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The inequality-resource curse of conflict

Heterogeneous effects of mineral deposit discoveries

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Abstract: Despite a sizeable literature, there is no consensus as to whether and how mineral resources are linked to conflict. In this paper, we estimate the relationship between giant mineral deposit discoveries and the intensity of armed conflict (measured by battle deaths) around the world in the post-war era. The impact of such discoveries is potentially heterogeneous with respect to mineral commodity type: metals with a low value-to-weight ratio are not easy to exploit and smuggle and will disproportionally aid governments in their counterinsurgency efforts and raise the opportunity cost of fighting, whereas the discovery of deposits of high value-to-weight ratio metals may increase incentives for rebellion and make insurgency feasible. The data indeed show discoveries of giant deposits to lower the intensity of conflict for low unit-value ores, but giant discoveries increase the intensity of conflict for high unit-value minerals. We also show that discoveries in countries with high ethnic inequality increase conflict intensity to a greater extent than in countries with low ethnic inequality—this heterogeneity is likely due to grievances related to the distribution of resource rents and revenues.

Keywords: resource discovery, mining, ethnic inequality, conflict intensity

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1. Introduction

How and when do natural resources affect armed conflict? The relation between natural resource wealth and conflict remains a much-debated topic in the political and economics sciences (Collier and Hoeffler, 1998, 2004, 2005; Brunnschweiler and Bulte, 2009; Basedau and Lay, 2009; Murshed and Tadjoeddin, 2009; Wick and Bulte, 2009; Cotet and Tsui, 2013). Several theories have been postulated on the link between resources and conflict (Grossman, 1991; Addison et al., 2002; Humphreys, 2005; Acemoglu et al., 2011), and it is ultimately an empirical matter which mechanisms are most relevant and under which conditions. This paper makes a contribution by studying one group of commodities, minerals, and by investigating how the discovery of giant mineral deposits affects conflict intensity, as measured by battle deaths.

One reason for the often contradictory findings in the literature is the dependence of results on methodological choices. The empirical relationship between resources and conflict depends among others on the resources measure, the unit of observation, the spatial and temporal coverage of the data, the commodities considered, the conflict measure, and the control variables included. A pervasive problem is the endogeneity of the resource variable.

Before coming to our contribution, we outline briefly five potential mechanisms linking resources and conflict proposed in the literature. Some of these mechanisms have only been proposed or analyzed empirically for the outcome variable of risk of conflict onset or incidence. However, the reasoning can often be extended to conflict intensity. Reviewing the potential mechanisms helps also to frame our contribution. First, increases in the value of resources raise the stakes of capturing territory (the 'rapacity' effect), making it more likely to see (more heavy) fighting in that region[1] (Besley and Persson, 2008; Collier and Hoeffler, 1998). Dube and Vargas (2013) for instance found that positive oil price shocks increase violence in Colombia. This mechanism is relevant both for intrastate conflict when regions eyed by rebel groups

[1]This mechanism is also referred to as the 'state prize' mechanism, for instance in Fearon and Laitin (2003) and Bazzi and Blattman (2014).

go through a resource boom as well as for interstate conflict, particularly when the resources are located in border regions of countries that can be annexed (as was found for oil reserves by Caselli et al. (2014))[2]. As a second mechanism, resource revenues and resource rents can be used to finance warring parties (Ross, 2004; Collier et al., 2009) and thereby make insurgency feasible (the 'feasibility' channel). Seminal work by Collier and Hoeffler (2004) and Collier et al. (2009) found evidence that higher primary commodities exports as a share of GDP proxying the viability of rebellion (albeit possibly endogenous to conflict risk) increases the risk of civil war incidence. Third, insofar as resource rents and revenues to a government increase military capacity and counterinsurgency efforts, this may lower conflict risk or shorten wars (Bazzi and Blattman, 2014). We conjecture that if around the globe, governments are aided disproportionaly on average by giant mineral deposit discoveries, then by the same token, increased value of resources may reduce the intensity of conflict through enhanced counterinsurgency capacity (the 'state military capacity' channel). The 'feasibility' and 'military capacity' channels above are essentially two sides of the same coin as they correspond to the ability of different parties to wage war. Fourth, the extraction and sale of raw resources generates income, assets and jobs, so that individuals have relatively 'more to lose' when joining an insurgency (the 'opportunity cost' effect) (Collier and Hoeffler, 2004). For the case of minerals, resource booms spur local economic activity around the mining site (Amankwah and Anim-Sackey, 2003; Bhattacharyya et al., 2015), which may increase the opportunity cost of residents around those sites to join rebel forces. As a fifth and final mechanism, grievances may be aggravated by an (anticipated) unequal distribution of resource wealth by governments (Ross, 2004). Most scholars of war agree that both greed and grievances have some power in explaining conflict risk (Nillesen and Bulte, 2014).

Minerals have a potentially appealing feature for the study of conflict: whereas mineral commodities are rather homogeneous goods (i.e. there is limited heterogeneity within a raw mineral commodity), between mineral commodities, there is substantial

[2]Examples of interstate wars in minerals-rich border regions are the Agacher Strip War between Burkina Faso and Mali in 1985 and the Cenepa war between Ecuador and Peru in 1995.

heterogeneity. In particular, there is large heterogeneity in the monetary value of the commodity per unit of mass as reflected in the price per kg in international markets. The reason why the commodity-specific value-to-weight ratio of minerals is relevant for the study of conflict is that it captures the ease of and incentives for exploitation, expropriation, transport and sale (illicitly) by rebels or rapacious governments (i.e., the 'rapacity' and 'feasibility' mechanisms). For low unit-value ores on the other hand, such incentives are much lower or absent, as such minerals require exploiters to ship and market the product through a single agency (i.e. an outside mining company) to reach the economies of scale to make the mining project economically viable. Consequently, the ability for governments to tax the production and export of such mineral commodities is also higher for low unit-value minerales. Hence, for low value-to-weight minerals, the 'opportunity cost' and 'state military capacity' channels will dominate, so that giant deposit discoveries of such ores lower conflict intensity.

In this paper, we exploit exogenous shocks to resource abundance, giant mineral deposit discoveries, to distill its effect on conflict intensity, in order to test the aforementioned predictions. For this, we rely on data on the discovery dates of deposit discoveries from 46 mineral commodities, for 124 countries from 1946 to 2008. By distinguishing between high value-to-weight ratio ((semi-)precious metals) and low value-to-weight ratio minerals (such as base metals), we are able to disentangle the 'rapacity' and 'feasibility' mechanisms from the 'state military capacity' and 'opportunity cost' channels. We indeed find evidence that the discovery of giant deposits of high-unit value minerals increases conflict intensity, whereas the discovery of low-unit value minerals lowers conflict intensity.

