Networks in Conflict: Theory and Evidence from the Great War of Africa[*]

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Abstract

We study from both a theoretical and an empirical perspective how a network of military alliances and enmities affects the intensity of a conflict. The model combines elements from network theory and from the politico-economic theory of conflict. We obtain a closed-form characterization of the Nash equilibrium. Using the equilibrium conditions, we perform an empirical analysis using data on the Second Congo War, a conflict that involves many groups in a complex network of informal alliances and rivalries. The estimates of the fighting externalities are then used to infer the extent to which the conflict intensity can be reduced through (i) dismantling specific fighting groups involved in the conflict; (ii) weapon embargoes; (iii) interventions aimed at pacifying animosity among groups. Finally, with the aid of a random utility model we study how policy shocks can induce the reshaping of the network structure.

1 Introduction

Alliances and enmities among armed actors – be they rooted in history or in mere tactical considerations – are part and parcel of warfare.[1] In many episodes, especially in civil conflicts, they are shallow links that are not sanctioned by formal treaties or war declarations. Even allied groups retain separate agendas and pursue self-interested goals in competition with each other. The command of armed forces remains decentralized, and coordination is minimal.

Understanding the role of informal networks of military alliances and enmities is important, not only for predicting outcomes, but also for implementing policies to contain or put an end to violence. These may be diplomatic initiatives promoted by international organizations to restore dialogue and reduce animosity between conflict participants, or military interventions of external forces against specific groups. Yet, with only few exceptions, the existing political and economic theories of conflict restrict attention to a small number of players, and do not consider network aspects. In this paper, we construct a theory of conflict focusing explicitly on informal networks of alliances and enmities, and apply it econometrically to the study of the Second Congo War and its aftermath.

The theoretical benchmark is a *contest success function,* henceforth CSF, in the spirit of Tullock (1980). In a standard CSF, the share of the prize accruing to each group is determined by the amount of resources (*fighting effort*) that each of them commits to the conflict. In our model, the network of alliances and enmities modifies the sharing rule of a standard CSF by introducing additional externalities. More precisely, we assume that the share of the prize accruing to group i is determined by the group's relative strength, which we label *operational performance* (OP). In turn, the OP is determined by group i's own fighting effort and by the fighting effort of its allied and enemy groups. The fighting effort of group i's allies increases group i's OP, whereas the fighting effort of its enemies decreases it. Thus, each group's fighting effort affects positively its allies' OP and negatively its enemies'. Instead, the costs of fighting are borne individually by each group. This raises a motive for strategic behavior among both enemy and allied groups. Note that in our theory all agents determine their effort in a non-cooperative way; even alliances are loose links and each allied group act in its own self-interest. The complex externality web affects the optimal fighting effort of all groups. We provide an analytical solution for the Nash equilibrium of the game. Absent other sources of heterogeneity, the fighting effort of each agent hinges on a measure of network centrality which is related to the Katz-Bonacich centrality (Ballester *et al.* 2006).

The model can be used to predict how the network structure of military alliances and rivalries affects the overall conflict intensity. This is measured by the sum of the fighting efforts of all contenders (total *rent dissipation*), which is our measure of the welfare loss associated with a conflict. Network externalities are a key driver of the escalation or containment of violence.

The main contribution of the paper is an empirical analysis based on the structural equations of the model. We focus on the Second Congo War, a large-scale conflict involving a rich network of alliances and enmities that erupted in Democratic Republic of Congo (DRC) in 1998, and its after-

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[1]Ghez (2011) distinguishes between tactical, historical, and natural alliances. Tactical alliances are formed "to counter an immediate threat or adversary that has the potential to challenge a state's most vital interests" (2011: 20). They are instrumental and often opportunistic in nature. Historical alliances are more resilient insofar as they hinge on a historical tradition of cooperation. However, they often remain informal. Natural alliances imply a more profound shared political culture and vision of the world (e.g., Western Europe and the U.S.). Contrary to tactical and historical alliances, they are often formalized. Our study focuses on tactical and historical alliances/enmities. In our theory, natural allies (e.g., the U.K and the U.S. during WWII) can be viewed as merged actors acting in a perfectly coordinated fashion.

math. To identify the network, we use information from a variety of expert sources, supplemented by information from the Armed Conflict Location Event Database (ACLED). The estimated network features numerous intransitivities, showing that this conflict cannot be described as the clash between two unitary camps (see Figure 3 below).

Our estimation strategy exploits panel variations in the yearly number of clashes involving 80 armed groups in 1998–2010. Fighting effort is proxied by the number of clashes in which each group is involved. Controlling for group fixed effects, we regress each group's fighting effort on the total fighting efforts of its degree-one allies and enemies, respectively. Since these efforts are endogenous and subject to a reflection problem, we adopt an instrumental variable (IV) strategy similar to that used by Acemoglu *et al.* (2015). Our identification strategy exploits the exogenous variation in the average weather conditions facing, respectively, the set of allies and of enemies of each group. The focus on weather shocks is motivated by the recent literature documenting that these have important effects on fighting intensity (see Dell 2012, Hidalgo *et al.* 2010, Jia 2014, Miguel *et al.* 2004, and Vanden Eynde 2011). Without imposing any restriction, we find that the two estimated externalities have the opposite-sign pattern which aligns with the predictions of the theory. Moreover, we find no external effect from the neutral groups, also in line with the theoretical predictions.

After estimating the network externalities, we perform a variety of counterfactual policy experiments. First, we consider targeted policies that affect the incentives for selected groups to drop out of the conflict and/or their marginal cost of fighting (e.g., arms embargoes). The analysis can guide international organizations in singling out armed groups whose decommissioning or weakening is most effective for scaling down conflict. Second, we study the effect of pacification policies aimed at reducing the hostility between enemy groups, e.g., through bringing selected actors to the negotiating table. Since enmities tend to increase the conflict intensity, bilateral or multilateral pacification tend to reduce violence. We find that in many cases the gain from pacification policies are large, at instances well in excess of the observed clashes between the groups whose bilateral hostilities are placated.

The results highlight the key role of Rwanda and Uganda in the conflict, although some smaller guerrilla groups such as the Lord Resistance Army (LRA) are also important drivers of violence. Simultaneously removing Uganda, Rwanda, and the groups associated with them is predicted to reduce violence by 46%, which is significantly more than the contribution of these groups to conflict in the data (34%). Arms embargoes that increase the fighting cost of groups without inducing them to demobilize are generally ineffective because the reduction in the targeted groups' activity is typically offset by an increase in the activity of the other groups. The most effective pacification policies are those bringing to an end the hostility between the government of the Democratic Republic of Congo (DRC) and Rwanda or Uganda. These interventions are more effective than breaking peace between the DRC government and the various factions of the Rally of Congolese Democracy (RCD) – the local proxies of the two powerful neighbors – although the military engagements of the DRC armed forces (FARDC) with the RCD are far more frequent than those with the armies of Rwanda and Uganda.

In most of the paper, we maintain the assumption of an exogenous network. This assumption is relaxed in an important extension, where we allow the network to adjust endogenously to policy shocks, based on the predictions of a random utility model. The recomposition of the network magnifies the effect of interventions targeting foreign groups. Removing all foreign groups reduces the conflict by 41%, significantly more than in the case of an exogenous network (27%). These

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results are in line with the narrative that foreign intervention is an important driver the DRC conflict.

Our contribution is related to various strands of the existing literature. First, our paper is linked to the growing literature on the economics of networks (e.g., Acemoglu and Ozdaglar 2011, Bramoullé *et al.* 2014**,** Jackson 2008, Jackson and Zenou 2014). The small literature that studies strategic interactions of multiple agents in conflict networks include Franke and Öztürk (2009) and Huremovic (2014). Neither of these papers consider, as we do, both alliances and enmities. Two recent theoretical papers study the endogenous formation of networks in conflict models. In Hiller (2012) agents can form alliances to coerce payoffs from enemies with fewer friends. Jackson and Nei (2014) studies the formation of alliances in multilateral interstate wars and the implications on trade relationships between them, showing that trade can have a mitigating effect on conflicts. Neither of these papers endogenizes the choice of fighting effort.

All of the above papers are theoretical. Our paper provides a quantification of the theory by estimating the key network externalities based on the structural equations of the theory. The estimated structural parameters are then used to perform counterfactual policy experiments. In this sense, our paper is related to recent work by Acemoglu *et al.* (2015), which estimates a political economy model of public goods provision using a network of Colombian municipalities. Their empirical strategy is related to ours, although they use historical variations in players' characteristics while we use panel variations (exogenous shocks in rainfall).

One of our three policy counterfactuals is closely related to the pioneer contribution by Ballester *et al.* (2006), which characterizes equilibrium effort choices in a game of strategic complements between neighboring nodes, and identify key players, i.e., the agents whose removal reduces equilibrium aggregate effort the most (see also Liu *et al.* 2011, and Lindquist and Zenou 2013).

Further, our study is broadly related to the growing politico-economic literature on conflict. The papers in this literature typically focus on two groups confronting each other (see, e.g., Rohner *et al.* 2013). A number of studies use a CSF (see, e.g., Grossman and Kim 1995, Hirshleifer 1989, and Skaperdas 1996). A few papers consider multiple groups comprising each a large number of players, and study collective action problems (see, e.g., Esteban and Ray 2001 and Rohner 2011). Other papers consider free riding problems in alliances, which is a salient feature of our theory – see, e.g., Esteban and Sakovics (2004), Konrad and Kovenock (2009), Olson and Zeckhauser (1966), and Nitzan (1991). Some papers introduce the important distinction between fighting and arming (Bates *et al.* 2002; Jackson and Morelli 2009), an issue we abstract from although we study the effects of arms embargoes among the policy counterfactual. For excellent surveys, see Bloch (2012) and Konrad (2009 and 2011).

Finally, our paper is related to the empirical literature on civil war, and in particular to the recent literature that studies conflict using very disaggregated micro-data on geolocalized fighting events, such as for example Cassar *et al.* (2013), Dube and Vargas (2013), La Ferrara and Harari (2012), Michalopoulos and Papaioannou (2013), and Rohner *et al.* (2013b). In a recent interesting paper on the DRC conflict, Sanchez de la Sierra (2014) studies how price shocks of particular metals (cobalt, gold) affect the incentives of armed groups to establish control of resource-producing villages in Eastern Congo.

The paper is organized as follows: Section 2 presents the theoretical model and characterizes the equilibrium; Section 3 discusses the context of the Second Congo War and the data. Section 4 presents the main estimation results and a number of robustness checks. Section 5 performs policy counterfactual analyses. Section 6 estimates, with the aid of a random utility model, how

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policy shocks can trigger changes in the network structure. Section 7 concludes. An appendix [henceforth, *the Main Appendix*] contains some technical analysis. An online appendix [henceforth, *the Appendix*] contains accessory material.

2 THEORY

2.1 ENVIRONMENT

We consider a population of $n \in \mathbb{N}$ agents (henceforth, *groups*) whose interactions are captured by a network $G \in \mathcal{G}^n$, where $\mathcal{G}^n$ denotes the class of graphs on n nodes. Each pair of groups can be in one of three states: alliance, enmity, or neutrality. We represent the set of bilateral states by the signed adjacency matrix $\mathbf{A} = (a_{ij})_{1 \leq i,j \leq n}$ associated with the network G, where, for all $i \neq j$,

$$
a_{ij} = \begin{cases} 1, & \text{if } i \text{ and } j \text{ are allies,} \\ -1, & \text{if } i \text{ and } j \text{ are enemies,} \\ 0, & \text{if } i \text{ and } j \text{ are in a neutral relationship.} \end{cases}
$$

Note that a neutral relationship is modeled as the absence of links. We conventionally set $a_{ii} = 0$.

Let $a_{ij}^+ \equiv \max\{a_{ij}, 0\}$ and $a_{ij}^- \equiv -\min\{a_{ij}, 0\}$ denote the positive and negative parts of a_{ij}, respectively. Then, $\mathbf{A} = \mathbf{A}^+ - \mathbf{A}^-$ where $\mathbf{A}^+ = (a_{ij}^+)_{1 \leq i,j \leq n}$ and $\mathbf{A}^- = (a_{ij}^-)_{1 \leq i,j \leq n}$. We denote the corresponding subgraphs as G^+ and G^-, respectively, so that G can be written as the graph join $G = G^+ \oplus G^-$. Finally, we define the number of group i's allies and enemies as $d_i^+ \equiv \sum_{j=1}^n a_{ij}^+$ and $d_i^- \equiv \sum_{j=1}^n a_{ij}^-$, respectively.

The n groups compete for a prize denoted by V. We assume payoffs to be determined by a generalized Tullock CSF. The CSF maps the relative fighting intensity each group devotes to a conflict into the share of the prize he appropriates after the conflict. More formally, we postulate a payoff function $\pi_i : \mathcal{G}^n \times \mathbb{R}^n \to \mathbb{R}$ given by

$$
\pi_i(G, \mathbf{x}) = \begin{cases} \frac{\varphi_i(G, \mathbf{x})}{\sum_{j=1}^n \max\{0, \varphi_j(G, \mathbf{x})\}} V - x_i, & \text{if } \varphi_i(G, \mathbf{x}) \geq 0, \\ \\ -D, & \text{if } \varphi_i(G, \mathbf{x}) < 0. \end{cases} \tag{1}
$$

$\mathbf{x} \in \mathbb{R}^n$ is a vector describing the fighting effort of each group (the choice variable), whereas $\varphi_i \in \mathbb{R}$ is group i's *operational performance* (OP). The parameter $D \geq 0$ is that *defeat cost* that groups suffer when their OP falls below zero (we discuss this feature below). Group i's OP is assumed to depend on group i's fighting effort x_i, as well as on its allies' and enemies' efforts. More formally, we assume that

$$
\varphi_i(G, \mathbf{x}) = x_i + \beta \sum_{j=1}^n (1 - \mathbb{1}_{\mathcal{D}}(j)) a_{ij}^+ x_j - \gamma \sum_{j=1}^n (1 - \mathbb{1}_{\mathcal{D}}(j)) a_{ij}^- x_j, \tag{2}
$$

where $\beta, \gamma \in [0, 1]$ are spillover parameters from allies' and enemies' fighting efforts, respectively. $\mathbb{1}_{\mathcal{D}}(j) \in \{0, 1\}$ is an indicator function that takes the unit value for groups j accepting defeat and paying the cost D – these groups are assumed to exert no externality. For simplicity, with slight abuse of notation, we henceforth set $x_j = 0$ in equation (2) when group j accepts defeat, and omit the indicator function.

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Note that the specification of equation (2) implies that the only source heterogeneity across groups is their position in the network. We introduce additional sources of heterogeneity (e.g., in military power) in Section 2.4 below.

Equation (2) postulates that each active group's OP increases in the total effort exerted by its allies and decreases in the total effort exerted by its enemies. These externalities compound with the one already embedded in a standard CSF, which equation (2) nests as a particular case when $a_{ij}^+ = a_{ij}^- = 0$ for all i and j. In this case, $\pi_i(G, \mathbf{x}) = \left(x_i / \sum_{j=1}^n x_j\right) V - x_i$, and each group's effort imposes a negative externality on the other groups in the contest only by increasing the denominator of the CSF. In the rest of the paper, we normalize V to unity.[2]

Consider, for example, a network such that $a_{kk'}^+ = 1$ for one and only one pair of groups (k, k') (while $a_{ij}^- = 0$ for all $i, j = 1, \ldots, n$). Then, $\pi_k(G, \mathbf{x}) = (x_k + \beta x_{k'}) / (\sum_{i=1}^n x_i + \beta(x_k + x_{k'})) - x_k$. In this case, an increase in the effort of k' affects the payoff of k via two channels: (i) the standard negative externality working through the denominator; (ii) the positive externality working through the numerator. Thus, holding efforts constant, an alliance between two groups increases the share of the prize jointly accruing to them, at the expenses of the remaining groups. To the opposite, enmity links strengthen the negative externality of the standard CSF.

Consider, finally, the defeat option. When the OP turns negative (for instance, because the enemies exert high effort), a group waves the white flag renouncing to fight for the prize altogether. In this case, the group suffers the defeat cost D – see equation (1).[3] We view this assumption as natural: too low an OP exposes groups to other armed groups' looting and ransacking.

2.2 Nash Equilibrium

In this section, we characterize the Nash equilibrium of the contest. More formally, each group chooses effort, x_i, non-cooperatively so as to maximize $\pi_i(G, [x_i, \mathbf{x}_{-i}])$, given $\mathbf{x}_{-i}$. The equilibrium is a fixed point of the effort vector.

Consider a candidate equilibrium where $\hat{n} \leq n$ groups participates actively in the contest. A necessary and sufficient condition for the optimal effort choice to be a concave problem is that, for $i = 1, 2, \ldots, \hat{n}$,[4]

$$\frac{\partial}{\partial x_i} \sum_{j=1}^{\hat{n}} \varphi_j = 1 + \beta d_i^+ - \gamma d_i^- > 0. \tag{3}$$

In the empirical analysis below, we check that this condition holds in the empirical network for our estimates of β and γ.

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[2]This is without loss of generality. In particular, in equilibrium, both x_i and π_i are proportional to V.

[3]By imposing appropriate restrictions on the network structure, one could set $D = 0$. However, we prefer to impose no such restriction. Nor do we impose any non-negativity constraint on x_i. Given the linearity of the payoff function, the zero effort level is a matter of normalization.

[4]Note that:

$$\pi_i = \frac{W_{ii}(G, \mathbf{x}_{-i}) + x_i}{\sum_{j \neq i} x_j + \sum_{k=1}^n W_{ik}(G, \mathbf{x}_{-i}) + x_i \left(1 + \beta d_i^+ - \gamma d_i^-\right)},$$

where $W_{ij}(G, \mathbf{x}_{-i}) = \sum_{k \neq i} \left(\beta a_{jk}^+ - \gamma a_{jk}^-\right) x_k \geq 0$. π_i is increasing and concave in x_i as long as the denominator of the CSF is increasing in x_i, which is guaranteed by condition (3). In the standard Tullock CSF, $\pi_i = x_i / \left(\sum_{j \neq i} x_j + x_i\right)$ is always increasing and concave in x_i. Relative to this benchmark, enmities (alliances) increase the marginal benefit of effort by rendering the maximization problem more convex (concave).

When condition (3) holds, the optimal effort choice of participants satisfies a system of First-Order Conditions (FOCs). Using equations (1)-(2), one obtains:

$$\frac{\partial \pi_i (G, \mathbf{x})}{\partial x_i} = 0 \iff \varphi_i = \frac{1}{1 + \beta d_i^+ - \gamma d_i^-} \left(1 - \sum_{j=1}^{\hat{n}} \varphi_j \right) \sum_{j=1}^{\hat{n}} \varphi_j.$$

Rearranging terms allows us to obtain a simple expression for the equilibrium OP level,

$$\varphi_i^* (G) = \Lambda^{\beta,\gamma} (G) \left(1 - \Lambda^{\beta,\gamma} (G)\right) \Gamma_i^{\beta,\gamma} (G), \tag{4}$$

and for the equilibrium share of the prize,

$$\frac{\varphi_i^*(G)}{\sum_{j=1}^{\hat{n}} \varphi_j^*(G)} = \frac{\Gamma_i^{\beta,\gamma} (G)}{\sum_{j=1}^{\hat{n}} \Gamma_j^{\beta,\gamma} (G)}, \tag{5}$$

where

$$\Gamma_i^{\beta,\gamma} (G) \equiv \frac{1}{1 + \beta d_i^+ - \gamma d_i^-} > 0 \text{ and } \Lambda^{\beta,\gamma} (G) \equiv 1 - \frac{1}{\sum_{i=1}^{\hat{n}} \Gamma_i^{\beta,\gamma} (G)}. \tag{6}$$

$\Gamma_i^{\beta,\gamma}(G) > 0$ is a measure of the local hostility level capturing the externalities associated with group i's first-degree alliance and enmity links. One can show that $0 < \Lambda^{\beta,\gamma} (G) < 1$, implying that $\varphi_i^* (G) > 0$.[5] Equation (5) implies that the share of the prize accruing to group i increases in the number of its allies and decreases in the number of its enemies.

The next proposition (proof in the *Main Appendix*) characterizes equilibrium.

Proposition 1. *Assume that $\beta + \gamma < 1/\max\{\lambda_{\max}(G^+), d_{\max}^-\}$, where $\lambda_{\max} (\mathbf{M})$ denotes the largest eigenvalue associated with the matrix $\mathbf{M}$, and that condition (3) holds true for all $i = 1, 2, ...n$. Then, $\exists \underline{D} < \infty$ such that, $\forall D > \underline{D}$, there exists an interior Nash equilibrium such that, $\forall i = 1, 2, \ldots, n$, the equilibrium effort levels and OPs are given by*

$$x_i^* (G) = \Lambda^{\beta,\gamma} (G) \left(1 - \Lambda^{\beta,\gamma} (G)\right) c_i^{\beta,\gamma} (G) \tag{7}$$

and $\varphi_i = \varphi_i^* (G) \geq 0$ as given by equation (4), for $\hat{n} = n$. Here, $\Gamma_i^{\beta,\gamma} (G)$ and $\Lambda^{\beta,\gamma} (G)$ are defined by equation (6), and

$$\mathbf{c}^{\beta,\gamma} (G) \equiv \left(\mathbf{I}_n + \beta \mathbf{A}^+ - \gamma \mathbf{A}^-\right)^{-1} \mathbf{\Gamma}^{\beta,\gamma} (G), \tag{8}$$

is a centrality vector, whose generic element $c_i^{\beta,\gamma} (G)$ describes group i's centrality in the network G. Finally, the equilibrium payoffs are given by

$$\pi_i^* (G) = (1 - \Lambda^{\beta,\gamma}(G)) \left(\Gamma_i^{\beta,\gamma} (G) - \Lambda^{\beta,\gamma} (G) c_i^{\beta,\gamma} (G)\right) > -D. \tag{9}$$

If, in addition, $\Gamma_i^{0,\gamma} > 0$ for all $i = 1, \ldots, n$, then, $\exists \underline{\underline{D}}$ (where $\underline{D} \leq \underline{\underline{D}} < \infty$) such that, $\forall D > \underline{D}$, the equilibrium is unique.

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[5]Moreover, both $\Gamma_i^{\beta,\gamma}(G)$ and $\Lambda^{\beta,\gamma}(G)$ are decreasing with β and increasing with γ (the proof can be obtained upon request from the authors).
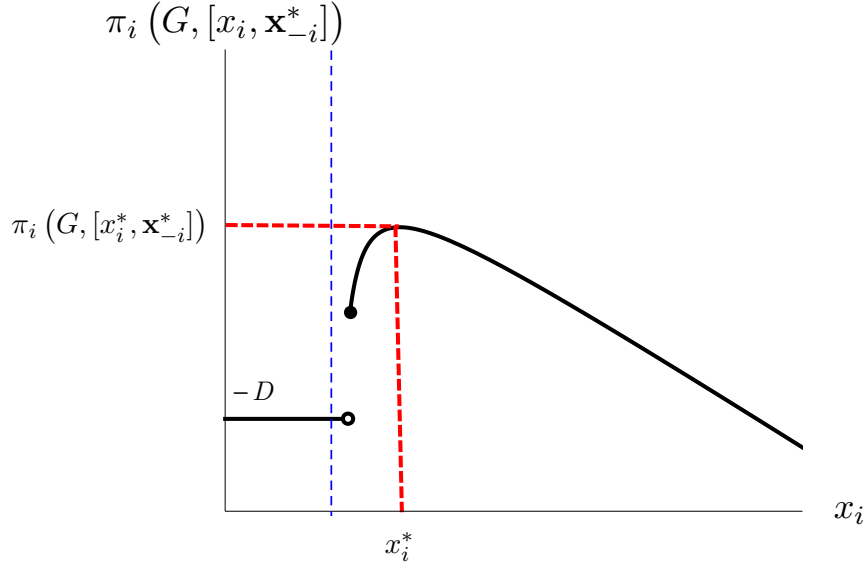
Figure 1: The figures shows the function $\pi_i\left(G, [x_i, \mathbf{x}^*_{-i}]\right)$ for different values of x_i.

The first part of the proposition yields an existence result. Condition (i) is a sufficient condition for the matrix in (8) to be invertible. Equation (7) follows from the set of FOCs. Figure 1 shows the properties of the payoff function $\pi_i\left(G, [x_i, \mathbf{x}^*_{-i}]\right)$ at the equilibrium strategy profile. Group i's payoff function is constant ($\pi_i = -D$) for all x_i below the threshold that guarantees the non-negativity of φ_i. At the threshold, the function is discontinuous, capturing the fact that when $\varphi_i \geq 0$ no defeat cost is due.[6] To the right of the threshold, condition (3) ensures that $\pi_i\left(G, [x_i, \mathbf{x}^*_{-i}]\right)$ is strictly concave in x_i. Moreover, the payoff function is hump shaped and reaches a maximum at $\varphi^*_i > 0$. For a sufficiently large D, an equilibrium exists where all groups participate in the contest.[7]

The second part of the proposition establishes that, under a stronger set of conditions, the Nash equilibrium where all agents participate is unique. In this case, setting D sufficiently high rules out equilibrium configurations in which a partition of groups takes the defeat option. For lower values of D, equilibria in which some groups accept defeat may instead exist, and multiple equilibria are possible.

2.2.1 Centrality

The centrality measure $c^{\beta,\gamma}_i(G)$ plays a key role in Proposition 1. Note, in particular, that the relative fighting efforts of any two groups equals the ratio between the respective centrality in the network:

$$\frac{x^*_i(G)}{x^*_j(G)} = \frac{c^{\beta,\gamma}_i(G)}{c^{\beta,\gamma}_j(G)}.$$

In Appendix A.1, we relate our centrality measure to the Katz-Bonacich centrality and provide

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[6]The hump-shaped function that follows the FOC has a negative asymptote in correspondence of the (negative) value of x_i that turns the denominator of equation (1) equal to zero.

[7]The focus on an equilibrium in which all groups are active is without loss of generality. The results are identical if there are $\tilde{n} \leq n$ groups waving the white flag. In our model, inactive groups exert no externality, and can therefore be ignored.

formal approximation results for networks in which the spillover parameters β and γ are small. In this case, our centrality measure can be approximated by the the sum of (i) the Katz-Bonacich centrality related to the network of enmities, G^-, (ii) the (negative-parameter) Katz-Bonacich centrality related to the network of alliances, G^+, and (iii) the local hostility vector, $\Gamma^{\beta,\gamma}(G)$.[8] When higher-order terms can be neglected, our centrality measure (8) is increasing in γ and in the number of first- and second-degree enmities, and is decreasing in β and in the number of first-degree alliances. Second-degree alliances have instead a positive effect on the centrality measure.[9] When β and γ are small, each group's fighting effort increases in the weighted difference between the number of enmities (weighted by γ) and of alliances (weighted by β), i.e., $d_i^- \gamma - d_i^+ \beta$. The opposite is true for the equilibrium payoff, that is increasing in $d_i^+ \beta - d_i^- \gamma$. Intuitively, a group with many enemies tends to fight harder and to appropriate a smaller share of the prize, whereas a group with many allies tends to fight less and to appropriate a large size of the prize.

2.2.2 Welfare

To discuss normative implications of the theory, it is useful to define the notion of total *rent dissipation,* given by the total equilibrium fighting effort. More formally,

$$\text{RD}^{\beta,\gamma}(G) \equiv \sum_{i=1}^n x_i^*(G) = \Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G)) \sum_{i=1}^n c_i^{\beta,\gamma}(G). \tag{10}$$

Since $\sum_{i=1}^n \pi_i^*(G) = 1 - \text{RD}^{\beta,\gamma}(G)$, minimizing rent dissipation is equivalent to maximizing welfare.

2.3 EXAMPLE: FROM HOBBES TO ROUSSEAU

We provide a simple illustration of the role of alliances and enmities in the model with the aid of a particular class of networks. A *regular* network, G_{k^+,k^-}, has the property that every group i has $d_i^+ = k^+$ alliances and $d_i^- = k^-$ enmities. Thus, all groups have the same centrality. Regular graphs are tractable and enable us to perform comparative statics with respect to the number of alliances or enmities. Given the symmetric structure, there exists a symmetric Nash equilibrium such that all groups exercise the same effort. Moreover, $\varphi_i^* = \varphi^* = 1/n$, implying an equal division of the pie. Under the conditions of Proposition 1, the equilibrium effort and payoff vectors are given by:

$$x^* \left(k^+, k^- \right) \equiv x_i^* \left(G_{k^+,k^-} \right) = \left(\frac{1}{1 + \beta k^+ - \gamma k^-} - \frac{1}{n} \right) \times \frac{1}{n}, \tag{11}$$

$$\pi^* \left(k^+, k^- \right) \equiv \pi_i^* \left(G_{k^+,k^-} \right) = \frac{1 + (1+n)(\beta k^+ - \gamma k^-)}{n(1 + \beta k^+ - \gamma k^-)} \times \frac{1}{n}. \tag{12}$$

Standard differentiation implies that x^* is decreasing in k^+ and increasing in k^-, whereas π^* is increasing in k^+ and decreasing in k^-. Intuitively, alliances (enmities) reduce (increase) effort and

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[8]More formally, as $\beta \to 0$ and $\gamma \to 0$, the centrality measure defined in equation (8) can be written as

$$\mathbf{c}^{\beta,\gamma}(G) = \mathbf{b}.(\gamma, G^-) + \mathbf{b}.(-\beta, G^+) - \Gamma^{\beta,\gamma}(G) + O(\beta\gamma),$$

where $O(\beta\gamma)$ involves second- and higher-order terms, and the ($\boldsymbol{\mu}$-weighted) Katz-Bonacich centrality with parameter α is defined as $\mathbf{b}.(\alpha, G) \equiv \mathbf{b}_{\Gamma^{\beta,\gamma}(G)}(\alpha, G) = (\mathbf{I}_n - \alpha\mathbf{A})^{-1} \Gamma^{\beta,\gamma}(G) = \sum_{k=0}^{\infty} \alpha^k \mathbf{A}^k \Gamma^{\beta,\gamma}(G)$, when α is smaller than the inverse of the largest eigenvalue of $\mathbf{A}$ (cf. Lemma 1 in the Appendix A.1.2).

[9]Suppose j is an ally of both i and k, but i and k are neutral. Then, an increase in k's effort reduces j's effort, and this in turn increases i's effort.

rent dissipation by decreasing (increasing) the marginal return of individual fighting effort. This basic intuition must be amended in general networks due to the asymmetries in higher-order links.

The regular graph nests three interesting particular cases. First, if $\beta = \gamma = 0$, we have a standard Tullock game, with $\text{RD}^{0,0}\left(G_{k^+,k^-}\right) = (n-1)/n$. Second, consider a complete network of alliances ($k^+ = n - 1$), where, in addition, $\beta \to 1$. Then, $x^* \to 0$ and $\text{RD}^{1,\gamma}\left(G_{n-1,0}\right) \to 0$, i.e., there is no rent dissipation. Namely, the society peacefully attains the equal split of the prize, as in Rousseau's *harmonious society*. The crux is the strong fighting externality across allied groups, which takes the marginal product of individual fighting effort down to zero. Third, consider, conversely, a society in which all relationships are hostile, i.e., $k^- = n - 1$. Then, $\text{RD}^{\beta,\gamma}\left(G_{0,n-1}\right) \to 1$ as $\gamma \to 1/(n-1)^2$: all rents are dissipated through fierce fighting and total destruction, as in Hobbes' *homo homini lupus* pre-contractual society.

2.4 Heterogeneous Fighting Technologies

So far, we have maintained that all groups have access to the same technology turning fighting effort into OP. This was useful for keeping the focus sharply on the network structure. In reality, armed groups typically differ in size, wealth, access to arms, leadership, etc. In this section, we generalize our model by allowing fighting technologies to differ across groups. We restrict attention to additive heterogeneity, since this is crucial for achieving identification in the econometric model presented below. Suppose that group i's OP is given by:[10]

$$\varphi_i(G, \mathbf{x}) = \tilde{\varphi}_i + x_i + \beta \sum_{j=1}^{n} a_{ij}^+ x_j - \gamma \sum_{j=1}^{n} a_{ij}^- x_j, \tag{13}$$

where $\tilde{\varphi}_i$ is a group-specific shifter affecting the OP.

In the Main Appendix, we show that the equilibrium OP is unchanged, and continues to be given by equation (4). Likewise, equation (5) continues to characterize the share of the prize appropriated by each group. Somewhat surprising, the share of resources appropriated by group i, $\varphi_i^*(G)/\sum_{j=1}^{n} \varphi_j^*(G)$, is independent of $\tilde{\varphi}_i$. However, $\tilde{\varphi}_i$ affects the equilibrium effort exerted by group i and its payoff. In particular, the vector of the equilibrium fighting efforts is now given by

$$\mathbf{x}^* = (\mathbf{I}_n + \beta \mathbf{A}^+ - \gamma \mathbf{A}^-)^{-1}(\Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))\mathbf{\Gamma}^{\beta,\gamma}(G) - \tilde{\boldsymbol{\varphi}}), \tag{14}$$

where $\tilde{\boldsymbol{\varphi}} = (\tilde{\varphi}_i)_{1 \le i \le n}$ is the vector of group-specific shifters and the definitions of $\Lambda^{\beta,\gamma}(G)$ and $\mathbf{\Gamma}^{\beta,\gamma}(G)$ are unchanged (see Proposition 2 in Appendix A.2).

Equation (13) will be the basis of our econometric analysis where we introduce both observable and unobservable sources of heterogeneity. In particular, time-varying shocks to $\tilde{\boldsymbol{\varphi}}$ will be the source of econometric identification.

3 Empirical Application - The Second Congo War

In this section, we focus on the recent civil conflict in the DRC with the goal of providing a quantitative evaluation of the theory. More specifically, we estimate the externality parameters β and γ from the structural equation (13) characterizing the Nash equilibrium of the model. Equipped

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[10]Although it is possible to solve for multiplicative heterogeneity, we abstract from it, since it hinders the possibility of an econometric identification of the parameters of the model.

Note that our model can be interpreted as the linear approximation of a *logit-form* CSF as in Skaperdas (1996).

with the point estimates of the structural parameters, we perform counterfactual policy experiments and assess their effectiveness in scaling down conflict. We start by presenting the historical context of the DRC conflict. Then, we discuss the data sources and how we infer the network structure from the data.

3.1 Historical Context

The DRC is the largest Sub-Saharan African country in terms of area, and is populated by about 75 million inhabitants. It is a failed state. After gaining independence from Belgium in 1960, it experienced recurrent political instability and wars that turned it into one of the poorest countries in the world, in spite of its abundant natural resources. The DRC is also a highly ethnically fragmented country with over 200 ethnic groups. The Congo conflict is emblematic of the role of natural resource rents and of the involvement of many inter-connected domestic and foreign actors. In particular, the conflict involved three Congolese rebel movements, 14 foreign armed groups, and several militias (Autesserre 2008). In such complex and fragmented warfare, alliances and enmities play a major role.

The war in Congo is intertwined with the ethnic conflicts in neighboring Rwanda and Uganda. In 1994, Hutu radicals took control of the Rwandan government and allowed ethnic militias to perpetrate the mass killing of nearly a million Tutsis and moderate Hutus in less than one hundred days. After losing power to the Tutsi-led Rwandan Patriotic Front, over a million Hutus fled Rwanda and found refuge in the DRC, that was ruled at that time by the dictator Mobutu Sese Seko. The refugee camps hosted, along with civilians, former militiamen and genocidaires who clashed regularly with the local Tutsi population, most notably in the Kivu region (Seybolt 2000).

As ethnic tensions mounted, a large coalition of African countries centered on Uganda and Rwanda supported an anti-Mobutu rebellion led by Laurent-Désiré Kabila. The First Congo War (1996-97) ended with Kabila's victory. However, the relationship of the new government of the DRC with his former Tutsi allies and their sponsors, Rwanda and Uganda, soon turned sour. Resenting the enormous political and military power exercised by the two neighbors, Kabila first dismissed his Rwandan chief of staff, James Kabarebe, and then ordered all Rwandan and Ugandan armed forces to leave the country. New ethnic clashes erupted in Eastern Congo, fueled on the one hand by the Rwanda-Uganda coalition, and on the other hand by Kabila himself who agitated the local populations and the Hutu refugees against the Tutsi hegemony. The crisis escalated into outright war. Rwanda and Uganda assisted the local Tutsi population (Banyamulenge) and armed a well-organized rebel group, the Rally for Congolese Democracy (RCD) that quickly took control of Eastern Congo. The main Hutu military organization, the Democratic Forces for the Liberation of Rwanda (FDLR), sided with Kabila, who also received the international support of Angola, Chad, Namibia, Sudan, and Zimbabwe, and of the local Mayi-Mayi militias.

Officially, the Second Congo War ended in July 2003. In reality, stable peace was never achieved, and significant fighting is still going on today (see Stearns 2011). The conflict is highly fragmented. In Prunier's words, "*the continent was fractured, not only for or against Kabila, but within each of the two camps*" (Prunier 2011: 187). Similarly, there was in-fighting among different pro-government paramilitary groups, such as the Mayi-Mayi militias. The FARDC themselves were notoriously prone to internal fights and mutinies, spurred by the fact that its units are segregated along ethnic lines and often correspond to former ethnic militias or paramilitaries that got integrated into the national army (Prunier 2011: 305ff; Turner 2007: 96). In summary, far from being a war between two unitary camps, the conflict engaged a complex web of alliances and enmities with

many non-transitive links.

After a major reshuffling at the end of the First Congo War, the web of alliances and enmities between the main armies and rebel groups has remained fairly stable in the period 1998-2010 (see Prunier 2011: 187ff). Yet, there were some notable exceptions. The relationship between Uganda and Rwanda cracked soon after the start of the conflict, culminating in a series of armed confrontations in the Kisangani area in the second half of 1999 and in 2000 that caused the death of over 600 civilians (see Turner 2007: 200).[11] The crisis spilled over to the local proxy of the two countries: the RCD split into the Uganda-backed RCD-Kisangani (RCD-K) and the Rwanda-backed RCD-Goma (RCD-G). After 2000, the relationship between Uganda and Rwanda lived in a knife-edge equilibrium where recurrent tensions and skirmishes were prevented from spiraling into a full-scale conflict (McKnight 2015).

The relationship between the FARDC and the FDLR is also troubled. In the earlier stage of the conflict, they were solid allies. Things changed after Laurent Kabila was assassinated in 2001. In 2002, a peace agreement signed at Sun City in South Africa allowed Joseph Kabila, Laurent's son, to remain in power in exchange for his commitment to end the support for anti-Rwanda rebel armies in Congo. As a result, the relations with the FARDC became volatile. The FDLR kept engaging Tutsi forces in the Kivu region, raising concern for a new full-fledge intervention of Rwanda. In 2009, the FDLR attacked civilians in some Kivu villages, prompting a major joint military operation of the FARDC and Rwanda against them.[12]

In addition, there were numerous local rebellions which led to the formation of new groups and break-away mutinies of pre-existing militias. An example is the 2002 revolt of the Banyamulenge, a Congolese Tutsi group, originating from a mutiny led by Patrick Masunzu that the mainstream Rwanda-backed RCD-G troops failed to crush (see Human Rights Watch 2002).

3.2 Data

We use a panel of annual observations for the period 1998–2010 drawing on a variety of data sources.[13] The unit of analysis is at the group×year level. The summary statistics are displayed in Table 1. In the rest of this section, we provide a summary description of the dataset. More details can be found in the appendix.

Groups – The main data source for the fighting effort and geolocalization of groups is ACLED (2012).[14] This dataset contains 4676 geolocalized violent events taking place in the DRC involving on the whole 80 groups: 4 Congolese state army groups, 47 domestic Congolese non-state militias, 11 foreign government armies and 18 foreign non-state militias.[15] A complete list of the groups is

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[11] After the crisis of 1999-2000, the relationship turned sour, and remained heavily strained until very recently. The two governments tried actively to destabilize each other by supporting opposition' movements. For instance, in 2011 Charles Ingabire, a Rwandan journalist and an outspoken critic of Kagame, was assassinated in Kampala, allegedly by Rwandan secret service officers.

[12] See BBC News, 13 May 2009, http://news.bbc.co.uk/2/hi/africa/8049105.stm.

[13] The reason why our sample ends in 2010 is twofold: First, after this date conflict intensity decreases significantly (in 2010 there were 301 events, while in 2011 only 89). Second, the rainfall data we use is only available until 2010.

[14] ACLED is a well-established source used by many recent papers including, among others, Berman *et al.* (2014), Cassar *et al.* (2013), Michalopoulos and Papaioannou (2013), and Rohner *et al.* (2013b).

[15] We only include organized armed groups in the dataset, and exclude other actors such as civilians. While we start out with 100 fighting groups in the raw data, we drop all non-bilateral fighting events where no armed group is involved in one of the two camps (e.g., events where an armed group attacks civilians). This leaves us with 80 fighting groups in the final sample.

