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MINERAL RESOURCES AND CONFLICTS IN DRC: A CASE OF ECOLOGICAL FALLACY

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Abstract

We estimate the impact of geo-located mining concessions on the number of conflict events recorded in the Democratic Republic of the Congo between 1997 and 2007. Instrumenting the variable of interest with historical concessions interacted with changes in international prices of minerals, we unveil an *ecological fallacy*: Whereas concessions have no effect on the number of conflicts at the territory level (lowest administrative unit), they do foster violence at the district level (higher administrative unit). We develop and validate empirically a theoretical model where the incentives of armed groups to exploit and protect mineral resources explain our empirical findings.

Keywords: Conflict, Natural Resources, Democratic Republic of the Congo

JEL Classification: Q34, O13, Q32, N57

1 Introduction

Over the last three decades a vast literature has developed around the concept of the *resource curse*. The resource curse broadly refers to the paradox that countries rich in non-renewable natural resources tend to display poor economic performance.[1] Conflict plays a prominent role among the several channels proposed to explain this paradox: valuable minerals foster civil wars which negatively affect economic performance (World Bank 2011). Yet, despite the large body of literature addressing the nexus, the evidence remains mixed (Blattman and Miguel 2010, Van der Ploeg 2011). Collier and Hoeffler (2004) show that countries with larger shares of primary commodity exports are more likely to experience civil wars. However, several shortcomings of Collier and Hoeffler's (2004) study have been highlighted. First, primary commodities are not homogeneous. As underlined by specialists of the field, there is an urge to categorize the various types of natural resources into diffuse resources such as agricultural production, and point resources such as mineral resources (Le Billon 2001, Wick and Bulte 2006), with the latter being seen as more conflictive (Ross 2004). On theoretical grounds, point resources - as opposed to diffuse resources - attract violent entrepreneurs that compete for the control of the rents (Mehlum et al. 2002). Recognizing the specificities of mineral resources, a series of papers have sought to identify the specific effect of mineral resources on civil conflicts. The initial evidence based on cross-country analyses pointed at the undisputable

[1] Recent contributions to the resource curse literature include Bruckner, Ciccone and Tesei (2012), Haber and Menaldo (2011), Wacziarg (2012).

role played by mineral resources in both igniting and sustaining civil conflicts (Lujala et al. 2005, Ross 2006, 2012, Lujala 2010).

Second, the relationship between mineral resources and conflict is potentially endogenous. For instance, mineral resource dependence may be a direct consequence of actual or expected civil war (Brunnschweiler and Bulte 2008, 2009). The confounding role of institutions is another source of endogeneity. Fearon and Laitin (2003) and Fearon (2005) emphasize the role of oil revenues in weakening state capacity. More recently, Besley and Persson (2010) formalize this argument by proposing a model of endogenous state capacity formation. They show that natural resource-rich countries will under-invest in state capacity formation, and will therefore be more prone to experiencing civil conflicts.

Third, the cross-country nature of the early contributions to this debate fails to capture the effects of within-country uneven distribution of resources. Cross-country analyses also fail to account for unobserved heterogeneity. More recent studies adopted a micro-founded approach by exploiting within country variations. By working with sub-national units of analysis, researchers can draw more accurate causal inference. Buhaug and Rod (2006), Angrist and Kugler (2008), and Dube and Vargas (2008) all identify a positive effect of the presence of natural resources on the occurrence of conflict events. Using geo-referenced data at the 100 square kilometer grid, Buhaug and Rod (2006) find a positive effect of oil and diamonds presence on the likelihood of civil conflict. Both Angrist and Kugler (2008) and Dube and Vargas (2008) study the impact of exogenous commodity-

price shocks on the level of violence in Colombia. The former show that positive price shocks on cocaine increased violence at the department level, while the latter show that at the municipality level the effect of oil and coffee prices increases have, respectively, a positive and negative effect on the number of violent events.

Findings from two recent studies suggest that mineral resources could work as a catalyst for peace, thus casting doubts upon the generalization of the above relationship between resources and conflict. Bellows and Miguel (2009), and Ziemke (2008) study, respectively, the civil conflicts of Sierra Leone and Angola, and conclude on the basis of geo-referenced data that the presence of diamonds contained the level of violence.

This paper enriches the micro-founded literature by focusing on the recent conflicts in the Democratic Republic of the Congo (DRC). More precisely, we estimate the impact of geo-located granted mining concessions in DRC between January 1997 and December 2007 on the location of conflict events.

The main contribution of this paper is to highlight the dramatic consequences of the level of analysis on the relationship between mineral resources and the incidence of conflict. By implementing a two-stage least square estimation at two geographical levels of analysis, i.e. the territory and the district levels, we unveil an *ecological fallacy*: Although granted concessions do not affect the number of conflict events at the territory level, they increase the frequency of conflicts at the district level.[2]

[2]The ecological fallacy refers to the erroneous assumption that relationships between variables at a more aggregate level imply the same relationships at a less aggregated level. It has also been called a problem of "aggregation bias" or a "modifiable area unit problem" (Wong 2009).

We propose a theoretical mechanism to rationalize these empirical findings, owing much to the literature on crime displacement (Repetto 1976, Barr and Pease 1990 and Johnson et al. 2012).[3] In line with anecdotal evidence, in our model violence affects negatively mining profitability, thus providing strong incentives for mining companies to keep fighting activities far from the production sites (Vlassenroot and Raeymaekers 2004, Raeymaekers 2010). This mechanism which we name the "protection effect" helps explaining the *ecological fallacy*: valuable minerals do foster conflict, but not in the immediate neighborhood of the mining sites where violence would disrupt the profitability of the business. Revisiting our econometrics by allowing for a heterogeneous spatial effect of mining concessions on conflict validates the theoretical findings.

This paper, therefore, sheds light on seemingly contradictory findings in the literature and it highlights the role of the spatial dimension in the empirical literature on conflicts. Our results suggest that valuable minerals do generate violent conflict, but since fighting tends to be located at some distance from the mining sites, the relationship can be identified only by choosing a sufficiently large unit of analysis or by carefully accounting for spatial spillover effects. Failing to do so may result in a non-significant relationship, as in our study, or even generate opposite predictions if the "protection effect" is sufficiently strong at the local level.

[3] Alternative explanations behind our empirical results are discussed in Section 6.

2 Background

Since 1996 the Democratic Republic of the Congo (DRC) has experienced a succession of wars and lower scale conflicts that according to a survey of the International Rescue Committee have been the cause of more than five million deaths over the 1998-2008 period (IRC 2008) and an estimated 1.7 million internally displaced people (Internal Displacement Monitoring Center 2011). Whether or not these exact figures are biased (Spiegel and Robinson 2010), their magnitude is indicative of the lethality of these conflicts. In a recent paper, Pelillo (2012) finds strong evidence of a substantial negative impact of this conflict on household living conditions. The causes of the Congo Wars are multiple, complex, and intermingled: the inefficiency of Mobutu's regime, ethnic polarization, spillover effects from the Rwandan genocide, regional control by foreign powers and natural wealth have all been listed among the key factors (Prunier 2009, Vlassenroot and Raeymaekers 2004).

The first Congolese War (1996-1997) started when Laurent Désiré Kabila, heading the *Alliance des Forces Démocratiques pour la Libération du Congo* (AFDL) and supported by the foreign governments of Rwanda, Uganda and other neighboring countries, contested Mobutu's leadership. The second Congolese war (1998-2003) had an even more international dimension since rival countries and factions saw in the conflict-hit DRC a convenient ground for waging proxy-wars. Although the end of the second war meant a retreat of international actors from the battlefield, it did not lead to the dissolution of the numerous rival armed groups and gangs that had formed over the course of the 7 years

wars. In fact the violence in DRC continues to affect the country's stability, especially in its Eastern regions.

Congo's natural wealth in mineral resources has often been blamed as the main driver of the violence, either as a way to finance warring parties or as a warfare objective in itself (Congdon Fors and Olsson 2004, Turner 2007, Stearns 2011, International Alert 2010, Gambino 2011). Over the years the United Nations has repeatedly issued reports of experts, of the UN Security Council, and of the UN Secretary General underlining that natural resources have fueled the conflicts in DRC. Among others, coltan - a high value mineral used in the manufacturing of electronic devices - has been designated as one of the main culprits of the Congo Wars (Jackson 2001, Montague 2002).[4] Austesserre (2012) challenges the primacy of mineral exploitation as a cause of violence in the country and even argues that the emphasis on minerals has led the international community to take inappropriate actions which exacerbated the conflict. It is hardly deniable, however, that many Congolese mining locations have been looted and the minerals exported illegally over the years by both Congolese and foreign rebels and by neighboring countries' militias

[4]Stearns (2011: 299) reports the interview of a pilot highly involved in military and mineral transportation during the Congolese wars : "The initial profits [in the first years of the second Congolese war], however, were nothing compared to what was to come. Everything changed in 2000, when the coltan price soared [said the interviewee]. It was a fluke. That year, the information technology bubble coincided with heightened demand for cell phones and the Christmas release of a Sony PlayStation Console. Demand for tantalum, the processed form of coltan, had been rising steadily for years, but now the market got caught up in a buying frenzy. Within months, the local market price for tantalum shot up from $ 10 to $ 380 per kilo, depending on the percentage of ore content, while the world price peaked at $ 600 per kilo of refined tantalum [...] Exports from the eastern Congo and Rwanda soared to somewhere between $ 150 and $ 240 million in 2000 alone, and profit margins were high [...] the profits facilitated the war".

