Resources, Conflict, and Economic Development in Africa*

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Abstract

Natural resources have driven both growth and conflict in modern Africa. We model the interaction of parties engaged in potential conflict over such resources. The likelihood of conflict depends on both the absolute and relative resource endowments of the parties. Resources fuel conflict by raising the gains from appropriation and by increasing fighting strength. Economic prosperity, as a result, is a function of resources and equilibrium conflict prevalence. Using high-resolution spatial data on resources, conflicts, and nighttime lights in sub-Saharan Africa, we find evidence confirming each of the model's predictions. Model fit is substantially better where institutions are weak, suggesting that policy interventions that improve institutions may be able to loosen the ties between resources, conflict, and growth in Africa.

Keywords: Conflict, Resource Curse, Nighttime Lights, Institutions, Africa
JEL Codes: D74, O13, Q34

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1 Introduction

No understanding of the development of modern Africa would be complete without an appreciation of the profound importance of natural resources and conflict. Profits from natural resources have the capacity to substantially improve levels of economic development. Yet, the countries with the highest resource endowments tend to have the slowest rates of growth (Gylfason, 2001; Sachs and Warner, 2001). One explanation explored in recent empirical work is that as the gains from expropriating resources rise, conflict becomes more likely (Buonanno et al., 2015; Caselli et al., 2015; De La Sierra, 2015; Dube and Vargas, 2013; Fearon, 2005). Another, is that resources empower the state and its rivals, and can be used to fuel repressive and destructive activities (Acemoglu and Robinson, 2001; Caselli and Tesei, 2015; Mitra and Ray, 2014; Nunn and Qian, 2014). Where these motives are salient, and where conflict is destructive enough, resource windfalls may actually hamper economic development (Bannon and Collier, 2003).

As evidence on the importance of these relationships in the African context, consider the following correlations in the spatial distributions of conflict prevalence, economic development, and natural resources. In Figure 1, we proxy for development by plotting log light density against a resource index for 0.5° by 0.5° grid cells across sub-Saharan Africa, grouped into percentile bins.[1] The resulting association is clearly non-monotonic: areas with the greatest resource endowments are no more developed than countries with very low levels of resources in Africa.[2] Figure 2 may help explain this inverse U-shape. In it, we graph conflict incidence against the resource index for sub-Saharan African countries in the same time period. The resulting correlation is different from the one in Figure 1: conflict is positively associated with the resource endowment, with a convex trend for areas with the highest levels of resources.

In this paper, we ask: when do natural resources spark conflict, and can this relationship indeed undo any positive effects of resource abundance on economic development? We shed light on these linkages through the lens of strategic interaction. In our model, two groups decide simultaneously whether or not to engage in conflict. Offensive and defensive capabilities for each group increase with accumulated resources. This endowment effect of resources on conflict is a feature of early models of conflict in the state of nature (e.g.,

[1]The resource index is comprised of the first principal component of (i) annual rainfall averaged over a ten year period (1998-2008), (ii) oil or gas reserves, (iii) lootable diamonds, (iv) gold, (v) zinc, and (vi) cobalt in the 0.5 x 0.5 degree grid cell.

[2]This is similar to, for example, Figure 1 in Sachs and Warner (2001).

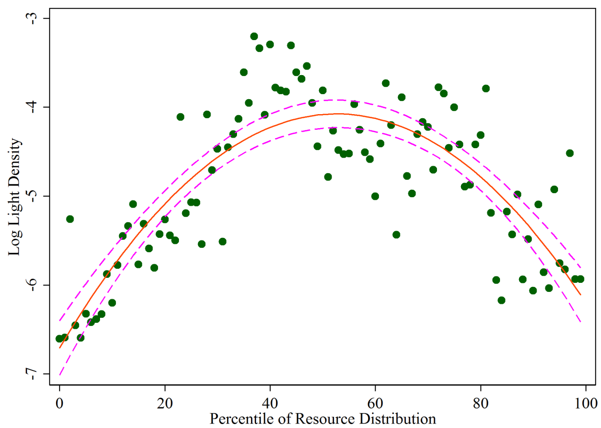


Figure 1: Log Light Density vs. Resources

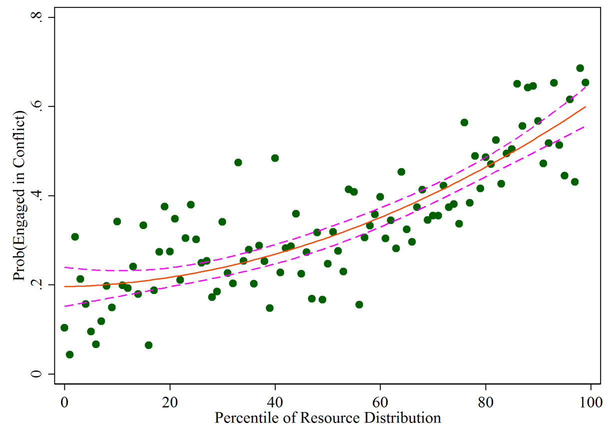


Figure 2: Prob(Conflict) vs. Resources

Observations for 0.5° by 0.5° grid cells across Sub Saharan Africa, as binned averages. Graphs plot quadratic fits with confidence intervals of the relationship between a resource index against (1) Log (Light Density) in 2008 and (2) Whether the region was engaged in conflict between 1998 and 2008. The Resource Index consists of the first principal component of (i) annual rainfall averaged over a ten year period (1998-2008), (ii) oil or gas reserves, (iii) lootable diamonds, (iv) gold, (v) zinc, and (vi) cobalt in the 0.5 x 0.5 degree grid cell.

Grossman and Kim (1995); Hirshleifer (1989)) though it has received limited attention in more recent empirical work, with the exception of some recent studies related in this vein Caselli et al. (2015); Dube and Vargas (2013); Mitra and Ray (2014).

Importantly, we capture a rapacity effect by positing that each group's return to fighting is increasing in the neighboring group's resources.[3] In our baseline model, there is a fixed cost of participating in conflict.[4] If both groups choose not to fight, the result is peace. If one group chooses to fight but the other does not, the former succeeds at expropriating a fraction of the latter's resources with probability 1. If both groups fight, the probability of success is determined by the relative strength of each group, which itself depends on resource endowments.

Nash equilibria in this model are determined by the resource endowments of each group

[3]In our baseline model, the only way in which the two groups interact is through the potential conflict between them. We extend the model by incorporating a sharing rule, and show within this augmented framework that societies who share more (e.g., who are spatially close, residing in the same country or agro-ecological zone, or from areas dominated historically by the same ethnic group) are less likely to choose conflict.

[4]We explore other functional forms in an extension of the model that incorporates the idea that the opportunity cost of engaging in conflict depends on the resource endowment, as in, e.g., Hsiang et al. (2013); Miguel et al. (2004).

(along with other fundamentals such as the cost of raiding and the fraction expropriated when raiding successfully). When both groups have low levels of resource accumulation, peace results. This is because neither group has much strength, and the gains from raiding are also not high for either group, since the contestable resources are few. When one group has accumulated *slightly more* resources (loosely speaking) than the other, a one-sided conflict equilibrium results – what one might call an "uncontested raid" – in which the relatively resource-poor group raids while the other chooses not to retaliate. When both groups have abundant resources, both are impelled to conflict. We model the quality of institutions as shifting the cutoffs for conflict onset, by either changing the costs of war or the fraction of appropriable resources (or both).[5]

We test the model's predictions using disaggregated spatial data on resource endowments, conflict, and satellite data on nighttime lights. We partition sub-Saharan Africa into a 0.5 x 0.5 degree grid. At each point, we match the likelihood of conflict events and the intensity of nighttime lights to a "natural resource" indicator (which equals 1 if any natural resource from the following is present: oil and natural gas reserves, deposits of "lootable" diamonds, gold, zinc, and cobalt) at that point. We use historical rainfall patterns as an alternative measure of resource abundance. We then match these points (i) to every neighbor (j) within a 500 kilometer radius. We use two sources of data on conflict, from (i) the Peace Research Institute Oslo (PRIO), which allows for good identification spatial intensity of conflicts, and (ii) the Armed Conflict Location & Event Data Project (ACLED), which allows us to focus on territorial conflicts. Using these data, we ascertain for each ij whether this *pair* was involved in shared conflict over the past 10 years.

The model's main predictions are related to the partitioning of the ij "resource space" into Nash equilibria regions. In the empirical analysis, we begin by drawing a heat map of the raw data on the involvement of shared conflict for points i and j with the resource index for these points on the x and y axes. In this simple plot, we find striking confirmation of the model's implications regarding equilibria regions over the ij resource space. Groups represented by our disaggregated points i and j behave in a manner entirely consistent with the predictions of our simple static model in the cross section.

Throughout the analysis we will focus on the longer-run accumulation of resources rather than contemporaneous shocks. In the immediate aftermath of a shock, there is often a greater likelihood of conflict because of the reduced opportunity cost of going to war (Grossman,

[5]This is in line with the mechanisms outlined in, e.g., Acemoglu and Johnson (2005); Acemoglu et al. (2001, 2005).

1991). This pattern has been well established in the empirical literature (Brückner and Ciccone, 2010; Hsiang et al., 2013; Jia, 2014; Miguel and Satyanath, 2011). Over the long run, however, we might expect different outcomes. Greater resource accumulation leads to a larger pie to fight over, leading to a rapacity effect (Grossman, 1991; Hirshleifer, 1989; Skaperdas, 1992). Further, better access to resources allows parties to raise stronger militias or build state-capacity for counter-insurgencies (Bazzi and Blattman, 2014; Besley and Persson, 2010). The longer-run accumulation of wealth could make one party relatively stronger and more likely to succeed in expropriating its rival's resources, and so could increase the likelihood of conflict.

Our test of these implications involves estimating the impacts of i- and j-specific natural resource endowments on ij conflict incidence.[6] We control for local geographic, agricultural, and climatological characteristics, as well as spatial fixed effects. Standard errors are clustered using conservatively defined geographic levels to account for potential spatial correlation in the error term.

The results of this analysis is in line with the heat map evidence and in strong support of the model's predictions. Resource endowments are both a statistically and economically significant determinant of the spatial distribution of conflict in sub-Saharan Africa. We complement this evidence with procedures relying on optimal bandwidth regression discontinuity (RD) methods (Calonico et al., 2014), to measure the rise in the likelihood of conflict when crossing the resource threshold from a peace to a conflict equilibrium region.

In keeping with the importance of institutions as mediators of conflict and development (Acemoglu and Johnson, 2005; Acemoglu et al., 2001, 2005), we show that model fit is substantially better for ij pairs where institutional quality (measured by property rights, risk of expropriation, political stability, and voice and accountability) is higher, and that the estimated cutoff value is lower (i.e., conflict is more likely to break out for smaller resource shocks) for these pairs. These results suggest that good institutions can not only mitigate the likelihood of conflict, but also break the link between resources and conflict.

Finally estimate analogous regression equations for satellite data on nighttime lights to highlight how the resource-conflict dependency results in a complex reduced form relationship between resource abundance and development. Again, we find confirmation of the

[6] When testing the model using rainfall data, we find a (two-dimensional) structural break in the relationship between region i and j's historical rainfall patterns on the one hand and conflict between the two groups on the other. Our empirical approach is an extension of structural break methods used by Card et al. (2008) and Gonzalo and Wolf (2005), in which we use two-thirds of the sample to find the optimal cutoff and the remaining one-third to perform regression analysis using the estimated cutoff value.

model's predictions using light intensity as a proxy for local economic development. Additional evidence using regression discontinuity methods and two-stage least squares analyses supports this story, showing that as regions move across the optimally determined threshold the rise in conflict correspondingly leads to a sharp drop in light density.

Our study relates to three main strands of work in economics. The first literature to which we contribute considers the role of geographic endowments in development. Geography and its correlates matter, particularly in Africa (Acemoglu et al., 2001; Alexeev and Conrad, 2009; Alsan, 2015; Barrios et al., 2010; Dell et al., 2012; Mehlum et al., 2006; Nunn and Puga, 2012). We add to this literature by focussing on spatial externalities: how does one group's natural resource endowment help or hurt a neighbor's development? We point to conflict as a primary mechanism for this externality.

Second, we study strategic interactions between rival factions in the face of economic shocks (Esteban et al., 2012; Esteban and Ray, 2011a,b; Mitra and Ray, 2014). In regard to this literature, it is crucial to understand how shocks to a rival group can affect one's own likelihood of engaging in conflict. Given that this interaction is strategic, a game-theoretic model is necessary to outline the conditions that may lead to the outbreak of conflict. Such strategic complementarities also featured prominently in earlier work on the economics of conflict (Grossman, 1991).

Finally, we contribute to the broad literature on the causes of conflict. A large body of work demonstrates the causal impacts of factors such as population composition, weather, natural resources and other forms of income, culture, and institutions on the incidence of conflict. This literature puts particular focus on Africa, given that continent's long and intense history of conflict.[7]

We add to this literature in two ways. First, while previous work has recognized why conflicts, resource endowments, and other characteristics of neighboring areas may lead to conflict (e.g., Michalopoulos and Papaioannou (2016)), the empirical literature on this question is relatively new. Many existing studies have looked primarily at the country level (Buhaug and Gleditsch, 2008; Caselli et al., 2015; Gleditsch et al., 2006), examine spillovers primarily as robustness (De La Sierra, 2015; Dube and Vargas, 2013), or consider a fairly narrow context (Balestri and Maggioni, 2014). Our paper is akin to recent work by Berman et al. (2014) and Harari and La Ferrara (2013); our addition is to consider complementarity in own and neighbors' resource endowments and the estimation, guided by theory, of

[7]See, e.g., Arbatli et al. (2015); Berman and Couttenier (2015); Brückner (2010); Caselli et al. (2015); Caselli and Tesei (2015); Esteban et al. (2015); Michalopoulos and Papaioannou (2016); Rohner et al. (2013).

thresholds above which spillover effects come into existence.

Second, we integrate several mechanisms into a single model that can be tested empirically. The literature has distinguished between the opportunity cost effect and the 'rapacity effect' by studying the type of shocks, who owns the resources, and the location and type of resource (Caselli et al., 2015; Dube and Vargas, 2013; Mitra and Ray, 2014). Similarly, different resources may accumulate over different spans of time. Wages may fall in the immediate aftermath of a negative shock, and lower the opportunity cost of conflict, but building armies and accumulating expropriable wealth is a longer-term process, during which the state-capacity effect or the rapacity effect may be more relevant. Our model integrates a rapacity effect and an endowment effect into a single framework (and the opportunity cost effect as well, in an extension). This gives testable predictions that differ from models in which it is only one's own opportunity cost of violence or the external returns to rapacity that create incentives for conflict.

The remainder of the paper is structured as follows. Section 2 sets up our model and delivers its main predictions through a set of lemmas and propositions. Section 3 describes our data. Section 4 details our empirical strategy, and section 5 describes our results. Finally, section 6 is a concluding discussion.

2 Model

We model the interaction of two parties, i and j, who play a symmetric, simultaneous game that determines peace or conflict between them. Our static model generates testable empirical predictions, and extensions to the basic model, including heterogeneity in institutional structures, provide additional refinements to our predictions. The parties choose strategies s from the set $\{R, N\}$, where R denotes the decision to raid (i.e., engage in conflict), and N denotes the decision not to raid. We denote a strategy profile by (s_i, s_j) for $s_i, s_j \in \{R, N\}$.

Each party is endowed with wealth, denoted $r_i, r_j \in (0, \infty)$ for resources in i and j, respectively. If neither party raids (N, N), each keeps its own wealth. If a party raids, it expends fixed cost c in conflict, which we assume for simplicity is the same for i and j. If a party raids *successfully*, it seizes a fraction δ of the opposing party's wealth. If one party raids and the other chooses not to fight ((R, N) or (N, R)), the raiding party succeeds with probability 1. If, on the other hand, both parties choose to raid (R, R), then with probability

$p \equiv \frac{r_i}{r_i+r_j}$ party i wins.[8] If i wins in this scenario, it seizes a proportion δ of j's *remaining* assets, (i.e. $\delta(r_j - c)$).

