018}	{0.0018}
		(0.0021)	(0.0021)
$NDIS_{i,t-1}$		0.0032*	0.0013
		{0.0019}	{0.0019}
		(0.0021)	(0.0021)
$DIS_{i,t}$	-0.0019	-0.0023	-0.0022
	{0.0027}	{0.0027}	{0.0027}
	(0.0031)	(0.0030)	(0.0030)
$DIS_{i,t-1}$	-0.0049**	-0.0057**	-0.0054**
	{0.0025}	{0.0025}	{0.0025}
	(0.0025)	(0.0025)	(0.0025)
$Conflict_{i,t-1}$	0.2315***	0.2298***	0.2297***
	(0.0105)	(0.0104)	(0.0104)
Observations	184,264	184,264	184,264
Number of Districts	5,944	5,944	5,944
Distance Cut-off	500km	500km	500km
District FE	YES	YES	YES
Country× Year	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES

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

Table B.3: Natural Disasters and Battle Diffusion at the District-Year Level - Disasters including Droughts

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$
Inverse Geodesic Distance			
$NDIS_{i,t}$	0.0081***		0.0080***
	(0.0031)		(0.0031)
$NDIS_{i,t-1}$	0.0112***		0.0107***
	(0.0032)		(0.0031)
Inverse Major Road Distance			
$NDIS_{i,t}$		0.0050**	0.0035*
		(0.0021)	(0.0020)
$NDIS_{i,t-1}$		0.0034	0.0015
		(0.0021)	(0.0020)
$DIS_{i,t}$	-0.0018	-0.0024	-0.0020
	(0.0029)	(0.0029)	(0.0029)
$DIS_{i,t-1}$	-0.0019	-0.0027	-0.0023
	(0.0028)	(0.0028)	(0.0028)
Observations	184,264	184,264	184,264
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
$NConflict_{i,t}$	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES

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

Table B.4: Direct and spillover effects of natural disasters on conflict - By disaster category

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$	(4) $Conflict_{i,t}$
Disaster Category	*Large*	*Small*	*Climatic*	*Geologic*
Inverse Geodesic Distance				
$NDIS_{i,t}$	0.0037	0.0062**	0.0057*	0.0144**
	(0.0038)	(0.0030)	(0.0032)	(0.0064)
$NDIS_{i,t-1}$	0.0109***	0.0045	0.0116***	0.0022
	(0.0037)	(0.0032)	(0.0032)	(0.0054)
Inverse Major Road Distance				
$NDIS_{i,t}$	0.0002	0.0068***	0.0044**	-0.0067
	(0.0024)	(0.0025)	(0.0020)	(0.0072)
$NDIS_{i,t-1}$	0.0022	0.0023	0.0024	-0.0081
	(0.0025)	(0.0024)	(0.0021)	(0.0078)
$DIS_{i,t}$	-0.0011	-0.0061	-0.0027	-0.0151
	(0.0033)	(0.0049)	(0.0030)	(0.0224)
$DIS_{i,t-1}$	-0.0050	-0.0082*	-0.0067**	0.0086
	(0.0034)	(0.0044)	(0.0028)	(0.0226)
Observations	184,264	184,264	184,264	184,264
Number of Districts	5,944	5,944	5,944	5,944
Distance Cut-off	500km	500km	500km	500km
District FE	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES

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

Table B.5: Direct and spillover effects of natural disasters on conflict - By disaster type