Table 1: Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Total Fighting	1,040	5.929	25.046	0	300
Total Fighting Enemies (TFE)	1,040	69.237	109.95	0	682
Total Fighting Allies (TFA)	1,040	48.603	85.75	0	563
Total Fighting Neutrals (TFN)	1,040	350.539	241.616	1	1042
d^- (#Enemies)	1,040	2.95	4.306	0	26
d^+ (#Allies)	1,040	2.4	3.45	0	21
Rainfall $(t-1)$	1,040	125.839	26.164	59.639	195.56

Note: The sample comprises the 80 fighting groups that are involved in at least one fighting event in ACLED during the period 1998–2010.

provided in Appendix B.1.2.

Our classification of groups strictly follows ACLED.[16] The cases of the FARDC and of Rwanda deserve a special mention. ACLED codes each of these two actors as split in two groups by the period of activity: "FARDC (1997-2001) (Kabila, L.)" (henceforth, FARDC-LK) and "FARDC (2001-) (Kabila, J.)" (henceforth, FARDC-JK); "Rwanda (1994-1999)" (henceforth, Rwanda-I) and "Rwanda (1999-)" (henceforth, Rwanda-II). In the case of the FARDC, the split is determined by the assassination of Laurent Kabila, followed by the peace agreement of 2002 that marks the official end of the Second Congo War. In the case of Rwanda, the threshold coincides with the deterioration of the relationships between Uganda and Rwanda. In our baseline estimation, we do not merge these groups since: (i) it would be inconsistent with the general rule not to change the ACLED coding; (ii) the discontinuities reflect genuine political breaking points. However, we also consider robustness checks in which these groups are merged.

Fighting events – For each event, ACLED provides information on the exact location, date and identity of the groups involved. ACLED draws primarily on three types of sources: information from local, regional, national, and continental media, reviewed on a daily basis; NGO reports; Africa-focused news reports and analyses. To the best of our knowledge, ACLED is the only source covering the entire DRC and reporting geolocalized information about violent events, including an indication of which groups fight on the same side and which fight on opposite sides.[17] ACLED data is subject to measurement error in two dimensions. First, many events go unreported (see Van der Windt and Humphreys 2016, discussed in more detail in the appendix). Second, the precision of the geolocalization provided by ACLED has been challenged (Eck 2012).[18] To address the geolocalization issue, we supplement the information in ACLED with the UCDP Georeferenced Event Dataset (GED) (Sundberg and Melander 2013). This dataset contains detailed georeferenced information on conflict events, but contrary to ACLED the GED dataset only reports one armed group involved for each side of the conflict. In addition, there are much fewer events (i.e., ca. one

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[16]We make an exception to this principle by merging the groups *Unnamed Mayi-Mayi Militia* (DRC)" and *Mayi-Mayi Militia* since we believe them to be the same group.

[17]Here is one example: "*On the 3rd of February 2000, the MLC together with the Military Forces of Uganda confronted the allied forces of the Military Forces of DRC and Interahamwe Hutu Ethnic Militia.*"

[18]In a case study of Algeria 1997, she documents that 30% of events contain inaccurate geo-localisation information, 6% of events are double-counted, and 2% missing. However, the precision is higher in a case study of Burundi 2000. There, she finds 9% of observations to have inaccurate longitude/latitude information, and 2% of observations to be double-counted, with no events missing.

third) in GED than in ACLED.

Our main dependent variable is group i's yearly *Fighting Effort*, x_{it}. This is measured as the sum over all ACLED fighting events involving group i in year t. In the robustness section, we construct alternative fighting effort measures by restricting the count to the more conspicuous events such as those classified by ACLED as battles or those involving fatalities.

Rainfall – For the purpose of our IV strategy, we build the yearly average of rainfall in each group's homeland. We use a gauge-based rainfall measure from the Global Precipitation Climatology Centre (GPCC) (Schneider *et al.* 2011), at a spatial resolution of $0.5° \times 0.5°$ grid-cells. This is a widely-used dataset. A group's homeland corresponds to the spatial zone of its military operations (i.e., the convex hull containing all geolocalized ACLED events involving that group at any time during the period 1998-2010). Then, for each year t, we compute the average rainfall in the grid-cell of the homeland centroid.

One potential concern is that there are few gauges in the DRC, mostly concentrated in the Congo basin. Thus, in large parts of the country the data are constructed by interpolation based on historical data and on the observed gauges. Thankfully, the problem is less severe in the East of the country, where fighting was most intense, since information there can exploit gauge stations in neighboring countries.

In the robustness section, we investigate potential measurement error issues by using satellite-based rainfall measures. These use atmospheric parameters (e.g., cloud coverage, light intensity) as indirect measures of rainfall, blended with some information from local gauges. The first comes from the Global Precipitation Climatology Project (GPCP) from NOAA and has a spatial resolution of $2.5° \times 2.5°$. The second dataset is the Tropical Rainfall Measuring Mission (TRMM) from NASA at a resolution of $0.25° \times 0.25°$.

Figure 2 displays the fighting intensity and average climate conditions for different ethnic homelands in the DRC. Weather conditions vary considerably both across regions of the DRC and over time.

Covariates – Given the large number of groups and years, we can control for time-varying shocks affecting groups with common characteristics. To this aim, we interact time dummies with three group-specific dummies. The first is a dummy for *Government Organization* that switches on for groups that are officially affiliated to a domestic or foreign government. This dummy covers 15 groups. The second is a dummy labelled *Foreign* that switches on for 29 groups which are coded as foreign actors. The third is a dummy labelled *Large* that switches on for groups that have at least 10 enmity links (this corresponds to the 90th percentile of groups with non-zero numbers of enemies). This dummy is intended to capture shocks affecting large armed groups.

3.3 THE NETWORK

Our primary sources of information to infer the network of enmities and alliances are: (i) the Yearbook of the Stockholm International Peace Research Institute, SIPRI (Seybolt 2000), (ii) "Non-State Actor Data" (Cunningham *et al.* 2013), (iii) Briefing on the Congo War by the International Crisis Group (1998), and (iv) Williams (2013). The four sources are consistent (i.e., they provide no conflicting information) and complementary. Groups are classified as allies or enemies not only on the basis of ground fighting, but also on that of political and logistical support (in particular, they include actors operating in different parts of the country). The four expert sources allow us
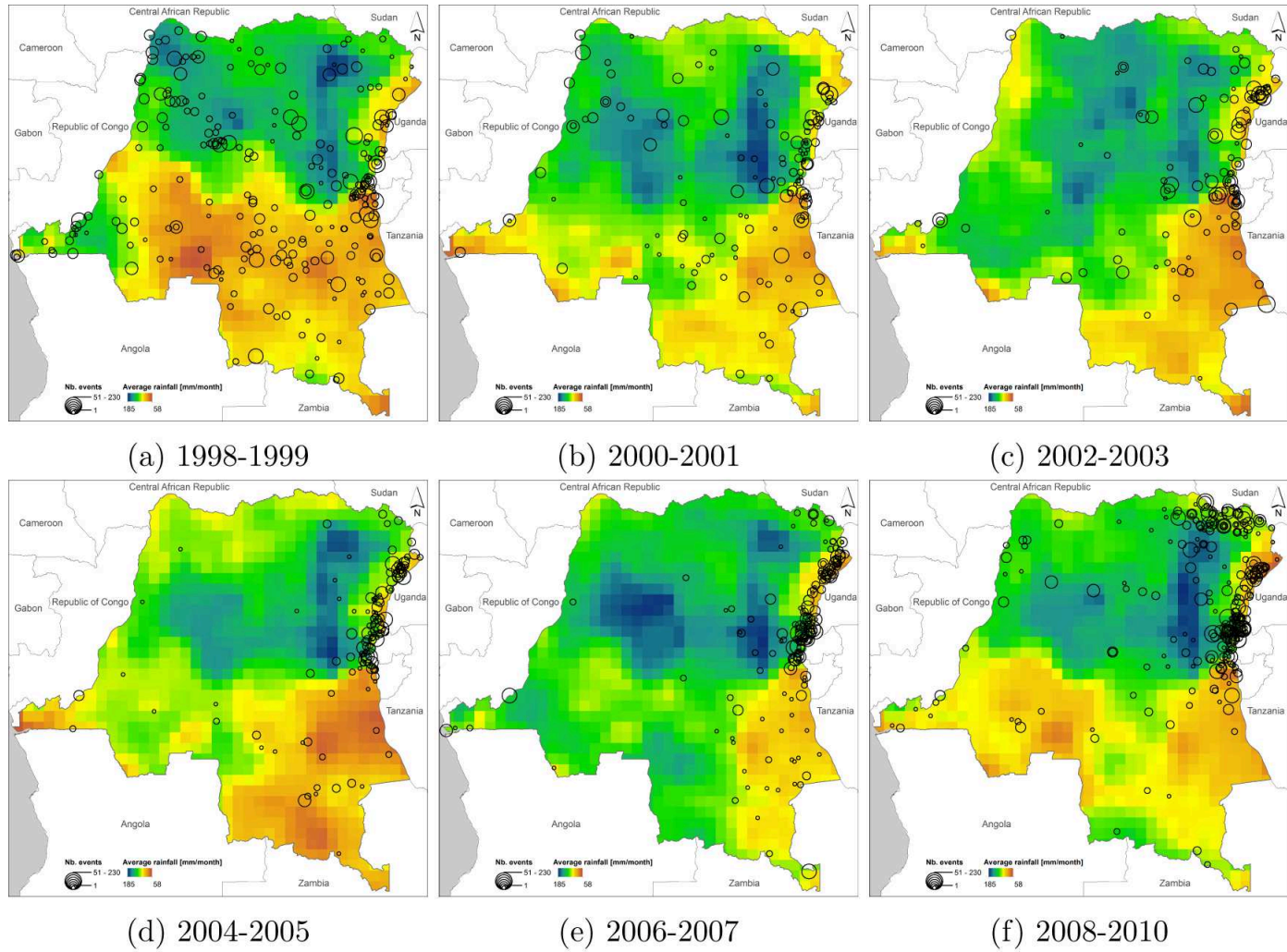
Figure 2: Map of the DRC with average rainfall data from GPCC at a spatial resolution of 0.5°×0.5° grid-cells, and number of violent events from ACLED. Warmer colors (i.e., red) means less rain, colder colors (i.e., blue) mean more rain. Larger circles mean more fighting events.
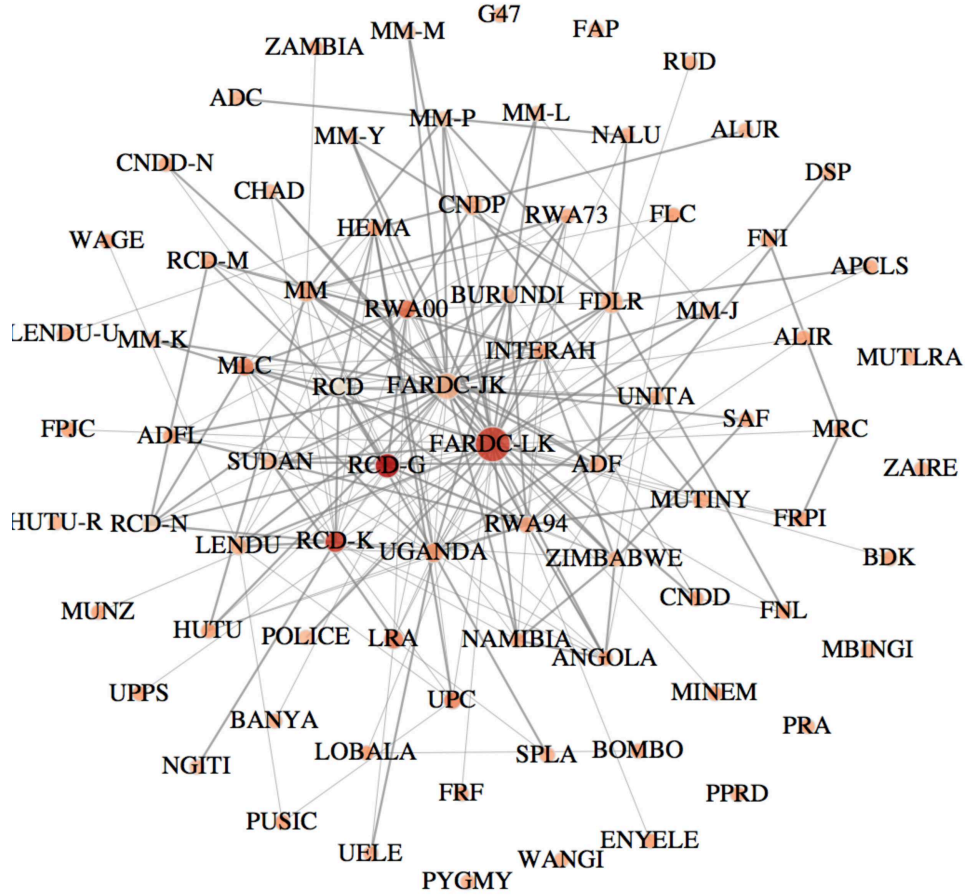
Figure 3: The figure displays the network of alliances and enmities between 80 fighting groups active in the DRC over the 1998-2010 period.

to code 80 alliances and 24 enmities.[19]

The main limitation of the expert coding is that it does not cover small armed groups and militias. For this reason, we complement its information with that inferred from the battlefield behavior in ACLED – with ACLED being strictly subordinate to the four expert sources. In particular, we code two groups (i, j) as *allies* if they have been observed fighting on the same side in at least one occasion during the sample period, and if, in addition, they have never been observed clashing against one another. Conversely, we code two groups as *enemies* if they have been observed fighting on opposite sides on at least two occasions, and they have never been observed fighting as brothers in arms. We code all other dyads as *neutral*. A concern might be that the construction of the network relies in part on the same ACLED data that we use to measure the outcome variable. In this respect, one must emphasize two important features. First, for constructing the network we exploit the bilateral information which is not used to construct the outcome variable. Second, the network is assumed to be time-invariant (at least in the baseline specification), whereas our econometric identification exploits the time variations in fighting efforts, controlling for group fixed effects, as discussed in more detail below.

Altogether, we code 192 dyads as allies and 236 dyads as enemies. The remaining 5892 dyads are classified as neutral. Figure 3 illustrates the network of alliances and rivalries in the DRC. Not

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[19]For the 15 actors with the greatest level of fighting involvement over the sample period, expert coding allows us to code 43 alliances (out of 101) and 13 enmities (out of 145).

surprisingly, the FARDC have the highest centrality. In line with the narrative, the other groups with a high centrality are Rwanda, Uganda, and the main branches of the RCD. On average, a group has 2.95 enemies and 2.4 allies (see Table 1).

In our baseline specification, we assume a time-invariant network. This is an important assumption that must be defended (although we relax it in an extension). As discussed above, the system of alliances underwent major changes at the end of the First Congo War, while remaining relatively stable thereafter (cf. Prunier 2011). The two main instances of changing relationships discussed in Section 3.1 involve the FARDC and Rwanda. Recall that ACLED splits the coding of Rwanda before and after 1999, and of the FARDC under Laurent and Joseph Kabila. This distinction is useful as it provides us with some flexibility in coding the two most important changes in the system of alliances. In particular, Rwanda-I is coded as an ally of Uganda and the RCD, while Rwanda-II is coded as an enemy of Uganda and of the RCD-K, and as an ally of the RCD-G. Similarly, we code the FARDC-LK and the FDLR as allies, and the FARDC-JK and the FDLR as neutral.[20] We test the robustness of the results to alternative assumptions (including merging Rwanda and the FARDC in two unified groups).

For the other dyads, we searched for patterns in ACLED that may be suggestive of an inconsistent behavior, i.e., sometimes fighting together and sometimes against each other (see appendix for details). We detected eight such cases, and among them only two clearly suggesting the possibility of a switch in the nature of the link.[21] We deal with the two problematic cases in the robustness analysis. While switching links appear to be rare, many groups are active only in few periods, and occasionally new groups are formed out of scissions of pre-existing groups. For this reason, in Section 4.2.1 we exploit an unbalanced sample where we allow entry and exit of groups.

Finally, we must acknowledge that our procedure is likely to miss some network links, namely to induce as to code as neutral some dyads that should instead be regarded as allies or enemies. Such missing links create measurement errors that can bias the estimates of the externalities (Chandrasekhar and Lewis 2016). We tackle this issue in Section 4.2.4.

4   ECONOMETRIC MODEL

Our empirical analysis is based on the model of Section 2.4 which allows for exogenous sources of heterogeneity in the OP of groups. Equation (13) can be estimated econometrically if one assumes that the individual shocks $\tilde{\varphi}_i$ comprise both observable and unobservable components. More formally, we assume that $\tilde{\varphi}_i = \mathbf{z}_i' \boldsymbol{\alpha} + \epsilon_i$, where $\mathbf{z}_i$ is a vector of group-specific observable characteristics, and ϵ_i is an unobserved shifter. Replacing x_i and φ_i by their respective equilibrium values yields the following structural equation:

$$x_i^* = \varphi_i^* (G) - \beta \sum_{j=1}^n a_{ij}^+ x_j^* + \gamma \sum_{j=1}^n a_{ij}^- x_j^* - \mathbf{z}_i' \boldsymbol{\alpha} - \epsilon_i, \tag{15}$$

where we recall that φ_i^* is a function of the structural parameters β and γ and of the time-invariant network structure while being independent of the realizations of individual shocks $(\mathbf{z}_j, \epsilon_j)$ (see

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[20]This accords with our coding rule (no expert coding, multiple fights on the same and opposite camps). It is also consistent with the narrative that the FARDC has fought the FLDR more for tactical reason (i.e., to prevent Rwanda's direct intervention) than because of a deep hostility.

[21]In the other cases, there is no time pattern, and the volatile behavior appears to be the outcome of tactical fighting. This suggests a bilateral relation that is neither an alliance nor an enmity. Hence, coding the link as neutral seems accurate.

equation (4) and the analysis in Section 2.4). Our goal is to estimate the network parameters β and γ. The estimation is subject to a simultaneity or reflection problem (Manski 1993; Boucher *et al.* 2012), a common challenge in the estimation of network externalities. In this class of models, it is usually difficult to separate contextual effects, i.e., the influence of players' characteristics, from endogenous effects, i.e., the effect of outcome variables via network externalities. In our model, the endogenous effect is associated with the fighting effort exerted by a group's allies and enemies. Although our theory postulates no contextual effect (at equilibrium they are ruled out from φ_i^*), it is plausible that omitted variables affecting x_i^* are spatially correlated, implying that one cannot safely assume spatial independence of ϵ_i. Ignoring this problem might yield inconsistent estimates of the spillover parameters.

The reflection problem can be tackled by an IV strategy. For instance, in a recent study on public good provision in a network of Colombian municipalities, Acemoglu *et al.* (2015) uses as instruments historical characteristics of local municipalities. In our case, it is difficult to single out time-invariant group characteristics that affect the fighting efforts of a group's allies or enemies without invalidating the exclusion restriction. For instance, cultural or ethnic characteristics of group i are likely to be shared by its allies. For this reason, we take the alternative route of identifying the model out of exogenous time-varying shifters affecting the fighting intensity of allies and enemies over time. This panel approach has the advantage that we can difference out any time-invariant heterogeneity, thereby eliminating the problem of correlated effects.

Panel Specification – We maintain the assumption of an exogenous time-invariant network, and assume the conflict to repeat itself over several years. We abstract from reputational effects, and regard each period as a one-shot game. These are strong assumptions, but they are necessary to retain tractability. The variation over time in conflict intensity is driven by the realization of group-and-time-specific shocks, amplified or offset by the endogenous response of the groups which, in turn, hinges on the network structure. More formally, we allow both x_i^* and $\tilde{\varphi}_i$ to be time-varying. x_{it}^* corresponds to the annual number of ACLED events involving i in year t, and

$$\tilde{\varphi}_{it} = \mathbf{z}_{it}'\boldsymbol{\alpha} + e_i + \epsilon_{it}. \tag{16}$$

Here, $\mathbf{z}_{it}$ is a vector of observable shocks with coefficients $\boldsymbol{\alpha}$, e_i is an unobservable time-invariant group-specific shifter, and ϵ_{it} is an i.i.d., zero-mean unobservable shock. Rainfall measures are examples of observable shifters $\mathbf{z}_{it}$ that will be key for identification. The panel analogue of equation (15) can then be written as:

$$\text{FIGHT}_{it} = \text{FE}_i - \beta \times \text{TFA}_{it} + \gamma \times \text{TFE}_{it} - \mathbf{z}_{it}'\boldsymbol{\alpha} - \epsilon_{it}, \tag{17}$$

where $\text{FIGHT}_{it} = x_{it}^*$ is group i's fighting effort at t, $\text{TFA}_{it} = \sum_{j=1}^{n} a_{ij}^+ x_{jt}^*$ is the total fighting effort of group i's allies, $\text{TFE}_{it} = \sum_{j=1}^{n} a_{ij}^- x_{jt}^*$ is the total fighting effort of group i's enemies, and $\text{FE}_i = +\varphi_i^*(G) - e_i$ is a group fixed effect capturing both the equilibrium OP level and unobservable time-invariant heterogeneity. The panel dimension allows us to filter out such heterogeneity by including group fixed effects. However, due to the reflection problem discussed above, the two covariates TFA and TFE are correlated with the error terms. OLS estimates are inconsistent due to an endogeneity bias: the fighting efforts of group i's allies and enemies are affected by group i's effort.

Instrumental variables (IV) – The problem can be addressed by a panel IV strategy. Identification requires exogenous sources of variation in the fighting efforts of group i's allies and enemies

that do not influence group i's fighting effort directly. To this aim, we use time-varying climatic shocks (rainfall) impacting the homelands of armed groups. In line with the empirical literature and historical case studies (Dell 2012), we focus on local rainfall as a time-varying shifter of OP, and hence the fighting effort of allies and enemies. More formally, our instruments are $\text{RA}_{it} = \sum_{j=1}^{n} a_{ij}^+ \times \text{RAIN}_{jt}^*$ and $\text{RE}_{it} = \sum_{j=1}^{n} a_{ij}^- \times \text{RAIN}_{jt}$, where RAIN_{jt} denotes the rainfall in group j's territory. Take TFE, for instance. Above-average rainfall in the homelands of group i's enemies (RE_{it}) reduces the enemy groups' propensity to fighting because it increases agricultural productivity, thereby pushing up the reservation wages of local workers to be recruited by enemy armed groups. In other words, rainfall increases the opportunity cost of fighting. In addition, high rainfall could pose an obstacle to war activities (e.g., through mud roads), reinforcing the opportunity cost effect. These channels linking rainfall to conflict is in line with earlier studies including, among others, Jia (2014), Hidalgo *et al.* (2010), Hsiang *et al.* (2013), Miguel *et al.* (2004), and Vanden Eynde (2011). There also potential offsetting effects: rainfall can increase revenues available to armed groups if agriculture is used as a source of taxation (see Fearon 2008). Our estimates below suggest that in our data this effect is dominated by the others.

To be a valid instrument, rainfall in the homelands of the allies (enemies) must be correlated with the allies' (enemies') fighting efforts. We document below that this is so in the data. In addition, rainfall must satisfy the exclusion restriction that rainfall in the homelands of group i's allies and enemies has no direct effect on group i's fighting effort. A first concern is that rainfall is spatially correlated, due to the proximity of the homelands of allied or enemy groups. However, this problem is addressed by controlling for the rainfall in group i's homeland in the second-stage regression. For instance, suppose that group i has a single enemy, group k, and that the two groups live in adjacent homelands. Rainfall in k's homeland is correlated with rainfall in i's homeland. However, rainfall in k's homeland is a valid instrument for k's fighting effort, as long as rainfall in i's homeland is included as a non-excluded instrument. A potential issue arises if rainfall is measured with error, and measurement error has a non-classical nature. We tackle this issue below in the robustness analysis.

Two additional threats to our exclusion restriction come from internal trade and migration. Rainfall may affect terms of trade. For instance, a drought destroying crops in Western Congo could cause an increases in the price of agricultural products throughout the entire DRC, thereby affecting fighting in the Eastern part of the country. Such a channel may be important in a well-integrated country with large domestic trade. However, inter-regional trade is limited in a very poor country like the DRC with a disintegrating government, very lacunary transport infrastructure, and a disastrous security situation. The war itself contributed to the collapse of internal trade, as documented by Zeender and Rothing (2010: 11). The result is a very localized economy dominated by subsistence farming where spillovers through trade are likely to be negligible.

Weather shocks could trigger migration and refugee flows. For instance, one could imagine a situation where an averse weather shock hitting the homeland of one of group i's enemies (say, group k) induces people to move from k's to i's homeland. The mass of displaced people could cause tensions and ultimately increase group i's fighting for reasons other than changes in the fighting effort of k. This would constitute a violation of the exclusion restriction. While we have no geolocalized statistical information to rule out this possibility formally, the evidence at the aggregate level suggests that this is unlikely to be a first-order issue in the DRC. According to White (2014), the quasi-totality of migration movements in the DRC in the last decades have been caused by armed conflicts and concerns about security rather than by economic factors. For

instance, only 0.7% of migrants indicate fleeing from natural catastrophes as the motivation for fleeing their homeland, while almost all refugees indicate that their movements are conflict- or security-related. It therefore appears very rare in the DRC that people are induced to migrate because of the scarcity of rain. In addition, even people who are forced to move because of fighting *"reportedly try to stay close to home so that they can monitor their lands and track the local security situation. (. . .) IDPs travel between half a day to one and a half days to reach a place of safety"* (White 2014: 6). Or in the words of the Internal Displacement Monitoring Centre (2009: 69), *"the nature of the displacement movements that we see in North Kivu and Ituri is often over short distances from 5 to 80 kilometers."* This means that even people seeking shelter are unlikely to travel far away and hence not overly likely to penetrate zones of activity of other groups.[22]

Similarly, rainfall could affect the activity of bandit groups. The effect of rainfall is ambiguous, since a drought reduces the resources available for predation, while making it easier for bandit groups to recruit new members. A threat to our identification would come if weather shocks induced bandit groups to move across different homelands with a systematic pattern (e.g., moving away from dry regions). Although we cannot rule out some confounding effects coming from this channel, it would be difficult to rationalize the opposite-sign effects that we find in the data by the activity of bandit groups (and, similarly, for migration). It is also worth noting that the boundaries between the activity of militias and bandit groups is thin in the DRC.

Spatial Autocorrelation – Since both violent events and climatic shocks are clustered in space, it is important to take into account spatial dependence in our data. For this reason, we estimate standard errors with a spatial HAC correction allowing for both cross-sectional spatial correlation and location-specific serial correlation, following Conley (1999 and 2008). However, there is no off-the-shelf application of these methods to panel IV regressions.[23] Therefore, we program a STATA code that allows us to estimate Conley standard errors in a flexible fashion.[24] In the spatial dimension we retain a radius of 150 km for the spatial kernel – corresponding to the 11th percentile of the observed distribution of bilateral distance between groups. More specifically, the weights in the covariance matrix are assumed to decay linearly with the distance from the central point of a group's homeland, reaching zero after 150km. We impose no constraint on the temporal decay for the Newey-West/Bartlett kernel that governs serial correlation across time periods. In other words, observations within the spatial radius can be correlated over time without any decay pattern. Robustness to alternative spatial and temporal kernels is explored in Appendix B.2.2.

A related challenge has been to adapt to our environment the test for weak instruments proposed by Kleinbergen and Paap (2006) (henceforth, KP). KP is a rank test of the first-stage VCE matrix that is standardly used with 2SLS estimators and cluster robust standard errors. The statistic is valid under general assumptions and the main requirement is that the first-stage estimates have a well defined asymptotic VCE. To the best of our knowledge, the test has never been implemented in panel IV regressions with spatial HAC correction. We tackled a similar issue for Hansen J overidentification test.

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[22]An extended discussion of migration within the DRC can be found in Appendix B.2.1.

[23]See Vogelsang (2011) for an asymptotic theory for test statistics in linear panel models that are robust to heteroskedasticity, autocorrelation, and/or spatial correlation. Hsiang et al. (2011) provide a useful STATA code to calculate spatially correlated standard errors in panel regressions. Also, IV regressions are dealt with by Jeanty (2012). However, neither routine handles spatial correlation in panel IV regressions.

[24]We owe a special thanks to Rafael Lalive for his generous help in this task.

In this section, we estimate the regression equation (17) using a panel of 80 armed groups over 1998-2010. In all specifications, we include group fixed effects and year dummies, and estimate standard errors assuming spatial and within-group correlation as discussed above. In addition, all specifications control for current and lagged rainfall at the centroid of the group's homeland, allowing for both a linear and a quadratic term.[25]

Table 2 displays the estimates of $-\beta$ and $+\gamma$ from second-stage regressions. Column 1 is an OLS specification. The enemies' fighting effort (TFE) is associated with a higher fighting effort for the group (consistent with the theory), whereas the allies' fighting effort (TFA) has no effect on it. Since the OLS estimates are subject to an endogeneity bias, in the remaining columns we run a set of IV regressions. Column 2 replicates the specification of column 1 in a 2SLS setup using the lagged fighting efforts of each group's set of enemies and allies as excluded instruments. In accordance with the predictions of the theory, the estimated coefficients of TFE and TFA are positive (0.13) and negative (-0.22), respectively, and statistically significant at the 5% level.

The associated first-stage regressions are reported in the corresponding columns of Table 3, where, for presentational purposes, only the coefficients of the excluded instruments are displayed. It is reassuring to see that the lagged rainfall in the enemies' homelands has a negative effect on the enemies' (while not on the allies') fighting effort, whereas the lagged rainfall in the allies' homelands has a negative effect on the allies' (while not on the enemies') fighting effort. This pattern, which conforms with the theoretical predictions, is confirmed in all specifications of Table 3. The KP-stat of 10.6 raises a (mild) concern about weak instruments, an issue to which we return below.

In the parsimonious specification of column 2 (Table 2), the coefficients of interest may spuriously reflect some time-varying shocks that affect the armed groups' incentives to fight asymmetrically. For instance, global economic or political shocks may change the pressure from international organizations, which in turn affects mainly the war activity of foreign armies, government organizations, or more generally of large combatant groups. To filter out such time-varying heterogeneity, in columns 3–8 we control for three time-invariant characteristics (*Government Organization, Foreign,* and *Large*) interacted with a full set of year dummies. The description of these three variables can be found in Section 3.2 above. Together with adding control variables, we expand the set of excluded instruments (i.e., the rainfall measures), in order to improve the predictive power of the first-stage regression.[26] The expanded set of instruments now comprises current-year and lagged-year rainfall (with a linear and a quadratic term) of allies and enemies, as well as current and lagged rainfall of degree-two neighbors (i.e., enemies' enemies and allies' enemies), both with a linear and a quadratic term.[27]

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[25] As discussed in Section 3.2, following the ACLED coding, the FARDC and Rwanda are each split in two groups according to the period of activity. When a group is inactive (e.g., the FARDC-JK during 1997-2001), its fighting effort is set equal to zero. To avoid that these artificial zero observations affect the estimates of the structural parameters β and γ, we always include in the regressions a group dummy interacted with a full set of year dummies for the period of inactivity. In Section 4.2, we show that the estimates are robust to merging Rwanda and FARDC into a unique group each.

[26] We also run the specification of column (2) with the expanded set of instruments. The estimated coefficients of interest are 0.15 for TFE (s.e. 0.05) and -0.15 for TFA (s.e. 0.06). The KP-test yields the value 19.7.

[27] When we use the current and past average rainfall in enemies' and allies' homelands as instruments, we also control for the current and past average rainfall in the group's homeland in the second-stage regression. This is important, since the rainfall in enemies' and allies' homelands is correlated with the rainfall in the own group homeland. Omitting the latter would lead to a violation of the exclusion restriction.

The results are robust to including further instruments, for instance, the allies' allies and the enemies' allies.

Table 2: Baseline regressions (second stage).

	OLS (1)	Reduced IV (2)	Full IV (3)	Neutrals (4)	Battles (5)	$(d^-, d^+) \geq 1$ (6)	GED coord. (7)	GED union (8)
Dependent variable: Total Fighting								
Total Fight. Enemies (TFE)	0.066***	0.130**	0.066***	0.083***	0.081***	0.091***	0.084***	0.125***
	(0.016)	(0.057)	(0.019)	(0.019)	(0.020)	(0.022)	(0.019)	(0.039)
Total Fight. Allies (TFA)	0.001	-0.218**	-0.117***	-0.114***	-0.117***	-0.157***	-0.112***	-0.117***
	(0.017)	(0.086)	(0.035)	(0.033)	(0.037)	(0.058)	(0.032)	(0.036)
Total Fight. Neutrals (TFN)				0.004	0.004	0.013	0.004	0.006
				(0.004)	(0.005)	(0.013)	(0.004)	(0.004)
Additional controls	Reduced	Reduced	Full	Full	Full	Full	Full	Full
Estimator	OLS	IV	IV	IV	IV	IV	IV	IV
Set of Instrument Variables	n.a.	Restricted	Full	Full	Full	Full	Full	Full
Kleibergen-Paap F-stat	n.a.	10.6	19.5	22.5	20.6	17.8	22.1	10.4
Hansen J (p-value)	n.a.	0.16	0.68	0.58	0.53	0.66	0.58	0.69
Observations	1040	1040	1040	1040	988	598	1040	1781
R-squared	0.510	0.265	0.579	0.568	0.567	0.537	0.569	0.516

Note: An observation is a given armed group in a given year. The panel contains 80 armed groups between 1998 and 2010. All regressions include group fixed effects and control for rainfall in the group's homeland. Columns 1–3 include time fixed effects. Robust standard errors corrected for Spatial HAC in parentheses. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Baseline regressions (first stage).

	IV regress. of col. (2)		IV regress. of col. (3)		IV regress. of col. (4)	
Dep. Variable:	TFE (1)	TFA (2)	TFE (3)	TFA (4)	TFE (5)	TFA (6)
Rain $(t-1)$ Enem.	**-1.595*****	-0.019	**-1.354*****	0.277*	**-1.327*****	0.291**
	(0.297)	(0.141)	**(0.332)**	(0.156)	**(0.322)**	(0.139)
Sq. Rain $(t-1)$ Enem.	0.000***	0.000	0.000***	-0.000	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rain $(t-1)$ All.	0.126	**-0.929*****	0.028	**-0.588*****	0.089	**-0.571****
	(0.283)	**(0.155)**	(0.222)	**(0.192)**	(0.219)	**(0.225)**
Sq. Rain $(t-1)$ All.	-0.000	0.000***	-0.000	0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Current Rain Enem.			**-1.125*****	0.131	**-0.936*****	0.073
			(0.243)	(0.102)	**(0.257)**	(0.108)
Sq. Curr. Rain Enem.			0.000***	-0.000***	0.000*	-0.000**
			(0.000)	(0.000)	(0.000)	(0.000)
Current Rain All.			-0.461**	**-0.366*****	-0.414**	**-0.448*****
			(0.204)	**(0.123)**	(0.210)	**(0.164)**
Sq. Curr. Rain All.			0.000	0.000***	0.000	0.000***
			(0.000)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap F-stat	10.6	10.6	19.5	19.5	22.5	22.5
Hansen J (p-value)	0.16	0.16	0.68	0.68	0.58	0.58
Observations	1040	1040	1040	1040	1040	1040

Note: An observation is a given armed group in a given year. The panel contains 80 armed groups between 1998 and 2010. All regressions include group fixed effects and control for rainfall in the group's homeland. Columns 1-4 contain time fixed effects. Robust standard errors corrected for Spatial HAC in parentheses. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The estimated coefficients in column 3 continue to feature the alternate sign pattern predicted by the theory. Their magnitude is smaller than in column 2, but the coefficients are estimated more precisely, being statistically significant at the 1% level. In column 4, we add to the vector of regressors TFN (Total Fighting of Neutrals), which is defined in analogy with TFA and TFE.[28] Hence, we now also add to the set of instruments the current and lagged rainfall in the territories of neutral groups (both as a linear and quadratic term). Since the theory predicts that the exogenous variation in TFN should have no effect on the dependent variable, this is a useful test of the theoretical predictions. The prediction is borne out in the data: the point estimate of TFN is very close to zero and statistically insignificant. The first-stage regressions yield large KP-stat (19.5 in column 3 and 22.5 in column 4), suggesting no weak instrument problem. Column 4 is our preferred specification and will be the basis of our robustness checks in the following sections below.

Our measure of fighting intensity is coarse insofar as it does not weigh events by the amount of military force involved. Ideally, we would like to have information about the number of casualties or other measures of physical destruction. However, this information is available only for very few events. This raises the concern that the results may be driven by small events (e.g., local riots or minor skirmishes). As discussed in Section 3.2, ACLED distinguishes between different categories of events. In column 5, we measure fighting effort in a more restrictive fashion, by only counting events that are classified in ACLED as battles. This addresses two issues: first, battles are less likely to get unreported by media; second, it would be reassuring to see that the estimates of β and γ are robust to excluding small events that represent a share of 42% of total events. The estimated coefficients are indeed very similar when we use only information on battles, with no evidence of weak instruments (KP-stat=20.6).[29]

A related concern is that many of the 80 groups are involved only in a small number of events. Although heterogeneity in group size is controlled for by fixed effects, one might be concerned that the estimation of the externalities hinges on the occasional operation of small groups. In lack of a direct measure of group size, in column 6 we restrict the analysis to the 46 groups that have at least one friend and one enemy, proxying for being relatively important actors. This restriction reduces the network size, causing a 40% drop in the number of observations. Reassuringly, the estimated externalities are larger than in column 4 ($\beta = 0.16$ and $\gamma = 0.09$). The KP-stat is 17.8.

The accuracy of the geolocalization in ACLED has been questioned, as discussed in Section 3.2 above. For this reason, we integrate ACLED with information from GED, which has been argued to be more accurate in terms of the geolocalization of events. We cannot simply replace ACLED with GED data because (i) the number of observation would drop by two thirds, aggravating underreporting concerns; (ii) for each event, GED lists at most one group on each side of the clash. However, in 1090 cases it is possible to match events in GED and ACLED beyond reasonable doubt. In these cases, we use the geolocalization in GED to identify the groups' homelands. For the events that cannot be matched, we continue to use the geolocalization in ACLED. The results, provided in column 7, are indistinguishable from those in column 4 (with KP=22.1).

In addition, we use the union set of the events in GED and ACLED, i.e., we construct a larger dataset that merges the matched events with all unmatched events in either dataset. By this procedure, the number of fighting events increases from 4676 to 5078.[30] There is also a larger

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[28]Note that when we include TFN we are not able to include annual time dummies anymore as they are multi-collinear to the sum of TFA+TFE+TFN.

[29]The number of observation falls to 988, as 4 of the 80 groups drop out of the sample for never being involved in any battles.

[30]In particular, of the 1641 groups in GED, 402 are very likely missing in ACLED, 1090 can be accurately matched

number of armed groups, 137 instead of 80. This procedure involves some heroic assumptions, and is subject to the risk that our algorithm fails to match some events that are in fact reported by both datasets, thereby causing an artificial duplication of events. With this *caveat* in mind, we find the estimates of TFE, TFA, and TFN to be, respectively, positive, negative, and insignificant, in accordance with the theory. The order of magnitude of the coefficients is comparable with those in column 4, and the point estimates are in fact larger in absolute value. However, the KP-stat is now lower (10.4). The details of the constructions of the merged dataset are in Appendix B.1.

The externalities are quantitatively large. Consider the estimates in column 4. The average number of yearly events in which a group is involved is 6, and its standard deviation is 25. Hence, a one standard deviation increase in TFE (i.e., 110 events) translates into a 0.37 increase in total fighting (i.e., 9 events). A one standard deviation increase in TFA (i.e., 86 events) translates into a 0.39 decrease in total fighting (i.e., 10 events). An estimate of the global effect of the network externalities is provided in Section 5.3 below.

We have also checked that, conditional on the estimates of β and γ, condition (3) holds true for *all* groups in conflict in all IV specifications of Table 3. Finally, the null hypothesis of the Hansen J test is not rejected in any specification, indicating that the overidentification restrictions are valid.

4.2 Robustness Analysis

This section summarizes the large battery of robustness checks that we performed. Formal results, tables and details about methodology are provided in Appendix B.2.

4.2.1 Variation over Time in the Network Structure

In our dataset, many groups are not active in all periods. We also observe new groups entering the conflict at a later stage, and a few groups which stop fighting.[31] While in the analysis of Section 4.1 we interpret zero fighting events as a low fighting effort, the absence of armed engagements could alternatively indicate that a group does not take part in the conflict in a particular subperiod. For this reason, in the first robustness check we address this concern by recognizing that the number of groups that are in the network may change over time.

We use a variety of expert sources to check when each group started its activity, and when, if at all, it ceased to be militarily active. We could gather information for 38 groups (many of them being active in the entire period). However, no official date of establishment or disbandment is available for informal organizations such as ethnic militias. For these groups, we construct a window $[S - \omega, T + \omega]$, where S and T are, respectively, the first and last year in which we see the group being active (i.e., $x_{it} > 0$). We add a window of $\omega \geq 0$ since the groups might have existed prior to their first or after their last recorded engagement. The details of the construction of the dataset are provided in Appendix 4.2.1.

