Conflicts in Spatial Networks*

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Abstract

We develop a network model of conflict in which players are involved in different battles. A negative shock in one locality affects the conflict in this locality but may also increase battles in path-connected localities depending on the location of the battle in the network and the strength of each locality involved in each battle. We then empirically test this model by analyzing the effect of local natural disasters on battles in Africa. We construct a novel panel-dataset that combines geo-referenced information about battle events and natural disasters at the monthly level for 5,944 districts in 53 African countries over the period from 1989 to 2015. At this fine temporal and spatial resolution, natural disasters are formidable exogenous shocks that affect the costs and benefits of fighting in a locality. We find that natural disasters decrease battle incidence in the affected locality and that this effect persists over time and space. This mitigating effect appears to be more pronounced in more developed localities. As highlighted by the model, these results can be explained by the fact that natural disasters divert fighting activity to surrounding localities, particularly those that are connected via geographic and road networks.

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1 Introduction

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

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

First, we develop a 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 a specific network structure to derive some comparative statics results. In a star network, there are two districts (or battles) and three players, one of which is involved in two battles. 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.

We then empirically test the results of this model. Our identification strategy exploits

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

the exogenous variation in local natural disasters as negative economic shocks that locally increase the costs and decrease the benefits of fighting. We construct a novel panel dataset at the district-month level for 5,944 African ADM2 (second subnational) units, over the period from 1989 to 2015, that combines geo-referenced data on battle events and disaster occurrences. The dataset's fine degree of spatial and temporal resolution allows us to include a large set of district $\times$ year fixed effects and thereby control, in the most flexible way, for a wide range of unobservable variables that might simultaneously drive battle and disaster incidents. Our estimates enable us to identify the within district-year variation in local battle events that is due to disaster shocks in each month. We only use natural disasters that occur suddenly (e.g. floods, storms) and exclude droughts, which often have a lengthy onset and are likely to be endogenous to local conflict even at the monthly level.

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

In the second step, we estimate a spatial econometric model to analyze the spatial spillover effects of local natural disasters on battle incidence in other districts. Our results show that, in contrast with the direct local effects which materialize in the very short run (as represented by the fine *monthly* level of temporal granularity), spatial spillovers of battle activities become prominent in the medium to long run. Indeed, we observe that local disasters divert battle activity to surrounding districts only at the *yearly* level of temporal aggregation. Moreover, we observe that battle spillovers occur in the same year if districts are linked by a *road network* and in the following year if districts are linked by *geographic* *proximity*. These results seem quite intuitive as roads provide an accessible means through which the spillovers can spread. When the connection is not through roads, it takes extra effort and planning for battles to be relocated, suggesting a longer time lag for spillovers to happen. Our empirical analysis further highlights the role of mining activity on the spatial dynamics of conflict spillovers. First, mining activity in the disaster-affected locality tends to decrease the chance that the combat activity will shift to neighboring localities. Second, disasters tend to increase the likelihood of conflict in those neighboring localities that are home to mining activities.

Following the results of our theoretical model, which highlights the importance of a locality's characteristics in the diffusion process, we explore the mechanisms behind these results. To do this, we include the characteristics of a locality in terms of economic activity (nighttime light), mining, and agricultural activities. We show that, if a locality has a mining activity, it will experience positive battle spillovers from the neighboring localities only if they are linked by roads.

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

Our study contributes to various strands of literature. First, there is a 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; Huremovic, 2019; Xu et al., 2019). 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. There is also a smaller body of empirical literature on networks and conflicts (Dell, 2015; König, et al., 2017; Brangewitz et al., 2019; Eubank, 2019; Kovenock et al., 2019). The study closest to ours is König, et al.'s (2017), who develop and test a model that investigates how a network of military alliances and enmities affects the intensity of a conflict. Using data from the Second Congo War, they show that the intensity of a conflict can be reduced through dismantling specific fighting groups, weapon embargoes, and interventions aimed at pacifying animosity among groups. Our model and empirical test are different as we model and test whether a negative shock in each district has an effect on that district and how it propagates to other path-connected districts.

Second, we relate to the literature that analyzes the causes and spread of violent conflicts, which has been the subject of a vast body of literature in economics and other social sciences (see the overviews by Rigterink, 2010, and Ray and Esteban, 2017). There is, first, an important body of literature using *national data* that follows the *grievance* or *opportunity cost* model (Collier and Hoeffler, 2004), which predicts a negative relationship between income shocks and the probability of a battle. Accordingly, higher incomes lead to fewer battles, because the opportunity cost of battle is high (e.g. Blattman and Miguel, 2010, Besley and Persson 2011). By the same argument, lower incomes lead to a higher probability of battles occurring, as people have "nothing to lose" following a battle (Miguel et al., 2004; Chassang and Padró i Miquel, 2009; Ciccone, 2011; Couttenier and Soubeyran, 2014; Hodler and Raschky 2014; Harari and La Ferrara, 2018). 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.

There is also a 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., 2017; McGuirk and Burke, 2017) and negative (e.g. Harari and La Ferrara, 2018; Berman et al., 2020) economic shocks influence the likelihood of local conflict. Although the focus of the theoretical models and empirical analyses in these studies is on the local effects of shocks on conflict, most of them include an empirical section that investigates whether these local shocks trigger violence in neighboring localities.

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

We complement this strand of the literature along three dimensions. First, we develop a theoretical framework that explicitly models the spatial spillovers using a network approach.

Second, our empirical analysis extends the level of disaggregation of these studies temporally, by analyzing the spillovers at the district-month level and for different types of networks. Third, whereas most existing studies exploit exogenous variations in factors that *increase* the likelihood of a battle locally, we focus on local and spatial spillover effects of exogenous events that *decrease* the likelihood of a battle locally. Particularly, our study highlights the importance of mining activity as a determinant of local conflict in Africa (e.g. Berman et al. 2017). We show that, following a negative shock, belligerents are less likely to shift combat activity away from an affected mining locality. However, if spatial combat spillovers occur, they are more likely to occur in neighboring localities that are home to a mining operation.

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

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

2 Theory

We develop a simple network model that provides a mechanism showing how a negative shock on a district affects the battle not only in this district but also in the neighboring districts.

2.1 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:

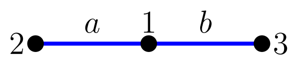


Figure 1: A star network

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

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

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

Districts From the network, we can aggregate the players and the battles to obtain a district. 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 1, there are two districts: district a, which encompasses players 1 and 2 and where battle a takes place, and district b, which is made of players 1 and 3, and where battle b takes place, so that $\omega_{ab} > 0$. This can be represented as follows:

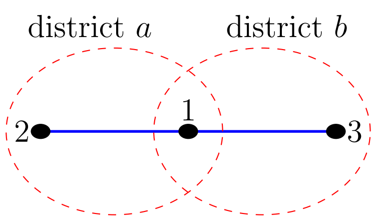


Figure 2: A star network

Of course, any other district representation can be made from Figure 1. In the empirical analysis, a district will be defined by its *geographical* position and there will be a link between two districts if there is a road between them and thus $\omega_{ab} > 0$.[2] For example, in Figure 2, there are two districts a and b and they are geographically adjacent to each other (i.e.,

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

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

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

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

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

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

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

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

Note that, in the data, 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 2. In our model, this translates by studying how a decrease in v^a (the value of battle a) affects $x_1^a + x_2^a$, the total battle in district a, and $x_1^b + x_3^b$, the total battle in the (spatially) adjacent district b.

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

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

Because this model is very general and the best response functions are non-linear, it is difficult to characterize the Nash equilibrium of this game and to derive comparative statics results. Because we have in mind an empirical application, 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 1 or Figure 2 because it is tractable and still provides all the intuition we need for our empirical analysis.[3]

2.2 Star network

2.2.1 The model

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

[3] We have also investigated other more complex network structures such as a bridge network and showed that our main results remain qualitatively the same.

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

2.2.2 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

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

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

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

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

We have the following results:[4]

Proposition 1. *Consider the star network depicted in Figure 1 and the payoff functions*

[4] All the proofs of the theoretical model can be found in Appendix A.

given by (4). Then, there exists a unique interior Nash equilibrium $(x_1^{a*}, x_1^{b*}, x_2^{a*}, x_3^{a*})$ that simultaneously solves:

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

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

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

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

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

We can see from equations (5)–(8) that Lemma 1 describes the best response function $x^*(\cdot)$. In particular, Lemma 1 shows that $x^*(\cdot)$ first increases with y up to the maximum, which occurs at $x^* = y$, and then decreases. There is therefore a *non-monotonic bell shaped* relationship between the efforts of two players involved in the same battle. Figure 3 depicts this relationship.