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$	(4) $Conflict_{i,t}$	(5) $Conflict_{i,t}$	(6) $Conflict_{i,t}$
$DisasterType$	$Flood$	$Landslide$	$Earthquake$	$Drought$	$Storm$	$Wildfire$
Inverse Geodesic Distance						
$NDIS_{i,t}$	0.0051	0.0081	0.0121	0.0027	-0.0010	-0.0022
	(0.0033)	(0.0082)	(0.0100)	(0.0054)	(0.0039)	(0.0089)
$NDIS_{i,t-1}$	0.0121***	-0.0016	0.0090	0.0051	0.0035	-0.0088
	(0.0033)	(0.0075)	(0.0071)	(0.0059)	(0.0041)	(0.0076)
Inverse Major Road Distance						
$NDIS_{i,t}$	0.0050**	-0.0083	-0.0039	-0.0011	-0.0009	0.0046
	(0.0022)	(0.0087)	(0.0092)	(0.0047)	(0.0036)	(0.0072)
$NDIS_{i,t-1}$	0.0020	-0.0117	-0.0027	0.0011	0.0031	0.0086
	(0.0022)	(0.0088)	(0.0093)	(0.0046)	(0.0038)	(0.0066)
$DIS_{i,t}$	-0.0054*	0.0087	-0.0403*	0.0025	0.0144	0.0039
	(0.0032)	(0.0354)	(0.0231)	(0.0073)	(0.0102)	(0.0156)
$DIS_{i,t-1}$	-0.0087***	-0.0146	-0.0155	0.0194**	0.0045	0.0050
	(0.0029)	(0.0261)	(0.0284)	(0.0096)	(0.0093)	(0.0186)
Observations	184,264	184,264	184,264	184,264	184,264	184,264
Number of Districts	5,944	5,944	5,944	5,944	5,944	5,944
Distance Cut-off	500km	500km	500km	500km	500km	500km
District FE	YES	YES	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES	YES	YES

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

Table B.6: SPEI and Conflict Diffusion at the District-Year Level

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$
Inverse Geodesic Distance			
$NSPEI_{i,t}$	0.0174**		0.0091
	(0.0076)		(0.0055)
$NSPEI_{i,t-1}$	0.0191**		0.0112**
	(0.0075)		(0.0056)
Inverse Major Road Distance			
$NSPEI_{i,t}$		0.0034	0.0022
		(0.0034)	(0.0033)
$NSPEI_{i,t-1}$		-0.0010	-0.0026
		(0.0035)	(0.0035)
$SPEI_{i,t}$	0.0007	0.0037	-0.0006
	(0.0042)	(0.0037)	(0.0039)
$SPEI_{i,t-1}$	-0.0080*	0.0014	-0.0036
	(0.0041)	(0.0039)	(0.0040)
Observations	172,376	172,376	172,376
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
$NConflict_{i,t}$	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES

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

Table B.7: Direct and spillover effects of natural disasters on conflict - By conflict type

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$
Conflict Type	*State*	*Non − State*	*Onesided*
Inverse Geodesic Distance			
$NDIS_{i,t}$	0.0025	0.0026*	-0.0069
	(0.0026)	(0.0015)	(0.0117)
$NDIS_{i,t-1}$	0.0042	0.0042***	0.0170
	(0.0026)	(0.0015)	(0.0136)
Inverse Major Road Distance			
$NDIS_{i,t}$	0.0028*	0.0003	0.0169
	(0.0015)	(0.0012)	(0.0140)
$NDIS_{i,t-1}$	0.0021	-0.0000	-0.0089
	(0.0016)	(0.0011)	(0.0147)
$DIS_{i,t}$	-0.0007	-0.0004	-0.0011
	(0.0022)	(0.0019)	(0.0212)
$DIS_{i,t-1}$	-0.0038*	-0.0008	-0.0007
	(0.0021)	(0.0019)	(0.0211)
Observations	184,264	184,264	184,264
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
$NConflict_{i,t}$	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES

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

Table B.8: Natural Disasters and Violence Diffusion at the District-Year Level - ACLED vs UCDP comparison