Another contribution of this paper is that it investigates the effect of giant mineral deposit discoveries conditional on the role ethnicity plays in a countries' politics. The 'grievances' channel discussed above can be expected to be more important when ethnic power relations are more skewed. To capture dimensions of ethnic inequalities potentially most relevant to conflict intensity, we rely on Cederman and Girardin's (2009) index of ethnic configuration, explained in Section 2. We indeed observe in the data a higher discovery-conflict response in countries where ethnic power relations are more skewed.

Several studies harness shocks to mineral resource value to study their effect on conflict onset, incidence and intensity. Maystadt et al. (2013) looked at the Democratic Republic of the Congo (DRC), the country most often associated with 'conflict minerals' in the popular media. They found that 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). Specifically for diamonds, Lujala et al. (2005) distinguished between primary diamond production, which stems from underground mines, and secondary diamond production, which concerns open pit mines that can be exploited with artisanal tools such as a shovel and a sieve. Their explanation for the findings is that primary diamond mines are often exploited by large (multinational) companies that are able to bear the investment costs, making these mines less 'lootable' than secondary diamond mines.

A few other studies have looked at minerals and conflict while going beyond a single country. Arezki et al. (2015), whose analysis at a grid level corresponding to a spatial resolution of 0.5 x 0.5 degree, found that giant mineral and oil deposit discoveries in Africa do not have a statistically significant effect on the risk of conflict onset. Contrary to Arezki et al. (2015), we consider the whole world, consider minerals only, perform the analysis at the country level, and distinguish between mineral commodities with high and low value-to-weight. One reason for the null results of Arezki et al. (2015) may be that the binary (conflict onset, incidence) and count (number of conflict events) outcome variables have a too low signal-to-noise ratio to reveal interesting effects. Our analysis uses a continuous outcome (battle deaths), which although potentially being more prone to measurement error (and being conceptually different from conflict onset or incidence), should contain more information than a binary outcome. Another study, Lujala (2009), like ours, uses conflict intensity as an outcome variable, but studies a broader range of commodities, namely drugs, gemstones and oil. They found that gemstone mining and oil and gas production in a conflict zone increased the severity of conflicts around the world.

Analysis of data covering the globe from 1946 to 2008 confirm the heterogeneous effects of shocks to mineral resource values on conflict intensity as measured by battle deaths. We find that giant deposit discoveries of minerals categorized as high value-to-weight increase conflict intensity, whereas giant deposit discoveries for minerals with a lower value-to-weight ratio lower conflict intensity. For both categories of minerals, giant deposit discoveries raise conflict intensity to a greater extent in countries characterized by high ethnic inequality.

We draw several conclusions. First, empirical analyses lumping together all mineral commodities risks overlooking important heterogeneity in the resource-conflict nexus. Resource pressure (low physical abundance coupled with high economic scarcity) as reflected in world prices provides a useful means of categorizing mineral (and potentially other) commodities. To have the most effect with least economic disruption, conflict mineral regulations should focus on minerals that are most 'conflict-prone'. Second, the resource-conflict response depends on prevailing horizontal inequalities at the country level, in that giant mineral deposit discoveries increase conflict intensity to a greater extent where ethnic inequality is more pronounced. Addressing these inequalities will likely lower grievances and thereby the social cost of war associated with the production and trade of high value-to-weight ratio minerals (and possibly other commodities).

The paper is organized as follows: Section 2 expands upon the discussion on mechanisms above, derives testable hypotheses and their operationalization. Section 3 presents the data. Section 4 displays the empirical analysis related to the effects of giant mineral deposit discoveries on conflict intensity, and Section 5 concludes.

2. Testing theories on the resource-conflict nexus

To summarize the trade-offs related to the choice of the level of observation as well as our theoretical predictions related to (different types of) giant mineral deposit discoveries, we tabulate them in Table 1. Sometimes there are trade-offs between the extent to which one captures causal channels and statistical power: some of the country-level mechanisms (the 'state capacity' channel and the 'fuelling of grievances' channel) are not fully captured if a much smaller spatial scale is chosen, but there is a trade-off with statistical power: the smaller the spatial (i.e. cross-sectional) unit, the higher possibly the signal-to-noise ratio for some of the channels. The choice for a continuous outcome (battle deaths) then, although potentially being more prone to measurement error (noise), should contain more information (signal) than a binary outcome. Of course, conflict risk and conflict intensity are conceptually different variables. Note however, that the cumulative 'severity' of a conflict can be seen as the integral (area under the curve) of the battle death function over time (from the start until the end year of the conflict). Our estimations (that are part of the robustness checks) where we include zero's of the outcome variable should therefore also capture the effects of giant mineral deposit discoveries on incidence, to some extent. Table 1 also lists some of the theoretical predictions based on the discussion in the Introduction, that we will now expand upon.

We use giant mineral deposit discoveries as shocks to resource value in a country-year. Even though it is possible to identify the area where minerals are likely to be found using geological data, it is not possible to accurately predict the timing of giant and major discoveries. Therefore, the discovery dates of giant reserves can be considered exogenous. The column 'Discovery' in Table 1 considers the instantaneous effect on conflict risk arising from the news shock that it brings about and in some cases, the start of production (often, production starts with a lag).

The last column of Table 1 requires some explanation. Some minerals, especially base and bulk metals with a low value-to-weight ratio, can be expected to disproportionally fund governments as they are hard(-er) to loot and smuggle by rebel forces (the 'state military capacity' channel). Minerals with a high value-to-weight ratio are more likely to play a role in sustaining insurgencies (the 'feasibility' channel): this includes precious stones and metals such as diamonds, gold, silver, platinum, palladium. Just below them come a range of commodities that have also been suggested to play a role in conflict, such as niobium, tantalum, tin, tungsten. The supply chains of the latter four minerals are regulated by the Dodd-Frank Act in the United States (US), and together with gold, are often referred to as 3TG[3]. We lump these two groups of minerals together and refer to them in the regression results tables as 'high value-to-weight min-

[3]Tantalum has a much higher value-to-weight ratio than niobium but these minerals typically co-exist in the columbite-tantalite (coltan) ore.

Table 1: Potential mechanisms through which giant mineral deposit discoveries may affect conflict intensity.

	Most appropriate level of analysis	Hypothesis regarding	Primarily expected for
Mechanism	country (c) or subcountry (s)	effect of discovery on conflict intensity	High or low value-to-weight (vtw)
'Rapacity' mechanism	c,s	+	high vtw
'Feasibility' mechanism	s	+	high vtw
State military capacity channel	c	-	low vtw
Opportunity cost channel	c,s	-	low vtw
(Anticipated) distribution of rents - grievances[1]	c	+	.

Source: authors' postulates based on a review of the literature (see main text).