To see the implication of this Lemma, for example, consider the first-order condition

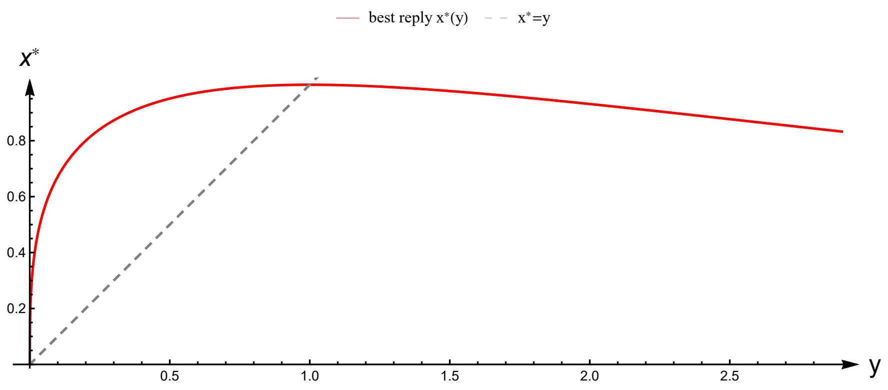


Figure 3: Best response function $x^*(y)$

of x_2^a, that is, $F_3(x_1^{a*}, x_2^{a*}) = 0$. Using Lemma 1, we know that the sign of $\frac{\partial x_2^{a*}}{\partial x_1^a}$ is the same as the sign of $(x_2^{a*} - x_1^{a*})$ and that the relationship is bell-shaped where the maximum occurs at $x_2^{a*} = x_1^{a*}$. Indeed, when $x_1^{a*} < x_2^{a*}$, which means that player 1 is "weak" because $p_1^a(x_1^a, x_2^a) = x_1^a/(x_1^a + x_2^a)$, 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.

2.2.3 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 2. In this section, we will study how a decrease in v^a and a negative shock on district a, affects $x_1^a + x_2^a$, the total battle in district a, $x_1^b + x_3^b$, and the total battle in the (spatially) adjacent district b.[5] 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 1 and 2 and the payoff functions given by (4). When v^a, the value of battle a, decreases,*

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

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

[5]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

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

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

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

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

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

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

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

In Figure 4, we illustrate our results by plotting the four efforts of the different players when v^a increases.[6] 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.

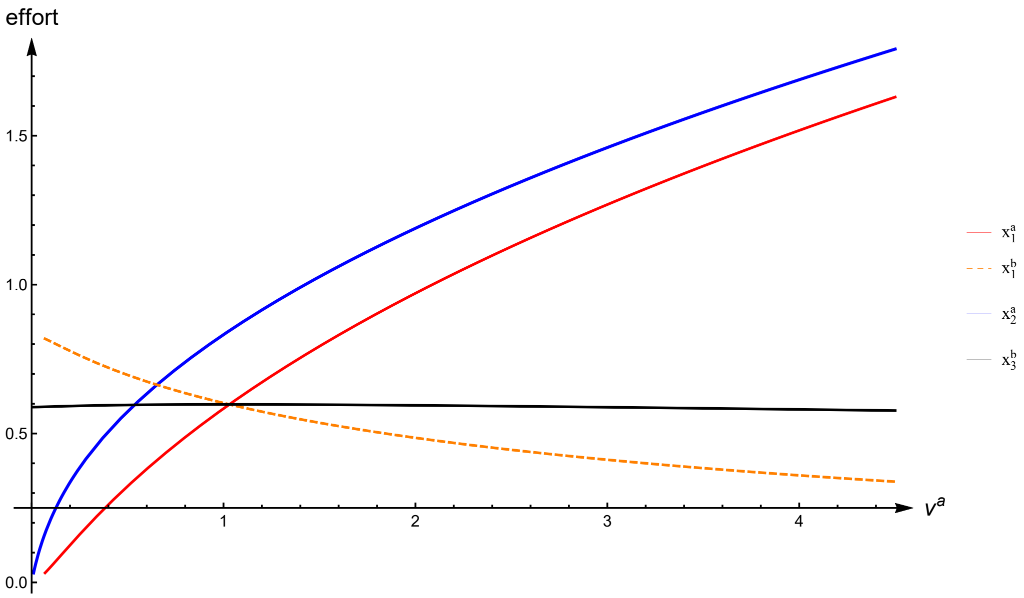


Figure 4: The effect of an increase of v^a on the effort of each agent involved in battles in the network described in Figure 1

More generally, our comparative statics results highlight the importance of three aspects of the model: (i) the cost linkage for a player/district participating in multiple battles, (ii)

[6]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.

We would now like to bring this model to the data. In particular, we would like to test parts 2 and 6 of Proposition 2, that is: (*i*) how a negative shock (a decrease in v^a in the model and a disaster in the data) on a given district affects the total battle in this district and (*ii*) how this negative shock affects the total battle in the (spatially) adjacent districts. Our answer to (*i*) is that the total battle in the affected district decreases because there are less resources to grab. Our answer to (*ii*) is that battles in spatially adjacent districts will increase, especially if the same player is involved in different battles and will fade away the longer the geographical distance from the district directly affected by the disaster is.

Clearly, as we will see below, in reality, spatial networks of districts are much more complex than those described in Figure 2 and the effect of a disaster can spread beyond the adjacent districts. However, the results of this simple network model goes beyond the star network and, even for more complex network structures, the intuition of the direct and indirect effect of a disaster on the total battles of districts and connected districts is similar.

3 Data

We use observations at the second, subnational administrative unit (ADM2, henceforth "districts") level, and the final dataset consists of 5,944 districts from 53 African countries over the period from 1989 to 2015.[7] We use two main units of observation, that is, *district-year* and *district-month*, to test Proposition 2 of the theoretical model, which shows how natural disasters (negative shock on v^α) affect the incidence of battles in own and adjacent (path-connected) districts.

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

3.1 Battles

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

Using the information on the precise location (i.e., latitude, longitude) of the violent event in the dataset, we first conduct a spatial analysis[8] where we geolocate each battle in the ADM2 districts. We then aggregate all such battle events at the district-year and district-month levels.

Our main indicator of a battle takes the form of a binary variable, which assumes a score of one if a battle leading to at least one death occurred in district i in the given time period, and zero otherwise.[9] Figure B.1 in Appendix B displays the distribution of battles in Africa over our sample period.

3.2 Natural Disasters

We capture a negative shock in a district, that is, a decrease in v^a in the theoretical model, through the occurrence of a natural disaster in that district. Data on natural disasters are drawn from the Emergency Events Database (EM-DAT) (see Guha-Sapir et al., 2016),

[8]This procedure was implemented in ArcMap 10.5

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

which is a global database on natural and technological disasters, containing data on the occurrence and effects of over 22,000 global mass disasters from 1900 to date. Any natural or man-made disaster where either (*i*) 10 or more people died, or (*ii*) 100 or more people were affected, or (*iii*) a state of emergency was declared, or (*iv*) a call for international assistance was made, is included in the dataset. For each natural disaster, there is information on, among others, location, disaster type, date, number of deaths, number of people affected, the estimated damage, as well as on whether aid from the Office of US Foreign Disaster Assistance (OFDA) was received following a disaster.[10]

The natural disaster category in EM-DAT is divided into 6 sub-groups, which, in turn, cover 15 disaster types and more than 30 sub-types. For our study's purpose, we consider natural disasters classified as geophysical (e.g., earthquake, volcanic activity), meteorological (e.g., extreme temperature, storm), hydrological (e.g., flood, landslide), climatological (e.g., wildfire), or extraterrestrial (space weather). We do not include in our analysis natural disasters classified as biological, such as epidemics or insect infestations. We also exclude droughts for two reasons. First, droughts are typically spread across multiple ADM2 districts, therefore the effects of a drought are not entirely local. Second, droughts can (albeit with a marginal probability) be the result of human actions. For instance, if a party to a battle gains control over the water supply of a district, a drought might arise, and this is then endogenous to the battle incidence.

The availability of EM-DAT data at the country level, however, is a challenge when conducting a district-level analysis. We overcome this challenge by manually geocoding 1,016 natural disasters that occurred in Africa over the period from 1989 to 2015. Natural disasters where the exact individual village or subnational district was identified were precisely geocoded; whereas, those recorded as having occurred in larger geographic units were as-

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

signed to all districts within that geographic unit. For each geocoded natural disaster, we allocate a precision score, which assigns a value of 4 for precision at the district level (i.e., the highest level of precision), a value of 3 for precision at the provincial level, 2 at the state level, and 1 at the country level (the lowest level of precision). We restrict our analysis to natural disasters geocoded with a precision score of 3 or 4, which accounts for over 96% of the total number of the geocoded natural disaster locations. Figure B.2 in Appendix B displays the distribution of natural disasters in Africa.

Our preferred indicator for natural disasters is a binary variable that assumes a value of 1 if a natural disaster occurred in district i in a time period, and zero otherwise. We also generate two other indicators to reflect different disaster categories. Following Gassebner et al. (2010) and Puzzello and Raschky (2014), we classify disasters that either (i) kill at least 1000 people, or (ii) affect at least 100,000 people in total, or (iii) cause damages of at least one billion (real) dollars as *large* natural disasters, and all other disasters as *small* natural disasters. Next, following Skidmore and Toya (2002), we generate indicators of climatic and geologic disasters.[11]

3.3 Other covariates

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

First, we identify districts with high and low economic activity levels, using satellite data on the intensity of *nighttime lights*, sourced from the National Oceanic and Atmospheric Administration (NOAA). Nighttime luminosity has been identified as an indicator of the level of economic activity, both at the national level (Henderson et al., 2012) and the subnational

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

level (Hodler and Raschky, 2014). NOAA provides annual data for the time period from 1992 onwards for output pixels that correspond to less than one square kilometer. The data are presented on a scale from 0 to 63, with higher values implying more intense nighttime lights.