The game is summarized in Figure 3. Note that in (R, R), we evaluate the expected payoff to each party given probability of success p defined above.

Figure 3: The payoff-matrix for the game between i and j.

		j: R	j: N
i	R	$p(r_i - c + \delta(r_j - c)) + (1-p)(1-\delta)(r_i - c)$, $(1-p)(r_j - c + \delta(r_i - c)) + p(1-\delta)(r_j - c)$	$r_i - c + \delta r_j$, $(1-\delta) r_j$
	N	$(1-\delta) r_i$, $r_j - c + \delta r_i$	r_i, r_j

Notes: p is the probability of victory for party i, r_k are the level of resources for parties $k = \{i, j\}$, c is the cost of engaging in conflict, and δ is the fraction of resources that the victorious party expropriates.

2.1 Best Responses

The best responses of each party to the other's actions depend on the model parameters, and in particular the realizations of wealth r_i and r_j. The following lemma determines the best response functions (denoted $BR_k(s_{-k})$ for $k \in \{i, j\}$) for i and j with wealth $(r_i, r_j) \in \mathbb{R}^2_+$.

Proposition 2.1 *The following are best response functions for agent k:*

1. $BR_k(s_{-k} = N) = \begin{cases} R, & \text{if } r_{-k} > \frac{c}{\delta} \\ N, & \text{else} \end{cases}$

2. *Let* $\psi(r_k) := \frac{-\delta r_k^2 + c(1+\delta) r_k}{\delta r_k - c(1-\delta)}$.

   $BR_k(s_{-k} = R) = R$, *for all* (r_k, r_{-k}) *such that*

$$\{(r_k, r_{-k}) : r_k \in (c\frac{1-\delta}{\delta}, \infty), r_{-k} > \psi(r_k)\} \quad (1)$$

   And $BR_k(s_{-k} = R) = N$, *for all* (r_k, r_{-k}) *such that*

$$\{(r_k, r_{-k}) : r_k \in (0, c\frac{1-\delta}{\delta})\} \cup \{(r_k, r_{-k}) : r_k \in (c\frac{1-\delta}{\delta}, \infty), r_{-k} < \psi(r_k)\} \quad (2)$$

[8] We choose this functional form for p for its parsimony and because intuitively p should be increasing in r_i and decreasing in r_j.

2.2 Equilibria

These best response functions help characterize the set of pure strategy Nash Equilibria in the (r_i, r_j) space. Figure 4 divides the (r_i, r_j) space into the Nash Equilibrium regions. The space can then be described by the following lemmas which are proved in Appendix A.1.:

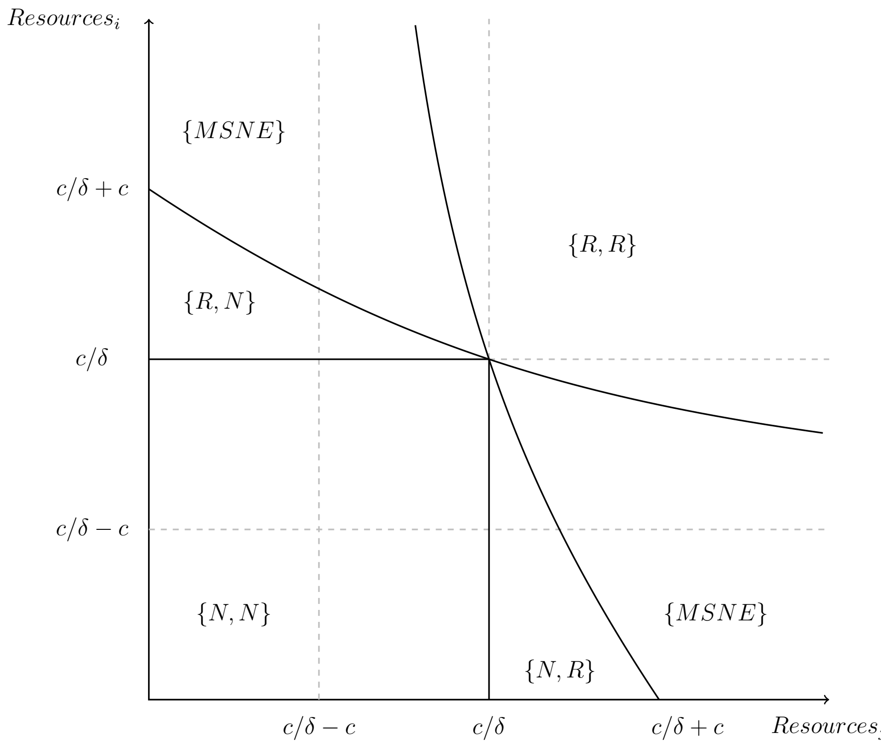
1. For $r_i, r_j \in (0, \frac{c}{\delta})$, (N, N) is the unique pure-strategy Nash Equilibrium.
2. (R, R) is the unique pure strategy Nash Equilibrium in the region $\{(r_i, r_j) : r_i \in (c\frac{1-\delta}{\delta}, \infty), r_j > \psi(r_i)\} \cap \{(r_i, r_j) : r_j \in (c\frac{1-\delta}{\delta}, \infty), r_i > \psi(r_j)\}$
3. (N, R) is the unique pure strategies Nash Equilibrium in the region $\{(r_i, r_j) : r_i \in (\frac{c}{\delta}, \infty), r_j < \psi(r_i)\}$
4. (R, N) is the unique pure strategies Nash Equilibrium in the region $\{(r_i, r_j) : r_j \in (\frac{c}{\delta}, \infty), r_i < \psi(r_j)\}$
5. $\exists$ a unique mixed-strategies Nash Equilibrium (MSNE) in the region $\{(r_i, r_j) : r_j \in (\frac{c}{\delta}, \psi(r_i)), r_i > \psi(r_j)\} \cup \{(r_i, r_j) : r_i \in (\frac{c}{\delta}, \psi(r_j)), r_j > \psi(r_i)\}$

Intuitively, these lemmas organize the (r_i, r_j) plane into several regions summarized in Figure 4. In the convex hull comprised of large realizations of wealth for both parties, each party's dominant strategy is R. This is brought on by two motives. First, when i and j both have high wealth, but i has relatively more, it is prone to raid because the probability of success in capturing some of j's wealth is relatively high. On the other hand, when j has relatively more, i prefers raiding because if it does win, it captures some of j's considerable wealth. The intuition behind the proposition that i wishes to raid j when j has higher wealth, comes from the 'rapacity effect', where i wishes to capture a fraction of j's larger resource pie. Whereas the intuition behind the finding that i wishes to raid when i has higher wealth comes from the 'relative strength' mechanism where i has more resources to build a stronger army and therefore a higher probability of victory against j.

2.3 A Sharing Rule

The possibility that conflict can be mitigated by the sharing of resources can be captured by a sharing rule, whereby each party shares a proportion ϕ of their wealth with the other party if and only if neither party raids the other. This changes the payoffs in the (N, N) portion

Figure 4: Nash Equilibria in the (r_i, r_j) space



The figure plots the Nash equilibrium regions for any given draw of resources for parties i and j. c is the cost of engaging in conflict, and δ is the fraction of resources that the victorious party expropriates.

of the game to be $(1-\phi)r_i + \phi r_j$ and $(1-\phi)r_j + \phi r_i$. That is, in the absence of any raids, party i receives $(1-\phi)$ of it's own resources, and a ϕ portion of party j's resources. The modified game is presented in Appendix Figure A1. This sharing rule expands the region of the (N, N) Nash Equilibrium as can be seen in Figure 5.[9]

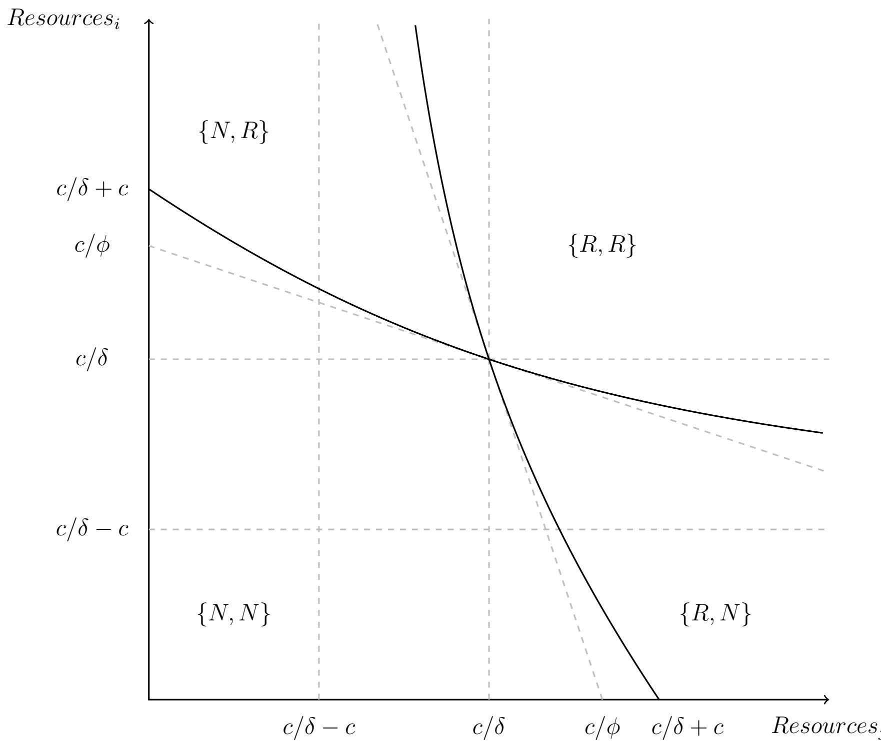
The best response functions, game matrices, proofs of propositions, and a description of the Nash Equilibrium regions under the sharing rule can be found in Appendix A.2. Intuitively, the easier it is to trade and share the fruits of higher resources with your neighbors, the lower is the likelihood of conflict.

2.4 The Opportunity Cost of Fighting

In many instances we may expect engaging in conflict to have a cost that varies with the amount of resources. For instance, the opportunity cost of war in terms of foregone earnings

[9]The figure restricts ϕ to values of $\delta > \phi > \frac{\delta}{1+\delta}$ for clarity.

Figure 5: Pure-strategy Nash Equilibria in the (r_i, r_j) space with the Sharing-Rule



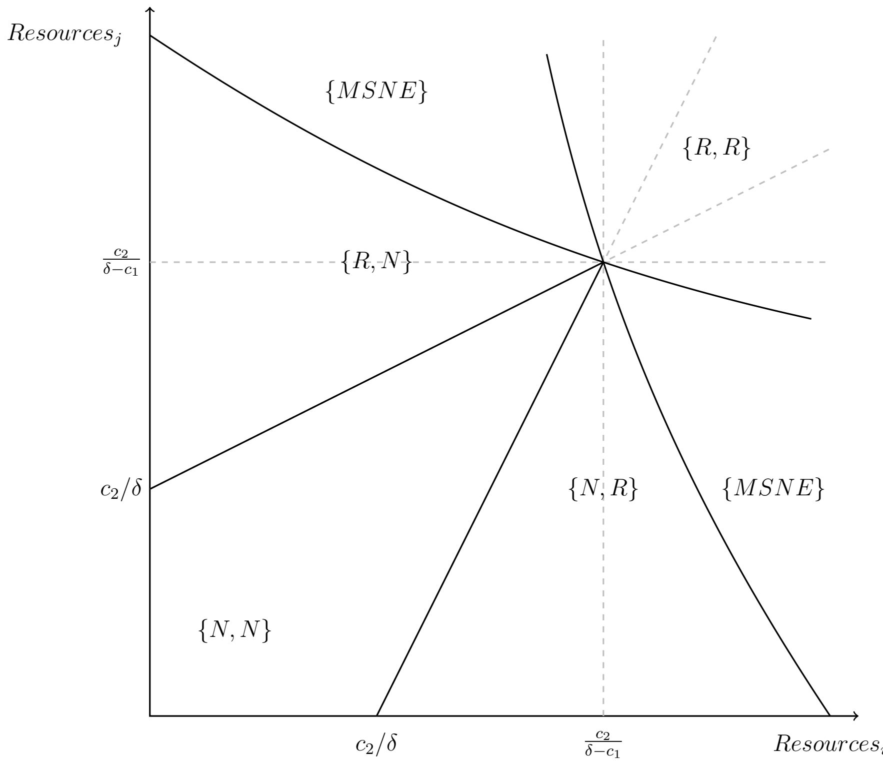
The figure plots the Nash equilibrium regions for any given draw of resources for parties i and j, in the presence of a sharing rule. c is the cost of engaging in conflict, and δ is the fraction of resources that the victorious party expropriates. ϕ is the fraction of resources shared.

in the labor market will be higher for richer economies. Since the strength of the labor market depends on the strength of the overall economy, we may expect that this opportunity cost is larger in places that have more resources. In order to incorporate this aspect into our baseline model, we disaggregate the cost of war term into two different types of costs – c_1 is a fixed proportion of the resources, whereas c_2 is the same fixed cost we had in the baseline model. The variable cost $c_1 \times r_k$ captures additional channels like the opportunity cost of war. The payoff matrix that includes this term is shown in Appendix Figure A2. These variable costs expand the (N, N) Nash Equilibrium regions, as in Figure 6:

The best response functions, game matrices, proofs of propositions, and a description of the Nash Equilibrium regions under the opportunity cost extension can be found in Appendix A.3. The $\{N, N\}$ region is now larger, since even as resources increase, the opportunity cost motive dampens the likelihood of conflict.

In general, across the various model specifications it is clear that the rapacity effect and

Figure 6: Nash Equilibria in the (r_i, r_j) space



The figure plots the Nash equilibrium regions for any given draw of resources for parties i and j. c_1 is the variable cost of engaging in conflict, c_2 is the fixed cost of engaging in conflict, and δ is the fraction of resources that the victorious party expropriates.

the relative-strength mechanism divide the resource space into a few areas with different probabilities of conflict. The sharing rule and opportunity cost extension change the shape of these areas, but maintain the overall predicted patterns. It is these patterns that we explore in the empirical section.

3 Data

We combine spatial data on rainfall, oil and gas reserves, diamond deposits, gold mines, zinc deposits, cobalt mines, conflicts, and nighttime lights. We begin with data set at the 0.5 degree by 0.5 degree latitude/longitude grid level covering the whole of Sub Saharan Africa.[10] Each observation is a grid-cell pair: the same cell will show up once as cell i, and

[10] In the tables shown we exclude the northern African countries of Algeria, Morocco, Egypt, Libya and Tunisia. We perform a robustness check of all our result by also including these countries and our results

multiple times as cell j.[11] We construct the pairs between any two grid-cells within a specific distance radius. In our main specifications we use a 500km radius, but we do robustness checks to show that our results are not sensitive to any specific radius, and, as we show, are even more powerful at smaller distances, such as at a 150km radius.

These are chosen to match the data on rainfall that are available in the well-known series from Matsuura and Willmott (2009). Hosted by the University of Delaware, these provide monthly temperature and rainfall for each 0.5 degree by 0.5 degree latitude/longitude grid between 1900 and 2010.[12] We use mean annual rainfall experienced in each grid cell over the period 1992 to 2008.[13] These data are commonly used in economic development (e.g. Dell et al. (2012)). We therefore collapse all our inter-temporal data into a single cross-section, allowing us to study the spatial patterns of conflict and development, rather than "shocks" to resources as much of the literature does. Even though our last year is constrained by the availability of the geographic coordinates of one of our conflict datasets, the first year of our data is chosen so as study conflict over a ten year period; we therefore do a robustness exercise and extend this window to be 20 or 30 years long.