(Montague 2002, Congdon Fors and Olsson 2004, Prunier 2009, Freedman 2011).

3 Baseline Analysis

3.1 Data

The empirical analysis is mainly based on the monthly variations of three variables. First, the dependent variable is the monthly sum of conflict events by territories or districts, as recorded in the Armed Conflict Location and Event Data (ACLED, Raleigh 2010). More than 3,300 conflict events occurred from January 1997 to December 2007, including 2,898 violent events. Figure 1 shows that most conflict events are concentrated in Orientale, North and South Kivu provinces, followed by the territory of Pweto in the Katanga province and Kinshasa. The geographical dispersion of the data tracks the degree to which various areas of the Democratic Republic of the Congo (DRC) have been affected by conflict, thus giving us confidence regarding the data quality. The relevance of Kinshasa is explained by the strategic and political importance of the capital city in the Congolese conflicts. Our results are nonetheless robust to the exclusion of the Kinshasa district (or related territory) from the analysis.

Over time, the evolution of conflict events exhibits large monthly variations. As illustrated in Figure 2, several peaks can be observed in May 1997, January 2001, June 2003, November 2005, January 2006, December 2006 and in particular, in August 1998,

November 1999, January 2000 and October 2008. Conflict events occurring after 2007 are not included in our sample due to other data constraints. The conflict trend based on ACLED data tracks well-documented increases of violence in DRC reported by secondary literature (see e.g. Turner 2007).

We also define alternative dependent variables by either restricting the dependent variable to violent conflict events based on the ACLED dataset or by computing the number of conflicts based on the Uppsala Conflict Data Program's (UCDP's) Georeferenced Events Datasets (Sundberg et al. 2010). The UCDP data adopt a more restrictive definition of conflict events and only comprise events reporting at least one direct death. Over the period investigated, there have been 793 conflict events recorded by UCDP in contrast with 2,898 violent events in the ACLED dataset. Despite the difference of coding, the geographical distribution of UCDP conflict events in Figure 3 provides a fairly similar picture to the one depicted in Figure 1.

Second, the main variable of interest relates to the mining concessions. Based on data provided by the Ministry of Mining (5,963 mining concessions granted over the period), we construct the monthly sum of mining concessions granted by territory or district. We will also use the size of these new concessions as an alternative proxy. The minerals involved include Gold, Copper, Diamonds, Lead, Silver, Tin, Zinc, Palladium, Tungsten, and Iron Ore. There are several types of mining concessions with different permits and associated fees. Due to sample size limitations, we do not distinguish between the two broad

categories: research and exploitation. The research permit (PR) confers to its owner the exclusive right to conduct, within the scope of which it is established and for the duration of its validity, the research work of the mineral substances classified as mines for which the permit is granted. The operating permit (PE) gives its owner the exclusive right to perform, inside the perimeter on which it is established and for the duration of its validity, the research, development, construction and exploitation of minerals for which the permit is established. A logarithm transformation is applied to the concession-related variables (adding the value 0.1 when there is no concession) to ease interpretation, although results are still robust without such transformation. In our database, concessions were granted in 1968, 1969, 1970, 1986 and between 1994 and 2007. Figure 4 indicates that mining concessions are mainly granted in Eastern and Southern DRC, which is consistent with the country geological conditions. Visually comparing Figures 1, 3 and 4 suggests that mining concessions may be spatially correlated with conflict.

Third, to improve the efficiency of our estimates we use rainfall data. As in Miguel et al. (2004), rainfall data controls for the climate-induced changes in agricultural income (in poorly irrigated countries) and the resulting changes in the incentives to participate to armed groups. Rainfall data are measured by the National Aeronautics and Space Administration (NASA) using a one degree latitude-longitude grid. We follow a standard approach to transform rainfall data into "anomalies", i.e. deviations from normal rainfall conditions. More specifically, the anomalies are computed at the unit of observation (terri-

tory or district) and measure the deviations from the long-term monthly mean, divided by its monthly long-run standard deviation. A positive (negative) anomaly therefore signals abnormally high (low) rainfall. The monthly basis is chosen to correct for seasonality pattern of rainfall data, while the long-run period is defined by the longest period of available data (1997-2010). We introduce the quadratic term of rainfall anomalies to allow for a detrimental impact of excessive rainfall deviations as compared to the normal conditions. Our central results depend neither on the inclusion of rainfall anomalies nor its quadratic term.

Table 1 provides the descriptive statistics of these variables. Given the relatively long time period used, the non-stationary nature of our variables may be a point of concern, leading to possible spurious relationships (Maddala and Wu 1999). We perform the Fisher panel data unit root test on the dependent and the explanatory variables (see Table 2). The tests reject the null hypothesis that the series in the panel contain a unit root. All series are stationary at any reasonable level of confidence.[5]

3.2 Identification Strategy

Our analysis exploits monthly (t) and geographical (i) variations in the occurrence of conflict events ($Conflicts_{i,t}$) and granting of mining concessions ($Concessions_{i,t}$) between January 1997 and December 2007 in order to to draw causal inference on the role of new

[5]Note on the other hand that the instrumental variable has a unit root. This is not surprising given the above described construction and it does not threaten our identification strategy.

or future mining activities on the level of violence in DRC. The period under investigation is dictated by data availability, which implies that our analysis is limited to the incidence of local conflict events rather than on the onset of the first Congolese war (end of 1996). Using sub-national within-variations, we are mainly capturing the local dynamics of the relationship between mining concessions and conflicts while failing to capture the wider geopolitical dimensions. Ideally we would like to estimate the following equation:

$$Conflicts_{i,t} = \alpha_i + \alpha_t + \beta Concessions_{i,t} + \epsilon_{i,t} \tag{1}$$

Yet, despite the introduction of territory/district fixed effects (α_i) and a series of month-year time dummies (α_t), in estimating (1) we are likely to face severe endogeneity problems (Brunnschweiler and Bulte 2008, 2009). In our case, the granting of mineral concessions may be highly endogenous because of simultaneity as mining companies might be less likely to invest in conflict-prone areas, or because of omitted factors since the granting of concessions may be driven by local politics that could equally directly influence the occurrence of conflict. In addition, measurement problems, in particular for the reported conflict events, are likely to correlate with conflict events thereby introducing additional biases. To deal with these methodological challenges, our estimation relies instead on an IV strategy similar to Brückner and Ciccone (2010). We exploit historical concessions coupled with changes in international prices of minerals to assess the causal relationship between mining concessions and conflict. Historical concessions are defined

as those granted before 1986. Mineral-specific international prices from the United Nations Conference on Trade and Development (UNCTAD)'s Commodity price statistics are normalized.[6] A price index is then constructed by interacting the number of past concessions of mineral j in location i ($PastConc_{i,j}$) with the time-varying international prices of the mineral j the mining concessions extract or aim at extracting ($P_{j,t}$). The constructed index may be expressed as follows:[7]

$$PriceIndex_{i,t} = \sum_j PastConc_{i,j} P_{j,t} \tag{2}$$

The two-stage least square estimation is implemented at two geographical levels of analysis, the territory and the district levels. A linear specification is adopted as non-linear methods in a two-stage framework imply strong specification assumptions (Angrist and Krueger 2001). Accordingly, our estimating equations are the following:

[6]If reported to be traded on different markets in the UNCTAD dataset, we select the US market as the international reference. The prices are normalized to 100 for the first month of 1997. The prices of Copper, Nickel, Zinc and Lead are not available for April 1998, which explains the slight reduction of observations for the price index compared to other variables (see Table 1).

[7]Notice that similar results are found when the price index is expressed as a proportion, i.e. when $PastConc_{i,j}$ is divided by $\sum_j PastConc_j$.

$$
\begin{aligned}
Conflicts_{i,t} &= \alpha_i + \alpha_t + \beta_1 \widehat{Concessions}_{i,t} + \beta_2 Rainfall_{i,t} + \epsilon_{i,t} \\
Concessions_{i,t} &= \alpha_i + \alpha_t + \gamma_1 PriceIndex_{i,t} + \gamma_2 Rainfall_{i,t} + \epsilon_{i,t}
\end{aligned} \tag{3}
$$

We add rainfall anomalies ($Rainfall_{i,t}$) to control for changes in the opportunity cost to fight that are unrelated to mining concessions. To control for other unobserved factors, our estimates introduce territory/district fixed effects (α_i) and a series of month-year time dummies (α_t).

The use of time-varying international prices, coupled with historical concessions, provides an exogenous shock on the probability to grant a new mining concession of a particular mineral type. The rationale for using international prices as an exogenous variation is that conflicts in one particular territory or district of the DRC cannot alone affect the international prices of these minerals.[8]

Changes in international prices instead do affect the demand for mining concessions: an increase in international prices should increase the attractiveness of obtaining a new

[8]The price of Coltan is excluded from the construction of the price index to ensure the exogenous nature of the price index as an instrument. DRC is indeed one of the major Coltan producers, producing in 2001 about 4 percent of the World production (Roskill Information Services 2002). However, the results remain unaltered when the price of Coltan is included in the price index. In that case, coltan prices are derived from Roskill Information Services (2002) and the US Geological Survey. We thank Olivier Dagnelie for sharing that data.

mining concession, given higher expected revenues. This is particularly true in areas where concessions of similar minerals have been granted in the past. The reasons may be related not only to the physical presence of these minerals but also to the investments needed to exploit these minerals such as investments in infrastructure, as well as the local labor market conditions, the existing contractual arrangements, etc. Anecdotal evidence suggests that changes in prices may have an immediate impact on mining exploitation and demand for concessions.[9]

Our identification strategy relies on the validity of our instrumental variable. While the relevance of that instrument may be directly tested, the exclusion restriction may be questioned. We assume the constructed price index to be uncorrelated with the error terms, which implies that this index affects conflicts exclusively through the contemporaneous granting of concessions. Asserting that the international prices of minerals are exogenous is a reasonable assumption.

