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This Mine is Mine! How Minerals Fuel Conflicts in Africa

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Abstract

We combine original geo-referenced data on mining extraction of 15 minerals with information on conflict events at spatial resolution of 0.5^o x 0.5^o for all Africa over 1997-2010. Exploiting exogenous variations in world prices, we find a positive impact of mining on conict at the local level. Quantitatively, the historical rise in prices (commodity super-cycle) explains 15-25 percent of average country-level violence in Africa. We then document how the appropriation of a mining area by a fighting group contributes to the escalation from local to global violence. Finally, we analyze the impact of corporate practices and transparency initiatives in the mining industry.

JEL-Code: C230, D740, Q340.

Keywords: minerals, mines, conflict, fighting, natural resources, rebellion.

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1 Introduction

Natural riches such as valuable minerals have often been accused of fueling armed fighting. A typical case that recently made the headlines is the heavy fighting that broke out between the Rizeigat and Bani Hussein, two Arab tribes, for the territorial control of the Jebel Amer gold mine in Darfur region, killing more than 800 people and displaced some 150,000 others since January 2013.[1] Armed groups extract revenues from mines without necessarily directly managing them, and extorsion or bribing practices have been widely documented in mineral-abundant conflict areas. An example is the financial and logistical support provided by the mining company AngloGold Ashanti in 2003-2004 to the "Nationalist and Integrationist Front" (FNI), a rebel group operating in the gold-rich district of Ituri in Eastern DRC.[2]

The present paper investigates the impact of mining on conflict by using geolocalized data on conflict events and mining extraction of 15 minerals for all African countries over the 1997-2010 period. Our results show that mining activity increases conflicts at the local level and then spreads violence across territory and time by enhancing the financial capacities of fighting groups. Our empirical analysis is based on the combination of an original dataset, *Raw Material Data* (RMD), documenting the location and the types of mines and minerals, and *Armed Conflict Location Events Data* (ACLED) that provides information on the location and type of conflict events and the involved actors. The units of analysis are cells of 0.5×0.5 degree latitude and longitude (approx. 55km $\times$ 55km at the equator) covering all Africa. The use of geo-referenced information enables causal identification: Including country$\times$year fixed-effects and cell fixed-effects, we exploit in most of our econometric specifications the within-mining area panel variations in violence due to changes in the world price of the main mineral extracted in the area.

In the first part of our analysis, we estimate the extent of mining-induced violence at the local level. We find a positive effect of mining activity on conflict probability: (i) in the cross-section, this probability is higher in cells with active mines; in the panel (within cells), it increases with mine opening/closing; (ii) a spike of mineral prices increases conflict risk in cells producing these commodities. These results are robust to a variety of consistency checks. We also find that countries with better government effectiveness and with less social cleavages are less affected by mining-induced violence; however, we detect no moderating effect of political institutions (e.g. democracy, rule of law, and voice and accountability). We then perform several quantification exercises to gauge the magnitude of the effect: A one-standard deviation increase in the price of minerals translates into an increase in probability of violence *in mining areas* from the benchmark 16.7% to a counterfactual 20.1%. When aggregated at the country level, the effect remains

[1]Fighters from the "Sudan Liberation Army" (SLA) have operated their own illicit gold mine in Hashaba to the east of Jebel Amer to finance their fighting. Other prominent examples of rebels sustaining their fighting efforts with the cash from running mines include for example rebels groups operating in Sierra Leone and Liberia such as the "Revolutionary United Front" (RUF) that financed weaponry with "blood diamonds" (Campbell, 2002), or the case of Angola's rebels from "União Nacional para a Independência Total de Angola" (UNITA) that financed their armed struggle with diamond money (Dietrich, 2000). See Reuters, 8 October 2013, "Special Report: The Darfur conflict's deadly gold rush". Another typical example is the Marikana Mine Massacre, where in a wildcat strike at a platinum mine owned by Lonmin in the Marikana area, close to Rustenburg, South Africa in 2012 several dozens of people were shot. Cf. BBC, 5 October 2012, "South African mine owner Amplats fires 12,000 workers".

[2]Human Right Watch brief, 5 June 2005, " D.R. Congo: Gold Fuels Massive Human Rights Atrocities". For the complete report, see Human Right Watch (2005). AngloGold Ashanti have been accused of having established a relationship with the FNI "who had effective control over the Mongbwalu gold mining area", "to facilitate their gold exploration activities". This relationship involved payments of bribes as well as logistical support, in particular through the transportation of FNI leaders.

sizeable. We quantify the effect of the historical rise in mineral prices between 1997 and 2010, which according to most scholars was mainly due to the sharp increase in the demand for minerals by emerging market countries such as China and India (Humphreys, 2010; Carter, Rausser and Smith, 2011). Our estimates suggest that the contribution of this so-called *commodities super cycle* to the average violence observed across African countries over the period lies between 15 and 25%.

In the second part of the paper we take a more global view and investigate the diffusion over space and time of mining-induced violence, a question of central importance for understanding how local conflicts escalate into regional or national wars. Looking at the nature of violent events, we find that mineral price spikes fuel both low-level violence (riots, protests) and organized violence (battles). The rationales behind each type of violence being different, we focus on battles, that involve 252 rebel groups in Africa over the period, and provide evidence that mines spread conflicts across space and time by making rebellions financially feasible. More precisely, we make use of the information contained in the ACLED data on the winners and losers of particular battle events. We show that the appropriation of a mining area by a rebel group increases the probability that this group perpetrates violence elsewhere in the rest of the country in the following years. Quantitatively, our estimates suggest that every conquest of a mining area more than doubles the subsequent fighting activity of a group. As an alternative empirical strategy, we show that spikes in the price of minerals produced in the ethnic homeland of a rebel group tend to spatially diffuse its fighting operations.

Having documented how mining allows rebel groups to expand their fighting activities, we show in the last part of the paper that the characteristics and behavior of extracting companies is also key. Mining companies have indeed an ambivalent role: On the one hand, they may be willing to secure areas where they plan to operate; on the other hand, they may contribute to the diffusion of violence by financing/bribing rebel groups. We provide suggestive evidence in line with the second channel. Our results show that mining-induced violence is mainly associated with foreign ownership. Nevertheless, among foreign companies, the ones that operate in the least corrupt countries, and the ones that comply to Corporate Socially Responsible practices are associated with less violence. Finally we evaluate the impact of the recent transparency/traceability initiatives that have been promoted by international agencies, but fail to detect any effect of those top-down policies.

Related literature. In the last ten years there has been an increasing interest of the empirical literature in linking natural resource abundance to civil conflict and other forms of violence.[3] Most existing papers have run pooled cross-country regressions finding that civil war onset and incidence correlate positively with natural resources, generally focusing on oil, diamonds or narcotics.[4] The main shortcoming of this "first generation" of papers is that resource-rich and resource-poor countries typically also differ in various geographic, demographic, political and economic

[3]Natural resources have also been found to empirically matter for homicides (Couttenier, Grosjean and Sangnier, 2014), for organized crime (Buonanno *et al.*, 2015), for interstate wars (Caselli, Morelli and Rohner, 2015) and for mass killings of civilians (Esteban, Morelli and Rohner, 2015).

[4]See De Soysa (2002), Fearon and Laitin (2003), Ross (2004, 2006), Fearon (2005), Humphreys (2005) in the case of oil; Lujala, Gleditsch and Gilmore (2005), Humphreys (2005), Ross, (2006) and Lujala (2010) focusing on diamonds; Angrist and Kugler (2008) and Lujala (2009) on narcotics. Collier and Hoeffler (2004) provide evidence more generally related to primary commodities. This cross-country literature has also found that lootable resources (e.g. alluvial gemstones, narcotics) prolong conflicts (Fearon, 2004; Ross, 2004, 2006; Lujala, 2010).

dimensions, and the risk of omitted variable bias and unobserved heterogeneity makes it hard to give a causal interpretation to such cross-country correlations.

A more recent literature tries to take into account this issue through the use of panel data and the inclusion of country fixed-effects, focusing on variations in prices or resource discoveries as an identification device. This has led to contradictory results: While Lei and Michaels (2014) find a positive effect of oil discoveries on conflict, Cotet and Tsui (2013) find that oil discoveries do not have an effect on conflict anymore when controlling for country fixed-effects. Commodity price shocks also have an unclear effect on conflict, and are found in particular to be unrelated to conflict onsets (Bazzi and Blattman, 2014). One of the reasons for these contradictory results could be that having as unit of observation the country-year level is just too aggregate, as in many countries conflicts are concentrated in particular regions (i.e. think e.g. of the Niger delta in Nigeria or the Kurdish part of Turkey). Given this within-country heterogeneity, aggregating information into a country-year panel may lead to noisy estimates and hence attenuation bias. Recently, some papers have used disaggregated data on natural resources and conflict for one particular country, such as Dube and Vargas (2013) on oil in Colombia; Aragon and Rud (2013) on a gold mine in Peru; and Maystadt *et al.* (2014) on minerals in the DRC, as well as Sanchez de la Sierra (2015) on coltran and gold in Eastern Congo. However, there does not exist so far a study of the nexus between natural resources and conflict with a panel of disaggregated cells covering all minerals and a whole continent (Africa), as we use in the current paper. This yields a big gain in terms of external validity.

The main drawback of the existing empirical literature is that it has typically been unable to distinguish between different mechanisms or channels of why natural resource abundance matters.[5] Theoretically, there are various reasons to expect natural resource abundance to fuel conflict. The first is that resources increase the "prize" that can be seized through the capture of the state – which has been referred to as "greed" or "rent-seeking". A second possibility is that natural resources make rebellion *feasible*, i.e. relax financing constraints and make it easier to set up and sustain a rebel movement[6]. None of these papers, however, presents direct evidence at the disaggregated level. The other mechanisms that have been mentioned by the literature relate to separatism (natural resources provide perspectives of viable independence to resource rich regions with ethnic minorities – Morelli and Rohner, 2013), state capacity (rentier states can rely on resource rents and do not build up enough state capacity, which makes them eventually more instable) and grievances (natural resources can exacerbate grievances, due to frustrations from environmental degradation, or banned access to lucrative mining jobs)[7].

In a nutshell, the novelty of our current paper is manifold: First, this is the first paper assessing systematically the impact on conflict of all major minerals. Second, it is the first study of resource abundance and conflict i) using data at a high spatial resolution, ii) covering all Africa and iii) going beyond pooled panel regressions. Third, it is the first study to provide direct, large-scale

[5] A notable exception is Humphreys (2005) who uses among others the distinction between production and reserves to distinguish between different channels, running pooled cross-country regressions.

[6] See for instance Reuveny and Maxwell (2001), Grossman and Mendoza (2003), Hodler (2006), van der Ploeg and Rohner (2012), Rohner, Thoenig and Zilibotti (2013), and Caselli and Coleman (2013) for the "rent seeking" mechanisms and Fearon (2004), Collier, Hoeffler and Rohner (2009), Nunn and Qian (2014), and Dube and Naidu (2015) for the "feasibility" mechanism.

[7] See for instance Fearon (2005), Besley and Persson (2011) and Bell and Wolford (2014) on the state capacity mechanism and Le Billon (2001), Ross (2004), and Humphreys (2005) for the grievances mechanism.

evidence of how capturing a mining area affects the diffusion of conflict over space and time. This yields findings that are in line with the view that resource rents can fuel diffusion of fighting by making it feasible to sustain rebellion. Fourth, we present novel results on how firm characteristics (ownership, Corporate Social Responsibility) can contain or boost mining violence.

The paper is organized as follows: Section 2 presents the data. Section 3 displays the empirical analysis related to the local impact of mining activity on violence. In section 4 we study the diffusion over space and time of mining-induced violence. Section 5 studies the role of mining companies and section 6 concludes.

2 Data

2.1 Data description

The structure of the dataset is a full grid of Africa divided in sub-national units of 0.5×0.5 degrees latitude and longitude (which means around 55×55 kilometers at the equator). We use this level of aggregation rather than administrative boundaries to ensure that our unit of observation is not endogenous to conflict events.[8] Our unit of observation is therefore a *cell-year* in the rest of the paper, i.e. we study how mineral resources affect the probability that a conflict takes place in a given cell, during a given year.

Conflict data. We use the Armed Conflict Location and Event dataset (ACLED, 2013) which contains information on the geo-location of conflict events in all African countries over the period 1997-2010. We have information about the date (precise day most of the time), longitude and latitude of conflict events within each country. These events are obtained from various sources, including press accounts from regional and local news, humanitarian agencies or research publications. ACLED records all political violence, including violence against civilians, rioting and protesting within and outside a civil conflict, without specifying a battle-related deaths threshold. A unique feature of the ACLED dataset is that it contains information on the type of events, as well as the characteristics of the actors on both sides of the conflicts. We know in particular if the event was a battle, the names of the groups involved, and who won the battle.[9] We shall make use of this information when testing for the channels of transmission.

The latitude and longitude associated with each event define a geographical "location". ACLED contains information on the precision of the geo-referencing of the events. The geo-precision is at least the municipality level in more than 95% of the cases, and is even finer (village) for more than 80% of the observations. For each data source, we aggregate the data by year and 0.5×0.5 degree cell. We construct a dummy variable which equals one if at least one conflict happened in the cell during the year, which we interpret as cell-specific *conflict incidence*, as well as a variable containing the number of events observed in the cell during the year, which we label *conflict*

[8]See e.g. La Ferrara and Harari (2014) or Besley and Reynal-Querol (2014) for papers using similar grid-cell level data combined with the same conflict data.