[1] As this channel refers to the effect of giant discoveries on fighting over royalties, there is no clear prediction as to whether the channel should be more relevant for high or for low value-to-weight minerals. We hypothesize that this channel is more important for countries that are characterized by high levels of (a conflict-relevant type of) ethnic inequality.

erals' (and to any other mineral commodity as 'low value-to-weight minerals'). See Table 7 in Appendix A for the world prices of the mineral commodities analyzed in this paper. For low unit-value ores on the other hand, there is a need to ship and market the product through a single agency (i.e. an outside mining company) to reach the economies of scale to make the project economically viable. Some of the minerals with a high value-to-weight ratio - notably beryllium, gallium, germanium, indium, lithium, tellurium - and are categorized under 'low value minerals' as they are not easily looted or appropriated. The reason is that those minerals co-exist with other minerals that have a low-value to weight ratio (such as aluminium, copper, zinc, phosphate and potash), and require skills, equipment and chemicals to be separated. This know-how can only come from outside mining companies, reducing the incentives for fighting over access to the mining site (the 'rapacity' channel) and making these minerals unlikely candidates to make insurgency feasible ('feasibility channel'). Extensive know-how and equipment is also needed for mining rare earth minerals, which are therefore also not included in the 'high value minerals' group. Another exception to the high/low value-to-weight classification is uranium, which has had a very high unit value in the last decade (see Table 7 in Appendix A). Uranium mining is subject to very strong oversight from the International Atomic Energy Agency (IAEA), which regulates the production and trade of the ore, strongly reducing the ease of and incentives for capture by rebels and rapacious government factions[4].

Another question pertains to the effect of giant mineral deposit discoveries conditional on the role ethnic inequalities play in a countries' politics. It can be expected that if ethnic inequalities are more pronounced in a society, then the 'grievances' channel above should play a larger role. To investigate this, using a proper measure of ethnic inequalities is crucial. The traditional measure based on the Herfindahl index, the ethnolinguistic fractionalization index (ELF), measure the probability that two randomly selected individuals from the entire population will be from different groups:

[4]Sometimes, as in Sierra Leone and DRC, soldiers participate in the plunder (Lujala, 2009).

$$ELF = 1 - \sum_{i=1}^{n} s_i^2 \quad (1)$$

where s is the share of group i out of a total of n groups in the country. The ELF therefore treats resource distribution between those in power and those excluded from power in a symmetric way. Given that (at least some) civil wars are fought over access to state power however, it is imperative for a measure of ethnic inequality relevant for conflict studies to account for which group is in power (ethnic group in power (EGIP), denotes s_0[5]) and which group(s) is/are not. To this end, Cederman and Girardin (2007) defined an indicator that captures ethnic power relations

$$N^*(n,k) = 1 - \prod_{i=1}^{n-1} \frac{\{r(i)/r\}^{-k}}{1 + \{r(i)/r\}^{-k}} \quad (2)$$

where $r(i) = s_i/(s_i + s_0)$ is group i's share of the total dyadic population and k a slope parameter. The variable N^* is built upon militaristic contest functions over power; the threshold parameter r in equation 2 stipulates at what demographic balance the odds are even for a challenge. This variable captures the fact that for a given level of ethnic inequality, conflict risk (and, we conjecture, intensity) is greater if the larger group is the one that is not in power. For notational ease, we refer to this variable as 'ethnic inequality' in this paper.

Based on the discussion above, we now postulate several hypothesis. For low value-to-weight minerals, the state capacity channel and the opportunity cost channel will dominate the other channels, so that for those minerals, the effect of mineral booms is to lower conflict intensity:

H_1: For low value-to-weight minerals, giant deposit discoveries lower the intensity of armed conflict.

[5]For operational purposes, Cederman and Girardin (2007) consider a group, or a coalition of groups, to be in power if their leaders serve (at least intermittently) in senior governmental positions, especially within the cabinet.

For high-value minerals however, the feasibility channel and the rapacity effect are likely to dominate: their higher value-to-weight ratio makes them easier to smuggle out of a country to finance insurgency (feasibility channel) and their 'prize' therefore is higher (the rapacity channel). Hence, for high value-to-weight minerals, mineral booms are expected to increase conflict intensity:

H_2: For high value-to-weight minerals, giant mineral deposit discoveries increase the intensity of armed conflict.

The (anticipated) unequal distribution of the (anticipation of) increased resource rents and revenues associated with a giant deposit discovery are likely to fuel grievances more in countries with high ethnic inequality (vis-a-vis countries with lower ethnic inequality), leading to increased recruitment by and popular support for armed rebellion:

H_3: The effect of the discovery of giant mineral deposit discoveries on conflict intensity is higher in countries characterized by high levels of ethnic inequality.

3. Data

The dependent variable and independent variables are drawn from different data sources. The unit of observation is always a country (using the country definitions of Gleditsch and Ward (2007)) in a given year.

3.1. Conflict data

For country-level information on conflict intensity, we draw on the PRIO Battle Deaths Dataset (Lacina and Gleditsch, 2005). The PRIO Battle Deaths dataset defines battle deaths as 'deaths resulting directly from violence inflicted through the use of armed force by a party to an armed conflict during contested combat'. An armed conflict is defined as 'a contested incompatibility between a government and one or more opposition groups that result in at least 25 battle deaths in a year'. The PRIO Battle Deaths Dataset is a dyadic dataset, and no information is provided on which side of

Table 2: Summary statistics.

Outcome in year:	Obs	Mean	St. dev.	First year of data	Last year of data
Indicator for giant mineral deposit discovery	12489	0.04	0.2	1946	2013
Indicator for high value-to-weight giant disc.	12489	0.02	0.1	1946	2013
Indicator for low value-to-weight giant disc.	12489	0.02	0.1	1946	2013
PRIO High-end battle deaths estimate	7749	18029	72067	1946	2008
PRIO Low-end battle deaths estimate	7749	4447	20448	1946	2008
UCDP 'best' battle deaths estimate	4850	1118	3128	1989	2015
Ethnic inequality index	6278	0.16	0.3	1946	2013
log(population size)	8752	0.76	0.37	1946	2013
Mean elevation in meters	8749	594	507	1946	2013
St. dev. of elevation in meters	8749	422	359	1946	2013

Source: authors calculations based on the datasets described in the main text.

the conflict the battle deaths occured, so we transformed it into a monadic dataset by copying (for international conflicts) battle deaths entries for each country in the dyad. For each conflict, the PRIO dataset contains a 'low', a 'best', and a 'high' estimate of the number of battle deaths. Since the 'best' estimate has missing values for 47% of the cases with a positive number of battle deaths, we perform all our estimates with both the low- and the high-end estimates of battle deaths (and not with the 'best' death estimates). As a robustness check, we also perform estimations using the 'best' death estimates from the monadic UCDP dataset, which are available from 1989 until 2015 (UCDP, 2015).