	(1) ACLED $Violence_{i,t}$	(2) UCDP $Violence_{i,t}$	(3) Pooled $Violence_{i,t}$	(4) ACLED $Military$ $Violence_{i,t}$	(5) ACLED $Civilian$ $Violence_{i,t}$
Inverse Geodesic Distance					
$NDIS_{i,t}$	0.0097**	0.0044	0.0109**	0.0010	0.0051
	(0.0042)	(0.0036)	(0.0046)	(0.0033)	(0.0034)
$NDIS_{i,t-1}$	0.0094**	0.0101***	0.0137***	0.0024	0.0075**
	(0.0042)	(0.0035)	(0.0045)	(0.0032)	(0.0035)
Inverse Major Road Distance					
$NDIS_{i,t}$	0.0050	0.0028	0.0041	0.0025	0.0028
	(0.0031)	(0.0023)	(0.0033)	(0.0022)	(0.0027)
$NDIS_{i,t-1}$	0.0031	0.0026	0.0040	0.0051**	0.0002
	(0.0030)	(0.0023)	(0.0032)	(0.0023)	(0.0026)
$DIS_{i,t}$	-0.0025	-0.0021	-0.0016	-0.0043	-0.0015
	(0.0042)	(0.0033)	(0.0046)	(0.0032)	(0.0036)
$DIS_{i,t-1}$	-0.0020	-0.0067**	-0.0033	-0.0008	-0.0025
	(0.0042)	(0.0030)	(0.0045)	(0.0031)	(0.0038)
Observations	136,712	136,712	136,712	136,712	136,712
Number of Districts	5,944	5,944	5,944	5,944	5,944
Distance Cutoff	500km	500km	500km	500km	500km
District FE	YES	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES	YES
$N(Outcome)_{i,t}$	YES	YES	YES	YES	YES
$N(Outcome)_{i,t-1}$	YES	YES	YES	YES	YES

DIS is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. The outcome variable in Column (1) is a binary variable indicating the presence (=1) or absence (=0) of a violent event as per the ACLED database. The outcome variable in Column (2) is a binary variable indicating the presence (=1) or absence (=0) of a violent event as per the UCDP database, for the same sample as in Column (1). The outcome variable in Column (3) is a binary variable indicating the presence (=1) or absence (=0) of a violent event as per either the ACLED or the UCDP database. The outcome variables in Columns (4) and (5) are binary variable indicating the presence (=1) or absence (=0) of a strategic violent event and violent events targeting civilians, as per the ACLED database. $NDIS$ and $N(Outcome)$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event or the outcome variable of interest, respectively, in any one of the district's neighbours. Neighbourhood is based on the altitude-adjusted inverse distance matrix and the inverse major road distance matrix, truncated at the indicated distance cut-off. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.9: Natural Disasters and Conflict Diffusion at the Grid Cell-Year Level

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$
Inverse Geodesic Distance			
$NDIS_{i,t}$	0.0022		0.0018
	(0.0014)		(0.0013)
$NDIS_{i,t-1}$	0.0035**		0.0024*
	(0.0015)		(0.0014)
Inverse Major Road Distance			
$NDIS_{i,t}$		0.0037	0.0032
		(0.0023)	(0.0023)
$NDIS_{i,t-1}$		0.0065***	0.0059***
		(0.0022)	(0.0022)
$DIS_{i,t}$	-0.0003	0.0001	-0.0001
	(0.0024)	(0.0023)	(0.0023)
$DIS_{i,t-1}$	-0.0034	-0.0041	-0.0043*
	(0.0026)	(0.0025)	(0.0025)
Observations	192,727	192,727	192,727
Distance Cut-off	500km	500km	500km
Grid Cell FE	YES	YES	YES
Country× Year FE	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES

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

Table B.10: Natural Disasters, Conflict Onset and Termination - District-Year level

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

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

Table B.11: Natural Disasters and Conflict Diffusion at the District-Year Level - Robustness to Alternative Distance Cut-offs