Our exclusion restriction, however, also requires that the unobserved political discretionary rules affecting the granting of mining concessions are different for the more recent mining concessions under Laurent Désiré Kabila and his son Joseph (1997-2007) and for the historical concessions granted under the Mobutu's regime. Notice first the different geographical origin of the leaders (Orientale province for Mubutu and Katanga province for Kabila) and their ethnic origin (Ngbandi for the former and Luba for the later) sug-

[9]For example, *The Economist* reports how mining companies came from all over the world to deal with the Governor of Katanga, home to about 5 percent of the world's copper and nearly half its cobalt, following the record rises in prices for these minerals (The Economist 2011).

gests that the rules of discretion in the granting of concessions are unlikely to have been the same in the two periods. Anecdotal evidence about the way mining concessions have been granted in the two periods seems to support our exclusion restriction. Under Mobutu, the mining sector was entirely nationalized and mining concessions were largely under the control of the centralized and authoritarian regime. Mining revenues were used to "fund Mobutu's patronage network instead of reinvesting earnings into infrastructure and development" (Stearns 2011: 289). The rules of the game gradually changed in 1995 when Mobutu allowed his prime minister, Kenga wa Dondo, to gradually privatize the mining sector. In 1997, "the rebellion [led by Laurent-Desire kabila] applied its half-Marxist, half-liberal approach to mining, adopting a slipshod policy that imposed harsh conditions on large foreign companies while favoring shadowy investors who often lacked the resources and expertise necessary to develop mining concessions" (Stearns 2011:290).

Finally, the economic conditions surrounding the mining concessions experienced important changes between the two periods. In the early years of Mobutu, characterized by high prices for copper, gold, and cobalt the mining sector was the largest source of employment and income in DRC. In the 1990s, low international prices for key exported minerals coupled with years of mismanagement dampened the profitability of mining activities. "Exports declined from a high of 465,000 tons in 1988 to 38,000 tons just before the war, while cobalt production slipped from 10,000 to 4,000 tons in the same period. Similar trends affected all other mineral exports" (Stearns 2011: 289).

3.3 Empirical Results

In Table 3, we implement the two-stage least square (2SLS) estimation described in the preceding section. At both levels of analysis (territory and district), the price index appears to be highly relevant in the sense that it strongly and positively affects the probability to receive a mining concession. The F-Test on excluded instruments allows us to unambiguously dismiss the risk of weak instruments. We also use a just-identified equation, which is known to be approximately unbiased. The second-stage regressions at the territorial level (Regressions (1) to (6) of Table 3) reveal that granted mining concessions, both in terms of number and size, do not affect the risk of conflict. This finding holds true whether using the ACLED database or the (more selective) UCDP dataset. At the district level, however, the instrumented mining concessions significantly increase the risk of conflict, and in particular of violent conflicts (Regressions (7) to (12) of Table 3).[10] At the district level, given the mean number of conflict events reported in Table 3, a 10 percent increase in both the number and the size of mining concessions would increase the likelihood of conflict by about 29 and 11 percent, respectively.[11] These results are robust

[10]Such results hold when violence against civilians and violent confrontations between armed groups (only possible with the ACLED dataset) are used instead of the violent conflicts variable. In turn, mining concessions do not seem to have any effect on non-violent events. Although not shown for presentation purposes, a *naive* OLS regression that assumes the mining concessions are exogenous indicates that the (potential) endogeneity of mining concessions is likely to introduce a downward bias: the granting of mining concessions significantly decreases the level of conflict at both the territory and the district levels.

[11]These effects are computed based on regressions (7) and (10) of Table 3. Using, respectively, the violent events from the ACLED and the UCDP databases, similar changes in the number of concessions would increase the likelihood of conflict by 31 and 48 percent (regressions (8) and (9)), respectively. The equivalent figures when modifying the size of the concessions are 11 and

to the use of the alternative definition of the mining concessions evaluated on the basis of the year of demand (instead of the year of granting). Not proceeding to the logarithmic transformation does not qualitatively alter the results. In addition, our findings are robust to the exclusion of the capital district (or the two corresponding territories), Kinshasa, from the sample. Qualitatively identical results are obtained when the dependent variable is replaced by a dummy variable indicating whether the concerned geographical unit records at least one conflict event for one particular month (using consequently a linear probability model).[12] Adopting standard errors clustered at the district/territory level does not affect our results. Finally, the ecological fallacy cannot be explained by a difference in variations between the two samples. First, in Section 5 we show that there is enough variation at the territory level to efficiently estimate the relationship of interest, provided the specification is in line with the theoretical mechanism linking mineral concessions and conflicts. Second, implementing an ANOVA analysis on the two samples suggests that the within-territory variation is actually larger than the within-district one.[13]

This result constitutes a case of *ecological fallacy* or aggregation problem, i.e. a misleading assumption that the relationship observed at an aggregated level (e.g. district) implies the same relationship at a different level of aggregation (e.g. territory). In the next section, a simple theoretical model is geared to explain this puzzling finding.

17 percent (regressions (11) and (12)).

[12]Finding similar results with the linear probability model suggests that the number or the size of mining concessions may also affect the "extensive margin" of conflicts, following similar mechanisms as the "intensive margin" of conflicts.

[13]All robustness checks are available upon request.

4 Theoretical Framework

We consider a region represented by a unit-length line inhabited by a uniformly distributed continuum of individuals of unit mass. These individuals are each endowed with a unit amount of time. We assume without loss of generality that all concessions are located at the line's origin. Concessions operating in the region belong to a mine-extraction company controlled by incumbent i. A challenger c endeavors taking over the region hosting the mining concessions by violent means. We model the externality of the ensuing conflict on the mining business as an increased cost of inputs.

Labor constitutes the unique input of the mining activity, and we assume that the mining company is a local monopsonist on the labor market. The profits from controlling the mining concession, π, read as follows:

$$\pi(x_m, d_v; A) = (\varphi(x_m) - y_m(x_m, d_v))\, n x_m \tag{4}$$

where φ is the unit return to labor when employed in mining, which we assume concave in the number of workers active in the mine, x_m. The parameter n captures the size or number of mining concessions. The workers are remunerated at the (endogenous) wage of y_m. The monopsonist will therefore determine the demand for mining labor. Individuals specialize either in mining, or farming. The number of farmers is denoted by $x_f = 1 - x_m$. The farming activity yields an income y_f. Mining is remunerated at the wage y_m, yet the

miners have to incur the unit commuting cost of $(1-d_v)\tau$ reach the mining company from their initial location, where d_v is the distance of conflict from the location of the mine. An individual k located at a distance d_k from the mine prefers working in the mining sector instead of farming if $y_m \geq y_f + (1-d_v)\tau d_i$. Notice that the proximity of conflict to the mining sites increases the commuting cost for miners, thereby reducing their net wage.

The incumbent maximizes his payoff with respect to three choice variables: (i) the number of miners x_m, (ii) the amount of soldiers to deploy against the challenger, x_i, given the exogenous unit cost $\bar{y}$ of the soldiers[14], and (iii) the location of its army, d_v, given an increasing and convex deployment cost $c(d_v)$.[15] We describe the probability that the incumbent beats the challenger by the function $p(x_i, x_c, d_v)$, with x_c standing for the challenger's number of soldiers, and the fighting technology satisfying some very general assumptions:

$$p(x_i, x_c, d_v) = \frac{g(x_i)e(d_v)}{e(d_v)g(x_i) + g(x_c)} \ , \ g^{'}(x_j) > 0 \ , \ g^{''}(x_j), e^{'}(d_v), e^{''}(d_v) < 0 \ , \ j = \{i, c\}$$

The probability that the incumbent is victorious in a confrontation with the challenger is assumed to depend positively on the incumbent's army strength $g(x_i)$, and on his relative fighting efficiency $e(d_v)$, while it is a negative function of the challenger's strength $g(x_c)$.

[14]Making the fighters' remuneration endogenous would unnecessarily complicate the model. Indeed, having assumed that the pool of workers is not influenced by the number of fighters recruited, the endogenous remuneration of the latter would simply amount to a rescaling of our results.

[15]All results remain qualitatively unchanged if the deployment cost is linear.

Moreover, we are assuming that the incumbent's relative fighting efficiency is the highest when his troops are deployed close to the incumbent's headquarters and that this fighting efficiency is monotonically decreasing in d_v.

Notice that deploying the army farther from the mines has three effects: first, it decreases the cost of labor (as it increases the net wage offered to miners); second, it increases the costs of deployment, $c\left(d_v\right)$; and third, it reduces the efficiency of fighting of the army, as soldiers have to patrol a larger territory.