3.2. Mineral deposit discovery data

The discovery years of giant mineral deposits are sourced from MinEx Consulting, which reports the location of 547 such events over the period 1946 to 2008, with information on the primary metal contained in the deposit. The resource variable we construct is a dummy variable taking the value one if at least one giant mineral deposit discovery is made in a country-year (and 0 otherwise). See Appendix B for a description of size cutoffs used to categorize deposit discoveries as giant or non-giant. Table 2 reports summary statistics for our measure of giant mineral deposit discoveries and for other variables that we describe above. The high-end battle death estimates are on average four time as high as the low-end battle death estimates. High and low value-

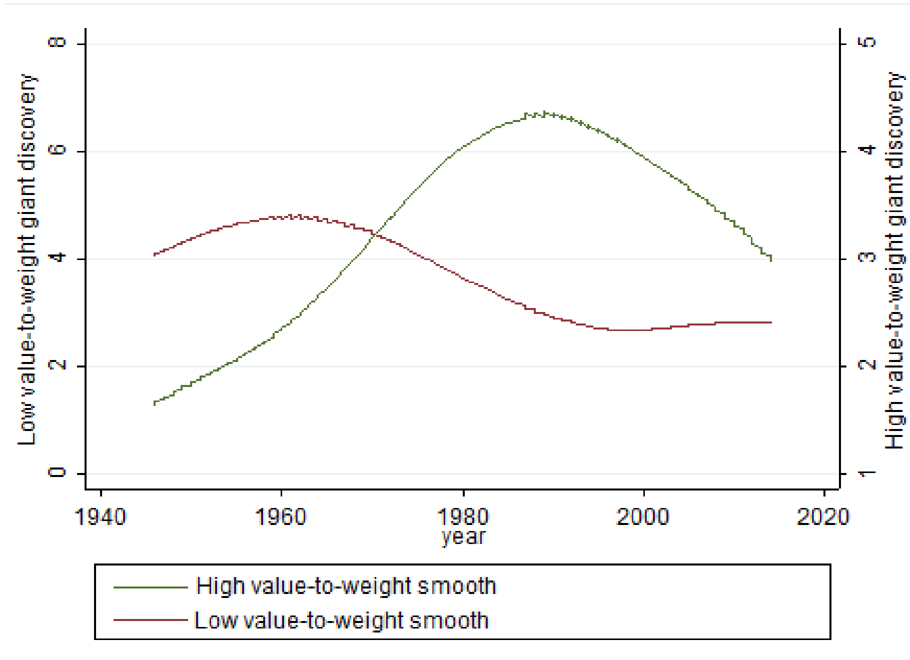

Figure 1: Running mean smooth of giant mineral deposit discoveries by value-to-weight category, 1946-2013.

Source: authors' estimations based on the MinEx data.

to-weight mineral deposit discoveries are about equally frequent. Low value-to-weight discoveries were more frequent up to around 1970, after which high value-to-weight discoveries became more frequent, see Figure 1. The year 1981 had the most high value-to-weight discoveries (8 discoveries); whereas the years 1955, 1965 and 1974 had the most giant deposit discoveries of low value-to-weight minerals. The reason for this change was the abandonment of the gold standard by the US in 1971, which caused the nominal gold price to increase from USD 36/oz (troy ounce) in 1970 to over USD 600/oz by 1980 (in real terms the increase was even larger) (USGS, 2013). This stimulated a huge increase in the exploration and development of gold projects. Gold is the mineral with the most disccovery dates for giant deposits in the discovery data (200 out of the 537 discovery dates or 35% of the giant discoveries).

3.3. Other data

The mineral commodity price data come from the United States Geological Survey (USGS), which are publicly available[6]. The data on horizontal ethnic inequality come from The Ethnic Power Relations Data Set Family (Vogt et al., 2015). In particular, we use the index of ethnic configuration developed by Cederman and Girardin (2007), to which they refer as n^* (we will refer to it simply as 'ethnic inequality'). This measure was found by Cederman and Girardin (2007) to have more predictive power for conflict risk than traditional measures of ethno-linguistic fractionalization. Our measures of log(population size), mean elevation and standard deviation of elevation[7] also come from the same Data Set Family.[8] A final control variable proxies for a potentially important confounder in the resource-conflict relationship: the political environment. For this we rely on a standard measure in the literature, the Polity 2 measure of democratization.

4. Results

This section begins by discussing our baseline empirical specification and estimates of the effect of giant mineral deposit discoveries on conflict intensity (Subsection 4.1). We then discuss the robustness of our estimates using a number of alternative specifications (Subsection 4.2). We conclude this section by estimating the giant mineral

[6]Available from http://pubs.usgs.gov/sir/2012/5188/

[7]The variables 'mean elevation' and 'standard deviation of elevation' are all but filtered out by the fixed effects. The exceptions are countries for which the size changes over the course of the data (such as Indonesia, North and South Korea, Russia, (North and South) Sudan and (Former) Yugoslavia).

[8]The inclusion of GDP as control variable, either from the World Bank World Development Indicators or the Penn World Tables (Feenstra et al., 2013), does not change model estimates significantly (available upon request). GDP is never (even nearly) statistically significant in any of the models and hardly changes results (except that it increases the noise in the estimates we are interested in). On the other hand, using nighttime luminosity data as proxy of economic performance would limit the time span and therewith the sample size too much for our purposes. Besides, controlling for GDP would potentially lead to post-treatment bias, as the opportunity cost effect predicts that income generated from mining lowers violence (for some commodities) by reducing the incentives to fight. We therefore exclude GDP from the set of control variables.

deposit discoveries-conflict response conditional on a country-year being characterized by a high or low level of ethnic inequality (Subsection 4.3).

4.1. Baseline specification

To examine the effect of major discoveries on the intensity of armed conflict taking place in country i in year t, we estimate the following specification:[9]

$$deaths_{i,t} = \alpha_i + \beta \times disc_{it} + X_{it}\gamma + \theta_2 \times t + \epsilon_{i,t} \tag{3}$$

where $deaths_{it}$ is an estimate of the number of battle deaths in country i in year t, $disc_{it}$ is the binary indicator for a giant mineral deposit discovery occuring, X_{it} is a vector of time-varying covariates, $country_i$ are country fixed effects and t is a time trend. Interest lies in β, the marginal effect of giant deposit discoveries on conflict intensity. Given the strong overdispersion in the outcome variable battle deaths, the model is estimated using Poisson quasi-Maximum likelihood (Quasi-ML) estimation with robust standard errors. Quasi-ML estimation allows for possible misspecification of the likelihood function (Wooldridge, 1997), which is important given the heavy-tailed distribution of the outcome variable battle deaths (Cirillo and Taleb, 2015).