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$	(4) $Conflict_{i,t}$	(5) $Conflict_{i,t}$
Inverse Geodesic Distance					
$NDIS_{i,t}$	-0.0042*	0.0039*	0.0045*	0.0036	0.0054*
	(0.0022)	(0.0023)	(0.0027)	(0.0028)	(0.0032)
$NDIS_{i,t-1}$	-0.0025	0.0008	0.0042	0.0078***	0.0100***
	(0.0021)	(0.0023)	(0.0027)	(0.0029)	(0.0032)
Inverse Major Road Distance					
$NDIS_{i,t}$	0.0042	0.0010	0.0031	0.0047**	0.0042**
	(0.0026)	(0.0023)	(0.0022)	(0.0021)	(0.0020)
$NDIS_{i,t-1}$	0.0038	0.0036*	0.0019	0.0014	0.0019
	(0.0025)	(0.0022)	(0.0022)	(0.0021)	(0.0021)
$DIS_{i,t}$	-0.0031	-0.0037	-0.0036	-0.0035	-0.0031
	(0.0027)	(0.0027)	(0.0028)	(0.0029)	(0.0030)
$DIS_{i,t-1}$	-0.0063**	-0.0070***	-0.0064**	-0.0062**	-0.0061**
	(0.0025)	(0.0027)	(0.0027)	(0.0028)	(0.0028)
Observations	184,264	184,264	184,264	184,264	184,264
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
$NConflict_{i,t}$	YES	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES	YES

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

Table B.12: Direct and spillover effects of natural disasters on conflict - Mechanisms

	(1) $Conflict_{i,t}$ Z=$Light$	(2) $Conflict_{i,t}$ Z=$Mine$	(3) $Conflict_{i,t}$ Z=$Agri$
Inverse Geodesic Distance			
$NDIS_{i,t}$	0.0045	0.0055	0.0034
	(0.0036)	(0.0034)	(0.0032)
$NDIS_{i,t-1}$	0.0102***	0.0102***	0.0093***
	(0.0035)	(0.0034)	(0.0032)
$NDIS_{i,t} \times Z_i$	0.0003	-0.0027	-0.0048
	(0.0070)	(0.0051)	(0.0044)
$NDIS_{i,t-1} \times Z_i$	-0.0107	0.0005	0.0015
	(0.0078)	(0.0054)	(0.0042)
$NDIS_{i,t} \times Z_j$	0.0035	0.0001	0.0095**
	(0.0035)	(0.0031)	(0.0037)
$NDIS_{i,t-1} \times Z_j$	0.0026	-0.0020	0.0022
	(0.0034)	(0.0035)	(0.0038)
Inverse Major Road Distance			
$NDIS_{i,t}$	0.0032	0.0042*	0.0035
	(0.0022)	(0.0022)	(0.0024)
$NDIS_{i,t-1}$	0.0018	0.0037	0.0014
	(0.0023)	(0.0023)	(0.0025)
$NDIS_{i,t} \times Z_i$	0.0065	0.0137***	-0.0021
	(0.0086)	(0.0051)	(0.0041)
$NDIS_{i,t-1} \times Z_i$	0.0016	0.0052	0.0016
	(0.0085)	(0.0048)	(0.0038)
$NDIS_{i,t} \times Z_j$	0.0018	-0.0042	0.0019
	(0.0030)	(0.0029)	(0.0030)
$NDIS_{i,t-1} \times Z_j$	-0.0006	-0.0088***	0.0002
	(0.0032)	(0.0030)	(0.0031)
$DIS_{i,t}$	-0.0034	-0.0030	-0.0034
	(0.0030)	(0.0030)	(0.0030)
$DIS_{i,t-1}$	-0.0062**	-0.0059**	-0.0063**
	(0.0028)	(0.0028)	(0.0028)
Observations	184,264	184,264	184,264
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
$NConflict_{i,t}$	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES

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

Table B.13: Natural Disasters and Conflict Diffusion - Mechanisms, horserace estimates