The utility of the incumbent is therefore given by:

$$u_i = p(x_i, x_c, d_v)\pi(x_m, d_v) - \bar{y}x_i - c\left(d_v\right) \tag{5}$$

Since the labor force, x, has two occupational choices and the commuting cost, τ, is incurred by the workers, it follows that for a mining wage y_m, any individual lying on the interval $[0, d_m]$ prefers mining to farming, where d_m is defined as:

$$d_m = \frac{y_m - y_f}{\tau(1 - d_v)}$$

We thus have the mining labor supply as follows:

$$x_m^s = \begin{cases} \frac{y_m - y_f}{\tau(1-d_v)} & \text{if } \frac{y_m - y_f}{\tau(1-d_v)} \leq 1 \\ 1 & \text{otherwise} \end{cases}$$

It then follows that the inverse labor supply function is given by:

$$y_m = \begin{cases} \tau x_m(1-d_v) + y_f & \text{if } x_m^s \leq 1 \\ \\ \tau(1-d_v) + y_f & \text{otherwise} \end{cases}$$

We can now write the incumbent's maximization problem as follows:

$$\max_{x_m, d_v, x_i} \left\{ \frac{g(x_i)e(d_v)}{e(d_v)g(x_i) + g(x_c)} \left[\varphi(x_m) - \tau x_m(1-d_v) - y_f\right] n x_m - \bar{y} x_i - c(d_v) \right\} \quad (6)$$

Optimizing yields the following first order conditions:

$$\frac{\partial u_i}{\partial x_m} = p(x_i, x_c, d_v) n \left(\varphi(x_m) - y_f + \varphi^{'}(x_m) x_m - 2\tau(1-d_v) x_m \right) = 0 \quad (7)$$

$$\frac{\partial u_i}{\partial d_v} = \frac{e^{'}(d_v) g(x_i) g(x_c)}{(e(d_v)g(x_i) + g(x_c))^2} \pi(x_m, d_v) + p(x_i, x_c, d_v) \tau n x_m^2 - c^{'}(d_v) = 0 \quad (8)$$

$$\frac{\partial u_i}{\partial x_i} = \frac{g^{'}(x_i) g(x_c) e(d_v)}{(e(d_v)g(x_i) + g(x_c))^2} \pi(x_m, d_v) - \bar{y} = 0 \quad (9)$$

We show in the appendix that the incumbent's utility function is quasi-concave in the decision variables, and this is sufficient to deduce that an equilibrium exists.

The challenger's optimization problem is analogously given by:

$$\max_{x_c} \left\{ \frac{g(x_c)}{e(d_v)g(x_i) + g(x_c)} \pi(x_m, d_v) - \bar{y}x_c \right\} \tag{10}$$

Optimizing gives the following F.O.C.:

$$\frac{\partial u_c}{\partial x_c} = \frac{g^{'}(x_c)g(x_i)e(d_v)}{(e(d_v)g(x_i) + g(x_c))^2} \pi(x_m, d_v) - \bar{y} = 0 \tag{11}$$

And it is straightforward to show that the challenger's objective function is concave in x_c.

Having showed that the problem is well behaved, we can deduce that a Nash Equilibrium for this game exists (see Mas-Colell et al. 1995, proposition $8.D.3$). Moreover, by combining equations (9) and (11), we can deduce that $g^{'}(x_i)g(x_c) = g^{'}(x_c)g(x_i)$, and since $g(.)$ is a concave function it is necessary that $x_i = x_c$. Equipped with these results, we can now conduct comparative statics on the parameter of interest.

Comparative statics - Changes in the size of the mining industry

Using Condition (7) and by the Implicit Function Theorem we can derive the following expression:

$$\frac{dx_m^*}{dn} = -\frac{p(x_i, x_c, d_v)\partial\pi(x_m, d_v)/\partial x_m}{\frac{\partial^2 u_i}{\partial x_m^2}} \tag{12}$$

The numerator is nil, as it equals the first order condition in (7) up to a multiplicative term n. Because the size of the concession n linearly affects the profitability of mining, changing the size or the number of the mining concessions, therefore, does not affect the optimal number of miners: both the marginal cost of hiring an additional worker, and his marginal return for the company are unaffected by the increase in n. This does not mean, however, that the industry has not become more profitable, rather, the incumbent will see his profits increase proportionally to the size of the mines he controls

Proceeding likewise with condition (8) we obtain:

$$\frac{dd_v^*}{dn} = -\frac{p(x_i, x_c, d_v)\left(\frac{e^{'}(d_v)g(x_c)}{e(d_v)g(x_i)+g(x_c)}\pi(x_m, d_v)/n + \tau x_m^2\right)}{\frac{\partial^2 u_i}{\partial d_v^2}} > 0 \tag{13}$$

Using the first order condition in (8), we deduce that the numerator of (13) is equal to expression (8) to which we substract its third term and divide the whole expression by n, thus implying that the numerator of (13) is positive and that $\partial d_v^*/\partial n > 0$.

The net effect of an increase in the size of the concessions on the optimal location of conflict is the result of two opposing forces. On the one hand the incentives to protect a resource that has become more valuable are higher, thus pushing the incumbent to wage conflict farther from the mining location so that the mining activity is less disrupted. On

the other hand, however, the same force induces the incumbent to reduce the distance of combat to the mine so that his troops' efficiency be enhanced. Eventually, since the marginal cost of troop deployment is unaffected by an increase in the number of mining sites, it follows that the marginal benefit from moving the conflict farther from the mining location outmatches the marginal cost in terms of foregone fighting efficiency.

Finally, we can derive the effect of a change in n on the intensity of conflict by using Condition (9):

$$\frac{dx_i^*}{dn} = -\frac{g^{'}(x_i)g(x_c)e(d_v)}{(e(d_v)g(x_i)+g(x_c))^2}\frac{\partial\pi(x_m,d_v)/\partial n}{\frac{\partial^2 u_i^*}{\partial x_i^2}} > 0 \tag{14}$$

The sign of this expression is as expected since, the marginal benefit of additional soldiers on the ground follows the increase in mining profits, while the marginal cost of this operation remains unchanged. As a consequence the incumbent will deploy more troops, and given the strategic complementarity between the forces of the incumbent and those of the challenger, the latter will equally deploy more troops at equilibrium.

5 Revisiting the empirical analysis

Our theoretical model suggests that the impact of mining concessions on conflict is non-homogeneous across space. In particular, increasing the size or number of mining sites has the potential not only of increasing overall conflict intensity but also of displacing

violent events farther from mineral deposits. A first indication of such spatial dependency is given in Table 4. The Lagrange Multiplier (LM) tests performed in columns (1) to (3) of Table 4 suggest significant spatial lags and error correlations at the territory level. At the district level, only UCDP variables display significant spatial correlation (column (6) of Table 4).

To explicitly assess the importance of spatial spillovers, we consider two models. First, we assess the role of spatially lagged mineral concessions, following Florax and Folmer (1992). We apply the method to our panel analysis following Anselin (2002). We augment equations (2) with a spatially lagged explanatory variable in the following way:

$$\begin{aligned}
Conflicts_{i,t} &= \alpha_i + \alpha_t + \beta_1 \widehat{Concessions}_{i,t} + \beta_2 W\widehat{Concessions}_{i,t} \\
&+ \beta_3 Rainfall_{i,t} + \epsilon_{i,t} \\
Concessions_{i,t} &= \alpha_i + \alpha_t + \phi_1 PriceIndex_{i,t} + \phi_2 WPriceIndex_{i,t} \\
&+ \phi_3 Rainfall_{i,t} + \epsilon_{i,t} \\
WConcessions_{i,t} &= \alpha_i + \alpha_t + \theta_1 PriceIndex_{i,t} + \theta_2 WPriceIndex_{i,t} \\
&+ \theta_3 Rainfall_{i,t} + \epsilon_{i,t}
\end{aligned} \tag{15}$$

We use a distance-based spatial matrix based on the inverse distance decay function. $WConcessions_{i,t}$ and $WPriceIndex_{i,t}$ are a weighted sum of the concession-based

variables and price indices at other locations. We can, for instance, express the variable $WConcessions_{i,t}$ as follows:

$$WConcessions_{i,t} = \sum_{j \neq i} w_i j Concessions_{j,t} \quad \text{where} \quad w_i j = \frac{d_{ij}^{-\gamma}}{\sum_j d_{ij}^{-\gamma}}$$

Where γ takes the values 1 or 2 as these are the most common integers used in spatial econometrics (Anselin 2002).

Second, we also estimate spatial panel models with time and location fixed effects using Matlab routines and methods developed by Elhorst (2003, 2010) . The estimation approach includes the bias correction procedure proposed by Lee and Yu (2011) for spatial panel data models containing spatial and/or time-period fixed effects. Because of the absence of convincing evidence of the presence of spatial correlation at the district level, in addition to possible small sample bias with respect to districts (only 38), we discuss only territory level estimates.