[9]Eight different types of events are included in ACLED: battle with no changes in territory; battle with territory gains for rebels; battle with territory gains for the government; establishment of a headquarter; non violent activity by rebels; rioting; violence against civilians; non violent acquisition of territory. Actors are classified according to the following typology: government or mutinous force; rebel force; political militia; ethnic militia; rioters; protesters; civilians; outside / external force (e.g. UN).

intensity. These are our main dependent variables in the rest of the paper. We also show that our results are robust to modeling cell-specific conflict onset and ending separately.

While the geo-coding of the events is cross-checked in the ACLED dataset, it is not immune to potential biases and measurement errors. We cannot rule out the possibility that the reporting of conflicts is biased towards certain types of countries, regions or events, as some regions might in particular have better media coverage. An event dataset such as ACLED cannot, by definition, be exhaustive. Our empirical methodology makes it however unlikely that this affects our results, as structural differences in media coverage or more generally in the reporting of events will be captured by cell and country-year fixed-effects. We also show that our results are quantitatively stable across events of different severity; this is reassuring as reporting biases are arguably more likely to occur for small-scale events.

Mines data. To each *cell-year*, we merge information on mines from *Raw Material Data* (RMD – IntierraRMG, 2013). The data contain information on the location of mining companies around the world since 1980.[10] We focus on the 1997-2010 period, which overlaps with ACLED. For each year, we know whether the mine is active or not, the specific minerals produced and the total production for each of them. We use this data to identify active mining areas, and the type of minerals they produce. For each cell k, we define M_{kt}, a dummy variable which equals one if a least one *active* mine is recorded in the cell during year t. As an alternative measure we also compute the number of mines. We also identify the main mineral produced in the cell or by the closest mine, defined as the mineral with the highest production over the entire period. We identify 22 main minerals in our sample of African countries. In the rest of the analysis we focus on the 15 minerals for which we have world price data.[11]

The RMD dataset collects information mostly for large-scale mines, usually operated by multinationals or the country's government. Hence small-scale mines, and those that are illegally operated, are not included in our sample. While these measurement errors could lead to some attenuation bias in our estimates, we believe that this concern is limited in practice, given our empirical strategy. First, our baseline specification is based on exogenous mineral price variations within cells with a permanently active RMD-registered mine; in other words, the measurement errors are unlikely to attenuate our estimates given the inclusion of cell fixed effects. Second, our unit of analysis being an area (i.e. a 0.5×0.5 degree cell) where a mine is active, we interpret our key explanatory variable M_{kt} as a proxy for the *extraction area* of a given mineral rather than as coding for a specific RMD-referenced mine. If minerals are spatially clustered, these mining areas will include all mines, including small ones. Note that we run a number of robustness exercises to ensure that our results are not sensitive to changes in the definition of a mining area. In particular, we include the surrounding cells (first and second degrees) or use 1×1 degree cells instead of 0.5×0.5. As shown later, results are consistent across specifications.

[10]More information is available at $http://www.snl.com/Sectors/metalsmining/Default.aspx$. Other recent research using the RMD data includes Kotsadam and Tolonen (2014) who study gender and local labor market effects of mining, as well as Kotsadam et al. (2015) who assess the impact of mining on local corruption.

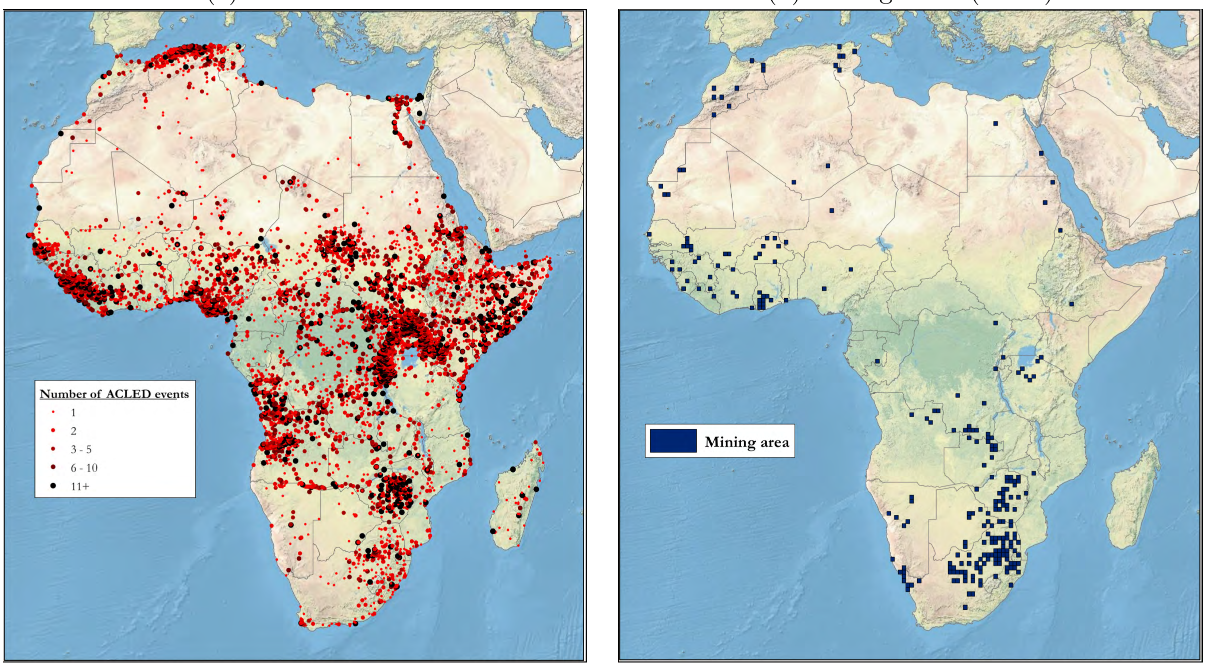
[11]These 15 minerals are: Bauxite (aluminum), Coal, Copper, Diamond, Gold, Iron, Lead, Manganese, Nickel, Platinum (and PGMs, i.e. Platinum Group Metals), Phosphate, Silver, Tin, Tungsten, and Zinc. We do not consider the following minerals: Antimony, Chromite, Cobalt, Lithium, Tantalum, Uranium, Zirconium. These are the main minerals of only 8% of the mining cells.

Other data. Our final dataset contains a number of additional variables. The appendix contains more details on the data construction and sources. In our baseline estimations, we use information on the world price of the minerals from the World Bank Commodities prices dataset. Real prices are measured in constant 2005 USD. We run robustness checks using nominal prices, and alternative commodity prices indices from UNCTAD. We also add diamond prices from Rapaport (2012).[12] Finally, we include cell-specific information, including the distance between the cell's centroid and international borders and to capital city (from PRIO-GRID - PRIO, 2013), yearly average level of rainfall and temperature, GDP and population (included in PRIO-GRID but originally from G-econ), and satellite nighttime lights from the National Oceanic and Atmospheric Administration (2010) as time-varying proxy for the level of economic activity.

2.2 Descriptive statistics

Figure 1: Conflict events and mining areas

(a) ACLED data (b) Mining areas (RMD)



Geo-location of conflict from the *Armed Conflict Location and Event dataset* (ACLED, 2013) and of active mining areas from *Raw Material Data* (RMD). Larger versions of these maps, featuring a distinction between different types of minerals, are provided in the online appendix.

Figure 1 contains a visual representation of both the geo-localization of conflict and mines. The main minerals present in the dataset are gold (30% of mining cells), diamond, copper and coal (around 10% each). As shown in Figure 5 in the appendix, the number of conflict events does not follow a specific trend over time, while the number of active mines is steadily increasing. At the end of the period, our dataset reports around 700 active mines (each possibly producing several minerals).

[12]Diamond is problematic as its price varies importantly according to the quality and type of diamond produced. As our mining data contains no information on these, we chose to drop diamond from our baseline estimations. We however show that our results are robust to the inclusion of this mineral.

Our final sample contains 52 countries and 15 minerals. Tables 14 and 15 in the appendix contain additional country-level descriptive statistics. On average, around 15 conflict events and 10 active mines are recorded each year in each country. Only four countries display no conflict events over the entire period[13], Somalia is the country with the highest number of events (almost 400 events on average by year over the period), while small countries like Burundi, Gambia and Rwanda display the highest share of cells affected by conflict incidence over the period. In 17 countries no active mine is recorded.[14] The highest numbers of mines are recorded in South Africa and Zimbabwe, but these are highly concentrated, as in both cases mining areas represent less than 20% of the cells. Note that – except in the case of South Africa – the countries contained in our sample are typically small producers of the minerals from a world perspective: the average market share of a country-mineral is 4.5% (and drops to 1.6% when we exclude South Africa).

Table 1: Descriptive statistics: cell-level

	Obs.	Mean	S.D.	Median
Pr(Conflict> 0)				
all	144690	0.06	0.24	0.00
if mines>0	2771	0.16	0.36	0.00
if mines = 0	141919	0.06	0.24	0.00
battles	144690	0.03	0.18	0.00
viol. against. civ.	144690	0.03	0.18	0.00
riots & protests	144690	0.02	0.13	0.00
# conflicts				
all cells	144690	0.33	4.238	0.00
if > 0	9098	5.23	16.10	2.00
Pr(Mine> 0)				
only cell	144690	0.02	0.14	0.00
incl. 1^{st} *surrounding cells*	140546	0.10	0.31	0.00
incl. 1^{st} *&* 2^{nd} *surrounding cells*	140546	0.16	0.37	0.00
# mines				
all cells	144690	0.05	0.55	0.00
if > 0	2771	2.43	3.15	1.00
Pr(# mines > 2)				
all cells	144690	0.01	0.09	0.00
if mine> 0	2771	0.41	0.49	0.00

Source: Authors' computations from PRIO-GRID, ACLED and RMD dataset.

Table 1 contains descriptive statistics on our final sample, which includes a bit more than 10,000 cells over 14 years. Several elements are worth mentioning. First, the unconditional probability of observing at least one conflict in a given cell and a given year is low at 6%. In the majority of cells no event occurs over the entire period. The probability of observing an active mine in a given cell is also low at 2%, but it increases to 10% (respectively, 16%) when we consider the neighboring cells (respectively, the first and second degree neighboring cells). Second, mines tend to be spatially clustered: conditional on observing at least one mine in a given cell, the average number of mines is 2.43. We can also see this clustering by noting that the probability of observing two mines or more in a given cell, conditional on observing at least on mine is very high

[13]Comoros, Cape verde, Mauritius and Sao Tome and Principe.

[14]Burundi; Benin; Central African Republic; Cameroon; Republic of Congo; Cape Verde; Djibouti; Eritrea; Gambia; Guinea-Bissau; Equatorial Guinea; Libya; Malawi; Mauritius; Somalia; Sao Tome and Principe; Chad.

(41%). Finally, the conflict probability is much higher in cells with active mines. Of course, this can be due to many unobserved cell characteristics, an issue we shall deal with in our estimations.

3 Mining-induced Violence: Baseline Results

We turn now to our empirical analysis. We first document correlations between the presence of mining areas and the likelihood of violent events at the cell-level. Then we discuss our strategy for identifying the causal impact of mining on violence and the baseline results are reported. We also provide a series of alternative specifications assessing the robustness of the results. Finally we perform various quantification exercises.

3.1 Correlations

The correlation between mining and cell-level violence is estimated in various ways, all based on specifications of the following form:

$$\textsc{conflict}_{kt} = \alpha \times M_{kt} + \mathbf{FE}_k + \mathbf{FE}_{it} + \mathbf{C_{kt}}'\beta + \varepsilon_{kt} \tag{1}$$

where (k, t, i) denote respectively cell, time and country. The dependent variable, $\textsc{conflict}_{kt}$, corresponds to the observation of violent events at the cell-year level where violence is measured either in term of incidence (i.e. a binary variable coding for non-zero events) or in term of intensity (i.e. number of events). Information on violent events is retrieved from the ACLED dataset on civil conflicts. The main explanatory variable, M_{kt}, measures mining activity at the cell-year level with two possible coding options: a discrete variable equal to the number of *active* mines, or a binary variable coding for the presence of at least one active mine. The vector $\mathbf{FE}_{it}$ corresponds to a set of country×year fixed-effects that filter out all countrywide time-varying characteristics affecting violence and activity of mines – e.g. a war-induced collapse of central state and property rights. $\mathbf{FE}_k$ is a battery of cell fixed-effects and $\mathbf{C_{kt}}$ is a set of potential time-varying co-determinants of local conflicts and mining activity that includes, in particular, the intensity of violence in the surrounding cells during year t.

In our baseline specifications, equation (1) is estimated with OLS or LPM in the case of a binary dependent variable. Our results are robust to alternative non-linear estimators such as a conditional logit or a Poisson pseudo-maximum-likelihood estimator (Table A.4 in the online appendix[15]). In all specifications (here and in other sections of the paper as well), standard errors are clustered at the country-level (note that all our results are robust to less demanding levels of clustering such as country×year or cell). We also check that our main results are robust to a non-parametric estimation of the standard errors allowing for both cross-sectional spatial correlation and location-specific serial correlation (Conley, 1999; Hsiang, Meng and Cane, 2011).

Results are displayed in Table 2. In columns (1) and (2) country×year fixed effects are included and the main source of identification corresponds to between-cell variations in mining activity and violence, for a given country in a given year. The presence of one or more mines is associated with a 8.9 percentage points increase in conflict probability. Part of the correlation could be spuriously

[15] In the online appendix we also consider pure cross-sectional specifications where all variables are averaged in the time dimension (see Table A.1).