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$
Inverse Geodesic Distance			
$NDIS_{i,t}$	0.0025		0.0028
	(0.0036)		(0.0036)
$NDIS_{i,t} \times Light_i$	0.0013		0.0001
	(0.0074)		(0.0070)
$NDIS_{i,t} \times Mine_i$	0.0048		-0.0025
	(0.0045)		(0.0050)
$NDIS_{i,t} \times Agri_i$	-0.0063		-0.0050
	(0.0041)		(0.0044)
$NDIS_{i,t} \times Light_j$	0.0029		0.0032
	(0.0036)		(0.0035)
$NDIS_{i,t} \times Mine_j$	-0.0035		-0.0025
	(0.0032)		(0.0032)
$NDIS_{i,t} \times Agri_j$	0.0114***		0.0101***
	(0.0039)		(0.0038)
$NDIS_{i,t-1}$	0.0107***		0.0097***
	(0.0036)		(0.0035)
$NDIS_{i,t-1} \times Light_i$	-0.0108		-0.0097
	(0.0078)		(0.0079)
$NDIS_{i,t-1} \times Mine_i$	0.0032		0.0005
	(0.0049)		(0.0053)
$NDIS_{i,t-1} \times Agri_i$	0.0013		0.0011
	(0.0040)		(0.0042)
$NDIS_{i,t-1} \times Light_j$	0.0019		0.0025
	(0.0035)		(0.0034)
$NDIS_{i,t-1} \times Mine_j$	-0.0052		-0.0031
	(0.0036)		(0.0036)
$NDIS_{i,t-1} \times Agri_j$	0.0027		0.0028
	(0.0039)		(0.0039)
Inverse Major Road Distance			
$NDIS_{i,t}$		0.0044*	0.0027
		(0.0026)	(0.0026)
$NDIS_{i,t} \times Light_i$		0.0040	0.0048
		(0.0085)	(0.0086)
$NDIS_{i,t} \times Mine_i$		0.0121***	0.0131***
		(0.0046)	(0.0051)
$NDIS_{i,t} \times Agri_i$		-0.0044	-0.0017
		(0.0037)	(0.0040)
$NDIS_{i,t} \times Light_j$		0.0030	0.0024
		(0.0032)	(0.0031)
$NDIS_{i,t} \times Mine_j$		-0.0054*	-0.0048
		(0.0031)	(0.0030)
$NDIS_{i,t} \times Agri_j$		0.0040	0.0021
		(0.0032)	(0.0032)
$NDIS_{i,t-1}$		0.0049*	0.0028
		(0.0027)	(0.0027)
$NDIS_{i,t-1} \times Light_i$		-0.0046	0.0013
		(0.0085)	(0.0086)
$NDIS_{i,t-1} \times Mine_i$		0.0059	0.0052
		(0.0045)	(0.0048)
$NDIS_{i,t-1} \times Agri_i$		0.0011	0.0014
		(0.0036)	(0.0038)
$NDIS_{i,t-1} \times Light_j$		0.0010	0.0002
		(0.0034)	(0.0033)
$NDIS_{i,t-1} \times Mine_j$		-0.0101***	-0.0100***
		(0.0031)	(0.0030)
$NDIS_{i,t-1} \times Agri_j$		0.0019	0.0014
		(0.0032)	(0.0032)
$DIS_{i,t}$	-0.0028	-0.0038	-0.0035
	(0.0030)	(0.0030)	(0.0030)
$DIS_{i,t-1}$	-0.0056**	-0.0063**	-0.0062**
	(0.0028)	(0.0028)	(0.0028)
Observations	184,264	184,264	184,264
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
$NConflict_{i,t}$	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES

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

Table B.14: Natural Disasters and Conflict Diffusion Mechanisms at the District-Year Level - Multiple Hypotheses Testing (Adjusted FDR p values)