We estimate the model by the following three strategies:

1. We add to the baseline specification a set of group-specific dummies switching on in all periods in which the group is suspected to be inactive.

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with very high probability to ACLED events, while 149 events are likely to refer to given events already in ACLED but the match cannot be proven with high enough probability. Hence, in column 8 we follow the conservative approach of only adding the GED events missing with very high probability in ACLED (i.e., 402 additional events) to avoid double counting.

[31]For instance, the CNDP did not exist before 2006, while the UCP abandoned military activity and turned into a political party in 2005.

Table 4: Time-varying network.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Total Fighting						
Total Fight. Enemies (TFE)	0.085***	0.074***	0.088***	0.138***	0.075	0.068**	0.211***
	(0.022)	(0.023)	(0.024)	(0.031)	(0.048)	(0.030)	(0.047)
Total Fight. Allies (TFA)	-0.115***	-0.097***	-0.106***	-0.212***	-0.143**	-0.128***	-0.251***
	(0.031)	(0.025)	(0.030)	(0.065)	(0.065)	(0.041)	(0.070)
Total Fight. Neutrals (TFN)	0.006	0.003	0.002	0.048**	0.022	0.006	-0.022**
	(0.005)	(0.004)	(0.005)	(0.023)	(0.021)	(0.010)	(0.009)
Kleibergen-Paap F-stat	27.1	8.7	11.7	9.2	5.5	15.3	n.a.
Hansen J (p-value)	0.61	0.48	0..60	0.71	0.74	0.51	n.a.
Observations	1040	1040	1040	469	322	637	1040
R-squared	0.603	0.634	0.594	0.501	0.627	0.594	0.179

Note: An observation is a given armed group in a given year. The panel contains 80 armed groups between 1998 and 2010. All regressions include group fixed effects and the full set of controls and instruments (like in baseline column 4 of Table 2). Columns 1-3 define windows of activity and include a group-specific dummy for periods when a group is inactive. In column 1, inactivity is defined by expert coding combined with ACLED information. In column 2, inactivity is defined based on ACLED information only. In column 3, inactivity is based on ACLED information + or - 3 years. Columns 4-6 implement an ILLE estimator on the unbalanced sample of active groups only using the same windows of activity as in columns 1-3. Column 7 performs an instrumented Tobit based on a Control Function approach. Cluster robust standard errors are corrected for Spatial HAC in columns 1–6 and are bootstrapped in column 7. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2. We adjust, in addition, the estimation procedure to make it fully consistent with the structural model. To see why, consider equations (4)–(6). When the number of groups in the network changes over time, one must replace $\varphi_i^* (G)$ by a time-varying analogue given by

$$\varphi_{i,t}^* (G; \beta, \gamma) = \left(1 - \frac{1}{\sum_{i=1}^{n,t} \Gamma_{i,t}^{\beta,\gamma} (G)} \right) \left(\frac{1}{\sum_{i=1}^{n} \Gamma_{i,t}^{\beta,\gamma} (G)} \right) \Gamma_{i,t}^{\beta,\gamma} (G) ,$$

where $\Gamma_{i,t}^{\beta,\gamma} (G) = 1/ \left(1 + \beta d_{i,t}^{+} - \gamma d_{i,t}^{-} \right)$. When $\varphi_{i,t}^*$ is time-varying, it is no longer absorbed by the group fixed effects. However, the model can still be estimated. In particular, one can then estimate the following regression equation:

$$\text{FIGHT}_{it} = \text{FE}_i + \varphi_{i,t}^* (G; \beta, \gamma) - \beta \times \text{TFA}_{it} + \gamma \times \text{TFE}_{it} - \mathbf{z}_{it}' \boldsymbol{\alpha} - \epsilon_{it}. \qquad (18)$$

Here, $\varphi_{i,t}^*$ can be estimated conditional on a prior for β and γ, as $d_{i,t}^{+}$ and $d_{i,t}^{-}$ are observable for all i and t. Thus, we implement the iterated linear least squares estimator (ILLE) developed by Blundell and Robin (1999).[32]

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[32]We start by guessing (β_0, γ_0) and $\varphi_{i,t}^* (G; \beta_0, \gamma_0)$. Then, we obtain a first set of estimates $(\hat{\beta}_1, \hat{\gamma}_1)$ conditional on the guess, update $\varphi_{i,t}^*(\hat{\beta}_1, \hat{\gamma}_1)$, and re-estimate the model iteratively until we converge to a fixed point. Computationally, we stop the iteration as soon as $\| (\hat{\beta}_n, \hat{\gamma}_n) - (\hat{\beta}_{n-1}, \hat{\gamma}_{n-1}) \| < 0.0001$ (i.e., two orders of magnitude smaller than the estimated standard errors). While Blundell and Robin (1999) address the issue of endogenous regressors with a control function approach (i.e. first stage estimated residuals included as regressors in the second stage), we iterate on our 2SLS estimator that accommodates spatially clustered robust standard errors. We checked that the control function-ILLE and 2SLS-ILLE yield identical point estimates.

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3. We estimate the model using instrumented Tobit based on a control function approach.

Table 4 displays the results. All columns report analogues of the baseline specification of column 4 in Table 2. Columns 1–3 correspond to the first approach. In column 1, the time window is set to $\omega = 0$; in column 3, we set $\omega = 3$; in column 2, we code as a period of possible inactivity any consecutive spell of zeros at the beginning or at the end of the sample, using only the information from ACLED. The estimates of β and γ are similar to those in column 4 in Table 2. The KP-stats are 25.3, 8.7, and 11.7, respectively. Columns 4–6 correspond to the second approach. In spite of a drastic sample size reduction, the coefficients continue to have the same order of magnitude as in the baseline table. In column 4, the coefficients are larger in absolute value, and the coefficient of TFN turns significant, while remaining much smaller than those of TFE and TFA. In column 5, the coefficient of TFE turns insignificant. In column 6, the results are very similar to column 4 in Table 2. The KP-stats are 6.5, 5.5, and 15.3, respectively. The weak instruments in columns 4 and 5 are not surprising, since the number of observations is, respectively, one third and one half of that in the full sample. Also, this specification is very demanding, since in many cases no reported involvement in ACLED events may indicate a low level of fighting activity rather than an outright withdrawal from the conflict. Column 7 is based on Tobit with a control function approach for the two-stage instrumentation. The estimated coefficients have the usual alternate sign pattern, but are now much larger in absolute value. Overall, we find these results reassuring.

4.2.2 Alternative Specifications

In this section, we consider three sets of robustness checks.

Second-Degree IV, Salient Events, and Alternative Network Construction: We start from a miscellaneous of important robustness checks whose results are summarized in Appendix Table B.7. In column 1, we use only the rainfall in the homeland of degree-two neighbors (e.g., the rain of enemies' enemies and of allies' enemies) as excluded instruments, following Bramoullé et al. (2009).[33],[34] In column 2, we use the information for the subperiod 1998-2002 to estimate the network links, and the panel for 2003-10 to estimate the spillover coefficients. In columns 3-4, we restrict attention to salient episodes for which measurement error is likely to be less important. In column 3, we drop all events with zero fatalities (while keeping events for which the number is unknown). In column 4, we restrict attention to battles, riots, and violent events. In column 5, we exclude all events involving group i when computing the total fighting efforts of allies and enemies of group i. For example, if the LRA's enemies are involved in 10 clashes in year 2000, and 3 of them involve the LRA, then the measure of TFE used in the regression would take the value of 7. In column 6, we control for the lagged total fighting effort of both enemies and allies. In columns 7-8, we test the robustness of the results to different definitions of enmities and alliances: in column 7 we code two groups as enemies if they have been observed clashing on at least *one* occasion, and if they have never been observed co-fighting on the same side; in column 8, we stick to the baseline

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[33]In particular, we continue to treat as excluded instruments the rainfall in the enemies' enemies' homelands, the rainfall in the allies' enemies' homelands, and the rainfall in the neutrals' homelands. However, the rainfall in the enemies' homelands and the rainfall in the allies' homelands are treated as control variables. For all rainfall measures we take the linear and square term and the current rain, first lag and second lag.

[34]Note that, contrary to their model, in our theory there is no reason why an instrumentation based on first-order links should yield inconsistent estimates. As discussed above, the case for our regressions to be contaminated by contextual effects is weak in our panel regression.

treatment for enemies, but only code two groups as allies if they have been observed co-fighting in at least *two* occasions during the sample period and if they have never been observed clashing. Finally, in column 9, we instrument the network links with dyadic characteristics (co-ethnicity, spatial proximity of group centroids, etc.). The observed links are replaced by probabilities of link formation as predicted by a random utility model discussed in Section 6.2 below.

The results are highly robust. The coefficient of TFE is always positive, highly significant, and stable. Likewise, the coefficient of TFA is always negative and significant with the exception of column 2. In most cases, the KP-stat is above 20. Last, but not least important, the coefficient of TFN is always very close to zero and insignificant. It is reassuring that the results are stable to different proxies for fighting activities and different rules for coding friends and enemies.[35]

Group Definition (FARDC, Rwanda & Others): In our benchmark analysis we have followed the rule of treating groups as separate entities whenever they are classified as such by ACLED. This agnostic way of proceeding has the advantage of not requiring any discretional coding decision. However, it is useful to check the robustness of our results in this dimension.[36] The results are summarized in Appendix Table B.8. In column 1, we treat the FARDC-LK and FARDC-JK as one single actor. In column 2, we merge all local Mayi-Mayi militia branches into one single actor. In column 3, we merge Rwanda-I and Rwanda-II into a single group. Finally, in column 4, we treat both the FARDC and Rwanda as two single actors. Reassuringly, the results are robust in all columns.

Ambiguous Network Links: The Appendix Table B.9 deals with ambiguous network links, i.e., links where the narrative might suggest different coding than the one we used. First, we consider the fragile relationship between Uganda and Rwanda (see Section 3.1 for historical background). In our baseline regression, our coding rule classifies Rwanda-I and Uganda as allies (until 1999), whereas Rwanda-II and Uganda are coded as enemies (after 1999). In columns 1 and 2, we code Rwanda and Uganda as always neutral and always allies, respectively. In column 3, instead, we code them as allies until 1999, and as neutral thereafter. Next, we consider another ambiguous relationship, i.e., FARDC *vs.* FDLR. In the baseline estimates they are first allies (until 2001), and then neutral. Here, we assume that they are enemies after 2001 (column 4), or neutral throughout the entire period (column 5). Next, we exclude the CNDD since this group appears to have switched its relation with the Mayi-Mayi militia (column 6). Next, we classify Uganda and the RCD-G as enemies (column 7). While this violates our coding rule (that classifies them as neutral), it is more consistent with the narrative. Next, we code all member states of the Southern African Development Community (SADC) as allies of each other and of the FARDC (column 8). Finally, we define as "governments allied to the FARDC" all governments allied to the FARDC in the baseline treatment plus all SADC member states. Finally, we let all "governments allied to the

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[35]In an earlier version of this paper, which was based on a different strategy to construct the network, we implemented a conservative identification strategy using the rainfalls in the groups' historical ethnic homelands as excluded instruments. Each armed group was linked when possible to a corresponding underlying main ethnic group. Next, we computed the rainfall averages on the polygons of all ethnic groups. Given that rainfall in ethnic homeland is an imperfect proxy for rainfall observed by groups in their actual current territory, we had a severe weak instrument problem (KP-stat=3.55). The coefficient of TFE was positive (+0.08) and significant, while that TFA was statistically insignificant. In the current version, we obtain similar results: the weak instrument problem persists (KP-stat=7.25), the coefficient of TFE is positive (+0.08) and significant, while that of TFA is statistically insignificant (with a p-value of 0.694) and has a positive point estimate.

[36]In all the robustness checks of Table B.8, we re-estimate the network for each of the different specifications.

FARDC" be (i) allied among themselves, (ii) allied to the FARDC, and (iii) enemies to Rwanda-I and Uganda (column 9). The results are in all cases similar to the baseline table.

4.2.3   Measurement Error in Rainfall

A concern with our IV strategy is that the rainfall variable may be subject to non-classical measurement error. In particular, fighting activities may destroy rain gauges located in battlefields. As a result, our gauge-based GPCC measure might systematically underreport precipitations in war zones. The issue is twofold: first, mismeasurement may result in a spurious negative correlation between rainfall and fighting in the first-stage regression.[37] Second, our identification hinges on rainfall in the homelands of group i's enemies/allies having no direct effect on group i's fighting effort after conditioning on the rainfall in group i's homelands. However, the exclusion restriction would be invalidated if the measurement error in the instruments were correlated with group i's fighting effort.

To study this potential problem, we consider satellite-based rainfall estimates from TRMM or GPCP (see the data description in Section 3.2). Clearly, satellite-based measurements are less affected by the dynamics of conflict. However, they provide less direct and far less accurate rainfall estimates than do gauges.[38]

Therefore, it is not surprising that, if we use satellite rainfall data instead of gauge-based data as instruments, we run into a weak instrument problem. However, the satellite estimates can be used to infer whether gauged-based measures are biased. To this aim, consider the following simple model:

$$
\begin{aligned}
\text{RAIN}_{ct}^{sat} &= \psi_c^{sat} + \text{RAIN}_{ct} + v_{ct}^{sat} \\
\text{RAIN}_{ct}^{gau} &= \psi_c^{gau} + \text{RAIN}_{ct} + \tilde{v}_{ct}^{gau}
\end{aligned}
\tag{19}
$$

where c denotes the grid-cell at which rainfall is measured, RAIN_{ct} is the true (unobservable) rainfall, and v_{ct}^{sat} and $\tilde{v}_{ct}^{gau}$ are the measurement errors. v_{ct}^{sat} is assumed to be i.i.d. The error term of the gauge measure is potentially subject to violence-driven measurement error. This possibility is allowed by letting $\tilde{v}_{ct}^{gau} = \xi \times \text{VIOLENCE}_{ct} + v_{ct}^{gau}$, where v_{ct}^{gau} is an i.i.d error term. One can eliminate $rain_{ct}$ from the previous system of equations and obtain:

$$
\text{RAIN}_{ct}^{gau} = \psi_c + \text{RAIN}_{ct}^{sat} + \xi \times \text{VIOLENCE}_{ct} + \nu_{ct},
\tag{20}
$$

where $\psi_c = \psi_c^{gau} - \psi_c^{sat}$ and $\nu_{ct} = v_{ct}^{gau} - v_{ct}^{sat}$ are, respectively, a grid-cell fixed effect and an i.i.d. disturbance. Our null hypothesis is that $\xi = 0$. If $\xi \neq 0$, the gauge-based measure suffers with non-classical measurement error.

We run a regression based on equation (20), measuring violence by the number of conflicts in ACLED. The Appendix Table B.10 summarizes the results. Columns 1–4 report the results when satellite-based rainfall measures are retrieved from TRMM. Column 1 is a cross-sectional specification; column 2 includes grid-cell fixed effects – consistent with equation (20). In columns 3 and 4 we consider a log-linear specification where the two rainfall measures are log-scaled; this

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[37]Remember, though, that we also use lagged rain to predict current fighting intensity.

[38]Romilly and Gebremichael (2011) discuss the shortcomings of satellite-based rainfall estimates. On the one hand, satellite rainfall estimates are contaminated by sources such as temporal sampling, instrument, and algorithm error. On the other hand, a number of studies based on U.S. data document that their performance varies systematically with season, region, and elevation, resulting in potentially severe biases.

corresponds to a multiplicatively separable specification of model 19. Finally, we replicate the same set of four specifications in columns 5–8 with the GPCP satellite measure. Year dummies are included in all regressions. Standard errors are clustered at the grid-cell level.[39]

As expected, there is a highly significant positive correlation between the gauge- and the satellite-based rainfall measures. Most important, all estimates of ξ are not significantly different from zero, with its point estimates switching signs across specifications. The hypothesis that ξ is negative due to the destruction of gauges in battlefields is strongly rejected, especially in specifications with grid-cell fixed effects, which are consistent with our panel specification where parameters are identified out of the variation in rainfall over time. The point estimates of ξ are consistently positive and statistically insignificant. We conclude that there is no evidence that the gauge-based GPCC precipitation data are subject to non-classical measurement error in the DRC.

4.2.4 Measurement Error in Network Links

Another concern here is that the network may be measured with error. Recent research by Chandrasekhar and Lewis (2016) shows that regression of economic outcomes on network neighbors' outcomes, in the presence of measurement error of network links, can give rise to inconsistent estimates.[40] Moreover, the bias can work in different directions, and there is no general remedy to correct it. To address this issue, we follow a Monte Carlo approach based on rewiring links in the observed network at random, and measuring the robustness of our estimates in such perturbed networks. We consider different assumptions about the extent and nature of measurement error of the network.

More specifically, we postulate a data generating process, and then we introduce a specific (plausible) model of mismeasurement of network links. Then, we estimate the model as if the econometrician did not know the true network, but had to infer it from data measured with error. This procedure is generated for a large number of realizations of mismeasurement errors (1,000 draws per each case). The procedure is exposed in more details in the appendix and the results are reported in Appendix Table B.11. The general lesson from this exercise is twofold. First, the Monte Carlo generated measurement error in the links leads to an attenuation bias. This suggests that, under the plausible assumption that some information about existing links is missing, our regression analysis underestimates the spillover effects. Second, the extent of the bias is quantitatively modest. A measurement error of the order of 10% (which we regard as fairly large) yields an underestimate of the spillover parameters of 12% for β and 23% for γ. Overall, the analysis confirms that our baseline estimates are robust to link measurement errors.

5 POLICY INTERVENTIONS

In this section, we perform counterfactual policy experiments. First, we consider interventions that selectively induce some fighting groups to exit of the contest. Next, we consider policies (such as an arms embargo) that increase the marginal cost of fighting for selected groups. Finally, we study the effect of pacification policies, where enmity links are selectively turned into neutral ones. The motivation of the analysis is to guide policy intervention. For instance, an international organization

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[39]Recall that the GPCP satellite measure is only available at the 2.5×2.5 degree level, i.e., for larger cells than the two other measures that are at the 0.5×0.5 degree level. In this case, we cluster at the 2.5×2.5 cell level.

[40]It has been proven, however, that likelihood-based inference while ignoring the missing data mechanism leads to unbiased estimates under the assumption of missingness at random (MAR) (Little and Rubin 2002). Mohan *et al.* (2013) provide conditions on the network for recoverability of parameters even when MAR is violated.

aiming at scaling down violence may be interested in the extent to which each of the combatant groups contributes to the conflict escalation.

The analysis is based on the simulation of counterfactual equilibria. To this aim, let G^b denote the benchmark network in which all groups fight. We set the externality parameters equal to their baseline point estimates $\hat{\beta} \approx 0.083$ and $\hat{\gamma} \approx 0.114$ (column 4, Table 2).[41] The equations (6) and (15)–(17) allow us to estimate e_i, the time-invariant unobserved heterogeneity. More formally:

$$\hat{e}_i = -\widehat{\text{FE}}_i + \Lambda^{\hat{\beta},\hat{\gamma}}(G^b)\left(1 - \Lambda^{\hat{\beta},\hat{\gamma}}(G^b)\right)\Gamma_i^{\hat{\beta},\hat{\gamma}}(G^b), \tag{21}$$

where $\widehat{\text{FE}}_i$ is the estimated group-specific fixed effect, $\Gamma_i^{\hat{\beta},\hat{\gamma}}(G^b) = 1/(1+\hat{\beta}d_i^+ - \hat{\gamma}d_i^-)$, and $\Lambda^{\hat{\beta},\hat{\gamma}}(G^b) = 1 - 1/(\sum_j \Gamma_j^{\hat{\beta},\hat{\gamma}}(G^b))$. We collapse the vector of time-varying shifters $\mathbf{z}_{it}$ (rainfall, etc.) to its sample average, $\bar{\mathbf{z}}_i = \sum_{t=1998}^{2010} \frac{\mathbf{z}_{it}}{13}$, and denote by $\bar{\mathbf{Z}} = \{\bar{\mathbf{z}}_\mathbf{i}\}$ the estimated matrix of shifters. In other words, we compare an average year of conflict in the benchmark model to its corresponding counterfactual. We consistently set the time-varying i.i.d. shocks ϵ_{it} to zero for all groups.

Following the analysis in Section 2.4, the vector of (Nash) equilibrium fighting efforts is obtained by inverting the system of equilibrium conditions implied by equations (15) and (16). In matrix form, this yields:

$$\mathbf{x}^*(G^b) = (\mathbf{I} + \hat{\beta}\mathbf{A}^+(G^b) - \hat{\gamma}\mathbf{A}^-(G^b))^{-1}\left[\Lambda^{\hat{\beta},\hat{\gamma}}(G^b)(1 - \Lambda^{\hat{\beta},\hat{\gamma}}(G^b))\mathbf{\Gamma}^{\hat{\beta},\hat{\gamma}}(G^b) - (\bar{\mathbf{Z}}\widehat{\boldsymbol{\alpha}} + \widehat{\mathbf{e}})\right]. \tag{22}$$

Based on this equilibrium, we evaluate the effects of unanticipated policy shocks that affect either the network G^b or some exogenous parameters. We measure the welfare effects by the counterfactual changes in rent dissipation as defined in equation (10).

The results of this section are subject to the *caveat* that policy shocks may induce a reshuffling of alliances and enmities. In Section 6 we allow the structure of the network to respond endogenously to policy interventions.

5.1 REMOVING ARMED GROUPS

Consider a policy intervention that induces some groups to leave the contest. Formally, this corresponds to an exogenous subsidy to exit. In the benchmark model, all groups suffer the same defeat cost, D, assumed to be prohibitively high relative to the payoff of staying in the contest. Here, we assume that an international organization can decrease group i's exit cost to $D - W_i$. $W_i > 0$ is an intervention that may entail both the stick and the carrot. On the one hand, targeted military operations from international peace-keeping forces may increase the cost of staying in the contest. On the other hand, the promise of impunity to militia commanders or the prospective integration in the political process of the DRC may increase the attractiveness of leaving the contest. We assume the policy treatment to be sufficiently strong to induce the targeted groups to leave, and study which intervention would be most effective in reducing rent dissipation.

The analysis bears a close similarity with the key-player analysis in Ballester *et al.* (2006). In their language, a key player is the agent whose removal triggers the largest reduction in rent dissipation. In Proposition 3 in Appendix A.3, we show that in our model the identity of the key player is related to our centrality measure defined in equation (8).

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[41] All second-order conditions (cf. equation (3)) continue to hold for all groups in the counterfactual experiments in which one player is removed.

To perform the analysis, let K denote a vector comprising a subset of cardinality k of the n groups (where $1 \leq k < n$). We denote by $G^b \backslash \{K\}$ the network after removing the subset K. The vector of equilibrium fighting efforts is given by equations which are analogous to equation (22) except that the dimension of the system is reduced by k, the adjacency matrix is $\mathbf{A}(G^b \backslash \{K\})$, and the parameters attached to the network structure are replaced by $\Lambda^{\hat{\beta},\hat{\gamma}}(G^b \backslash \{K\})$ and $\mathbf{\Gamma}^{\hat{\beta},\hat{\gamma}}(G^b \backslash \{K\})$. We compute the rent dissipation before and after the removal of the subgroup K. Formally, the change in rent dissipation equals $\Delta \mathrm{RD}_K^{\hat{\beta},\hat{\gamma}} \equiv \mathrm{RD}^{\hat{\beta},\hat{\gamma}}\left(G^b \backslash \{K\}\right) - \mathrm{RD}^{\hat{\beta},\hat{\gamma}}\left(G^b\right)$, where $\mathrm{RD}^{\hat{\beta},\hat{\gamma}}\left(G^b \backslash \{K\}\right) \equiv \sum_{i=1}^{k} x_i^*\left(G^b \backslash \{K\}\right)$.

We start with policies targeting single groups ($k = 1$). We exclude the FARDC and the DRC police from the set of potential targets (except for mutinies), because we do not view removing local government organizations as a policy-relevant option.[42] Table 5 summarizes the results for the 15 groups whose removal yields the largest reduction in rent dissipation at the baseline estimates of column 4 in Table 2. These groups include the most important actors in the conflict. If we exclude the activity of the FARDC, they account jointly for 82% of the total fighting. A complete list of the groups is provided in Appendix Table B.1. For each group we report the number of its enemies and allies, the observed share in total fighting $x_k^*\left(G^b\right) / \sum_{i=1}^{n} x_i^*\left(G^b\right)$, the reduction in rent dissipation $(-\Delta \mathrm{RD}_K^{\hat{\beta},\hat{\gamma}})$ associated with its removal, and a *multiplier* defined as the ratio between the reduction in rent dissipation and the share in total fighting. The multiplier is a useful measure of the impact of the policy weighted by the importance of the group being removed. The fourth and fifth columns are evaluated at the baseline estimates of β and γ of column 4 in Table 2. In the last two columns we report intervals centered on the baseline estimates with the range of plus and minus one standard deviation. More precisely, we set $(\hat{\beta}, \hat{\gamma}) \approx (0.085, 0.063)$ and $(\hat{\beta}, \hat{\gamma}) \approx (0.142, 0.103)$. This yields a range of variation of the effects as the externality parameters change.

Two findings are noteworthy. First, although there is a high correlation between the observed contribution of each group to total fighting and the reduction in total fighting associated with its removal, the correlation is significantly below unity for the most active groups. For instance, this correlation is 83% in the subsample of the ten most active groups. Second, there is heterogeneity in the multipliers. Rwanda-backed RCD-G, the most active armed group, accounts for less than 9% of the total military activity in the data. Its removal would reduce aggregate fighting by over 15%, with a multiplier of 1.7. Likewise, Uganda-backed RCD-K accounts for 6% of military activity. Its removal would reduce fighting by more than 9%, with a multiplier of 1.6. Removing the Lord Resistance Army would reduce rent dissipation by 6%, a larger effect than that from removing more active groups such as the FDLR, the Mayi-Mayi militia, and the CNDP. Large multipliers are also associated with the UPC and the MLC.

Consider, next, the simultaneous removal of multiple groups. For computational reasons, we focus on the 14 top groups in the single-group analysis (i.e., those leading to $-\Delta \mathrm{RD}_K^{\hat{\beta},\hat{\gamma}}$ above 1%). Since the excluded groups account for a very small fraction of total fighting, we believe this restriction to be unimportant. Let us start by removing pairs of groups. The Appendix Table B.13 reports the results. Removing Rwanda and its closest ally, the RCD-G, yields a 24% reduction in fighting activity, significantly larger than their 14% contribution to total violence. There is some complementarity in the joint intervention: the effect of their joint removal is 12% larger than the sum of the individual effects. The effect is larger than that of jointly removing the RCD-G

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[42]In addition, we consider the Rwandan army as a single entity, namely, we always simultaneously remove the two separate groups associated by ACLED to Rwanda.

Table 5: Welfare effects of removing individual armed groups.

Group	# Enmities	# Allies	Share fight.	$-\Delta$RD	Multipl.	$-\Delta$RD ($\pm$ 1 SD)	Multipl. ($\pm$ 1 SD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RCD-G	14	4	0.087	0.151	1.7	[0.125, 0.181]	[1.4, 2.1]
RCD-K	13	5	0.060	0.094	1.6	[0.070, 0.151]	[1.2, 2.5]
Rwanda	17	9	0.053	0.066	1.2	[0.053, 0.109]	[1.0, 2.0]
LRA	6	1	0.041	0.056	1.4	[0.038, 0.115]	[0.9, 2.8]
FDLR	5	6	0.066	0.055	0.8	[0.059, 0.044]	[0.9, 0.7]
Mayi-Mayi	6	7	0.057	0.046	0.8	[0.054, 0.022]	[1.0, 0.4]
Uganda	13	9	0.043	0.043	1.0	[0.038, 0.048]	[0.9, 1.1]
CNDP	3	2	0.043	0.041	0.9	[0.041, 0.040]	[0.9, 0.9]
MLC	7	4	0.031	0.039	1.3	[0.026, 0.074]	[0.8, 2.4]
UPC	5	1	0.022	0.030	1.4	[0.018, 0.057]	[0.8, 2.6]
Lendu Ethnic Mil.	6	3	0.024	0.022	0.9	[0.039, -0.012]	[1.6, 0.5]
Mutiny FARDC	3	2	0.016	0.016	1.0	[0.009, 0.045]	[0.6, 2.8]
Interahamwe	7	5	0.014	0.014	1.0	[0.024, -0.017]	[1.7, 1.2]
ADF	3	4	0.013	0.012	0.9	[0.011, 0.017]	[0.8, 1.3]
FRPI	2	1	0.009	0.010	1.1	[0.003, 0.031]	[0.4, 3.7]

Note: The computation of the counterfactual equilibrium is based on the baseline point estimates of column 4 in Table 2. For each group, we report the number of its enemies and allies (cols. 1-2); the observed share of total fighting involving this group (col. 3); the counterfactual reduction in rent dissipation associated with its removal (col. 4); a multiplier defined as the ratio of col. 4 over col. 3 (col. 5); the reduction in RD and its associated multiplier for a set of parameters equal to the baseline estimates $\pm$1 SD (cols. 6-7).

and RCD-K, the two most active groups. Similarly, we detect some complementarity in the joint removal of the RCD-K and Uganda, its international sponsor. An even stronger complementarity (16%) is observed when Uganda is matched with the MLC, another close ally.

Consider, next, triplets of groups. The Appendix Table B.14 reports the top 50 triplets in the two experiments. All such triplets include the RCD-G. The top 7 triplets also include Rwanda.[43] The most effective intervention is the removal of Rwanda in combination with the RCD-G and CNDP (-29.5%, with a multiplier of 1.6), two of Rwanda's allies. The effect of this intervention is 14% larger than the sum of the effects of individually removing the three groups. More generally, interventions involving the RCD-G and Rwanda have large multipliers.[44] Similar results obtain when five groups (instead of three) are targeted simultaneously (see Appendix Table B.15). Here, the most effective intervention is to remove Rwanda, the RCD-G, and the CNDP (the top triplet above) along with Uganda and the RCD-K. This policy yields a counterfactual fall in rent dissipation of 39%, with a multiplier of 1.4.

Finally, consider the effect of targeting selected subsets of armed groups that have particular connections with each other. The upper panel of Table 6 summarizes the results. At the baseline estimates, removing the 29 groups with a foreign affiliation reduces rent dissipation by 27%, in line with their share in total fighting. We show below that the effect of this intervention increases

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[43]Among the top 50, Rwanda, RCD-K, FDLR, and LRA appear 12 times, Uganda and CNDP 8 times, Mayi-Mayi Militia 7 times, UPC, and Lendu Ethnic Milita 6 times.

[44]The largest multipliers obtain when Rwanda and the RCD-G are matched with, respectively (in ranked order), Lendu Ethnic Militia, UPC, Mutiny of FARDC, ADF. Each of these triplets has a multiplier of ca. 1.7, and exhibits significant complementarities.

Table 6: Welfare effects of removing selected multiple armed groups.

Set of Groups	# groups	Sh. fight.	$-\Delta$RD	Multiplier	MAD	New enm. & all. (at the median)	Regression coeffs. [enmities,alliances]
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EXOGENOUS NETWORK							
Foreign Groups	29	0.280	0.268	1.0	–	–	–
Ituri	9	0.086	0.094	1.1	–	–	–
Out of Rwanda	6	0.092	0.087	0.9	–	–	–
Rwa&Uga&ass.	10	0.336	0.456	1.4	–	–	–
Large Groups	16	0.802	0.677	0.8	–	–	–
WITH ENDOGENOUS NETWORK RECOMPOSITION							
Foreign Groups	29	0.280	0.412	1.5	0.029	[-11, +8]	[-0.010, +0.008]
Ituri	9	0.086	0.094	1.1	0	[+0, +0]	[-0.003, +0.011]
Out of Rwanda	6	0.092	0.117	1.3	0.031	[0, +2]	[-0.009, +0.011]
Rwa&Uga&ass.	10	0.336	0.332	1.0	0.044	[+3, -6]	[-0.011, +0.011]
Large Groups	16	0.802	0.719	0.9	0.008	[0, +9]	[-0.003, +0.002]

Note: The computation of the counterfactual equilibrium is based on the baseline point estimates of column 4 in Table 2. For each policy experiment, we display the results with an exogenous network (top panel) and the results with an endogenous network recomposition based on 1,000 Monte Carlo simulations (bottom panel). For each experiment, we report the set of removed groups (col. 1); the number of removed groups (col. 2); the observed share of total fighting involving this set of groups (col. 3); the counterfactual reduction (or its median in the bottom panel) in rent dissipation associated with their removal (col. 4); a multiplier defined as the ratio of col. 4 over col. 3 (col. 5); the Median Absolute Deviation in reduction in RD (col. 6); the post-recomposition number of new enmities and alliances at the median Monte Carlo draw (col. 7); the OLS coefficients of enmities and alliances of a regression across Monte Carlo draws of post-recomposition reduction in RD on reduction in RD (exogenous network) and the post-recomposition numbers of new enmities and alliances (col. 8).

significantly when we allow an endogenous adjustment of the network. Removing the 11 groups involved in the Ituri conflict causes a reduction in rent dissipation of 9%.[45] Removing the 6 groups associated with the Hutu exodus of Rwanda scales down conflict by a mere 9% (lower than the observed activity of these groups).[46] Removing Uganda, Rwanda, and all their associates reduces fighting by 46%, significantly more than the contribution of these groups to conflict in the data.[47] Finally, removing the 16 groups with more than five enemies reduces fighting by 68%. This is a large share, though lower than the 80% share of total fighting they account for in the data. In this case, the model predicts some crowding-in of violence from the surviving groups. Overall, these findings confirm the wisdom that the fragmentation in the DRC conflict makes it difficult for international organizations to deliver a single decisive blow.

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[45]Ituri is a province of north-eastern DRC that has witnessed a long-lasting conflict between the agriculturalist Lendu and pastoralist Hema ethnic groups. The apex of the conflict was in 1999-2003, although this continues at a lower level until the current days. The groups involved in this conflict for which we have information include: Front for Patriotic Resistance of Ituri, Hema Ethnic Militia, Lendu Ethnic Militia, Nationalist and Integrationist Front, Ngiti Ethnic Militia, Party for the Unity and Safekeeping of Congo's Integrity, Popular Front for Justice in Congo, Revolutionary Movement of Congo, Union of Congolese Patriots.

[46]These groups are (according to ACLED definitions): ALIR, Former Military Forces of Rwanda, FDLR, Hutu Rebels, Hutu Refugees, Interahamwe.

[47]These groups include: all factions of RCD, the armies of Rwanda and Uganda, CNDP, MLS, and UPC.
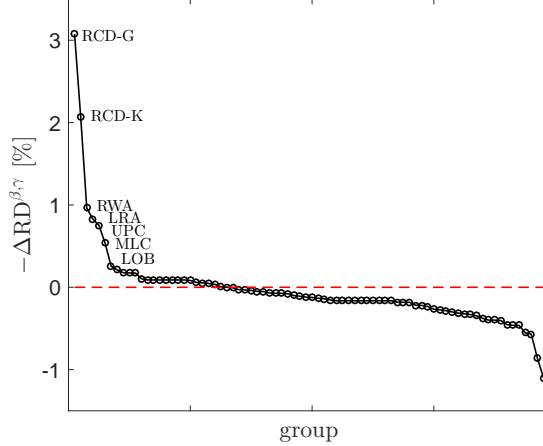
Figure 4: The figure shows the decrease in rent dissipation (relative to the baseline equilibrium) associated with an arms embargo policy targeting each individual group (except the FARDC) separately by setting $s_i = 9$. Groups are rank-ordered from the largest to the smallest decrease in rent dissipation. A negative number means that targeting a particular group yields an increase in rent dissipation relative to the benchmark.

5.2 Arms Embargo

Forcing armed groups out of the contest may be very costly or even politically infeasible. In this section, we study the effect of a less radical policy that operates along the intensive margin, namely, by increasing the marginal cost of fighting for targeted groups without removing them from the contest. As in the analysis above, we study the change in rent dissipation associated with counterfactual scenarios. We interpret this intervention as targeted sanctions such as an arms embargo. An arms embargo may constrain the stock of arms and ammunitions at the target groups' disposal, or force them to acquire extra equipment at higher prices in the black market. Formally, we increase the fighting cost in equation (1) from $-x_i$ to $-(1 + s_i) x_i$, where s_i is the policy parameter capturing the size of the intervention.

From a welfare perspective, we continue to measure total rent dissipation by the sum of the fighting efforts of all groups, since this measures the extent of destructive violence. We do not compute as a welfare cost the additional cost suffered by the armed groups per unit of fighting. Moreover, we abstract from enforcement costs. As we will see, even if embargoes can be enforced costlessly, their benefits are quantitatively small. A more formal analysis of the equilibrium conditions is provided in Appendix A.4.

We start from policies targeting individual groups. Figure 4 summarizes the results of a tenfold increase in the marginal cost (i.e., $s_i = 9$). The most significant gains accrue from targeting the two RCD factions, followed by Rwanda and by the LRA. Interestingly, the effects are never large. An embargo on the RCD-G or one on the RCD-K cause, respectively, a 3% and 2% reduction in total fighting. Note that the interventions have a sizeable effect on the group targeted, typically inducing a reduction in their fighting activity by 40-60%. However, the non-targeted groups typically fight slightly more, resulting in modest aggregate gains. In several cases embargoes are counterproductive. For instance, an embargo against Zimbabwe makes this group less active, but increases the activity of the FARDC, its main ally, and of other groups so much that rent dissipation is higher than under no intervention.

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s	Gr. 1	Gr. 2	Gr. 3	Gr. 4	Gr. 5	Gr. 6
1-2	LRA	MLC	RCD-G	RCD-K	RWA	UPC
3	LRA	RCD-G	RCD-K	UPC		
4	LRA	RCD-G	RCD-K			
5-16	RCD-G	RCD-K				
17-49	RCD-G					
50-100	RCD-K					
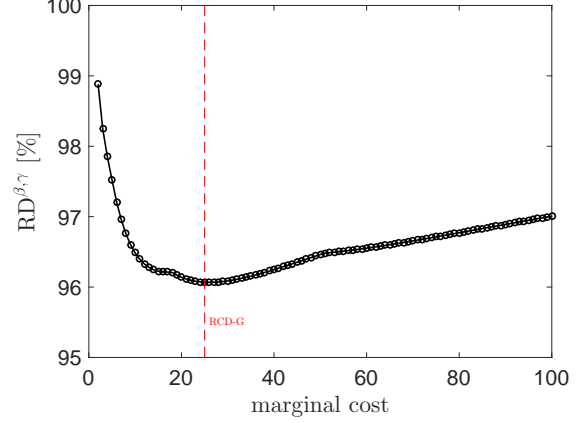
Figure 5: The left panel lists the groups whose (joint) targeting by an arms embargo yields the largest decrease in rent dissipation for different values of s. For instance, when $s = 4$, targeting the LRA, RCD-G, and RCD-K yields a larger fall in rent dissipation than any other group partition among the top 15 groups in Figure 4 (the number of possible partitions considered is $16,383$). The right panel displays the minimum rent dissipation (as a percentage of the rent dissipation in the benchmark) that can be attained by the most effective arms embargo policy conditional on s. For instance, when $s = 4$, the lowest rent dissipation (97.52% of the benchmark) can be attained by targeting the LRA, RCD-G, and RCD-K. The largest decline in the rent dissipation with an arms embargo is 3.93%, and is attained when the planner targets only the RCD-G by increasing its marginal cost of fighting to 26.

Next, we consider simultaneously removing many groups (focusing on the top 15 groups). The table in the left panel of Figure 5 summarizes the result by showing the optimal target for different ranges of s_i. Surprisingly, the optimal target group includes only a small subset of groups. For low levels of s_i, it is optimal to set an embargo on six groups. However, as we increase s_i the cardinality of the optimal number of groups falls. For $s_i \geq 16$, it becomes optimal target only a single group. To see why, consider the case in which $s_i = 25$ and the RCD-G is subject to an arms embargo. Consider a suboptimal policy which targets also a second group, the CNDP. Relative to the optimal policy, the fighting effort of the CNDP falls by a fourth. However, the gain is offset by a generalized increase in the fighting of the other groups, and by some bouncing back of the RCD-G effort. Overall, the net effect is more rent dissipation than if the RCD-G were targeted alone. This example is representative of the typical effect of targeting several groups.

The right-hand panel of Figure 5 shows the rent dissipation relative to the benchmark when the optimal arms embargo policy is implemented (note: a lower level here indicates a more effective policy) for different levels of s_i. The welfare gain is U-shaped, the maximum gain being attained by targeting only the RCD-G with a policy of $s_i = 25$.[48]

In summary, the welfare gains of policies that increase fighting costs are small.[49] Typically, the fighting effort of the targeted group falls. However, the response of the other groups is often the opposite and offsets large parts of the gain. Moreover, targeting many groups is ineffective. It is

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[48]We ruled out the FARDC as target for the usual reasons. If we include the FARDC among the possible targets, the results are similar. For sufficiently large s_i, the most effective embargo policy would indeed be one against the FARDC. The maximum reduction in rent dissipation remains ca. 4%.