Table 2: Conflicts and mines: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimator				OLS			
Dep. var.	Incidence	# Events	Incidence	# Events	Incidence	# Events	Incidence
mine > 0	0.089^a	0.145^b	0.040^b	0.021	0.046^b	0.018	
	(0.026)	(0.058)	(0.018)	(0.029)	(0.019)	(0.030)	
log precipitation					0.001	0.001	0.001
					(0.003)	(0.004)	(0.003)
average temperature					0.011^b	0.012^c	0.011^b
					(0.005)	(0.006)	(0.005)
# neighbouring cells in conflict					0.035^a	0.065^a	0.035^a
					(0.005)	(0.009)	(0.005)
# mines							0.009^b
							(0.004)
Observations	144690	144690	144690	144690	119016	119016	119016
R^2	0.124	0.154	0.447	0.562	0.451	0.568	0.451
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	No	No	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. $log(x + 1)$ used for dependent variables in columns (2), (4), and (6). mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell in year t. # neighbouring cells in conflict is the number of neighbouring cells, among the 8 surrounding cells, in which at least a conflict event occurs in year t.

driven by omitted time-invariant cell-specific characteristics such as the local determinants of state capacity, property rights enforcement or political instability (e.g. ethnic cleavages). In order to control for this source of unobserved heterogeneity, we include cell fixed-effects in the remaining columns. We obtain a positive and significant (at the 5 percent level) coefficient in column 3, but it loses its significance when violent events at the cell-year level are measured in term of intensity (column 4). In term of magnitude, the within-cell estimates correspond to half of their between-cell counterparts confirming that part of the correlation in column (1) and (2) is driven by time-invariant cell characteristics. Columns (5) and (6) include time-varying cell-specific controls. Despite a substantial reduction in the sample size, our coefficient of interest remains stable and significant in column 5. The opening of a mine in a given cell is associated with a 4.6 percentage points increase in conflict probability in this cell. The coefficient of interest loses significance for explaining the number of conflicts in column 6. Finally column (7) replicates column (5) with the main explanatory variable being the *number of active* mines in the cell. The coefficient of mining activity is positive and statistically significant at the conventional threshold.

3.2 Exogenous changes in the value of mines – Baseline Results

Though demanding, the within-cell specifications in Table 2 are not immune to endogeneity issues. The most obvious concern relates to the reverse causation from local violence to mine opening/closing. The direction of this bias is most likely negative, i.e. conflict incidence might impact negatively the likelihood of a mine being active. This should therefore work against our findings of a significant positive correlation between mining activity and conflict. However, we cannot rule out the possibility that conflicts affect the value of a mine in a non-trivial way, for instance if the state uses part of the mines production to fight insurgency. Guidolin and La Ferrara (2007) actually find evidence that conflicts increase the value of extractive firms.[16]

In order to address causality, we focus on exogenous variations in the economic value of mines. The idea is that more valuable mines increases local rent-seeking and, consequently, the likelihood of violence.[17] To abstract from local determinants of violence and guarantee exogeneity, we exploit the variations in the world prices of minerals. More precisely, we estimate the following specification:

$$\text{CONFLICT}_{kt} = \alpha_1 M_{kt} + \alpha_2 \ln p^W_{kt} + \alpha_3 \left(M_{kt} \times \ln p^W_{kt} \right) + \mathbf{FE}_k + \mathbf{FE}_{it} + \varepsilon_{kt} \tag{2}$$

The variable p^W_{kt} is time-varying and cell-specific and it corresponds to the world price of the main mineral produced by the mines present in cell k, i.e. the one with the highest total production over the *entire* 1997-2010 period. We code p^W_{kt} as a zero for the cells where no active mine ever produces over the period; by contrast, it is non-zero for cells with a mine that is inactive only *temporary*. This coding strategy being non neutral, we check below that our estimates are robust when restricted to the sub-sample of cells with only permanently active mine.[18] Note that we do not include the controls $\mathbf{C_{kt}}$ in our baseline estimations as they reduce significantly the sample size without affecting the estimates of our coefficient of interest, as shown later in the robustness section.

We are primarily interested in α_3, the coefficient of the interaction term between the world price and the dummy for mining activity. This coefficient captures the impact on local violence of an exogenous increase in the world price of a given mineral, in cells where mining extraction of this mineral takes place. Given the fact that we include country×year fixed-effects in all specifications, our identification strategy relies on the exogeneity of the interaction term, $M_{kt} \times \ln p^W_{kt}$, with respect to the local determinants of conflict. We discuss hereafter this identification assumption.

a/ Exogeneity of Prices – This seems a reasonable assumption for the world price of minerals, p^W_{kt}, as mentioned earlier. Still, one might argue that some mines are large enough to affect world prices, in which case the occurrence of conflict in these cells might also affect these prices. Although our sample contains only few countries with potentially large market power on the mineral market, we nevertheless test whether our results are robust to excluding from the sample all cells located in countries belonging to the top ten world producers of a specific mineral (see subsection 3.3.1).

b/ Exogeneity of mining activity – As discussed above, potential reverse causation from conflicts to mining opening/closing is a severe concern. As a consequence, our coefficient of interest, α_3, could be partly identified through conflict-induced shift in the binary variable M_{kt}. To account for this issue, we can restrict the estimate of equation (2) to the sub-sample of cells without opening/closing of mine over the period (i.e. $\text{Var}(M_{kt}) = 0$ for

[16]They mention several reasons that might explain this finding: during conflict, (i) entry barriers might be higher; (ii) the bargaining power of governments might be lower and hence licensing cheaper; (iii) lower transparency leads to more unofficial deals which are profitable to the firms; (iv) the manufacturing sector leaves the country, forcing it to specialize in natural resources.

[17]See Dube and Vargas (2013) for a similar methodology applied to coffee and oil production in Colombia.

[18]We also run robustness checks where instead of replacing p^W_{kt} by zero for cells with no active mine ever, we replace it by a price index representing the average price level of the minerals in country i, during year t, weighted by the relative frequency of each mineral in each country over the period. As discussed in subsection 3.3.4, the results are very similar.

a given k). Given that $M_{kt} = 0$ or $M_{kt} = 1$ for all years, this variable is now absorbed by the cell fixed effects and the covariates $\ln p^W_{kt}$ and $(M_k \times \ln p^W_{kt})$ become identical; we accordingly include only the interaction term and the specification takes the following simpler expression:

$$\text{CONFLICT}_{kt} = \alpha_3 \left(M_k \times \ln p^W_{kt}\right) + \mathbf{FE}_k + \mathbf{FE}_{it} + \varepsilon_{kt} \tag{3}$$

This specification ensures that our coefficient of interest, α_3, is identified within cells through the changes in world commodity prices conditional on having a *permanent* active mine (i.e. $M_{kt} = 1$ for all t), and not through the potentially endogenous opening/closing of mines. Note also that including country×year dummies is crucial, as they absorb common shocks (or trends) on world prices and country-level conflicts. However, from a data perspective, estimating this set of 935 dummies is very demanding. In this respect, keeping in the sample not only cells with a permanent mine opening but also the large amount of cells with no mines ($M_{kt} = 0$ for all t) conveys information which is decisive for estimating these dummies. This is why we favor, in our baseline estimations, specifications using the full sample of cells without opening/closing. Alternatively, in the robustness checks, we report the estimates when the sample is restricted to cells with a permanent active mine (see subsection 3.3.4).

Table 3: Conflicts and mineral prices

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			OLS			
Dep. var.	Conflict incidence		# conflicts		Conflict incidence	
Sample	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0
mine > 0	0.042		0.025			
	(0.028)		(0.039)			
ln price main mineral	-0.042		-0.090^b		0.018	
	(0.027)		(0.044)		(0.012)	
ln price × mines > 0	0.109^a	0.076^a	0.197^a	0.101^a		
	(0.037)	(0.022)	(0.057)	(0.032)		
# mines					0.009^a	
					(0.003)	
ln price × # mines					0.019^a	0.026^c
					(0.006)	(0.015)
Observations	143775	142257	143775	142257	144060	142184
R^2	0.446	0.446	0.562	0.563	0.447	0.446
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell producing the main mineral in year t. Var(M_{kt}) = 0 means that we consider only cells in which the mine variable (the binary version or the number of mines) takes always the same value over the period. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period. Estimations (1), (3) and (5) include controls for the average level of mineral world price interacted with the mines variables.

Table 3 reports the baseline results for various sample compositions and definitions of the variables. The dependent variable is conflict incidence, except in columns (3) and (4) where we consider the number of events. Mines activity is coded as a dummy variable except in columns (5) and (6) where it is measured by the number of active mines in the cell. Columns (1), (3) and (5) are estimated on the full sample (equation 2); while columns (2), (4) and (6) are restricted on the sub-sample of cells without mine opening/closing (equation 3). We see that in all columns but (6), our coefficient of interest is positive and significant at the 1 percent level. Thus, a spike of mineral prices increases the conflict risk in cells producing these commodities. Columns (2) and (4) are our preferred regressions.

3.3 Robustness

In this subsection we show that the baseline estimates of Table 3 are robust to a large battery of sensitivity checks —the main ones relating to exogeneity of world prices, alternative definitions of mining areas and measurement errors in the mining/conflict data. For the sake of exposition most tables are relegated to the online appendix.

3.3.1 Exogeneity of world prices

We start by testing the consistency of our empirical strategy that is based on exogenous variations in world mineral prices. A first threat to our identification strategy could consist in the potential reversed causality from local violence to world prices. In particular, it is conceivable that the occurrence or the anticipation of a conflict in a major producer country leads to an increase in the world prices of the relevant minerals. To address this concern, we drop mining cells belonging to countries that are top-10 world producers of the main mineral produced in the cell. We replicate our baseline Table 3 on this restricted sample with no large producers. Results are statistically robust and quantitatively close to our baseline estimates (Table A.5 in the online appendix).

Secondly, we want to rule out the fact that time-varying omitted variables could co-determine world prices and local violence in mining areas. We believe that the inclusion of country×year fixed effects in our baseline specifications alleviates most of this problem. However it could be that the residual unobserved heterogeneity still co-moves with the world prices of minerals. We perform a placebo analysis to exclude this last concern and check the validity of our approach. Our idea is to replace the price of the mineral produced in the cell by the price of a mineral that is *not* produced in the cell. More precisely, we randomly assign a mineral to each of the mining cells and run specification (2) of Table 3 with this fake $M_{kt} \times \ln p_{kt}^W$ variable. We repeat this Monte Carlo procedure in 1,000 draws. Figure 6 displays the sampling distribution of the coefficient of the interaction term. Reassuringly, the Monte Carlo coefficients are distributed far from our baseline estimate (0.076) and are massively insignificant. This confirms that our baseline results are not driven by co-movements in world prices.

3.3.2 Alternative definitions of a mining area

In this subsection we enquire robustness to alternative sizes of the units of observation. As discussed in Section 2, the RMD dataset does not survey small-scale (potentially illegally operated) mines. Because of spatial clustering of mineral deposits, our main explanatory variable, M_{kt}, must be interpreted as a proxy for the extraction area of a given mineral rather than as coding for a specific RMD-referenced mine. Imagine now for example that mining areas could on average be larger than our cells of a spatial resolution of 0.5 × 0.5 degree. In this case, focusing on the impact of mines on the conflict likelihood in its surrounding cell of 0.5 × 0.5 degree may underestimate the real impact of being in a mining area. Hence, in what follows we broaden the scope of a mining area.

Table 4: Conflicts and mineral prices, including neighboring cells

	(1)	(2)	(3)	(4)
Estimator	OLS			
Dep. var.	Conflict incidence		# conflicts	
Sample	All	$\text{Var}(M_{kt}) = 0$	All	$\text{Var}(M_{kt}) = 0$
mine > 0	0.053^c		0.037	
	(0.031)		(0.044)	
ln price main mineral	-0.051^c		-0.108^b	
	(0.027)		(0.045)	
ln price × mines > 0	0.108^a	0.068^b	0.197^a	0.090^b
	(0.038)	(0.029)	(0.057)	(0.043)
mine > 0 (neighboring cells)	-0.028		-0.043	
	(0.018)		(0.031)	
ln price × mine > 0 (neighbouring cells)	0.020^b	0.027^b	0.041^c	0.047^b
	(0.010)	(0.011)	(0.024)	(0.021)
Observations	136033	125611	136033	125611
R^2	0.442	0.436	0.554	0.551
Country×year dummies	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell producing the main mineral in year t. $\text{Var}(M_{kt}) = 0$ means that we consider only cells in which the mine variable (including the one for surrounding cells) takes always the same value over the period. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period. All estimations include controls for the average level of mineral world price interacted with the mines variables.

In Table 4 we study the impact on conflict of mineral price shocks in neighboring cells (of degrees 1 and 2) of a cell containing a RMD-referenced mine. As shown by the coefficient of the second interaction term, we detect in all specifications a positive and significant impact, which is consistent with the view that some mining areas are indeed larger than our 0.5 × 0.5 degree cells. Note however that the effect is much lower than for the cell itself (i.e. the first interaction term). Alternatively, in Table A.6 we reproduce our baseline table for a grid of cells at a larger resolution (1 degree × 1 degree).

Finally, in Table A.7 we use a number of alternative definitions of a mining area. Until now these were defined as areas where active mining is observed in year t. In Table A.7 we also consider cells in which a mine is observed at least once over the entire 1997-2010 period (columns (3) and (7)) or has been observed at some point since the start of our sample (columns (4) and (8)). The coefficients are slightly lower, which was expected as in these estimations we also define as mining areas places where mining does not necessarily take place in the current year; yet, in all cases our results remain highly statistically significant.