Estimating the system of equations (15), Table 5 indicates that at the territory level (regressions (1) to (3)) the granting of mining concessions in the neighboring territory significantly increases the risk of conflict (especially violent conflicts). The coefficient of the non-spatially lagged variable is negative and significantly different from zero (very close to significant in regression (3)). Table 5 indicates that these results are robust to the use of an alternative spatial matrix of order 1, instead of 2, and to the size of the concessions rather than their number (regressions (4) to (12) in Table 5). In Table 6, we report

estimation results using explicit spatial models for panel data based on the methods developed by Elhorst (2003, 2010), along with the bias correction procedure proposed by Lee and Yu (2010) for spatial panel data models containing spatial and/or time-period fixed effects. The results suggest the existence of significant spillovers in conflict intensity in both the error term and the spatial dependent variable. In other words, conflicts erupting in territories are not independent from each other; consequently, any strategy to address these conflicts should be comprehensive and inclusive. Even with these spatial specifications, our estimates remain very stable, especially for the number of concessions. Based on regressions (1) and (4) of Table 6 and given the mean number of conflict events reported in Table 1, a 10 percent increase in the number and the size of mining concessions would respectively decrease the likelihood of conflict events by about 60 and 1 percent in the same territory. However, a similar increase in the number and size of the concessions would also increase the number of conflicts by about 165 and 2 percent, respectively, in the neighboring territory. Although significantly different from zero, the much lower effect resulting from a change in the size of concessions compared to the number of concessions may suggest that the size of the concessions is much less directly associated with an increase in mining profits. At the district level, no spatial effect is found. Results are robust to the use of alternative definitions of the mining concessions such as those based on the years of demand and those not using a logarithmic transformation for the concession-based variables.

Overall, these result are consistent with the theoretical prediction that a larger size or number of mining sites increases the protection effect thereby reducing violence around the mine(s); gives the incentives to the incumbent to move the conflict location farther from the mining site (potentially in a neighboring territory); and results in a higher level of violence at the aggregate level (adequately captured at the district level). Our results are therefore supportive of the spatial-based theoretical mechanisms proposed in the previous section and are likely to explain the case of ecological fallacy found in Section 3.3. In other words, the absence of a statistically significant relationship between mining concessions and (violent) conflicts at the territory level in our baseline regression is driven by an omitted spatial effect, explained by the incumbent's incentives to protect the mining business. When spatial spillovers are taken into account, a mining concession tends to decrease the risk of conflict in the same territory but increases the risk in neighboring territories. That in turn explains why a change in mining concessions would translate at a more aggregated effect (i.e. the district level) into an increase in conflict intensity.

Finally, it should be noted that rainfall anomalies retain a significant and negative sign throughout the empirical analysis. One should be cautious, however, in interpreting this result since this variable is only a proxy for agricultural income. A tentative explanation would therefore be that improved agricultural yields reduce the intensity of conflict.

6 Alternative explanations

In interpreting our empirical results we propose an explanation based on the incentive of extractive companies to protect their business. How does our "protection effect" mechanism perform against alternative explanations?

Three alternative explanations are compatible with natural resource wealth having a non significant effect on conflict at the very local level and a significant and substantial impact at the higher level of aggregation. The first relates to measurement error: conflict events may be measured with more noise at the territory level as underlying sources may be less accurate about the precise territory in which the event takes place. This would generate relatively larger standard errors in our analysis at the territory level. We cannot completely rule out this explanation. However, repeating the analysis with the two most commonly used geo-referenced dataset on conflict (ACLED and UCDP) does not affect our findings. Moreover, this criticism would likewise invalidate a substantial share of recent conflict studies which moved the focus of the analysis to more disaggregated geographic levels.

Second, the presence of valuable minerals may translate into a higher *opportunity cost* for armed group potential recruits, thereby generating a pacifying effect at the local level. This is an appealing theory, well established in the conflict literature. There are a number of reasons why we do not believe opportunity cost to be the mechanism driving our results. First, it can not account for the increase in conflict generated by minerals in

neighboring territories (effect highlighted in Table 6). Neither is it consistent with the reality of DRC conflicts, where many of the armed factions were substantially composed by foreigners (Prunier 2009, Vlassenroot and Raeymaekers 2004). Finally, even if local recruitment was affected by mining activities, the opportunity cost channel cannot explain the location of the violence: irrespective of the area of recruitment, why would the fighting occur at a certain distance from the mining site?

Third, large mineral deposits may ensure a regular stream of wealth favoring the development of better local institutions. Territories featuring good local institutions would safeguard their population and divert violence more successfully. Institution-based explanations are intriguing and are currently gaining support in the literature. Yet, this interpretation would contradict much of the literature on the resource curse, which suggests minerals to be associated with weak institutions (e.g., Besley and Persson 2010). Moreover, how would good local institutions displace violence to neighboring territories? Military capacity seems the only credible channel - an alternative "protection effect" - stemming from local institutions instead of the minerals' controllers. Since the extractive companies capture the largest share of mining profits, we believe that they may have substantially higher stakes in shielding their business.

7 Conclusion

We explore the mineral resources-conflict nexus by focusing on the mineral-rich and conflict-ridden Democratic Republic of the Congo from 1997 to 2007. Using geo-referenced data, we investigate whether the DRC government's granting of mineral concessions in particular geographical areas has had an impact on the intensity of conflict. To overcome endogeneity concerns, we instrument concessions granted over the period of analysis by the interaction of historical concessions and the prices of mineral resources. Our study reveals a case of ecological fallacy: At the territory level, granting concessions does not affect the level of conflict; at the district level, however, the right to exploit mineral wealth is shown to exacerbate the level of violence.

To rationalize this finding, we set up a theoretical model which relies on the incentives of violent entrepreneurs to protect the mining activities by avoiding armed confrontations with competing entrepreneurs nearby the mining activity. Securing a peaceful environment close to the mining sites enhances the mining laborers' security, thereby reducing the cost of the labor force for the entrepreneurs in control of the mining location. A larger number of mining sites in a particular geographical location is shown to increase the intensity of conflict and to provoke a displacement of conflict to more remote locations.

Our paper brings forward a crucial element in the understanding of the roots of conflicts, namely the importance of the geographical unit of observation. Neglecting the spatial dimension may misguide policies. Indeed, we have shown that natural resources

may constitute a blessing for populations located in the neighborhood of mines since resource-greedy entrepreneurs will deploy means to protect their source of income. The same resources, however, can be characterized as a curse for the wider geographical area since the intensity of conflict in surrounding areas is likely to experience an increase.

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8 Appendix

Existence of equilibrium

To show that there exists an equilibrium for this game, it is sufficient to show that the incumbent's utility function is quasi-concave in his decision variables. Let us sequentially consider the second order conditions.

$$\frac{\partial^2 u_i(x_m)}{\partial x_m^2} = p(x_i, x_c, d_v)n\left(2\varphi^{'}(x_m) - 2\tau(1-d_v) + \varphi^{''}(x_m)x_m\right) \tag{16}$$

To establish the utility function's quasi-concavity, it is sufficient to show that $\partial\pi(x_m)/\partial x_m \leq 0 \Rightarrow \partial^2\pi(x_m)/\partial x_m^2 < 0$. Notice first that in the above bracketed expression, the third term is negative. A sufficient condition for establishing the unicity of x_m^* is that $\partial\pi(x_m)/\partial x_m \leq 0 \Rightarrow \varphi^{'}(x_m) < \tau(1-d_v) < 0$

We can next re-express $\partial\pi(x_m)/\partial x_m \leq 0$ as:

$$\varphi^{'}(x_m) \leq 2\tau(1-d_v) - \frac{\varphi(x_m) - y_f}{x_m}$$

Thus, to establish (strict) quasi-concavity, it is sufficient to show that:

$$2\tau(1-d_v) - \frac{\varphi(x_m) - y_f}{x_m} < \tau(1-d_v) \Leftrightarrow \tau(1-d_v)x_m < \varphi(x_m) - y_f$$

And since this last inequality is always verified if $\pi(x_m) > 0$, we can deduce that there exists a unique $x_m(x_i, x_c, d_m)$.

The others SOCs are given by:

$$\frac{\partial^2 u_i}{\partial d_v^2} = \frac{e^{''}(d_v)g(x_i)g(x_c)(g(x_i)+g(x_c)) - 2(e^{'}(d_v))^2 g(x_i)^2 g(x_c)}{(e(d_v)g(x_i)+g(x_c))^3}\pi(x_m, d_v)$$

$$+2\frac{e^{'}(d_v)g(x_i)g(x_c)}{(e(d_v)g(x_i)+g(x_j))^2}\tau n x_m^2 - c(d_v)^{''} < 0 \tag{17}$$

$$\frac{\partial^2 u_i}{\partial x_i^2} = p_{x_i x_i}(x_i, x_c)\pi(x_m, d_v) < 0 \tag{18}$$

The sign of the last expression is a consequence of $p_{x_i x_i} \leq 0$, which can straightforwardly be computed.

9 Tables and Maps

Table 1: Descriptive Statistics

	Level of analysis: Territory				
Variable	Obs	Mean	Std. Dev.	Minimum	Maximum
Conflict Number (ACLED)	19800	0.1536364	1.024244	0	41
Violent Conflict Number (ACLED)	19800	0.1326768	0.9604655	0	41
Conflict Number (UCDP)	19800	0.046818	0.336929	0	11
Mining Concessions	19800	0.2802525	1.756388	0	46
Rainfall Anomalies	19800	1.08E-09	0.9534867	-2.770797	3.003923
Price Index	19650	506.0248	2965.579	0	57774.78

	Level of analysis: District				
Variable	Obs	Mean	Std. Dev.	Minimum	Maximum
Conflict Number (ACLED)	5016	0.6064593	2.44326	0	43
Violent Conflict (ACLED) Number	5016	0.5237241	2.241598	0	43
Conflict Number (UCDP)	5016	0.184809	0.849571	0	16
Mining Concessions	5016	1.10626	5.46692	0	103
Rainfall Anomalies	5016	-3.09E-09	0.9155268	-2.541199	2.990951
Price Index	4978	1997.466	7107.281	0	63507.28

Note: The prices of Copper, Nickel, Zinc and Lead are not available for one particular month, i.e. in April 1998. That explains the slight reduction of observations for the price index compared to other variables.