We generate a time-invariant binary indicator as a proxy for the level of economic activity in a district. This indicator is based on *initial nighttime light*, which is the nighttime light value for the year 1992, the starting point of this data. Districts with a nighttime light value of 10 and above in 1992 receive a score of 1 (high level of economic activity), and those with a value of less than 10 in 1992 receive a score of 0 (low level of economic activity). Because of its time-invariant nature, this variable filters out short-term negative shocks on economic activity due to the occurrence of natural disasters, thereby addressing potential endogeneity concerns. We identify 8% of the districts as displaying a high level of economic activity.

Second, we use data on mining activity in subnational districts in Africa, obtained from the SNL Mining & Metals database. This database covers mining projects across Africa that were active during our sample period. For each project, it contains information about the point location, that is, the geographic coordinates, and the (potentially multiple) resources extracted at this location. For this study's purpose, we use the point locations of the mining projects to assign them to districts and identify all districts where a mine was active for at least one year during our sample period. We use this information to construct a time-invariant indicator of mining activity, which is a binary variable that equals 1 if at least one active mining project operated in the district over the period, and zero otherwise.[12]

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.[13] For each district, we calculate the fraction of agriculturally suitable land and we classify districts

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

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

with over 50% agriculturally suitable land as agricultural. In our data, 29% of the districts qualify as agricultural.

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

[Table 1 about here]

3.4 Connectivity matrices

To test part 6 of Proposition 2, we follow Amarasinghe et al. (2018) and construct two[14] spatial weighting matrices based on geographic and road connectivity.[15]

3.4.1 Geographic connectivity

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

In using the inverse of the altitude-adjusted geodesic distance, we weight the geographic connectivity between two districts along two dimensions. Accounting for variability in alti-

[14] 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.

[15] In the theoretical model, we measure the connectivity between districts by their geographical proximity but we could have measured it in other ways as we do in this section.

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

3.4.2 Road connectivity

Given the importance of roads in maintaining links between districts, we construct a *road-based connectivity matrix*. For this purpose, we use data on the primary and secondary road network in Africa from OpenStreetMap (OSM).[16] To generate a network graph of the road network, we intersect these roads with district boundary polygons using the following steps.[17] First, we split the road polylines into segments whenever they intersect with a district boundary. For each segment (edge) we calculate the road travel distance in km between each intersection (node).[18] 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

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

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

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

adjacent and connected via a major road, we assign a distance value of 1km. If districts A and B are not adjacent, but connected via the road network, they are assigned the road distance between the closest road and district boundary node of A and the closest road and district boundary node of B (i.e., the road travel distance through the whole district that one has to cross to get from district A to district B). The final road connectivity matrix assigns a value equal to the inverse of the road distance in km between districts i and j if they are connected via a major road, and 0 if they are not connected. As with the altitude-adjusted inverse distance matrix, we again construct different weighting matrices by truncating at different cutoff distances.

4 Direct effects of natural disasters on battles

4.1 Direct effects - district-year level analysis

In the first part of the empirical analysis, we estimate the direct effect of natural disasters on battles in a district (Proposition 2, part 2). We conduct this estimation at two different levels of aggregation, that is, district-year level and district-month level.[19] For the district-year level analysis, we use the following econometric specification:

$$Battle_{iy} = \beta_0 DIS_{iy} + \beta_1 DIS_{i,y-1} + \gamma Battle_{i,y-1} + \mathbf{FE_i} + \mathbf{FE_{cy}} + \epsilon_{iy} \tag{12}$$

Panel unit i is districts in a given country c in year y. Our dependent variable $Battle_{iy}$ is a binary variable that switches to one if there was at least one battle, resulting in at least one death, in district i in year y, and zero otherwise. Our empirical proxy for the negative shock is DIS_{iy}, which is a binary indicator that equals one if a natural disaster event occurred in district i in year y, and zero otherwise. We also include the temporal lag of this independent

[19] Estimates at the country level are provided in Table C.1 of Appendix C.

variable, that is, $DIS_{i,y-1}$, to evaluate the effect of a disaster on a battle after the time lag.

To separate the effect of autocorrelation of battles in the temporal dimension, we include the temporal lag of the dependent variable, that is, $Battle_{i,y-1}$ as a control in equation (12).[20] In our preferred specification, we include district ($\mathbf{FE_i}$) and country$\times$ year ($\mathbf{FE_{cy}}$) fixed effects, which absorb time-invariant district-specific characteristics and time-variant country-specific shocks, respectively. This relatively conservative set of fixed effects also addresses the concern of non-random underreporting of natural disasters. Finally, ϵ_{iy} is an error term.

The construction of a new data set of natural disasters incorporating their fine spatial and temporal distribution provides us with a neat localized economic shock. Moreover, being *natural*, they are by definition *exogenous* shocks, which minimizes any concern on potential simultaneity. The exogeneity of the negative income shock, coupled with the comprehensive set of fixed effects, allows us to causally interpret β_0 and β_1, the coefficients of interest. Our model (part 2 of Proposition 2) predicts that these coefficients should be negative.

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

[Table 2 about here]

However, region and year fixed effects *per se* may be insufficient to claim a causal

[20]Including a lagged dependent variable in a fixed effects specification can result in the well-known Nickell bias. Panel A in Table C.16 presents results of specifications without the lagged dependent variable as well as results of an LDV model. The results show that the coefficients of our key explanatory variables remain very similar.

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

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

4.2 Direct effects - district-month level analysis

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

$$Battle_{iym} = \sum_{\tau=0}^{\tau=1} \beta_\tau DIS_{iy,m-\tau} + \gamma Battle_{iy,m-1} + \mathbf{FE_m} + \mathbf{FE_{iy}} + \epsilon_{iy,m} \tag{13}$$

The coefficients of interest are again β_τ, which capture the effect of a natural disaster in district i on the probability of a battle in i, in the current month and the next month, respectively. We control for the potential temporal autocorrelation of battles by including the lagged dependent variable $Battle_{iy,m-1}$.[23]

[21] In Tables C.9 to C.11 in Appendix C, we conduct a number of robustness checks using alternative definitions of the dependent and independent variables.

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

[23] Panel B in Table C.16 presents the results of district-month specifications without the lagged dependent variable as well as the results of the LDV model. The results show that the coefficients of our key explanatory variables remain very similar.

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

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

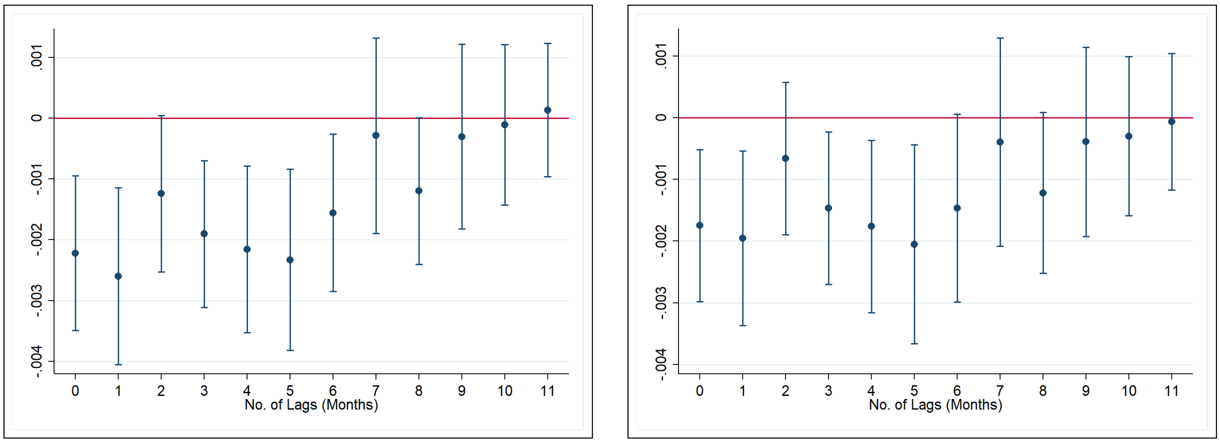
[Table 3 about here]

The results in Tables 2 and 3, while confirming the proposition in our model, also highlight a key empirical contribution of this study. Almost all studies on conflicts have so far relied on data at the yearly level. We show, in Table 2, that there is no statistically significant relationship between natural disasters and battles at the yearly level. The statistically significant relationship is only observed at the disaggregated monthly level.

[24]In Tables C.2 to C.6 in Appendix C, we conduct a number of robustness checks at the district-month level, using alternative definitions of the dependent and independent variables. Particularly, in Table C.2 we show that the baseline estimates remain robust when using spatial HAC standard errors, allowing for spatial correlation up to 100km and for infinite serial correlation.

Temporal disaggregation not only enables us to measure the negative effect of natural disasters on battles with greater precision, but also gives us the opportunity of examining the persistence of this effect over the following months. We do this by extending the specification in equation (13) to include up to 11 additional lags of the independent variable $DIS_{iy,m}$. Figure 5 plots the point estimates and 90% confidence intervals for each monthly lag starting with the effect in the current month. In Panel (a), we only include one autoregressive term (i.e. $Battle_{iy,m-1}$); whereas, in Panel (b), we include up to 11 autoregressive terms. We observe in both panels that there is a persistent negative effect of natural disasters on battles, spreading up to a 6 month lag.

Figure 5: The Effect of Natural Disasters on Battles Over Time—District-Month Level



(a) (b)

Notes: Dots on Panels (a) and (b) show the regression results using Eq. (13) and including up to 11 temporal lags of the independent variable $Disaster_{iym}$. Panel (b) further includes higher order autoregressive terms of up to 11 lags. Vertical lines show the 90% confidence interval based on standard errors clustered at the country×year level.