3.3.3 Measurement Errors

ACLED data. Given that the ACLED data is based on press accounts and news reports, there may be concerns that media coverage is correlated with mining activity. It could for example be that mining areas have better infrastructure and thus provide easier access to journalists and NGOs. However, as we include cell and country$\times$year fixed-effects, systematic differences in event coverage across mining and non mining areas cannot affect our results. The only reporting bias that would be problematic could arise in case conflict events were more likely to be reported in mining areas during periods of high prices. We cannot rule out this possibility a priori, although we think that it is unlikely that media coverage (typically driven by slow-moving factors such as travel facilities) should be responsive to variations in mining prices (that can be very fast-moving). Still, following Dafoe and Lyall (2015), we run our baseline specifications on different categories of events defined by severity, i.e. by the number of fatalities. The idea is that if there were to be a reporting bias, it should be lower for more severe events: The coefficients for smaller-scale events may be biased downwards but the coefficients for large-scale events should be relatively unbiased (as it is unlikely that any media outlets miss out on big events). We implement this approach in Table A.8 where we estimate the impact of mineral price variations on the probability of conflict for various levels of severity, based on quartiles of number of fatalities. We see that our coefficient of interest is always of the expected sign and statistically significant, even for the highest severity category (which contains events for which the reporting bias should be – if anything – very small). Further, the estimates are quantitatively stable across these different categories of severity, which is at odds with the potential presence of reporting bias. Finally, note that we consider in Section 4 alternative categories of severity, i.e. by types of event, not by fatalities. Here again, the estimates are robust across the different categories. In particular the results hold if we restrict ourselves to battle events, which are very visible and unlikely to be missed out by any news reports.

Mines data. The RMD data only includes big, industrially operated mines, and hence do not report direct information on small-scale artisanal production sites. In presence of classical measurement errors, our empirical strategy that is based on spatial clustering of deposit and variations in prices, limits the extent of the attenuation bias (see our discussion in Section 2). However, the scale of operation of extractive activity— big industrial mines or small artisanal sites – does not only depend on geographical features; it may also be correlated with the presence of conflict. Hence, there could be non-classical measurement errors affecting our mining data points and the resulting estimation bias is unclear. Suppose for example that multinationals only go to places with low political risk. In this case there would be more missing mines in high-risk areas, and focusing on industrial mines could bias downward the effect we find. On the contrary, if big mining companies were to benefit from political instability (which could make the bribing of officials easier), in this case there could be more missing mines in peaceful zones and our analysis could suffer from over-stated estimates of the effect of mining extraction on conflict. Notice that, in both cases, the inclusion of cell and country$\times$year fixed-effects alleviates most of our concern. The only estimation bias that would be problematic could arise in case these non-classical measurement errors were more likely in periods of high prices. In Section 2.3 in the online appendix we study this potential problem, following a recent approach developed by Koenig *et al.* (2015).

The basic idea consists in gauging the potential impact of non-classical measurement errors by regressing a subsample of our RMD mining data on a quasi-exhaustive list of mines and to see whether the residual variation in RMD coverage can be significantly explained by conflict. The empirical answer is a clear no and we conclude from our exercise that there is no evidence that the RMD data are subject to non-classical measurement errors.

3.3.4 Other robustness checks

Population/economic size and time-varying controls. We want to rule out the fact that our baseline estimates are driven by an increase in population size resulting from more intense mining activity (induced by raising mineral prices). To this purpose, we control in Table A.10 for economic size, proxied by night light satellite data, and, more importantly, for the interaction of luminosity and mineral prices. The results are unchanged. Similarly, Table A.11 goes further and includes a number of alternative cell-specific, time-varying controls which might be correlated with commodity price variations (climate variables, such as rainfall and temperature) or mining activity (number of conflicts in the surrounding cells, or number of conflicts observed in the cell since the start of the period). In all cases, our coefficients of interest remain stable and highly significant.

Alternative price data – We also investigate robustness to alternative prices data (Table A.12). In particular, we use nominal instead of real prices in column (1) and (2), prices from UNCTAD in columns (3) and (4), and replace the price variables by a country-specific index when no mine is ever recorded in the cell in columns (5) and (6).[19] In all columns the coefficient of interest is still highly significant and quantitatively close to our baseline estimates.

Subset of metals – Are our results driven by a particular subset of minerals? We respectively include diamonds in our estimations or exclude gold, silver and diamond mines from our set of minerals (Tables A.13 and A.14).[20] Our coefficient of interest keeps its positive sign and is highly significant in all columns, indicating that our results generalize to a broad category of minerals, and that they are not driven by the most precious minerals only.

Sample restrictions – In the baseline specifications cells without mines are included in the sample with the purpose of estimating the large set of fixed effects (see our discussion in Section 3.2). In Table A.15 we report the estimates when the sample is restricted to cells with a permanent active mine. Column (1) reports our preferred specification on the full sample. Column (2) replicates this specification on the subsample of cells with permanent active mines. The coefficient of interest remains positive but much less accurately estimated, the reason being a massive sample size reduction (1078 observations) with a set of country×year dummies remaining large (280). In column (4), we consequently exclude those dummies and this restores statistical significance. In column (3), for the sake of comparison, we replicate column (4) on the full sample of cells.

[19] The price series from UNCTAD correspond to weighted indices, calculated from commodity prices tables, for selected commodities exported by developing economies. The weights used in the construction of the indices represent the relative values of exports from developing countries for the period 1999-2001. Data are available at http://knoema.com/UNCTADFMCPI2015Feb/free-market-commodity-price-indices-monthly-january-1960-january-2015.

[20] There is a large heterogeneity in diamond quality across mines and the price series for different qualities can move in opposite directions. Having no information on the quality of diamonds, we prefer to exclude diamonds from our baseline estimates in order to limit measurement errors.

Conflict onset and ending – In all tables we focus on conflict incidence, which reflects our interest in explaining the general presence of conflict. A higher conflict incidence can of course be due to either more conflicts breaking out or due to existing conflicts lasting longer. Hence, in the civil war literature, a number of papers focus on civil war outbreaks (onsets) and endings separately.[21] In Table A.16, we study cell-specific conflict onsets and endings of conflict separately. We find that our variable of interest significantly both increases the risk of conflict onset (column (2)), and reduces the likelihood of conflict ending, although the coefficient is less precisely estimated for conflict ending (p-value of 0.117 in column (4)). This suggests that the higher conflict incidence due to mines is both due to more conflicts breaking out and to existing conflicts lasting longer.

Non linear estimators – Table A.17 of the online appendix replicates our baseline specifications using a class of estimators specifically designed for binary dependent variables and count data, i.e. fixed effects logit (whenever the dependent variable is conflict incidence) or a Poisson pseudo-maximum-likelihood (PPML, whenever the dependent variable is the number of conflict events). Our results are very similar to our baseline estimates. The LPM is however our preferred estimator as it allows for a more straightforward interpretation of the coefficients and does not suffer from certain econometric problems due to the inclusion of both cell and country×year fixed effects.[22]

Spatial clustering of standard-errors – In all tables standard errors are clustered at the country-level. Alternatively, we allow for various levels of cross-sectional spatial correlation and cell-specific serial correlation, applying the method developed by Conley (1999) and Hsiang, Meng and Cane (2011). We display the standard errors for our six main specifications when allowing for spatial correlation of 100 or 1000 kilometers, and for a serial correlation over 1 or 5 years (Table A.18). For all combinations of spatial and serial correlation considered, the standard errors are such that our coefficients of interest are still statistically significant at the conventional level.

3.4 Country characteristics and mining induced violence

Is the abundance of valuable mines always a curse for political stability? Countries' institutions and social characteristics may play a role, as suggested by the rent-seeking models of Mehlum, Moene and Torvik (2006) and Hodler (2006). In particular, minerals could exacerbate instability in countries where the conflict risk is already latently present due to social cleavages or weak institutions. This would be in line with the idea that minerals are not necessarily the deep cause of conflict but make them feasible – a mechanism we shall investigate in detail in the second part of the paper. In this sub-section we consider how country characteristics may modify the average effect of mineral price variations on local conflicts. While asking this question is important, we should be aware that finding strong results would come as a surprise: in most

[21] A potential issue with using conflict incidence as a dependent variable has recently been raised by the macro-level literature. Conflict being a persistent variable, one should estimate a dynamic model with the lagged conflict variable included on the right hand side, or equivalently, model onset and ending separately (Bazzi and Blattman, 2014). Note that the problem is less clear in our case as local conflict incidence is much less persistent than country-specific incidence: at the cell-level, the vast majority of events – around 75% – do no last more than 2 years.

[22] The estimations shown in Table A.17 include year dummies instead of country×year dummies for two reasons; first, because the logit and PPML estimator fail to reach convergence when including country×year dummies; second, because the inclusion of two different large sets of fixed effects in logit and Poisson models might lead to an incidental parameter problem (Charbonneau, 2012).

resource-rich economies in our sample, local heterogeneity in politics and institutions is relatively high and we should not expect strong effects of national characteristics on local violence.

3.4.1 Domestic Institutions: Can Good Governance Stop the Guns?

While natural resources have often been thought of as affecting the nature and quality of institutions (e.g., as generating corruption, autocracies and more generally a weaker accountability of the state), only relatively little attention has been paid to the impact of the interaction between institutional quality and natural resource abundance on political stability and prosperity.[23] There are indeed reasons to expect natural resource extraction to have a stronger impact in weak states: it might be easier for local armed groups to extract rents from mining areas in such countries, or the lack of redistribution of mining revenues might create grievances. Starting from our preferred specification (Table 3, column (2)) we now consider the triple interaction between our main explanatory variable ($M_k \times \ln p^W_{kt}$) and a country-level index of institutional quality IQ_i — a binary variable equal to 1 when a country's institutional score averaged over 1997-2010 is above the sample median.

Table 5: Heterogeneous effects: Institutional Quality

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	Incidence	# conflicts	Incidence	# conflicts	Incidence	# conflicts
Institutions	ICRG		Gov. Effectiv.		Rule of Law	
ln price × mines > 0	0.147^a	0.125^a	0.143^a	0.204^a	0.106^b	0.097^a
	(0.033)	(0.026)	(0.027)	(0.075)	(0.045)	(0.035)
ln price × mines > 0 × Inst.Qual.	-0.084^b	-0.015	-0.094^a	-0.144^c	-0.038	0.017
	(0.041)	(0.055)	(0.032)	(0.077)	(0.051)	(0.061)
Observations	115586	115586	131686	131686	131686	131686

	(7)	(8)	(9)	(10)
Dep. var.	Incidence	# conflicts	Incidence	# conflicts
Institutions	Voice/Account.		Polity IV	
ln price × mines > 0	0.092^c	0.087^b	0.100^b	0.087^a
	(0.049)	(0.038)	(0.039)	(0.032)
ln price × mines > 0 × Inst.Qual.	-0.016	0.032	-0.030	0.035
	(0.055)	(0.062)	(0.047)	(0.063)
Observations	131686	131686	131672	131672

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. All estimations include country×year dummies and cell fixed effects. $log(x + 1)$ used for dependent variable in columns (2), (4), (6), (8) and (10). Estimations include cells for which $\text{Var}(M_{kt}) = 0$, i.e. cells in which the mine variable takes always the same value. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. Inst. Qual. is a dummy taking the value 1 if the country is above the sample median of the corresponding variable.

Table 5 displays the results. The dependent variable is the incidence of violence (odd columns) or the number of ACLED events (even columns). In columns (1) and (2), the variable IQ_i corresponds to the *ICRG Indicator of Quality of Government* (International Country Risk Guide,

[23]One of the most prominent empirical findings is by Mehlum, Moene and Torvik (2006) who show that natural resources hamper economic growth only in the presence of bad institutions. There is also a study by Andersen and Aslaken (2008) that distinguishes different types of democratic institutions in the context of a cross-sectional analysis with economic growth as dependent variable. Our exercise is quite different, as we use disaggregated data and consider conflicts, not economic growth, as a dependent variable.

2013), a standard and synthetic measure of institutional quality at the country-level. In both specifications, the coefficient of the triple interaction is negative, and statistically significant in column (1), while insignificant in column (2). This measure being very coarse, in the following specifications we draw on several more specific indicators of institutional quality, making use of the WGI ("Worldwide Governance Indicators") dataset from Kaufmann, Kraay, and Mastruzzi (2013).[24] We measure IQ_i with the WGI indicators of *Government Effectiveness* (columns (3) and (4)), *Rule of Law* (col. (5) and (6)) and *Voice and Accountability* (col. (7) and (8)). Finally, in columns (9) and (10) we make use of the standard democracy score of Polity IV (2013). Like the previous indicators, Polity IV scores relate to governance and civil servant behavior; but they also capture the other main dimensions of democracy, i.e. political representation and free elections. In columns (3) and (4), the triple interaction has a negative and statistically significant coefficient suggesting that countries with better government effectiveness are less affected by the political instability induced by mining price shocks. By contrast, we detect no effect for *Rule of Law*, *Voice and Accountability*, and for democracy. These results suggest that institutions have an ambiguous effect, with government effectiveness reducing the conflict risk, but freedom of assembly and electoral politics having no impact.

3.4.2 Inequality and Diversity: How Does the Social Fabric Matter?

Social cleavages are considered in the literature as important sources of grievances and conflicts. A natural question consists in assessing whether they also amplify mining-induced violence.[25] In the following we consider three alternative variables of social cleavages at the country-level, namely economic inequality, and ethnic and religious fractionalization. As in Table 5, we binarize each of these variables, a one (zero otherwise) coding for a time-average of the variable that is larger than the cross-country sample median.