Table 2: Panel Unit Root Test (Maddala and Wu 1999)

Level of Analysis	Territory	District
Conflict Number (ACLED)	6470.2***	1489.46***
Violent Conflict (ACLED)	6432.27***	1503.91***
Conflict Number (UCDP)	5069.57***	1517.041***
Mining Concessions (number)	5223.01***	1317.53***
Mining Concessions (number, log)	4390.79***	1035.36***
Mining Concessions (size)	5818.43***	1517.97***
Mining Concessions (size, log)	4403.62***	1063.39***
Rainfall Anomalies	62.03***	1573.52***
Price Index	0.193	0.174

Note: *** $p < 0.01$

Table 3: Baseline results : A case of ecological fallacy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Level of Analysis	Territory	Territory	Territory	Territory	Territory	Territory	District	District	District	District	District	District
	Second-stage regressions											
Dep. Var.	Conflicts ACLED	Violent Conflicts ACLED	Conflicts UCDP	Conflicts ACLED	Violent Conflicts ACLED	Conflicts UCDP	Conflicts ACLED	Violent Conflicts ACLED	Conflicts UCDP	Conflicts ACLED	Violent Conflicts ACLED	Conflicts UCDP
Concessions (log)	-0.104	0.013	0.089				1.752**	1.640**	0.885**			
	[0.165]	[0.137]	[0.054]				[0.802]	[0.718]	[0.361]			
Concessions Size (log)				-7.32E-10	9.36E-11	6.25E-10				0.642**	0.601**	0.324**
				[1.16e-09]	[9.69e-10]	[4.11e-10]				[0.290]	[0.260]	[0.131]
Rainfall Anomalies	-0.025**	-0.023**	-0.008**	-0.026***	-0.023**	-0.008**	-0.162**	-0.144**	-0.052*	-0.168***	-0.150**	-0.055*
	[0.009]	[0.009]	[0.003]	[0.0099]	[0.009]	[0.004]	[0.063]	[0.058]	[0.029]	[0.063]	[0.058]	[0.029]
Rainfall^2 Anomalies	-0.0001	0.001	-0.0004	-0.0008	0.001	0.0002	0.078	0.07	0.027	0.081*	0.072	0.028
	[0.006]	[0.006]	[0.002]	[0.007]	[0.006]	[0.003]	[0.049]	[0.046]	[0.022]	[0.048]	[0.045]	[0.021]
Yr-Mth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Territory/district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	19,650	19,650	19,650	19,650	19,650	19,650	4,978	4,978	4,978	4,978	4,978	4,978
Nbr of Territories/ Districts	150	150	150	150	150	150	38	38	38	38	38	38
Underid test	24.2***	24.2***	24.2***	8.186***	8.186***	8.186***	26.99	26.99	26.99	27.42	27.42	27.42
Root MSE	0.98	0.92	0.33	1.008	0.92	0.39	2.81	2.61	1.18	2.73	2.54	1.18
	First-stage regressions											
Dep. Var.	Concessions						Concessions					
	(log)	(log)	(log)	Size (log)	Size (log)	Size (log)	(log)	(log)	(log)	Size (log)	Size (log)	Size (log)
Price Index	4.7e-05***	4.7e-05***	4.7e-05***	6,723***	6,723***	6,723***	4.6e-05***	4.6e-05***	4.6e-05***	1.3e-04***	1.3e-04***	1.3e-04***
	[8.31e-06]	[8.31e-06]	[8.31e-06]	[2,142]	[2,142]	[2,142]	[7.45e-06]	[7.45e-06]	[7.45e-06]	[1.92e-05]	[1.92e-05]	[1.92e-05]
Rainfall Anomalies	0.0159**	0.0159**	0.0159**	1.14e-06	1.14e-06	1.14e-06	0.029	0.029	0.029	0.088	0.088	0.088
	[0.008]	[0.008]	[0.008]	[3.4e-06]	[3.4e-06]	[3.4e-06]	[0.021]	[0.021]	[0.021]	[0.056]	[0.056]	[0.056]
Rainfall^2 Anomalies	-0.009*	-0.009*	-0.009*	-2.29e-06	-2.29e-06	-2.29e-06	-0.033**	-0.033**	-0.033**	-0.094**	-0.094**	-0.094**
	[0.005]	[0.005]	[0.005]	[2.7e-06]	[2.7e-06]	[2.7e-06]	[0.015]	[0.015]	[0.015]	[0.038]	[0.038]	[0.038]
Yr-Mth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Territory/district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	19,650	19,650	19,650	19,650	19,650	19,650	4,978	4,978	4,978	4,978	4,978	4,978
R sq.	0.21	0.21	0.21	0.068	0.068	0.068	0.306	0.306	0.306	0.297	0.297	0.297
Nbr of Territories/ Districts	150	150	150	150	150	150	38	38	38	38	38	38
F-Test	12.11***	12.11***	12.11***	3.17***	3.17***	3.17***	7.19***	7.19***	7.19***	7.42***	7.42***	7.42***
F-test on excl. IV	32.37***	32.37***	32.37***	9.86***	9.86***	9.86***	38.97***	38.97***	38.97***	43.67***	43.67***	43.67***

Note : *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$*; Robust standard errors are in brackets.*

Table 4: Lagrange Multiplier (LM) Tests for spatial correlations

	(1)	(2)	(3)	(4)	(5)	(6)
Level of	Territory	Territory	Territory	District	District	District
Dep. Var.	Conflicts ACLED	Violent Conflicts ACLED	Conflicts UCDP	Conflicts ACLED	Violent Conflicts ACLED	Conflicts UCDP
Tests	LM test	LM test	LM test	LM test	LM test	LM test
Variable of interest	Concessions (log)	Concessions (log)	Concessions (log)	Concessions (log)	Concessions (log)	Concessions (log)
Spatial lag	73.69***	73.69***	390.098***	3.2	3.8	6.89***
Spatial error	73.49***	73.49***	385.95***	2.7	3.4	6.38***
Variable of Interest	Concessions Size (log)	Concessions Size (log)	Concessions Size (log)	Concessions Size (log)	Concessions Size (log)	Concessions Size (log)
Spatial lag	90.98***	73.6868***	390.098***	3.2	3.8	6.89***
Spatial error	91.95***	73.49***	385.98***	2.7	3.4	6.38***

Note : *** $p < 0.01$

Table 5: Results with spatial dependency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Level of Analysis	Territory	Territory	Territory	Territory	Territory	Territory	Territory	Territory	Territory	Territory	Territory	Territory
Order of Spatial Matrix	2	2	2	2	2	2	1	1	1	1	1	1
Dep. Var.	Conflicts ACLED	Violent Conflicts ACLED	Conflicts UCDP	Conflicts ACLED	Violent Conflicts ACLED	Conflicts UCDP	Conflicts ACLED	Violent Conflicts ACLED	Conflicts UCDP	Conflicts ACLED	Violent Conflicts ACLED	Conflicts UCDP
Concessions (log)	-0.542**	-0.404*	-0.109				-0.911**	-0.737**	-0.194*			
	[0.276]	[0.234]	[0.0793]				[0.416]	[0.363]	[0.115]			
Neighboring Concessions (log)	3.337***	3.105***	1.441***				2.367***	2.175***	0.807***			
	[1.102]	[1.009]	[0.362]				[0.794]	[0.740]	[0.258]			
Concessions Size (log)				-3.36e-09*	-2.45E-09	-6.12E-10				-5.65E-09	-4.50E-09	-1.12E-09
				[1.99e-09]	[1.62e-09]	[5.36e-10]				[3.63e-09]	[3.02e-09]	[9.34e-10]
Neighboring Concessions Size (log)				0.400**	0.378***	0.180***				0.630*	0.579**	0.216**
				[0.163]	[0.140]	[0.0479]				[0.337]	[0.287]	[0.0927]
Rainfall Anomalies	-0.0317**	-0.0301**	-0.0108**	-0.0372**	-0.0349**	-0.0128**	-0.0461***	-0.0432***	-0.0146***	-0.0543*	-0.0502*	-0.0168**
	[0.0129]	[0.0120]	[0.00445]	[0.0182]	[0.0155]	[0.00537]	[0.0163]	[0.0149]	[0.00545]	[0.0305]	[0.0259]	[0.00829]
Rainfall^2 Anomalies	0.00326	0.00362	0.00098	0.00367	0.00495	0.00234	0.000187	0.000758	-0.00034	0.00519	0.00625	0.00241
	[0.00775]	[0.00719]	[0.00270]	[0.0130]	[0.0107]	[0.00350]	[0.00922]	[0.00835]	[0.00289]	[0.0202]	[0.0169]	[0.00495]
Yr-Mth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	18,000	18,000	18,000	18,000	18,000	18,000	18,000	18,000	18,000	18,000	18,000	18,000
Nbr of Territories	150	150	150	150	150	150	150	150	150	150	150	150
Underid test	19.7***	19.7***	19.7***	6.103***	6.103***	6.103***	15.31***	15.31***	15.31***	3.211***	3.211***	3.211***
Root MSE 2d stage	1.147	1.072	0.39	1.601	1.363	0.458	1.357	1.248	0.42	2.41	2.054	0.62