We then combine this rainfall data with data on oil and gas reserves and lootable diamonds, available from the International Peace Research Institute, Oslo (PRIO). The diamonds dataset, first created by Gilmore et al. (2005), lists all known diamond deposits in the world, coded with precise geographic coordinates. The oil and gas reserves dataset, developed by Lujala et al. (2007), depicts polygons for each deposit. We take the centroid of the polygon and merge this data with data on mines from the United States Geological Survey (USGS).[14] The USGS has geolocations for mines across the world, and we pick the most prevalent resources for our analysis. We merge this resources data with data on conflict at the 0.5 degree by 0.5 degree latitude/longitude grid level. Since we construct grid-cell conflict pairs, each conflict will have more than one observation, one for each party involved. A grid-cell pair will have $conflict_{ij} = 1$ if they were ever in conflict with each other during that 10 year period, and $conflict_{ij} = 0$

We use two main sources of conflict data. The first is the Uppsala Conflict Data Program

hold for the entire African continent.

[11]It is possible to do a similar analysis at the ethnic-group level, as some of the literature has done. However, as we are not studying ethnic war, but rather a model of territorial control of resources, the grid-level data allows us to focus on this issue at the greatest extent possible.

[12]See *http://climate.geog.udel.edu/˜climate/*.

[13]This time period is chosen so as to overlap with the conflict datasets described below, but is robust to using 20 or 30 year long rainfall averages.

[14]See *https://data.usgs.gov/*

(UCDP) / International Peace Research Institute, Oslo (PRIO) Armed Conflict Dataset, Version 4 - 2011. This is a widely used data set (Miguel and Satyanath (2011)) that lists conflicts and the years during which they occur. Initially coded by Gleditsch et al. (2002), these data report conflicts occurring between 1946 and 2010. To assign geographic coordinates to these conflicts, we add additional data, taken from Raleigh et al. (2006). For conflicts in the base PRIO data up to 2008, these report a latitude/longitude coordinate as well as a radius in kilometers. The circle defined by these numbers is taken as the area affected by the conflict, and we consider any rainfall point lying within this circle, in the year of conflict, as experiencing conflict. Additional information on these data are provided by Raleigh et al. (2006) and Hallberg (2012). In particular, the latitude and longitude coordinate for a conflict is defined as the mid-point of all known locations of battles. The radius is constructed in multiples of 50 km and encompasses all of these battle locations, except for sporadic violence far from the the remaining events.

Our second source of conflict data is The Armed Conflict Location & Event Data Project (ACLED) database records conflicts at each latitude and longitude, the parties involved, and the type of conflict. We define two different ACLED observations to be part of the same conflict if the parties involved are the same, and they take place within a 500km radius from each other. We then study the effects on territorial conflicts and exclude observations that correspond with riots, protests or non-violent events. While restricting our analysis to territorial conflicts lowers the number of conflicts we study, the advantage is that we are then focusing on precisely the types of interactions that our model analyzes.

We also consider the development implications of resources and conflict. We follow past researchers such as Michalopoulos and Papaioannou (2013) and Henderson et al. (2012) in using night-time lights as a proxy for economic activity. Luminosity data are taken from the Defense Meteorological Satellite Program's Operational Linescan System. Major advantages of these data include their arbitrary divisibility, their consistency across multiple political jurisdictions, their high spatial resolution, and their availability given the weaknesses of official data on African economic activity (Jerven, 2013). Henderson et al. (2012) provide additional information on the data. These data are constructed as an annual average of satellite images of the earth taken daily between 20:30 and 22:00 local time. The raw data are at a 30 second resolution, which implies that each pixel in the raw data is roughly one square kilometer. We average over pixels within a rainfall point. The raw luminosity data for each pixel is reported as a six-bit integer ranging from 0 to 63.

4 Estimation Strategy

The theoretical model allows us to divide the conflict-resources space into four distinct Nash Equilibrium regions. When there are low resources for both parties, there is a lower probability of conflict as neither party has resources to build an army and there is little wealth to expropriate from one's neighbor. On the other hand, having a large amount of resources for either party leads to more conflict, and this is especially true when both parties have high levels of resources.

In order to capture this pattern produced by the Nash regions in Figure 4, we use the following regression specification at the $i - j$ grid-cell pair level:

$$conflict_{ij} = \gamma_0 + \gamma_1 r_i + \gamma_2 r_j + \gamma_3 (r_i \times r_j) + \gamma_{\mathbf{x}} \mathbf{X} + \nu_a + \epsilon_{ij} \ , \tag{3}$$

where $conflict_{ij} = 1$ if the grid-cell i was ever in conflict with grid cell j between 1998 and 2008. Our first resource measure, the presence of oil or gas, diamonds, gold, zinc or cobalt, is a discrete measure. Therefore, we can define $r_k = 1$ for $k = \{i, j\}$ if the region k contains any of these resources. The γ_0 captures the (No, No) region in the south-west section of Figure 4 where neither party raids. Similarly, $\gamma_0 + \gamma_1$ captures the north-western quadrant of the graph, which is represented by a $(Raid, No)$ region and a MSNE region. $\gamma_0 + \gamma_2$ corresponds to the $(No, Raid)$ and the MSNE region in the south-east section of the graph, and $\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3$ captures the $(Raid, Raid)$ quadrant in the north-eastern portion of the figure. Given the model's predictions, we should therefore expect $\gamma_1 \geq 0$, $\gamma_2 \geq 0$ and sum of coefficients, $\gamma_1 + \gamma_2 + \gamma_3 > 0$.

When using a continuous variable, like rainfall, our model predicts that conflict will be higher above certain rainfall cutoffs r^c:

$$conflict_{ij} = \beta_0 + \beta_1 \mathbb{1}_{r_i > r^c} + \beta_2 \mathbb{1}_{r_j > r^c} + \beta_3 \mathbb{1}_{r_i > r^c} * \mathbb{1}_{r_j > r^c} + \beta_{\mathbf{x}} \mathbf{X} + \nu_a + \epsilon_{ij} \tag{4}$$

In this formulation, r^c represents the cutoffs in Figure 4 separating the Nash regions. As a region's own resources r_i cross the cutoff r^c, we enter a different Nash region. Like before, β_0 captures the (No, No) region in the south-west section of Figure 4, $\beta_0 + \beta_1$ captures the north-western quadrant of the graph, and $\beta_0 + \beta_2$ corresponds to the south-eastern quadrant. Finally, $\beta_0 + \beta_1 + \beta_2 + \beta_3$ captures the $(Raid, Raid)$ quadrant in the north-eastern portion of the figure. Given the model's predictions, we should expect $\beta_1 \geq 0$, $\beta_2 \geq 0$ and sum of coefficients, $\beta_1 + \beta_2 + \beta_3 > 0$.

While the amount and geographic location of resources is exogenous, in the sense that it is taken as given by the actors involved, it is important to control for other factors, $\mathbf{X}$, that otherwise influence the likelihood of conflict in Africa and that may be correlated with resource accumulation. These controls include (for both points i and j) latitude and longitude, measures of land quality, malaria prevalence, humidity, population density, ruggedness and a quadratic in the distance between the two points. The results are robust to omitting these controls and to including the controls in other functional forms, like logarithmic transformations or quadratic formulations of population density, and higher order polynomials of the distance between two points. Furthermore, we also restrict attention to the variation within continuous regions by including fixed effects, ν_a, for Agro-Ecological Zones (AEZ) and, alternately, latitude-longitude grids of various sizes.

In order to estimate Equation 4 for a continuous variable like rainfall, it is necessary to identify the cutoff r^c. One simple approach would be to simply use the median level of resources. While all our results are consistent with using the median as a cutoff, there is no reason to believe that the median is the correct threshold. The literature on structural breaks has made progress in identifying such cutoffs in various contexts (Bai, 1997a,b, 2010; Bai and Perron, 1998; Gonzalo and Pitarakis, 2002; Gonzalo and Wolf, 2005; Hansen, 2000). These papers propose that the cutoff can be estimated by using a search algorithm that identifies the threshold that minimizes the residual sum of squares of the model, or alternatively maximizes the partial R-squared for the the variable of interest. Under a correctly specified model, this process leads to a consistent estimate of the cutoff and the parameters of interest.

While most of this literature focuses on structural breaks in time-series data, there are applications using cross-sectional micro-data (Card et al., 2008). In these cases, likelihood ratio (LR) tests under the null of no structural breaks do not allow for conventional hypothesis testing, and instead alternative methods that do not suffer from the drawbacks of such LR tests are used (Gonzalo and Wolf, 2005). An advantage of having a large sample is that we can use a split-sample approach – while one portion of the sample is used to identify the cutoff, the rest is utilized in running the regression of interest taking the cutoff as given (Angrist et al., 1999; Angrist and Krueger, 1995). Due to the independence of the subsamples, the cutoff has a standard distribution under the null. One application of this can be found in Card et al. (2008), who use two-thirds of the sample to identify a threshold and the remaining one-third to identify the coefficients of interest. Similarly, Gonzalo and Wolf (2005) use the intuition behind Politis and Romano (1994) to propose using many randomly

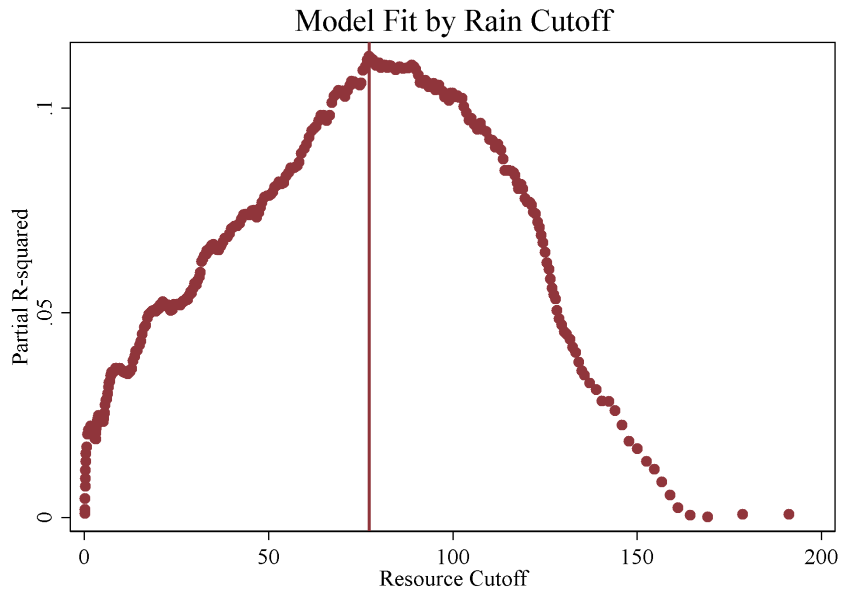


Figure 7: Model Fit and Optimal Cutoff

The figure plots the partial R-square of the regression model in Equation 4 for each rainfall cutoff. Rainfall measure is annual rainfall, in mm, averaged over 1998 to 2008. The optimal cutoff is at 77.68mm of rainfall.

selected sub-samples to describe the distribution of cutoffs and coefficients of interest.

In keeping with the literature, therefore, the following empirical strategy is used. Two-thirds of the data are randomly selected, upon which the search algorithm is performed to identify the cutoff that minimizes the residual sum of squares. This can be seen in Figure 7, which identifies the value of the resources cutoff for which the partial R-squared is maximized in Equation 4. The remaining one-third is then used to identify the coefficients in the equation. This process is repeated with various randomly selected sub-samples to describe the distribution of the cutoffs and the parameters estimated. In our case, however, the process of repeatedly picking different sub-samples did not affect the estimates, largely because there was little to no change in the optimal cutoff across iterations.[15]

While identifying the cutoff is necessary for estimating β_1, β_2 and β_3, it is also an informative parameter in itself since it represents the threshold amount of resources that pushes parties into conflict. As theory suggests, this threshold may be lower for regions that either have a lower cost of conflict, or higher potential returns to conflict. Facilitation of trade or any other sharing-rules may, alternatively, raise the threshold necessary for the outbreak of

[15]Since our estimated resource cutoff parameter has little to no variation, we do not report a standard error on the cutoff value.

conflict. Indeed, we test for one dimension of heterogeneity in the optimal cutoff and model fit below. We investigate whether the optimal cutoff is lower, and corresponding model fit improved, where institutions are weaker.

One additional issue is that of the estimation of standard errors. A standard result in the structural break literature is that the sampling error in the break can be ignored when estimating the size of the break (Bai, 1997b; Card et al., 2008). Given the iterative nature of the split-sample approach, it is possible to obtain a distribution of the coefficients of interest. However, in our context, this produces extremely tight standard errors due to a very precisely estimated cutoff-value, and a more conservative approach may be warranted. Given the possibility of spatial correlation in the errors, the approach we use is to cluster the standard errors at various geographic levels. The data consists of points of a size spanned by 0.5×0.5 degree in latitude and longitude, matched to each of its neighboring points within a 500km radius. Standard errors can therefore be clustered at the point level, or two-way clustered errors can be calculated for the point and its neighboring region, accounting for the correlations among both the parties involved Cameron et al. (2011). Estimates that allow for a greater degree of spatial correlation can be obtained by calculating errors at latitude-longitude grids of larger sizes, ranging from a 1×1 degree grid, to a more conservative 2×2 degree grid which consists of sixteen adjacent points and spans approximately 50 thousand square kilometers at the equator.[16]

We then estimate a similar regression model to study how light density changes at these resource index cutoffs. After identifying the cutoffs based on structural breaks in the likelihood of conflict, we regress log light density on these cutoffs.[17] Since rainfall directly affects light density, we also control for continuous measures of own rainfall, neighbor's rainfall and the interaction between the two.

The cutoffs not only allow for the estimation of Equation 4, but also the estimation of the size of the discontinuity at each boundary. In doing so, we can rely on the Regression Discontinuity (RD) literature to identify how the probability of conflict changes at each threshold. We do this using the latest methods developed by Calonico et al. (2014), who calculate the optimal bandwidths, and provide a robust bias-corrected estimate of the coefficients and standard errors. The methods developed by the RD literature can be used for two different results.[18] The first is just to see what happens to conflict when the region's

[16]The results are robust to aggregating the data to larger grid-sizes.

[17]We also do a robustness check where we transform the light density variable to be log(light density+0.001) to account for the 0 values, as Michalopoulos and Papaioannou (2013) do in the context of Africa.

[18]Our exercise is not strictly an RD since we are using an estimation procedure to first identify the

own rainfall crosses the threshold, whereas the second looks at the effect of the neighboring region's rainfall at the cutoff. We should expect the likelihood of conflict to discontinuously rise at the cutoff, and in turn we should expect light density to jump down in response to this increase in the likelihood of conflict. Given this response, we perform a two-stage least squares exercise, again using the RD methods, where in the first stage we estimate the increase in the likelihood of conflict in crossing the resource cutoff, and in the second stage the corresponding fall in light density. The assumption underlying this 2SLS exercise is that, other than conflict, there are no alternative underlying features of the data that produce discontinuous jumps to light-density at the cutoff. With the help of this assumption we measure the impact of conflict on light-density and regional development.[19]

5 Results

In this section, we present and discuss empirical evidence in support of the model developed in section 2. The analysis is carried out in multiple stages as discussed in section 4 above.