The results are reported in Table 6. In columns (1) and (2) we focus on the Gini index of gross income distribution of the "Standardized World Income Inequality Database" (Solt, 2014). Higher Gini scores correspond to larger inequality. The positive estimate of the triple interaction term indicates that higher income inequality amplifies the undesirable effect of mining price shocks; the coefficient is significant at the 10% level in column (2) and the p-value is 0.12 in column (1). The next four columns estimate heterogeneous effects with respect to ethnic and religious fractionalization (both variables are from Reynal-Querol, 2014). While the triple interaction with ethnic fractionalization is not statistically significant in columns (3) and (4), we find in columns (5) and (6) that higher religious fractionalization significantly exacerbates the conflict inducing

[24]The indicators of this dataset are based on a great number of individual variables from 32 data sources. These individual measures are mapped into clusters of key dimensions of government quality, with higher scores indicating better governance. *Government Effectiveness* captures "perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies". *Rule of Law* captures "perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence". *Voice and Accountability* captures "perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media."

[25]There is a small literature finding that the resource curse is mostly present in ethnically fractionalized countries. In particular, Hodler (2006) finds for a cross-section of 92 countries that natural resources reduce economic output only when ethnic or religious fractionalization is large.

Table 6: Heterogeneous effects: Inequality and Diversity

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	Incidence	# conflicts	Incidence	# conflicts	Incidence	# conflicts
Ctry Charac.	Gini		Ethnic Frac.		Religious Frac.	
ln price × mines > 0	0.025	0.032^c	0.069^b	0.076^a	0.020	0.015
	(0.026)	(0.019)	(0.028)	(0.020)	(0.033)	(0.022)
ln price × mines > 0 × Charac.	0.074	0.133^c	0.018	0.082	0.075^c	0.118^b
	(0.047)	(0.078)	(0.049)	(0.092)	(0.043)	(0.048)
Observations	108768	108768	127627	127627	127627	127627

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. All estimations include country×year dummies and cell fixed effects. $log(x+1)$ used for dependent variable in columns (2), (4) and (6). Estimations include cells for which $\text{Var}(M_{kt}) = 0$, i.e. cells in which the mine variable takes always the same value. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. Charac. is a dummy taking the value 1 if the country is above the sample median of the corresponding variable.

impact of mining price spikes.

3.5 Quantification

How large is the effect of mineral price variations on the conflict probability? In our preferred specification (Table 3, column (2)) a standard-deviation increase in the price of all minerals from their mean translates into an increase in probability of violence from 0.167 to 0.201. This is of non negligible magnitude, but concerns only the cells where active mining takes place. When we also consider the surrounding cells (Table 4, column (2)), conflict probability rises from 0.177 to 0.219.

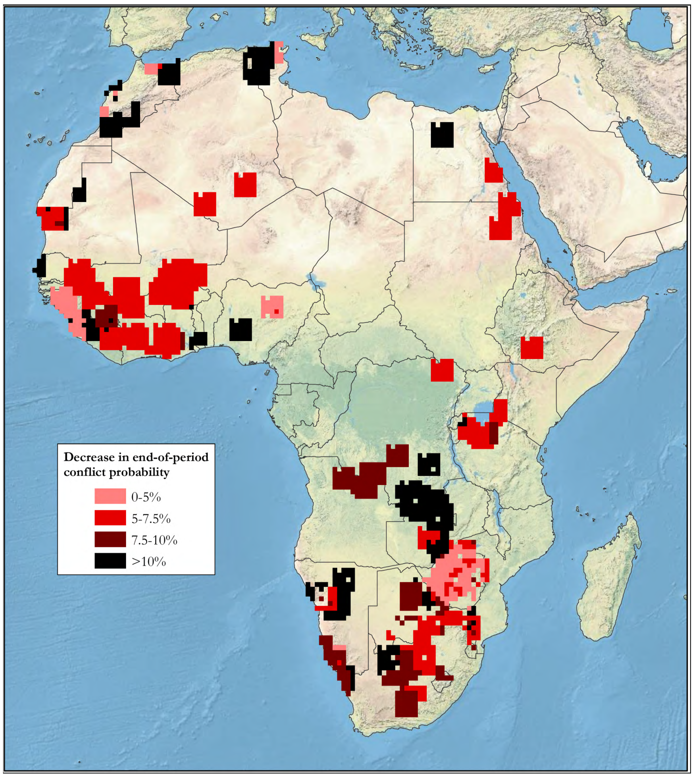
Over the period of our study mineral prices more than doubled on average.[26] For instance, in constant 2005 USD, the ounce of gold was valued at $338 in 1997, and reached $1084 in 2010. This spectacular rise of mineral prices over the 2000-2009 period, known as the *2000s commodity boom* or *commodities super cycle* has attracted quite a lot of attention. There is a consensus among scholars that no contraction of resource supply is to blame, but rather a rapid and substantial increase in demand, particularly so from the BRICS countries. As pointed out by Carter, Rausser and Smith (2011), "strong global demand, especially in lower-middle-income countries" helped set the stage for this commodity price boom, and "this strong demand was reflected in low real interest rates, a declining U.S. dollar, and strong GDP growth, and it contributed to the reduction in inventory levels that made commodity markets vulnerable to supply and demand shocks" (2011: 107). Similarly, Humphreys (2010) points out that the great metals boom between 2003 and 2008 "can be readily explained by the unusual strength of the demand shock and the lagged response of the supplying industry, with prices receiving an additional boost from the activities of commodity investors" (2010: 1).

What has been the effect of the commodity super cycle on conflicts in Africa? Figure 2 shows, by cell, the predicted decrease in the conflict probability that would be observed in 2010 if the prices were the same as in 1997.[27] The regions where conflict probability increases the most

[26] More precisely, they have been multiplied by 2.8 in constant USD. Figure A.6 in the online appendix shows the evolution of the price of each of the minerals.

[27] This counterfactual exercise is based on the estimated coefficients of Table 4, column (2), a specification

Figure 2: The contribution of rising mineral prices to the probability of conflict in Africa

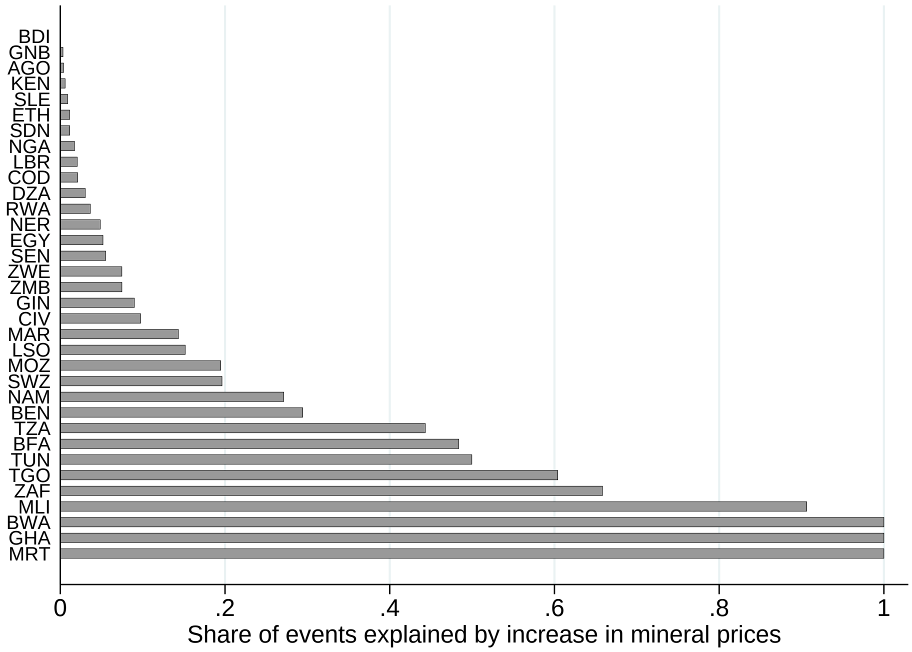


are Western and Southern Africa. When aggregated at the country level, the magnitude of the effect obviously varies with the number of active mining areas in the country. In Figure 3, we compute, for each country with recorded mines, the contribution to the observed violence of this historical rise in mineral prices (see Figure A.1 in the online appendix for the map equivalent).[28] The effect is highly heterogeneous across countries. Averaging across all countries with at least one recorded mine, we find that the historical rise in mineral prices contributed on average to 25% of the observed country-level violence. As is apparent in Figure 3, this number is however inflated by countries, such as Ghana or Mauritania, in which only few conflict events are recorded (see Table 15). When we adopt a more conservative approach and consider only countries with more than 50 events observed over the period, we find that the observed rise in mineral prices

restricted to cells with a permanently active mine over the entire period ($\text{Var}(M_{kt}) = 0$). Our exercise is based on the in-sample predictions for those cells that we complement with the out-of-sample predictions for cells that have a transiently active mine for which price data is available. Put differently, we apply the estimated coefficients of Table 4, column (2), to all cells contained in Table 4, column (1). Note that a number of cells still do not appear in this map as price data is not available for all minerals.

[28]This quantification exercise consists in computing the counterfactual share of events that would not have happened if prices had stayed stable across the entire period. We proceed as follows. First, we compare for each year and cell the predicted number of events for the observed prices with the counterfactual prediction when prices are set at their 1997 level. These predictions are based on column (4) of Table 4, which considers the number of conflict events as a dependent variable. Then, we sum events across cells and years for each country. Finally, we take the ratio of these counterfactual "prevented" events over the total number of events observed in the country during the 1998-2010 period. We consider both in and and out of sample predictions. For quantifications restricted to the cells present in column (4) of Table 4, see online appendix, Figure A.2.a. Also in the online appendix, Figure A.2.b contains a similar quantification but based on column (2) of Table 3, i.e. it does not take into account the mines active in surrounding cells. As expected, the effects are smaller.

Figure 3: The contribution of rising mineral prices to violence in Africa



contributed to a 14.5% of the observed violence.[29] In the online appendix (Figures A.3.a and A.3.b) we consider a more extreme thought experiment where we quantify the impact on violence of a closing of all mines in Africa. As expected, the effects are even larger: the number of conflicts falls by as much as 60-80% in Zimbabwe or Burkina Faso; and in most countries, the number of conflicts decreases by more than 20%.

We have several reasons to believe that these numbers are conservative estimates. First, our dataset is not exhaustive: only two percent of the cells contain active mines; we consider surrounding cells as well, but many small-scale mines are not included, although they may have a significant impact on violence, adding up to the one we identify here; further, not all minerals are taken into account in these estimations. Therefore, Figure 2 is probably a lower bound of what would be predicted if the same estimations were run on an exhaustive dataset. Second and more importantly, our results only deal so far with the local and contemporaneous impact of mining on violence. In the next section, we emphasize how mining can diffuse violence over space and time, by improving the financial means of armed groups.

4 The diffusion of mining-induced violence over space and time

So far our empirical analysis has focused on local violence, i.e. in the immediate surroundings of mining areas. In this section we take a more global view by investigating the diffusion over space and time of mining-induced violence. The idea is to understand whether mining activity is a factor of escalation from local violence to large-scale conflict. This would be the case if

[29] Alternatively we can aggregate violence *at the continental level*. In that case the contribution of mineral prices to violence is 4.6%, reflecting the fact that increases in prices have a relatively small effect on the countries in which the lion's share of conflict events are recorded (Angola, Democratic Republic of Congo).

mineral rents finance rebellions, i.e. make rebel movements easier to set up and sustain, or, put differently, make conflict *feasible*. The main objective of this section is to test for this mechanism by exploiting the various dimensions of our data – time-series, geo-location, information on the outcome of the violent events, their type, and the identity of the perpetrators.

4.1 The nature of mining-induced violence

From the Wild West to South Africa, there is an abundance of narratives about how dangerous and lawless the mining areas are. They attract a selected subsample of the population, mainly composed of young and uneducated males; labor regulation is often lenient, not to say absent; property rights enforcement is a challenge and this weak institutional environment makes them particularly crime-prone (see Couttenier, Grosjean, and Sangnier (2014) for statistical evidence on homicide rates in US mining areas). By nature, such violence, rooted in riots and protests, is likely to be spatially concentrated around mining areas. By contrast, battles between fighting groups over the control of mines can spread over the space as appropriation relaxes the financing constraints of future fighting capacity. Uncovering the nature of mining-induced violence is thus crucial for understanding whether it can escalate from the local to the global level. Here we provide evidence that different types of events (in terms of scale and objectives) are affected by changes in mineral prices.

Table 7: Minerals price and types of conflict events

	(1)	(2)	(3)	(4)	(5)	(6)
			OLS			
Sample	$\text{Var}(M_{kt}) = 0$		$\text{Var}(M_{kt}) = 0$		$\text{Var}(M_{kt}) = 0$	
Dependent conflict var.	Battles		Violence against civ.		Riots / Protests	
	Incidence	# events	Incidence	# events	Incidence	# events
ln price × mines > 0	0.018^a	0.014^b	0.046^b	0.027	0.041^a	0.076^b
	(0.006)	(0.006)	(0.023)	(0.017)	(0.015)	(0.030)
Observations	142257	142257	142257	142257	142257	142257
R^2	0.357	0.446	0.384	0.499	0.402	0.543
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. $log(x+1)$ used for dependent variable in columns (2), (4) and (6). $\text{Var}(M_{kt}) = 0$: only cells in which the mine variable takes always the same value. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t.