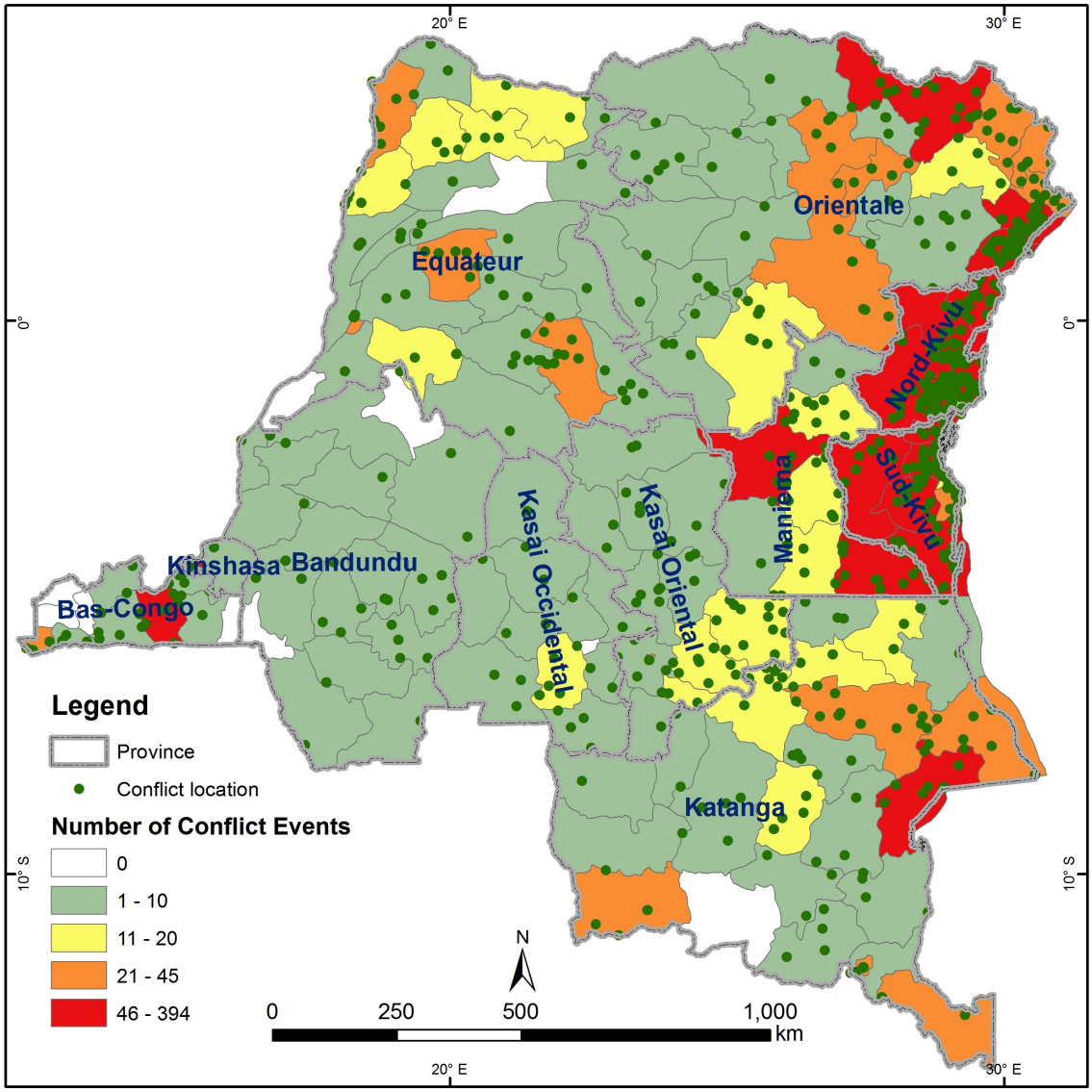
Note : *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; *Robust standard errors are in brackets.*

Table 6: Results with spatial dependency, including spatially lagged dependent and independent variables and a spatially correlated error terms

	(1)	(2)	(3)	(4)	(5)	(6)
Level of Analysis	Territory	Territory	Territory	Territory	Territory	Territory
Order of Spatial Matrix	1	1	1	1	1	1
Dep. Var.	Conflicts ACLED	Violent Conflicts ACLED	Conflicts UCDP	Conflicts ACLED	Violent Conflicts ACLED	Conflicts UCDP
Spatially lagged Dep. var.	0.102949*** (8.962629)	0.093942*** (8.145395)	0.213974*** (19.680156)	0.099997*** (8.842622)	0.095996*** (8.330796)	0.213974*** (19.680155)
Concessions (log)	-0.929731*** (-8.20325)	-0.780477*** (-7.40765)	-0.200213*** (-5.744683)			
Neighboring Concessions (log)	2.534542*** (12.828088)	2.254936*** (12.277626)	0.655634*** (10.792875)			
Concessions Size (log)				-0.010269* (-1.64964)	-0.275182*** (-7.411657)	-0.070541*** (-5.744686)
Neighboring Concessions Size (log)				0.030875*** (2.840914)	0.794126*** (12.26997)	0.230999*** (10.792876)
Rainfall Anomalies	-0.025828 (-1.062632)	-0.020719 (-0.904529)	-0.012011 (-1.506879)	1.041329*** (701.383624)	-0.021528 (-0.940009)	-0.01222 (-1.533284)
Rainfall Squared	0.002528 (0.182405)	0.001049 (0.080342)	-0.001955 (-0.430292)	-0.000478 (-0.182242)	0.000378 (0.028972)	-0.002128 (-0.468628)
Neighboring Rainfall	-0.0108 (-0.381019)	-0.012104 (-0.45315)	0.004163 (0.447898)	-0.09241*** (-7.541886)	-0.009688 (-0.362809)	0.004848 (0.521729)
Neighboring Rainfall^2	-0.018576 (-1.082606)	-0.015474 (-0.957215)	-0.003709 (-0.660009)	-0.000862 (-0.265764)	-0.013521 (-0.837552)	-0.003143 (-0.559999)
Spatial error Correlation	0.28152*** (12.71644)	0.294532*** (12.759904)	0.341217 (12.930554)	0.496263*** (13.652167)	0.294326*** (12.759201)	0.341217*** (12.930554)
Yr-Mth FE	Yes	Yes	Yes	Yes	Yes	Yes
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	19,800	19,800	19,800	19,800	19,800	19,800
Nbr of Territories	150	150	150	150	150	150
Log. Likelihood	-502	-476	-8027	-289	-291	-802

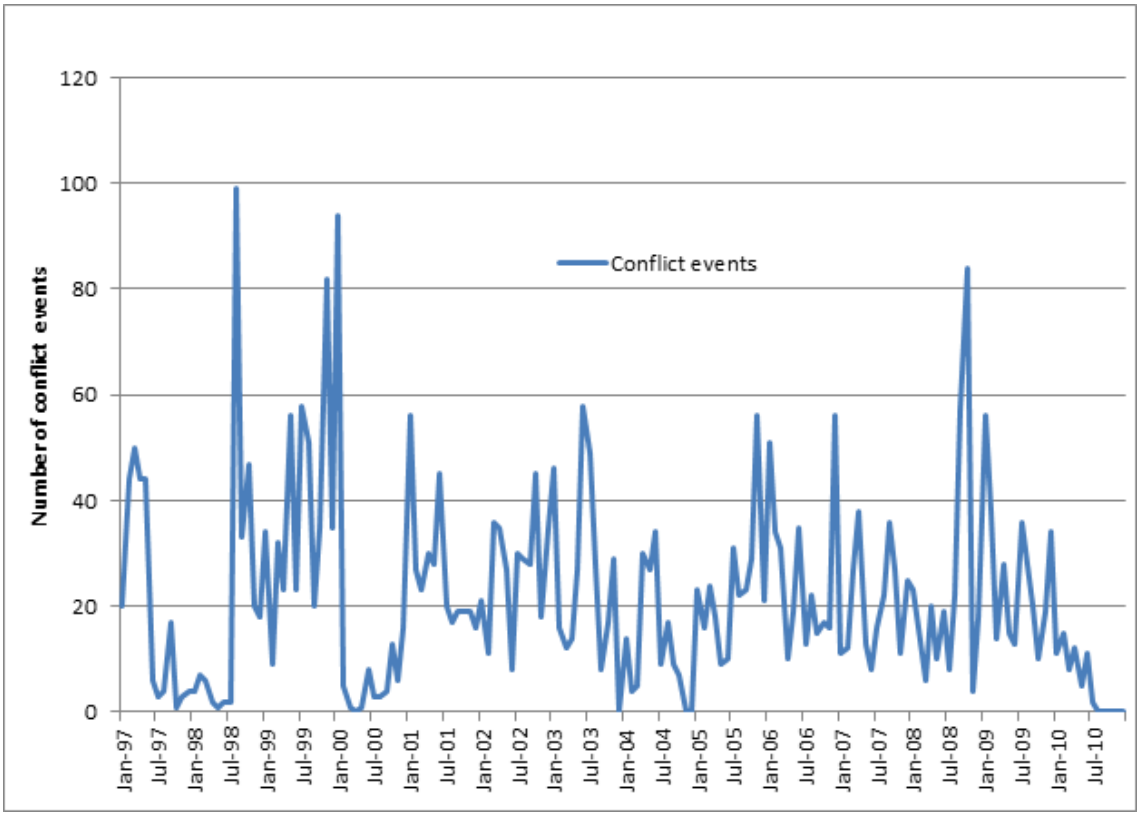
Note : *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*; Asymetric T-statistics are in parentheses.*