4.3 Direct effects - mechanisms

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

For this purpose, we test the following equation:

$$\begin{aligned} Battle_{iym} = \sum_{\tau=0}^{\tau=2} \beta_\tau DIS_{iy,m-\tau} + \sum_{\tau=0}^{\tau=2} \theta_\tau (DIS_{iy,m-\tau} \times \mathbf{Z_i}) \\ + \gamma Battle_{iy,m-1} + \mathbf{FE_{iy}} + \mathbf{FE_m} + \epsilon_{iy,m} \end{aligned} \tag{14}$$

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

Our theoretical model predicts that 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.

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

[Table 4 about here]

5 Natural disasters and battles: Spatial spillover effects

5.1 Spatial spillover effects - district-month level analysis

Considering the spatial distribution of both our dependent and independent variables, it is likely that spatial spillovers of these variables occur across districts. In this second part of the empirical analysis, we turn our attention to such spatial battle spillovers of natural disasters, in order to test part 6 of Proposition 2. For this purpose, we use the following specification, which takes the form of a spatial Durbin model that allows for spatial autoregressive processes in the dependent and explanatory variables.

$$\begin{aligned} Battle_{iym} = &\sum_{\tau=0}^{t} \beta_{\tau} DIS_{iy,m-\tau} + \sum_{\tau=0}^{t} \delta_{\tau} NDIS_{iy,m-\tau} \\ &+ \gamma_1 Battle_{iy,m-1} + \gamma_2 NBattle_{iy,m} + \mathbf{FE_{iy}} + \mathbf{FE_{m}} + \epsilon_{iy,m} \end{aligned} \tag{15}$$

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

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

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

where, as in the theoretical model, 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. In the data, we use two forms of connectivity: $\mathbf{\Omega_1}$ captures *geographic connectivity*; whereas, $\mathbf{\Omega_2}$ captures *road connectivity*. $NDIS_{iy,m}$ is therefore the binary transformation of the spatial lag of the natural disaster variable, which identifies whether at least one "neighboring" district experienced a natural disaster in month m of year y ($NDIS_{iy,m} = 1$) or not ($NDIS_{iy,m} = 0$).

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

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

Accordingly, the coefficients of interest δ_τ respectively capture the *spatial* and *spatial*$\times$*temporal* spillover effects of natural disasters occurring in neighboring districts on district i's own battle probability. Part 6 of Proposition 2 predicts that δ_τ should be positive, indicating that natural disasters divert battle activities to neighboring districts.

In Table 5, we examine the magnitude of spatial spillover effects at the district and month level, at a cutoff distance of 500km from each district.[25] Column (1) considers diffusion based

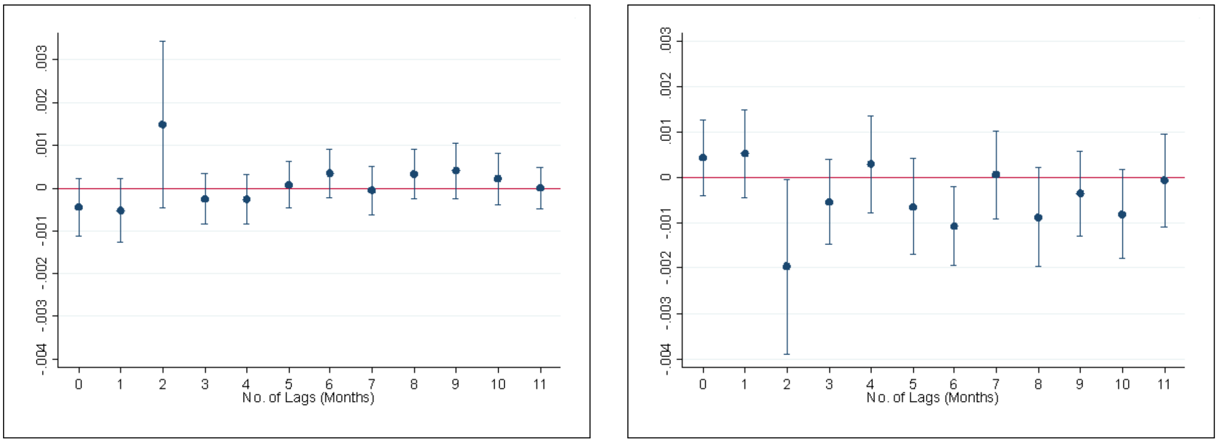
[25] In Table C.8 in Appendix C, we consider alternative cutoff distances as robustness checks.

purely on the altitude-adjusted inverse geodesic distance and Column (2) considers only the inverse road distance. In Column (3) we consider both types of connectivity together. In all three columns, the coefficients on the variables of interest, $NDIS_{iy,m}$ and $NDIS_{iy,m-1}$, are statistically insignificant.

[Table 5 about here]

Next, we look at whether the diffusion effect is present at the monthly level when using higher order temporal lags. Figure 6 shows the estimation of battle spillovers at the district-month level, when including up to 11 monthly lags. Panel (a) displays the coefficients on $NDIS_{iym}$ when the neighborhood is defined using the altitude-adjusted inverse geodesic distance matrix; whereas, in panel (b), the neighborhood is defined using the inverse road distance matrix.

Figure 6: Battle Diffusion at the District-Month Level



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

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

Notes: Dots show the estimated coefficients on $NDIS$ using Eq. 15, when including up to 11 temporal lags of the explanatory variables. Panel (a) displays the coefficient on $NDIS_{iym}$ when neighborhood is defined as per the altitude-adjusted inverse geodesic distance matrix; whereas, in Panel (b) neighborhood is defined using the inverse road distance matrix. Vertical lines show the 90% confidence interval based on standard errors clustered at the country×year level.

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

5.2 Spatial spillover effects - district-year level analysis

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

$$\begin{aligned} Battle_{iy} = \beta_0 DIS_{iy} + \beta_1 DIS_{i,y-1} + \delta_0 NDIS_{iy} + \delta_1 NDIS_{i,y-1} \\ + \gamma_1 Battle_{i,y-1} + \gamma_2 NBattle_{iy} + \mathbf{FE_i} + \mathbf{FE_{cy}} + \epsilon_{iy} \end{aligned} \tag{16}$$

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

Table 6 presents the results for the specification with spatial spillover effects over the course of a year. They confirm part 6 of Proposition 2, which predicts positive and significant battle spillovers following a natural disaster shock.

[Table 6 about here]

In column (1), we consider spillovers between neighbors as defined by the altitude-adjusted inverse geodesic distance matrix, truncated at a distance of 500km from the centroid of each district.[26] We do not observe any evidence of spillovers of battles attributable to natural disasters in the same period. However, we observe that, in the year following a natural disaster, battles do spillover to neighboring districts, and this result is statistically significant at the 1% level.

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

To identify whether one form of connectivity dominates the spillover effects, in column (3) we consider "horse race" specifications using a combination of these connectivity networks. These results confirm those found in columns (1) and (2). Indeed, we observe that battle spillovers occur in the current year if districts are linked by road network, and in the following year if they are linked by geographic proximity. Intuitively, it seems reasonable that battle spillovers are observed rapidly in districts linked by roads, as roads provide an accessible means through which the spillovers can spread. When the connection is not through roads, it takes extra effort and planning for battles to be relocated, suggesting a longer time lag for spillovers to materialize.[27]

Moreover, comparing the results in Table 6 with those in Table 5, we observe that, although there is no evidence of battle spillovers attributable to natural disasters in the *short run*, there is systematic evidence of natural disasters increasing the likelihood of a battle in neighboring districts in the *medium* to *long-run*.

[26] In Table C.15 in Appendix C, we consider alternative distance cut-offs at the district-year level.

[27] Moreover, in Table C.14 in Appendix C, we observe that these estimates remain robust when using spatial HAC standard errors, allowing for spatial correlation up to 500km and for infinite serial correlation.

5.3 Spatial spillover effects - mechanisms

Let us attempt to understand the mechanisms underlying the spatial spillover effects. As discussed in Section 3.3, our data enables us to categorize districts based on their levels of economic, mining, and agricultural activities. We use these time-invariant features of districts to explore whether any of these mechanisms play a role in battle diffusion following a natural disaster shock.

We approach this question in two ways. First, we consider the features of district i, which is the target/recipient of the battle spillovers following its neighbors' natural disaster shock. Here, we investigate whether the spillover of a battle is determined by the characteristics of the district to which the battles spill over. To capture this, we define an interaction term $NDIS_{iy} \times \mathbf{Z_i}$, where $\mathbf{Z_i}$ is defined as in Section 4.3 and is a vector of time-invariant variables that contains information about different characteristics of district i, that is, $Light_i$ (average nighttime light intensity), $Mine_i$ (mineral mine) and $Agri_i$ (over 50% agriculturally suitable land).

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

These two ways of testing spillover effects follow from the results of Proposition 2 in the theoretical model of Section 2, which predicts that, after a negative shock, the spillover effects depend on whether the new opponents of the new battles are "weak" or "strong". Here we capture the "weakness" or "strength" of a district by its characteristics such as light or mining, as described above.

Accordingly, we use the following specification to explore the mechanisms underlying the spatial spillovers of battles.