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$
Inverse Geodesic Distance			
$NDIS_{i,t}$	0.0025		0.0028
	[0.5960]		[1.0000]
$NDIS_{i,t} \times Light_i$	0.0013		0.0001
	[0.9280]		[1.0000]
$NDIS_{i,t} \times Mine_i$	0.0048		-0.0025
	[0.5890]		[1.0000]
$NDIS_{i,t} \times Agri_i$	-0.0063		-0.0050
	[0.3660]		[1.0000]
$NDIS_{i,t} \times Light_j$	0.0029		0.0032
	[0.5960]		[1.0000]
$NDIS_{i,t} \times Mine_j$	-0.0035		-0.0025
	[0.5890]		[1.0000]
$NDIS_{i,t} \times Agri_j$	0.0114**		0.0101**
	[0.0240]		[0.0490]
$NDIS_{i,t-1}$	0.0107**		0.0097**
	[0.0240]		[0.0490]
$NDIS_{i,t-1} \times Light_i$	-0.0108		-0.0097
	[0.3730]		[1.0000]
$NDIS_{i,t-1} \times Mine_i$	0.0032		0.0005
	[0.5960]		[1.0000]
$NDIS_{i,t-1} \times Agri_i$	0.0013		0.0011
	[0.7920]		[1.0000]
$NDIS_{i,t-1} \times Light_j$	0.0019		0.0025
	[0.6020]		[1.0000]
$NDIS_{i,t-1} \times Mine_j$	-0.0052		-0.0031
	[0.3660]		[1.0000]
$NDIS_{i,t-1} \times Agri_j$	0.0027		0.0028
	[0.5960]		[1.0000]
Inverse Major Road Distance			
$NDIS_{i,t}$		0.0044	0.0027
		[0.1760]	[1.0000]
$NDIS_{i,t} \times Light_i$		0.0040	0.0048
		[0.5360]	[1.0000]
$NDIS_{i,t} \times Mine_i$		0.0121**	0.0131**
		[0.0270]	[0.0049]
$NDIS_{i,t} \times Agri_i$		-0.0044	-0.0017
		[0.2620]	[1.0000]
$NDIS_{i,t} \times Light_j$		0.0030	0.0024
		[0.3600]	[1.0000]
$NDIS_{i,t} \times Mine_j$		-0.0054	-0.0048
		[0.1700]	[0.4300]
$NDIS_{i,t} \times Agri_j$		0.0040	0.0021
		[0.2620]	[1.0000]
$NDIS_{i,t-1}$		0.0049	0.0028
		[0.1700]	[1.0000]
$NDIS_{i,t-1} \times Light_i$		-0.0046	0.0013
		[0.5360]	[1.0000]
$NDIS_{i,t-1} \times Mine_i$		0.0059	0.0052
		[0.2620]	[1.0000]
$NDIS_{i,t-1} \times Agri_i$		0.0011	0.0014
		[0.5360]	[1.0000]
$NDIS_{i,t-1} \times Light_j$		0.0010	0.0002
		[0.5360]	[1.0000]
$NDIS_{i,t-1} \times Mine_j$		-0.0101***	-0.0100**
		[0.0060]	[0.0110]
$NDIS_{i,t-1} \times Agri_j$		0.0019	0.0014
		[0.5360]	[1.0000]
$DIS_{i,t}$	-0.0028	-0.0038	-0.0035
	[0.5890]	[0.2620]	[1.0000]
$DIS_{i,t-1}$	-0.0056	-0.0063*	-0.0062
	[0.1480]	[0.0730]	[0.1120]
Observations	184,264	184,264	184,264
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
$NConflict_{i,t}$	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES

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 2 in Xu et al. (2022). Indeed, the cost function is quadratic, and therefore convex and strongly monotone, and the Tullock contest success function (CSF), given by (4), satisfies the assumption on the CSF assumption in Xu et al. (2022). This shows the existence and uniqueness of the Nash equilibrium. Moreover, Xu et al. (2022) also show the unique equilibrium satisfies the property that every conflict contains at least two contestants with positive efforts. Since, in the star depicted in Figure 6, each conflict only has two contestants, this unique equilibrium is interior. □

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

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

and

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

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

Moreover, by the implicit function theorem,

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

Since

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

so

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

This completes the proof of the lemma. □

Proof of Proposition 2: By applying the implicit function theorem to system (11) 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 (11) 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:

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

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

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

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

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

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

This completes the proof of the proposition. □