[49]This result is in line with the skeptical conclusions of recent studies on the impact of arms embargoes, see Tierney (2005) and Brzoska (2008), although this literature mainly emphasizes the difficulties in implementing them.

useful to recall here that in this section we have maintained a prohibitive cost of decommissioning, and only focused on the effect of the policy on an intensive margin. To the extent to which an arms embargo induces a group to drop out of the conflict, the results of Section 5.1 apply.[50] This section shows that the scope for policies that act on the intensive margin is limited in a contest with a large number of fighting groups like the DRC war.

5.3 Pacification Policies

In this section, we study the effect of pacification policies aimed at reducing ethnic and political hostility between groups. More formally, we turn some enmity links into neutral links. We view this analysis as especially relevant for policy. International organizations may decide to invest in bringing hostile groups to the negotiating table or in de-escalating specific parts of the conflict, subject to limited economic or diplomatic resources (see Hoerner *et al.* 2015 for a recent study on mediation and conflict, as well as for an extensive overview of the literature on mediation). The analysis casts light on which among such interventions would be most effective.

To provide a benchmark for the potential scope of pacification policies, consider first a drastic counterfactual in which all enmity links are rewired into neutral ones. The effect is large: aggregate fighting is reduced by 65% at the baseline estimates of β and γ. Not only enmities but also alliance links are important for the containment of the conflict: an even more dramatic counterfactual scenario is obtained by rewiring all enmity and neutral relationships into alliance links. The result is a reduction of aggregate violence in the order of 90% - almost full peace. Since wiping out all enmities in the DRC would be utopistic, we consider more realistic interventions targeting specific links.

We consider first the effect of pacifying enmity links *vis-a-vis* the FARC and the DRC police. Table 7 summarizes the results for the 15 groups whose pacification yields the largest reduction in rent dissipation at the baseline estimates. These 15 groups account for 71% of the conflict with the FARDC (and for 70% of the total fighting in the DRC excluding the activity of FARDC). Table B.1 in the appendix provides a complete list .

For each group we report the observed share in total fighting, the share of total bilateral fighting involving this group and the FARDC, the change in rent dissipation associated with pacifying the link between this group and all factions of the FARDC, and a *multiplier*, defined as the ratio between the third and second columns. Here, the multiplier measures the impact of the policy relative to the size of the conflict between the targeted group and the FARDC. A multiplier of one means then that the pacification yields a mere suppression of the bilateral conflict between two groups. Interestingly, with the exception of the CNDP, all multipliers are well above one, and in some cases are very large. This indicates that pacification produces important spillovers through the network.

The largest absolute gain stems from pacifying the FARDC with Rwanda (6% reduction in fighting), despite the fact that direct military operations between the two armies account for only 1% of total violence. The multiplier of 6 is similar to that of Uganda. Pacifying the FARDC with the two main branches of the RCD is also important. Making peace with the UPC is especially fruitful: while bilateral fighting with the FARDC accounts for a mere 0.2% of total fighting, pacification grants a reduction of violence of 2.4%. The bilateral conflict with the mutiny of FARDC ranks top 8. This confirms the importance of internal fights within the Congolese army. Remarkably, the

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[50]One could try to combine the results of both sessions. It is difficult however to have a good empirical assessment of when a group can be induced to leave.

Table 7: Welfare effects of pacifying individual armed groups with the FARDC.

Group	Sh. fight.	Sh. bilat. fight.	$-\Delta$RD	Multiplier	$-\Delta$RD ($\pm$ 1 SD)	Mutipl. ($\pm$ 1 SD)
	(1)	(2)	(3)	(4)	(5)	(6)
Rwanda	0.053	0.010	0.063	6.0	[0.040, 0.140]	[3.8, 13.5]
RCD-G	0.087	0.030	0.056	1.9	[0.033, 0.132]	[1.1, 4.4]
RCD-K	0.060	0.030	0.050	1.6	[0.028, 0.125]	[0.9, 4.1]
LRA	0.041	0.023	0.037	1.6	[0.022, 0.088]	[1.0, 3.9]
MLC	0.031	0.019	0.034	1.8	[0.020, 0.086]	[1.1, 4.6]
Uganda	0.043	0.006	0.031	5.7	[0.020, 0.062]	[3.7, 11.2]
UPC	0.022	0.002	0.024	11.2	[0.014, 0.053]	[6.6, 24.9]
Mutiny FARDC	0.016	0.015	0.023	1.6	[0.015, 0.054]	[1.0, 3.6]
CNDP	0.043	0.038	0.019	0.5	[0.013, 0.033]	[0.4, 0.9]
Lobala Mil.	0.001	0.000	0.017	52.7	[0.011, 0.039]	[32.8, 119.7]
FPJC	0.006	0.006	0.017	2.6	[0.010, 0.037]	[1.7, 5.8]
FRPI	0.009	0.007	0.017	2.4	[0.010, 0.037]	[1.5, 5.3]
BDK	0.002	0.002	0.016	8.1	[0.010, 0.036]	[5.2, 18.3]
Enyele Ethnic Mil.	0.001	0.001	0.016	24.2	[0.010, 0.035]	[15.3, 54.6]
Munzaya Ethnic Mil.	0.001	0.000	0.016	32.3	[0.010, 0.035]	[20.4, 72.7]

Note: The computation of the counterfactual equilibrium is based on the baseline point estimates of column 4 in Table 2. For each group, we report the observed share of total fighting involving this group (col. 1); the observed share of total fighting involving this group against the FARDC (col. 2); the counterfactual reduction in rent dissipation associated with its pacification (col. 3); a multiplier defined as the ratio of col. 3 over col. 2 (col. 4); the reduction in RD and its associated multiplier for a set of parameters equal to the baseline estimates $\pm$1 SD (cols. 5-6).

analysis identifies a set of small ethnic militias such as the Lobala Militia, Bunda Dia Kongo (BDK), Enyele Ethnic Militia, and Munzaya Ethnic Militia, whose pacification with the FARDC would be very effective. The armed activity between each of these militias and the FARDC accounts for less than 0.1% of total violence, and yet putting to an end the bilateral hostility of any of them with the FARDC would reduce violence by 1.6-1.7%.

The analysis of the simultaneous pacification of multiple groups confirms the salient role of Rwanda (see Appendix Tables B.17, B.18, and B.19). Consider the case in which three groups are treated simultaneously. The largest effect stems from targeting Rwanda, the RCD-G and the RCD-K, whose joint pacification with the FARDC scales down violence by 17%, with a multiplier of 2.6. Similar results are attained by interventions targeting smaller armed groups such as the MLC or the LRA.[51] The largest multipliers accrue from triplets involving Rwanda and Uganda, along with, respectively, the MLC (mult. 3.6) and LRA (mult. 3). This confirms that the largest relative gains accrue from targeting the international sponsors rather to their local proxies, despite the fact that the latter are more active in fighting. The analysis also confirms the effectiveness of pacifications involving small groups. As many as 11 ethnic militias (or other small groups) enter triplets with a multiplier of 3 or more.[52]

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[51]More generally, Rwanda is by far the most important actor for pacification purposes: it features in 40 out of the top 50 triplets, and in 8 out of the top 9 triplets. The RCD-G and RCD-K feature 29 times each, while Uganda, MLC and LRA features 5 times each.

[52]Overall we find no evidence of strong complementarity nor substitution. The simultaneous pacification of three players usually yields an effect that is close to the sum of the effects of individually pacifying each of the three players. More precisely, the average effect of simultaneous removal of three players is 97% of the sum of the individual effects in the top 20 triplets. The overall picture is similar when one moves to five-player pacification. In this case, the effect of the most effective intervention is a reduction of conflict in the order of 20-22%.

Table 8: Welfare effects of pacifying selected multiple armed groups with FARDC.

Set of Groups	# groups	Sh. bil. fight. FARDC	$-\Delta$RD	Multipl.	MAD	New enm. & all. (at median)	Regression coeffs.
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EXOGENOUS NETWORK							
Foreign Groups	29	0.213	0.185	0.9	–	–	–
Ituri	9	0.086	0.099	1.2	–	–	–
Out of Rwanda	6	0.062	0.014	0.2	–	–	–
Rwa&Uga&ass.	10	0.217	0.240	1.1	–	–	–
Large Groups	16	0.621	0.338	0.5	–	–	–
WITH ENDOGENOUS NETWORK RECOMPOSITION							
Foreign Groups	29	0.213	0.184	0.9	0.041	[1, +15]	[-0.007, +0.005]
Ituri	9	0.086	0.095	1.1	0.018	[+7, +1]	[-0.004, +0.008]
Out of Rwanda	6	0.062	0.014	0.2	0.000	[+0, +0]	[-0.004, +0.014]
Rwa&Uga&ass.	10	0.217	0.165	0.8	0.052	[-3, +11]	[-0.008, +0.007]
Large Groups	16	0.621	0.313	0.5	0.035	[-6, +19]	[-0.004, +0.005]

Note: The computation of the counterfactual equilibrium is based on the baseline point estimates of column 4 in Table 2. For each policy experiment, we display the results with an exogenous network (top panel) and the results with an endogenous network recomposition based on 1,000 Monte Carlo simulations (bottom panel). For each experiment, we report the set of pacified groups (col. 1); the number of pacified groups (col. 2); the observed share of total fighting involving this set of groups against the FARDC (col. 3); the counterfactual reduction (or its median in the bottom panel) in rent dissipation associated with their pacification (col.4); a multiplier defined as the ratio of col. 4 over col. 3 (col. 5); the Median Absolute Deviation in reduction in RD (col. 6); the post-recomposition number of new enmities and alliances at the median Monte Carlo draw (col. 7); the OLS coefficients of enmities and alliances of a regression across-Monte Carlo draws of post-recomposition reduction in RD on reduction in RD (exogenous network) and the post-recomposition numbers of new enmities and alliances (col. 8).

Table 8 summarizes the result of pacification for the subconflicts already discussed in Table 6 above. Here, the policy treatment consists of reconciling all enmities both *vis-a-vis* the FARDC and between the actors in each subconflict. The reconciliation of all foreign groups yields a reduction in rent dissipation of 18%. Interestingly, the reconciliation of the Ituri conflict reduces rent dissipation by 10% – a larger effect than that of wiping out all groups in Table 6. The reconciliation of all groups associated with Uganda and Rwanda yields a 24% reduction in violence.

Finally, we study the effect of pacifying inter- and intraethnic conflicts between Hutu- and Tutsi-affiliated groups.[53] First, we consider rewiring all inter- or intra-Hutu-Tutsi enmities to neutrality. The effect is a reduction in conflict of 9%. The effect becomes much larger if one rewires all bilateral Hutu-Tutsi links to neutrality and all Hutu-Tutsi co-ethnic links to friendships. In this case, the conflict is reduced by 21%.

6   ENDOGENOUS NETWORK RECOMPOSITION

In the analysis thus far, we have maintained the assumption of an exogenous network structure. The analysis implicitly stipulates that alliances and enmities can be traced back to historical relations among groups that are not affected by the warfare dynamics. In some cases (e.g., the historical

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[53]We code Tutsi and Hutu affiliation following the ethnic group data from Cederman *et al.* (2009). In our sample, 14 groups are ethnical Tutsis, and 11 are ethnical Hutus.

tensions between Hutus and Tutsis) this is a reasonable assumption. In other cases, such as the alliances forged during the First Congo War, relationships are more malleable.

The exogenous network is a straightjacket when we run counterfactual policy experiments. For instance, removing Rwanda or Uganda would likely affect the system of alliances within the DRC. Ideally, one would like to model a fully endogenous network. There are two main difficulties in our environment. First, for many pairs information is scant, limiting our ability to predict the nature of the link. Second, enmities are by design difficult to rationalize in terms of payoffs, as they often harm both parties involved. Therefore, in a model of endogenous network formation it would be natural to dissolve such links.[54] Since these disadvantageous links exist and persist in the data, they must stem from (often unobservable) historical factors such as grievances and past conflicts.

In this section, we construct a model of semi-endogenous network formation that predicts the resilience of network links to exogenous policy shocks. We postulate a discrete choice Random Utility Model (RUM) where each pair of groups selects the bilateral link (either enmity, alliance, or neutrality) in order to maximize utility. We make the important assumption that the formation of the link $\{i, j\}$ depends on the characteristics of i and j (including their position in the network), being otherwise independent of all other links. Conditional independence is a strong (albeit common) assumption. Clearly, in a fully microfounded model where each group decides in a rational and sophisticated fashion which links to add or break, spillovers across different decisions might arise and the IIA assumption could be challenged. Such an alternative model would be more complicated to analyze, and go beyond the scope of this extension.

Our approach is close in spirit to Fafchamps and Gubert (2007a,b), although in their papers interactions between groups have a binary nature. It is also close to Leskovec *et al.* (2010), who use a logistic regression to estimate signed networks, and to Jiang (2015), who studies a stochastic block model for signed graphs.

6.1 RANDOM UTILITY MODEL

We estimate a choice model of link formation that is based on the following RUM:

$$U_{ij}(a) = \alpha \times CSF_{ij}(a) + \mathbf{X}_{ij} \times \boldsymbol{\xi}(a) + \mathbf{Z}_{ij} \times \boldsymbol{\zeta}(a) + FE_i(a) + FE_j(a) + \tilde{u}_{ij}(a), \qquad (23)$$

where $a \in \{-1, 0, 1\}$ and U_{ij} is the joint utility of dyad ij associated with the alternative a. Each dyad chooses the link that maximizes its surplus, $a_{ij}^* = \arg\max U_{ij}(a)$. We abstract from distributional issues by assuming that each dyad makes the efficient choice and can then arrange within-dyad transfers so as to ensure that the choice is acceptable to both parties.[55] The utility of each of the three alternatives depends on observable and unobservable factors comprising:

1. $CSF_{ij}(a)$, the equilibrium joint payoff of the dyad ij in the second stage CSF game (equation 1) where the network structure has alternative a for link $\{i, j\}$, the other network links being unchanged. CSF_{ij} can be inferred from our structural equation (22) once the parameters β and γ are known and the network structure G is adjusted for alternative a.

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[54]This issue is specific to our model. For instance, R&D links, customer relationships, financial links or criminal connections typically add some values to players.

[55]Note that in the (unspecified) intra-dyad negotiation protocol, enmity can be considered as the default option and so there is no transfer and no need for commitment under this alternative. Potential transfers take place only under neutrality and alliance.

2. $\mathbf{X}_{ij}$, a vector of dyad-specific characteristics including the spatial distance between the centroids of i and j, and categorical variables capturing the fact that they are affiliated to the same ethnic group (from Cederman *et al.* 2009), whether they have a common or opposite Tutsi-Hutu background, whether at least one of them is a foreign army, whether at least one of them is a government actor. These characteristics are likely predictors of patterns of alliance or enmity. For instance, the Hutu-Tutsi antagonism is expected to increase the utility associated with $a = -1$.

3. $\mathbf{Z}_{ij}$, network-dependent characteristics, in the spirit of Leskovec *et al.* (2010) that are likely to have a systematic effect on the nature of the link. These comprise the number of common allies and common enemies of i and j, and the number of common conflicting neighbors (namely, i's enemies that are j's allies, or vice versa).

4. Alternative-dependent group-specific fixed effects $FE_i(a)$ that capture the unconditional propensity of i to form the alternative a.

5. $\tilde{u}_{ij}(a)$, i.e., type I extreme-value distributed random utility shocks.

This model is estimated by maximum likelihood as a standard conditional logit estimator. We run an alternative-specific conditional logit for $a_{ij} = +1$ (alliance) and $a_{ij} = -1$ (enmity) setting neutrality as the reference state. This yields an estimated probability that the link $\{i, j\}$ is an alliance, resp. an enmity, relative to neutrality. The estimation results are reported in Table B.20 in the appendix.

The coefficient α – the only coefficient that is not alternative-specific – is insignificant, implying that conflict-specific payoffs under the different alternatives have very low predictive power. This finding is reassuring, being consistent with our assumption that the network structure is exogenous to our baseline CSF game. In contrast, both $\mathbf{X}_{ij}$ and $\mathbf{Z}_{ij}$ have significant explanatory power, with signs broadly in line with prior expectations. In particular, when i is Hutu and j is Tutsi (or vice versa) the probability of an enmity ($a = -1$) is significantly higher than that of neutrality and alliance. As expected, spatial proximity is a strong positive predictor of both alliances and enmities relative to neutrality. Moving to network-dependent characteristics, common enmities increase the probability of being allied and reduce the probability of being enemies (both effects being highly significant). Similarly, having conflicting relationships with a third group (e.g., i is an enemy of k, while j is an ally of k) increases the probability that i and j are enemies and reduces the probability that they are allies. More surprisingly, common alliances decrease the probability for the two groups to be allied – the effect on being enemies being close to zero. This is in line with the narrative that many links are non-transitive.

The model fits the data well (see Appendix B.4.1). Appendix Figure B.1 shows that the predicted probability of a link being an enmity (alliance) conditional on the actual link being an enmity (alliance) is significantly higher than it is conditional on the actual link not being an enmity (alliance). Figure B.2 shows how the model fits the distribution of some network characteristics (degree-one enemies, degree-one allies, number of degree-one links, common enemies, common allied and conflicting neighbors) in the data. Consider, for instance, common enemies. The solid line shows that, in the data, 40% of the dyads have no common enemies, 27% have one common enemy, 14% have two common enemies, etc. The dashed line shows the mean prediction of the RUM across 1,000 Monte Carlo draws, with an associated confidence interval (plus-or-minus one standard

deviation). The simulated distribution tracks the data very closely, with no data observation falling outside the confidence interval of the RUM. The same is true in all other panels.

6.2 RE-ESTIMATING THE MODEL USING THE NETWORK STRUCTURE PREDICTED BY THE RUM

The main goal is to use the RUM to predict the changes in the network structure induced by policy shocks. Before turning to that, we take a brief de-tour to re-estimate the model using the network structure predicted by the RUM as an instrument for the observed network. Consider the regression equation (17), and in particular the IV regression where TFE_{it} and TFA_{it} are instrumented by the rainfall in allies' and enemies' territories. Here, we replace RE_{it} and RA_{it} by $\widehat{\text{RE}}_{it} = \sum_{j=1}^{n} \hat{p}_{ij}^{-} \times \text{RAIN}_{jt}$ and $\widehat{\text{RA}}_{it} = \sum_{j=1}^{n} \hat{p}_{ij}^{+} \times \text{RAIN}_{jt}$, where $\hat{p}_{ij}^{-} \in [0,1]$ and $\hat{p}_{ij}^{+} \in [0,1]$ are the probabilities that groups i and j are allies and enemies as predicted by the RUM.[56] Relative to the baseline estimation, $\hat{p}_{ij}^{-}$ and $\hat{p}_{ij}^{+}$ replace the (observed) links, a_{ij}^{-} and a_{ij}^{+} in the construction of the instruments for the 2SLS estimator. Thus, the exogenous source of variation is the rainfall shocks in other groups' territories and the set of dyadic characteristics (ethnicity, spatial proximity, etc.) and network-specific covariates in equation (23). Note that the results are robust to restricting the RUM to the set of dyadic characteristics only.

The results are shown in column 9 of Table B.7, which displays the analogue of the baseline estimation in column 4 of Table 2.[57] The coefficients are in the ball park of the baseline estimates. The coefficients of TFE and TFA are, respectively, 0.11 (s.e. 0.03) and -0.11 (s.e. 0.05). In spite of the low KP-stat of 4 indicating a weak instrument problem, we find the results reassuring, given the challenge of estimating a complex network like the one in the DRC war.

6.3 ENDOGENOUS NETWORK ADJUSTMENTS AFTER POLICY SHOCKS

In this section, we use our estimated choice model of link formation to predict the changes in the network structure triggered by policy shocks. This intervention affects both $CSF_{ij}(a)$ and $\mathbf{Z}_{ij}$ in equation (23), which in turn affects the prediction of the RUM. We allow post-intervention network recomposition and quantify the impact of the policy on fighting in the recomposed network.

Since the conditional logit model does not yield estimates of the unobserved random utility shocks $\tilde{u}_{ij}(a)$ in equation (23), our analysis must rely on Monte Carlo simulations. More precisely, for each policy experiment we perform Monte Carlo simulations of the network recomposition, and obtain a counterfactual distribution of fighting efforts. In the tables below we focus on the effects at the median realization, although in some cases we show the entire distribution.

For a given policy experiment, we iterate the following algorithm 1,000 times:

1. We draw a vector of random utility shock $\tilde{\mathbf{u}}_{ij}$ for each dyad ij from a truncated multivariate type I extreme value distribution with unconditional mean and variance being, respectively, 0.577 (the Euler-Mascheroni constant) and $\sqrt{\pi}/6$. The support of the distribution corresponds

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[56]The prediction of the observed component of utility in equation (23) is given by

$$\hat{V}_{ij}(a \,|\, G, \mathbf{X}_{ij}, \mathbf{Z}_{ij}) = \hat{\alpha} \times CSF_{ij}(a) + \mathbf{X}_{ij} \times \hat{\boldsymbol{\xi}}(a) + \mathbf{Z}_{ij} \times \hat{\boldsymbol{\zeta}}(a) + \widehat{FE}_i(a) + \widehat{FE}_j(a)$$

with the normalization $\boldsymbol{\xi}(0) = \boldsymbol{\zeta}(0) = FE_i(0) = FE_j(0) = 0$. In turn, the predicted conditional probabilities are given by the standard formula $\mathbb{P}_{ij}(a \,|\, G, \mathbf{X}_{ij}, \mathbf{Z}_{ij}) = e^{V_{ij}(a)}/(e^{V_{ij}(-1)} + e^{V_{ij}(0)} + e^{V_{ij}(+1)})$. Henceforth, $\hat{p}_{ij}^{-} \equiv \mathbb{P}_{ij}(a = -1 \,|\, G, \mathbf{X}_{ij}, \mathbf{Z}_{ij})$ and $\hat{p}_{ij}^{+} \equiv \mathbb{P}_{ij}(a = +1 \,|\, G, \mathbf{X}_{ij}, \mathbf{Z}_{ij})$.

[57]The results are also robust when we consider a time-varying network as in Section 4.2.1. Table B.21 in the Appendix shows the set of main results for the benchmark specifications in Tables 2 and 4.

to the domain of $\tilde{\mathbf{u}}_{ij}$ that is compatible with the link observed in the data. This ensures that, in the absence of policy intervention, there is no network recomposition.[58]

2. For each dyad ij, we compute the post-policy values of CSF_{ij} and $\mathbf{Z}_{ij}$ (the other covariates in equation (23) are not affected). Given these and the estimated parameters, we compute the after-policy observable component of utility $V_{ij}^{post}(a)$.

3. For each Monte Carlo draw we compute the post-policy optimal link: $a_{ij}^{post} = \underset{a \in \{-1,0,+1\}}{\arg \max} V_{ij}^{post}(a) + \tilde{u}_{ij}(a)$. Rewiring occurs when $a_{ij}^{obs} \neq a_{ij}^{post}$. This yields the post-policy recomposed network G^{post}.

4. The counterfactual equilibrium vector of fighting efforts is obtained from the structural equation (22) and G^{post}.

Typically, allowing network recomposition in response to policy shocks increases (decreases) rent dissipation relative to the exogenous network benchmark whenever the policy shock triggers an increase (reduction) in the number of enmities and a reduction (increase) in the number of alliances. Note that a policy may affect both the number of alliances and enmities in the same direction causing ambiguous net effects.

6.3.1 Removing Armed Groups

In this section, we study the effect of removing one or more groups from the conflict (cf. Section 5.1) when endogenous network adjustments are allowed.[59] Table 9 summarizes the findings focusing, for comparability, on the top 15 groups in Table 5. All but three groups remain in the top 15 even after allowing for network recomposition.[60] The UPC is especially interesting. This is a medium-large group whose activity accounts for 2.2% of the total violence. Its removal in Table 5 yields a reduction in violence of the order of 3%, with a sizable multiplier of 1.4. However, the recomposition of the network after its removal offsets two thirds of the gains.

The left panel in Figure 6 shows the reduction in rent dissipation with and without network recomposition for the top 15 groups. The correlation is high (81%), implying that the short-run effects of Section 5.1 are overall robust to network recomposition. Among the groups whose removal

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[58]Our sampling procedure for drawing the random utility shocks from a truncated multivariate distribution follows a standard accept-reject algorithm (see Train 2003, Chapter 9), where the definition of the acceptance domain $\tilde{\mathbf{u}}_{ij}$ follows from the RUM. We first draw a candidate triplet $\tilde{\mathbf{u}}_{ij}$ from the unconditional density. Denoting by $V_{ij}(a)$ the observed utility in equation (23), we retain the draw if it is compatible with the observed link a_{ij}^{obs}, namely $V_{ij}(a_{ij}^{obs}) + \tilde{u}_{ij}(a_{ij}^{obs}) = \underset{a \in \{-1,0,+1\}}{\max} V_{ij}(a) + \tilde{u}_{ij}(a)$. If the triplet does not satisfy the previous condition, we reject this draw and we draw a new triplet. The procedure stops when 1,000 accepted draws have been obtained for each dyad ij.

This conditional approach implies that the simulated network recompositions are entirely driven by the policy-driven changes in $CSF_{ij}(a)$ and $\mathbf{Z}_{ij}$ and not by re-sampling of the unobserved utility shocks.

[59]Arms embargoes do not change the network, and generate no variation to predict network recomposition. Pacification is based on an exogenous change in the nature of links. It is ambiguos how one should think of an endogenous network recomposition in response to the shock.

[60]The three groups that drop out of the top 15 are the UPC, Mutiny of FARC, and FRPI. The group entering the top 15 are two branches of the RCD (the first collects all events involving "unspecified" RCD; the second is the group labeled RCD-National; both are likely to suffer with large measurement error) and the National Army for the Liberation of Uganda.

Table 9: Welfare effect of removing armed groups with network recomposition.

Group	Sh. fight.	$-\Delta$RD (exog. netw.)	$-\Delta$RD (end. netw.)	Multipl. (end. netw.)	MAD	$-\Delta$RD due to rewiring	New enm. at med.	New all. at med.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RCD-G	0.087	0.151	0.137	1.6	0.025	-0.014	1	-2
RCD-K	0.060	0.094	0.076	1.3	0.027	-0.018	2	0
Rwanda	0.053	0.066	0.103	1.9	0.040	0.037	-5	0
LRA	0.041	0.056	0.051	1.2	0.005	-0.005	0	-1
FDLR	0.066	0.055	0.058	0.9	0.008	0.004	-1	1
Mayi-Mayi	0.057	0.046	0.083	1.5	0.024	0.037	-2	1
Uganda	0.043	0.043	0.066	1.5	0.034	0.023	-4	4
CNDP	0.043	0.041	0.041	0.9	0.011	0.000	0	0
MLC	0.031	0.039	0.054	1.7	0.018	0.015	-2	1
UPC	0.022	0.030	0.011	0.5	0.020	-0.020	0	-1
Lendu Ethnic Mil.	0.024	0.022	0.049	2.0	0.020	0.027	-3	0
Mutiny FARDC	0.016	0.016	0.016	1.0	0	0	0	0
Interahamwe	0.014	0.014	0.027	2.0	0.024	0.013	0	-1
ADF	0.013	0.012	0.036	2.7	0.012	0.024	-2	1
FRPI	0.009	0.010	0.010	1.1	0	0	0	0

Note: The computation of the counterfactual equilibrium is based on the baseline point estimates of column 4 in Table 2. The results are based on 1,000 Monte Carlo simulations of an endogenous network recomposition. For each group, we report the observed share of total fighting involving this group (col. 1); the counterfactual reduction in rent dissipation associated with its removal (exogenous network) (col. 2); the counterfactual reduction in rent dissipation associated with its removal with network recomposition (col. 3); a multiplier defined as the ratio of col. 3 over col. 1 (col. 4); the Median Absolute Deviation in reduction in RD across Monte Carlo draws (col. 5); the difference between col. 3 and col. 2 (col. 6); post-rewiring number of new enmities and alliances at the median Monte Carlo draw (cols. 7-8).
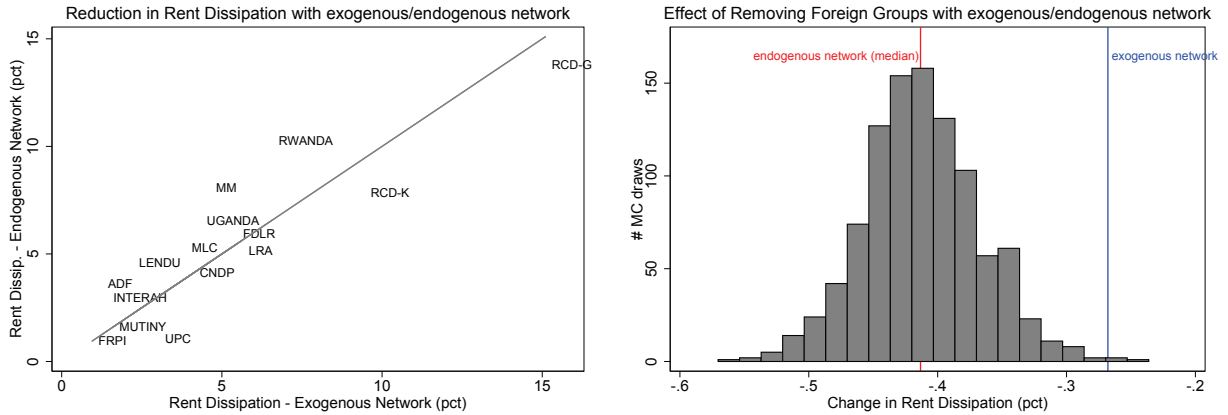
Figure 6: (Left panel) This figure displays the reduction in rent dissipation with and without network recomposition following the removal of each of the top 15 groups. (Right panel) This figure displays the Monte Carlo distribution of reduction in rent dissipation following the removal of 24 foreign groups (1,000 simulated network recompositions).

causes the largest network recomposition we find the armies of Rwanda and Uganda. Recall that removing Rwanda causes a reduction of 6.6% in rent dissipation when the network is exogenous. The adjustment of the network causes a further 3.7% reduction, lifting the median total effect of removing Rwanda to 10.3% (more than twice as large as its observed fighting share). This additional effect is due to five enmities switching to neutral links. Similarly, removing Uganda triggers some network recomposition (4 enmities destroyed, 4 alliances formed). Two groups whose removal is especially consequential for the network structure are the Lendu Ethnic Militia and the ADF. In both cases, the indirect effect of removing them from the contest exceeds the direct effect of the policy under an exogenous network.

Consider, next, the effect of removing selected groups of groups. The results are reported in the lower panel of Table 6. The most remarkable new result is in the experiment where we remove all groups with a foreign affiliation. In this case, the reduction in rent dissipation increases from 27% (exogenous network) to 41%. The effect is estimated precisely, with a median absolute deviation (MAD) of 4.1%. The large extra reduction in fighting efforts accrue from both a reduction in the number of enmities (9 at the median) and an increase in the number of friendly links (6 at the median).[61]

The effect of removing the groups associated with the Hutu exodus is also magnified significantly by the network recomposition (from 8.7% to 12.2%). The same is true for the set of large groups. In other cases, the recomposition of the network has an attenuating effect or no effect.

7 CONCLUSION

In this paper, we construct a theory of conflict in which different groups compete over a fixed amount of resources. We introduce a network of alliances and enmities that we model as externalities added to a Tullock contest success function. Alliances are beneficial to each member, but are not unitary coalitions. Rather, each group acts strategically *vis-a-vis* both allies and enemies. We view our theory as especially useful in conflicts characterized by high fragmentation, non-transitive relations and decentralized military commands, all common features of civil conflicts.

We apply the theory to the analysis of the Second Congo War, one of the bloodiest civil conflicts in modern history. Our estimation of the network externalities is methodologically similar to that followed in the recent work of Acemoglu *et al.* (2015), who tackle a reflection problem through an instrumental variable strategy. While they rely on historical information, we exploit the exogenous variation in weather conditions over space and time. The signs of the estimated coefficients conform with the prediction of the theory. Each group's fighting effort is increasing in the total fighting of its enemies and decreasing in the total fighting of its allies. We then use our structural model to quantify the efficiency of various pacification policies. In particular, we study which groups contribute most to the escalation of the conflict, either directly or indirectly, via the externalities they exercise on the other groups' fighting effort.

The analysis yields a number of policy-relevant findings. The importance of Rwanda and Uganda goes well beyond the battlefield contribution to the conflict of these two major state actors. Breaking peace between the DRC government and its powerful neighbors would make a significant contribution to the reduction of violence. In contrast, interventions such as targeted

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[61]To assess the average effect of the change in the number of enmities and alliances, we regress the rent dissipation on the number of new alliances and new enmities across the 1,000 Monte Carlo draws. The estimated effects are 0.010 and -0.008, respectively. The effect at the median is consistent with this average effect. Figure 6 shows the distribution of Monte Carlo realizations.

arms embargo that increase the cost of fighting of specific groups without removing them from the contest are found to be ineffective. We consider an extension in which not only the groups' fighting effort but also the network of alliances and enmities is allowed to respond endogenously to policy interventions. This extension strengthens the findings about the key role of Uganda and Rwanda, and more generally of foreign groups in the DRC war. Removing all groups with a foreign affiliation is predicted to yield a reduction in violence of the order of 41% – well above their joint contribution to observed violence.

The Congo War is a natural testing ground for our theory for being a conflict where most alliances and enmities are shallow links, and where many allied actors do not coordinate their actions. However, informal alliances and enmities and intransitive links are by no means unique to Congo. Rather, they are common in most modern civil conflicts, and pervasively so, for example, in the recent conflicts of Afghanistan, Somalia, Iraq, Sudan, and Syria.

Even in the case of more conventional international wars, shallow links and intransitive links are not uncommon. For instance, the anti-Nazi alliance between the Soviet Union and the Anglo-Americans during World War II was a tactical alliance to defeat a common enemy. Well before the war was over, the Soviet Union and the Anglo-Americans were fighting strategically for conflicting objectives, each trying to secure the best political and military post-war outcome.[62] Another example is the intricate situation in the Balkans during WWII.[63] Similar considerations apply to earlier wars, from the Peloponnesian War in ancient Greece, to the Napoleonic Wars (Ke *et al.* 2013), or to the alliances between warlords in China after the proclamation of the Republic in 1912.

Our analysis takes the first step towards understanding how webs of alliances and enmities can lead to escalation or containment of conflict. Future work can build on this to propose a full-fledged model of endogenous network formation. In work in progress, we are extending the analysis to other fragmented conflicts such as the recent civil war in Syria.

MAIN APPENDIX

Proof of Proposition 1. We first establish the existence of a Nash Equilibrium in which all groups participate in the contest (an *interior* equilibrium). Let $\mathbf{x}^* = (x_1^*, \ldots, x_n^*)^\top \in R^n$ denote the candidate equilibrium effort vector that satisfies the FOCs; let $\mathbf{x}_{-i}^* \in \mathbb{R}^{n-1}$ denote the same vector without the i'th component. Let $\pi_i(G; x_i, \mathbf{x}_{-i}^*) = \varphi_i(G; x_i, \mathbf{x}_{-i}^*)/\sum_{j=1}^n \varphi_j(G; x_i, \mathbf{x}_{-i}^*) - x_i$ denote the payoff function of a deviation from the equilibrium effort, in the range where $\varphi_i \geq 0$.

The FOCs of the profit maximization problem yields:

$$0 = \frac{\partial \pi_i}{\partial x_i}(G; x_i^*, \mathbf{x}_{-i}^*) = \frac{\sum_{j=1}^n \varphi_j^* - \varphi_i^*(1 + \beta d_i^+ - \gamma d_i^-)}{\left(\sum_{j=1}^n \varphi_j^*\right)^2} - 1. \tag{24}$$

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[62] Several episodes corroborate this view. In August 1944, the Red Army refused to support the British-sponsored Polish Home Army during the Warsaw Uprising. This tragic event was by-and-large a proxy war between two formally allied governments to gain control over Poland after the war.

[63] The Independent State of Croatia led by Ante Pavelic was sponsored by Nazi Germany, but was in poor terms with Italy, the main ally of Germany at the time, that occupied large sectors of Croatian Dalmatia. During the same period, Serbia under Milan Nedic was a Nazi puppet state collaborating with both Germany and Italy. The two sides – Croatian Ustasa and Serbian Chetniks – ran a parallel ferocious ethnic war against each other (Goldstein 2013). Yet, the two enemies had a common enemy in Tito's partisan National Liberation Army.

Here we have used the fact that $\partial \varphi_j^*(G; x_i, \mathbf{x}_{-i}^*)/\partial x_i = \delta_{ij} + \beta a_{ij}^+ - \gamma a_{ij}^-$ (where $\delta_{ij} = 0$ if $i \neq j$ and $\delta_{ii} = 1$), consequently, $\sum_{j=1}^n \partial \varphi_j^*/\partial x_i = 1 + \beta d_i^+ - \gamma d_i^-$. Standard algebra yields:

$$\varphi_i^* = \frac{1}{1 + \beta d_i^+ - \gamma d_i^-} \left(1 - \sum_{j=1}^n \varphi_j^*\right) \sum_{j=1}^n \varphi_j^*. \tag{25}$$

Next, define $\Gamma_i^{\beta,\gamma}(G) \equiv \left(1 + \beta d_i^+ - \gamma d_i^-\right)^{-1} > 0$ and $\Lambda^{\beta,\gamma}(G) \equiv 1 - \left(\sum_{i=1}^n \Gamma_i^{\beta,\gamma}(G)\right)^{-1}$, where the inequality follows from (3). Summing over i's in equation (25) implies that

$$\varphi_i^* = \Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))\Gamma_i^{\beta,\gamma}(G) > 0. \tag{26}$$

The inequality hinges on establishing that $\Lambda^{\beta,\gamma}(G) > 0$, or equivalently $\sum_{i=1}^n \Gamma_i^{\beta,\gamma}(G) > 1$. Observe that $\sum_{i=1}^n \Gamma_i^{\beta,\gamma}(G) = \sum_{i=1}^n \frac{1}{1 + \beta d_i^+ - \gamma d_i^-} \geq \sum_{i=1}^n \frac{1}{1 + \beta d_i^+} \geq \frac{n}{1 + \beta d_{\max}^+} > 1$. The last inequality holds true if and only if $\beta < \frac{n-1}{d_{\max}^+}$, which is in turn is necessarily true if $\beta < 1$. This, in turn, follows from the assumption that $\beta + \gamma < 1/\max\{\lambda_{\max}(G^+), d_{\max}^-\}$ that implies that $\beta + \gamma < 1/\max\{\lambda_{\max}(G^+), \lambda_{\max}(G^-)\}$, since $\lambda_{\max}(G^-) < d_{\max}^-$ (Cvetkovic *et al.* 1995). Moreover, for any non-empty graph G, $\lambda_{\max}(G) \geq 1$, because for any graph G, $\lambda_{\max}(G) \geq \max_{i=1,\ldots,n} \sqrt{d_i}$ (Cvetkovic *et al.* 1995), and $\max_{i=1,\ldots,n} d_i \geq 1$ when G is not empty. Thus, $\beta \leq \beta + \gamma < 1$. This establishes that $\varphi_i^* \geq 0$ for all $i = 1, \ldots, n$.

Next, we compute $\mathbf{x}^*$. Combining (2) with (26) yields:

$$x_i^* + \beta \sum_{j=1}^n a_{ij}^+ x_j^* - \gamma \sum_{j=1}^n a_{ij}^- x_j^* = \Lambda^{n,\beta}(G)(1 - \Lambda^{n,\beta}(G))\Gamma_i^{\beta,\gamma}(G). \tag{27}$$

Denoting by $\mathbf{\Gamma}^{\beta,\gamma}(G) \equiv (\Gamma_1^{\beta,\gamma}(G), \ldots, \Gamma_n^{\beta,\gamma}(G))^\top$, we can write this system in matrix form as

$$(\mathbf{I}_n + \beta \mathbf{A}^+ - \gamma \mathbf{A}^-)\mathbf{x}^* = \Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))\mathbf{\Gamma}^{\beta,\gamma}(G). \tag{28}$$

The fact that $\beta + \gamma < 1/\max\{\lambda_{\max}(G^+), \lambda_{\max}(G^-)\}$ also ensures that the matrix $\mathbf{I}_n + \beta \mathbf{A}^+ - \gamma \mathbf{A}^-$ is invertible.[64] Then, (28) yields the effort levels:

$$\mathbf{x}^* = \Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))\mathbf{c}^{\beta,\gamma}(G), \tag{29}$$

where $c^{\beta,\gamma}(G)$ is the centrality measure defined by equation (8)). Equation (29) is the matrix-form version of equation (7) in the proposition. Evaluating $\pi_i(G, x)$ at $x = x^*$ yields equation (9) in the proposition.