Table 3 reports results Poisson Quasi-ML estimates predicting battle deaths over the span of the data. Giant mineral deposit discoveries reduce the intensity of war. Splitting the mineral deposit according to type (high value, non-high value), the effect remains for the non-high value minerals only. The statistical insignificance of the coefficient on high-value discoveries is due to the early years after the Second World War. Starting the period of analysis in later years than 1946, the coefficient on giant deposit discoveries gradually increases in size and statistical significance[10], the reason for which may be the higher dominance of deposit discoveries of minerals with a

[9]Inclusion of year fixed effects leads to non-convergence of the estimation routine, so year fixed effects are not included. The same holds for country-specific time trends. Estimations including quadratic and/or cubic time trends return mostly similar results, as do estimations with decadal or quinquennial dummies (although for estimations with quinquennial dummies, the coefficient on high and low unit-value deposit discoveries shrink a bit). These estimations are available from the authors upon request.

[10]Convergence of the estimation routine fails when letting the starting year of the data be later than 1973.

high value-to-weight ratio (see Figure 1). Table 4 reports estimates where the starting year of analysis is 1970; the effect estimates of high value-to-weight mineral deposit discoveries is now also highly statistically significant. A possible explanation for the increasing coefficient size and statitistical significance on high-value mineral deposit discoveries when restricting the start of the timespan of the data to later years was given in Subsection 3.3. Another reason could be that the battle death data in the early post-war years contain more noise, and in general the quality of battle death estimates is likely to have increased over time.

In the estimations of Table 3 and 4, zero's in the outcome battle deaths are not included, because otherwise it would not strictly be solely about conflict intensity anymore, but also about the onset and duration of conflict. Moreover, since armed conflict is defined as a conflict with at least 25 battle deaths in a year, there would be substantial measurement error around zero (both peace and conflicts with less than 25 casualities a year would be coded as 0). In Table 8 and 9 in Appendix C however, we perform estimations whereby the outcome variable includes zero's. The results are qualitatively the same as in Table 3 and Table 4.

Table 3: Poisson Quasi-ML estimates predicting battle deaths, 1946-2008.

	(1)	(2)	(3)	(4)	(5)	(6)
	Deaths high	Deaths low	Deaths high	Deaths low	Deaths high	Deaths low
Giant discovery	-0.8556***	-1.0507***				
	(0.33)	(0.39)				
High value-to-weight			-0.3815	-0.5121		
giant disc.			(0.51)	(0.52)		
Low value-to-weight					-1.1236***	-1.4457***
giant disc.					(0.24)	(0.39)
Ethnic inequality	1.2703***	1.4208***	1.2814***	1.4356***	1.2459***	1.4132***
	(0.29)	(0.43)	(0.29)	(0.43)	(0.31)	(0.43)
log(pop. size)	-1.7575	-1.0636	-1.9197	-1.1555	-1.6716	-1.0264
	(1.61)	(2.30)	(1.60)	(2.25)	(1.62)	(2.30)
Mean elev.	0.0202	0.0138	0.0209	0.0144	0.0202	0.0138
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
sd(elev)	-0.0166	-0.0068	-0.0184*	-0.0083	-0.0165	-0.0069
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Polity IV score	-0.0292	-0.0295	-0.0285	-0.0276	-0.0295	-0.0294
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Year trend	-0.0021	0.0047	-0.0013	0.0056	-0.0026	0.0045
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	1179	1179	1179	1179	1179	1179
Wald	35.47	44.45	32.42	36.11	82.93	52.55
BIC	18733225.18	5099144.06	19058608.82	5176867.84	18732900.08	5101604.91

Source: authors' computations.

(1) Robust standard errors in parentheses.

(2) * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 4: Poisson Quasi-ML estimates predicting battle deaths, 1970-2008.

	(1)	(2)	(3)	(4)	(5)	(6)
	Deaths high	Deaths low	Deaths high	Deaths low	Deaths high	Deaths low
Giant discovery	-0.0896	-0.3622				
	(0.27)	(0.38)				
High value-to-weight			0.5747***	0.4161**		
giant disc.			(0.21)	(0.19)		
Low value-to-weight					-0.8260**	-1.1831***
giant disc.					(0.39)	(0.46)
Ethnic inequality	0.5142	0.4702	0.4847	0.4633	0.4618	0.4593
	(0.40)	(0.47)	(0.71)	(0.36)	(0.41)	(0.44)
log(pop. size)	1.3108	2.2659	1.4202	2.2517	1.5153	2.3586
	(1.38)	(1.80)	(8.31)	(1.78)	(1.48)	(1.84)
Mean elev.	0.0409	0.0094	0.0412	0.0097	0.0410	0.0095
	(0.06)	(0.03)	(0.06)	(0.03)	(0.06)	(0.03)
sd(elev)	-0.0443	0.0218	-0.0449	0.0209	-0.0438	0.0217
	(0.12)	(0.06)	(0.12)	(0.06)	(0.12)	(0.06)
Polity IV score	-0.0154	-0.0230	-0.0153	-0.0223	-0.0138	-0.0224
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
Year trend	-0.0403**	-0.0506**	-0.0408**	-0.0511***	-0.0402**	-0.0506***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
N	925	925	925	925	925	925
Wald	104.06	158.98	94.26	332.29	91.06	147.06
BIC	9913309.35	3187815.84	9871573.39	3189456.52	9846918.93	3168307.60

Source: authors' computations.

(1) Robust standard errors in parentheses.

(2) * p<0.1, ** p<0.05, *** p<0.01

4.2. Robustness of the main results

A caveat relating to the estimates in Subsection 4.1 is that one discovery may lead to another, so that the giant discovery variable is serially correlated. Therefore, as a robustness check, we include past discoveries as a control variable. Specifically, we control for a variable equaling the number of years with a giant discovery in country i between year $t-10$ and $t-1$. The results, reported in Table 10 and 11 in Appendix D, mostly confirm those of the baseline specification reported in Table 3 and Table 4.

There may be another concern, that not only the timing of giant mineral discoveries is serially correlated, but also the outcome, conflict intensity. Parties that are attacked may attempt to take revenge or re-organize and attempt to retake territory. To account for this state dependence, we estimate dynamic versions of the Poisson Quasi-ML estimations performed in Section 4.1, using the estimator of (Hsiao et al., 2002)[11], which was shown by (Hayakawa and Pesaran, 2015) to still be consistent in the presence of cross-sectional heteroskedasticity. These estimates do not converge with the PRIO battle death data, so we use the UCDP best deaths estimate[12]. The results are reported in Table 12 and 13 in Appendix E. The sign of the coefficients on high and low value-to-weight minerals are in line with those found above, but (as often happens when switching from static to dynamic models), statistical significance of the main explanatory variable is lost.