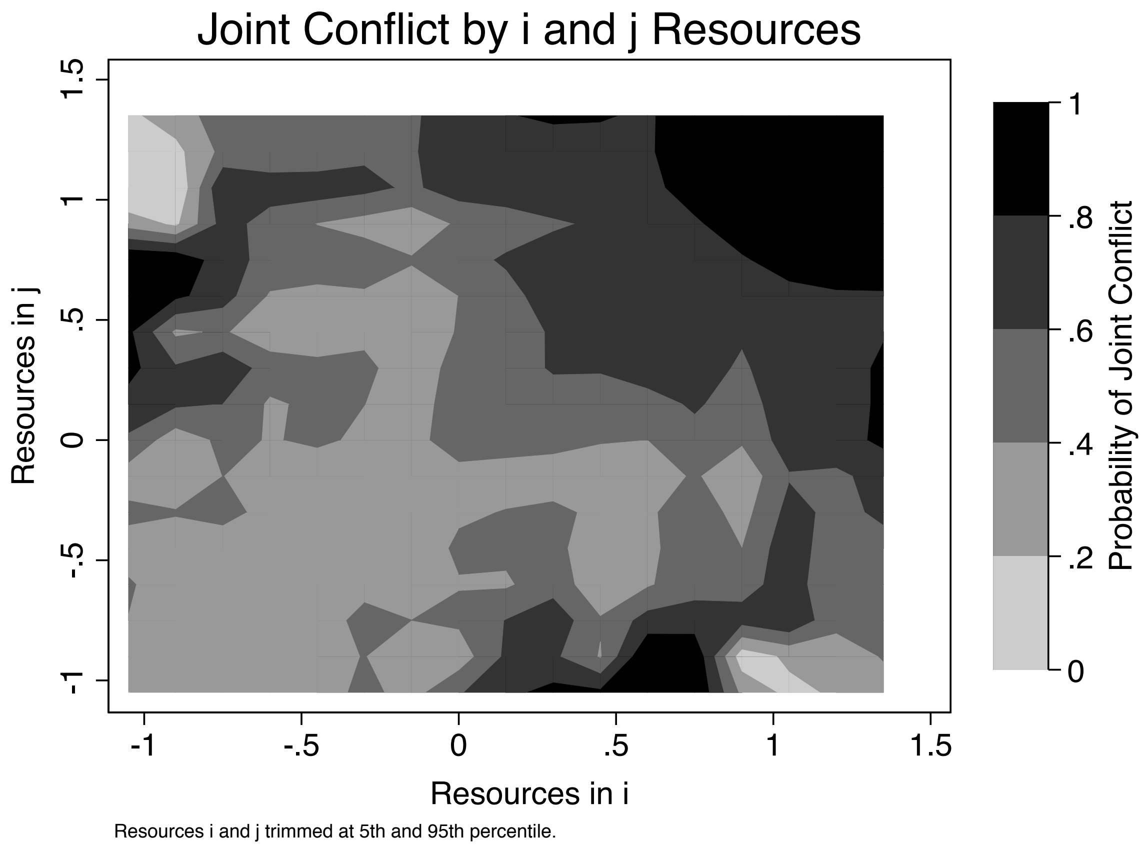
5.1 Joint Conflict

We start by showing a heat map of joint conflict between points i and j as a function of the relative resource accumulations between the points in the pair. The heat map, shown in Figure 8, bears remarkable resemblance to the graph depicting the model predictions in Figure 4. That is, the region adjacent to the origin shows little to no likelihood of joint conflict; while the upper-right quadrant of the heat map corresponds to the highest likelihood of joint conflict, as predicted by the model. The no conflict region at the origin extends along both the x and y axes until a distinct boundary, beyond which the likelihood of conflict jumps up discontinuously. Specifically, a high degree of inequality between resources in i and j leads to a higher probability of joint conflict, as one region has the resources to raid its neighbor, and the other wishes to expropriate its neighbor's resources. This probability of conflict diminishes as the inequality diminishes (i.e., resources in j approach the high level of resources in i), but then jumps up again as we approach equally high resource levels for both i and j (i.e., as we approach the upper-right quadrant). Note further that the

discontinuity. Our exercise using RD methods is to provide an estimate of the corresponding size of this discontinuity.

[19]For the exercise we translate light density into GDP using the elasticities for low-income countries and Africa discussed in the literature (Henderson et al., 2012; Michalopoulos and Papaioannou, 2013).

Figure 8: Heat Map of the Probability of Conflict by Resource Index



Resources is the first principal component of annual rainfall averaged over 1998 and 2008. Probability of joint conflict is the likelihood of ever being involved in the same conflict over a ten year period (1998 to 2008).

corner portions of the lower-right and upper-left quadrants representing extreme inequality actually show a reduction in conflict corresponding to the mixed strategy equilibrium regions in Figure 4. This non-monotonicity in the conflict-resource relationship lends preliminary empirical support to the predictions of the model.

Next, we discuss results from a more formal regression analysis of the model's predictions. We split up our main results into two tables – Table 1 uses PRIO conflict data and covers all conflicts, whereas Table 2 focuses in on territorial conflicts based on the ACLED data.

For both sets of tables, in our first two columns we look at the effect of the presence of any resource – oil, gas, diamonds or mines – on the probability of region i and j being in conflict, whereas in our last two columns we do a similar exercise for rainfall being above the cutoff. Using the procedure discussed in section 4, we estimate the cutoff level of rainfall

Table 1: The Effect of Resources on Conflict (PRIO)

Dependent Variable: Probability(Region i&j in same conflict)				
Resource variable:	**Oil, diamonds, mines**		**Rainfall**	
Resource i	**0.0639**	**0.0305**	**0.0728**	**0.0598**
SE cluster: Point i	(0.0180)***	(0.0105)***	(0.0140)***	(0.00921)***
2 by 2 grid	(0.0315)**	(0.0164)*	(0.0351)**	(0.0198)***
2-way: Point i&j	(0.0216)***	(0.0238)	(0.0241)***	(0.0312)*
Resource j	**0.0680**	**0.0129**	**0.135**	**0.0602**
SE cluster: Point i	(0.00387)***	(0.00277)***	(0.00857)***	(0.00451)***
2 by 2 grid	(0.0124)***	(0.00878)	(0.0250)***	(0.0114)***
2-way: Point i&j	(0.0210)***	(0.0236)	(0.0177)***	(0.0260)**
Resource i&j	-0.0170	0.00610	0.0835	0.0641
SE cluster: Point i	(0.0115)	(0.00871)	(0.0118)***	(0.00720)***
2 by 2 grid	(0.0224)	(0.0152)	(0.0345)**	(0.0199)***
2-way: Point i&j	(0.0195)	(0.0187)	(0.0198)***	(0.0210)***
Sum of Coefficients	**0.115**	**0.050**	**0.292**	**0.184**
SE cluster: Point i	(0.021)***	(0.013)***	(0.014)***	(0.010)***
2 by 2 grid	(0.041)***	(0.023)	(0.038)***	(0.026)***
2-way: Point i&j	(0.036)***	(0.035)	(0.033)***	(0.047)***
R-squared	0.334	0.631	0.354	0.639
Controls (i & j)	All	All	All	All
Fixed Effects	AEZ	Grid 7 by 7	AEZ	Grid 7 by 7
Observations	1,901,074	1,901,074	633,821	633,821
Mean dependent var	0.34	0.34	0.34	0.34
Resource cutoff	-	-	77.68	77.68

Conflict data: PRIO. Oil, diamonds and mines: PRIO and USGS. Rainfall: University of Delaware.
Regressions of ever being involved in the same conflict over a ten year period (1998 to 2008) on resources for the region and neighboring region.
In the first two columns, our resource measure is binary to indicate whether or not the region has any oil, gas, diamonds, gold, zinc or cobalt deposits.
In the last two columns our resource measure is binary to indicate whether rainfall is above the optimal cutoff. Search algorithm for the rainfall cutoff is described in the empirical section and estimated cutoff is reported in the table above. One-third of the sample were randomly selected for the search procedure. Rainfall data is averaged over a ten year period between 1998 and 2008.
Observations including region $i\&j$ pairs where region j is within 500 kilometers of region i.
Controls include Agro-Ecological Zone Fixed Effects or Grid Fixed Effects, and measures of (for both points i and j) latitude, longitude, ruggedness index, land quality index, humidity, malaria, population density, and a quadratic of the distance between two points in kms. Robustness to specifications without controls shown in other tables.
Standard errors clustered at latitude-longitude degree grids - For instance, a 2 by 2 grid consists of sixteen adjacent points.

Table 2: The Effect of Resources on Conflict (ACLED)

Dependent Variable: Probability(Region i&j in same conflict)				
Resource variable:	**Oil, diamonds, mines**		**Rainfall**	
Resource i	**0.0205**	**0.0133**	**0.0225**	**0.00509**
SE cluster: Point i	(0.00505)***	(0.00449)***	(0.00270)***	(0.00219)**
2 by 2 grid	(0.00712)***	(0.00557)**	(0.00577)***	(0.00386)
2-way: Point i&j	(0.00540)***	(0.00572)**	(0.00388)***	(0.00432)
Resource j	**0.0198**	**0.0137**	**0.0201**	**0.00777**
SE cluster: Point i	(0.00166)***	(0.00146)***	(0.00190)***	(0.00135)***
2 by 2 grid	(0.00362)***	(0.00292)***	(0.00375)***	(0.00219)***
2-way: Point i&j	(0.00529)***	(0.00553)**	(0.00310)***	(0.00371)**
Resource i&j	0.0464	0.0460	0.0104	0.0126
SE cluster: Point i	(0.00781)***	(0.00758)***	(0.00229)***	(0.00204)***
2 by 2 grid	(0.0141)***	(0.0135)***	(0.00435)**	(0.00397)***
2-way: Point i&j	(0.0105)***	(0.0106)***	(0.00317)***	(0.00334)***
Sum of Coefficients	**0.087**	**0.073**	**0.053**	**0.026**
SE cluster: Point i	(0.010)***	(0.010)***	(0.004)***	(0.003)***
2 by 2 grid	(0.018)***	(0.016)***	(0.009)***	(0.006)***
2-way: Point i&j	(0.014)***	(0.015)***	(0.007)***	(0.007)***
R-squared	0.045	0.079	0.045	0.078
Controls (i & j)	All	All	All	All
Fixed Effects	AEZ	Grid 7 by 7	AEZ	Grid 7 by 7
Observations	1,901,074	1,901,074	633,821	633,821
Mean dependent var	0.028	0.028	0.028	0.028
Resource cutoff	-	-	20.67	20.67

Conflict data: ACLED, sub-sample of territorial conflicts only. Oil, diamonds and mines: PRIO and USGS. Rainfall: University of Delaware.

Regressions of ever being involved in the same conflict over a ten year period (1998 to 2008) on resources for the region and neighboring region.

In the first two columns, our resource measure is binary to indicate whether or not the region has any oil, gas, diamonds, gold, zinc or cobalt deposits.

In the last two columns our resource measure is binary to indicate whether rainfall is above the optimal cutoff. Search algorithm for the rainfall cutoff is described in the empirical section and estimated cutoff is reported in the table above. One-third of the sample were randomly selected for the search procedure. Rainfall data is averaged over a ten year period between 1998 and 2008.

Observations including region $i\&j$ pairs where region j is within 500 kilometers of region i.

Controls include Agro-Ecological Zone Fixed Effects or Grid Fixed Effects, and measures of (for both points i and j) latitude, longitude, ruggedness index, land quality index, humidity, malaria, population density, and a quadratic of the distance between two points in kms. Robustness to specifications without controls shown in other tables.

Standard errors clustered at latitude-longitude degree grids - For instance, a 2 by 2 grid consists of sixteen adjacent points.

above which the probability of joint conflict is higher. Using this cutoff value, we then regress the probability of a joint conflict between points i and j on indicators for presence of a resource or for rainfall in i being above the cutoff, and similarly for point j, and both i and j combined. As discussed in section 4, we estimate two different specifications with different fixed effects. These are our most conservative specifications, and the specifications without controls or fixed effects is shown in Table 4. The results of these regressions are presented in Table 1 and 2 with the controls and fixed effects denoted for each column in the rows below the estimated coefficients and standard errors.

In Tables 1 and 2 it is evident that the presence of a resource raises the likelihood of conflict. More resources in i increase the probability of a joint conflict, as do more resources in j. Furthermore, as predicted by the model, the probability of a joint conflict increases further when both i and j resources are high. Together, the estimates suggest that the likelihood of conflict is higher when moving from south-west to the north-east portion of the resource distribution represented in Figure 4. These results verify that the patterns depicted in the heat map in Figure 8 (i.e., low probability of joint conflict in the lower-left quadrant, a higher probability of conflict in the upper-left and lower-right quadrants and the highest probability of conflict in the upper-right quadrant) are indeed statistically significant.

For the PRIO data in Table 1, the increase in the probability of conflict relative to the baseline is also economically significant – the presence of oil, diamonds or mines raises the likelihood of conflict by at least 15% relative to the baseline, when moving from the lower-left no-conflict region to the upper-right high conflict region. This increase is even larger, an increase of at least 54%, if rainfall crosses the optimal cutoff into the upper-right high-conflict region. Lastly, we find the optimal rainfall cutoff to be 77.7 mm (reported in the last row of Table 1), which corresponds to the discontinuity depicted in Figure 8 quite well. The distribution around this estimate of the cutoff for the full sample of data is shown in Figure 7.

The ACLED results display a similar pattern in Table 2 for the sub-sample of territorial conflicts. While the baseline level of conflicts is small, the percentage increase in conflict in going from the lower-left low conflict quadrant to the upper-right high conflict region is high: around 92% for rainfall being above the cutoffs.

The results are robust across the different specifications including controls for both points i and j, along with fixed effects for agro-ecological zones (AEZ). The statistical significance of the results is unaffected when clustering standard errors at larger squares of the point i geospatial grid as well as two way clustering by squares in both the i and j geospatial grids.

5.2 Different Samples and Specifications

We next demonstrate the robustness of these main results in three important ways – changing the sample of analysis, using different model specifications, and focusing on specific resources. We then extend the analysis using RD methods to estimate the size of the discontinuity at these resource thresholds.

In Table 3 we replicate our main results for different cuts of the data. First, we use the entire African continent rather than Sub-Sahara, and show that across both data sets (ACLED and PRIO) and across different resources (rainfall and the combination of oil, diamonds or other mines), our results are both economically and statistically strong. Second, we restrict the sample only to i and j pairs that are of different ethnicities as defined by the Murdock (1959) Atlas of Africa. Since ethnic wars are a major focus of the large part of this literature, we are comforted to see that our results are strong for such conflicts as well. Thirdly, we narrow the radius of i-j pairs to be only for pairs within 150km of each other. This restricts the sample to only 9% of our total observations. Once again, across data sets and resources, our results tell the same story.

In Table 4 we are able to study how sensitive our results are to different modeling specifications. In the top half of the table we show specifications without controls and without fixed effects. These results are similar to our baseline results. Our empirical analysis depends crucially on the validity of the comparison between i and j pairs. Most importantly, estimates should ideally be obtained from a comparison of pairs with sufficient variation in relative resources but otherwise common unobservables. That is, we want to be careful to not confuse differences in unobservables across disparate regions of the continent with the marginal deviations in relative resources underlying the intuition of the model's predictions. While the specification including AEZ fixed effects presented in Tables 1 and 2 start to address this concern, we show further robustness of the results to restricting identifying variation within smaller contiguous areas as captured by the 5 degrees by 5 degrees grid fixed effects in the bottom half of Table 4.

We then proceed to focus in on specific resources in Table 5. Given that the literature on conflict in Africa has often discussed the presence of oil and gas, and the presence of diamond mines as drivers of conflict, we study whether the presence of these resources in neighboring regions also predict conflict as our model suggests. Indeed, we find that a region having these resources predicts conflict with a neighboring region, and the same is true if the neighboring region possesses the resource as well.