Thus far, we have established that $\mathbf{x}^*$ and φ^* satisfy the FOCs. In order to prove that the FOCs pin down a Nash equilibrium, we must establish that, for all $i = 1, 2, \ldots n$, x_i^* is a global maximum of $\pi_i(G; x_i, \mathbf{x}_{-i}^*)$ for all $x_i \in \mathbb{R}$. To prove the result, we split the horizontal line at the cutoff value $\hat{x}_i$, uniquely defined by the condition $\varphi_i(G, \hat{x}_i, x_{-i}^*) = 0$. For $x_i < \hat{x}_i$, $\pi_i(G; x_i, \mathbf{x}_{-i}^*) = -D$. For $x_i \geq \hat{x}_i$, standard algebra establishes that $\left(\partial^2 \pi_i/\partial x_i^2\right)(G; x_i, x_{-i}^*) = -2/(\Gamma_i^{\beta,\gamma}(G) \times \Lambda^{\beta,\gamma}(G)) < 0$, where the inequality follows from the facts, established above, that $\Gamma_i^{\beta,\gamma}(G) > 0$ and $\Lambda^{\beta,\gamma}(G) > 0$. Thus, $\pi_i(G, x_i, x_{-i}^*)$ is strictly concave in x_i in the subdomain $x_i \geq \hat{x}_i$. Moreover, equation (4) establishes that $\varphi_i^* > 0 = \varphi_i(G, \hat{x}_i, x_{-i}^*)$. This, together with the fact that φ_i is increasing in x_i, establishes that $x_i^* > \hat{x}_i$. The facts that (i) $\pi_i(G, x_i, x_{-i}^*)$ is strictly concave in x_i, and (ii) $x_i^* > \hat{x}_i$ jointly imply that $\pi_i(G, x_i^*, x_{-i}^*)$ is a global maximum of the π_i function in the subdomain $x_i \geq \hat{x}_i$. It is immediate that $\pi_i(G, x_i^*, x_{-i}^*) < \infty$. Define $\underline{D} = \max_i -\pi_i(G, x_i^*, x_{-i}^*)$. Then, for

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[64] This follows from standard linear algebra results. The determinant of a matrix of the form $I_n - \sum_{j=1}^p \alpha_j W_j$ is strictly positive if $\sum_{j=1}^p |\alpha_j| < 1/\max_{j=1,\ldots,p} \|W_j\|$, where $\|W_j\|$ is any matrix norm, including the spectral norm, which corresponds to the largest eigenvalue of W_j.

all $D > \underline{D}$, we have that $\pi_i(G, x_i^*, x_{-i}^*) > -D$, namely, defeat is not a profitable deviation. This completes the proof of existence of an interior Nash Equilibrium.

Next, we prove uniqueness. We assume that, contrary to the statement of the proposition, for all $D < \infty$, there exists an equilibrium where $n - \hat{n} > 0$ groups take the defeat option. Then, we show that this induces a contradiction. Since we have proved that when all n groups participate in the contest there exists a unique equilibrium, this establishes global uniqueness.

The condition that $\Gamma_i^{0,\gamma} > 0$, $\forall i = 1, 2, ...n$, ensures that, in a candidate equilibrium in which only $\hat{n} < n$ groups participate in the contest, all such $\hat{n}$ groups choose a finite effort level (this follows immediately from the analysis of the case where all n groups participate). The effort level of participants is $x_{\hat{n}}^* = \Lambda^{\beta,\gamma}(G_{\hat{n}})(1 - \Lambda^{\beta,\gamma}(G_{\hat{n}}))c^{\beta,\gamma}(G_{\hat{n}})$ where the graph $G_{\hat{n}}$ only includes the participating groups. Consider a non-participating group ν. For this group, in the assumed equilibrium, $\pi_\nu = -D$. Suppose group v deviates and chooses, instead, $x_\nu = x_\nu^0$, where x_ν^0 is the unique threshold such that $\varphi_\nu(G_{\hat{n}+1}, x_\nu^0, \hat{x}_{-\nu}^*) = 0$. The payoff of this deviation payoff is $\pi_\nu(G_{\hat{n}+1}, x_\nu^0, \hat{x}_{-\nu}^*) = -x_\nu^0 > -\infty$. Thus, for any $D > x_\nu^0$, this deviation is profitable. Repeating the argument for all partitions establishes that there exists $\underline{D} < \infty$ such that, for all $D > \underline{D}$, any candidate equilibrium where $n - \hat{n} > 0$ groups take the defeat option is susceptible to a profitable deviation (hence, it is not an equilibrium). Thus, the only equilibrium is interior, completing the proof. ∎

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Online Appendix for "Networks in Conflict: Theory and Evidence from the Great War of Africa"

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In this Appendix we provide additional results complementing the discussion in the main part of the paper. First, Appendix A.1 complements the discussion in Section 2.2.1. In particular, in Appendix A.1.2 we consider networks in which the spillover parameters β and γ are small. This special case allows us to build additional intuition for the interpretation of our centrality measure of equation (8), and relate it to other existing centrality measures in the literature that are discussed in Appendix A.1.1. Appendix A.2 provides the proofs related to the material of Section 2.4. Appendix A.3 gives a complete characterization of the groups whose removal results in the greatest reduction in the rent dissipation that are analyzed in Section 5.1. In Appendix A.4 we develop the theoretical underpinning of the arms embargo that has been introduced in Section 5.2. Finally, additional results related to our dataset, the estimation method and policy analysis can be found in Appendix B.

A   Theory Appendix

A.1   Appendix to Section 2.2.1

In this appendix, we discuss the relation of our theory to the Katz-Bonacich centrality due to Katz (1953) and later extended by Bonacich (1987). We first define the notion of Katz-Bonacich centrality, and then discuss how it relates to our results.

A.1.1   Katz-Bonacich Centrality

Let $\mathbf{A}$ be the symmetric $n \times n$ adjacency matrix of the network G and $\lambda_{\max}$ its largest real eigenvalue. The matrix $\mathbf{M}(G, \alpha) = (\mathbf{I} - \alpha\mathbf{A})^{-1}$ exists and is non-negative if and only if $\alpha < 1/\lambda_{\max}$.[65] Under this condition it can be written as

$$\mathbf{M}(G, \alpha) = \sum_{k=0}^{\infty} \alpha^k \mathbf{A}^k. \tag{30}$$

The vector of Katz-Bonacich centralities is then given by

$$\mathbf{b_u}(G, \alpha) = \mathbf{M}(G, \alpha)\mathbf{u}, \tag{31}$$

where $\mathbf{u} = (1, \ldots, 1)^\top$ is an n-dimensional vector of ones. We can write the vector of Katz-Bonacich centralities as

$$\mathbf{b_u}(G, \alpha) = (\mathbf{I} - \alpha\mathbf{A})^{-1}\mathbf{u} = \sum_{k=0}^{\infty} \alpha^k \mathbf{A}^k \mathbf{u}.$$

For the components $b_{\mathbf{u},i}(G, \alpha)$, $i = 1, \ldots, n$, we get

$$b_{\mathbf{u},i}(G, \alpha) = \sum_{k=0}^{\infty} \alpha^k (\mathbf{A}^k \cdot \mathbf{u})_i = \sum_{k=0}^{\infty} \alpha^k \sum_{j=1}^{n} a_{ij}^{[k]}, \tag{32}$$

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[65]The proof can be found e.g. in Debreu and Herstein (1953).

where $a_{ij}^{[k]}$ is the ij-th element of $\mathbf{A}^k$. Because $N_{k,i}(G) \equiv \sum_{j=1}^{n} a_{ij}^{[k]}$ counts the number of all walks of length k in G starting from i, the Katz-Bonacich centrality of group i, $b_{\mathbf{u},i}(G,\alpha)$, is thus equivalent to the number of all walks in G starting from i, where the walks of length k are weighted by a geometrically decaying factor α^k.

Further, the sum of the Katz-Bonacich centralities, $\sum_{i=1}^{n} b_{\mathbf{u},i}(G,\alpha) = \mathbf{u}^\top \mathbf{b_u}(G,\alpha) = \mathbf{u}^\top \mathbf{M}(G,\alpha)\mathbf{u}$, is equivalent to *walk generating function* of the graph G, denoted by $N(G,\alpha)$ (cf. Cvetkovic 1995). To see this, let $N_k(G) \equiv \sum_{i=1}^{n} N_{k,i}(G)$ denote the number of walks of length k in G. Then we can write $N_k(G)$ as follows $N_k(G) = \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij}^{[k]} = \mathbf{u}^\top \mathbf{A}^k \mathbf{u}$. The walk generating function is then defined as

$$N(G,\alpha) \equiv \sum_{k=0}^{\infty} N_k(G)\alpha^k = \mathbf{u}^\top \left(\sum_{k=0}^{\infty} \alpha^k \mathbf{A}^k \right) \mathbf{u} = \mathbf{u}^\top \left(\mathbf{I}_n - \alpha\mathbf{A} \right)^{-1} \mathbf{u} = \mathbf{u}^\top \mathbf{M}(G,\alpha)\mathbf{u}.$$

Moreover, the generating function of the number of closed walks that start and terminate at node i is given by

$$W_i(G,\alpha) \equiv \sum_{k=0}^{\infty} a_{ii}^{[k]} \alpha^k. \tag{33}$$

The matrix of equation (30) is also a measure of structural similarity of the groups in the network, called *regular equivalence*. Blondel *et al.* (2004) and Leicht *et al.* (2006) define a similarity score b_{ij}, which is high if nodes i and j have neighbors that themselves have high similarity, given by $b_{ij} = \alpha \sum_{k=1}^{n} a_{ik} b_{kj} + \delta_{ij}$. In matrix-vector notation this reads $\mathbf{M} = \alpha\mathbf{A}\mathbf{M} + \mathbf{I}$. Rearranging yields $\mathbf{M} = (\mathbf{I} - \alpha\mathbf{A})^{-1} = \sum_{k=0}^{\infty} \alpha^k \mathbf{A}^k$, assuming that $\alpha < 1/\lambda_{\max}$. We hence obtain that the similarity matrix $\mathbf{M}$ is equivalent to the matrix from equation (30). The average similarity of group i is $\frac{1}{n} \sum_{j=1}^{n} b_{ij} = \frac{1}{n} b_{\mathbf{u},i}(G,\alpha)$, where $b_{\mathbf{u},i}(G,\alpha)$ is the Katz-Bonacich centrality of i. It follows that the Katz-Bonacich centrality of i is proportional to the average regular equivalence of i. Groups with a high Katz-Bonacich centrality are then the ones which also have a high average structural similarity with the other groups in the network.

The interpretation of eingenvector-like centrality measures as a similarity index is also important in the study of correlations between observations in principal component analysis and factor analysis (cf. Rencher and Christensen 2012). Variables with similar factor loadings can be grouped together. This basic idea has also been used in the economics literature on segregation (e.g. Ballester and Vorsatz 2014; Echenique and Fryer Jr. 2007; Echenique *et al.* 2006).

A.1.2   The Case of Small Externalities

Consider our the centrality measure $c_i^{\beta,\gamma}(G)$ in equation (8). This depends, in general, on the entire network structure. However, it is instructive to consider networks in which the spillover parameters β and γ are small. In this case, our centrality measure can be approximated by the the sum of (i) the Katz-Bonacich centrality related to the network of enmities, G^-, (ii) the (negative-parameter) Katz-Bonacich centrality related to the network of alliances, G^+, and (iii) the local hostility vector, $\Gamma^{\beta,\gamma}(G)$.[66]

Lemma 1. *Assume that the conditions of Proposition 1 are satisfied. Then, as $\beta \to 0$ and $\gamma \to 0$, the centrality measure defined in equation (8) can be written as*

$$\mathbf{c}^{\beta,\gamma}(G) = \mathbf{b}.(\gamma, G^-) + \mathbf{b}.(-\beta, G^+) - \Gamma^{\beta,\gamma}(G) + O(\beta\gamma),$$

where $O(\beta\gamma)$ involves second and higher order terms, and the (weighted) Katz-Bonacich centrality with parameter α is defined as $\mathbf{b}.(\alpha, G) \equiv \mathbf{b}_{\Gamma^{\beta,\gamma}(G)}(\alpha, G) = (\mathbf{I}_n - \alpha\mathbf{A})^{-1} \Gamma^{\beta,\gamma}(G)$ assuming that α is smaller than the inverse of the largest eigenvalue of $\mathbf{A}$.

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[66]See the Appendix A.1.1 for a more detailed discussion of the Katz-Bonacich centrality. A discussion of the Katz-Bonacich centrality with a negative parameter can be found in Bonacich (2007).

Proof of Lemma 1. The proof of the lemma builds on a first-order Taylor approximation in β and γ of the centrality $\mathbf{c}^{\beta,\gamma}(G)$ defined in equation (8). Using the fact that $\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^- = (\mathbf{I}_n + \beta\mathbf{A}^+)(\mathbf{I}_n - \gamma\mathbf{A}^-) + \beta\gamma\mathbf{A}^+\mathbf{A}^- = (\mathbf{I}_n + \beta\mathbf{A}^+)(\mathbf{I}_n - \gamma\mathbf{A}^-) + O(\beta\gamma)$, and $[(\mathbf{I}_n + \beta\mathbf{A}^+)(\mathbf{I}_n - \gamma\mathbf{A}^-)]^{-1} = (\mathbf{I}_n - \gamma\mathbf{A}^-)^{-1}(\mathbf{I}_n + \beta\mathbf{A}^+)^{-1}$, where $(\mathbf{I}_n - \gamma\mathbf{A}^-)^{-1} = \sum_{k=0}^{\infty} \gamma^k(\mathbf{A}^-)^k$ and $(\mathbf{I}_n + \beta\mathbf{A}^+)^{-1} = \sum_{k=0}^{\infty}(-1)^k\beta^k(\mathbf{A}^+)^k$, we can write

$$
(\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-)^{-1} = (\mathbf{I}_n - \gamma\mathbf{A}^-)^{-1}(\mathbf{I}_n + \beta\mathbf{A}^+)^{-1} + O(\beta\gamma)
$$

$$
= \left(\mathbf{I}_n + \gamma\mathbf{A}^- + \sum_{k=2}^{\infty}\gamma^k(\mathbf{A}^-)^k\right)\left(\mathbf{I}_n - \beta\mathbf{A}^+ + \sum_{k=2}^{\infty}(-1)^k\beta^k(\mathbf{A}^+)^k\right) + O(\beta\gamma)
$$

$$
= \mathbf{I}_n + \gamma\mathbf{A}^- - \beta\mathbf{A}^+ + \sum_{k=2}^{\infty}\gamma^k(\mathbf{A}^-)^k + \sum_{k=2}^{\infty}(-1)^k\beta^k(\mathbf{A}^+)^k + \gamma\mathbf{A}^-\sum_{k=2}^{\infty}(-1)^k\beta^k(\mathbf{A}^+)^k
$$

$$
+ \sum_{k=2}^{\infty}\gamma^k(\mathbf{A}^-)^k\beta\mathbf{A}^+ + \left(\sum_{k=2}^{\infty}\gamma^k(\mathbf{A}^-)^k\right)\left(\sum_{k=2}^{\infty}(-1)^k\beta^k(\mathbf{A}^+)^k\right) + O(\beta\gamma)
$$

$$
= \mathbf{I}_n + \sum_{k=1}^{\infty}\gamma^k(\mathbf{A}^-)^k + \sum_{k=1}^{\infty}(-1)^k\beta^k(\mathbf{A}^+)^k + O(\beta\gamma). \tag{34}
$$

Hence, in leading order in β and γ the centrality in equation (8) can then be written as follows

$$
\mathbf{c}^{\beta,\gamma}(G) = \left(\sum_{k=0}^{\infty}\gamma^k(\mathbf{A}^-)^k + \sum_{k=0}^{\infty}(-1)^k\beta^k(\mathbf{A}^+)^k - \mathbf{I}_n\right)\mathbf{\Gamma}^{\beta,\gamma}(G) + O(\beta\gamma)
$$

$$
= \mathbf{b}_{\mathbf{\Gamma}^{\beta,\gamma}(G)}(\gamma, G^-) + \mathbf{b}_{\mathbf{\Gamma}^{\beta,\gamma}(G)}(-\beta, G^+) - \mathbf{\Gamma}^{\beta,\gamma}(G) + O(\beta\gamma). \tag{35}
$$

This completes the proof. ∎

Lemma 1 states that the centrality $\mathbf{c}^{\beta,\gamma}(G)$ can be expressed as a linear combination of the weighted Katz-Bonacich centralities $\mathbf{b}_{.}(\gamma, G^-)$, $\mathbf{b}_{.}(-\beta, G^+)$ and the vector $\mathbf{\Gamma}^{\beta,\gamma}(G)$. Each Katz-Bonacich centrality gauges the network multiplier effect attached to the system of enmities and alliances, respectively. In particular, $\mathbf{b}_{.}(\gamma, G^-)$ captures how a group i is In the case of of weak network externalities (i.e. when $\beta \to 0$ and $\gamma \to 0$), the Katz-Bonacich centrality can be itself approximated as follows:

$$
b_{.,i}\left(\gamma, G^-\right) = \Gamma_i^{\beta,\gamma}(G) + \gamma\sum_{j=1}^{n} a_{ij}^-\Gamma_j^{\beta,\gamma}(G) + \gamma^2\sum_{j=1}^{n}a_{ij}^-\sum_{k=1}^{n}a_{jk}^-\Gamma_k^{\beta,\gamma}(G) + O\left(\gamma^3\right), \tag{36}
$$

$$
b_{.,i}(-\beta, G^+) = \Gamma_i^{\beta,\gamma}(G) + (-\beta)\sum_{j=1}^{n} a_{ij}^+\Gamma_j^{\beta,\gamma}(G) + (-\beta)^2\sum_{j=1}^{n}a_{ij}^+\sum_{k=1}^{n}a_{jk}^+\Gamma_k^{\beta,\gamma}(G) + O\left(\beta^3\right). \tag{37}
$$

Thus, Lemma 1 suggests that, when higher order terms can be neglected, our centrality measure is increasing in γ and in the number of first- and second-degree enmities, whereas it is decreasing in β and in the number of first-degree alliances. Second-degree alliances have instead a positive effect on the centrality measure.[67]

We can provide an illustration with a simple example. Figure A.1 shows a path graph, P_5, with five agents and their centralities for $\gamma = 0.1$ and $\beta = 0$, where agents are connected through rivalries only, and $\gamma = 0$ and $\beta = 0.1$, where agents are connected through alliances only.

In the first case, when $\gamma = 0.1, \beta = 0$ (rivalries only), we know from equation (35) that the agents' centralities are determined by the Katz-Bonacich centrality $b_{.,i}\left(\gamma, G^-\right)$ of equation (36). The Katz-Bonacich

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[67]The intuition for this property is as follows. If i is allied with j and j is allied with k, an increase in the fighting effort of k reduces the fighting effort of j and this, in turn, increases the fighting effort of i. Consider, instead, the case in which i is an enemy of j and j is an enemy of k. Then, an increase in the fighting effort of k increases the fighting effort of j and this, in turn, increases the fighting effort of i.

$$\gamma = 0.1, \beta = 0$$

| 0.176252 | 0.213579 | 0.216972 | 0.213579 | 0.176252 |

| 0.149682 | 0.120913 | 0.124109 | 0.120913 | 0.149682 |

$$\gamma = 0, \beta = 0.1$$
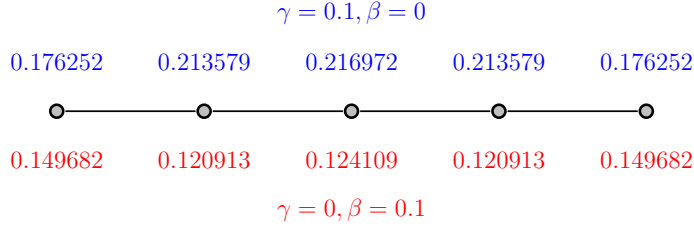
Figure A.1: *The figure shows a path graph, P_5, with five agents and their centralities for $\gamma = 0.1, \beta = 0$ (rivalries only) at the top and $\gamma = 0, \beta = 0.1$ (alliances only) at the bottom.*

centrality measure related to the network of hostilities, $b_{.,i}(\gamma, G^-)$, measures the local hostility levels along all walks reaching i using only hostility connections, where walks of length k are weighted by the geometrically decaying hostility externality γ^k (see Section A.1.1 above). Since the discounted number of walks emanating from a node in a path graph is the higher the more central an agent is, we find that the agent in the middle of the path has the highest centrality, and centralities decrease moving away from the middle of the path.

The outcome is different for the case of $\beta = 0.1, \gamma = 0$ (alliances only). Equation (35) tells us that in this case the agents' centralities are determined by the Katz-Bonacich centrality $b_{.,i}(-\beta, G^+)$. When the parameter of the Katz-Bonacich centrality is negative, $b_{.,i}(-\beta, G^+)$, then we know from equation (37) that negative weight is given to an agent's neighbors, but positive weight to the neighbors of the neighbors. The peripheral agents at the ends of the path have the lowest number of direct neighbors and thus have the highest centrality. This leads to a lower levels of centrality for the agents in the intermediate positions, which in turn leads to a higher level of centrality for the agent in the middle of the path.

Moreover, we can also obtain a simple approximate expression for the equilibrium efforts and the payoffs in Proposition 1.[68]

Lemma 2. *As $\beta \to 0$ and $\gamma \to 0$, the equilibrium effort and payoff of group i in network G can be written as*

$$x_i^*(G) = A_1^{\beta,\gamma}(G) - B_1\left(\beta d_i^+ - \gamma d_i^-\right) + O\left(\beta\gamma\right),$$
$$\pi_i^*(G) = A_2^{\beta,\gamma}(G) + B_2\left(\beta d_i^+ - \gamma d_i^-\right) + O\left(\beta\gamma\right),$$

where $A_1^{\beta,\gamma}(G), B_1, A_2^{\beta,\gamma}(G)$ and B_2 are positive constants with $A_1^{\beta,\gamma}(G)$ and $A_2^{\beta,\gamma}(G)$ being of the order of $O(\beta) + O(\gamma)$.

Proof of Lemma 2. The proof of the lemma builds on a first-order Taylor approximation in β and γ of the equilibrium fighting efforts $x_i^*(G)$ in equation (7) and payoffs $\pi_i^*(G)$ from equation (9). First, observe that for $\beta \to 0$ and $\gamma \to 0$ we have that

$$\Gamma_i^{\beta,\gamma}(G) = \frac{1}{1 + \beta d_i^+ - \gamma d_i^-} = 1 - \beta d_i^+ + \gamma d_i^- + O\left(\beta^2\right) + O\left(\gamma^2\right) + O\left(\beta\gamma\right),$$

and

$$1 - \Lambda^{\beta,\gamma}(G) = \frac{1}{\sum_{i=1}^n \Gamma_i^{\beta,\gamma}(G)} = \frac{1}{n} + \frac{2}{n^2}\left(\beta m^+ - \gamma m^-\right) + O\left(\beta^2\right) + O\left(\gamma^2\right) + O\left(\beta\gamma\right),$$

where we have denoted by $m^+ = \frac{1}{2}\sum_{i=1}^n d_i^+$ and $m^- = \frac{1}{2}\sum_{i=1}^n d_i^-$. Also, we have that

$$\Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G)) = \frac{n-1}{n^2} - \frac{2m^-(n-2)\gamma}{n^3} + \frac{2m^+(n-2)\beta}{n^3} + O\left(\beta^2\right) + O\left(\gamma^2\right) + O\left(\beta\gamma\right).$$

---

[68] See the proof of Lemma 2 for the explicit expressions for the constants $A^{\beta,\gamma}(G), B, C^{\beta,\gamma}(G)$ and D.

It is useful to note that, when $\beta = \gamma = 0$, then $\Lambda^{\beta,\gamma}(G) = 1 - \frac{1}{n}$, and $c_i^{\beta,\gamma}(G) = 1$. Then, the equilibrium expressions in Proposition 1 simplify to $x_i^*(G) = (n-1)/n^2$ and $\pi_i^*(G) = 1/n^2$ which are the standard solutions in the Tullock CSF.

4

Moreover, from equation (34) in the proof of Lemma 1 we have that

$$(\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-)^{-1} = (\mathbf{I}_n - \gamma\mathbf{A}^-)^{-1}(\mathbf{I}_n + \beta\mathbf{A}^+)^{-1} + O(\beta\gamma)$$
$$= (\mathbf{I}_n + \gamma\mathbf{A}^-)(\mathbf{I}_n - \beta\mathbf{A}^+)(\mathbf{u} + \gamma\mathbf{d}^+ - \beta\mathbf{d}^- + O(\beta^2) + O(\gamma^2) + O(\beta\gamma)$$
$$= \mathbf{I}_n + \gamma\mathbf{A}^- - \beta\mathbf{A}^+ + O(\beta^2) + O(\gamma^2) + O(\beta\gamma).$$

It then follows that

$$(\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-)^{-1}\mathbf{\Gamma}^{\beta,\gamma}(G) = (\mathbf{I}_n + \gamma\mathbf{A}^- - \beta\mathbf{A}^+)(\mathbf{u} + \gamma\mathbf{d}^- - \beta\mathbf{d}^+) + O(\beta^2) + O(\gamma^2) + O(\beta\gamma)$$
$$= \mathbf{u} + 2\gamma\mathbf{d}^- - 2\beta\mathbf{d}^+ + O(\beta^2) + O(\gamma^2) + O(\beta\gamma),$$

and we get for the equilibrium fighting efforts $x_i^*(G)$ that

$$x_i^*(G) = \Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))((\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-)^{-1}\mathbf{\Gamma}^{\beta,\gamma}(G))_i$$
$$= \left(\frac{n-1}{n^2} - \frac{2m^-(n-2)\gamma}{n^3} + \frac{2m^+(n-2)\beta}{n^3}\right)(1 + 2\gamma d_i^- - 2\beta d_i^+) + O(\beta\gamma)$$
$$= \left(\frac{n-1}{n^2} - \frac{2(n-2)m^- - 2n(n-1)d_i^-}{n^3}\gamma + \frac{2(n-2)m^+ - 2n(n-1)d_i^+}{n^3}\beta\right) + O(\beta\gamma).$$

Denoting by $A_1^{\beta,\gamma}(G) \equiv \frac{n-1}{n^2} + \beta\frac{2(n-2)}{n^3}m^+ - \gamma\frac{2(n-2)}{n^3}m^-$ and $B_1 \equiv \frac{2(n-1)}{n^2}$, we can write this as follows

$$x_i^*(G) = \left(A_1^{\beta,\gamma}(G) - B_1\left(\beta d_i^+ - \gamma d_i^-\right)\right) + O(\beta\gamma). \tag{38}$$

Next, note that the group i's equilibrium payoff is given by $\pi_i^*(G) = (1 - \Lambda^{\beta,\gamma}(G))\Gamma_i^{\beta,\gamma}(G) - x_i^*(G)$. Using the equilibrium effort from above it then follows that the equilibrium payoff of group i is given by

$$\pi_i^*(G) = (1 - \Lambda^{\beta,\gamma}(G))\Gamma_i^{\beta,\gamma}(G) - x_i^*(G)$$
$$= \left(\frac{1}{n} - \frac{2\gamma m^- - 2\beta m^+}{n^2}\right)(1 + \gamma d_i^- - \beta d_i^+) - x_i^*(G) + O(\beta\gamma)$$
$$= \left(\frac{1}{n^2} + \frac{4m^+ + n(n-2)d_i^+}{n^3}\beta - \frac{4m^- + n(n-2)d_i^-}{n^3}\gamma\right) + O(\beta\gamma).$$

Denoting by $A_2^{\beta,\gamma}(G) \equiv \frac{1}{n^2} + \beta\frac{4}{n^3}m^+ - \gamma\frac{4}{n^3}m^-$ and $B_2 \equiv \frac{n-2}{n^2}$, this can be written as follows

$$\pi_i^*(G) = \left(A_2^{\beta,\gamma}(G) + B_2\left(\beta d_i^+ - \gamma d_i^-\right)\right) + O(\beta\gamma).$$

This completes the proof. ∎

Figure A.2 shows an illustration of the first-order approximation used to derive the equilibrium efforts in equation (38), and the exact value for the total centrality $\sum_{i=1}^{n} c_i^{\beta,\gamma}(G)$ for different values of β and γ for a bowtie graph.

Lemma 2 shows that, when network externalities are small, a group's fighting effort increases in the weighted difference between the number of enmities (weighted by γ) and alliances (weighted by β), i.e. the *net local externalities* $d_i^-\gamma - d_i^+\beta$. The opposite is true for the equilibrium payoff, which is increasing in $d_i^+\beta - d_i^-\gamma$. Thus, *ceteris paribus*, an increase in the spillover from alliances (enmities), parameterized by β (γ), and an increase in the number of allies (enemies) decreases (increases) group i's fighting effort and increases (reduces) its payoff. Intuitively, a group with many enemies tends to fight harder and to appropriate a smaller share of the prize, whereas a group with many friends tends to fight less and to appropriate a large size of the prize.

One must remember, however, that this simple result may fail to hold true if β and γ are not small and higher-degree links have sizeable effects.

5
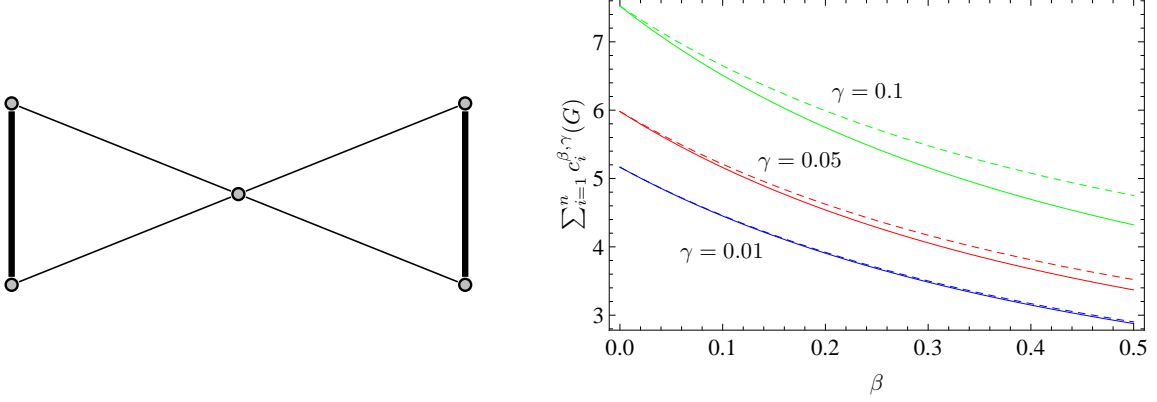
Figure A.2: (Left panel) Illustration of a bowtie graph, where the central agent is in conflict with all other agents and the peripheral pairs of agents are allied. Alliances are indicated with thick lines while conflict relationships are indicated with thin lines. (Right panel) The first-order approximation (dashed lines) used to derive the equilibrium efforts in equation (38), and the exact value (solid lines) for the total centrality $\sum_{i=1}^n c_i^{\beta,\gamma}(G)$ for different values of β and γ in the bowtie graph.

A.2 APPENDIX TO SECTION 2.4

In the following we provide a complete equilibrium characterization of the extension of our model that we have introduced in Section 2.4. When the fighting strength φ_i of group i depends on an idiosyncratic shifter $\tilde{\varphi}_i$ as in equation (13) then the following proposition characterizes the corresponding Nash equilibrium.

Proposition 2. *Let $\Gamma_i^{\beta,\gamma}(G)$ and $\Lambda^{\beta,\gamma}(G)$ be defined as in equation (6), and let*

$$\mathbf{c}_{\boldsymbol{\mu}}^{\beta,\gamma}(G) \equiv \left(\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-\right)^{-1}\boldsymbol{\mu} \tag{39}$$

be a centrality vector, whose generic element $c_{\boldsymbol{\mu},i}^{\beta,\gamma}(G)$ describes the centrality of group i in the network for some vector $\boldsymbol{\mu} \in \mathbb{R}^n$, and assume that the same parameter restrictions on β and γ hold as in Proposition 1. Then for the cost of defeat, D, large enough there exists a unique Nash equilibrium of the n–player simultaneous move game with payoffs given by equation (1), groups' OPs in equation (13) and strategy space $\mathbb{R}^n$, where the equilibrium effort levels are given by

$$x_i^*(G) = \Lambda^{\beta,\gamma}(G)\left(1 - \Lambda^{\beta,\gamma}(G)\right)c_{\mathbf{\Gamma}^{\beta,\gamma}(G),i}^{\beta,\gamma}(G) - c_{\tilde{\boldsymbol{\varphi}},i}^{\beta,\gamma}(G), \tag{40}$$

for all $i = 1, \ldots, n$. Moreover, aggregate operational performance at equilibrium is

$$\sum_{i=1}^n \varphi_i = \Lambda^{\beta,\gamma}(G), \tag{41}$$

individual operational performance at equilibrium as

$$\varphi_i = \Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))\Gamma_i^{\beta,\gamma}(G), \tag{42}$$

and the equilibrium payoffs are given by

$$\pi_i^*(G) \equiv \pi_i(\mathbf{x}^*, G) = (1 - \Lambda^{\beta,\gamma}(G))\left(\Gamma_i^{\beta,\gamma}(G) - \Lambda^{\beta,\gamma}(G)c_{\mathbf{\Gamma}^{\beta,\gamma}(G),i}^{\beta,\gamma}(G)\right) + c_{\boldsymbol{\varphi},i}^{\beta,\gamma}(G). \tag{43}$$

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Proof of Proposition 2. We start by considering an equilibrium in which all groups participate in the contest (i.e. an interior equilibrium). With equation (13) we can write group i's payoff as follows

$$
\begin{aligned}
\pi_i(G, \mathbf{x}) &= \frac{\varphi_i}{\sum_{j=1}^n \varphi_j} - x_i \\
&= \frac{x_i + \beta \sum_{j=1}^n a_{ij}^+ x_j - \gamma \sum_{j=1}^n a_{ij}^- x_j + \tilde{\varphi}_i}{\sum_{j=1}^n \left(x_j + \beta \sum_{k=1}^n a_{jk}^+ x_k - \gamma \sum_{k=1}^n a_{jk}^- x_k + \tilde{\varphi}_j \right)} - x_i.
\end{aligned}
\tag{44}
$$

The partial derivatives are given by

$$
\begin{aligned}
\frac{\partial \pi_i}{\partial x_i} &= \frac{\frac{\partial \varphi_i}{\partial x_i} \sum_{j=1}^n \varphi_j - \varphi_i \sum_{j=1}^n \frac{\partial \varphi_j}{\partial x_i}}{\left(\sum_{j=1}^n \varphi_j \right)^2} - 1 \\
&= \frac{\sum_{j=1}^n \varphi_j - \varphi_i(1 + \beta d_i^+ - \gamma d_i^-)}{\left(\sum_{j=1}^n \varphi_j \right)^2} - 1,
\end{aligned}
\tag{45}
$$

where we have used the fact that $\frac{\partial \varphi_j}{\partial x_i} = \delta_{ij} + \beta a_{ij}^+ - \gamma a_{ij}^-$ and consequently $\sum_{j=1}^n \frac{\partial \varphi_j}{\partial x_i} = 1 + \beta d_i^+ - \gamma d_i^-$. The FOCs are then given by $\frac{\partial \pi_i}{\partial x_i} = 0$. From the partial derivative in equation (45) the FOC for group i can be written as follows

$$
\frac{\partial \pi_i}{\partial x_i} = \frac{\sum_{j=1}^n \varphi_j - \varphi_i(1 + \beta d_i^+ - \gamma d_i^-)}{\left(\sum_{j=1}^n \varphi_j \right)^2} - 1 = 0,
$$

from which we get

$$
\varphi_i = \frac{1}{1 + \beta d_i^+ - \gamma d_i^-} \left(1 - \sum_{j=1}^n \varphi_j \right) \sum_{j=1}^n \varphi_j.
$$

Summation over i gives

$$
\sum_{i=1}^n \varphi_i = \left(1 - \frac{1}{\sum_{i=1}^n \frac{1}{1 + \beta d_i^+ - \gamma d_i^-}} \right).
$$

With $\Gamma_i^{\beta,\gamma}(G)$ and $\Lambda^{\beta,\gamma}(G)$ as in equation (6) we can write the aggregate operational performance as

$$
\sum_{i=1}^n \varphi_i = \Lambda^{\beta,\gamma}(G),
$$

which is equivalent to equation (41). The individual operational performance can be written as

$$
\varphi_i(G, \mathbf{x}) = \Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))\Gamma_i^{\beta,\gamma}(G),
\tag{46}
$$

which is equivalent to equation (41). We then get

$$
\varphi_i(G, \mathbf{x}) = x_i + \beta \sum_{j=1}^n a_{ij}^+ x_j - \gamma \sum_{j=1}^n a_{ij}^- x_j + \tilde{\varphi}_i = \Lambda^{n,\beta}(G)(1 - \Lambda^{n,\beta}(G))\Gamma_i^{\beta,\gamma}(G).
\tag{47}
$$

We can write

$$
x_i + \beta \sum_{j=1}^n a_{ij}^+ x_j - \gamma \sum_{j=1}^n a_{ij}^- x_j = \varphi_i - \tilde{\varphi}_i = \Lambda^{n,\beta}(G)(1 - \Lambda^{n,\beta}(G))\Gamma_i^{\beta,\gamma}(G) - \tilde{\varphi}_i.
$$

7

Denoting by $\mathbf{\Gamma}^{\beta,\gamma}(G) \equiv (\Gamma_1^{\beta,\gamma}(G), \ldots, \Gamma_n^{\beta,\gamma}(G))^\top$, we can write this in vector-matrix form as

$$(\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-)\mathbf{x} = \Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))\mathbf{\Gamma}^{\beta,\gamma}(G) - \tilde{\boldsymbol{\varphi}}.$$

When the matrix $\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-$ is invertible,[69] we obtain a unique solution given by

$$\mathbf{x} = \Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))(\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-)^{-1}\mathbf{\Gamma}^{\beta,\gamma}(G) - (\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-)^{-1}\tilde{\boldsymbol{\varphi}}. \tag{48}$$

With the definition of the centrality in equation (39) we then can write equation (48) in the form of equation (40) in the proposition. Moreover, using the fact that equilibrium payoffs are given by $\pi_i(\mathbf{x}^*, G) = \frac{\varphi_i^*(G)}{\sum_{j=1}^n \varphi_j^*(G)} - x_i^*$ we obtain equation (43) in the proposition.

Next, note that from equation (45) we find that

$$\frac{\partial^2 \pi_i}{\partial x_i^2} = -\frac{2}{\Lambda^{\beta,\gamma}(G)\Gamma_i^{\beta,\gamma}(G)} = -2\frac{\sum_{j=1}^n \Gamma_j^{\beta,\gamma}(G)}{\sum_{j=1}^n \Gamma_j^{\beta,\gamma}(G) - 1}(1 + \beta d_i^+ - \gamma d_i^-), \tag{49}$$

which is negative under the same parameter restrictions on β and γ as in Proposition 1. Further, as in the proof of Proposition 1 one can then proceed to establish that there exists a unique interior Nash equilibrium when the cost of defeat, D, is large enough. ∎

A.3   Appendix to Section 5.1

We next provide a complete characterization of the groups whose removal results in the greatest reduction in the rent dissipation in terms of their position in the network.

Proposition 3. *Let $G \backslash \{i\}$ be the network obtained from G by removing group i and assume that the conditions in Proposition 1 hold. Then group $i^* \in \overline{\mathcal{N}} \equiv \{1, \ldots, n\} \cup \emptyset$ whose removal results in the greatest reduction in the rent dissipation is given by*

$$i^* = \arg\max_{i \in \overline{\mathcal{N}}} \left\{ \mathrm{RD}^{\beta,\gamma}(G) - \mathrm{RD}^{\beta,\gamma}(G \backslash \{i\}) \right\},$$

where

$$\mathrm{RD}^{\beta,\gamma}(G) - \mathrm{RD}^{\beta,\gamma}(G \backslash \{i\})$$

$$= V\Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G)) \left\{ \sum_{j=i}^n c_j^{\beta,\gamma}(G) + \sum_{j \neq i} \frac{h_i^{\beta,\gamma}(G)(1 - (1 - \Lambda^{\beta,\gamma}(G))h_i^{\beta,\gamma}(G))}{1 - \Lambda^{\beta,\gamma}(G)} \right.$$

$$\times \sum_{k=1}^n \left[\left(m_{jk}^{\beta,\gamma}(G) - \frac{m_{ij}^{\beta,\gamma}(G)m_{ik}^{\beta,\gamma}(G)}{m_{ii}^{\beta,\gamma}(G)} \right) \Gamma_k^{\beta,\gamma}(G) \left(\frac{1 + \beta d_k^+ - \gamma d_k^-}{1 + \beta(d_k^+ - 1) - \gamma d_k^-} \mathbb{1}_{\{k \in \mathcal{N}_i^+\}} \right. \right.$$

$$\left. \left. \left. + \frac{1 + \beta d_k^+ - \gamma d_k^-}{1 + \beta d_k^+ - \gamma(d_k^- - 1)} \mathbb{1}_{\{k \in \mathcal{N}_i^-\}} + \mathbb{1}_{\{k \notin (\mathcal{N}_i^+ \cup \mathcal{N}_i^-)\}} \right) \right] \right\}, \tag{50}$$

and we have defined by

$$h_i^{\beta,\gamma}(G) \equiv \left(1 - \beta \sum_{j \in \mathcal{N}_i^+} \frac{\Gamma_j^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))}{1 + \beta(d_j^+ - 1) - \gamma d_j^-} - \gamma \sum_{j \in \mathcal{N}_i^-} \frac{\Gamma_j^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))}{1 + \beta d_j^+ - \gamma(d_j^- - 1)} \right)^{-1},$$

with $m_{ij}^{\beta,\gamma}(G)$ being the ij-th element of the matrix $\mathbf{M}^{\beta,\gamma}(G) = (\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-)^{-1}$.