Figure 1: Distribution of ACLED conflict events in the Democratic Republic of the Congo (DRC), 1997-2007



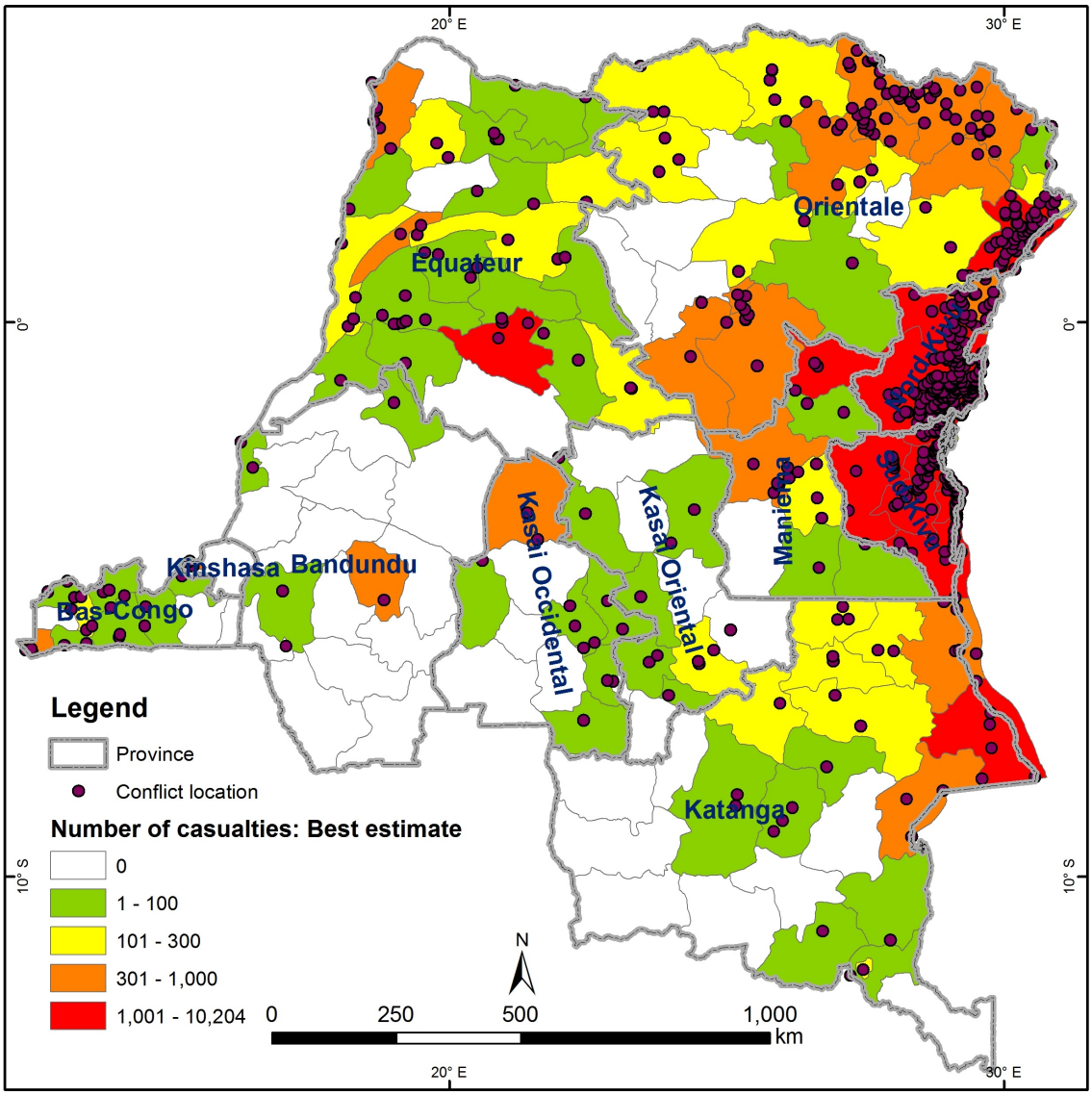
Source: Authors' construction based on Armed Conflict Location and Event Data (ACLED, Raleigh et al. 2010). Note: Green points represent the raw ACLED events.

Figure 2: Number of ACLED conflict events in the Democratic Republic of the Congo (DRC), 1997-2010)



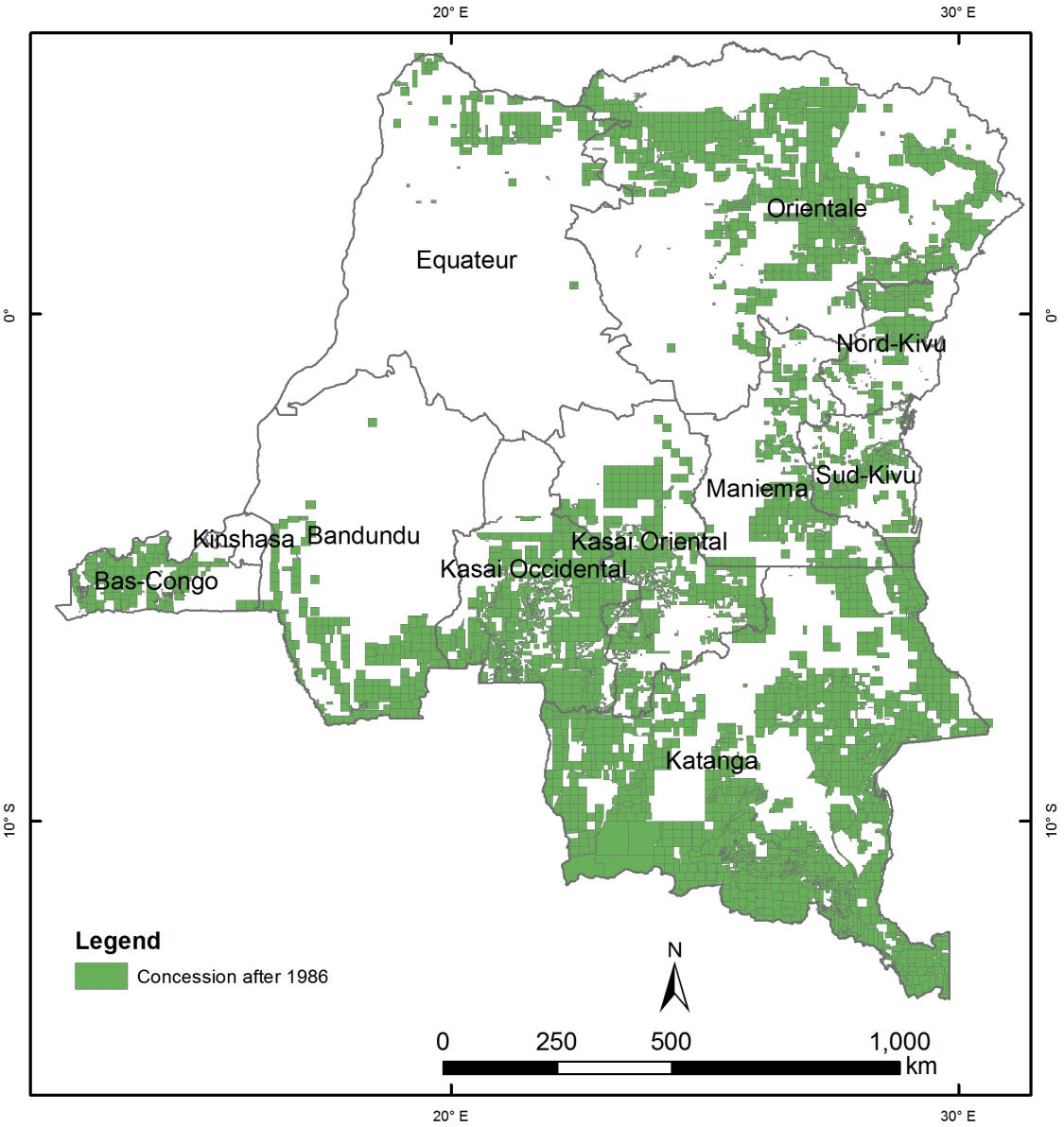
Source: Authors' construction based on Armed Conflict Location and Event Data (ACLED, Raleigh et al. 2010).

Figure 3: Distribution of UCDP conflict events in the Democratic Republic of the Congo, 1997-2007



Source: Authors' construction based on Uppsala Conflict Data Program (UCDP, Sunderg et al. 2012). Note: Points represent the raw UCDP events.

Figure 4: Distribution of mining concessions in the Democratic Republic of the Congo (DRC)



Source: Authors' construction based on data provided by the DRC Ministry of Mining.