Another potential concern is that of reverse causation, in that conflicts deter mineral exploration activity and thereby lower the probability of a giant mineral deposit discovery in a country-year. This would bias the coefficient on mineral deposit discovery variable downwards. In order to obtain estimates free of reverse causation bias, we construct a database of the number of mineral exploration sites in country-years from the year 1995 until 2004 from the USGS mineral exploration reviews (Wilburn, 2005). The results with this variable included as control are reported in Table 14 in Appendix F. The findings confirm the results from the baseline specification for high unit-value minerals, whereas the coefficient estimates on giant deposit discoveries turn statistically insignificant. The coefficient on any giant mineral deposit discovery, in the baseline results seems indeed to be downward biased, as the coefficient now turns positive (and statistically significant for the 'high end' deaths estimate).

4.3. Effect size heterogeneity: the role of ethnic configuration

To test hypothesis 3, we estimate the conflict intensity model for subsamples defined by having high (higher or equal than the sample 90th percentile) and lower (ethnic inequality (lower than the 90th percentile) ethnic inequality. Table 5 reports results from the PRIO high end battle death estimates, whereas Table 6 reports results based on PRIO's lower bound death estimates. Control variables are omitted due to space

[11] Using the STATA add-on of (Kripfganz, 2015).

[12] The estimation routine for the static (i.e. non-dynamic) estimations do not converge for the UCDP data.

constraints and because their coefficient estimates do not reach statistical significance in most of the models. The results generally are in line with hypothesis 3 that was postulated in Section 2. First, note that for countries with high ethnic inequality, the effect of any giant mineral deposit discovery on conflict intensity is positive (columns (1) and (2) in Table 5 and 6). Second, for most estimations, the coefficient on discovery is higher in the subsample with high ethnic inequality and lower in countries with lower ethnic inequality (compare column (1) to column (2), column (3) to (4), and (5) to (6) in Table 5 and 6 - the only exception is column (5) and (6) in Table 6).

Table 5: Poisson Quasi-ML estimates predicting battle deaths (high end battle death estimates), 1949-2008: sumbsamples for which the ethnic inequality measure is above or below its sample 90^{th} percentile.

	(1) High ethnic inequality	(2) Low ethnic inequality	(3) High ethnic inequality	(4) Low ethnic inequality	(5) High ethnic High ethnic	(6) Low ethnic inequality
Giant discovery	0.8969***	-1.2699***				
	(0.23)	(0.38)				
High-value giant disc.			0.9044***	-0.9695		
			(0.22)	(0.71)		
Non-high value giant disc.					-0.2459***	-1.3608***
					(0.06)	(0.27)
Ethnic inequality	-9.6799***	3.1332	-9.6923***	3.1228	-8.7135**	3.1342
	(2.48)	(1.91)	(2.48)	(1.97)	(2.98)	(1.91)
N	173	1090	173	1090	173	1090
Wald	73.06	120.41	74.21	57.13	1.47e+11	173.24
BIC	3962419.25	20118080.28	3961808.75	20755416.16	3991361.83	20348681.72

Source: authors' computations.

(1) Robust standard errors in parentheses.

(2) * $p<0.1$, ** $p<0.05$, *** $p<0.001$

Table 6: Poisson Quasi-ML estimates predicting battle deaths (low end battle death estimates), 1949-2008: sumbsamples for which the ethnic inequality measure is above or below its sample 90^{th} percentile.

	(1) High ethnic inequality	(2) Low ethnic inequality	(3) High ethnic inequality	(4) Low ethnic inequality	(5) High ethnic High ethnic	(6) Low ethnic inequality
Giant discovery	0.2916	-1.3997**				
	(0.44)	(0.44)				
High-value giant disc.			0.3652	-1.0432		
			(0.44)	(0.65)		
Non-high value giant disc.					-1.6899***	-1.5873***
					(0.03)	(0.37)
Ethnic inequality	-11.4168***	3.1378	-11.4268***	3.1998	-11.3826***	3.1484
	(0.78)	(2.22)	(0.78)	(2.28)	(0.81)	(2.23)
N	173	1090	173	1090	173	1090
Wald	2519.06	27.88	2304.37	18.73	9.78e+11	35.78
BIC	1020609.20	5392096.55	1020387.14	5521868.36	1020581.11	5442709.06

Source: authors' computations.

(1) Robust standard errors in parentheses.

(2) * $p<0.1$, ** $p<0.05$, *** $p<0.001$

5. Discussion

This paper adds one piece to the puzzle of how resources affect conflict. By drawing on data on the discovery of giant mineral deposit discoveries, we identify the effect of shocks to mineral resource value to the intensity of conflicts around the world. Empirical analyses lumping together all mineral commodities risks overlooking important heterogeneity in the resource-conflict nexus. Resource pressure (low physical abundance coupled with high economic scarcity), as reflected in world prices provide a useful means of categorizing mineral (and potentially other) commodities. Whereas we find that for minerals with a low value-to-weight ratio, giant deposit discoveries lower conflict intensity, giant deposit discoveries for minerals with a high value-to-weight ratio raise conflict intensity. This evidence is consistent with the 'state military capacity' and 'opportunity cost' channels dominating for low unit value minerals, and the 'feasibility of war' and the 'rapacity' channels dominating for high-value minerals channels.

A second finding is that the resource-conflict response depends on prevailing horizontal inequalities at the country level and is much more adverse in countries with higher levels of ethnic inequality. It may thus be more appropriate to speak of an 'inequality-resource curse'. Independent of the mineral variables, the n^* measure of ethnic inequality is a statistically significant predictor of conflict intensity in most of the estimations performed. Addressing these horizontal inequalities will likely lower grievances and thereby the social cost of war associated with the production and trade of minerals (and possibly other commodities).

Our findings provide inputs for policy makers seeking to reduce the toll of war. To have the most effect with least economic disruption, conflict mineral regulations should focus on minerals that are most 'conflict-prone'. The findings in this paper are a step forward in categorizing (mineral) commodities into those that are more and those that are less 'conflict-prone'. This is imperative, given the growing mineral-intensity of the global economy and the lack of substitutability of many of the world's minerals (Graedel et al., 2015; Krausmann et al., 2009).

Future research may aim to exploit price variations to obtain sharper resource measures and to gauge to what extent downward pressure on prices (e.g. through increased recycling) may help reduce the societal costs related to the production of some mineral commodities. Ideally, gemstones would also be included in analyses of the link between minerals and conflicts, but challenges will need to be overcome regarding heterogeneity in quality of the stones and a paucity of data. It should also be noted that our analysis does not capture possible cross-country spillover effects, whereby countries (or their military allies) increase military spending to prevent attacks in resource-rich regions, and such weaponry is replaced by more modern substitutes (after years or possibly decades). The old weaponry may then be exported and may ultimately end up in regions that are less stable, increasing violence there. That would be another interesting avenue for further research.