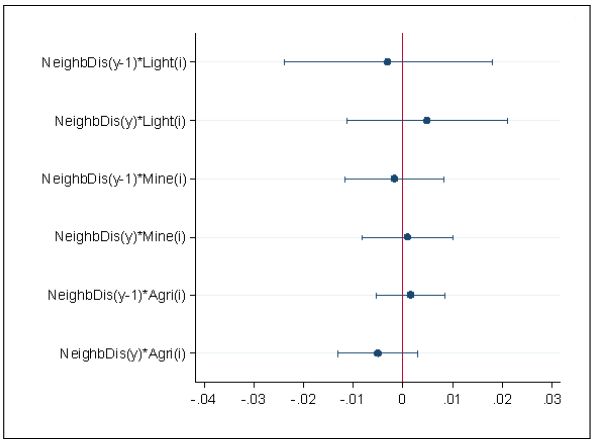
$$
\begin{aligned}
Battle_{iy} = {} & \beta_0 DIS_{iy} + \beta_1 DIS_{i,y-1} + \delta_0 NDIS_{iy} + \delta_1 NDIS_{i,y-1} \\
& + \lambda_0 (NDIS_{iy} \times \mathbf{Z_i}) + \lambda_1 (NDIS_{i,y-1} \times \mathbf{Z_i}) \\
& + \mu_0 (NDIS_{iy} \times \mathbf{Z_j}) + \mu_1 (NDIS_{i,y-1} \times \mathbf{Z_j}) \\
& + \gamma_1 Battle_{i,y-1} + \gamma_2 NBattle_{iy} + \mathbf{FE_i} + \mathbf{FE_{cy}} + \epsilon_{iy}
\end{aligned} \tag{17}
$$

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

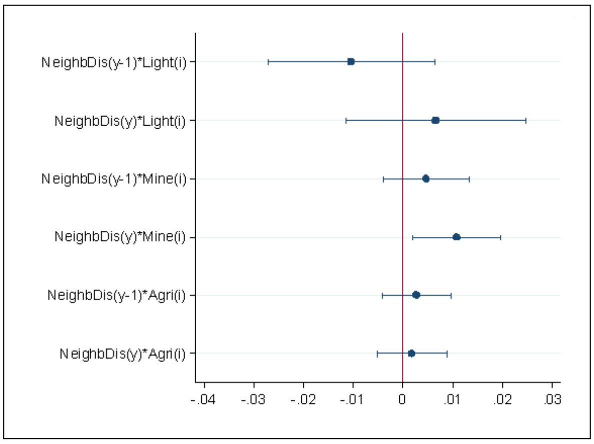
Table 7 displays the results while Figure 7 plots them. Let us focus on Figure 7. In panel (a), neighbors are defined by the altitude-adjusted inverse distance matrix; whereas, in panel (b), they are defined by the inverse road distance matrix. We do not observe any evidence that the characteristics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

[Table 7 about here]

Figure 7: Mechanisms of Battle Diffusion - Local Features



(a) Battle Diffusion in the Inverse geodesic Distance Network

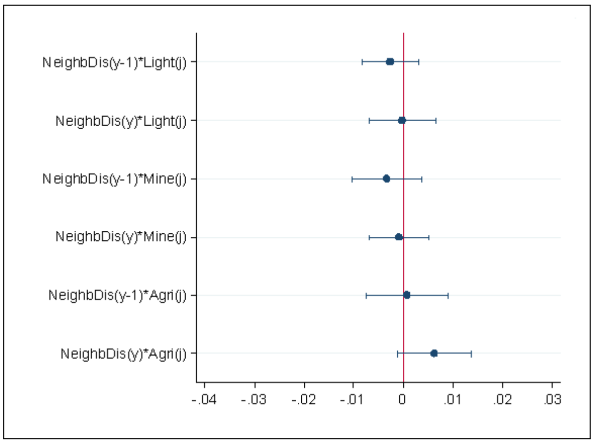


(b) Battle Diffusion in the Inverse Road Distance Network

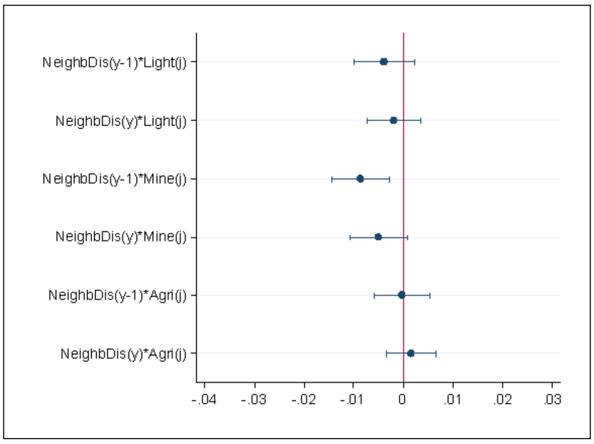
Notes: Dots show the estimated coefficients on $NeighbDisaster_{iy} \times \mathbf{Z_i}$ and $NeighbDisaster_{iy-1} \times \mathbf{Z_i}$ using Eq. (17), where $\mathbf{Z_i}$ refers to the time-invariant features of district i, as classified by the variables $Light_i$, $Mine_i$ and $Agri_i$. See Section 3.3 for more details on these variables. In Panel (a), neighborhood is defined as per the altitude-adjusted inverse geodesic distance matrix; whereas, in Panel (b) neighborhood is defined using the inverse road distance matrix. Horizontal lines show the 90% confidence interval based on standard errors clustered at the country×year level.

Next, in Figure 8, we look at whether the battle diffusion depends on the characteristics of the neighboring districts ($\mathbf{Z_j}$). Again, in panel (a), we do not observe evidence of $\mathbf{Z_j}$ affecting battle spillovers when neighborhood is defined by the altitude adjusted inverse distance matrix. In panel (b), however, we observe a negative spillover effect in the road connectivity matrix, when district j is a mining district.

Figure 8: Mechanisms of Battle Diffusion - Neighbors' Features



(a) Battle Diffusion in the Inverse geodesic Distance Network



(b) Battle Diffusion in the Inverse Road Distance Network

Notes: Dots show the estimated coefficients on $NeighbDisaster_{iy} \times \mathbf{Z_j}$ and $NeighbDisaster_{iy-1} \times \mathbf{Z_j}$ using Eq. 17, where $\mathbf{Z_j}$ refers to the time-invariant features of district j (i.e. neighboring district), as classified by the variables $Light_i$, $Mine_i$ and $Agri_i$. See Section 3.3 for more details on these variables. In Panel (a), neighborhood is defined as per the altitude-adjusted inverse geodesic distance matrix; whereas, in Panel (b) neighborhood is defined using the inverse road distance matrix. Horizontal lines show the 90% confidence interval based on standard errors clustered at the country×year level.

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

6 Conclusion

We develop a 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 goes down while the total battle in neighboring districts goes up. We test this model empirically by analyzing the effect of natural disasters on battles in Africa. We construct a novel panel-dataset that combines geo-referenced information about battle events and natural disasters at the monthly level for 5,944 districts in all 53 African countries over the period from 1989 to 2015. Our results reveal that natural disasters do indeed decrease battle incidence in the affected district and that they divert fighting activity to surrounding districts, particularly those that are better connected via the geographic and road networks. This shift in combat activity occurs with some significant time lag. In addition, our results highlight that mining activity also 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 new combat activity.

References

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

Amarasinghe, A., Hodler, R., Raschky, P. A. and Y. Zenou (2018), "Diffusion of Economic Shocks in Networks," CEPR Discussion Papers No. 12854.

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

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, N., M. Couttenier, D. Rohner, and M. Thoenig (2017), “This mine is mine! How minerals fuel conflicts in Africa,” *American Economic Review* 107, 1564–1610.

Berman, N., M. Couttenier, and R. Soubeyran (2020), “Fertile ground for conflict,” *Journal of the European Economic Association*, forthcoming.

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.

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

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

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 of Applied Economics* 3(4), 215–227.

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

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

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.

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*.

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.

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

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.

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

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

Guha-Sapir, D., Below, R. 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., Storeygard A. 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.

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

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

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

Huremovic, K. (2019), "A noncooperative model of contest network formation," Unpublished manuscript, IMT School for Advanced Studies, Lucca, Italy.

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

Jackson, M.O., Rogers, B.W. 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.

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.

Kovenock, D., Roberson, B. and R.M. Sheremeta (2019), "The attack and defense of weakest-link networks," *Public Choice* 179, 175–194.

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

McGuirk, E. and M. Burke (2017), "The economic origins of conflict in Africa, "NBER Working Paper 23056.

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

Murdock, G.P. (1959), *Africa: its peoples and their culture history*, New York: McGraw-Hill Book Company.

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.

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.

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

Xu, J., Zenou, Y. and J. Zhou (2019), "Networks in Conflict: Theory and Applications," CEPR Discussion Paper No. 13647.

Tables

Table 1: Descriptive Statistics for Key Variables

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

Battle and *DIS* are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, and a natural disaster event, respectively, in district i in in the given time unit. Disasters exclude droughts. $Light = 1$ if *Initial Light* in district $i \geqslant 10$ (on a scale of 0-63) and $= 0$ otherwise. $Mine = 1$ if at least one active mine was present in district i over the sample period, and $= 0$ otherwise. $Agri = 1$ if more than 50% of the land area of district i was agriculturally suitable, and $= 0$ otherwise.