Table 3: Alternative Samples

Type	Data	Variable	Resource i	Resource j	Sum of Coeffs
Full Africa	PRIO	Resources	0.058	0.046	0.121
			(0.007)***	(0.00309)***	(0.010)***
Full Africa	PRIO	Rain	0.050	0.055	0.145
			(0.008)***	(0.00475)***	(0.010)***
Full Africa	ACLED	Resources	0.009	0.009	0.010
			(0.002)***	(0.000987)***	(0.003)***
Full Africa	ACLED	Rain	0.005	0.008	0.026
			(0.002)**	(0.00135)***	(0.003)***
Diff Ethnic	PRIO	Resources	0.063	0.066	0.111
			(0.018)***	(0.00394)***	(0.022)***
Diff Ethnic	PRIO	Rain	0.084	0.141	0.303
			(0.014)***	(0.00834)***	(0.014)***
Diff Ethnic	ACLED	Resources	0.017	0.016	0.073
			(0.004)***	(0.00161)***	(0.010)***
Diff Ethnic	ACLED	Rain	0.023	0.020	0.053
			(0.002)***	(0.00190)***	(0.004)***
Radius 150km	PRIO	Resources	0.102	0.115	0.153
			(0.0197)***	(0.00980)***	(0.024)***
Radius 150km	PRIO	Rain	0.0489	0.0467	0.194
			(0.0210)**	(0.0172)***	(0.017)***
Radius 150km	ACLED	Resources	0.0348	0.0361	0.154
			(0.00964)***	(0.00668)***	(0.018)***
Radius 150km	ACLED	Rain	0.0526	0.0524	0.074
			(0.0105)***	(0.00786)***	(0.010)***

Each row is a separate regression of $conflict_{ij}$ on resources and rainfall.
'Full Africa' replicates main results for the entire continent. 'Diff Ethnic' restricts the sample to be only for i and j pairs of different ethnicities. 'Radius 150km' restricts the sample to be only for i and j pairs within 150km of each other.
Conflict: ACLED or PRIO. Oil, diamonds and mines: PRIO & USGS. Rainfall: University of Delaware.
Regressions of ever being involved in the same conflict over a ten year period (1998 to 2008) on resources for the region and neighboring region.
Resources: measure is binary to indicate whether or not the region has any oil, gas, diamonds, gold, zinc or cobalt deposits.
Rainfall: whether rainfall is above the optimal cutoff. Search algorithm for the rainfall cutoff is described in the empirical section and estimated cutoff is reported in the table above. One-third of the sample were randomly selected for the search procedure. Rainfall data is averaged over a ten year period between 1998 and 2008.
Observations including region $i\&j$ pairs where region j is within 500 kilometers of region i.
Controls include Agro-Ecological Zone Fixed Effects, and measures of (for both points i and j) latitude, longitude, ruggedness index, land quality index, humidity, malaria, population density, and a quadratic of the distance between two points in kms. Standard errors clustered at latitude-longitude degree grid level.

Table 4: Alternative Specifications

Type	**Data**	**Variable**	**Resource i**	**Resource j**	**Sum of Coeffs**
No controls	PRIO	Resources	0.058	0.052	0.104
			(0.021)***	(0.00527)***	(0.022)***
No controls	PRIO	Rain	0.119	0.119	0.367
			(0.013)***	(0.0109)***	(0.009)***
No controls	ACLED	Resources	0.025	0.024	0.107
			(0.005)***	(0.00189)***	(0.011)***
No controls	ACLED	Rain	0.005	0.004	0.038
			(0.001)***	(0.00133)***	(0.001)***
No Fixed Effects	PRIO	Resources	0.085	0.080	0.125
			(0.018)***	(0.00454)***	(0.022)***
No Fixed Effects	PRIO	Rain	0.173	0.176	0.456
			(0.013)***	(0.00917)***	(0.011)***
No Fixed Effects	ACLED	Resources	0.020	0.019	0.084
			(0.005)***	(0.00175)***	(0.010)***
No Fixed Effects	ACLED	Rain	0.022	0.021	0.050
			(0.002)***	(0.00198)***	(0.004)***
Grid 5x5 FE	PRIO	Resources	0.022	0.004	0.040
			(0.008)**	(0.0027)	(0.013)***
Grid 5x5 FE	PRIO	Rain	0.025	0.045	0.129
			(0.008)***	(0.00439)***	(0.009)***
Grid 5x5 FE	ACLED	Resources	0.007	0.011	0.065
			(0.004)	(0.00133)***	(0.009)***
Grid 5x5 FE	ACLED	Rain	0.003	0.005	0.022
			(0.003)	(0.00126)***	(0.003)***

Each row is a separate regression of $conflict_{ij}$ on resources and rainfall.
'Grid 5x5 FE' looks at the variation only within small grid-cells of 5 degrees latitude by 5 degrees longitude. 'No Fixed Effects' is the specification with all controls but no fixed effects. 'No controls' is the specification with no controls nor fixed effects.
Conflict: ACLED or PRIO. Oil, diamonds and mines: PRIO & USGS. Rainfall: University of Delaware.
Regressions of ever being involved in the same conflict over a ten year period (1998 to 2008) on resources for the region and neighboring region.
Resources: measure is binary to indicate whether or not the region has any oil, gas, diamonds, gold, zinc or cobalt deposits.
Rainfall: whether rainfall is above the optimal cutoff. Search algorithm for the rainfall cutoff is described in the empirical section and estimated cutoff is reported in the table above. One-third of the sample were randomly selected for the search procedure. Rainfall data is averaged over a ten year period between 1998 and 2008.
Observations including region i&j pairs where region j is within 500 kilometers of region i.
Controls include Agro-Ecological Zone Fixed Effects, and measures of (for both points i and j) latitude, longitude, ruggedness index, land quality index, humidity, malaria, population density, and a quadratic of the distance between two points in kms. Standard errors clustered at latitude-longitude degree grid level.

Table 5: Oil and Diamonds

Type	**Data**	**Resource i**	**Resource j**	**Sum of Coeffs**
Diamonds	PRIO	0.102	0.139	0.290
		(0.026)***	(0.00535)***	(0.022)***
Oil and Gas	PRIO	0.093	0.020	0.009
		(0.033)***	(0.00795)***	(0.035)
Diamonds	ACLED	0.014	0.015	0.129
		(0.008)*	(0.00279)***	(0.017)***
Oil and Gas	ACLED	0.065	0.062	0.174
		(0.013)***	(0.00525)***	(0.024)***

Each row is a separate regression of $conflict_{ij}$ on a specific resource: oil or gas, and diamond mines.
Conflict: ACLED or PRIO. Oil, diamonds: PRIO & USGS
Regressions of ever being involved in the same conflict over a ten year period (1998 to 2008) on resources for the region and neighboring region.
Observations including region $i\&j$ pairs where region j is within 500 kilometers of region i.
Controls include Agro-Ecological Zone Fixed Effects, and measures of (for both points i and j) latitude, longitude, ruggedness index, land quality index, humidity, malaria, population density, and a quadratic of the distance between two points in kms. Standard errors clustered at latitude-longitude degree grid level.

5.2.1 The Size of the Discontinuity

Next, having verified the differences in the probability of joint conflict across the four quadrants depicted in Figure 8, we test whether the relationships between the probability of joint conflict and resources in points i and j are in fact discontinuous at the cutoffs estimated. We present graphical depictions of discontinuities in joint conflict as a function of i and j resources, in turn, in Appendix Figures B.3 to B.6. We test statistically for these discontinuities more formally using the latest semi-parametric methods developed in Calonico et al. (2014). The method determines an optimal data-driven bandwidth h for both the primary estimation and a bias-correction exercise with a larger bandwidth and different polynomial order p. The RD estimate is: $\tau(h,p) = \beta_{+}(h,p) - \beta_{-}(h,p)$, where β_{+} is the estimate above the cutoff, and β_{-} is the estimate below the cutoff.

Table 6 reports results from the estimation of regression discontinuity specifications analogous to the exercises depicted in Figures B.3 to B.6 for both the PRIO and ACLED data. The results show that the discontinuities in the probability of joint conflict at the cutoff values in resources are indeed statistically significant. At the cutoff, there is an increase of about 0.1 percentage points in the likelihood of conflict for the PRIO conflicts

Table 6: Discontinuity Methods: Probability of Conflict at the Cutoff

Dependent Variable: Probability(Region i&j in same conflict)		
PRIO Data	**Own Cutoff**	**Neighbor's Cutoff**
RD Estimate	0.101	0.127
	(0.0160)***	(0.00648)***
Robust Confidence Intervals	[0.065, 0.140]	[0.118, 0.144]
Mean dependent variable	0.340	0.340
Dependent Variable: Probability(Region i&j in same conflict)		
ACLED Data	**Own Cutoff**	**Neighbor's Cutoff**
RD Estimate	0.0158	0.0132
	(0.00772)**	(0.00270)***
Robust Confidence Intervals	[-0.001, 0.008]	[0.034, 0.02]
Mean dependent variable	0.028	0.028

Regression discontinuity estimates of the change in the probability of conflict at the estimated conflict cutoff. Top panel uses PRIO data, whereas bottom panel uses ACLED data. Search algorithm for rainfall cutoffs described in the empirical section, where cutoffs predict largest changes in probability of conflict. Running variable is annual rainfall averaged over 1998 and 2008. Optimal bandwidth selection procedure, as described in Calonico et al. (2014). The robust, bias corrected confidence intervals reported using the Calonico et al. (2014) where the standard errors are clustered at the point i level using 150 nearest neighbors. Conventional standard errors reported in parentheses, centered around the point estimate.

and a 0.013 percentage point increase in the likelihood of territorial conflicts as determined by the ACLED data.

We interpret these large and significant discontinuities in the probability of joint conflict as further evidence in support of the model. While the patterns depicted in Figure 8 and verified statistically in Table 1 validate the non-monotonic relationship between resources and conflict that the model predicts should arise from the strategic interaction, the regression discontinuity results demonstrate strong support of the specific functional form of this relationship. In addition, the strength of these results validates the structural break estimation methodology we employ to identify the resource cutoff.

5.3 Institutions and Mitigating Conflict

We next investigate the degree to which the strength of the conflict-resource relationship predicted by the model is impacted by local institutions. In particular, we investigate whether stronger institutions weakens the impulse for strategic conflict. If stronger institutions reduce the return to raiding (e.g., by introducing some probability of legal retribution) or increases the cost of conflict, the model predicts that the resource cutoff above which conflict becomes the optimal strategy should rise. In addition, we might suspect that stronger institutions might dampen the ability of the model to predict the drivers of conflict overall as the model focuses on rapacity and relative strength in conflict which should become less important as institutions such as those protecting legal rights become stronger.

We use various measures of institutions including measures from the Aggregate Governance Indicators, and the International Country Risk Guide published by the Political Risk Services Group. We use measures from 1996, pre-dating the first year of our data. These measures are commonly employed in related studies (see, e.g., Acemoglu et al. (2001); Michalopoulos and Papaioannou (2015)).

To first study how institutions affect the optimal cuttoff, we repeat the exercise presented in Figure 7 for sub-samples of points with above and below the median measure of our institutions measure. Then, to study the explanatory power of the model, we estimate the partial R-squared at the optimal cutoff.

In Figures 9 and 10 we present an example of the full structural estimation for one of our measures of institutions – the quality of property rights. To estimate the full model, we estimate the optimal cutoff c/δ and the corresponding cost of war c, that maximizes the explanatory power of the model. We do this for sub-samples above and below the median measure of property rights and create figures analogous to Figure 4, with estimated structural parameters. We see that, indeed, better property rights produces a higher cutoff as the model would predict – indicating that in the presence of good institutions, the rapacity effect and endowment effect would have to be a lot stronger to be able to cause conflict.

In Table 7 we summarize this exercise for four different measures of baseline institutional quality. As is evident from the table, for every measure and type of data, poor institutions at baseline correspond to lower rain-cutoffs. A lower rain-cutoff indicates that even at low levels of resources, an increase in resources can lead to conflict. Good institutions mitigate this, and better institutions have higher rain cutoffs. Furthermore, the difference in the partial R-squared shows that the overall ability of the model to explain the relationship between

Figure 9: PRIO: by Property Rights

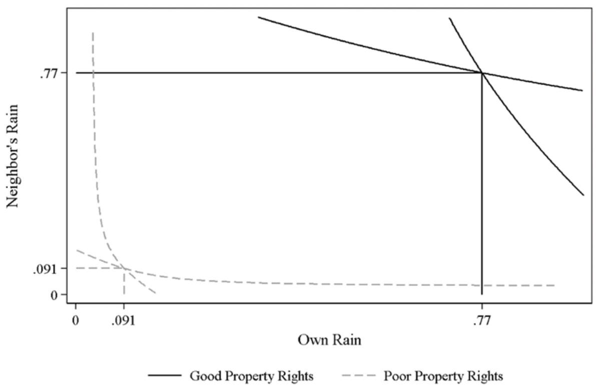
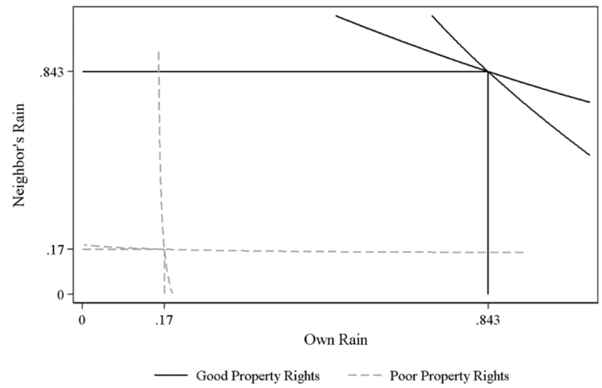


Figure 10: ACLED: by Property Rights



Structural estimates for cutoffs, costs of war c and fraction appropriated δ were estimated by simultaneously finding the optimal values that maximize the explanatory power of the model. For 'Good Property Rights', the sample is restricted to countries that have an above median measure of property rights. For 'Poor Property Rights' the sample is restricted to countries that have a below median measure of property rights.

Table 7: Institutions as a Mitigating Factor

		PRIO		**ACLED**	
		Rain Cutoff	**R^2 ratio**	**Rain Cutoff**	**R^2 ratio**
Baseline		77.68	1.00	20.67	1.00
Property Rights	Poor	63.84	1.42	20.51	1.08
Property Rights	Good	76.67	0.35	84.25	0.93
Risk of Expropriation	Poor	72.58	1.45	21.31	1.37
Risk of Expropriation	Good	76.33	0.90	81.81	0.80
Political Stability	Poor	2.32	1.11	21.59	1.38
Political Stability	Good	79.77	0.85	96.17	0.40
Voice and Accountability	Poor	10.24	2.32	20.28	1.43
Voice and Accountability	Good	88.56	0.61	24.55	0.62

Institutional measures from Aggregate Governance Indicators (1996), and the International Country Risk Guide (Political Risk Services Group).
For each exercise, the sample is divided at the median measure of institutions, after which the optimal rainfall cutoff is estimated using the method described in Section 4 and Figure 7.
The R^2 ratio is the ratio of the R^2 from the estimated model to the baseline model.

conflict and resources in i and j is diminished. Our model is a better predictor of conflict in regions that have poor baseline institutional quality.

5.4 Development: Night Time Illumination

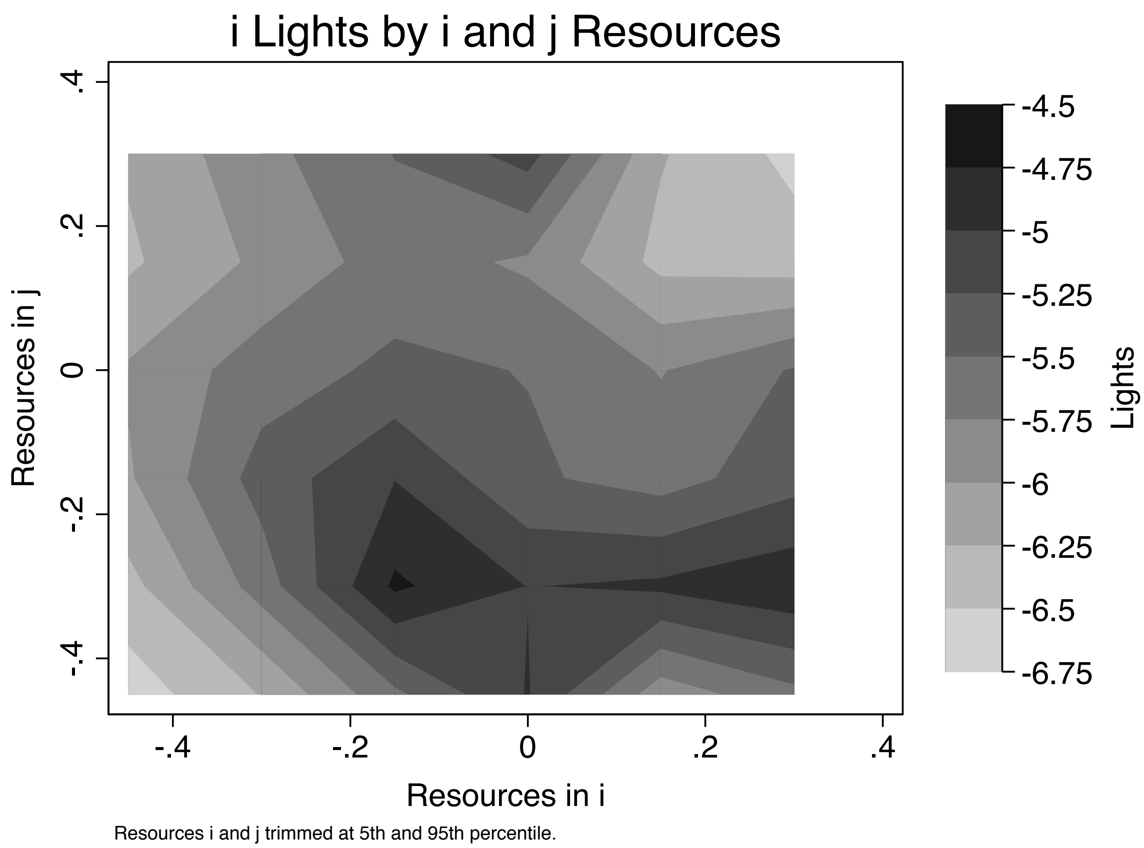


Figure 11: Heat Map of Light-Density by Resources

Resources is annual rainfall averaged over 1998 and 2008. Probability of joint conflict is the likelihood of ever being involved in the same conflict over a ten year period (1998 to 2008).