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Appendix A

Table 7: World prices of mineral commodities, sorted by the average of the prices in 1980, 1990, 2000 and 2010. Nominal prices are used, as the aim is to make cross-sectional comparisons.

Mineral commodity	World price in USD/kg (1980)	World price in USD/kg (1990)	World price in USD/kg (2000)	World price in USD/kg (2010)
diamond	443002.67	350121.97	282917.50	440713.83
platinum	21766.0239	15014.3769	17650.7343	51955.5312
gold	19694.25	12375.78	9005.42	39465.33
palladium	6462.29	3665.18	22248.28	17072.02
germanium	653.00	1060.00	1250.00	1200.00
gallium	630.00	475.00	595.00	600.00
silver	663.27	154.97	160.75	649.44
uranium	70.09	21.47	18.28	101.32
zirconium	26.46	23.15	23.15	99.76
rare earths[1]	115.00	175.00	100.00	51.50
beryllium	54.43	122.02	37.65	48.53
tellurium	8.97	14.06	1.03	45.52
molybdenum	20.69	6.29	5.63	34.83
tin	18.65	8.52	8.16	27.34
tantalum	47.85	14.97	99.79	24.49
lithium	7.78	13.61	17.71	15.13
mercury	11.22	7.18	4.47	25.94
tungsten[2]	14.33	6.72	6.61	21.38
nickel	6.53	8.86	8.64	21.80
chromium	7.68	6.58	5.98	10.00
cobalt	9.90	4.58	6.88	9.46
niobium	2.95	1.47	2.83	7.77
copper	2.23	2.72	1.94	7.68
vanadium	1.39	1.39	0.83	3.14
titanium	3.18	2.15	1.60	2.21
antimony	0.68	0.37	0.30	1.82
magnesium	0.57	0.65	0.58	1.10
graphite	0.29	0.70	0.54	0.80
indium	0.53	0.22	0.18	0.55
lead	0.19	0.21	0.20	0.49
aluminium	0.35	0.34	0.34	0.47
zinc	0.17	0.34	0.25	0.46
fluorspar	0.15	0.19	0.13	0.16
ironore	0.00	0.03	0.03	0.10
manganese	0.002	0.004	0.002	0.009

Source: authors' calculations based on USGS (2013).

[1] Cerium prices are reported.

[2] Prices of tungsten trioxide (WO_3) are reported.

Appendix B

The size classification ‘giant’ is based on the deposits’ pre-mined resource. This is the current published Measured, Indicated & Inferred Resource (as defined by the Australasian Joint Ore Reserves Committee (JORC)) plus cumulative historic production (adjusted for mining and processing losses).

A deposit discovery is categorized as ’giant’ if it exceeds mineral commodity-specific size cutoffs: $>$6 Moz Au (gold), $>$1 Mt Ni (nickel), $>$5 Mt Cu equiv, $>$12 Mt Zn+Pb (zinc or led), $>$300 Moz Ag (silver), $>$125 kt U_3O_8 (uranium oxide), $>$1000 Mt Fe, $>$1000 Mt Thermal Coal, $>$500 Mt Coking Coal, or its equivalent in-situ value for other metals (based on long run commodity prices).

Appendix C

Table 8: Poisson Quasi-ML estimates predicting battle deaths (zero's included), 1946-2008.

	(1) Deaths high	(2) Deaths low	(3) Deaths high	(4) Deaths low	(5) Deaths high	(6) Deaths low
Giant discovery	-0.6488*	-0.8498**				
	(0.36)	(0.41)				
High value-to-weight			-0.2793	-0.4137		
giant disc.			(0.58)	(0.57)		
Low value-to-weight					-0.8621***	-1.1730***
giant disc.					(0.25)	(0.34)
Ethnic inequality	1.4028***	1.6933***	1.4281***	1.7148***	1.3991***	1.6889***
	(0.53)	(0.43)	(0.53)	(0.43)	(0.53)	(0.43)
log(pop. size)	1.8032	1.9878	1.7503	1.9497	1.8530	2.0123
	(3.21)	(3.44)	(3.22)	(3.43)	(3.19)	(3.43)
Mean elev.	0.0168	0.0127	0.0175	0.0133	0.0168	0.0127
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
sd(elev)	-0.0110	-0.0043	-0.0125	-0.0057	-0.0109	-0.0042
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Polity IV score	-0.0048	-0.0041	-0.0048	-0.0037	-0.0047	-0.0041
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Year trend	0.0056	0.0130	0.0059	0.0134	0.0055	0.0130
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	4588	4588	4588	4588	4588	4588
Wald	16.39	25.78	13.75	21.95	45.22	34.67
BIC	41217653.95	10073735.30	41397222.69	10122015.88	41213731.09	10075018.42

Source: authors' computations.

(1) Robust standard errors in parentheses.

(2) * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 9: Poisson Quasi-Maximum Likelihood regression estimates predicting battle deaths, 1970-2008.

	(1) Deaths high	(2) Deaths low	(3) Deaths high	(4) Deaths low	(5) Deaths high	(6) Deaths low
Giant discovery	0.1484	-0.1800				
	(0.33)	(0.35)				
High value-to-weight			0.8331**	0.5960*		
giant disc.			(0.36)	(0.35)		
Low value-to-weight					-0.6206**	-0.9738***
giant disc.					(0.30)	(0.36)
Ethnic inequality	0.4813	0.5199	0.4858	0.5167	0.4588	0.5179
	(0.43)	(0.44)	(0.43)	(0.45)	(0.44)	(0.45)
log(pop. size)	4.1920**	4.4914*	4.2916**	4.5658**	4.1900**	4.4867**
	(2.12)	(2.31)	(2.08)	(2.31)	(2.06)	(2.28)
Mean elev.	0.0473	0.0174	0.0475	0.0175	0.0475	0.0176
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
sd(elev)	-0.0507	0.0059	-0.0511	0.0058	-0.0513	0.0054
	(0.10)	(0.07)	(0.10)	(0.07)	(0.10)	(0.07)
Polity IV score	0.0042	0.0131	0.0054	0.0139	0.0056	0.0139
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Year trend	-0.0384***	-0.0483***	-0.0386***	-0.0485***	-0.0386***	-0.0484***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	2969	2969	2969	2969	2969	2969
Wald	66.48	128.28	76.11	126.44	57.69	134.69
BIC	18405812.42	5257077.26	18322177.28	5250402.21	18373544.48	5241548.62

Source: authors' computations.

(1) Robust standard errors in parentheses.

(2) * p<0.1, ** p<0.05, *** p<0.01

Appendix D

Table 10: Poisson Quasi-ML estimates predicting battle deaths, 1946-2008.