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

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

Battle and *DIS* are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, and a natural disaster event, respectively, in district i in year y. Disasters exclude droughts. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

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

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

Battle and *DIS* are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, and a natural disaster event, respectively, in district i in month m of year y. Disasters exclude droughts. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the *country* × *year* level in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

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

VARIABLES	(1) $Battle_{iym}$	(2) $Battle_{iym}$	(3) $Battle_{iym}$	(4) $Battle_{iym}$
DIS_{iym}	-0.0015**	-0.0013*	-0.0015**	-0.0010
	(0.0006)	(0.0008)	(0.0007)	(0.0008)
$DIS_{iy,m-1}$	-0.0013*	-0.0013	-0.0018**	-0.0006
	(0.0007)	(0.0009)	(0.0007)	(0.0008)
$DIS_{iy,m-2}$	-0.0005	-0.0010	-0.0006	-0.0007
	(0.0007)	(0.0008)	(0.0007)	(0.0009)
$DIS_{iym} \times Light_i$	-0.0011			-0.0014
	(0.0026)			(0.0025)
$DIS_{iy,m-1} \times Light_i$	-0.0065**			-0.0071***
	(0.0025)			(0.0019)
$DIS_{iy,m-2} \times Light_i$	-0.0034			-0.0031
	(0.0029)			(0.0027)
$DIS_{iym} \times Agri_i$		-0.0011		-0.0012
		(0.0011)		(0.0010)
$DIS_{iy,m-1} \times Agri_i$		-0.0018		-0.0024**
		(0.0012)		(0.0011)
$DIS_{iy,m-2} \times Agri_i$		0.0013		0.0010
		(0.0012)		(0.0013)
$DIS_{iym} \times Mine_i$			-0.0013	-0.0013
			(0.0021)	(0.0024)
$DIS_{iy,m-1} \times Mine_i$			0.0003	0.0004
			(0.0016)	(0.0016)
$DIS_{iy,m-2} \times Mine_i$			-0.0014	-0.0012
			(0.0017)	(0.0018)
Observations	1,913,968	1,913,968	1,913,968	1,913,968
Number of Districts	5,944	5,944	5,944	5,944
Month FE	YES	YES	YES	YES
District × Year FE	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES

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

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

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

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

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

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

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

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

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

Online Appendix

Conflicts in Spatial Networks

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

A Proofs of the Theoretical Model

Proof of Proposition 1: The existence and uniqueness result of the Nash equilibrium result of this proposition follows directly from Theorems 1 and 3 in Xu et al. (2019). Indeed, the cost function is quadratic, and therefore convex and strongly monotone, and the Tullock contest success function (CSF), given by (2), satisfies the assumption on the CSF assumption in Xu et al. (2019). This shows the existence and uniqueness of the Nash equilibrium. Moreover, Xu et al. (2019) also show the unique equilibirum satisfies the property that every battle contains at least two contestants with positive efforts. Since, in the star depicted in Figure 1, each battle only has two contestants, this unique equilibrium is interior. □

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

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

and

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

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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 (9) for the parameter v^a, we obtain:

$$\begin{pmatrix} \frac{\partial x_1^a}{\partial v^a} \\ \\ \frac{\partial x_1^b}{\partial v^a} \\ \\ \frac{\partial x_2^a}{\partial v^a} \\ \\ \frac{\partial x_3^b}{\partial v^a} \end{pmatrix} = -\mathbf{M}^{-1} \begin{pmatrix} \frac{\partial f_1}{\partial v^a} \\ \\ \frac{\partial f_2}{\partial v^a} \\ \\ \frac{\partial f_3}{\partial v^a} \\ \\ \frac{\partial f_4}{\partial v^a} \end{pmatrix} \tag{A.1}$$

where

$$\mathbf{M} := \begin{pmatrix} \frac{\partial f_1}{\partial x_1^a} & \frac{\partial f_1}{\partial x_1^b} & \frac{\partial f_1}{\partial x_2^a} & \frac{\partial f_1}{\partial x_3^b} \\ \frac{\partial f_2}{\partial x_1^a} & \frac{\partial f_2}{\partial x_1^b} & \frac{\partial f_2}{\partial x_2^a} & \frac{\partial f_2}{\partial x_3^b} \\ \frac{\partial f_3}{\partial x_1^a} & \frac{\partial f_3}{\partial x_1^b} & \frac{\partial f_3}{\partial x_2^a} & \frac{\partial f_3}{\partial x_3^b} \\ \frac{\partial f_4}{\partial x_1^a} & \frac{\partial f_4}{\partial x_1^b} & \frac{\partial f_4}{\partial x_2^a} & \frac{\partial f_4}{\partial x_3^b} \end{pmatrix} \quad and \quad \begin{pmatrix} \frac{\partial f_1}{\partial v^a} \\ \frac{\partial f_2}{\partial v^a} \\ \frac{\partial f_3}{\partial v^a} \\ \frac{\partial f_4}{\partial v^a} \end{pmatrix} = \begin{pmatrix} \frac{x_2^a}{(x_1^a+x_2^a)^2} \\ 0 \\ \frac{x_1^a}{(x_1^a+x_2^a)^2} \\ 0 \end{pmatrix} \tag{A.2}$$

with

$$\frac{\partial f_1}{\partial x_3^b} = \frac{\partial f_2}{\partial x_2^a} = \frac{\partial f_3}{\partial x_1^b} = \frac{\partial f_3}{\partial x_3^b} = \frac{\partial f_4}{\partial x_1^a} = \frac{\partial f_4}{\partial x_2^a} = 0 \tag{A.3}$$

$$\begin{aligned} \frac{\partial f_1}{\partial x_1^a} = -s_1 - \frac{2v^a x_2^a}{(x_1^a + x_2^a)^3}, \frac{\partial f_1}{\partial x_1^b} = -s_1, \frac{\partial f_1}{\partial x_2^a} = \frac{v^a}{(x_1^a + x_2^a)^2} - \frac{2v^a x_2^a}{(x_1^a + x_2^a)^3}, \\ \frac{\partial f_2}{\partial x_1^a} = -s_1, \frac{\partial f_2}{\partial x_1^b} = -s_1 - \frac{2v^b x_3^b}{(x_1^b + x_3^b)^3}, \frac{\partial f_2}{\partial x_3^b} = \frac{v^b}{(x_1^b + x_3^b)^2} - \frac{2v^b x_3^b}{(x_1^b + x_3^b)^3}, \\ \frac{\partial f_3}{\partial x_1^a} = \frac{v^a}{(x_1^a + x_2^a)^2} - \frac{2v^a x_1^a}{(x_1^a + x_2^a)^3}, \frac{\partial f_3}{\partial x_2^a} = -s_2 - \frac{2v^a x_1^a}{(x_1^a + x_2^a)^3}, \\ \frac{\partial f_4}{\partial x_1^b} = \frac{v^b}{(x_1^b + x_3^b)^2} - \frac{2v^b x_1^b}{(x_1^b + x_3^b)^3}, \frac{\partial f_4}{\partial x_3^b} = -s_3 - \frac{2v^b x_1^b}{(x_1^b + x_3^b)^3}. \end{aligned} \tag{A.4}$$

Note that $\mathbf{M}$ is just the Jacobian matrix of system (9) with respect to $(x_1^a, x_1^b, x_2^a, x_3^b)$. We can easily verify that the sign of the determinant of $\mathbf{M}$ is given by:

$$det(\mathbf{M}) := J = \begin{vmatrix} \frac{\partial f_1}{\partial x_1^a} & \frac{\partial f_1}{\partial x_1^b} & \frac{\partial f_1}{\partial x_2^a} & \frac{\partial f_1}{\partial x_3^b} \\ \frac{\partial f_2}{\partial x_1^a} & \frac{\partial f_2}{\partial x_1^b} & \frac{\partial f_2}{\partial x_2^a} & \frac{\partial f_2}{\partial x_3^b} \\ \frac{\partial f_3}{\partial x_1^a} & \frac{\partial f_3}{\partial x_1^b} & \frac{\partial f_3}{\partial x_2^a} & \frac{\partial f_3}{\partial x_3^b} \\ \frac{\partial f_4}{\partial x_1^a} & \frac{\partial f_4}{\partial x_1^b} & \frac{\partial f_4}{\partial x_2^a} & \frac{\partial f_4}{\partial x_3^b} \end{vmatrix} > 0. \tag{A.5}$$

We apply the Cramer's rule to compute each component of the left-hand side (LHS) of

(A.1). After some simplifications, we obtain:

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

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

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

$$\begin{aligned}\frac{\partial x_2^a}{\partial v^a} =& \frac{s_1 \Big[(v^b)^2 x_1^a (x_1^a + x_2^a)^2 + s_3 v^a x_2^a (x_3^b + x_1^b)^4 + 2v^b (x_3^b + x_1^b)(s_3 x_1^a x_3^b (x_1^a + x_2^a)^2 + v^a x_2^a x_1^b) \Big]}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^4} \\ &+ \frac{v^a v^b x_2^a (v^b + 2s_3 x_3^b (x_3^b + x_1^b))}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^4} > 0\end{aligned} \tag{A.9}$$