---

[69]See the proof of Proposition 1 for sufficient conditions that guarantee invertibility.

Proof of Proposition 3. Let $G\backslash\{i\}$ be the network obtained from G by removing group i. Then the key player $i^* \in \overline{\mathcal{N}} = \{1, \ldots, n\} \cup \emptyset$ is given by

$$i^* = \arg\max_{i \in \overline{\mathcal{N}}} \left\{ \mathrm{RD}^{\beta,\gamma}(G) - \mathrm{RD}^{\beta,\gamma}(G\backslash\{i\}) \right\}.$$

We can write the change in rent dissipation due to the removal of group i as follows

$$\mathrm{RD}^{\beta,\gamma}(G) - \mathrm{RD}^{\beta,\gamma}(G\backslash\{i\}) = V\Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))$$
$$\times \left(\sum_{j=1}^{n} c_j^{\beta,\gamma}(G) - \frac{\Lambda^{\beta,\gamma}(G\backslash\{i\})(1 - \Lambda^{\beta,\gamma}(G\backslash\{i\}))}{\Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))} \sum_{j=1}^{n} c_j^{\beta,\gamma}(G\backslash\{i\}) \right).$$

With $\sum_{j=1}^{n} c_j^{\beta,\gamma}(G) = \sum_{j=1}^{n} m_{jk}^{\beta,\gamma}(G)\Gamma_k^{\beta,\gamma}(G)$, where $m_{ij}^{\beta,\gamma}(G)$ is the ij-th element of the matrix $\mathbf{M}^{\beta,\gamma}(G) = (\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-)^{-1}$, we can write this as

$$\mathrm{RD}^{\beta,\gamma}(G) - \mathrm{RD}^{\beta,\gamma}(G\backslash\{i\}) = V\Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G)) \left[c_i^{\beta,\gamma}(G) + \sum_{j \neq i} \sum_{k} \left(m_{jk}^{\beta,\gamma}(G)\Gamma_k^{\beta,\gamma}(G) \right. \right.$$
$$\left. \left. - \frac{\Lambda^{\beta,\gamma}(G\backslash\{i\})(1 - \Lambda^{\beta,\gamma}(G\backslash\{i\}))}{\Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))} m_{jk}^{\beta,\gamma}(G\backslash\{i\})\Gamma_k^{\beta,\gamma}(G\backslash\{i\}) \right) \right].$$

Using the fact that (cf. Lemma 1 in Ballester *et al.* 2006)

$$m_{jk}^{\beta,\gamma}(G\backslash\{i\}) = m_{jk}^{\beta,\gamma}(G) - \frac{m_{ij}^{\beta,\gamma}(G)m_{ik}^{\beta,\gamma}(G)}{m_{ii}^{\beta,\gamma}(G)},$$

and denoting by

$$h_i^{\beta,\gamma}(G) \equiv \frac{\Lambda^{\beta,\gamma}(G\backslash\{i\})(1 - \Lambda^{\beta,\gamma}(G\backslash\{i\}))}{\Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G))}$$
$$= \left(1 - \beta \sum_{j \in \mathcal{N}_i^+} \frac{\Gamma_j^{\beta,\gamma}(1 - \Lambda^{\beta,\gamma}(G))}{1 + \beta(d_j^+ - 1) - \gamma d_j^-} - \gamma \sum_{j \in \mathcal{N}_i^-} \frac{\Gamma_j^{\beta,\gamma}(1 - \Lambda^{\beta,\gamma}(G))}{1 + \beta d_j^+ - \gamma(d_j^- - 1)} \right)^{-1},$$

one can show that

$$\mathrm{RD}^{\beta,\gamma}(G) - \mathrm{RD}^{\beta,\gamma}(G\backslash\{i\})$$
$$= V\Lambda^{\beta,\gamma}(G)(1 - \Lambda^{\beta,\gamma}(G)) \left\{ \sum_{j=1}^{n} c_j^{\beta,\gamma}(G) + \sum_{j \neq i} \frac{h_i^{\beta,\gamma}(G)(1 - (1 - \Lambda^{\beta,\gamma}(G)))h_i^{\beta,\gamma}(G)}{1 - \Lambda^{\beta,\gamma}(G)} \right.$$
$$\times \sum_{k=1}^{n} \left[\left(m_{jk}^{\beta,\gamma}(G) - \frac{m_{ij}^{\beta,\gamma}(G)m_{ik}^{\beta,\gamma}(G)}{m_{ii}^{\beta,\gamma}(G)} \right) \Gamma_k^{\beta,\gamma}(G) \left(\frac{1 + \beta d_k^+ - \gamma d_k^-}{1 + \beta(d_k^+ - 1) - \gamma d_k^-} \mathbb{1}_{\{k \in \mathcal{N}_i^+\}} \right. \right.$$
$$\left. \left. \left. + \frac{1 + \beta d_k^+ - \gamma d_k^-}{1 + \beta d_k^+ - \gamma(d_k^- - 1)} \mathbb{1}_{\{k \in \mathcal{N}_i^-\}} + \mathbb{1}_{\{k \notin (\mathcal{N}_i^+ \cup \mathcal{N}_i^-)\}} \right) \right] \right\}, \tag{51}$$

where $\mathbb{1}_{\{k \in \mathcal{N}_i^+\}}$ and $\mathbb{1}_{\{k \in \mathcal{N}_i^-\}}$ are indicator variables taking the value of one if, respectively, $k \in \mathcal{N}_i^+$ and

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$k \in \mathcal{N}_i^-$, and zero otherwise. Then, the key player can be computed explicitly as

$$
\begin{aligned}
i^* \;=\; & \arg\max_{i\in\overline{\mathcal{N}}} \left\{ \sum_{j=1}^{n} c_j^{\beta,\gamma}(G) + \sum_{j\neq i} \frac{h_i^{\beta,\gamma}(G)\left(1 - \left(1 - \Lambda^{\beta,\gamma}(G)\right) h_i^{\beta,\gamma}(G)\right)}{1 - \Lambda^{\beta,\gamma}(G)} \right. \\
& \times \sum_{k=1}^{n} \left[\left(m_{jk}^{\beta,\gamma}(G) - \frac{m_{ij}^{\beta,\gamma}(G)\, m_{ik}^{\beta,\gamma}(G)}{m_{ii}^{\beta,\gamma}(G)} \right) \Gamma_k^{\beta,\gamma}(G) \left(\frac{1 + \beta d_k^+ - \gamma d_k^-}{1 + \beta\left(d_k^+ - 1\right) - \gamma d_k^-} \mathbb{1}_{\{k\in\mathcal{N}_i^+\}} \right. \right. \\
& \left. \left. \left. + \frac{1 + \beta d_k^+ - \gamma d_k^-}{1 + \beta d_k^+ - \gamma\left(d_k^- - 1\right)} \mathbb{1}_{\{k\in\mathcal{N}_i^-\}} + \mathbb{1}_{\{k\notin(\mathcal{N}_i^+\cup\mathcal{N}_i^-)\}} \right) \right] \right\}.
\end{aligned}
\tag{52}
$$

■

Observe that the group i^* identified in Proposition 3 differs from the "key player" introduced in Ballester *et al.* (2006). In the latter, the key player is defined as $i^* = \arg\max_{i\in\mathcal{N}} b_{\mathbf{u},i}(G,\alpha)/W_i(G,\alpha)$ with $b_{\mathbf{u},i}(G,\alpha)$ being the Katz-Bonacich centrality of group i in G and $W_i(G,\alpha)$ being the generating function of the number of closed walks that start and terminate at node i.[70] Compared with our key player formula in equation (50) we find that it is more involved. This is not surprising as the contest success function makes our payoff function generically non-linear.

A.4   Appendix to Section 5.2

In the following sections we develop the theoretical underpinning of the arms embargo that has been introduced in Section 5.2. In Section A.4.1 we generalize our payoff function to allow for a arms embargo that increases the marginal cost of fighting of the groups. We then show that this policy is equivalent to reducing the fighting efforts of the groups by a proportional factor. Section A.4.2 defines the planner's problem as a two-stage game where, in the first stage, the planner chooses the policy intervention with the objective to minimize the rent dissipation, while in the second stage, the groups take the policy as given and choose the fighting efforts so as to maximize their payoffs. In particular, Section A.4.2 solves for the Nash equilibrium of the second stage of the game, in which groups choose fighting efforts optimally, taking the policy as given. Section A.4.2 then provides an explicit expression for the planner's problem in the first stage, taking into account the Nash equilibrium effort levels from the second stage, assuming that the planner chooses a bilevel policy with only two possible values for the marginal fighting costs of the groups.

A.4.1   Payoffs

Consider a policy $\mathbf{s} \in \mathcal{S} \subset \mathbb{R}_+^n$ introduced by the planner to minimize the rent dissipation.[71] We assume that the policy $\mathbf{s}$ affects the operational performance of the groups. That is, the marginal cost of fighting of each group i changes from one to $1 + s_i$, so that the group i's payoff can be written as follows:

$$
\pi_i(G, \mathbf{x}) = \begin{cases} \dfrac{\varphi_i(G,\mathbf{x})}{\sum_{j=1}^n \max\{0, \varphi_j(G,\mathbf{x})\}} - (1 + s_i)x_i, & \text{if} \quad \varphi_i(G,\mathbf{x}) \geq 0, \\[2mm] -D, & \text{if} \quad \varphi_i(G,\mathbf{x}) < 0, \end{cases}
\tag{53}
$$

where the operational performance φ_i of group i depends on an idiosyncratic shifter $\tilde{\varphi}_i$ as in equation (13). The payoff function in equation (53), assuming that the operational performance of i is positive, can then be written as

$$
\pi_i(G, \mathbf{x}) = \frac{x_i + \beta \sum_{j=1}^n a_{ij}^+ x_j - \gamma \sum_{j=1}^n a_{ij}^- x_j + \tilde{\varphi}_i}{\sum_{j=1}^n \max\left\{0, x_j + \beta \sum_{k=1}^n a_{jk}^+ x_k - \gamma \sum_{j=1}^n a_{jk}^- x_k + \tilde{\varphi}_j\right\}} - (1 + s_i)x_i.
\tag{54}
$$

---

[70]See also equation (33) in the Appendix A.1.1.

[71]See also Section A.4.2 below.

Observe that when denoting by $\eta_i \equiv \frac{1}{1+s_i}$ and introducing the the rescaled effort levels $y_i \equiv \frac{1}{\eta_i}x_i = (1+s_i)x_i$, equation (54) can be written as

$$\pi_i(G, \mathbf{y}) = \frac{\eta_i y_i + \beta \sum_{j=1}^n a_{ij}^+ \eta_j y_j - \gamma \sum_{j=1}^n a_{ij}^- \eta_j y_j + \tilde{\varphi}_i}{\sum_{j=1}^n \max\left\{0, \eta_j y_j + \beta \sum_{k=1}^n a_{jk}^+ \eta_k y_k - \gamma \sum_{j=1}^n a_{jk}^- \eta_k y_k + \tilde{\varphi}_j\right\}} - y_i. \tag{55}$$

Solving the Nash equilibrium for $\mathbf{y}^*$ then yields the corresponding Nash equilibrium for $\mathbf{x}^*$. Hence, there exists a duality between efforts and cost rescaling. Notice also that without the network, G, and the shifters, $\tilde{\varphi}$, equation (55) is equivalent to a contest success game with different relative effectiveness, $(\eta_i)_{1 \leq i \leq n}$, as it has been considered in Stein (2002) and Baik (1994).

A.4.2 The Planner's Problem

The planner's objective is to maximize welfare defined as

$$W^{\beta,\gamma}(G, \mathbf{s}) = \sum_{i=1}^n \pi_i^*(G, \mathbf{s}) = 1 - \sum_{i=1}^n x_i^*(G, \mathbf{s}) = 1 - \mathrm{RD}^{\beta,\gamma}(G, \mathbf{s}), \tag{56}$$

where the rent dissipation is

$$\mathrm{RD}^{\beta,\gamma}(G, \mathbf{s}) \equiv \sum_{i=1}^n x_i^*(G, \mathbf{s}),$$

and $x_i^*(G, \mathbf{s})$ are the Nash equilibrium effort levels in the presence of the policy $\mathbf{s}$. Obviously, maximizing welfare is equivalent to minimizing the rent dissipation. Then planner then has to solve to following 2-stage game:

First Stage: The planner (international agency) announces a policy $\mathbf{s} \in \mathcal{S}$ to change the opportunity costs of fighting of the groups in order to minimize the rent dissipation in equation (56).

Second Stage: After observing $\mathbf{s}$, the groups choose their fighting efforts optimally (Nash equilibrium), taking $\mathbf{s}$ as given. Then, payoffs are realized.

Second Stage In this section we solve the second stage of the game, in which groups choose fighting efforts optimally, taking the policy $\mathbf{s}$ as given. The following proposition characterizes the corresponding Nash equilibrium.

Proposition 4. *Denote by $\mathbf{D}(\mathbf{s}) \equiv \mathrm{diag}(s_1, \ldots, s_n)$, define the local hostility level as*

$$\Gamma_i^{\beta,\gamma}(G) \equiv \frac{1}{1 + \beta d_i^+ - \gamma d_i^-},$$

and let the weighted total local fighting intensity be given by

$$\tilde{\Lambda}^{\beta,\gamma}(G, \mathbf{s}) \equiv \frac{\mathbf{u}^\top \mathbf{\Gamma}^{\beta,\gamma}(G) - 1}{\mathbf{u}^\top (\mathbf{I}_n + \mathbf{D}(\mathbf{s})) \mathbf{\Gamma}^{\beta,\gamma}(G)}. \tag{57}$$

Assume that the same parameter restrictions on β and γ hold as in Proposition 1. Then for the cost of defeat, D, large enough there exists a unique Nash equilibrium of the n–player simultaneous move game with payoffs given by equation (53), groups' OPs in equation (13) and strategy space $\mathbb{R}^n$, where the equilibrium effort levels are given by

$$\mathbf{x}^*(G, \mathbf{s}) = (\mathbf{I}_n + \beta \mathbf{A}^+ - \gamma \mathbf{A}^-)^{-1} \left[\tilde{\Lambda}^{\beta,\gamma}(G, \mathbf{s})(\mathbf{I}_n - \tilde{\Lambda}^{\beta,\gamma}(G, \mathbf{s})(\mathbf{I}_n + \mathbf{D}(\mathbf{s})) \mathbf{\Gamma}^{\beta,\gamma}(G) - \tilde{\varphi} \right], \tag{58}$$

for all $i = 1, \ldots, n$.

Proof of Proposition 4. We start by considering an equilibrium in which all groups participate in the contest (i.e. an interior equilibrium). The necessary FOCs can be written as

$$\frac{1}{1+s_i}\frac{\partial \pi_i}{\partial x_i} = \frac{1}{1+s_i}\frac{\sum_{j=1}^{n}\varphi_j - \varphi_i(1+\beta d_i^+ - \gamma d_i^-)}{\left(\sum_{j=1}^{n}\varphi_j\right)^2} - 1 = 0. \tag{59}$$

We then get

$$\varphi_i = \frac{1}{1+\beta d_i^+ - \gamma d_i^-}\left(1 - (1+s_i)\sum_{j=1}^{n}\varphi_j\right)\sum_{j=1}^{n}\varphi_j.$$

Summation over all i gives

$$\sum_{j=1}^{n}\varphi_j = \frac{1}{\sum_{j=1}^{n}\frac{1+s_j}{1+\beta d_j^+ - \gamma d_j^-}}\left(\sum_{j=1}^{n}\frac{1}{1+\beta d_j^+ - \gamma d_j^-} - 1\right).$$

In the following we denote by

$$\tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s}) \equiv \frac{1}{\sum_{j=1}^{n}\frac{1+s_j}{1+\beta d_j^+ - \gamma d_j^-}}\left(\sum_{j=1}^{n}\frac{1}{1+\beta d_j^+ - \gamma d_j^-} - 1\right)$$

$$= \frac{1}{\sum_{i=1}^{n}(1+s_i)\Gamma_i^{\beta,\gamma}(G)}\left(\sum_{i=1}^{n}\Gamma_i^{\beta,\gamma}(G) - 1\right) = \frac{\mathbf{u}^\top\mathbf{\Gamma}^{\beta,\gamma}(G) - 1}{\mathbf{u}^\top(\mathbf{I}_n + \mathbf{D}(\mathbf{s}))\mathbf{\Gamma}^{\beta,\gamma}(G)},$$

so that we can write aggregate effective fighting effort as follows

$$\sum_{j=1}^{n}\varphi_j = \tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s}).$$

We then get

$$\varphi_i = \tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s})\left(1 - (1+s_i)\tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s})\right)\Gamma_i^{\beta,\gamma}(G),$$

and so we can write

$$x_i + \beta\sum_{j=1}^{n}a_{ij}^+ x_j - \gamma\sum_{j=1}^{n}a_{ij}^- x_j + \tilde{\varphi}_i = \tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s})\left(1 - (1+s_i)\tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s})\right)\Gamma_i^{\beta,\gamma}(G).$$

In vector-matrix notation this is

$$\left(\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-\right)\mathbf{x} = \tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s})\mathbf{\Gamma}^{\beta,\gamma}(G,\boldsymbol{\lambda}) - \tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s})^2(\mathbf{I}_n + \mathbf{D}(\mathbf{s}))\mathbf{\Gamma}^{\beta,\gamma}(G,\boldsymbol{\lambda}) - \mathbf{z},$$

where $\mathbf{D}(\mathbf{s}) = \text{diag}\{s_1,\ldots,s_n\}$. When the matrix $(\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-)$ is invertible,[72] we can write

$$\mathbf{x} = \tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s})\left(\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-\right)^{-1}\mathbf{\Gamma}^{\beta,\gamma}(G)$$

$$- \tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s})^2\left(\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-\right)^{-1}(\mathbf{I}_n + \mathbf{D}(\mathbf{s}))\mathbf{\Gamma}^{\beta,\gamma}(G) - \left(\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-\right)^{-1}\mathbf{z}.$$

If we denote by $\mathbf{M}^{\beta,\gamma}(G) \equiv (\mathbf{I}_n + \beta\mathbf{A}^+ - \gamma\mathbf{A}^-)^{-1}$ then we can write this as follows

$$\mathbf{x} = \tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s})\mathbf{M}^{\beta,\gamma}(G)\left(\mathbf{I}_n - \tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s})(\mathbf{I}_n + \mathbf{D}(\mathbf{s}))\right)\mathbf{\Gamma}^{\beta,\gamma}(G) - \mathbf{M}^{\beta,\gamma}(G)\tilde{\boldsymbol{\varphi}}.$$

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[72]See the proof of Proposition 1 for sufficient conditions that guarantee invertibility.

From equation (59) we further find that

$$\frac{\partial^2 \pi_i}{\partial x_i^2} = -\frac{2}{\tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s})\Gamma_i^{\beta,\gamma}(G)} = -2\frac{\sum_{i=1}^n (1+s_i)\Gamma_i^{\beta,\gamma}(G)}{\sum_{i=1}^n \Gamma_i^{\beta,\gamma}(G) - 1}(1 + \beta d_i^+ - \gamma d_i^-),\tag{60}$$

which is negative if $\tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s}) > 0$ and $1 + \beta d_i^+ - \gamma d_i^- > 0$. The last inequality implies that the local hostility level of group i is positive, i.e. $\Gamma_i^{\beta,\gamma}(G) > 0$. Observe from the definition of $\tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s}) > 0$ in equation (57) that $\tilde{\Lambda}^{\beta,\gamma}(G,\mathbf{s}) > 0$ if $\Lambda^{\beta,\gamma}(G) > 0$. Hence, the same parameter restrictions as in Proposition 1 can be applied here. Moreover, as in the proof of Proposition 1 one can then proceed to establish that there exists a unique interior Nash equilibrium when the cost of defeat, D, is large enough. ∎

From Proposition 4 it follows that the share of the territory appropriated by group i in the equilibrium is given by

$$\frac{\varphi_i}{\sum_{j=1}^n \varphi_j} = \left(1 - \frac{\sum_{j=1}^n \Gamma_j^{\beta,\gamma}(G) - 1}{\sum_{j=1}^n \frac{1+s_j}{1+s_i}\Gamma_j^{\beta,\gamma}(G)}\right)\Gamma_i^{\beta,\gamma}(G),$$

and thus is decreasing with s_i, the policy targeting group i.

First Stage In the following sections we provide an explicit expression for the planner's problem, taking into account the Nash equilibrium effort levels from the second stage (cf. Section A.4.2), when the planner chooses a bilevel policy with two possible values $s_1 \neq s_2$ and $s_i = s_1$ for all $i \in \mathcal{N}_1$ while $s_i = s_2$ for all $i \in \mathcal{N}_2$ with $\mathcal{N} = \{1, 2, \ldots, n\} = \mathcal{N}_1 \cup \mathcal{N}_2$.[73] W.l.o.g. we set $s_2 = 0$, $s_1 = s$, and let $\mathcal{N}_1 = \{1, \ldots, n_1\}$ and $\mathcal{N}_2 = \{n_1 + 1, \ldots, n\}$. We then have that

$$\mathbf{D}(s) = \begin{pmatrix} s & 0 & \cdots & & \cdots & 0 \\ 0 & \ddots & \ddots & & & \vdots \\ \vdots & \ddots & s & \ddots & & \vdots \\ \vdots & & & 0 & \ddots & 0 \\ \vdots & & & \ddots & \ddots & 0 \\ 0 & \cdots & & \cdots & 0 & 0 \end{pmatrix},$$

and we can write

$$\begin{aligned}\tilde{\Lambda}^{\beta,\gamma}(G,s) &= \frac{\mathbf{u}^\top \mathbf{\Gamma}^{\beta,\gamma}(G) - 1}{\mathbf{u}^\top (\mathbf{I}_n + \mathbf{D}(\mathbf{s}))\mathbf{\Gamma}^{\beta,\gamma}(G)} \\ &= \frac{\sum_{i=1}^n \Gamma_i^{\beta,\gamma}(G) - 1}{(1+s)\sum_{i=1}^{n_1} \Gamma_i^{\beta,\gamma}(G) + \sum_{i=n_1+1}^n \Gamma_i^{\beta,\gamma}(G)} \\ &= \frac{\mathbf{u}^\top \mathbf{\Gamma}^{\beta,\gamma}(G) - 1}{(1+s)\mathbf{u}_1^\top \mathbf{\Gamma}^{\beta,\gamma}(G) + \mathbf{u}_2^\top \mathbf{\Gamma}^{\beta,\gamma}(G)},\end{aligned}$$

where we have denoted by $\mathbf{u}_1 = (1, \ldots, 1, 0, \ldots, 0)^\top$ and $\mathbf{u}_2 = (0, \ldots, 0, 1, \ldots, 1)^\top$. Further, let $\mathbf{M}^{\beta,\gamma}(G) = (\mathbf{I}_n + \beta \mathbf{A}^+ - \gamma \mathbf{A}^-)^{-1}$, $\mathbf{u}$ be a column vector of ones, then with equation (58) we can write the rent dissipation

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[73]Note that the number of partitions of $\mathcal{N}$ into two mutually disjoint non-empty subsets whose union is $\mathcal{N}$ is given by $2^{n-1} - 1$ (see Prop. 3.10, in Joshi 1989: 101). For $n = 80$ this is 6.0446×10^{23}. Because this large number is computationally infeasible, in our experiments in Section 5.2 we consider only partitions among up to 15 groups with $16,383$ possible cases.

as follows

$$
\begin{aligned}
\mathrm{RD}^{\beta,\gamma}(G,s) &= \mathbf{u}^\top \mathbf{x}^*(G,s) \\
&= \mathbf{u}^\top \mathbf{M}^{\beta,\gamma}(G) \left[\tilde{\Lambda}^{\beta,\gamma}(G,s)(\mathbf{I}_n - \tilde{\Lambda}^{\beta,\gamma}(G,s)(\mathbf{I}_n + \mathbf{D}(\mathbf{s}))\boldsymbol{\Gamma}^{\beta,\gamma}(G) - \tilde{\boldsymbol{\varphi}} \right] \\
&= \tilde{\Lambda}^{\beta,\gamma}(G,s)\mathbf{u}^\top \mathbf{M}^{\beta,\gamma}(G)\boldsymbol{\Gamma}^{\beta,\gamma}(G) \\
&\quad - \tilde{\Lambda}^{\beta,\gamma}(G,s)^2 \mathbf{u}^\top \mathbf{M}^{\beta,\gamma}(G)(\mathbf{I}_n + \mathbf{D}(\mathbf{s}))\boldsymbol{\Gamma}^{\beta,\gamma}(G) \\
&\quad - \mathbf{u}^\top \mathbf{M}^{\beta,\gamma}(G)\tilde{\boldsymbol{\varphi}}.
\end{aligned} \tag{61}
$$

The planner's problem is then to choose a value of s such that the rent dissipation $\mathrm{RD}^{\beta,\gamma}(G,s)$ from in equation (61) is minimized, given the partition $\mathcal{N} = \mathcal{N}_1 \cup \mathcal{N}_2$.

B Empirical Analysis Appendix

This section contains a discussion of the data construction, robustness checks, and additional econometric results.

B.1 Appendix to Section 3

B.1.1 Fighting Groups

In the paper, we discuss pros and cons of different datasets. In column 7 of the baseline Table 2 we show robustness of the main findings with respect to using geo-coordinates from GED for the ACLED events to which they can be matched. This serves the purpose of addressing the concerns of Eck (2012) arguing that geo-coordinates of ACLED are sometimes imprecise. We proceed as follows:

1. The first step is to automatically match events based on the date. In particular, to each event in ACLED, all those events in GED are associated that may be matches given information on the date of the event. We construct a time buffer of +/-2 days around each event in GED to allow for possibly imprecise measurement of the date. We also account for differences in the definition of multi-day events across both data sets by splitting the GED event into a separate event for each day of its duration.

2. Among these candidate matches we keep only those event-pairs for which at least one armed group of the potential match is present for both data sets.

3. To further reduce the set of acceptable event-pairs we require that either of the following two conditions holds true: i) The GED event involves only non-civilians and for both sides of the conflict, we can find at least one common fighting party across the datasets. ii) The GED event is a conflict between civilians and some armed group, which is also involved (on either side) in the corresponding ACLED event (here we account for the fact that GED tends to report *civilians* when ACLED would report armed groups).

4. Next, whenever an event in either of the datasets comes with information about fatalities, we use this information to classify the event according to three "atrocity categories": low (# fatalities < 25th percentile), medium (# fatalities ≥ 25th percentile & < 75th percentile) or high (# fatalities ≥ 75 percentile). We eliminate candidate matches for which fatality numbers are high in one dataset and low in the other one.

5. Finally, for every ACLED event that is still associated with more than one event from GED, we keep only the event pair that minimizes the distance between the specified locations in GED and ACLED.

6. We then go manually through the set of these candidate matches, comparing any available information describing a particular event in the datasets. We confirm a match whenever the distance between two algorithmically matched events (steps 1-5) is lower than a hundred kilometers and/or our manual inspection reveals that the events are identical.

Out of the total of 1641 events in GED, the ones that successfully pass through all six steps are called *confirmed match* (1090 events), the ones going through the most basic automatic steps 1-2 but being weeded out afterwards are called *inconclusive* (149 events), while all other GED events are called *unmatched* (402 events). For the confirmed matches, we replace in column 7 the coordinates in ACLED with the respective coordinates in GED. This conservative coding minimizes the risk of introducing wrong georeferences in the dataset.

In column 8 of the baseline Table 2 we build a so-called *superdataset* that is the union of GED and ACLED. In particular, we start out from the dataset of column 7 that has replaced the ACLED geo-coordinates with GED geo-coordinates for the 1090 confirmed matches. To this dataset we add the 402 clear-cut unmatched cases for which we can be confident that they are not present in the ACLED dataset. This conservative approach minimizes the risk of double-counting events.

Other alternative georeferenced datasets Below we shall discuss two further georeferenced datasets of violence in the DRC, and discuss for which reasons we could not draw on them in our study.

First of all, Van der Windt and Humphreys (2016) conduct a localized study (*Voix des Kivus*) in 18 villages in the Southern Kivu province in 2011 entrusting selected villagers to collect information and send SMS coded reports about violent events (e.g. violence against women, riots or attacks against the village). During a period of eighteen months Voix des Kivus received about 5,000 messages, while ACLED reports only 50 events. It is not surprising that villagers report minor episodes that do not make their way into the press. Although this pilot study is very useful, it is difficult for us to draw formal comparisons, since Voix des Kivus does for confidentiality reasons not reveal the name of the village where a given event took place.

Another georeferenced dataset of political violence is GDELT (Leetaru and Schrodt 2013), which follows a "Big Data" approach and relies on automatic computer coding. Compared to ACLED and GED, GDELT has the advantage of worldwide coverage. However, it is –at least as far as the DRC is concerned– much less precise and more prone to errors. In particular, in most cases different rebel groups are not distinguished and just called "rebels" or "Congolese". The computer algorithm also relatively often fails to filter out the correct actors involved (e.g. "Reuters" often appears as actor rather than source). Further, like GED, GDELT restricts the number of actors in an event to a total of two, which makes it unsuitable to be used for detecting alliances.

B.1.2 The Network

While in the main text we discuss the construction of the fighting network in some depth, there are two aspects on which we shall elaborate here. First, we shall explain in more detail the rationale underlying the choice of our four sources of expert coding. Second, we will discuss in more details the few cases showing changes in alliances and enmities.

As listed in the main text, our primary sources for constructing the network of enmities and alliances are four expert classifications of links in the Second Congo War. In particular, (i) the Yearbook of the Stockholm International Peace Research Institute, SIPRI (Seybolt 2000), (ii) "Non-State Actor data" (Cunningham *et al.* 2013), (iii) Briefing on the Congo War by the International Crisis Group (1998), and (iv) a summary account of the war by Williams (2013).

The sources (i) and (ii) are most comprehensive and cover the large actors. SIPRI lists both alliances and enmities between the major actors, including both actors operating in the same region and groups fighting in different parts of the country but supporting each other logistically. The "Non-State Actor data" is based on the Uppsala Armed Conflict Data about civil conflicts augmented with information about the non-state actors involved and about the external support to active groups.

The sources (iii) and (iv) supplement the main information from (i) and (ii), by covering also some smaller groups that are left out by (i) and (ii). Source (iii) has the advantage of being collected by a major intelligence provider on conflict with extensive local knowledge. However, it has the disadvantage of dating back to the beginning of the conflict. In contrast, source (iv) is more recent.

The second aspect of network construction that we want to emphasize here is the potential worry about possible changes in the system of alliances involving small groups that we might be unaware of. To detect possible such cases, we focus on dyads classified as neutral featuring an inconsistent battlefield behavior, namely neutral dyads that are observed fighting more than once as brother-in-arms and and more than once on opposite sides. With this definition, we have 8 inconsistent dyads. Among them, we should be especially

worried about cases where we observe a clear structural break, namely, when there exists a threshold year $T \in \{1998, \dots, 2010\}$ such that two groups would be classified as allies (enemies) if one restricted attention to the years up to T, while the same two groups would be classified as enemies (allies) if one considered the years after T. This would suggest a reshuffle in the alliance in conflict with our assumption of a stable network. Altogether, this problem arises for only two dyads.[74] This suggests that the problem of changing alliances is not severe. In the remaining six cases, inconsistencies may arise from tactical behavior, thereby suggesting that two groups are neither solid allies nor enemies. Four of the eight inconsistent observations concern the Mayi-Mayi militia, a group that has no centralized structure and that is prone to tactical shifts.

List of network links   Table B.1 below reports a list of all 80 groups of our sample indicating the number of allies (d^+) and the number of enemies (d^-) of each group, as well as listing the acronyms of allies and enemies.[75]

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[74]The two dyads are the Burundi-based CNDD(FDD) and the RCD-G, and the RCD and MayMay Militia. In the first case, the narrative is inconclusive. In the second case, the narrative would suggest a hostile relationship. However, we have no information from our expert sources. In addition the two groups fight alongside in one quarter of the events. Therefore, we stick to our rule not to hand-code links, and classify them as neutral.

[75]In the Appendix tables, we use the shorter acronyms RWA94 and RWA00 for Rwanda-I and Rwanda-II, respectively. When listing groups we order them according to their Africa-wide involvement in fighting events (i.e. we list more active groups first).

Table B.1: List of groups with their alliances and enemies.

Name	Acronym	d^+	d^-	Names allies	Names enemies
LRA: Lord's Resistance Army	LRA	1	6	SUDAN	UGANDA, SPLA, FARDC-LK, FARDC-JK RWA00, UELE
UNITA: National Union for the Total Independence of Angola	UNITA	4	3	UGANDA, RWA94, RCD, DSP	ANGOLA, FARDC-LK, NAMIBIA
FAA/MPLA: Military Forces of Angola (1975-)	ANGOLA	4	5	FARDC-LK, ZIMBABWE, FARDC-JK NAMIBIA	UNITA, UGANDA, RCD-G, RWA94, RCD-K
Military Forces of Uganda (1986-)	UGANDA	9	13	UNITA, BURUNDI, SPLA, RWA94 RCD-K, MLC, RCD, HEMA, UELE	LRA, ANGOLA, HUTU, SUDAN, FARDC-LK ADF, FDLR, MM, INTERAH, FARDC-JK UPC, LENDU, RWA00
Hutu Rebels	HUTU	2	3	FARDC-LK, MM	UGANDA, RCD-G, RWA94
Military Forces of Burundi (1996-2005)	BURUNDI	3	1	UGANDA, RWA94, RCD	CNDD
SPLA/M: Sudanese People's Liberation Army/Movement	SPLA	1	1	UGANDA	LRA
Military Forces of Sudan (1993-)	SUDAN	4	3	LRA, FARDC-LK, ADF, FARDC-JK	UGANDA, RCD-K, MLC
FNL: National Forces of Liberation	FNL	1	2	FDLR	CNDD, FARDC-JK
Military Forces of Democratic Republic of Congo (Kabila, L.)	FARDC-LK	21	16	ANGOLA, HUTU, SUDAN, ADF, FDLR, MM, CNDD, ZIMBABWE, CHAD, INTERAH LENDU, ADFL, NAMIBIA, RWA73, SAF MM-P, MM-Y, MM-K, MM-L, MM-J, MM-M	LRA, UNITA, UGANDA, RCD-G, RWA94, RCD-K, MLC, RCD, HEMA, MUTINY, ALIR, FLC, RWA00, BANYA, RCD-M, RCD-N
ADF: Allied Democratic Forces	ADF	4	3	SUDAN, FARDC-LK, MM, NALU	UGANDA, RWA94, FARDC-JK
RCD: Rally for Congolese Democracy (Goma)	RCD-G	4	14	RWA94, RCD, RWA00, RCD-N	ZIMBABWE, INTERAH, RCD-K, MLC, FARDC-JK, ADFL, NAMIBIA, RWA73, SAF, CNDD-N
FDLR: Democratic Forces for the Liberation of Rwanda	FDLR	6	5	FNL, FARDC-LK, INTERAH, MM-P, MM-Y, APCLS	UGANDA, CNDP, POLICE, RWA00, RUD
Military Forces of Rwanda (1994-1999)	RWA94	7	10	UNITA, UGANDA, BURUNDI, RCD-G, ADFL, RCD, MUTINY	ANGOLA, HUTU, FARDC-LK, ADF, ZIMBABWE, INTERAH, FARDC-JK, NAMIBIA, RWA73, ALIR
Mayi-Mayi Milita	MM	7	6	HUTU, FARDC-LK, ADF, FARDC-JK, RWA73, MM-P, CNDD-N	UGANDA, RCD-G, RCD-K, FLC, RWA00, ZAMBIA
CNDD-FDD: National Council for the Defence of Democracy – Forces for the Defence of Democracy	CNDD	1	3	FARDC-LK	BURUNDI, FNL, INTERAH
Military Forces of Zimbabwe (1980-)	ZIMBABWE	6	4	ANGOLA, FARDC-LK, INTERAH FARDC-JK, NAMIBIA, SAF	RCD-G, RWA94, RCD-K FLC
Military Forces of Chad (1990-)	CHAD	2	1	FARDC-LK, FARDC-JK	RCD-K
Interahamwe Hutu Ethnic Militia	INTERAH	5	7	FARDC-LK, FDLR, ZIMBABWE FARDC-JK, RCD-M	UGANDA, RCD-G, RWA94, CNDD, MLC, RCD, RWA00
RCD: Rally for Congolese Democracy (Kisangani)	RCD-K	5	13	UGANDA, LENDU, RCD, NGITI, RCD-N	ANGOLA, SUDAN, FARDC-LK RCD-G, MM, ZIMBABWE CHAD, MLC, FARDC-JK, UPC, NAMIBIA, HEMA, RWA00
CNDP: National Congress for the Defense of the People	CNDP	2	3	MUTINY, RWA00	FDLR, FARDC-JK, MM-P

Table B.1 cont.: List of groups with their alliances and enemies.

Name	Acronym	d^+	d^-	Names allies	Names enemies
MLC: Congolese Liberation Movement	MLC	4	7	UGANDA, RCD, RWA00, RCD-N	SUDAN, FARDC-LK, RCD-G, INTERAH, RCD-K, FARDC-JK, IHEMA
Military Forces of Democratic Republic of Congo (Kabila, J.)	FARDC-JK	16	26	ANGOLA, SUDAN, MM, ZIMBABWE CHAD, INTERAH, LENDU, NAMIBIA, RWA73, POLICE, MM-P, MM-Y, MM-K, MM-L, MM-J, MM-M	LRA, UGANDA, FNL, ADF RCD-G, RWA94, RCD-K, CNDP, MLC, UPC, RCD, FNI, FPJC, FRPI, MUTINY, MRC, NALU, RWA00, UPPS, BDK, ENYELE, LOBALA, FRF, APCLS, MUNZ, MINEM
UPC: Union of Congolese Patriots	UPC	1	5	HEMA	UGANDA, RCD-K, FARDC-JK, LENDU, PUSIC
Lendu Ethnic Militia (DRC)	LENDU	3	6	FARDC-LK, RCD-K, FARDC-JK	UGANDA, UPC, RCD, HEMA, PUSIC, WAGE
ADFL: Alliance of Democratic Forces for Liberation (Congo-Zaire) (1996-1997)	ADFL	2	2	FARDC-LK, RWA94	RCD-G, RWA00
RCD: Rally for Congolese Democracy	RCD	11	4	UNITA, UGANDA, BURUNDI, RCD-G, RWA94, RCD-K, MLC, HEMA, RWA00, RCD-M, RCD-N	FARDC-LK, INTERAH, FARDC-JK, LENDU
Military Forces of Zaire (1965-1997)	ZAIRE	0	0		
Military Forces of Namibia (1990-2005)	NAMIBIA	4	4	ANGOLA, FARDC-LK, ZIMBABWE, FARDC-JK	UNITA, RCD-G, RWA94, RCD-K
FNI: Nationalist and Integrationist Front	FNI	1	1	MRC	FARDC-JK
Former Military Forces of Rwanda (1973-1994)	RWA73	3	3	FARDC-LK, MM, FARDC-JK	RCD-G, RWA94, RWA00
FPJC: Popular Front for Justice in Congo	FPJC	0	1		FARDC-JK
FRPI: Front for Patriotic Resistance of Ituri	FRPI	1	2	MRC	FARDC-JK, MUTINY
Hema Ethnic Militia (DRC)	HEMA	4	5	UGANDA, UPC, RCD, ALUR	FARDC-LK, RCD-K, MLC, LENDU, LENDU-U
Mutiny of Military Forces of Democratic Republic of Congo (2003-)	MUTINY	2 / 2	3 / 3	RWA94, CNDP	FARDC-LK, FARDC-JK, FRPI
ALIR: Army for the Liberation of Rwanda	ALIR	0	2		FARDC-LK, RWA94
MRC: Revolutionary Movement of Congo	MRC	2	1	FNI, FRPI	FARDC-JK
NALU: National Army for the Liberation of Uganda	NALU	2	1	ADF, ADC	FARDC-JK
FLC: Congolese Liberation Front	FLC	0	3		FARDC-LK, MM, ZIMBABWE
Military Forces of South Africa (1994-1999)	SAF	2	1	FARDC-LK, ZIMBABWE	RCD-G
Police Forces of Democratic Republic of Congo (2001-2011)	POLICE	1	1	FARDC-JK	FDLR
Mayi Mayi Militia (PARECO)	MM-P	4	1	FARDC-LK, FDLR, MM, FARDC-JK	CNDP
PUSIC: Party for the Unity and Safekeeping of Congo's Integrity	PUSIC	0	2		UPC, LENDU

Table B.1 cont.: List of groups with their alliances and enemies.