In Table 7 we replicate our baseline specifications (columns (2) and (4) of Table 3) for each of the three categories of violent events covered by the ACLED dataset: battles between fighting groups, protests/riots, and violence against civilians. As expected, we find that an increase in mineral prices leads to more riots and protests (columns (5) and (6)) and more violence against civilians, though with a less significant coefficient (columns (3) and (4)). More importantly, however, the occurrence of battles is also significantly affected by changes in the value of mines, as shown in columns (1) and (2) confirming that the appropriation of mines is a key driver of violence.[30]

[30]The size of the coefficients is smaller here than in our baseline results, reflecting the fact that the unconditional probability of observing specific types of events is smaller than the probability of observing any type of event, as shown in Table 1.

4.2 Feasibility and the diffusion of violence

We now focus our empirical analysis on the channel of feasibility. The logic is that rebel groups, by controlling mining areas, can step up their military capacity and enlarge the scope of their operations. This can result in spatial diffusion and escalation of the conflict. Rebel groups do not need to operate the mines themselves; they can also extract rents from mining areas through bribing / extorsion. The main empirical challenge consists in retrieving information on the effective presence and influence of groups in mining territories. We follow two different approaches. First, we assume that rebel groups benefit disproportionally more from the extractive rent of mines that are located in their ethnic homeland. This has the statistical virtue of leading to a relatively large sample of mine-group combinations. Still, the match between ethnic affiliation and effective control of mining rents may not always be fully accurate, as some groups operate far beyond their group homelands. Hence, we also follow a second approach where we use unique ACLED information on battle-induced territorial changes in areas with or without mines. This second approach is more precise, but is based on a relatively small number of events.

In the following, we extend our dataset in a new dimension, namely the fighting group operating in each grid cell. We restrict our analysis to the 252 rebel groups that are active in our sample, ignoring other types of fighting groups. ACLED considers as rebel groups "political organizations whose goal is to counter an established national governing regime by violent acts."[31] We do not consider smaller groups (e.g. "political militias" and "communal militias") because they are more local, and contrary to rebel groups, their objective is not to replace or change the political regime in power.[32]

4.2.1 Mines located in ethnic homelands

We first test whether positive price shocks on the minerals extracted in the ethnic homeland of a rebel group boost its fighting operations. Exploiting ACLED information on the identity of the rebel groups, we assign to each group a main ethnic affiliation, based on the ethnicity of the group's leaders and troops. Out of the 252 rebel groups of our sample, we are able to identify the presence or the absence of an ethnic affiliation for 83% of the rebel groups; the 17 remaining percent are dropped from the analysis.[33] Then we use the geo-coordinates of ethnic homelands from the "Georeferencing of ethnic groups" (GREG) dataset (Weidmann, Rod and Cederman, 2010) to build the number of mines and main minerals produced in the ethnic homeland of each armed group.[34] Equipped with this new dataset, we define (rebel group$\times$year) as an observation

[31] The rest of the definition states that "Rebel groups have a stated political agenda for national power, are acknowledged beyond the ranks of immediate members, and use violence as their primary means to pursue political goals. Rebel groups often have predecessors and successors due to diverging goals within their membership. ACLED tracks these evolutions."

[32] This is the distinction that ACLED makes between these groups and rebel groups: "militia activity is orientated towards altering political power to the benefit of their patrons within the confines of current regimes, whereas the goal of a rebel group is the replacement of a regime."

[33] Examples of matches are "Lord's Resistance Army" that is linked to the "Acholi" ethnic group, "National Movement for the Liberation of Azawad" that is composed of "Tuaregs", and "Ogaden National Liberation Front" that is associated to the "Somali" ethnic group.

[34] GREG includes the geographical location of all ethnic groups, based on the famous "Soviet Atlas Narodov Mira" from 1964. While this Atlas has the downside of being somewhat dated, it has the advantage of addressing concerns of reversed causation that would arise if we were to use current ethnic group homelands (i.e. our dependent variable, conflict in the years 2000, could affect current group location). Note that the main competing dataset, GeoEPR, suffers from the fact that it only includes ethnic groups that are judged as politically relevant, which

cell and we estimate the following specification:

$$\textsc{Conflict}_{gt} = \beta_1 \ln p_{gt}^W + \beta_2 \ln p_{gt}^W \times M_g + \mathbf{FE}_{gi} + \mathbf{FE}_{it} + \varepsilon_{gt}$$

where g denotes a specific rebel group, t the year and i the country. $\textsc{Conflict}_{gt}$ is a dummy for the incidence of conflict or the number of events recorded for group g during year t. $\ln p_{gt}^W$ is the world price of the main mineral produced by mines located in the homeland of the main ethnicity of rebel group g (the mineral observed in the largest number of cells) and M_g is the average number of mines producing this mineral in the homeland over the period. The coefficient of interest, β_2, is a proxy for the mining-related financial capacity of the group. We expect it to have a positive sign, as better funded groups are able to extend their fighting operations. Note that this is a somewhat imprecise proxy of effective control of the mining rents – subject to measurement errors – as the historical ethnic homelands information corresponds to a snapshot of the 1960's.

Table 8: Feasibility - Mines in ethnic homelands

	(1)	(2)	(3)	(4)
Estimator	OLS			
Dep. var.	Incidence	# conflicts	Incidence	# conflicts
Conflict zone	Unrestricted		Outside ethnic homelands	
ln price main mineral	-0.409^c	-0.609	-0.366	-0.571
	(0.238)	(0.467)	(0.229)	(0.457)
ln price × # mines	0.334^b	0.379	0.305^b	0.354
	(0.140)	(0.297)	(0.137)	(0.294)
Observations	2226	2226	2184	2184
R^2	0.425	0.539	0.427	0.554
Country×year FE	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by actor in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. All estimations include country× year and actor×country fixed effects. Cols. 3-4 keep in the sample only the cells which are never considered as mining areas over the period (including surrounding cells).

Table 8 displays the results. In column (1) the dependent variable is (unrestricted) conflict incidence accounting for violence involving the rebel group inside and outside its ethnic homeland. As expected, the coefficient of the interaction term is positive and statistically significant. In column (2) the dependent variable corresponds to the (unrestricted) number of conflict events. The coefficient is again positive but we lose statistical significance. We replicate these specifications in columns (3) and (4) with the restricted definition of the dependent variable that now accounts for conflict incidence (or number of conflict events) only *outside* the ethnic homelands of the rebel group. The estimates are unchanged. Hence this last result shows that a rise in the price of minerals extracted in their ethnic homelands enables groups to increase their fighting activity out of their homeland. This is a first piece of evidence documenting the spatial diffusion of mining-induced violence.

could result in a selected sample.

4.2.2 Changes in territory

An alternative approach consists in assessing directly the impact on groups' future fighting activity of conquering a mining area after a victorious battle. For each battle, our data detail the name and type of fighting groups on each side – government, rebel groups, militias, foreign powers, civilians – and the outcome of the battle – who won and gained (or kept) the territory. This information is at the core of identifying the feasibility mechanism.

We use a balanced dataset containing, for each rebel group, all combinations of grid cells × years where the group can potentially be active. Here we allow each rebel group to be potentially present in all cells of the countries in which it has been involved in at least one event over the period.[35] The unit of observation is now a grid cell × year × rebel group. We replicate Table 3 on this sample and check that our baseline results are robust to this data reshuffling and to restricting violence to battle events only (Table A.20).

To test for the diffusion over space and time of mining-induced battles, we further restrict our analysis to rebel groups and estimate a LPM of the probability of outbreak of a *new* event involving a group g in cell k in year t:

$$\text{ONSET}_{gk,t} = \alpha \times \text{BATTLE}^{0}_{g,t-1} + \beta \times \text{BATTLE}^{\mathbf{m}}_{g,t-1} + \mathbf{FE}_{gk} + \mathbf{FE}_{it} + \varepsilon_{gkt}, \qquad (4)$$

where $\mathbf{FE}_{gk}$ are group×cell fixed-effects. $\text{ONSET}_{gk,t}$ is a binary variable equal to one if group g is involved in an event in year t in a cell k that was at peace in $t-1$; it is zero if the cell is still at peace in year t. Notice that we deliberately focus on event outbreak and not on incidence; henceforth the observation is dropped out of the sample if g perpetrates violence in k in $t-1$. Our main explanatory variables are $\text{BATTLE}^{0}_{g,t-1}$ and $\text{BATTLE}^{\mathbf{m}}_{g,t-1}$. The first corresponds to the total number of battles won by the group g the year before, conditional on none of the battles being won in mining areas. $\text{BATTLE}^{\mathbf{m}}_{g,t-1}$ is the total number of battles won in $t-1$, conditional on at least one battle being won within a mining area.[36] The two coefficients α and β could be either positive or negative depending on the underlying process governing the dynamics of battles: negative if battle occurrence is mean reverting; positive in presence of unobserved transient shocks that, for example, impact the fighting capacity of a group. However, our test of the spatial and time diffusion of mining-induced violence does not rest upon the absolute level of these coefficients but on their relative value as we expect $\beta > \alpha$: winning in $t-1$ a territory containing active mining increases the probability of battle onset *in other cells* in t more than winning a territory with no active mine. The implicit assumption here is that winning a battle on a mining area enables the rebel groups to appropriate mining rents. In all specifications, the standard errors are clustered at the same level than our main explanatory variables, namely at the rebel group level.

Before turning to regression results, we first report some simple statistics. The sample size is very large (more than 1.9 millions observations) as the unit of observation is now a grid cell × year × group. It contains 252 groups operating in 39 countries. Each group operates in 1.7 countries on average. The dependent variable $\text{ONSET}_{gk,t}$ is equal to one for 4,298 observations (0.21% of the observations). The number of battles won is non-zero for 151,567 observations

[35] For instance, the Lord's Resistance Army is assumed to be potentially operating in all cells of Central African Republic, DRC, Sudan and Uganda.

[36] We include the establishment of headquarters in the battles won, as it is also a case of rebel groups gaining the territory. The results are similar if we exclude these.

(7.28%). Among these, 6,340 correspond to battles won in mining areas. This may seem to be a large amount of observations, but it actually represents only 0.30% of the sample size and 67 events. This data limitation prevents us from including an interaction term with the world price of minerals.

Table 9: Feasibility and the diffusion of war (1/2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Conflict onset						Conflict onset
Estimator	OLS						OLS
$\text{Battle}_{g,t-1}$ outcome	Rebels won territory						No change
$\text{Battle}_{g,t-1}$ (dummy)	0.005^{a}						
	(0.001)						
# $\text{battles}_{g,t-1}$		0.003^{a}					
		(0.001)					
$\text{Battle}_{g,t-1}$ (dummy, no mine)			0.004^{a}		0.004^{a}		
			(0.001)		(0.001)		
$\text{Battle}_{g,t-1}$ (dummy, mine)			0.023^{a}		0.024^{a}		
			(0.003)		(0.004)		
# $\text{battles}_{g,t-1}$ (no mine)				0.002^{a}		0.002^{a}	
				(0.000)		(0.000)	
$\text{Battle}_{g,t-1}$ (dummy, mine)				0.007^{a}		0.007^{a}	
				(0.002)		(0.002)	
# $\text{battles}_{g,t-1}$ (no mine)							0.002^{a}
							(0.000)
# $\text{battles}_{g,t-1}$ (mine)							0.002^{a}
							(0.001)
Difference in coefs.			0.018^{a}	0.005^{b}	0.020^{a}	0.005^{c}	0.001
			(0.004)	(0.002)	(0.005)	(0.002)	(0.001)
Observations	1942340	1942340	1942340	1942340	1942340	1942340	1942340
Year dummies	Yes	Yes	Yes	Yes	No	No	Yes
Country×year FE	No	No	No	No	Yes	Yes	No
Actor-Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by actor, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. # battles variables are expressed as $\log(x+1)$.

Table 9 displays the results. In columns (1) and (2), the explanatory variable corresponds to a dummy taking the value 1 if a rebel group won at least one battle in $t-1$ (column (1)) or to total number of battles won by a rebel group (column (2)). In both specifications we find a positive and significant coefficient, meaning that rebel groups winning a battle in a given year tend to initiate more fighting one year later. This finding could be either driven by the empowerment of rebels after victory or by some unobserved time-persistent variation in rebel strength (i.e. aggressive and strong rebels are more likely to win today and attack tomorrow). In columns (3) to (6), we estimate equation 4 where battles won in mining areas are accounted separately from battles won in non-mining areas. Whatever the coding strategy (dummy or number of battles) and whatever the battery of fixed effects, we find that β is statistically significantly larger than α in all specifications. This finding shows that the appropriation of mining areas increases the probability of perpetrating violence elsewhere in the territory one year after. We interpret it as supportive of the view that mineral rents finance rebellions.

Note that one potential bias in our estimation could arise if groups attacking mines had different unobserved characteristics than other groups engaged in battles in non-mining areas. However, time-invariant group differences are filtered out by group×cell fixed-effects. Hence, if for example a given group is always much bigger and stronger or of other ideological orientation than some other group, this difference would be picked up by the group×cell fixed-effects and no bias in our estimates would arise. Still, it would be more worrying if time-varying group characteristics were correlated with the decision to fight in mining areas, e.g. a situation where groups get stronger or weaker over time and only dare attacking a mine when they are strong. We implement in column (7) a simple placebo test with the idea of testing that our results are not driven by such unobserved transient shocks affecting groups' fighting capacity. To this purpose, we estimate equation (4) for battles that have *not* been won by rebels (i.e., events in which there is no change of territory). As expected, we find that α and β are extremely close and not statistically different at standard confidence levels. We go further in the online appendix (Table A.21) by replicating Table 9 with group-specific time trends included in all specifications. This is a pretty demanding exercise. Reassuringly, the estimates are stable and β is statistically significantly larger than α in all regressions.