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

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

This completes the proof of the proposition. □

B Additional figures

Figure B.1: Distribution of battles in Africa

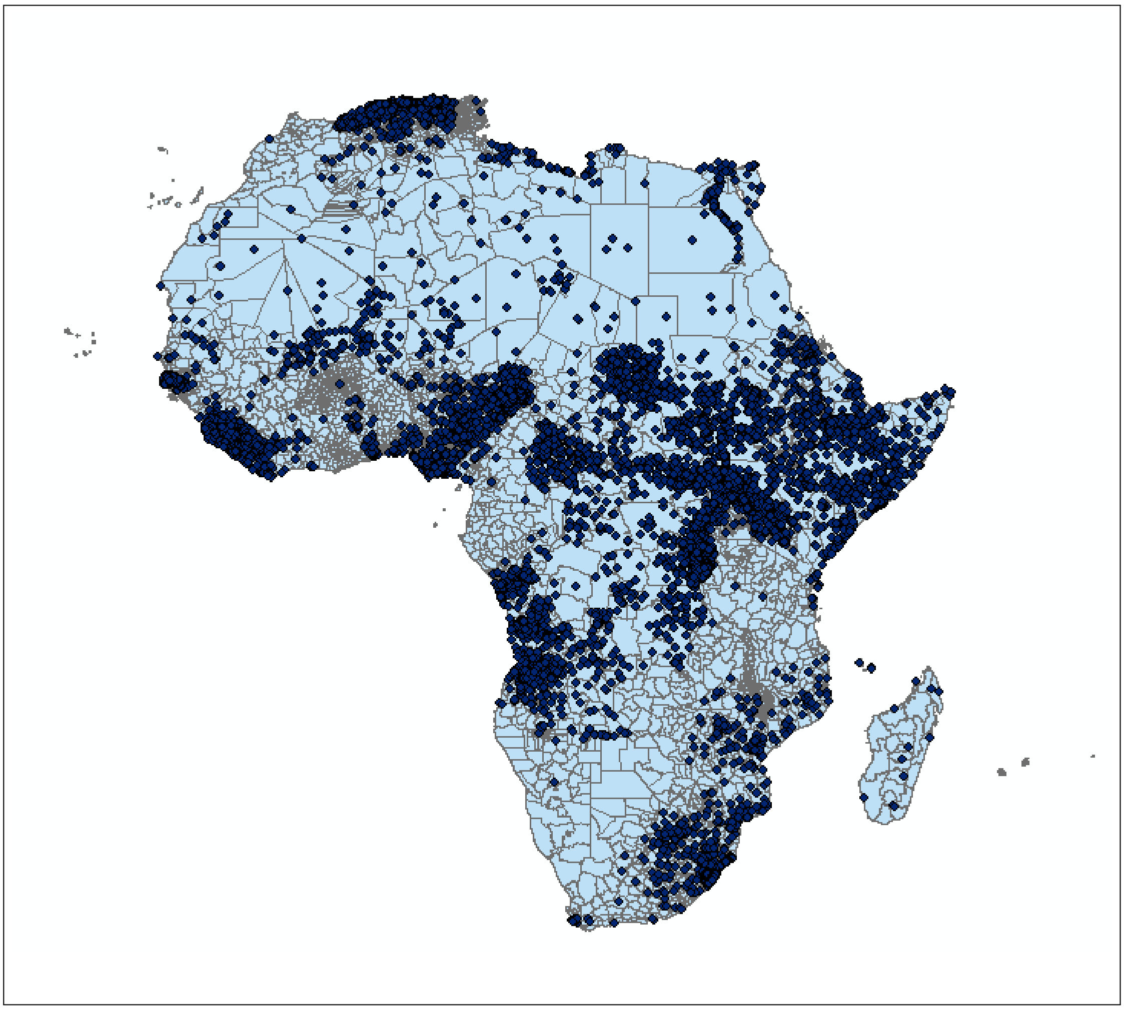


Figure B.2: Distribution of natural disasters in Africa

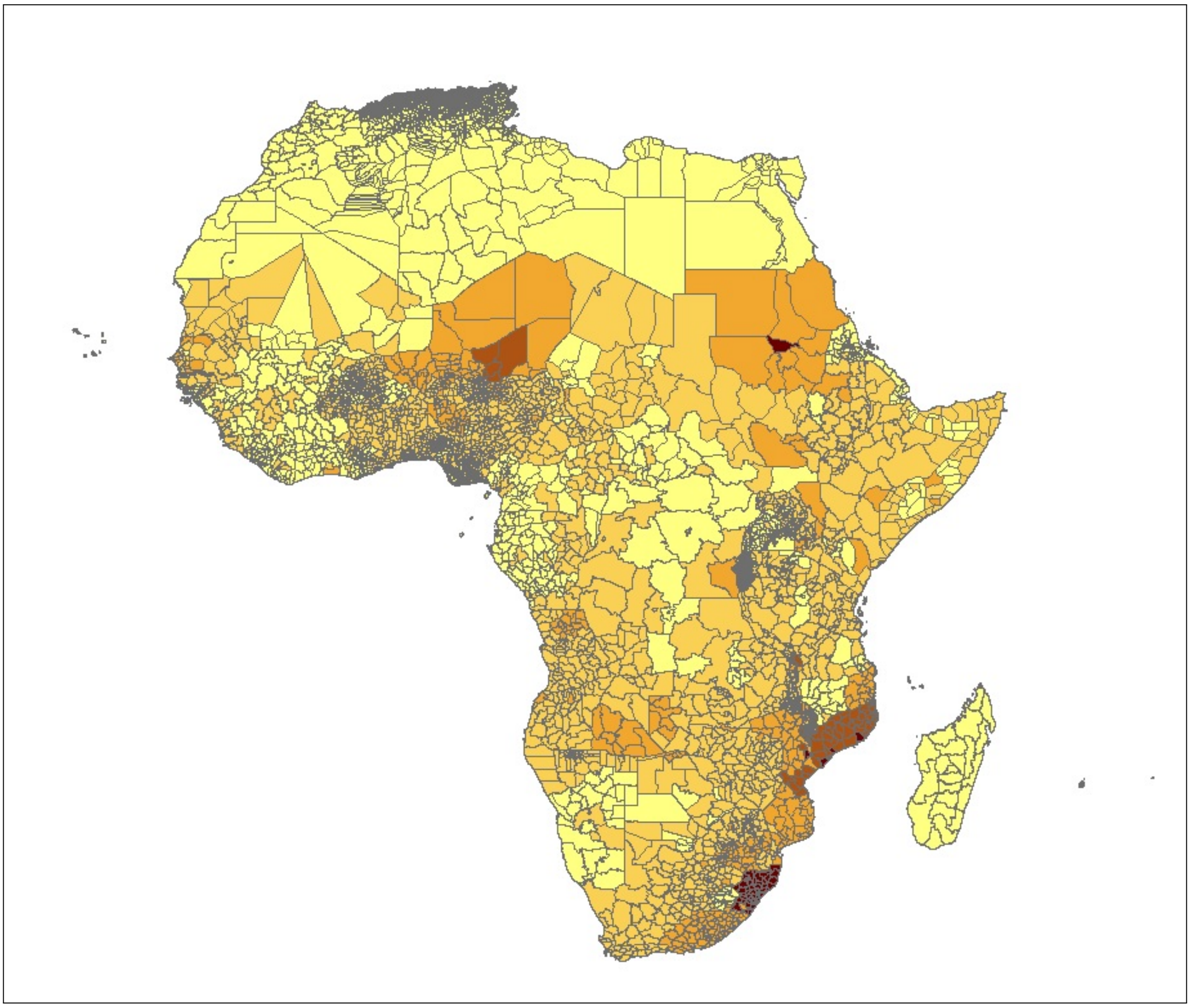
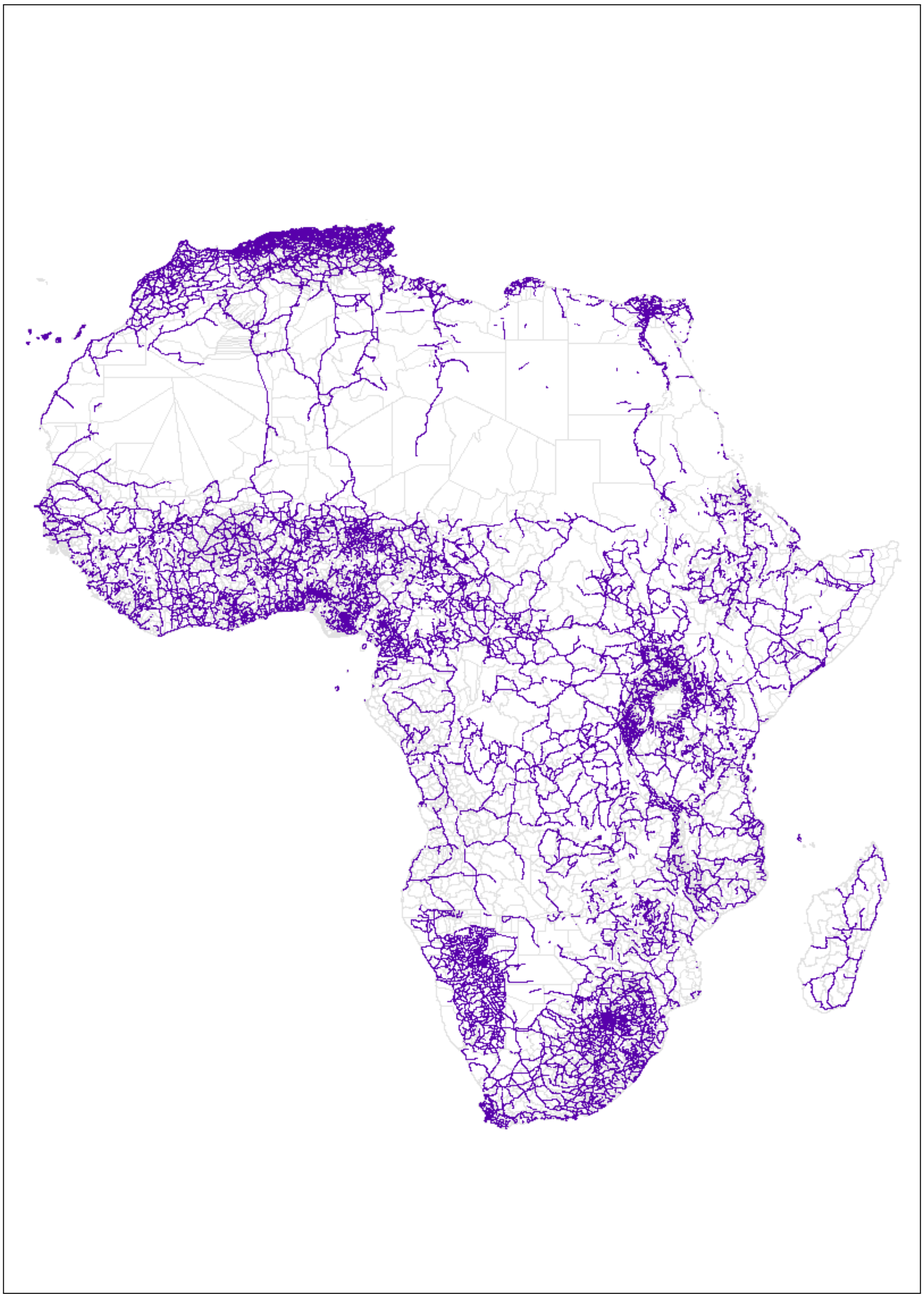