Finally, we present evidence of the relationship between development in point i as proxied by a measure of night time illumination (lights) and resources in points i and j, net of any intervening conflict. Figure 11 repeats the exercise in Figure 8 for log(lights) as a function of resources in both points i and j. We see a pattern similar to the one depicted in Figure 1 – at first luminosity increases with rainfall, only to fall at high levels of rainfall. We see that the regions of joint conflict prevalence (e.g., upper-right) in Figure 8 correspond to low levels of lights or development in Figure 11; while the region of little to no conflict (i.e., lower-left) corresponds to low to moderate development as resources are low, but conflict is also low. The highest levels of development appear in the center of the heat map where resources are moderately high and conflict is avoided. These results are broadly consistent with the predictions of the model.

In Table 8 we show how light-density falls as resources cross the estimated cutoffs. Using the cutoffs estimated for the conflict regression, we regress light-density on the cutoffs, controlling for continuous measures of own resources, neighbors' resources and the interaction between the two. As there are many grid cells with no light density, we show that our results are consistent across various measures of lights. We see that light density falls at each of these cutoffs: own, neighbor's and the sum of all three. This shows how an increase in conflict may lead to a fall in local economic activity.

In Table 9 we conduct various robustness checks for this exercise. First, we look at variation only within small grid-cells by including 5 by 5 degree grid fixed effects. We also restrict the sample to different ethnic groups, and lastly, instead of lights, we use the G-Econ measure of disaggregated GDP.[20] Our results are robust across these specifications.

We push this empirical test of the model one final step further by conducting the analogous analysis using the RD methods for light-density at the resource cutoffs estimated in the conflict results above. The results from these analyses are presented in the top panel of Table 10 and once again lend further support to the predictions of the model. Non-monotonicity in the relationship between resource accumulation and development as proxied by lights is a particularly striking prediction, but one that helps to explain the relationship depicted in Figures 1 and 2. More striking still, however, is a sharp drop at the threshold, in an otherwise positive relationship between resources and development, and one not easily explained by any mechanism other than the intervention of conflict predicted by the model. We see in Table 10 that indeed there is a significant drop in lights at the precise resource cutoff at which the likelihood of conflict spikes up.

As a final empirical exercise, we exploit this common discontinuity in the resource-conflict and resource-lights relationships to obtain an estimate of how conflict affects overall economic activity. Our assumption underlying this exercise is that there are no other underlying factors that cause conflict to change discontinuously at the threshold. In the bottom panel of Table 10, we report results from a two-stage least squares analysis of how log light density changes as the probability of conflict jumps at the resource cutoff. We then convert this to measures of GDP using the elasticities discussed in Henderson et al. (2012) and Michalopoulos and

[20] To learn more about this measure, see *http://gecon.yale.edu/*.

Table 8: The Effect of Resources on Light Density

Dependent Variable:	Log(Light Density)	Inverse Hyperbolic Sine	Log(Light+0.001)	Lights>0
Rain i>cutoff	**-0.485**	**-0.171**	**-1.094**	**-0.171**
SE cluster: Point i	(0.133)***	(0.0251)***	(0.128)***	(0.0222)***
2 by 2 grid	(0.183)***	(0.0486)***	(0.225)***	(0.0359)***
2-way: Point i&j	(0.145)***	(0.0252)***	(0.144)***	(0.0251)***
Rain j> cutoff	**-0.136**	**-0.0649**	**-0.526**	**-0.0884**
SE cluster: Point i	(0.0605)**	(0.0111)***	(0.0575)***	(0.00984)***
2 by 2 grid	(0.0911)	(0.0250)***	(0.120)***	(0.0186)***
2-way: Point i&j	(0.0787)*	(0.0134)***	(0.0800)***	(0.0134)***
Rain i&j> cutoff	-0.00677	0.0112	0.127	0.0203
SE cluster: Point i	(0.0903)	(0.0161)	(0.0805)	(0.0133)
2 by 2 grid	(0.107)	(0.0237)	(0.143)	(0.0238)
2-way: Point i&j	(0.113)	(0.0182)	(0.102)	(0.0169)
Sum of coefficients	**-0.628**	**-0.225**	**-1.494**	**-0.239**
SE cluster: Point i	(0.122)***	(0.024)***	(0.123)***	(0.021)***
2 by 2 grid	(0.194)***	(0.057)***	(0.250)***	(0.038)***
2-way: Point i&j	(0.143)***	(0.024)***	(0.152)***	(0.027)***
R-squared	0.092	0.071	0.098	0.087
Controls (i & j)	All	All	All	All
Fixed Effects	AEZ	AEZ	AEZ	AEZ
Observations	143,346	635,549	635,549	635,549
Mean dependent var	-1.299	-5.56	0.135	0.23
Resources cutoff		77.68		

Regressions of Light Density on resources for the region and neighboring region being above an estimated cutoff. Light density measures averaged over 1998 to 2008.

Each column uses a different specification of light density. 'Inverse Hyperbolic Sine' is $log(lights + \sqrt{(}lights^2 + 1))$. $Lights > 0$ is a binary indicator for whether or not there are any lights there or not.

Controls include continuous values of own resources and neighbor's resources (both increase light density), and the interaction between the two continuous measures.

Rainfall measure is annual rainfall averaged over 1998 and 2008. Search algorithm for resource cutoffs described in the empirical section 4, where cutoffs predict largest changes in probability of conflict. Estimated cutoff is reported in the table above. One-third of the sample were randomly selected for the search procedure.

Observations including region $i\&j$ pairs where region j is within 500 kilometers of region i- Data is averaged over a ten year period between 1998 and 2008. Controls include Agro-Ecological Zone Fixed Effects, and measures of (for both points i and j) latitude, longitude, and a quadratic of the distance between two points in kms. Standard errors clustered at latitude-longitude degree grids - For example, a 2 by 2 grid consisting of sixteen adjacent points.

Table 9: Robustness: The Effect of Resources on Light Density

Type	**Resource i**	**Resource j**	**Sum of Coeffs**
Grid 5 by 5 Fixed Effect	-0.262	-0.0738	-0.277
	(0.12)**	(0.04)*	(0.12)**
Different Ethnicity	-0.374	-0.152	-0.364
	(0.13)***	(0.07)**	(0.12)***
GDP (Dependent Variable)	-0.287	-0.16	-0.472
	(0.0581)***	(0.0378)***	(0.07)***

Regressions of Log(Light Density) or GDP on resources for the region and neighboring region being above an estimated cutoff. Light density measures averaged over 1998 to 2008.

Controls include continuous values of own resources and neighbor's resources (both increase light density), and the interaction between the two continuous measures.

Rainfall measure is annual rainfall averaged over 1998 and 2008. Search algorithm for resource cutoffs described in the empirical section 4, where cutoffs predict largest changes in probability of conflict. Estimated cutoff is reported in the table above. One-third of the sample were randomly selected for the search procedure.

Observations including region $i\&j$ pairs where region j is within 500 kilometers of region i- Data is averaged over a ten year period between 1998 and 2008. Controls include Agro-Ecological Zone Fixed Effects, and measures of (for both points i and j) latitude, longitude, and a quadratic of the distance between two points in kms. Standard errors clustered at latitude-longitude degree grids - For example, a 2 by 2 grid consisting of sixteen adjacent points.

Table 10: Discontinuity Methods: Effect of Conflict on Light Density

Dependent Variable: Log Light Density		
	Own Cutoff	Neighbor's Cutoff
RD Estimate	-0.299	-0.148
	(0.109)***	(0.0570)***
Robust Confidence Intervals	[-0.586, -0.085]	[-0.295, -0.068]
Dependent Variable: Log Light Density – 2SLS on Prob (Conflict)		
	Own Cutoff	Neighbor's Cutoff
RD Estimate	-2.249	-0.969
	(0.976)**	(0.423)**
Robust Confidence Intervals	[-4.797, -0.329]	[-1.938, -0.262]

Regression discontinuity estimates display the change in log light density (top panel) and two-stage least squares fuzzy RD (bottom panel), where the dependent variable in the first stage is the probability of conflict on the cutoff, and the dependent variable in the second stage is the log light density. Search algorithm for resource cutoffs described in the empirical section, where cutoffs predict largest changes in probability of conflict. Resources include annual rainfall averaged over 1998 and 2008. Optimal bandwidth selection procedure, as described in Calonico et al. (2014). The robust, bias corrected confidence intervals reported using the Calonico et al. (2014) where the standard errors are clustered at the point i level using 150 nearest neighbors. Conventional standard errors reported in parentheses, centered around the point estimate.

Papaioannou (2013).[21] Together these results suggest that as we vary the probability of conflict over the interquartile range, GDP falls by 0.15 log points at the neighbor's resource cutoff and 0.33 log points at the own resources cutoff. This suggests that an increase from a 25% to a 75% likelihood of conflict can reduce GDP by as much as one-third. These tabulations suggest a significant effect of conflict on the economic prosperity of the region.

6 Conclusion

We present a model of resource-driven conflict and development, and test its implications in sub-Saharan Africa. In our model, natural resources impel societies to conflict by increasing both the capacity for aggression as well as the gains from expropriation. We extend the model to account for 1) the idea that resources raise the opportunity costs of conflict, and 2) the possibility that neighboring societies share resources.

We test the predictions of this model by constructing a pairwise dataset of grid points in sub-Saharan Africa containing information on resource endowments, joint conflict, and nighttime illumination (a proxy for local development). We find cutoffs for conflict onset in these data using a two-dimensional structural break estimator. We also study the impacts of resources on economic development around these cutoffs. The results are a striking confirmation of our theory, and are robust to functional form assumptions and alternative data sources.

The back-of-the-envelope exercise conducted in the previous section gives a sense of the import of our results for understanding the development of sub-Saharan Africa in the context of natural resource-driven conflict. Moving from the bottom to the top end of the interquartile range of the probability of conflict, we estimate a GDP reduction of 33%, based on the results in Table 10. Though rough, these numbers convey the extent to which conflict stunts growth, and helps to explain the striking stylized fact that the most resource-rich countries grow no faster (indeed, often slower) than the most resource-poor countries.

[21] For low income countries the elasticity of light density and GDP is about 0.3.

References

Acemoglu, D. and Johnson, S. (2005). Unbundling Institutions. *Journal of Political Economy*, 113(5).

Acemoglu, D., Johnson, S., and Robinson, J. A. (2001). The Colonial Origins of Comparative Development: An Empirical Investigation. *The American Economic Review*, 91(5):1369–1401.

Acemoglu, D., Johnson, S., and Robinson, J. A. (2005). Institutions as a fundamental cause of long-run growth. *Handbook of economic growth*, 1:385–472.

Acemoglu, D. and Robinson, J. A. (2001). A theory of political transitions. *American Economic Review*, 91(4):938–963.

Alexeev, M. and Conrad, R. (2009). The elusive curse of oil. *The Review of Economics and Statistics*, 91(3):586–598.

Alsan, M. (2015). The Effect of the Tsetse fly on African Development. *American Economic Review*, 105(1):382–410.

Angrist, J. D., Imbens, G. W., and Krueger, A. B. (1999). Jackknife instrumental variables estimation. *Journal of Applied Econometrics*.

Angrist, J. D. and Krueger, A. B. (1995). Split-Sample Instrumental Variables Estimates of the Return to Schooling. *Journal of Business & Economic Statistics*, 13(2):225–235.

Arbatli, C. E., Ashraf, Q. H., and Galor, O. (2015). The Nature of Conflict. *NBER Working Paper No. 21079*.

Bai, J. (1997a). Estimating Multiple Breaks One at a Time. *Econometric Theory*, 13(3):315–352.

Bai, J. (1997b). Estimation of a Change Point in Multiple Regression Models. *Review of Economics and Statistics*, 79(4):551–563.

Bai, J. (2010). Common breaks in means and variances for panel data. *Journal of Econometrics*, 157(1):78–92.

Bai, J. and Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 66(1):47–78.

Balestri, S. and Maggioni, M. A. (2014). Blood diamonds, dirty gold and spatial spill-overs measuring conflict dynamics in West Africa. *Peace Economics, Peace Science and Public Policy*, 20(4):551–564.

Bannon, I. and Collier, P. (2003). *Natural resources and violent conflict: Options and actions.* World Bank Publications.

Barrios, S., Bertinelli, L., and Strobl, E. (2010). Trends in rainfall and economic growth in Africa: A neglected cause of the African growth tragedy. *The Review of Economics and Statistics*, 92(2):350–366.

Bazzi, S. and Blattman, C. (2014). Economic shocks and conflict: Evidence from commodity prices. *American Economic Journal: Macroeconomics*, 6(4):1–38.

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

Berman, N., Couttenier, M., Rohner, D., and Thoenig, M. (2014). This mine is mine! How minerals fuel conflicts in Africa. *CEPR Discussion Paper No. DP10089*.

Besley, T. and Persson, T. (2010). State capacity, conflict, and development. *Econometrica*, 78(1):1–34.

Brückner, M. (2010). Population Size and Civil Conflict Risk: Is there a Causal Link? *The Economic Journal*, 120(544):535–550.

Brückner, M. and Ciccone, A. (2010). International Commodity Prices, Growth and the Outbreak of Civil War in Sub-Saharan Africa. *The Economic Journal*, 120(544):519–534.

Buhaug, H. and Gleditsch, K. S. (2008). Contagion or Confusion? Why Conflicts Cluster in Space. *International Studies Quarterly*, 52(2):215–233.

Buonanno, P., Durante, R., Prarolo, G., and Vanin, P. (2015). Poor institutions, rich mines: Resource curse in the origins of the sicilian mafia. *The Economic Journal*, 125(586):F175–F202.

Calonico, S., Cattaneo, M. D., and Titiunik, R. (2014). Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs. *Econometrica*, 82(6):2295–2326.

Cameron, C., Gelbach, J., and Miller, D. (2011). Robust Inference with Multi-way Clustering. *Journal of Business and Economic Statistics*, 29(2):238–249.

Card, D., Mas, A., and Rothstein, J. (2008). Tipping and the Dynamics of Segregation. *The Quarterly Journal of Economics*, 123(1):177–218.

Caselli, F., Morelli, M., and Rohner, D. (2015). The Geography of Inter-State Resource Wars. *The Quarterly Journal of Economics*, 130(1):267–315.