Name	Acronym	d^+	d^-	Names allies	Names enemies
Military Forces of Rwanda (2000-)	RWA00	4	11	RCD-G, CNDP, MLC, RCD	LRA, UGANDA, FARDC-LK, FDLR, MM, INTERAH, RCD-K, FARDC-JK, ADFL, RWA73, RCD-M
UPPS: Union for Democracy and Social Progress Party (DRC)	UPPS	0	1		FARDC-JK
Mayi-Mayi Militia (Yakutumba)	MM-Y	3	0	FARDC-LK, FDLR, FARDC-JK	
PRA: People's Redemption Army	PRA	0	0		
BDK: Bunda Dia Kongo	BDK	0	1		FARDC-JK
Military Forces of Zambia (1991-2002)	ZAMBIA	0	1		MM
PPRD: People's Party for Reconstruction and Democracy	PPRD	0	0		
RUD: Gathering for Unity and Democracy	RUD	0	1		FDLR
Enyele Ethnic Militia (DRC)	ENYELE	0	1		FARDC-JK
Lobala (Enyele) Militia	LOBALA	0	2		FARDC-JK, BOMBO
Mayi-Mayi Militia (Kifuafua)	MM-K	2	0	FARDC-LK, FARDC-JK	
FRF: Federal Republican Forces	FRF	0	1		FARDC-JK
APCLS: Alliance of Patriots for a Free and Sovereign Congo	APCLS	1	1	FDLR	FARDC-JK
Banyamulenge Ethnic Militia (DRC)	BANYA	0	1		FARDC-LK
Lendu Ethnic Militia (Uganda)	LENDU-U	0	1		HEMA
Munzaya Ethnic Militia (DRC)	MUNZ	0	1		FARDC-JK
Alur Ethnic Militia (Uganda)	ALUR	1	0	HEMA	
Haut-Uele Resident Militia	UELE	1	1	UGANDA	LRA
Mayi Mayi Milita (Cmdt La Fontaine)	MM-L	2	1	FARDC-LK, FARDC-JK	MM-J
Mayi-Mayi Militia (Cmdt Jackson)	MM-J	2	1	FARDC-LK, FARDC-JK	MM-L
Minembwe Dissidents	MINEM	0	1		FARDC-JK
Bomboma Ethnic Militia	BOMBO	0	1		LOBALA
DSP: Division Speciale Presidentelle	DSP	1	0	UNITA	
Group of 47	G47	0	0		
Ngiti Ethnic Militia	NGITI	1	0	RCD-K	
RCD: Rally for Congolese Democracy (Masunzu)	RCD-M	3	2	INTERAH, RCD, RCD-N	FARDC-LK, RWA00
Wageregere Ethnic Militia	WAGE	0	1		LENDU
Alliance for Democratic Change	ADC	1	0	NALU	
CNDD-FDD: National Council for the Defense of Democracy-Ndayikengurukiye faction	CNDD-N	1	1	MM	RCD-G
RCD: Rally for Congolese Democracy (National)	RCD-N	5	1	RCD-G, RCD-K, MLC, RCD, RCD-M	FARDC-LK
FAP: Popular Self-Defense Forces	FAP	0	0		
Hutu Refugees (Rwanda)	HUTU-R	0	0		
Mayi Mayi Militia (Mbuayi)	MM-M	2	0	FARDC-LK, FARDC-JK	
Mbingi Community Militia (DRC)	MBINGI	0	0		
Mutiny of LRA: Lord's Resistance Army	MUTLRA	0	0		
Pygmy Ethnic Group (DRC)	PYGMY	0	0		
Wangilima Ethnic Militia	WANGI	0	0		

B.2.1   Migration

The outbreak of the Second Congo War in 1998 has led to large-scale internal migration, with the peak of 3.4 million internally displaced people (IDPs) being reached at the end of 2003 (White 2014). The number of IDPs has somewhat dropped since then, but remains high until today (fluctuating between one and three million people in the past 10 years). Most IDPs are accounted for by North Kivu, Province Orientale (mainly Ituri), South Kivu and Katanga (Internal Displacement Monitoring Centre 2009).

According to Zeender and Rothing (2010: 10), "the vast majority of IPD's find refuge outside camp settings, whether with host families in other villages and urban areas, or in forests. Very often people are displaced on multiple occasions but for a short time". Ethnic and family ties play a crucial role and drive moving decisions to large extent: "Displaced would reportedly go to a location where they knew they had family or at least members of their same ethnic group. If there were difficulties in going to a place where family or their ethnic group could be found, groups of displaced would go to larger towns with a mixed ethnic profile, such as Kiwanja/Rutshuru or Goma" (Internal Displacement Monitoring Centre 2009: 69).

One challenge to the exclusion restriction could be migration triggered by weather shocks. One could imagine a situation where averse weather shocks hitting a group i's allies j or enemies k leads people from j or k to move to i, and the presence of new arrivers could cause tensions and ultimately increase fighting effort of i. In this case there would be a violation of the exclusion restriction that j and k's rainfall should only affect i's fighting effort through the channel of j and k's fighting effort. While in some countries this could be a valid concern, in the case of the DRC this seems unlikely to matter empirically. According to White (2014) the quasi-totality of migration movements in the DRC in the last decades have been caused by conflict and concerns about security (i.e. only 0.7% of migrants indicate fleeing from "natural catastrophies", with all other reported categories been conflict/security related). Given that the displacements are a consequence of conflict (Refugee Studies Center 2010), it seems hence very unlikely in the DRC context that lack of rain lets people leave their fields, which is often the only resource they have at disposal for making a living.

This strong reliance on access to their fields also makes that "people reportedly try to stay close to home so that they can monitor their lands and track the local security situation. (. . .) IDPs travel between half a day to one and a half days to reach a place of safety" (White 2014: 6). Or in the words of the Internal Displacement Monitoring Centre (2009: 69), "Generally, respondents indicated a preference to stay as close to their home locations as possible. Reasons for this included, being in a familiar rural environment, being close to their homes to monitor security or to access their banana plantations, root crops or fields. (. . .) The nature of the displacement movements that we see in North Kivu and Ituri is often over short distances from 5 to 80 kilometers". This means that even when people seek shelter, they are unlikely to travel far away and hence not overly likely to penetrate zones of activity of other groups.

Further, if there were to be isolated cases of rainfall shocks triggering migration waves, one would –a priori—expect the impact of rain on the willingness to migrate to be similar for different groups j and k, while in our first stage regressions we detect opposite signs for rainfall shocks hitting allies and enemies of a given group i.

Note also that the waging of the war and the implied displacements have also led to a collapse of internal trade: "The displacement of farmers, the burning of fields and food stocks, and the destruction of infrastructure have made trade and commerce extremely difficult (. . .)" (Zeender and Rothing 2010: 11). This has important consequences for our identification strategy. A potential threat to the exclusion restriction would be that rain fall shocks hitting group i's allies j and enemies k could affect internal trade and thereby could have a direct impact on fighting effort of group i, other than going through the fighting efforts of j and k. However, the fact that fighting led to a collapse in internal trade attenuates concerns about the violation of the exclusion restriction.

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B.2.2   Alternative Spatial Kernels

In Section 4, we discuss issues related to spatial dependence in our data. In Section 4.1, we estimate standard errors with a spatial HAC correction allowing for both cross-sectional spatial correlation and location-specific serial correlation, following Conley (1999 and 2008). We program a STATA code that allows us to estimate Conley standard errors in a flexible fashion. In the spatial dimension we retain a radius of 150 km for the spatial kernel. More specifically, the weighs in the covariance matrix are assumed to decay linearly with the distance from the central point of a group's homeland, reaching zero after 150km. We impose no constraint on the temporal decay for the Newey-West/Bartlett kernel that governs serial correlation across time periods.

In this section, we show the robustness of our results to an alternative spatial kernel. In Tables B.2 and B.3 we replicate the baseline tables of the main text (second stage Table 2 and first stage Table 3), but using a spatial threshold for correlated standard errors of 500 km (instead of 150 km). The results are very similar to the baseline and –if anything– stronger.

Further, in Tables B.4 and B.5 we take the other extreme stand and shut down all spatial correlation. Concretely, we simply cluster standard errors at the group level. Again, the results are very similar to the ones presented in the baseline Tables 2 and 3.

Table B.2: Benchmark second stage (spatial 500km).

		Dependent variable: Total Fighting						
	OLS	Reduced IV	Full IV	Neutrals	Battles	$d^- \geq 1 \wedge d^+ \geq 1$	GED coord.	GED union
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total Fight. Enemies (TFE)	0.066***	0.130**	0.066***	0.083***	0.081***	0.091***	0.084***	0.125***
	(0.014)	(0.053)	(0.016)	(0.016)	(0.016)	(0.020)	(0.016)	(0.030)
Total Fight. Allies (TFA)	0.001	-0.218***	-0.117***	-0.114***	-0.117***	-0.157***	-0.112***	-0.117***
	(0.012)	(0.081)	(0.024)	(0.023)	(0.024)	(0.034)	(0.021)	(0.025)
Total Fight. Neutrals (TFN)	–	–	–	0.004	0.004	0.013	0.004	0.006
	–	–	–	(0.004)	(0.004)	(0.009)	(0.003)	(0.003)
Additional controls	Reduced	Reduced	Full	Full	Full	Full	Full	Full
Estimator	OLS	IV	IV	IV	IV	IV	IV	IV
Set of Instrument Variables	n.a.	Restricted	Full	Full	Full	Full	Full	Full
Kleibergen-Paap F-stat	n.a.	17.4	48.0	62.0	52.0	77.0	60.1	31.2
Hansen J (p-value)	n.a.	0.32	0.97	0.99	0.99	0.99	0.99	0.99
Observations	1040	1040	1040	1040	988	598	1040	1781
R-squared	0.510	0.265	0.579	0.568	0.567	0.537	0.569	0.516

Note: An observation is a given armed group in a given year. The panel contains 80 armed groups between 1998 and 2010. All regressions include group fixed effects and control for rainfall in the group's homeland. Columns 1-3 include time fixed effects. Robust standard errors corrected for Spatial HAC in parentheses (distance threshold 500 km). Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Baseline first stage (spatial 500 km).

	IV regression of column (2)		IV regression of column (3)		IV regression of column (4)	
Dep. Variable:	TFE (1)	TFA (2)	TFE (3)	TFA (4)	TFE (5)	TFA (6)
Rain $(t-1)$ **Enem.**	**-1.595*****	-0.019	**-1.354*****	0.277	**-1.327*****	0.291**
	(0.195)	(0.141)	**(0.259)**	(0.172)	**(0.243)**	(0.139)
Sq. Rain $(t-1)$ Enem.	0.000***	0.000	0.000***	-0.000	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rain $(t-1)$ **All.**	0.126	**-0.929*****	0.028	**-0.588*****	0.089	**-0.571*****
	(0.308)	**(0.117)**	(0.232)	**(0.149)**	(0.224)	**(0.188)**
Sq. Rain $(t-1)$ All.	-0.000*	0.000***	-0.000	0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Current Rain Enem.	–	–	**-1.125*****	0.131*	**-0.937*****	0.073
	–	–	**(0.165)**	(0.076)	**(0.168)**	(0.089)
Sq. Curr. Rain Enem.	–	–	0.000***	-0.000***	0.000***	-0.000***
	–	–	(0.000)	(0.000)	(0.000)	(0.000)
Current Rain All.	–	–	-0.461**	**-0.366*****	-0.414*	**-0.448*****
	–	–	(0.205)	**(0.080)**	(0.226)	**(0.139)**
Sq. Curr. Rain All.	–	–	0.000	0.000***	0.000	0.000***
	–	–	(0.000)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap F-stat	17.4	17.4	48.0	48.0	62.0	62.0
Hansen J (p-value)	0.32	0.32	0.97	0.97	0.99	0.99
Observations	1040	1040	1040	1040	1040	1040

Note: An observation is a given armed group in a given year. The panel contains 80 armed groups between 1998 and 2010. All regressions include group fixed effects and control for rainfall in the group's homeland. Columns 1-4 contain time fixed effects. Robust standard errors corrected for Spatial HAC in parentheses (spatial threshold 500 km). Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Benchmark second stage (clustering at group level).

| | OLS | Reduced IV | Full IV | Neutrals | Battles | $d^- \geq 1 \wedge d^+ \geq 1$ | GED coord. | GED union |
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Dependent variable: Total Fighting				
Total Fight. Enemies (TFE)	0.066***	0.130**	0.066***	0.083***	0.081***	0.091***	0.084***	0.125***
	(0.015)	(0.055)	(0.021)	(0.021)	(0.022)	(0.025)	(0.021)	(0.037)
Total Fight. Allies (TFA)	0.001	-0.218***	-0.117***	-0.114***	-0.117**	-0.157**	-0.112***	-0.117***
	(0.020)	(0.082)	(0.045)	(0.043)	(0.047)	(0.068)	(0.041)	(0.042)
Total Fight. Neutrals (TFN)	–	–	–	0.004	0.004	0.013	0.004	0.006
	–	–	–	(0.005)	(0.005)	(0.013)	(0.004)	(0.005)
Additional controls	Reduced	Reduced	Full	Full	Full	Full	Full	Full
Estimator	OLS	IV	IV	IV	IV	IV	IV	IV
Set of Instrument Variables	n.a.	Restricted	Full	Full	Full	Full	Full	Full
Kleibergen-Paap F-stat	n.a.	10.3	11.1	13.7	12.9	12.3	14.0	6.8
Hansen J (p-value)	n.a.	0.11	0.67	0.50	0.39	0.55	0.48	0.46
Observations	1040	1040	1040	1040	988	598	1040	1781
R-squared	0.510	0.265	0.579	0.568	0.567	0.537	0.569	0.516

Note: An observation is a given armed group in a given year. The panel contains 80 armed groups between 1998 and 2010. All regressions include group fixed effects and control for rainfall in the group's homeland. Columns 1-3 include time fixed effects. Robust standard errors clustered at group level in parentheses. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: Baseline first stage (clustering at group level).

	IV regression of column (2)		IV regression of column (3)		IV regression of column (4)	
Dep. Variable:	TFE (1)	TFA (2)	TFE (3)	TFA (4)	TFE (5)	TFA (6)
Rain $(t-1)$ Enemies	**-1.595*****	-0.019	**-1.354*****	0.277*	**-1.327*****	0.291*
	(0.250)	(0.143)	**(0.322)**	(0.161)	**(0.311)**	(0.155)
Sq. Rain $(t-1)$ Enem.	0.000***	0.000	0.000***	-0.000	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rain $(t-1)$ Allies	0.126	**-0.929*****	0.028	**-0.588*****	0.089	**-0.571****
	(0.309)	**(0.164)**	(0.262)	**(0.203)**	(0.262)	**(0.227)**
Sq. Rain $(t-1)$ All.	-0.000	0.000***	-0.000	0.000***	-0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Current Rain Enemies	–	–	**-1.125*****	0.131	**-0.936*****	0.073
	–	–	**(0.259)**	(0.127)	**(0.274)**	(0.126)
Sq. Curr. Rain Enem.	–	–	0.000***	-0.000**	0.000*	-0.000*
	–	–	(0.000)	(0.000)	(0.000)	(0.000)
Current Rain Allies			-0.461**	**-0.366*****	-0.414**	**-0.448*****
			(0.210)	**(0.135)**	(0.203)	**(0.160)**
Sq. Curr. Rain All.	–	–	0.000	0.000***	0.000	0.000***
	–	–	(0.000)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap F-stat	10.3	10.3	11.1	11.1	13.7	13.7
Hansen J (p-value)	0.11	0.11	0.67	0.67	0.50	0.50
Observations	1040	1040	1040	1040	1040	1040

Note: An observation is a given armed group in a given year. The panel contains 80 armed groups between 1998 and 2010. All regressions include group fixed effects and control for rainfall in the group's homeland. Columns 1-4 contain time fixed effects. Robust standard errors clustered at group level in parentheses. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.2.3 Variation over Time in the Network Structure (Section 4.2.1)

In Subsection 4.2.1 we show that our baseline results are robust to a time-varying network, taking into account periods of activities of the armed groups in our sample. Table B.6 below lists the window of activity used for every group.

Table B.6: Window of activity used for every group.

Name	Start	End	Name	Start	End
LRA	1998	2010	POLICE	2001	2010
UNITA	1998	2010	MM-P	2006	2009
ANGOLA	1998	2010	PUSIC	2003	2004
UGANDA	1998	2010	RWA00	2000	2010
HUTU	1998	2005	UPPS	2005	2010
BURUNDI	1998	2010	MM-Y	2008	2010
SPLA	1998	2010	PRA	2006	2006
SUDAN	1998	2010	BDK	2006	2008
FNL	1998	2010	ZAMBIA	1998	2010
FARDC-LK	1998	2001	PPRD	2006	2010
ADF	1998	2010	RUD	2008	2008
RCD-G	1998	2010	ENYELE	2009	2010
FDLR	2000	2010	LOBALA	2009	2010
RWA94	1998	1999	MM-K	2009	2009
MM	1998	2010	FRF	2002	2010
CNDD	1998	2002	APCLS	2008	2010
ZIMBABWE	1998	2010	BANYA	2001	2001
CHAD	1998	2010	LENDU-U	2002	2003
INTERAH	1998	2010	MUNZ	2009	2010
RCD-K	1998	2010	ALUR	2002	2002
CNDP	2006	2010	UELE	2009	2009
MLC	1998	2010	MM-L	2007	2007
FARDC-JK	2002	2010	MM-J	2007	2007
UPC	2001	2005	MINEM	2007	2007
LENDU	1999	2003	BOMBO	2009	2009
ADFL	2002	2002	DSP	1998	1999
RCD	1999	2004	G47	2007	2008
ZAIRE	2004	2004	NGITI	2002	2009
NAMIBIA	1998	2010	RCD-M	2002	2002
FNI	2003	2010	WAGE	1999	1999
RWA73	1999	2004	ADC	2010	2010
FPJC	2008	2010	CNDD-N	2002	2002
FRPI	2002	2010	RCD-N	2002	2002
HEMA	2000	2003	FAP	1999	1999
MUTINY	1998	2008	HUTU-R	2009	2009
ALIR	1998	2001	MM-M	2007	2007
MRC	2005	2007	MBINGI	2009	2009
NALU	1998	2010	MUTLRA	2008	2008
FLC	2001	2001	PYGMY	2009	2009
SAF	1998	2010	WANGI	2000	2000

Note: This table lists the windows of activity of groups defined by expert coding and ACLED, as used in columns 1 and 4 of Table 4 (for the other columns see the explanations in the text). We did not restrict the windows of activity of state actors because these are always in existence (besides for DRC and Rwanda, as discussed). For the other groups, when no expert sources were available we sticked to the ACLED window of activity. For the groups with expert sources available, see listed below the sources used (with clickable links): LRA: Human Rights Watch; UNITA: Encyclopedia Britannica; FNL: International Crisis Group Africa Briefing, 6 August 2002 (p. 6); ADF: International Crisis Group Africa Briefing N93 (p. 1); RCD: GlobalSecurity.org; FDLR: UN report: S/2008/43 (p. 9); Interahamwe Hutu Ethnic Militia: Human Rights Watch (p. 8); RCD: GlobalSecurity.org; CNDP: Human Rights Watch (p. 3); MLC: Human Rights Watch (p. 15); UPC: Terrorism Research & Analysis Consortium; FPJC: UN report: S/2008/773 (p. 30); FRPI: Human Rights Watch (p. 16); ALIR: UN Report (footnote 1094 on p. 306); NALU: UN Report (p. 173); FLC: UN Report (p. 221); PUSIC: Human Rights Watch (p. 16); UPPS: RefWorld.org; BDK: GlobalSecurity.org; PPRD: BBC.co.uk; RUD: International Crisis Group (footnote, p. 5); FRF: Congosiasa Blog; APCLS: IRINnews.org; Minembwe Dissidents: Syfia Grands Lacs; RCD: IRINnews.org; CNDD-FDD: International Crisis Group Arica Briefing, 6 August 2002 (p. 8); RCD: Human Rights Watch (p. 36); FAP: Politique Africaine N-084-RDC (footnote 20, p. 25); UNAFEC: LaConscience.com (Archived).

B.2.4   Alternative Specifications (Section 4.2.2)

In this section, we report the result of the analysis summarized in Section 4.2.2 (Tables B.7, B.8, and B.9).

Table B.7: Second-Degree IV, Salient Events, and Alternative Network Construction.

	Only degree 2	Sample split	Only violent	Batt, riots, viol.	Excl. bilateral	Lags	1 evts. enem.	2 evts. all.	RUM
	Dependent variable: Total fighting								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Total Fight. Enemies (TFE)	0.074***	0.147**	0.083***	0.083***	0.063***	0.090***	0.119***	0.089***	0.106***
	(0.027)	(0.062)	(0.019)	(0.019)	(0.023)	(0.026)	(0.029)	(0.019)	(0.033)
Total Fight. Allies (TFA)	-0.207**	0.002	-0.114***	-0.114***	-0.110***	-0.104***	-0.170***	-0.107***	-0.112**
	(0.083)	(0.079)	(0.033)	(0.034)	(0.033)	(0.040)	(0.051)	(0.033)	(0.050)
Total Fight. Neutrals (TFN)	0.008	0.011	0.004	0.004	0.004	0.007	0.005	0.002	0.002
	(0.006)	(0.007)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.004)	(0.006)
Additional controls	Full	Full	Full	Full	Full	Full	Full	Full	Full
Estimator	IV	IV	IV	IV	IV	IV	IV	IV	IV
Set of Instrument Variables	Full	Full	Full	Full	Full	Full	Full	Full	Full
Kleibergen-Paap F-stat	13.4	37.7	22.5	24.6	20.4	20.3	11.8	25.3	4.0
Hansen J (p-value)	0.28	0.84	0.58	0.58	0.54	0.69	0.51	0.51	0.62
Observations	1040	640	1040	1027	1040	960	1040	1040	1040
R-squared	0.489	0.589	0.568	0.570	0.550	0.577	0.394	0.571	0.554

Note: An observation is a given armed group in a given year. The panel contains 80 armed groups between 1998 and 2010. All regressions include group fixed effects and control for rainfall in the group's homeland. Robust standard errors corrected for Spatial HAC in parentheses. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: Robustness: Group Definition (FARDC, Rwanda & Others).

	Dependent variable: Total Fighting			
Merge	FARDC	MayMay	Rwanda	FARDC & RWA
	(1)	(2)	(3)	(4)
Total Fight. Enemies (TFE)	0.040**	0.068***	0.074***	0.040**
	(0.019)	(0.022)	(0.022)	(0.020)
Total Fight Allies (TFA)	-0.058*	-0.084***	-0.108***	-0.066*
	(0.034)	(0.032)	(0.032)	(0.037)
Total Fight. Neutrals (TFN)	-0.002	-0.000	0.003	-0.003
	(0.004)	(0.005)	(0.005)	(0.004)
Additional controls	Full	Full	Full	Full
Estimator	IV	IV	IV	IV
Set of Instrument Variables	Full	Full	Full	Full
Kleibergen-Paap F-stat	34.6	15.4	19.7	29.8
Hansen J (p-value)	0.44	0.66	0.59	0.51
Observations	1027	962	1027	1014
R-squared	0.631	0.614	0.589	0.642

Note: An observation is a given armed group in a given year. The panel contains 80 armed groups between 1998 and 2010. All regressions include group fixed effects and control for rainfall in the group's homeland. Robust standard errors corrected for Spatial HAC in parentheses. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.9: Robustness: Ambiguous Network Links.

	Uga-Rwa neutral (1)	Uga-Rwa allies (2)	Uga-Rwa allies then neutral (3)	FARDC-FDLR allies then enemies (4)	FARDC-FDLR neutral (5)	Exclude CNDD (6)	Uga-RCD-G enemies (7)	SADC allies (8)	Dyadic closure main groups (9)
	Dependent variable: Total Fighting								
Total Fight. Enemies (TFE)	0.082***	0.081***	0.082***	0.090***	0.083***	0.083***	0.074***	0.082***	0.075***
	(0.021)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)
Total Fight Allies (TFA)	-0.105***	-0.109***	-0.112***	-0.116***	-0.112***	-0.111***	-0.104***	-0.116***	-0.100***
	(0.031)	(0.033)	(0.033)	(0.033)	(0.036)	(0.033)	(0.031)	(0.035)	(0.031)
Total Fight. Neutrals (TFN)	0.004	0.003	0.004	0.003	0.003	0.002	0.004	0.004	0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Additional controls	Full	Full	Full	Full	Full	Full	Full	Full	Full
Estimator	IV	IV	IV	IV	IV	IV	IV	IV	IV
Set of Instrument Variables	Full	Full	Full	Full	Full	Full	Full	Full	Full
Kleibergen-Paap F-stat	19.9	20.2	19.8	16.7	23.4	27.2	20.8	19.2	12.7
Hansen J (p-value)	0.60	0.59	0.58	0.60	0.56	0.54	0.57	0.55	0.58
Observations	1040	1040	1040	1040	1040	1027	1040	1040	1040
R-squared	0.574	0.573	0.569	0.577	0.565	0.574	0.577	0.573	0.589

Note: An observation is a given armed group in a given year. The panel contains 80 armed groups between 1998 and 2010. All regressions include group fixed effects and control for rainfall in the group's homeland. Robust standard errors corrected for Spatial HAC in parentheses. Significance levels are indicated by $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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B.2.5 Measurement Error in Rainfall (Section 4.2.3)

In this section, we report the result of the analysis summarized in Section 4.2.3 (Table B.10).

Table B.10: Measurement error in rainfall.

	Dependent variable: GPCC gauge rainfall measure							
Model	Linear		Log-linear		Linear		Log-linear	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
# ACLED conflict events	0.017	0.008	0.009	0.001	-0.069	0.016	-0.016	0.005
	(0.032)	(0.012)	(0.008)	(0.003)	(0.057)	(0.014)	(0.014)	(0.004)
TRMM satellite rainfall measure	0.639***	0.513***	0.714***	0.619***	–	–	–	–
	(0.018)	(0.012)	(0.015)	(0.013)	–	–	–	–
GPCP satellite rainfall measure	–	–	–	–	0.790***	1.073***	0.843***	1.233***
	–	–	–	–	(0.044)	(0.081)	(0.055)	(0.100)
(0.5 x 0.5) Grid Cell FE	No	Yes	No	Yes	No	Yes	No	Yes
Annual TE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9893	9893	9893	9893	9893	9893	9893	9893
R-squared	0.578	0.667	0.604	0.684	0.555	0.601	0.541	0.587

 Note: An observation is a given cell of resolution 0.5 x 0.5 degrees in a given year. The panel contains 761 cells covering DRC between 1998 and 2010. In Columns 3,4,5,6 all rainfall variables are in log. Robust standard errors are clustered at the (0.5 x 0.5) cell level in Columns 1-4 and at the (2.5 x 2.5) cell level in Columns 5-8. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.2.6   Measurement Error in Network Links (Section 4.2.4)

In this section, we discuss in more details the Monte Carlo approach of Section 4.2.4 that is based on rewiring links in the observed network at random, and measuring the robustness of our estimates in such perturbed networks. For each Monte Carlo draw, we consider a data generating process based on the reduced form equation (14): The true parameters correspond to our baseline estimates, $\beta = 0.114$ and $\gamma = 0.083$, and the true network corresponds to the one used in our baseline estimation *after rewiring* a (sub-)set of alliances/enmities/neutral links according to a binomial process with a probability that is invariant across the draws. Then the benchmark 2SLS specification (Column 4, Table 2) is estimated on this fake dataset under the assumption that the network observed by the econometrician is identical to the baseline one *before* rewiring. Iterating over 1,000 Monte Carlo draws yields the sampling distribution of the estimates of β and γ subject to link measurement error. We consider different assumptions about the extent and nature of measurement error of the network.

The results are reported in Table B.11. Each pair of columns refers to a particular mismeasurement probability, namely the probability governing the binomial re-wiring process. From left to right, we assume that the probability that links are measured with error is zero (no measurement error), 1%, 10%, 20%, 50% and one (pure noise), respectively. In all cases we report the mean and standard deviations of the sampling distribution based on 1,000 simulations.

In the absence of measurement error – Columns 1 and 2 – we see that the mean of the sampling distribution is close to the true value of the parameter (difference arises at the 3 digit level due to finite-sampling). This confirms that our estimator is consistent. Consider, next, the pair of columns corresponding to interior probabilities of mismeasurement (1%, 10%, 20% and 50%). For instance, focus on the 10% measurement error case (fifth and sixth columns). In the first row (*enmity links only*), we draw from a distribution where each enmity link has a probability 10% to be in reality a neutral relationship (no link), whereas each neutral (no link) has a probability 10% to be in fact an enmity link. Since the number of neutrals exceeds by far that of enmities, this perturbation implies that in reality there are more enmity links than we observe. As expected, this experiment affects the estimate of γ more than it affects that of β. The estimate of β is close to the no measurement error benchmark (first column) at the two digit level, whereas the estimate of γ falls from 0.085 to 0.077. Namely, measurement error implies an attenuation bias. Next, consider the second row (*alliance links only*). This is the polar opposite scenario: alliance (rather than enmity) links are measured with error. Now, the estimate of β also falls from 0.119 to 0.107. Finally, in the third row, we allow mismeasurement of both enmity and alliance links. In this case the estimate of β falls to 0.101 and that of γ falls to 0.067. A similar pattern is observed in the other interior columns. As one moves to the right, i.e., towards larger measurement errors, the attenuation bias becomes stronger. In the last two columns, when the econometrician observes pure noise for enmity (alliance) links, the estimates of γ and β tend to zero.

The lesson from this section is twofold. First, the Monte Carlo generated measurement errors in the links leads to an attenuation bias. This suggests that, under the plausible assumption that some information about existing links is missing, our regression analysis underestimates the spillover effects. Second, the extent of the bias is quantitatively modest. A measurement error of the order of 10% (which we regard as fairly large) yields an underestimate of the spillover parameters of the order of 12% for β and 23% for γ.

Table B.11: Monte Carlo simulations testing link mismeasurement.

Probability of mismeasurement		0		0.01		0.1		0.2		0.5		1	
		β	γ	β	γ	β	γ	β	γ	β	γ	β	γ
Enmity links only	Mean	0.118	0.085	0.117	0.084	0.112	0.077	0.106	0.0713	0.102	0.046	0.119	0.002
	S.D.	0.012	0.011	0.012	0.011	0.014	0.013	0.019	0.022	0.024	0.020	0.018	0.015
Alliance links only	Mean	0.119	0.085	0.117	0.0843	0.107	0.075	0.095	0.066	0.059	0.055	0.000	0.083
	S.D.	0.012	0.011	0.014	0.011	0.019	0.015	0.023	0.019	0.027	0.022	0.008	0.008
Alliance & Enmity links	Mean	0.118	0.085	0.116	0.083	0.101	0.067	0.086	0.051	0.040	0.012	0.001	-0.001
	S.D.	0.012	0.010	0.014	0.012	0.022	0.019	0.028	0.023	0.037	0.028	0.017	0.014

Note: This table reports the mean and standard deviations (S.D.) of the Monte Carlo sampling distributions (1000 draws) of the 2SLS estimates of β and γ for different probabilities of link mismeasurement. The data generating process is based on true $\beta = 0.114$ and true $\gamma = 0.083$.

B.3 Appendix to Section 5

In this section, we provide the appendix tables that are referred to in Section 5.

Table B.12: Complete list of group removal.

Group	Sh. aggr. fight.	$-\Delta$RD	Multiplier
RCD-G	0.087	0.151	1.740
RCD-K	0.060	0.094	1.587
RWANDA	0.053	0.066	1.232
LRA	0.041	0.056	1.365
FDLR	0.066	0.055	0.822
MM	0.057	0.046	0.814
UGANDA	0.043	0.043	0.996
CNDP	0.043	0.041	0.946
MLC	0.031	0.039	1.254
UPC	0.022	0.030	1.406
LENDU	0.024	0.022	0.912
MUTINY	0.016	0.016	0.979
INERAH	0.014	0.014	1.013
ADF	0.013	0.012	0.939
FRPI	0.009	0.010	1.107
HEMA	0.009	0.009	0.975
FNI	0.008	0.009	1.033
CNDD	0.007	0.008	1.173
FPJC	0.006	0.007	1.146
SPLA	0.007	0.007	0.961
HUTU	0.005	0.006	1.163
ZIMBABWE	0.007	0.005	0.699
MRC	0.005	0.004	0.878
ALIR	0.004	0.004	1.081
ANGOLA	0.004	0.004	1.044
PUSIC	0.003	0.003	1.177
NAMIBIA	0.003	0.003	0.940
SAF	0.003	0.003	1.009
NALU	0.003	0.002	0.905
BURUNDI	0.003	0.002	0.811
RWA73	0.002	0.002	0.956
BDK	0.002	0.002	1.136
MM-P	0.004	0.002	0.564
SUDAN	0.002	0.002	0.749
FLC	0.002	0.002	1.112
ENYELE	0.001	0.001	1.126
MUNZ	0.001	0.001	1.126
PPRD	0.001	0.001	0.979
LOBALA	0.001	0.001	1.201
UNITA	0.001	0.001	0.779
FNL	0.001	0.001	1.098
BOMBO	0.001	0.001	1.060
MM-Y	0.001	0.001	0.582
MINEM	0.001	0.001	1.108
ADFL	0.001	0.001	1.079
LENDU-U	0.001	0.001	1.035
APCLS	0.001	0.001	0.995
UELE	0.001	0.001	0.924
FRF	0.000	0.001	1.094
WAGE	0.000	0.000	1.013
ZAMBIA	0.000	0.000	1.006

Table B.12 cont.: Complete list of group removal.

Group	Sh. aggr. fight.	$-\Delta$RD	Multiplier
RUD	0.000	0.000	1.005
MM-L	0.001	0.000	0.707
MM-J	0.001	0.000	0.707
RCD-M	0.000	0.000	0.902
CHAD	0.000	0.000	0.801
UPPS	0.000	0.000	1.066
CNDD-N	0.000	0.000	1.006
BANYA	0.000	0.000	0.916
G47	0.000	0.000	0.914
MBINGI	0.000	0.000	0.914
ALUR	0.000	0.000	0.786
NGITI	0.000	0.000	0.647
MM-K	0.000	0.000	0.613
HUTU-R	0.000	0.000	0.829
PRA	0.000	0.000	0.829
PYGMY	0.000	0.000	0.829
FAP	0.000	0.000	0.829
MUTLRA	0.000	0.000	0.829
WANGI	0.000	0.000	0.829
DSP	0.000	0.000	0.738
ADC	0.000	0.000	0.727
MM-M	0.000	0.000	0.519
RCD-N	0.000	0.000	0.036
RCD	0.018	-0.002	0.142

Table B.13: Joint removal of two groups (top 50).

Group 1	Group 2	$-\Delta$RD	Sh. aggr. fight.	Multiplier	Cumul. $-\Delta$RD sep. removal	Multi-player complem.
RWANDA	RCD-G	0.243	0.140	1.735	0.217	1.122
RCD-K	RCD-G	0.213	0.146	1.455	0.245	0.867
FDLR	RCD-G	0.209	0.153	1.362	0.206	1.015
RCD-G	LRA	0.208	0.128	1.620	0.207	1.001
RCD-G	UGANDA	0.195	0.130	1.498	0.194	1.004
CNDP	RCD-G	0.190	0.130	1.463	0.192	0.992
MM	RCD-G	0.187	0.144	1.306	0.197	0.950
UPC	RCD-G	0.180	0.108	1.658	0.181	0.991
LENDU	RCD-G	0.178	0.111	1.601	0.173	1.027
MLC	RCD-G	0.169	0.118	1.435	0.190	0.890
RCD-G	ADF	0.165	0.100	1.650	0.163	1.010
MUTINY	RCD-G	0.165	0.103	1.601	0.167	0.989
INTERAH	RCD-G	0.159	0.101	1.582	0.165	0.965
RCD-K	UGANDA	0.155	0.103	1.501	0.138	1.122
RCD-K	FDLR	0.151	0.126	1.196	0.149	1.011
RCD-K	LRA	0.149	0.101	1.479	0.151	0.989
RCD-K	RWANDA	0.147	0.113	1.303	0.160	0.919
CNDP	RCD-K	0.136	0.103	1.324	0.136	1.006
LENDU	RCD-K	0.134	0.084	1.601	0.117	1.151
RCD-K	MM	0.130	0.116	1.118	0.141	0.924
UPC	RCD-K	0.118	0.081	1.459	0.125	0.948
CNDP	RWANDA	0.118	0.097	1.216	0.107	1.102
MLC	RCD-K	0.116	0.090	1.279	0.133	0.869
MLC	RWANDA	0.113	0.084	1.342	0.104	1.083
RWANDA	FDLR	0.112	0.120	0.937	0.120	0.933
RCD-K	INTERAH	0.111	0.073	1.508	0.109	1.021
FDLR	LRA	0.111	0.108	1.027	0.111	0.997
RWANDA	LRA	0.110	0.095	1.163	0.122	0.902
RCD-K	ADF	0.109	0.073	1.501	0.107	1.022
MUTINY	RCD-K	0.109	0.076	1.437	0.110	0.987
RWANDA	MM	0.108	0.110	0.978	0.112	0.962
MM	LRA	0.105	0.098	1.069	0.103	1.021
RWANDA	UGANDA	0.102	0.097	1.049	0.109	0.932
CNDP	LRA	0.098	0.085	1.155	0.098	1.004
MM	FDLR	0.098	0.123	0.793	0.101	0.969
MLC	FDLR	0.098	0.097	1.002	0.093	1.045
MLC	LRA	0.096	0.072	1.325	0.095	1.006
MLC	UGANDA	0.095	0.074	1.285	0.082	1.165
UPC	RWANDA	0.094	0.075	1.256	0.096	0.980
UGANDA	LRA	0.092	0.085	1.083	0.100	0.921
RWANDA	LENDU	0.091	0.078	1.177	0.088	1.040
CNDP	MM	0.090	0.100	0.895	0.087	1.027
CNDP	FDLR	0.089	0.110	0.813	0.096	0.934
FDLR	UGANDA	0.089	0.110	0.808	0.098	0.907
MLC	MM	0.086	0.088	0.982	0.085	1.014
UPC	LRA	0.085	0.063	1.348	0.087	0.977
CNDP	UGANDA	0.085	0.087	0.976	0.084	1.005
MM	UGANDA	0.084	0.100	0.837	0.090	0.937
UPC	FDLR	0.084	0.088	0.950	0.085	0.985
RWANDA	MUTINY	0.084	0.070	1.199	0.082	1.023

Table B.14: Results for 3 groups removal (top 50).