Figure B.3: Road connectivity in Africa



C Robustness checks

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

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

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

In Table C.3, we replicate the specification in Eq (13), but additionally includes higher order autoregressive terms. We show that the magnitude and statistical significance of the variable of interest does not change drastically once these controls are included. In Table C.4, we use the count of battles at the district-month level instead of a binary indicator. We observe that the negative effect of disasters is still there under this definition of battles as well. In Table C.5, we use alternative definitions of the dependent variable. We identify that the negative effect of natural disasters on battles stems mostly from battles involving state and non-state actors and not from one-sided battles.

In Table C.6, we use alternative definitions of the independent variable. Large disasters show a negative effect on battles in the period of occurrence, while the negative effect of small disasters occurs with a time lag. Climatic disasters lead to a reduction of battle incidence at the 1% level of statistical significance, while the effect of geologic disasters is statistically

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

insignificant.

We distinguish between battle onset and termination in Table C.7. IN order to do this, we first generate binary indicators to identify the first period of battle in a district (onset) and the last period of battle in a district (termination). Results indicate that natural disasters have a statistically significant effect on increasing the termination of battles, and no statistically significant effect on battle onset. This result further proves that natural disasters lead to a permanent appeasing effect in the context of Africa.

Next we look at the diffusion of battles along the geographic network at different distance cutoffs (Table C.8). As discussed before, in the short run, we do not see an effect of battle diffusion along the geographic network, even when truncated at shorter distances.

In Section C.3 we conduct the same robustness checks as in Section C.2, but at the *district-year* level of aggregation. We observe that the local effect (Tables C.9 to Table C.13) are less precisely defined at the district-year level than at the district-month level. By contrast, the diffusion effects (Table C.15) are more prominent in the medium to long run i.e. at the year level.

Finally, in Table C.16 we address concerns on the potential occurrence of the well-known Nickell bias when including a lagged dependent variable in a fixed effects specification. Panel A in Table C.16 presents results of specifications without the lagged dependent variable as well as results of a LDV model. The results show that the coefficients of our key explanatory variables remain very similar.

C.1 Robustness Checks at the Country-Year Level

Table C.1: Natural Disasters and Battles at Country Level

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

Battle and *DIS* are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, and natural disaster event, respectively, in the given geographic unit in the given time period. Disasters exclude droughts. Additional controls include $Battle_{it-1}$. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

C.2 Robustness Checks at the District-Month Level

Table C.2: Natural Disasters and Battles at the District-Month Level - Spatial Clustering of Standard Errors

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

Battle and *DIS* are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, and a natural disaster event, respectively, in district i in month m of year y. Disasters exclude droughts. Other controls include $Battle_{iy,m-1}$. Spatial HAC standard errors, allowing for spatial correlation up to 100km and for infinite serial correlation, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.3: Natural Disasters and Battles at the District-Month Level - With Higher Order Autoregressive Terms

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

This Table includes higher order autoregressive terms i.e. $Battle_{iy,m-1}$ $Battle_{iy,m-2}$ and $Battle_{iy,m-3}$ as additional controls. *Battle* and *DIS* are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, and a natural disaster event, respectively, in the given district in the given time period. Disasters exclude droughts. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the *country* × *year* level in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

Table C.4: Natural Disasters and Battles at the District-Month Level - Battle Intensity

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

Battle is a count variable indicating the sum of all battle events resulting in at least one death in the given district in the given time period. DIS is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. Disasters exclude droughts. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the *country* × *year* level in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

Table C.5: Alternative Definition of the Dependent Variable

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

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

Table C.6: Alternative Definition of the Independent Variable - District-Month Level

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

Battle and *DIS* are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death and a natural disaster event, respectively, in the given district in the given time period. *Large DIS* is a binary variable indicating the presence (=1) or absence (=0) of a disasters that either (*i*) kills at least 1000 people, or (*ii*) affects at least 100,000 people in total, or (*iii*) causes damages of at least one billion (real) dollars. *Climatic* (*Geologic*) *DIS* is a binary variables indicating the presence (=1) or absence (=0) of a climatic (geologic) natural disaster event in the given district in the given time period. Disasters exclude droughts. Geologic disasters include volcanic eruptions, natural explosions, avalanches, landslides, and earthquakes. Climatic disasters include floods, cyclones, hurricanes, ice storms, snowstorms, tornadoes, typhoons, and storms. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.7: Natural Disasters, Battle Onset and Termination - District-Month level

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

$Onset$ is a binary indicator = 0 in periods with no battle events; = 1 in the first time period a district experiences a battle; and missing in subsequent time periods. $Termination$ is a binary indicator = 0 in periods of battle; = 1 in the first period with no battle; and missing in subsequent time periods. DIS is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. Disasters exclude droughts. Other controls include $Battle_{iy,m-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.8: Natural Disasters and Battle Diffusion at the District-Month Level - Robustness to Alternative Distance Cut-offs

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

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

C.3 Robustness Checks at the District-Year Level

Table C.9: Alternative Definitions of the Dependent Variable - District-Year Level

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

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

Table C.10: Natural Disasters and Battles at the District-Year Level - Battle Intensity

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

Battle is a count variable indicating the sum of battles that occurred in the given district in the given year. *DIS* is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. Disasters exclude droughts. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the $country \times year$ level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.11: Alternative Definitions of the Independent Variable - District-Year Level

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

Battle and DIS are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death and a natural disaster event, respectively, in the given district in the given time period. *Large* DIS is a binary variable indicating the presence (=1) or absence (=0) of a disasters that either (*i*) kills at least 1000 people, or (*ii*) affects at least 100,000 people in total, or (*iii*) causes damages of at least one billion (real) dollars. *Climatic* (*Geologic*) DIS is a binary variables indicating the presence (=1) or absence (=0) of a climatic (geologic) natural disaster event in the given district in the given time period. Disasters exclude droughts. Geologic disasters include volcanic eruptions, natural explosions, avalanches, landslides, and earthquakes. Climatic disasters include floods, cyclones, hurricanes, ice storms, snowstorms, tornadoes, typhoons, and storms. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.12: Natural Disasters and Battles at the District-Year Level: Channels

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

Battle and DIS are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death and natural disaster event, respectively, in the given district in the given time period. Disasters exclude droughts. $Light_i$=1 if average nighttime light in 1992 (i.e. initial light) >10 (on a scale of 0-63), and 0 otherwise. $Agri_i$=1 if the fraction of land suitable for agriculture in district i is above 50%, and 0 otherwise. $Mine = 1$ if the district hosted at least one active mining project over the sample period, and 0 otherwise. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.13: Natural Disasters, Battle Onset and Termination - District-Year level

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

Onset is a binary indicator = 0 in periods with no battle events; = 1 in the first time period a district experiences a battle; and missing in subsequent time periods. *Termination* is a binary indicator = 0 in periods of battle; = 1 in the first period with no battle; and missing in subsequent time periods. *DIS* is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. Disasters exclude droughts. Other controls include $Battle_{iy-1}$. Standard errors, clustered at the *country* × *year* level, in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table C.14: Natural Disasters and Battle Diffusion at the District-Year Level - Spatial Clustering of Standard Errors

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

Battle and *Disaster* are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. *NeighbDisaster* (*NeighbBattle*) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (battle), in any one of the district's neighbours, within the given time period. Neighbourhood is based on the altitude-adjusted inverse distance matrix and the inverse road distance matrix, truncated at the indicated distance cut-off. Other controls include $Battle_{iy-1}$. Disasters exclude droughts. Spatial HAC standard errors, allowing for spatial correlation up to 100km and for infinite serial correlation, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.15: Natural Disasters and Battle Diffusion at the District-Year Level - Robustness to Alternative Distance Cut-offs

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

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

Table C.16: Fixed Effects and Lagged Dependent Variable Specifications

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

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