Caselli, F. and Tesei, A. (2015). Resource windfalls, political regimes, and political stability. *Forthcoming in the Review of Economics and Statistics.*

De La Sierra, R. S. (2015). On the Origin of States: Stationary Bandits and Taxation in Eastern Congo. *Mimeo.*

Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

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

Esteban, J., Mayoral, L., and Ray, D. (2012). Ethnicity and conflict: An empirical study. *The American Economic Review*, 102(4):1310–1342.

Esteban, J. and Ray, D. (2011a). A model of ethnic conflict. *Journal of the European Economic Association*, 9(3):496–521.

Esteban, J. and Ray, D. (2011b). Linking conflict to inequality and polarization. *The American Economic Review*, 101(4):1345–1374.

Esteban, J. M., Morelli, M., and Rohner, D. (2015). Strategic mass killings. *Journal of Political Economy*, 123(5):1087–1132.

Fearon, J. D. (2005). Primary commodity exports and civil war. *Journal of Conflict Resolution*, 49(4):483–507.

Gilmore, E., Gleditsch, N. P., Lujala, P., and Rod, J. K. (2005). Conflict Diamonds: A New Dataset. *Conflict Management and Peace Science*, 22(3):257–292.

Gleditsch, N., Wallensteen, P., Eriksson, M., Sollenberg, M., and Strand, H. (2002). Armed conflict 1946-2001: A new dataset. *Journal of Peace Research*, 39(5):615–637.

Gleditsch, N. P., Furlong, K., Hegre, H., Lacina, B., and Owen, T. (2006). Conflicts over shared rivers: Resource scarcity or fuzzy boundaries? *Political Geography*, 25(4):361–382.

Gonzalo, J. and Pitarakis, J.-Y. (2002). Estimation and model selection based inference in single and multiple threshold models. *Journal of Econometrics*, 110(2):319–352.

Gonzalo, J. and Wolf, M. (2005). Subsampling inference in threshold autoregressive models. *Journal of Econometrics*, 127(2):201–224.

Grossman, H. I. (1991). A General Equilibrium Model of Insurrections. *The American Economic Review 81(4): 912-21.*

Grossman, H. I. and Kim, M. (1995). Swords or plowshares? A theory of the security of claims to property. *Journal of Political Economy*, 103(6):1275–1288.

Gylfason, T. (2001). Natural resources, education, and economic development. *European Economic Review*, 45(4):847–859.

Hallberg, J. D. (2012). PRIO conflict site 1989–2008: A geo-referenced dataset on armed conflict. *Conflict Management and Peace Science*, 29(2):219–232.

Hansen, B. E. (2000). Sample Splitting and Threshold Estimation. *Econometrica*, 68(3):575–603.

Harari, M. and La Ferrara, E. (2013). Conflict, Climate and Cells: A Disaggregated Analysis. *CEPR Discussion Paper No. DP9277.*

Henderson, J. V., Storeygard, A., and Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, 102(2):994–1028.

Hirshleifer, J. (1989). Conflict and rent-seeking functions: Ratio versus difference models of relative success. *Public Choice, 63, 101-12.*

Hsiang, S. M., Burke, M., and Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, 341(6151):1235367.

Jerven, M. (2013). *Poor numbers: How we are misled by African development statistics and what to do about it.* Cornell University Press.

Jia, R. (2014). Weather shocks, sweet potatoes and peasant revolts in historical China. *The Economic Journal*, 124(575):92–118.

Lujala, P., Rod, J. K., and Thieme, N. (2007). Fighting over Oil: Introducing A New Dataset. *Conflict Management and Peace Science*, 24(3):239–256.

Matsuura, K. and Willmott, C. J. (2009). Terrestrial precipitation: 1900–2008 gridded monthly time series. *Center for Climatic Research, University of Delaware.*

Mehlum, H., Moene, K., and Torvik, R. (2006). Institutions and the resource curse. *The Economic Journal*, 116(508):1–20.

Michalopoulos, S. and Papaioannou, E. (2013). Pre-Colonial Ethnic Institutions and Contemporary African Development. *Econometrica*, 81(1):113–152.

Michalopoulos, S. and Papaioannou, E. (2015). On the ethnic origins of African development: Chiefs and precolonial political centralization. *The Academy of Management Perspectives*, 29(1):32–71.

Michalopoulos, S. and Papaioannou, E. (2016). The long-run effects of the scramble for Africa. *American Economic Review*, 106(7):1802–1848.

Miguel, E. and Satyanath, S. (2011). Re-examining Economic Shocks and Civil Conflict. *American Economic Journal: Applied Economics, 3(4): 228-232.*

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

Mitra, A. and Ray, D. (2014). Implications of an economic theory of conflict: Hindu-Muslim violence in India. *Journal of Political Economy*, 122(4):719–765.

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

Nunn, N. and Puga, D. (2012). Ruggedness: The blessing of bad geography in Africa. *Review of Economics and Statistics*, 94(1):20–36.

Nunn, N. and Qian, N. (2014). US food aid and civil conflict. *The American Economic Review*, 104(6):1630–1666.

Politis, D. N. and Romano, J. P. (1994). Large Sample Confidence Regions Based on Subsamples under Minimal Assumptions. *The Annals of Statistics*, 22(4):2031–2050.

Raleigh, C., Cunningham, D., Wilhelmsen, L., and Gleditsch, N. P. (2006). Conflict Sites 1946–2005. *UCDP/PRIO Armed Conflicts Dataset*, 2.

Rohner, D., Thoenig, M., and Zilibotti, F. (2013). Seeds of distrust: Conflict in Uganda. *Journal of Economic Growth*, 18(3):217–252.

Sachs, J. D. and Warner, A. M. (2001). The curse of natural resources. *European Economic Review*, 45(4):827–838.

Skaperdas, S. (1992). Cooperation, Conflict, and Power in the Absence of Property Rights. *American Economic Review, 82(4): 720-39.*

A Nash Equilibria Proofs

A.1 Baseline Model

Lemma A.1 *For $r_i, r_j \in (0, \frac{c}{\delta})$, (N, N) is the unique pure-strategy Nash Equilibrium.*

Proof. Consider i's best response to $s_j = N$. i will choose N iff $r_i > r_i - c + \delta r_j$, which reduces to $\frac{c}{\delta} > r_j$. Similarly, j's best response to $s_i = N$ is N iff $\frac{c}{\delta} > r_i$. Thus for $r_i, r_j \in (0, \frac{c}{\delta})$, N constitutes the best response to N for both i and j, and we have that (N, N) is a Nash equilibrium.

To show that (N, N) is the unique NE in this case, it must be that (R, R) *is not* a NE.[22] We can show that (R, R) will not lie in this region. Take i's best response to $s_j = R$. This best response is R iff

$$(1-\delta)r_i < p(r_i - c + \delta(r_j - c)) + (1-p)(1-\delta)(r_i - c). \tag{5}$$

Given $p = \frac{r_i}{r_i + r_j}$, this inequality is equivalent to

$$r_j \quad < \quad \frac{-\delta r_k^2 + c(1+\delta)r_k}{\delta r_k - c(1-\delta)} \qquad \text{for} \qquad r_i \in (0, c\frac{1-\delta}{\delta}) \tag{6}$$

$$r_j \quad > \quad \frac{-\delta r_k^2 + c(1+\delta)r_k}{\delta r_k - c(1-\delta)} \qquad \text{for} \qquad r_i \in (c\frac{1-\delta}{\delta}, \frac{c}{\delta}) \tag{7}$$

Equation 6 would require that $r_j < 0$ and equation 7 that $r_j > \frac{c}{\delta}$. There is thus no $r_i, r_j \in (0, \frac{c}{\delta})$ for which the R is the best response for $s_j = R$

■

Lemma A.2 *Let $\psi(r_k) := \frac{-\delta r_k^2 + c(1+\delta)r_k}{\delta r_k - c(1-\delta)}$. (R, R) is the unique pure strategies Nash Equilibrium in the region $\{(r_i, r_j) : r_i \in (c\frac{1-\delta}{\delta}, \infty), r_j > \psi(r_i)\} \cap \{(r_i, r_j) : r_j \in (c\frac{1-\delta}{\delta}, \infty), r_i > \psi(r_j)\}$*

Proof. Consider i's best response to $s_j = R$ in this region. i will choose R iff $p(r_i - c + \delta(r_j - c)) + (1-p)(1-\delta)(r_i - c) > (1-\delta)r_i$, which amounts to the region $\{(r_i, r_j) : r_i \in (c\frac{1-\delta}{\delta}, \infty), r_j >$

[22] Note that for $r_i, r_j \in (0, \frac{c}{\delta})$, (R, N) and (N, R) cannot be NE, given that if one party plays N, the other's best response must be N for values of r_i and r_j in the specified range.

$\psi(r_i)\}$. Similarly j's best response to $s_i = R$ is R iff $(1-p)(r_j - c + \delta(r_i - c)) + p(1-\delta)(r_j - c) > (1-\delta)r_j$, which is the region $\{(r_i, r_j) : r_j \in (c\frac{1-\delta}{\delta}, \infty), r_i > \psi(r_j)\}$. Thus (R, R) is a Nash equilibrium in the intersection of these regions.

To show that (R, R) is the unique pure strategies Nash Equilibrium, it must be that (N, N) is not an equilibrium.[23] We can show that (N, N) cannot be an equilibrium in this region. i's best response to $s_j = N$ will be N iff $r_j < \frac{c}{\delta}$ and j's best response to $s_i = N$ will be N iff $r_i < \frac{c}{\delta}$. However, the intersections of the regions $\{(r_i, r_j) : r_i \in (c\frac{1-\delta}{\delta}, \infty), r_j > \psi(r_i)\} \cap \{(r_i, r_j) : r_j \in (c\frac{1-\delta}{\delta}, \infty), r_i > \psi(r_j)\}$ and the region $r_i, r_j \in (0, \frac{c}{\delta})$ is a null set. In $\mathbb{R}^2_+$, $\psi(r_i) = \psi(r_k)$ at the point $(\frac{c}{\delta}, \frac{c}{\delta})$. There is therefore no region in $\mathbb{R}^2_+$, for which $r_i > \psi(r_j)$, $r_j > \psi(r_i)$ and $r_i, r_j \in (0, \frac{c}{\delta})$.

■

Lemma A.3 *Let* $\psi(r_k) := \frac{-\delta r_k^2 + c(1+\delta)r_k}{\delta r_k - c(1-\delta)}$. *$(N, R)$ is the unique pure strategies Nash Equilibrium in the region* $\{(r_i, r_j) : r_i \in (\frac{c}{\delta}, \infty), r_j < \psi(r_i)\}$

Proof. Consider i's best response to $s_j = R$ in this region. i will choose N iff $p(r_i - c + \delta(r_j - c)) + (1-p)(1-\delta)(r_i - c) < (1-\delta)r_i$, which amounts to the region $\{(r_i, r_j) : r_i \in (c\frac{1-\delta}{\delta}, \infty), r_j < \psi(r_i)\}$. Similarly j's best response to $s_i = N$ is R iff $\frac{c}{\delta} < r_i$. Thus (N, R) is a Nash equilibrium if $r_i > \frac{c}{\delta}$ and $r_j < \psi(r_i)$.

To show that (N, R) is the unique pure strategies Nash Equilibrium, we must rule out the other equilibria. (N, N) can be ruled out because j's best response $s_i = N$ cannot be N if $\frac{c}{\delta} < r_i$. Similarly, (R, R) cannot be a Nash Equilibrium in this region because i's best response to $s_j = R$ cannot be R if $\{(r_i, r_j) : r_i \in (\frac{c}{\delta}, \infty), r_j < \psi(r_i)\}$. Lastly, we must rule out (R, N). i's best response to $s_j = N$ is R iff $r_j > \frac{c}{\delta}$. However, $\{(r_i, r_j) : r_i \in (\frac{c}{\delta}, \infty), r_j < \psi(r_i)\} \cap \{(r_i, r_j) : r_j > \frac{c}{\delta}\} = \emptyset$, thus precluding an (R, N) equilibrium in this region.

■

Lemma A.4 *Let* $\psi(r_k) := \frac{-\delta r_k^2 + c(1+\delta)r_k}{\delta r_k - c(1-\delta)}$. *$(R, N)$ is the unique pure strategies Nash Equilibrium in the region* $\{(r_i, r_j) : r_j \in (\frac{c}{\delta}, \infty), r_i < \psi(r_j)\}$

Proof. Consider j's best response to $s_i = R$ in this region. j will choose N iff $\{(r_i, r_j) : r_j \in (c\frac{1-\delta}{\delta}, \infty), r_i < \psi(r_j)\}$. Similarly i's best response to $s_j = N$ is R iff $\frac{c}{\delta} < r_j$. Thus (R, N) is a Nash equilibrium if $r_j > \frac{c}{\delta}$ and $r_i < \psi(r_j)$.

[23] Note that in this region, (R, N) and (N, R) cannot be NE, given that if one party plays R, the other's best response must be R for values of r_i and r_j in the specified range.

To show that (R,N) is the unique pure strategies Nash Equilibrium, we must rule out the other equilibria. (N,N) can be ruled out because i's best response $s_j = N$ cannot be N if $\frac{c}{\delta} < r_j$. Similarly, (R,R) cannot be a Nash Equilibrium in this region because j's best response to $s_i = R$ cannot be R if $\{(r_i, r_j) : r_j \in (\frac{c}{\delta}, \infty), r_i < \psi(r_j)\}$. Lastly, we must rule out (N,R). j's best response to $s_i = N$ is R iff $r_i > \frac{c}{\delta}$. However, $\{(r_i, r_j) : r_j \in (\frac{c}{\delta}, \infty), r_i < \psi(r_j)\} \cap \{(r_i, r_j) : r_i > \frac{c}{\delta}\} = \emptyset$, thus preventing the possibility of an (N,R) equilibrium in this region.

■

Lemma A.5 *Let* $\psi(r_k) := \frac{-\delta r_k^2 + c(1+\delta) r_k}{\delta r_k - c(1-\delta)}$. *∃ a mixed-strategies Nash Equilibrium (MSNE) in the region* $\{(r_i, r_j) : r_j \in (\frac{c}{\delta}, \psi(r_i)), r_i > \psi(r_j)\} \cup \{(r_i, r_j) : r_i \in (\frac{c}{\delta}, \psi(r_j)), r_j > \psi(r_i)\}$

Proof. In this region, each party k will play a mixed-strategy where they *Raid*, with probability q_k:

$$q_k = \frac{(\delta r_k - c)(r_k + r_{-k})}{\delta(r_{-k}^2 - r_k^2 - c(r_k + r_{-k} - 2))} \tag{8}$$

Given these probabilities that each party *Raid*s, the expected payoff from raiding and not-raiding are equalized.

■

A.2 Sharing Rule

Proposition A.6 *For* $\delta > \phi > \frac{\delta}{1+\delta}$ *and* $(r_i, r_j) \in \mathbb{R}_+^2$, *the following are best response functions for agent k under a sharing-rule agreement:*

1. $BR_k(s_{-k} = N) = \begin{cases} R, & \text{if } r_{-k} > \frac{c - \phi r_k}{\delta - \phi} \\ N, & \text{else} \end{cases}$

2. *Let* $\psi(r_k) := \frac{-\delta r_k^2 + c(1+\delta) r_k}{\delta r_k - c(1-\delta)}$.

   $BR_k(s_{-k} = R) = R$, *for all* (r_k, r_{-k}) *such that*

$$\{(r_k, r_{-k}) : r_k \in (c\frac{1-\delta}{\delta}, \infty), r_{-k} > \psi(r_k)\} \tag{9}$$

And $BR_k(s_{-k} = R) = N$*, for all* (r_k, r_{-k}) *such that*

$$\{(r_k, r_{-k}) : r_k \in (0, c\frac{1-\delta}{\delta})\} \cup \{(r_k, r_{-k}) : r_k \in (c\frac{1-\delta}{\delta}, \infty), r_{-k} < \psi(r_k)\} \qquad (10)$$

The change in the best response functions, leads to an expansion of the (N, N) region of the Nash equilibrium.