	(1)	(2)	(3)	(4)	(5)	(6)
	Deaths high	Deaths low	Deaths high	Deaths low	Deaths high	Deaths low
Giant discovery	-0.6494	-0.9961**				
	(0.40)	(0.44)				
# of giant discoveries	-0.4758***	-0.6394***				
in year [t-10,t-1]	(0.14)	(0.23)				
High value-to-weight			-0.5114	-0.7095		
giant disc.			(0.60)	(0.60)		
# high value-to-weight giant			-0.3093	-0.4820*		
disc.'s in year [t-10,t-1]			(0.33)	(0.28)		
Low value-to-weight					-0.7409	-1.3302**
giant disc.					(0.51)	(0.55)
# high value-to-weight giant					-0.6767***	-0.9789***
disc.'s in year [t-10,t-1]					(0.21)	(0.36)
Ethnic inequality	1.2262***	1.3619***	1.2664***	1.4243***	1.2094***	1.3443***
	(0.29)	(0.43)	(0.30)	(0.43)	(0.30)	(0.43)
Year trend	-0.0024	0.0029	-0.0008	0.0059	-0.0035	0.0017
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	1179	1179	1179	1179	1179	1179
Wald	34.93	41.47	33.59	41.87	57.01	46.50
BIC	17760978.24	4797073.20	18961468.34	5127895.43	17596996.09	4750560.12

Source: authors' computations.

(1) Robust standard errors in parentheses.

(2) * $p<0.1$, ** $p<0.05$, *** $p<0.01$

(3) Same set of controls as in Table 3.

Table 11: Poisson Quasi-ML estimates predicting battle deaths, 1970-2008.

	(1) Deaths high	(2) Deaths low	(3) Deaths high	(4) Deaths low	(5) Deaths high	(6) Deaths low
Giant discovery	-0.1663	-0.5899				
	(0.34)	(0.43)				
# of giant discoveries	-0.4435	-0.8539**				
in year [t-10,t-1]	(0.28)	(0.38)				
High value-to-weight			0.6363***	0.4073*		
giant disc.			(0.19)	(0.21)		
# high value-to-weight giant			0.1267	-0.0236		
disc.'s in year [t-10,t-1]			(0.15)	(0.20)		
Low value-to-weight					-0.8186**	-1.3268**
giant disc.					(0.40)	(0.53)
# Low value-to-weight giant					-0.6745*	-1.1038**
disc.'s in year [t-10,t-1]					(0.38)	(0.43)
Ethnic inequality	0.3598	0.4629	0.5128	0.4630	0.3982	0.4530*
	(0.44)	(0.29)	(0.39)	(0.35)	(0.40)	(0.25)
Year trend	-0.0405**	-0.0517***	-0.0411**	-0.0510***	-0.0418***	-0.0534***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
N	925	925	925	925	925	925
Wald	42.88	589.48	196.78	313.18	42.14	4.14e+11
BIC	9655444.97	3019842.34	9861688.55	3189392.73	9445471.02	2962355.39

Source: authors' computations.

(1) Robust standard errors in parentheses.

(2) * $p<0.1$, ** $p<0.05$, *** $p<0.01$

(3) Same set of controls as in Table 3.

Appendix E

Table 12: Dynamic Poisson Quasi-ML estimates predicting UCDP battle deaths for high value-to-weight minerals, 1989-2008.

	(1)	(2)
	Deaths high	Deaths low
Deaths(t-1)	0.5697***	0.5710***
	(0.07)	(0.07)
High value-to-weight	110.6849	61.2100
giant disc.	(75.12)	(64.74)
# of giant discoveries		-5.6103
in year [t-10,t-1]		(16.23)
Ethnic inequality	-25.5744	-39.1988
	(124.80)	(124.35)
log(pop. size)	-212.0157	-224.6133
	(362.86)	(370.72)
Mean elev.	31.2339	28.3249
	(99.59)	(102.17)
sd(elev)	18.3286	7.3421
	(73.99)	(75.79)
Polity IV score	-4.7146	-4.9232
	(5.02)	(5.15)
Year trend	-7.1203*	-7.0013
	(4.32)	(4.29)
N	2344	2344
BIC	40561.02	40567.35

Source: authors' computations.

(1) Robust standard errors in parentheses.

(2) * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 13: Dynamic Poisson Quasi-ML regression estimates predicting battle deaths for low value-to-weight minerals, 1989-2008.

	(1)	(2)
	Deaths high	Deaths low
Deaths(t-1)	0.5697***	0.5704***
	(0.07)	(0.07)
Low value-to-weight	-65.9092	-82.3753
giant disc.	(66.63)	(77.92)
# of giant discoveries		-15.2459
in year [t-10,t-1]		(27.44)
Ethnic inequality	-35.1694	-40.3721
	(129.24)	(127.98)
log(pop. size)	-213.7064	-75.9967
	(399.26)	(468.44)
Mean elev.	36.6989	18.6173
	(103.15)	(116.22)
sd(elev)	23.2923	9.5022
	(76.14)	(86.47)
Polity IV score	-4.7746	-4.5831
	(5.19)	(5.42)
Year trend	-7.3402*	-7.3503*
	(4.37)	(4.38)
N	2344	2344
BIC	40560.88	40568.17

Source: authors' computations.

(1) Robust standard errors in parentheses.

(2) * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Appendix F

Table 14: Poisson Quasi-ML estimates predicting battle deaths (number of mineral exploration sites included as regressor), 1970-2008.

	(1) Deaths high	(2) Deaths low	(3) Deaths high	(4) Deaths low	(5) Deaths high	(6) Deaths low
Giant discovery	0.4596***	0.3219				
	(0.13)	(0.28)				
High value-to-weight giant disc.			0.4686***	0.3581		
			(0.13)	(0.31)		
Low value-to-weight giant disc.					-0.0174	-0.1548
					(0.20)	(0.65)
# of exploration sites	-0.0433***	-0.0602**	-0.0394***	-0.0568*	-0.0316**	-0.0542
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.04)
Ethnic inequality	-0.5751	-1.7736***	-0.6485	-1.8128***	-0.3705	-1.7377***
	(0.79)	(0.48)	(0.80)	(0.50)	(0.84)	(0.54)
Year trend	-0.0902***	-0.0795*	-0.0905***	-0.0792*	-0.1088***	-0.0893**
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)
N	189	189	189	189	189	189
Wald	36.60	50.24	37.90	54.22	40.62	43.17
BIC	499655.97	291401.55	499268.26	291244.43	512983.17	292350.02

Source: authors' computations.

(1) * $p<0.1$, ** $p<0.05$, *** $p<0.01$

(2) Given that these estimations use only 10 years of data, the model complexity has to be reduced to make estimation feasible. Therefore, the controls population size, mean and standard deviation of elevation are excluded. This should not generate much bias as the exploration sites variable theoretically is a much more important confounder (and this is confirmed by the statistical significance of its coefficient in this table).