We now document the spatial and time decays of this process of diffusion of mining-induced violence. In Table 10 we restrict our analysis to the rebel groups that were active in $t-1$. Columns (1) and (2) reproduce the estimations of Table 9, columns (4) and (5), on the sample of rebel groups active in $t-1$. Our results are very similar. In columns (3) and (4) we include the first and second time-lags of $\text{BATTLE}^{0}_{g,t-1}$ and $\text{BATTLE}^{\mathbf{m}}_{g,t-1}$. The difference between the coefficients of the two variables is still significant for battle won in $t-2$ (column (3)), but becomes insignificant in $t-3$ (column (4)). In columns (5) and (6), we study how the probability of conflict in t depends on the *distance* to previous battles. In column (5) we interact the lagged battles variable with the average distance between these battles and the cell's centroid; we indeed find that winning battles in $t-1$ increases conflict probability more in cells located nearby. In column (6) we distinguish battles won in cells located in a mining region. We find that conflicts first diffuse to neighboring cells in both cases; however, when mines are involved, the scope of the diffusion is much larger. This can be seen in Figure 4 where we have plotted the marginal effect of battles won in $t-1$ on the probability of conflict onset in t as a function of distance to the battles from column (6) (hence the log-linear shape). The probability of conflict increases by around 1 percentage point if a territory containing no mine was won within a 100 kilometers. The effect is significant up to around 400 kilometers (Figure 4.a). In cases where battles happened in mining areas (Figure 4.b), on the other hand, the probability increases by up to 5 percentage points in the close surroundings of the battles and remains significant up to 1000 kilometers around. This clearly suggests that mining-induced violence diffuses across space.

Finally we can quantify in a simple way the extent to which the conquest of a mining area exacerbates future violence. From Table 9 we see that the appropriation of a mining area in year t increases by 2.3 percentage points the cell-level probability of an event occurring in year $t+1$. Given that a rebel group is active in 419 cells on average, this leads to $0.023 \times 419 = 9.6$ additional events. This represents a 250% increase in rebel fighting activity (average number of events by group-year being 3.78). Admittedly this back-of-the-envelop calculation is very rough.

Table 10: Feasibility and the diffusion of war (2/2)

	(1)	(2)	(3)	(4)	(5)	(6)
			Conflict onset			
Estimator			OLS			
Sample			Groups active in $t-1$			
# battles$_{g,t-1}$	0.002				0.039^a	
	(0.002)				(0.010)	
# battles$_{g,t-1}$ (no mine)		0.002	0.001	0.002		0.036^a
		(0.002)	(0.002)	(0.002)		(0.010)
# battles$_{g,t-1}$ (mine)		0.007^a	0.008^a	0.008^a		0.170^a
		(0.002)	(0.002)	(0.002)		(0.017)
# battles$_{g,t-2}$ (no mine)			-0.001	0.000		
			(0.001)	(0.001)		
# battles$_{g,t-2}$ (mine)			0.004^a	0.005^a		
			(0.002)	(0.002)		
# battles$_{g,t-3}$ (no mine)				-0.002^b		
				(0.001)		
# battles$_{g,t-3}$ (mine)				-0.002		
				(0.005)		
ln average distance to battles$_{t-1}$					0.003	0.003
					(0.003)	(0.003)
# battles$_{g,t-1}\times$ ln av. dist.					-0.006^a	
					(0.001)	
# battles$_{g,t-1}$ (no mine) $\times$ ln av. dist						-0.005^a
						(0.001)
# battles$_{g,t-1}$ (mine)$\times$ ln av. dist.						-0.024^a
						(0.003)
Observations	217704	217704	217704	201948	217704	217704
R^2	0.369	0.369	0.369	0.374	0.369	0.370
Country$\times$year FE	Yes	Yes	Yes	Yes	Yes	Yes
Actor-Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by actor, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. # battles variables are expressed as $\log(x+1)$.

But it supports the view that mining activity, through the feasibility channel, is an important driver of escalation from local violence to large-scale conflict.

5 Turning the Mining Curse Into a Blessing: the role of mining companies

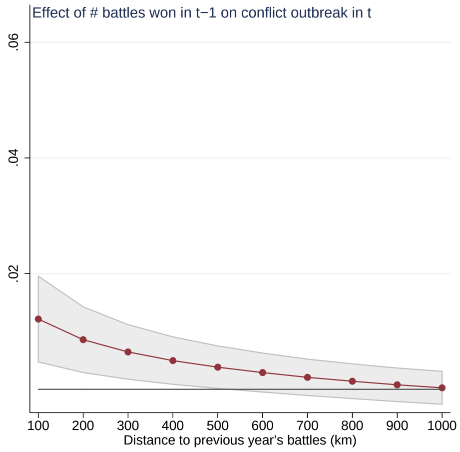
The previous section has focused on the role of fighting groups. But the behavior of mining companies may also play an important part. In this section, we study specifically the role of companies' characteristics and management practices on the presence and propagation of violence.

5.1 Companies' Characteristics: Does Mine Ownership Matter?

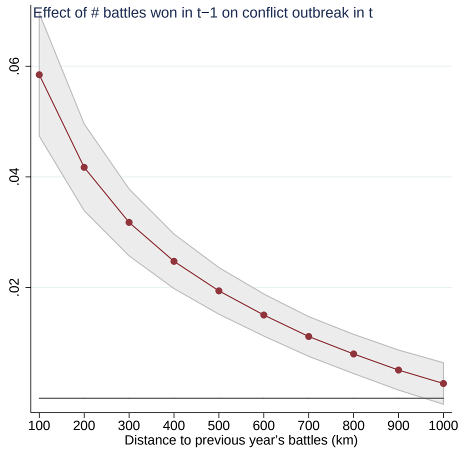
By operating mines in conflict-prone environments, companies potentially play a central role

Figure 4: Feasibility and the spatial diffusion of conflicts

(a) No mines won in $t-1$



(b) Mines won in $t-1$



in the logic of violence: At the local level they could be more or less willing to secure mining areas where they plan to operate (e.g. with the help of governmental troops or private militias). And even more importantly, the escalation of conflict may be impacted by their propensity to finance/bribe, often in an illegal and opaque way, the rebel groups that control the territories surroundings the mines – the terms of the implicit agreement being bribes in exchange of "protection" by rebel groups in order to guarantee companies' efficiency in large-scale extraction. Hence, understanding the role of firms' behavior is clearly of foremost importance, both from a positive and policy perspective.[37] For this purpose we exploit a unique feature of our dataset, i.e. that it contains information on the identity of the owning company and the country of its headquarter.

Let us start first with a short overview of the companies that are present in our dataset. Table 16 in the appendix displays some descriptive statistics. Most of the firms that we observe in our sample are foreign owned (56 percent). A tenth of mines are publicly owned by the domestic government and the residual category (34 percent) is composed of domestic private firms. We should typically expect that not all foreign firms benefit from the same level of protection by the domestic government. A US firm operating in a country with a traditionally left-leaning government may not be as well protected as a firm belonging to a country with strong connections to the local elite, such as, say, a Belgian company operating in the Democratic Republic of Congo. One somewhat crude classification of foreign firms that captures this divide is the distinction between firms from a foreign colonizer country versus foreign firms with registered headquarter in a country without colonial ties to the country where the mine is located. We can see that among foreign firms, roughly a fifth have their headquarter located in the country that was the former colonizer. Another salient distinction is between major (i.e. large) foreign firms and smaller ones, whereas about 60 percent or foreign firms belong to the group of large multinational firms.[38]

[37] While, as discussed above, there has been some related work on the impact of institutions on the resource curse, the modulating role of firm characteristics is severely under-studied. One of the reasons for this gap in the literature is that in most datasets precise firm characteristics are typically missing.

[38] In the RMD dataset, a mine is considered as owned by a "major" company if the corresponding company belongs to the world top ten in terms of production of the corresponding mineral in a given year.

In Table 11 we investigate how the type of ownership impacts mining-induced violence. Each category of ownership, Foreign firms, Domestic public firms and Dom. private firms, is coded with a dummy variable that is interacted with our main effect ($M_k \times \ln p^W_{kt}$). We retain the ownership status at the beginning of the sample period for the sake of exogeneity (i.e. self-selection). Note that due to perfect collinearity with the three (triple) interaction terms, the baseline interaction term ($M_k \times \ln p^W_{kt}$) drops from the specification.

Table 11: Heterogeneous effects: Firm ownership

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.	—— All Events ——				—— Battles ——			
	Incidence	# conflicts	Incidence	# conflicts	Incidence	# conflicts	Incidence	# conflicts
ln price × mines × Dom. private	0.051^a	0.043	0.014	0.014	0.011	0.011	0.014	0.017
	(0.016)	(0.041)	(0.009)	(0.009)	(0.009)	(0.009)	(0.015)	(0.011)
ln price × mines × Dom. Public	0.025	0.052	-0.009	-0.007	-0.007	-0.005	-0.007	-0.005
	(0.041)	(0.067)	(0.014)	(0.015)	(0.013)	(0.014)	(0.012)	(0.014)
ln price × mines × Foreign Fims	0.091^b	0.153^a	0.030^a	0.024^b				
	(0.036)	(0.057)	(0.011)	(0.011)				
ln price × mines × Fgn (colonizer)					-0.011	-0.012^c	-0.008	-0.004
					(0.010)	(0.006)	(0.013)	(0.014)
ln price × mines × Fgn (non col.)					0.057^a	0.048^a	0.060^b	0.055^b
					(0.018)	(0.017)	(0.025)	(0.026)
ln price × mines × Large							-0.005	-0.011
							(0.020)	(0.019)
Observations	142145	142145	142145	142145	142145	142145	142145	142145
R^2	0.446	0.563	0.357	0.446	0.357	0.446	0.357	0.446

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. $log(x+1)$ used for dependent variable in even numbered columns. Estimations include cells for which $\mathrm{Var}(M_{kt}) = 0$, i.e. cells in which the mine variable takes always the same value. mine is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. The companies characteristics (foreign, domestic public, domestic private, etc) are dummies coded 1 if the cell contains at least one mine of the corresponding type. Cells containing only mines with missing ownership information are dropped.

In columns (1) and (2) all conflict events are included, while in columns (3) and (4) only battle events are considered, for which the role of political protection and connections are arguably particularly salient. While there is some weak support for the hypothesis that mineral price shocks fuel violence for domestic privately owned firms, the only consistent and statistically significant effect in all columns is found for foreign firms. In contrast, there is no indication that mining price shocks induce conflict in mining areas controlled by domestic publicly owned firms. This finding is consistent with at least two explanations: First, it could be that state owned companies are better protected by the national army and hence harder to capture by rebels (who are deterred to attack them), and/or second, it could be that they are reluctant to pay bribes and extortion money, which would make indirect control of the mining area by rebel forces less lucrative. By analogy, the fact that we find strongly significant effects for foreign firms is consistent with either the view that mining areas operated by foreign firms are less well protected and/or the view that foreign firms are more easily willing to pay extortion money to rebels. In columns (5) and (6) we replicate columns (3) and (4) with the foreign firms category that is now split into "foreign firms from former colonizer country" and "foreign firms without colonial ties". We find striking differences: Foreign firms with a headquarter in the former colonizer country are very comparable to domestic state-owned firms as they are not associated to any political instability after mineral price shocks. In contrast, mines owned by foreign firms without colonial ties experience a quantitatively large, statistically significant effect on boosting the conflict potential when mineral prices rise. The difference between the triple interaction coefficients of FOREIGN FIRMS (COLONIZER) and FOREIGN FIRMS (NON COLONIZER) is statistically significant at the 1 percent level. Again, this could be due to greater vulnerability in the absence of state protection, or due to "dirty" business practices such as paying bribes and extortion money that could invite mining area takeovers by rebels. In columns (7) and (8) we control for the interaction with LARGE FIRM. The results are unchanged, meaning that the previous finding is not a sheer size effect.

Are these results due to stronger protection of certain types of mines or to the companies' practices? In order to inquire in further depth what mechanisms (protection or extortion) could drive these heterogeneous effects with respect to different ownership categories, we focus below on battles won, as in subsection 4.2.2. Studying the scope for conflict diffusion after the conquest of a mining territory by a rebel group is a way to abstract from the fact that some mining areas are potentially better protected than others. Hence, if we find heterogeneous effects across categories of firms in the aftermath of a conquest, this is likely to be linked to differential reactions to extortion attempts by rebels.

Table 12: Heterogeneous effects: Battles won

	(1)	(2)
	Conflict onset	
Estimator	LPM	
$\text{Battle}_{g,t-1}$ outcome	Rebels won territory	
$\text{Battle}_{g,t-1}$ (dummy, no mine)	0.004^{a}	
	(0.001)	
$\text{Battle}_{g,t-1}$ (dummy, mine)	0.028^{a}	
	(0.001)	
$\text{Battle}_{g,t-1}$ (dummy, mine) × Public Firms	-0.024^{a}	
	(0.005)	
# $\text{battles}_{g,t-1}$ (no mine)		0.002^{a}
		(0.000)
# $\text{battles}_{g,t-1}$ (mine)		0.010^{a}
		(0.002)
# $\text{battles}_{g,t-1}$ (mine) × Public Firms		-0.029^{a}
		(0.004)
Observations	1942340	1942340
R^2	0.148	0.148

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by actor, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. # battles variables are expressed as $\log(x+1)$.