Proposition A.7 *The sharing-rule expands the Nash Equilibrium region of (No raid, No raid)*

Figure A1: The game with a sharing-rule.

		j: R	j: N
i	R	$p(r_i - c + \delta(r_j - c)) + (1-p)(1-\delta)(r_i - c)$, $(1-p)(r_j - c + \delta(r_i - c)) + p(1-\delta)(r_j - c)$	$r_i - c + \delta r_j$, $(1-\delta)r_j$
	N	$(1-\delta)r_i$, $r_j - c + \delta r_i$	$(1-\phi)r_i + \phi r_j$, $(1-\phi)r_j + \phi r_i$

p is the probability of victory for party i, r_k are the level of resources for parties $k = \{i, j\}$, c is the cost of engaging in conflict, δ is the fraction of resources that the victorious party expropriates, and ϕ is the fraction of resources shared.

Lemma A.8 *Let* $\chi(r_k) = \frac{c-\phi r_k}{\delta-\phi}$*.* (N, N) *is the unique pure-strategy Nash Equilibrium for the region* $\{(r_i, r_j) : r_j < \chi(r_i),\ r_i < \chi(r_j)\}$*.*

Proof. Consider i's best response to $s_j = N$. i will choose N iff $(1-\phi)r_i + \phi r_j > r_i - c + \delta r_j$, which reduces to $\chi(r_i) > r_j$. Similarly, j's best response to $s_i = N$ is N iff $\chi(r_i) > r_i$. Thus for $\{(r_i, r_j) : r_j < \chi(r_i),\ r_i < \chi(r_j)\}$, N constitutes the best response to N for both i and j, and we have that (N, N) is a Nash equilibrium.

To show that (N, N) is the unique NE in this case, it must be that (R, R) *is not* an NE.[24] We can show that (R, R) will not lie in this region. Take i's best response to $s_j = R$. This best response is R iff

$$(1-\delta)r_i < p(r_i - c + \delta(r_j - c)) + (1-p)(1-\delta)(r_i - c). \qquad (11)$$

[24]Note that for $r_i, r_j \in (0, \frac{c}{\delta})$, (R, N) and (N, R) cannot be NE, given that if one party plays N, the other's best response must be N for values of r_i and r_j in the specified range.

Given $p = \frac{r_i}{r_i + r_j}$, this inequality is equivalent to

$$r_j \quad < \quad \frac{-\delta r_k^2 + c(1+\delta) r_k}{\delta r_k - c(1-\delta)} \qquad \text{for} \qquad r_i \in (0, c\frac{1-\delta}{\delta}) \tag{12}$$

$$r_j \quad > \quad \frac{-\delta r_k^2 + c(1+\delta) r_k}{\delta r_k - c(1-\delta)} \qquad \text{for} \qquad r_i \in (c\frac{1-\delta}{\delta}, \frac{c}{\phi}) \tag{13}$$

Equation 12 would require that $r_j < 0$ and equation 13 that $r_j > \chi(r_i)$ for $\delta > \phi > \frac{\delta}{1+\delta}$. There is thus no $\{(r_i, r_j) : r_j < \chi(r_i),\ r_i < \chi(r_j)\}$ for which the R is the best response for $s_j = R$

■

Lemma A.9 *Let* $\psi(r_k) := \frac{-\delta r_k^2 + c(1+\delta) r_k}{\delta r_k - c(1-\delta)}$. (R, R) *is the unique pure strategies Nash Equilibrium in the region* $\{(r_i, r_j) : r_i \in (c\frac{1-\delta}{\delta}, \infty), r_j > \psi(r_i)\} \cap \{(r_i, r_j) : r_j \in (c\frac{1-\delta}{\delta}, \infty), r_i > \psi(r_j)\}$.

Proof. Consider i's best response to $s_j = R$ in this region. i will choose R iff $p(r_i - c + \delta(r_j - c)) + (1-p)(1-\delta)(r_i - c) > (1-\delta) r_i$, which amounts to the region $\{(r_i, r_j) : r_i \in (c\frac{1-\delta}{\delta}, \infty), r_j > \psi(r_i)\}$. Similarly j's best response to $s_i = R$ is R iff $(1-p)(r_j - c + \delta(r_i - c)) + p(1-\delta)(r_j - c) > (1-\delta) r_j$, which is the region $\{(r_i, r_j) : r_j \in (c\frac{1-\delta}{\delta}, \infty), r_i > \psi(r_j)\}$. Thus (R, R) is a Nash equilibrium in the intersection of these regions.

To show that (R, R) is the unique pure strategies Nash Equilibrium, it must be that (N, N) is not an equilibrium.[25] We can show that (N, N) cannot be an equilibrium in this region. i's best response to $s_j = N$ will be N iff $r_j < \frac{c}{\delta}$ and j's best response to $s_i = N$ will be N iff $r_i < \frac{c}{\delta}$. However, the intersections of the regions $\{(r_i, r_j) : r_i \in (c\frac{1-\delta}{\delta}, \infty), r_j > \psi(r_i)\} \cap \{(r_i, r_j) : r_j \in (c\frac{1-\delta}{\delta}, \infty), r_i > \psi(r_j)\}$ and the region $r_i, r_j \in (0, \frac{c}{\delta})$ is a null set. In $\mathbb{R}^2_+$, $\psi(r_i) = \psi(r_k)$ at the point $(\frac{c}{\delta}, \frac{c}{\delta})$. There is therefore no region in $\mathbb{R}^2_+$, for which $r_i > \psi(r_j)$, $r_j > \psi(r_i)$ and $r_i, r_j \in (0, \frac{c}{\delta})$.

■

Lemma A.10 *Let* $\psi(r_k) := \frac{-\delta r_k^2 + c(1+\delta) r_k}{\delta r_k - c(1-\delta)}$, *and let* $\chi(r_k) = \frac{c - \phi r_k}{\delta - \phi}$. (N, R) *is the unique pure strategies Nash Equilibrium in the region* $\{(r_i, r_j) : r_i \in (0, \frac{c}{\delta} - c), \chi(r_j) < r_i\} \cup \{(r_i, r_j) : r_i \in (\frac{c}{\delta} - c, \infty), r_j < \psi(r_i)\}$

[25] Note that in this region, (R, N) and (N, R) cannot be NE, given that if one party plays R, the other's best response must be R for values of r_i and r_j in the specified range.

Proof. Consider i's best response to $s_j = R$ in this region. i will choose N iff $p(r_i - c + \delta(r_j - c)) + (1-p)(1-\delta)(r_i - c) < (1-\delta)r_i$, which amounts to the region $\{(r_i, r_j) : r_i \in (c\frac{1-\delta}{\delta}, \infty), r_j < \psi(r_i)\}$. Similarly j's best response to $s_i = N$ is R iff $\chi(r_j) < r_i$. Thus (N, R) is a Nash equilibrium in the region $\{(r_i, r_j) : r_i \in (0, \frac{c}{\delta} - c), \chi(r_j) < r_i\} \cup \{(r_i, r_j) : r_i \in (\frac{c}{\delta} - c, \infty), r_j < \psi(r_i)\}$.

To show that (N, R) is the unique pure strategies Nash Equilibrium, we must rule out the other equilibria. (N, N) can be ruled out because j's best response $s_i = N$ cannot be N if $\chi(r_j) < r_i$. Similarly, (R, R) cannot be a Nash Equilibrium in this region because i's best response to $s_j = R$ cannot be R if $\{(r_i, r_j) : r_i \in (\frac{c}{\delta}, \infty), r_j < \psi(r_i)\}$. Lastly, we must rule out (R, N). i's best response to $s_j = N$ is R iff $r_j > \chi(r_i)$. However, $\{(r_i, r_j) : r_i \in (\frac{c}{\delta}, \infty), r_j < \psi(r_i)\} \cap \{(r_i, r_j) : r_j > \chi(r_i)\} = \emptyset$, thus precluding an (R, N) equilibrium in this region.

■

Lemma A.11 *Let* $\psi(r_k) := \frac{-\delta r_k^2 + c(1+\delta) r_k}{\delta r_k - c(1-\delta)}$, *and let* $\chi(r_k) = \frac{c - \phi r_k}{\delta - \phi}$. (R, N) *is the unique pure strategies Nash Equilibrium in the region* $\{(r_i, r_j) : r_j \in (0, \frac{c}{\delta} - c), \chi(r_i) < r_j\} \cup \{(r_i, r_j) : r_j \in (\frac{c}{\delta} - c, \infty), r_i < \psi(r_j)\}$

Proof. Consider j's best response to $s_i = R$ in this region. j will choose N iff $\{(r_i, r_j) : r_j \in (c\frac{1-\delta}{\delta}, \infty), r_i < \psi(r_j)\}$. Similarly i's best response to $s_j = N$ is R iff $\chi(r_i) < r_j$. Thus (R, N) is a Nash equilibrium in the region $\{(r_i, r_j) : r_j \in (0, \frac{c}{\delta} - c), \chi(r_i) < r_j\} \cup \{(r_i, r_j) : r_j \in (\frac{c}{\delta} - c, \infty), r_i < \psi(r_j)\}$.

To show that (R, N) is the unique pure strategies Nash Equilibrium, we must rule out the other equilibria. (N, N) can be ruled out because i's best response $s_j = N$ cannot be N if $\chi(r_i) < r_j$. Similarly, (R, R) cannot be a Nash Equilibrium in this region because j's best response to $s_i = R$ cannot be R if $\{(r_i, r_j) : r_j \in (\frac{c}{\delta}, \infty), r_i < \psi(r_j)\}$. Lastly, we must rule out (N, R). j's best response to $s_i = N$ is R iff $r_i > \chi(r_j)$. However, $\{(r_i, r_j) : r_j \in (\frac{c}{\delta}, \infty), r_i < \psi(r_j)\} \cap \{(r_i, r_j) : r_i > \chi(r_j)\} = \emptyset$, thus precluding an (N, R) equilibrium in this region.

■

A.3 The Opportunity Cost of Conflict

Figure A2: The payoff-matrix for the game between i and j.

		j: R	j: N
i	R	$p(r_i(1-c_1)-c_2+\delta(r_j(1-c_1)-c_2))+(1-p)(1-\delta)(r_i(1-c_1)-c_2)$, $(1-p)(r_j(1-c_1)-c_2+\delta(r_i(1-c_1)-c_2))+p(1-\delta)(r_j(1-c_1)-c_2)$	$r_i(1-c_1)-c_2+\delta r_j$, $(1-\delta)r_j$
	N	$(1-\delta)r_i$, $r_j(1-c_1)-c_2+\delta r_i$	r_i, r_j

Notes: p is the probability of victory for party i, r_k are the level of resources for parties $k=\{i,j\}$, c_1 is the variable cost of engaging in conflict, c_2 is the fixed cost of conflict, and δ is the fraction of resources that the victorious party expropriates.

Proposition A.12 *For $\delta^2 > c_1$ and $(r_i, r_j) \in \mathbb{R}^2_+$, the following are best response functions for agent k:*

1. $BR_k(s_{-k}=N) = \begin{cases} R, & \text{if } r_{-k} > \frac{c_2+c_1 r_k}{\delta} \\ N, & \text{else} \end{cases}$

2. *Let* $\psi(r_k) := \frac{-(\delta-c_1)r_k^2+c_2(1+\delta)r_k}{(\delta-c_1)r_k-c_2(1-\delta)}$.

   $BR_k(s_{-k}=R)=R$, *for all* (r_k, r_{-k}) *such that*

$$\{(r_k, r_{-k}) : r_k \in \left(c_2\frac{1-\delta}{\delta-c_1}, \infty\right), r_{-k} > \psi(r_k)\} \tag{14}$$

   And $BR_k(s_{-k}=R)=N$, *for all* (r_k, r_{-k}) *such that*

$$\{(r_k, r_{-k}) : r_k \in \left(0, c_2\frac{1-\delta}{\delta-c_1}\right)\} \cup \{(r_k, r_{-k}) : r_k \in \left(c_2\frac{1-\delta}{\delta-c_1}, \infty\right), r_{-k} < \psi(r_k)\} \tag{15}$$

Proofs of proposition available on request.

B Additional Tables and Figures

Figure B.3: PRIO: Conflict on own rainfall

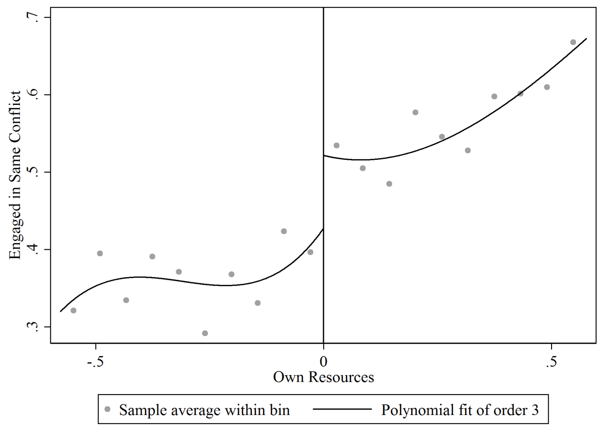


Figure B.5: ACLED: Conflict on own rainfall

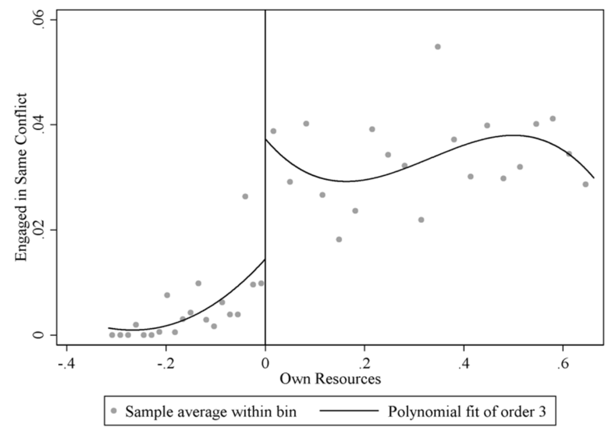


Figure B.4: PRIO: Conflict on neighbor's rain

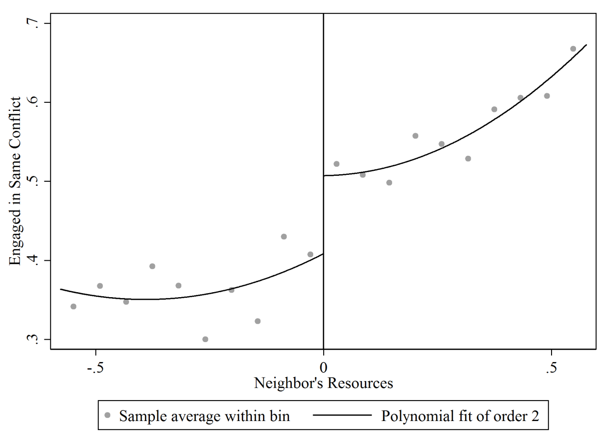
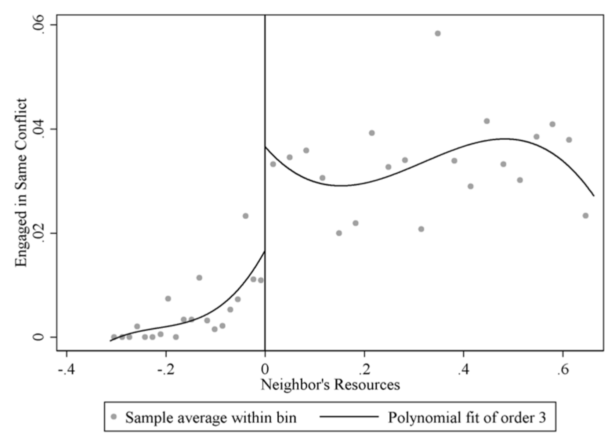


Figure B.6: ACLED: On neighbor's rain



RD graphs of being engaged in the same conflict on rainfall. Rainfall centered around estimated cutoff. Graphs were produced using the Calonico et al. (2014) procedure of identifying the optimal bin sizes.