Group 1	Group 2	Group 3	$-\Delta$RD	Share aggr. fight.	Multipl.	Cumul. $-\Delta$RD sep. remov.	Multi-player compl.
CNDP	RWANDA	RCD-G	0.294	0.184	1.604	0.258	1.142
RWANDA	FDLR	RCD-G	0.292	0.207	1.413	0.271	1.076
RWANDA	RCD-K	RCD-G	0.290	0.200	1.453	0.311	0.933
RWANDA	RCD-G	LRA	0.286	0.181	1.575	0.273	1.047
RWANDA	RCD-G	UGANDA	0.279	0.184	1.520	0.260	1.073
LENDU	RWANDA	RCD-G	0.275	0.164	1.673	0.239	1.151
MM	RWANDA	RCD-G	0.274	0.197	1.394	0.263	1.044
RCD-K	FDLR	RCD-G	0.272	0.213	1.276	0.300	0.905
RCD-K	RCD-G	UGANDA	0.271	0.190	1.427	0.289	0.938
UPC	RWANDA	RCD-G	0.269	0.162	1.666	0.247	1.091
RCD-K	RCD-G	LRA	0.268	0.188	1.428	0.302	0.888
RWANDA	MLC	RCD-G	0.266	0.171	1.556	0.255	1.042
FDLR	RCD-G	LRA	0.265	0.195	1.361	0.262	1.011
RWANDA	MUTINY	RCD-G	0.260	0.157	1.659	0.233	1.115
LENDU	RCD-K	RCD-G	0.254	0.171	1.491	0.268	0.951
RWANDA	RCD-G	ADF	0.254	0.153	1.656	0.229	1.109
CNDP	RCD-K	RCD-G	0.253	0.190	1.334	0.287	0.884
RWANDA	INTERAH	RCD-G	0.248	0.154	1.613	0.231	1.076
CNDP	RCD-G	LRA	0.247	0.172	1.442	0.249	0.996
MM	RCD-G	LRA	0.246	0.185	1.330	0.254	0.969
RCD-G	UGANDA	LRA	0.244	0.172	1.420	0.251	0.972
FDLR	RCD-G	UGANDA	0.243	0.197	1.237	0.249	0.978
MM	FDLR	RCD-G	0.242	0.210	1.153	0.252	0.962
RCD-K	MM	RCD-G	0.242	0.203	1.192	0.292	0.830
CNDP	FDLR	RCD-G	0.242	0.197	1.229	0.247	0.980
LENDU	RCD-G	LRA	0.238	0.152	1.558	0.230	1.035
UPC	RCD-K	RCD-G	0.236	0.168	1.409	0.276	0.858
UPC	FDLR	RCD-G	0.236	0.175	1.350	0.236	1.000
CNDP	RCD-G	UGANDA	0.235	0.174	1.353	0.235	0.999
UPC	RCD-G	LRA	0.234	0.150	1.565	0.238	0.985
LENDU	FDLR	RCD-G	0.234	0.178	1.317	0.228	1.027
MLC	FDLR	RCD-G	0.229	0.184	1.247	0.244	0.939
CNDP	MM	RCD-G	0.229	0.187	1.225	0.238	0.961
RCD-K	RCD-G	ADF	0.229	0.160	1.434	0.258	0.887
MM	RCD-G	UGANDA	0.226	0.187	1.211	0.240	0.941
MUTINY	RCD-K	RCD-G	0.226	0.163	1.389	0.261	0.865
MLC	RCD-G	LRA	0.226	0.159	1.420	0.246	0.917
INTERAH	FDLR	RCD-G	0.225	0.167	1.343	0.220	1.022
MUTINY	FDLR	RCD-G	0.224	0.170	1.320	0.222	1.010
RCD-K	INTERAH	RCD-G	0.223	0.160	1.393	0.260	0.860
MLC	RCD-G	UGANDA	0.223	0.161	1.383	0.233	0.956
FDLR	RCD-G	ADF	0.222	0.167	1.332	0.218	1.017
MLC	RCD-K	RCD-G	0.222	0.177	1.252	0.284	0.781
RCD-G	ADF	LRA	0.220	0.141	1.559	0.220	1.002
MUTINY	RCD-G	LRA	0.220	0.145	1.520	0.223	0.983
UPC	CNDP	RCD-G	0.219	0.152	1.440	0.222	0.983
LENDU	CNDP	RCD-G	0.218	0.155	1.408	0.214	1.016
INTERAH	RCD-G	LRA	0.218	0.142	1.531	0.222	0.982
LENDU	RCD-G	UGANDA	0.217	0.155	1.401	0.216	1.000
UPC	MM	RCD-G	0.216	0.165	1.308	0.228	0.949

Table B.15: Results for 5 groups removal (top 50).

Group 1	Group 2	Group 3	Group 4	Group 5	$-\Delta$RD	Share aggr. fight.	Multipl.	Cumul. $-\Delta$RD sep. remov.	Multi-player compl.
CNDP	RCD-K	RWANDA	RCD-G	UGANDA	0.388	0.287	1.355	0.396	0.982
LENDU	CNDP	RCD-K	RWANDA	RCD-G	0.388	0.267	1.450	0.374	1.036
RWANDA	LENDU	RCD-K	FDLR	RCD-G	0.384	0.290	1.322	0.388	0.990
RWANDA	RCD-K	FDLR	RCD-G	LRA	0.384	0.307	1.249	0.422	0.910
RWANDA	CNDP	RCD-K	FDLR	RCD-G	0.384	0.310	1.240	0.407	0.944
CNDP	RCD-K	RWANDA	RCD-G	LRA	0.383	0.284	1.348	0.409	0.938
RWANDA	LENDU	RCD-K	RCD-G	LRA	0.382	0.265	1.439	0.390	0.979
RWANDA	RCD-K	FDLR	RCD-G	UGANDA	0.381	0.310	1.229	0.409	0.930
RWANDA	CNDP	FDLR	RCD-G	LRA	0.378	0.291	1.297	0.369	1.025
LENDU	RCD-K	RWANDA	RCD-G	UGANDA	0.378	0.267	1.412	0.377	1.003
RCD-K	RWANDA	RCD-G	UGANDA	LRA	0.375	0.284	1.318	0.411	0.913
RWANDA	LENDU	CNDP	RCD-G	LRA	0.372	0.249	1.491	0.336	1.105
CNDP	MM	RWANDA	RCD-G	LRA	0.371	0.282	1.319	0.360	1.031
LENDU	RCD-K	FDLR	RCD-G	LRA	0.370	0.278	1.328	0.379	0.976
RWANDA	CNDP	RCD-K	MM	RCD-G	0.369	0.300	1.229	0.398	0.925
LENDU	RWANDA	FDLR	RCD-G	LRA	0.368	0.272	1.351	0.350	1.051
MM	RWANDA	FDLR	RCD-G	LRA	0.367	0.305	1.204	0.374	0.981
RWANDA	LENDU	CNDP	FDLR	RCD-G	0.366	0.274	1.335	0.335	1.095
CNDP	MM	RWANDA	FDLR	RCD-G	0.366	0.307	1.194	0.359	1.021
RWANDA	CNDP	RCD-G	UGANDA	LRA	0.366	0.268	1.365	0.358	1.024
RCD-K	FDLR	RCD-G	UGANDA	LRA	0.365	0.298	1.227	0.400	0.913
RWANDA	RCD-K	MM	FDLR	RCD-G	0.365	0.323	1.129	0.412	0.885
RWANDA	MUTINY	CNDP	RCD-K	RCD-G	0.365	0.259	1.405	0.368	0.990
CNDP	RWANDA	FDLR	RCD-G	UGANDA	0.364	0.294	1.240	0.356	1.023
RWANDA	UPC	CNDP	RCD-K	RCD-G	0.363	0.265	1.371	0.383	0.949
RWANDA	UPC	RCD-K	FDLR	RCD-G	0.362	0.288	1.258	0.396	0.914
RCD-K	MM	RWANDA	RCD-G	LRA	0.361	0.298	1.213	0.414	0.873
RWANDA	MLC	CNDP	RCD-G	UGANDA	0.361	0.258	1.400	0.340	1.062
RWANDA	MUTINY	CNDP	FDLR	RCD-G	0.361	0.266	1.354	0.328	1.098
RWANDA	UPC	CNDP	RCD-G	LRA	0.361	0.247	1.463	0.345	1.047
CNDP	RCD-K	FDLR	RCD-G	LRA	0.361	0.298	1.212	0.398	0.907
RWANDA	MLC	CNDP	FDLR	RCD-G	0.360	0.281	1.283	0.351	1.027
MLC	RWANDA	FDLR	RCD-G	LRA	0.360	0.279	1.293	0.366	0.983
RWANDA	UPC	CNDP	FDLR	RCD-G	0.360	0.272	1.326	0.343	1.051
RCD-K	MM	RWANDA	RCD-G	UGANDA	0.360	0.300	1.200	0.401	0.898
RWANDA	FDLR	RCD-G	UGANDA	LRA	0.359	0.291	1.233	0.371	0.968
RWANDA	UPC	FDLR	RCD-G	LRA	0.359	0.270	1.333	0.358	1.003
MLC	RCD-K	RWANDA	RCD-G	UGANDA	0.359	0.274	1.310	0.393	0.913
CNDP	MM	RWANDA	RCD-G	UGANDA	0.359	0.284	1.264	0.347	1.033
RWANDA	MLC	CNDP	RCD-G	LRA	0.359	0.256	1.403	0.353	1.017
RWANDA	LENDU	RCD-K	MM	RCD-G	0.359	0.281	1.278	0.380	0.945
RWANDA	MUTINY	CNDP	RCD-G	LRA	0.359	0.241	1.486	0.330	1.086
CNDP	RCD-K	RCD-G	UGANDA	LRA	0.358	0.275	1.304	0.386	0.927
RWANDA	LENDU	CNDP	MM	RCD-G	0.358	0.265	1.352	0.326	1.097
MUTINY	RCD-K	RWANDA	FDLR	RCD-G	0.358	0.283	1.266	0.382	0.937
RWANDA	LENDU	CNDP	RCD-G	UGANDA	0.357	0.251	1.419	0.323	1.103
RWANDA	MLC	RCD-K	FDLR	RCD-G	0.356	0.297	1.199	0.404	0.881
LENDU	RCD-K	RCD-G	UGANDA	LRA	0.356	0.255	1.393	0.367	0.969
RCD-K	INTERAH	RWANDA	FDLR	RCD-G	0.355	0.280	1.267	0.380	0.934
MLC	CNDP	RCD-K	RWANDA	RCD-G	0.355	0.274	1.295	0.391	0.908

Table B.16: Pacifying top 33 groups.

Group	Sh. fight.	Sh. bilat. fight.	$-\Delta$RD	Multiplier
RWANDA	0.053	0.010	0.063	6.048
RCD-G	0.087	0.030	0.056	1.864
RCD-K	0.060	0.030	0.050	1.643
LRA	0.041	0.023	0.037	1.640
MLC	0.031	0.019	0.034	1.813
UGANDA	0.043	0.006	0.031	5.684
UPC	0.022	0.002	0.024	11.205
MUTINY	0.016	0.015	0.023	1.571
CNDP	0.043	0.038	0.019	0.515
LOBALA	0.001	0.000	0.017	52.721
FPJC	0.006	0.006	0.017	2.612
FRPI	0.009	0.007	0.017	2.369
BDK	0.002	0.002	0.016	8.138
ENYELE	0.001	0.001	0.016	24.226
MUNZ	0.001	0.000	0.016	32.301
MINEM	0.001	0.000	0.016	32.151
FRF	0.000	0.000	0.016	32.101
FNL	0.001	0.001	0.016	24.063
UPPS	0.000	0.000	0.016	48.076
FNI	0.008	0.008	0.015	1.873
ADF	0.013	0.004	0.015	3.884
APCLS	0.001	0.000	0.014	28.728
NALU	0.003	0.003	0.013	4.547
MRC	0.005	0.005	0.012	2.621
FLC	0.002	0.000	0.010	30.517
ALIR	0.004	0.002	0.009	4.167
HEMA	0.009	0.002	0.009	4.093
BANYA	0.000	0.000	0.009	
RCD-M	0.000	0.000	0.009	
UNITA	0.001	0.001	0.007	11.134
FDLR	0.066	0.047	0.004	0.092
RCD-N	0.000	0.000	0.003	
RCD	0.018	0.003	-0.006	2.163

Table B.17: Results for 2 groups reconciliation (top 50).

Group 1	Group 2	$-\Delta$RD	Share aggr. fight. Congol. troops	Multipl.	Cumul. $-\Delta$RD sep. reconcil.	Multi-player compl.
RWANDA	RCD-G	0.113	0.040	2.791	0.119	0.949
RWANDA	RCD-K	0.111	0.041	2.743	0.112	0.990
RCD-K	RCD-G	0.110	0.060	1.828	0.105	1.043
RWANDA	LRA	0.097	0.033	2.953	0.100	0.975
RWANDA	MLC	0.095	0.029	3.235	0.097	0.977
RWANDA	UGANDA	0.093	0.016	5.872	0.094	0.992
MLC	RCD-G	0.091	0.049	1.858	0.090	1.007
RCD-G	LRA	0.088	0.053	1.668	0.093	0.944
RWANDA	UPC	0.085	0.012	6.814	0.086	0.985
RWANDA	MUTINY	0.085	0.025	3.366	0.086	0.984
RCD-G	UGANDA	0.084	0.036	2.360	0.087	0.960
MLC	RCD-K	0.083	0.049	1.681	0.084	0.984
RCD-K	LRA	0.082	0.053	1.559	0.087	0.950
RWANDA	CNDP	0.081	0.048	1.684	0.082	0.986
LOBALA	RWANDA	0.079	0.011	7.413	0.080	0.993
RCD-K	UGANDA	0.079	0.036	2.206	0.081	0.973
FPJC	RWANDA	0.079	0.017	4.706	0.079	0.991
RWANDA	FRPI	0.079	0.017	4.526	0.079	0.991
BDK	RWANDA	0.078	0.012	6.335	0.079	0.993
MUNZ	RWANDA	0.078	0.011	7.178	0.078	0.994
RWANDA	FNL	0.078	0.011	7.071	0.078	0.995
MINEM	RWANDA	0.078	0.011	7.173	0.078	0.994
FRF	RWANDA	0.078	0.011	7.171	0.078	0.994
UPPS	RWANDA	0.078	0.011	7.278	0.078	0.994
UPC	RCD-G	0.078	0.032	2.414	0.080	0.974
FNI	RWANDA	0.077	0.018	4.181	0.078	0.992
MUTINY	RCD-G	0.076	0.045	1.706	0.079	0.965
APCLS	RWANDA	0.076	0.011	7.024	0.077	0.994
RWANDA	ADF	0.076	0.014	5.324	0.078	0.976
UPC	RCD-K	0.075	0.032	2.321	0.073	1.024
NALU	RWANDA	0.075	0.013	5.703	0.075	0.995
RWANDA	MRC	0.075	0.015	4.954	0.075	0.995
CNDP	RCD-G	0.073	0.068	1.084	0.075	0.975
LOBALA	RCD-G	0.072	0.030	2.365	0.073	0.982
FPJC	RCD-G	0.071	0.036	1.957	0.072	0.981
FRPI	RCD-G	0.071	0.037	1.921	0.072	0.980
MUTINY	RCD-K	0.071	0.045	1.571	0.073	0.970
BDK	RCD-G	0.071	0.032	2.208	0.072	0.983
ENYELE	RCD-G	0.070	0.031	2.298	0.072	0.983
MUNZ	RCD-G	0.070	0.030	2.310	0.072	0.983
MINEM	RCD-G	0.070	0.030	2.308	0.072	0.983
RCD-G	FNL	0.070	0.031	2.296	0.072	0.984
FRF	RCD-G	0.070	0.030	2.308	0.072	0.983
UPPS	RCD-G	0.070	0.030	2.319	0.072	0.983
RCD-G	ADF	0.070	0.034	2.071	0.071	0.988
FNI	RCD-G	0.070	0.038	1.833	0.071	0.982
MLC	LRA	0.069	0.042	1.659	0.071	0.965
APCLS	RCD-G	0.069	0.030	2.256	0.070	0.984
UGANDA	LRA	0.068	0.028	2.419	0.068	0.994
CNDP	RCD-K	0.068	0.068	0.994	0.069	0.978

Table B.18: Results for 3 groups reconciliation (top 50).

Group 1	Group 2	Group 3	$-\Delta$RD	Share aggr. fight. Congol. troops	Multipl.	Cumul. $-\Delta$RD sep. reconcil.	Multi-player compl.
RWANDA	RCD-K	RCD-G	0.166	0.071	2.354	0.168	0.987
MLC	RWANDA	RCD-G	0.147	0.059	2.470	0.153	0.958
MLC	RCD-K	RWANDA	0.143	0.060	2.401	0.147	0.974
RWANDA	RCD-G	LRA	0.142	0.063	2.262	0.156	0.914
RCD-K	RWANDA	LRA	0.141	0.063	2.240	0.149	0.947
MLC	RCD-K	RCD-G	0.141	0.079	1.780	0.140	1.007
RWANDA	RCD-G	UGANDA	0.140	0.046	3.053	0.150	0.934
RCD-K	RWANDA	UGANDA	0.139	0.046	3.026	0.144	0.970
RCD-K	RCD-G	LRA	0.138	0.083	1.673	0.142	0.972
RCD-K	RCD-G	UGANDA	0.136	0.066	2.075	0.137	0.996
UPC	RCD-K	RWANDA	0.135	0.043	3.168	0.136	0.994
UPC	RWANDA	RCD-G	0.133	0.042	3.127	0.142	0.933
UPC	RCD-K	RCD-G	0.133	0.062	2.130	0.129	1.028
RWANDA	MUTINY	RCD-G	0.131	0.055	2.383	0.142	0.926
MUTINY	RCD-K	RWANDA	0.131	0.055	2.368	0.136	0.966
MUTINY	RCD-K	RCD-G	0.129	0.075	1.719	0.129	1.001
RWANDA	CNDP	RCD-G	0.129	0.078	1.648	0.138	0.932
CNDP	RCD-K	RWANDA	0.128	0.078	1.638	0.132	0.973
LOBALA	RWANDA	RCD-G	0.128	0.041	3.142	0.136	0.942
MLC	RWANDA	LRA	0.127	0.052	2.454	0.134	0.949
FPJC	RWANDA	RCD-G	0.127	0.047	2.721	0.135	0.940
LOBALA	RWANDA	RCD-K	0.127	0.041	3.108	0.129	0.981
FRPI	RWANDA	RCD-G	0.127	0.047	2.681	0.135	0.939
BDK	RWANDA	RCD-G	0.127	0.042	2.993	0.135	0.942
RWANDA	RCD-G	FNL	0.127	0.041	3.086	0.134	0.943
ENYELE	RWANDA	RCD-G	0.127	0.041	3.086	0.134	0.942
MINEM	RWANDA	RCD-G	0.127	0.041	3.098	0.134	0.942
FRF	RWANDA	RCD-G	0.127	0.041	3.097	0.134	0.942
UPPS	RWANDA	RCD-G	0.127	0.041	3.109	0.134	0.942
RWANDA	UGANDA	LRA	0.126	0.038	3.291	0.131	0.965
CNDP	RCD-K	RCD-G	0.126	0.098	1.289	0.125	1.011
FPJC	RCD-K	RWANDA	0.126	0.047	2.693	0.129	0.980
FRPI	RCD-K	RWANDA	0.126	0.048	2.653	0.129	0.978
RWANDA	FNI	RCD-G	0.126	0.048	2.596	0.134	0.940
BDK	RWANDA	RCD-K	0.126	0.042	2.961	0.128	0.982
RWANDA	RCD-K	FNL	0.126	0.041	3.053	0.128	0.983
ENYELE	RCD-K	RWANDA	0.126	0.041	3.052	0.128	0.982
MINEM	RWANDA	RCD-K	0.126	0.041	3.063	0.128	0.982
FRF	RCD-K	RWANDA	0.126	0.041	3.063	0.128	0.982
UPPS	RWANDA	RCD-K	0.126	0.041	3.075	0.128	0.982
RWANDA	RCD-G	ADF	0.125	0.044	2.832	0.134	0.937
LOBALA	RCD-K	RCD-G	0.125	0.060	2.069	0.123	1.021
APCLS	RWANDA	RCD-G	0.125	0.041	3.060	0.133	0.942
MLC	RWANDA	UGANDA	0.125	0.035	3.584	0.129	0.972
FNI	RCD-K	RWANDA	0.125	0.049	2.568	0.128	0.980
FPJC	RCD-K	RCD-G	0.124	0.066	1.871	0.122	1.020
FRPI	RCD-K	RCD-G	0.124	0.067	1.851	0.122	1.019
RWANDA	RCD-K	ADF	0.124	0.044	2.796	0.127	0.975
APCLS	RCD-K	RWANDA	0.124	0.041	3.025	0.126	0.983
BDK	RCD-K	RCD-G	0.124	0.062	1.996	0.121	1.022

Table B.19: Results for 5 groups reconciliation (top 50).

Group 1	Group 2	Group 3	Group 4	Group 5	$-\Delta$RD	Sh. aggr. fight. Cong. troops	Multipl.	Cumul. $-\Delta$RD sep. reconcil.	Multi-player compl.
RWANDA	MLC	RCD-K	RCD-G	UGANDA	0.223	0.095	2.344	0.234	0.952
MLC	RCD-K	RWANDA	RCD-G	LRA	0.222	0.112	1.983	0.240	0.928
RCD-K	RWANDA	RCD-G	UGANDA	LRA	0.218	0.099	2.208	0.237	0.920
RWANDA	UPC	MLC	RCD-K	RCD-G	0.217	0.092	2.369	0.226	0.959
RWANDA	UPC	RCD-K	RCD-G	UGANDA	0.214	0.078	2.731	0.223	0.957
RWANDA	MUTINY	MLC	RCD-K	RCD-G	0.213	0.104	2.044	0.226	0.944
UPC	RCD-K	RWANDA	RCD-G	LRA	0.213	0.095	2.234	0.229	0.929
LOBALA	MLC	RCD-K	RWANDA	RCD-G	0.211	0.090	2.350	0.220	0.961
MLC	CNDP	RCD-K	RWANDA	RCD-G	0.211	0.127	1.657	0.222	0.950
RWANDA	FPJC	MLC	RCD-K	RCD-G	0.210	0.096	2.193	0.219	0.959
BDK	RWANDA	MLC	RCD-K	RCD-G	0.210	0.091	2.296	0.219	0.961
FRPI	MLC	RCD-K	RWANDA	RCD-G	0.210	0.096	2.176	0.219	0.958
MLC	RCD-K	RWANDA	RCD-G	FNL	0.210	0.090	2.328	0.218	0.962
ENYELE	RWANDA	MLC	RCD-K	RCD-G	0.210	0.090	2.328	0.218	0.961
FRF	RWANDA	MLC	RCD-K	RCD-G	0.210	0.090	2.332	0.218	0.962
UPPS	RWANDA	MLC	RCD-K	RCD-G	0.210	0.090	2.336	0.218	0.962
MLC	RCD-K	RWANDA	RCD-G	ADF	0.209	0.093	2.241	0.218	0.961
RWANDA	FNI	MLC	RCD-K	RCD-G	0.209	0.098	2.141	0.218	0.960
APCLS	RWANDA	MLC	RCD-K	RCD-G	0.208	0.090	2.315	0.217	0.962
MUTINY	RCD-K	RWANDA	RCD-G	LRA	0.208	0.108	1.931	0.228	0.912
MUTINY	RCD-K	RWANDA	RCD-G	UGANDA	0.208	0.091	2.288	0.223	0.933
RWANDA	MRC	MLC	RCD-K	RCD-G	0.207	0.094	2.198	0.215	0.963
NALU	MLC	RCD-K	RWANDA	RCD-G	0.207	0.092	2.244	0.215	0.962
LOBALA	RCD-K	RWANDA	RCD-G	LRA	0.207	0.093	2.211	0.222	0.929
RWANDA	CNDP	RCD-K	RCD-G	LRA	0.206	0.131	1.578	0.225	0.919
CNDP	RCD-K	RWANDA	RCD-G	UGANDA	0.206	0.114	1.809	0.219	0.940
LOBALA	RCD-K	RWANDA	RCD-G	UGANDA	0.206	0.076	2.696	0.217	0.950
FPJC	RCD-K	RWANDA	RCD-G	LRA	0.206	0.099	2.068	0.222	0.927
RWANDA	RCD-K	RCD-G	FNL	LRA	0.205	0.094	2.191	0.221	0.930
BDK	RWANDA	RCD-K	RCD-G	LRA	0.205	0.095	2.161	0.221	0.929
ENYELE	RWANDA	RCD-K	RCD-G	LRA	0.205	0.094	2.191	0.221	0.929
RWANDA	FRPI	RCD-K	RCD-G	LRA	0.205	0.100	2.052	0.222	0.926
FRF	RWANDA	RCD-K	RCD-G	LRA	0.205	0.094	2.194	0.221	0.930
UPPS	RCD-K	RWANDA	RCD-G	LRA	0.205	0.093	2.198	0.221	0.930
RWANDA	FPJC	RCD-K	RCD-G	UGANDA	0.205	0.082	2.488	0.216	0.948
RCD-K	RWANDA	RCD-G	FNL	UGANDA	0.205	0.077	2.670	0.215	0.952
RCD-K	RWANDA	RCD-G	ADF	UGANDA	0.205	0.080	2.561	0.215	0.954
BDK	RWANDA	RCD-K	RCD-G	UGANDA	0.205	0.078	2.625	0.215	0.950
RWANDA	FRPI	RCD-K	RCD-G	UGANDA	0.205	0.083	2.466	0.216	0.947
ENYELE	RWANDA	RCD-K	RCD-G	UGANDA	0.205	0.077	2.669	0.215	0.951
FRF	RWANDA	RCD-K	RCD-G	UGANDA	0.205	0.077	2.674	0.215	0.951
UPPS	RWANDA	RCD-K	RCD-G	UGANDA	0.205	0.076	2.680	0.215	0.951
RWANDA	RCD-K	RCD-G	ADF	LRA	0.205	0.097	2.110	0.220	0.929
RWANDA	FNI	RCD-K	RCD-G	LRA	0.204	0.101	2.020	0.220	0.928
MUTINY	UPC	RCD-K	RWANDA	RCD-G	0.204	0.087	2.334	0.215	0.948
APCLS	RCD-K	RWANDA	RCD-G	LRA	0.204	0.094	2.179	0.219	0.930
FNI	RCD-K	RWANDA	RCD-G	UGANDA	0.204	0.084	2.422	0.215	0.949
APCLS	RWANDA	RCD-K	RCD-G	UGANDA	0.203	0.077	2.655	0.214	0.952
MRC	RCD-K	RWANDA	RCD-G	LRA	0.203	0.098	2.072	0.218	0.931
RWANDA	NALU	RCD-K	RCD-G	LRA	0.203	0.096	2.114	0.218	0.930

B.4.1   Random Utility Model Fit

In this section, we display the results of the multinomial logit estimation in Table B.20, the results of the Random Utility Model with time-varying network in Table B.21, and present further evidence on the goodness of fit. In particular, Figure B.1 reports the cross-dyad distribution of predicted probabilities for enmities (left panel) and alliances (right panel). In the left panel, the dark sample represents the distribution for observed enmities (alliances) and the light sample represents the distribution for the other observed links. Figure B.2 displays the observed and predicted distributions of six network statistics that play an important role in our baseline model: degree one enemies (panel a), degree one allies (panel b), number of degree one links (panel c), common enemies (panel d), common allies (panel e), and conflicting neighbors (panel f). For each statistic, the panel compares the data with the average distribution over 1000 simulated networks as predicted by the conditional logit model (plus/minus one standard deviation interval). The figure shows that all these important moments of the data are predicted accurately. More precisely each Monte Carlo draw consists in drawing a random utility shock $\tilde{u}_{ij}(a)$ for each dyad ij and alternative a from a type I extreme value distribution with mean $\gamma \approx 0.577$ (the Euler-Mascheroni constant), and variance, $\sqrt{\pi}/6$. Using equation (23) we compute each simulated alternative-dependent joint surplus $U_{ij}^{sim}(a)$ and select the predicted link for dyad ij as $a_{ij}^{pre} = \arg\max U_{ij}^{sim}(a)$. This leads to a simulated network for which we can compute the 6 distributions of network statistics. This procedure is iterated 1000 times. Each panel reports the average distribution ($\pm$ 1 SD) across the Monte Carlo draws.

Table B.20: Table multinominal logit.

CSF Surplus	0.000	
	(0.000)	
	Enmity link	Alliance link
Common enemy	-0.387**	0.425**
	(0.183)	(0.181)
Common allied	0.097	-0.529***
	(0.194)	(0.175)
Common allied and enemy	0.454***	-0.727***
	(0.119)	(0.161)
Geodistance	-0.003***	-0.004***
	(0.001)	(0.001)
Same ethnic group	0.842	0.865
	(0.595)	(0.601)
Same Hutu Tutsi	0.831	0.550
	(0.813)	(0.787)
Different Hutu Tutsi	1.295**	-0.914
	(0.596)	(1.148)
Zero Government	-1.977***	0.849
	(0.711)	(0.763)
Zero Foreign	1.514***	0.761
	(0.523)	(0.576)
Number of observations	9480	
Log likelihood	-445.92	

Note: Group fixed effects included, standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

Table B.21: RUM with time varying network.

	Dep. var.: Total Fighting		
	(1)	(2)	(3)
Total Fight. Enemies (TFE)	0.106***	0.114***	0.110***
	(0.033)	(0.035)	(0.038)
Total Fight. Allies (TFA)	-0.112**	-0.122**	-0.137**
	(0.050)	(0.053)	(0.062)
Total Fight. Neutrals (TFN)	0.002	0.001	0.011
	(0.006)	(0.006)	(0.023)
Kleibergen-Paap F-stat	4.0	3.6	5.1
Hansen J (p-value)	0.62	0.67	0.73
Observations	1040	1040	469
R-squared	0.554	0.579	0.597

Note: An observation is a given armed group in a given year. The panel contains 80 armed groups between 1998 and 2010. All regressions include group fixed effects and control for rainfall in the group's homeland. Robust standard errors corrected for Spatial HAC in parentheses. Column (1) replicates the baseline specification of the main table (column (4), Table 2) but with RUM. Column (2) replicates Column (1) of Table 4 but with RUM, while column (3) replicates column (4) of Table 4 but with RUM. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
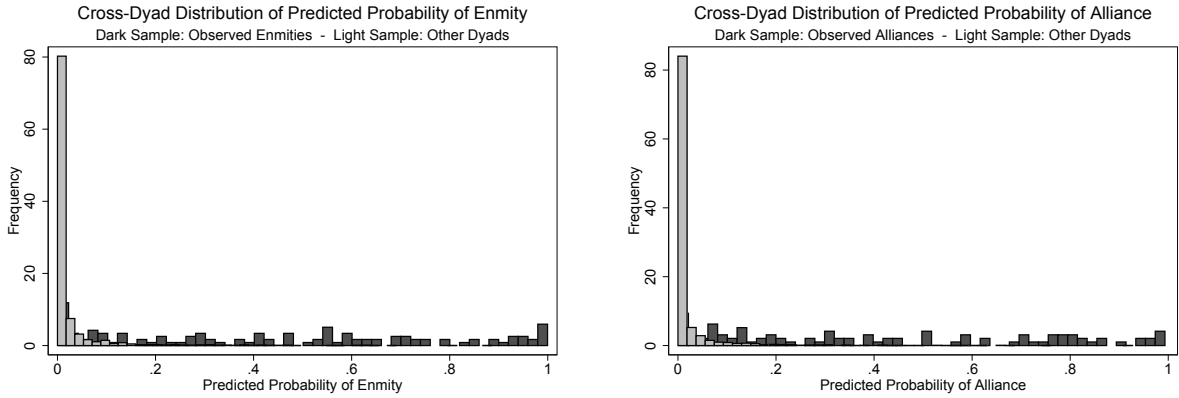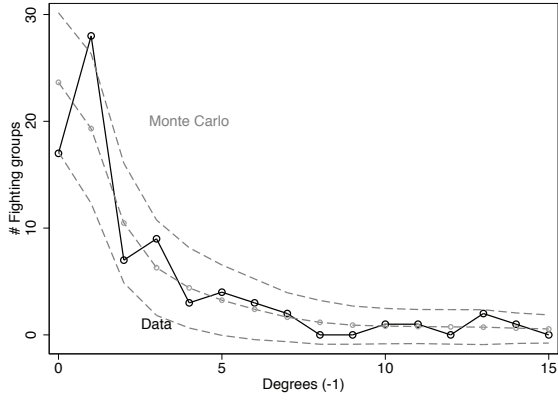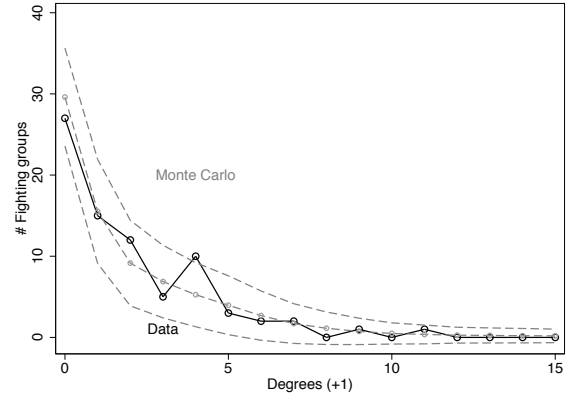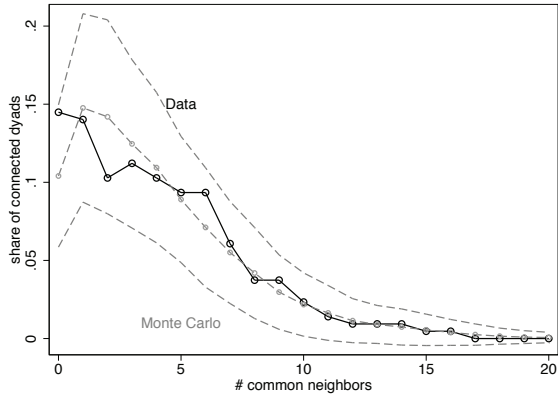

Figure B.1: *Predicted probabilities of enmities and alliances.*
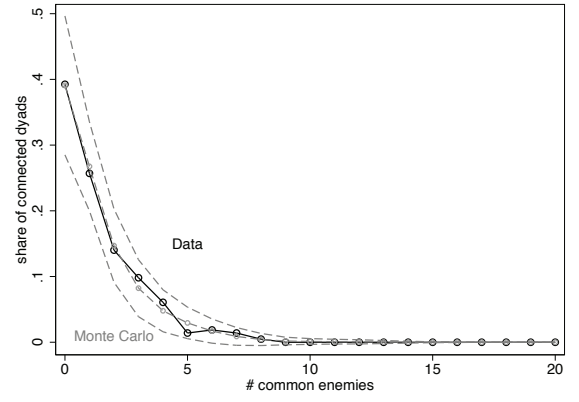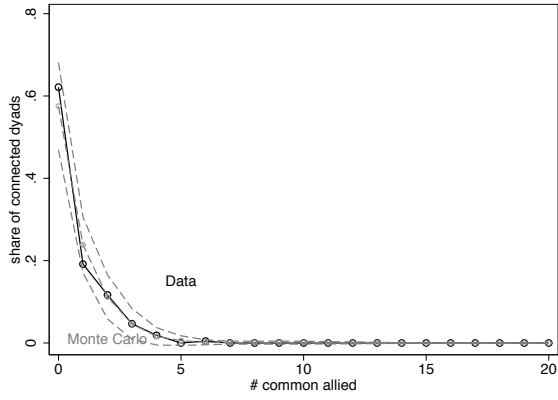
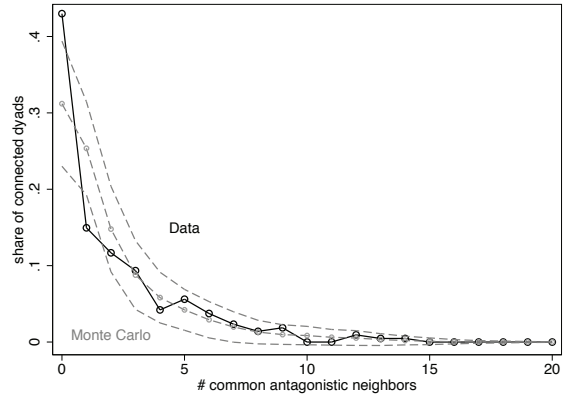(a) Degree one enemies.

(b) Degree one allies.

(c) Number of degree one links.

(d) Common enemies.

(e) Common allies.

(f) Conflicting neighbors.

Figure B.2: *Goodness of fit statistics.*

Table B.22: Complete list of group removal with rewiring.

Group	Sh. aggr. fight.	$-\Delta$RD	Multiplier	$-\Delta$RD rewiring (median)	$-\Delta$RD rewiring (M.A.D)	New enmities at median	New alliances at median
RCD-G	0.087	0.151	1.740	0.138	0.025	0	0
RCD-K	0.060	0.094	1.587	0.079	0.027	0	0
RWANDA	0.053	0.066	1.232	0.103	0.040	-5	0
LRA	0.041	0.056	1.365	0.051	0.005	0	-1
FDLR	0.066	0.055	0.822	0.059	0.008	-1	1
MM	0.057	0.046	0.814	0.081	0.024	-2	1
UGANDA	0.043	0.043	0.996	0.065	0.034	-4	4
CNDP	0.043	0.041	0.946	0.041	0.011	0	0
MLC	0.031	0.039	1.254	0.053	0.018	-2	1
UPC	0.022	0.030	1.406	0.011	0.020	0	-1
LENDU	0.024	0.022	0.912	0.046	0.020	0	0
MUTINY	0.016	0.016	0.979	0.016	0.000	0	0
INTERAH	0.014	0.014	1.013	0.029	0.024	0	-1
ADF	0.013	0.012	0.939	0.036	0.012	-2	1
FRPI	0.009	0.010	1.107	0.010	0.000	0	0
HEMA	0.009	0.009	0.975	0.003	0.012	1	0
FNI	0.008	0.009	1.033	0.009	0.000	0	0
CNDD	0.007	0.008	1.173	0.008	0.000	0	0
FPJC	0.006	0.007	1.146	0.007	0.000	0	0
SPLA	0.007	0.007	0.961	0.007	0.000	0	0
HUTU	0.005	0.006	1.163	0.006	0.000	0	0
ZIMBABWE	0.007	0.005	0.699	0.022	0.010	-3	0
MRC	0.005	0.004	0.878	0.004	0.000	0	0
ALIR	0.004	0.004	1.081	0.004	0.000	0	0
ANGOLA	0.004	0.004	1.044	0.009	0.014	-1	2
PUSIC	0.003	0.003	1.177	0.003	0.000	0	0
NAMIBIA	0.003	0.003	0.940	0.011	0.009	-1	1
SAF	0.003	0.003	1.009	0.003	0.000	0	0
NALU	0.003	0.002	0.905	0.035	0.000	-1	1
BURUNDI	0.003	0.002	0.811	0.002	0.000	0	0
RWA73	0.002	0.002	0.956	0.007	0.016	0	0
BDK	0.002	0.002	1.136	0.002	0.000	0	0
MM-P	0.004	0.002	0.564	0.014	0.012	0	1
SUDAN	0.002	0.002	0.749	0.031	0.024	-2	0
FLC	0.002	0.002	1.112	0.002	0.000	0	0
MUNZ	0.001	0.001	1.126	0.001	0.000	0	0
ENYELE	0.001	0.001	1.126	0.001	0.000	0	0
PPRD	0.001	0.001	0.979	0.001	0.000	0	0
LOBALA	0.001	0.001	1.201	0.001	0.000	0	0
UNITA	0.001	0.001	0.779	0.002	0.001	-1	-1
FNL	0.001	0.001	1.098	0.001	0.000	0	0
BOMBO	0.001	0.001	1.060	0.001	0.000	0	0
MM-Y	0.001	0.001	0.582	0.001	0.000	0	0
MINEM	0.001	0.001	1.108	0.001	0.000	0	0
ADFL	0.001	0.001	1.078	0.001	0.007	0	0
LENDU-U	0.001	0.001	1.035	0.001	0.000	0	0
APCLS	0.001	0.001	0.995	0.001	0.000	0	0
UELE	0.001	0.001	0.924	0.001	0.000	0	0
FRF	0.000	0.001	1.094	0.001	0.000	0	0
WAGE	0.000	0.000	1.013	0.000	0.000	0	0

Table B.22 cont.: Complete list of group removal with rewiring.

Group	Sh. aggr. fight.	$-\Delta$RD	Multiplier	$-\Delta$RD rewiring (median)	$-\Delta$RD rewiring (M.A.D)	New enmities at median	New alliances at median
ZAMBIA	0.000	0.000	1.006	0.000	0.000	0	0
RUD	0.000	0.000	1.005	0.000	0.000	0	0
MM-L	0.001	0.000	0.707	0.000	0.000	0	0
MM-J	0.001	0.000	0.707	0.000	0.000	0	0
RCD-M	0.000	0.000	0.902	0.000	0.000	0	0
CHAD	0.000	0.000	0.801	0.000	0.000	0	0
UPPS	0.000	0.000	1.066	0.000	0.000	0	0
CNDD-N	0.000	0.000	1.006	0.000	0.000	0	0
BANYA	0.000	0.000	0.916	0.000	0.000	0	0
G47	0.000	0.000	0.914	0.000	0.000	0	0
MBINGI	0.000	0.000	0.914	0.000	0.000	0	0
ALUR	0.000	0.000	0.786	0.000	0.000	0	0
NGITI	0.000	0.000	0.647	0.000	0.000	0	0
MM-K	0.000	0.000	0.613	0.000	0.000	0	0
HUTU-R	0.000	0.000	0.829	0.000	0.000	0	0
FAP	0.000	0.000	0.829	0.000	0.000	0	0
PRA	0.000	0.000	0.829	0.000	0.000	0	0
MUTLRA	0.000	0.000	0.829	0.000	0.000	0	0
PYGMY	0.000	0.000	0.829	0.000	0.000	0	0
WANGI	0.000	0.000	0.829	0.000	0.000	0	0
DSP	0.000	0.000	0.738	0.000	0.000	0	0
ADC	0.000	0.000	0.727	0.000	0.000	0	0
MM-M	0.000	0.000	0.519	0.000	0.000	0	0
RCD-N	0.000	0.000	0.036	0.032	0.018	-2	1
RCD	0.018	-0.002	0.142	0.079	0.029	-6	6

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