In our dataset, among the battles won by rebel groups, we do not observe any instances of rebels capturing a foreign owned mine. This means that the only comparison we can make is between mines owned by domestic private firms and mines owned by domestic state-owned firms. Note that in Table 11 we find some support for the fact that mines owned by domestic private firms experience more violence in the presence of price shocks. In contrast, we detect no effect for state-owned firms. Starting from our preferred specifications of Table 9 (columns (3) and (4)) we include an interaction term between the variable of interest, battles won in mining areas, and a dummy coding for the owning company being public. Results are shown in Table 12. From column (1), the main effect remains positive and statistically significant but is counterbalanced by the interaction term that is negative, statistically significant, with the same magnitude. Hence the conquest of a mining territory by a rebel group leads to conflict diffusion only when the the mine is owned by a domestic private firm; the effect goes away when the mine is state owned. Column (2) displays similar results for the number of battles won. One of the potential mechanisms that is consistent with these results is the view that state-owned firms are more reluctant to pay bribes and extortion money to rebel forces and this makes the control of a mining area less lucrative for rebels. As they find it harder to extract quick cash of the mines their conflict escalation effort is brought to a halt.

5.2 Promoting Good Practices: Does Transparency Matter?

A government that is respectful of property rights may find it difficult to engineer the ownership status of mining companies operating in its national territory. Yet, policy interventions targeting bribing practices of mining companies might be able to curb conflict. International policy makers have recently started to promote transparency and traceability in the mining industry. Examples include the US legislation requiring US firms to certify that their purchases of particular minerals are "DRC conflict free", as well as the several international initiatives aimed at encouraging good practices among extractive companies and tracking the origins of minerals. For instance, the "Mineral Certification Scheme of the International Conference on the Great Lakes Region (ICGLR)" tracks the sales of gold, cassiterite, wolframite, and coltan. Similar certification efforts are underway in the tin and tantalum industries. In the same vein, several countries have adopted international standards for managing in an open and accountable way the extractive rent, e.g. by fully disclosing royalties.

While many conceptual policy memos have been written on transparency and certification schemes, there is virtually no hard evidence so far on the conflict-decreasing impact of these schemes in reality. We address this issue in Table 13. The analysis is restricted to battle events and foreign firms, which is the category of firms that drives most of the conflict-fueling effect of mining price spikes (see Table 11). The dependent variable is battle incidence, respectively number of battles, and we exclude from the sample all mines that are not foreign owned.

In columns (1) and (2) the variable of interest is the interaction of mining price shocks with a country-level score of anti-corruption from Transparency International (2012).[39] The estimates show that mining-induced violence is maximal for highly corrupt countries, and vanishes in highly clean countries. In columns (3) and (4) we interact mining price shocks with a dummy coding for firms' membership to the "International Council on Mining and Metals" (ICMM) —a network of companies promoting Corporate Social Responsibility in the mining industry.[40] We find in column (3) that mines operated by companies complying to CSR practices are associated with less violence. In column (4) the coefficient of interest keeps its sign but loses significance.

This suggests that firms' compliance to socially responsible behaviors reduces violence. Could

[39]The "Corruption Perceptions Index" focuses on public sector corruption and "relates to perceptions of the degree of corruption as seen by business people, risk analysts and the general public". It ranges between 0 (highly corrupt) and 10 (highly clean).

[40]See http://www.icmm.com.

Table 13: Heterogeneous effects: The Role of Transparency

Dep. var.	(1) Incidence	(2) # conflicts	(3) Incidence	(4) # conflicts	(5) Incidence	(6) # conflicts	(7) Incidence	(8) # conflicts
ln price × mines	0.121^a	0.103^a	0.058^b	0.062^b	0.060^b	0.064^c	0.048^c	0.061^c
	(0.035)	(0.035)	(0.027)	(0.030)	(0.030)	(0.032)	(0.026)	(0.032)
ln price × mines × Large Firms	-0.026	-0.046	-0.030	-0.046	-0.035	-0.048	-0.025	-0.046
	(0.034)	(0.038)	(0.032)	(0.033)	(0.031)	(0.032)	(0.030)	(0.034)
ln price × mines × Anti-Corruption (TI)	-0.020^a	-0.012^a						
	(0.005)	(0.004)						
ln price × mines × Firm CSR (ICMM)			-0.028^a	-0.008				
			(0.009)	(0.010)				
ln price × mines × Tracea. Init. (EITI)					-0.000	-0.001		
					(0.001)	(0.001)		
ln price × mines × Tracea. Init. (GLR)							0.003	0.000
							(0.004)	(0.002)
Observations	131182	131182	141697	141697	141697	141697	141697	141697
R^2	0.357	0.453	0.357	0.447	0.357	0.447	0.357	0.447

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. $log(x+1)$ used for dependent variable in even numbered columns. Only foreign firms and battle events considered in this table. Estimations include cells for which $\text{Var}(M_{kt}) = 0$, i.e. cells in which the mine variable takes always the same value. mine is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. See main text for a description of the various transparency variables.

it be that top-down initiatives aiming at imposing good practices have such as a dampening effect? We consider in columns (5)-(8) two country-level transparency initiatives, the "Extractive Industries Transparency Initiative" (EITI) and the "Mineral Certification Scheme of the International Conference on the Great Lakes Region (ICGLR)". The former initiative imposes to its member countries to fully disclose taxes and payments made by mining companies to their governments; the latter tracks the origin of a number of metals.[41] The ICGLR aims – among others - at identifying mines which are related to conflicts, e.g. through illegal control, taxation, or extortion.[42]

In each specification we interact mineral prices with a dummy coding for country membership (for the relevant minerals). In none of these specifications any significant effect can be detected. Aside from measurement errors, this suggest that international transparency schemes have not been fruitful (yet) in reducing mining-induced violence. This is in line with many recent press releases that point out that these transparency schemes are in many cases not implemented.[43]

6 Conclusion

In this paper we provide a systematic analysis of the impact of all major mineral extraction on the likelihood of armed conflict in Africa, using novel and very fine-grained panel data with a spatial resolution of 0.5 × 0.5 degree latitude and longitude and covering the 1997-2010 period. After carrying out the cross-sectional comparison between mining areas and non-mining areas, we have analyzed the within-cell variations in violence driven by the opening and closing of mines. We have then moved to a tighter identification strategy based on exogenous variations in the world

[41] See https://eiti.org/eiti. and http://www.pacweb.org/en/regional-certification.

[42] See http://www.oecd.org/investment/mne/49111368.pdf.

[43] For example, "a report by Amnesty International and Global Witness has alleged that nearly 80 percent of US firms are failing to adequately check their supply chains for conflict minerals" (BBC, 22 April 2015, http://m.bbc.com/news/business-32403315).

prices of minerals produced in the area. We find a strongly significant and quantitatively large impact of mining activities on the likelihood of conflict incidence. According to our estimates, the *commodities super cycle* (i.e. steep increase in mineral prices during the 2000s) accounts for 15 to 25% of the average violence observed in African countries over 1997-2010. We perform numerous sensitivity tests and show that the results are robust to a variety of alternative specifications, addressing concerns related to the exogeneity of world prices, measurement issues and other estimation biases.

This first systematic disaggregate study of the causal impact of minerals on fighting has the virtue of closing a gap in the literature on conflict. Maybe even more importantly, our fine-grained data also allow us to carry out an in-depth analysis of possible mechanisms through which mineral rents could fuel fighting efforts and lead to the escalation of violence over space and time. In particular, we find that mining activity does not only increase the scope for localized protests and riots, but that it also systematically fuels larger-scale battles. Importantly, we document that gaining the territorial control of a mining area leads rebel groups to intensify and spread their fighting activity elsewhere in the territory in the successive periods, while winning a battle outside a mining area does not have such a conflict diffusion effect.

Our findings have important policy implications. The fact that capturing a mine relaxes financing constraints of rebels suggests that it is still relatively easy for armed groups to sell illicitly minerals on the black market, and for succeeding to do this they necessarily benefit from tacit or active support in various places of society. Our results suggest that one way for the domestic government to dampen these rebellion feasibility effects would be to put in place a more efficient government and stringent anti-corruption policies. Also the multinational foreign firms have their homework to do, as we find that mines operated by companies complying to socially responsible practices are less at risk to fuel violence.

In future work, we plan to extend our research to the study of how multinational mining companies adapt to the conflict risk in mining areas. Other interesting research questions include to quantify the impact of trade embargoes on particular mineral types (e.g. "blood diamonds") on the conflict risk.

References

[1] ACLED (2013): "Armed Conflict Location Events Data" (url).

[2] Andersen, Jorgen Juel, and Silje Aslaksen (2008): "Constitutions and the resource curse", *Journal of Development Economics* 87: 227-246.

[3] Angrist, Joshua and Adriana Kugler (2008): "Rural Windfall or a New Resource Curse? Coca, Income, and Civil Conflict in Colombia", *Review of Economics and Statistics* 90: 191-215.

[4] Aragon, Fernando, and Juan Pablo Rud (2013): "Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine", *American Economic Journal: Economic Policy* 5: 1-25.

[5] Bazzi, Samuel, and Chris Blattman (2014): "Economic Shocks and Conflict: The Evidence from Commodity Prices", *American Economic Journal: Macroeconomics* 6: 1-38.

[6] Bell, Curtis, and Scott Wolford (2014): "Oil Discoveries, Shifting Power, and Civil Conflict," forthcoming in *International Studies Quarterly.*

[7] Besley, Timothy, and Torsten Persson (2011): "The Logic of Political Violence", *Quarterly Journal of Economics* 126: 1411-1445.

[8] Besley, Timothy, and Marta Reynal-Querol (2014): "The Legacy of Historical Conflict: Evidence from Africa", *American Political Science Review* 108: 319-336.

[9] Buonanno, Paolo, Ruben Durante, Giovanni Prarolo, and Paolo Vanin (2015): "Poor Institutions, Rich Mines: Resource Curse and the Origins of the Sicilian Mafia ", forthcoming *Economic Journal.*

[10] Campbell, Greg (2002): *Blood Diamonds: Tracing the Deadly Path of the World's Most Precious Stones*, Boulder, Colorado: Westview Press.

[11] Carter, Colin, Gordon Rausser, and Aaron Smith (2011): "Commodity Booms and Busts", *Annual Review of Resource Economics* 3: 87-118.

[12] Caselli, Francesco and Wilbur John Coleman II (2013): "On the Theory of Ethnic Conflict," *Journal of the European Economic Association* 11: 161-192.

[13] Caselli, Francesco, Massimo Morelli, and Dominic Rohner (2015): "The Geography of Inter State Resource Wars," *Quarterly Journal of Economics* 130: 267-315.

[14] Charbonneau, Karyne (2012): "Multiple fixed effects in nonlinear panel data models: theory and evidence ", *unpublished manuscript*, Princeton University.

[15] Collier, Paul and Anke Hoeffler (2004): "Greed and Grievance in Civil War", *Oxford Economic Papers* 56: 563-95.

[16] Collier, Paul, Anke Hoeffler, and Dominic Rohner (2009): "Beyond Greed and Grievance: Feasibility and Civil War", *Oxford Economic Papers* 61: 1-27.

[17] Conley, Timothy G. (1999): "GMM Estimation with Cross Sectional Dependence", *Journal of Econometrics* 92: 1-45.

[18] Cotet, Anca M., and Kevin K. Tsui (2013): "Oil and Conflict: What Does the Cross Country Evidence Really Show?", *American Economic Journal: Macroeconomics* 5: 49-80.

[19] Couttenier, Mathieu, Pauline Grosjean, and Marc Sangnier (2014): "The Wild West is Wild: The Homicide Resource Curse", mimeo, University of Lausanne.

[20] Dafoe, Allan, and Jason Lyall (2015): "From Cell Phones to Conflict? Reflections on the Emerging ICT-Political Conflict Research Agenda", forthcoming, *Journal of Peace Research.*

[21] De Soysa, Indra (2002): "Paradise Is a Bazaar? Greed, Creed and Governance in Civil War, 1989-99," *Journal of Peace Research* 39: 395-416.

[22] Dietrich, Christian (2000): "Power struggles in the diamond fields" in Jakkie Cilliers and Christian Dietrich (editors), *Angola's War Economy: The Role of Oil and Diamonds*, Pretoria: Institute for Security Studies (ISS).

[23] Dube, Oendrila, and Suresh Naidu (2015): "Bases, Bullets and Ballots: the Effect of U.S. Military Aid on Political Conflict in Colombia", *Journal of Politics* 77: 249-267.

[24] Dube, Oendrila, and Juan Vargas (2013): "Commodity Price Shocks and Civil Conflict: Evidence from Colombia", *Review of Economics Studies* 80: 1384–1421.

[25] Esteban, Joan, Massimo Morelli, and Dominic Rohner (2015): "Strategic Mass Killings," forthcoming *Journal of Political Economy*.

[26] Fearon, James (2004): "Why Do Some Civil Wars Last So Much Longer than Others?" *Journal of Peace Research* 41: 275-301.

[27] Fearon, James (2005): "Primary Commodity Exports and Civil War," *Journal of Conflict Resolution* 49: 483-507.

[28] Fearon, James and David Laitin (2003): "Ethnicity, Insurgency, and Civil War," *American Political Science Review* 97: 75-90.

[29] Gilmore, Elisabeth, Paivi Lujala, Nils Petter Gleditsch, and Jan Rod (2005): "The Diamond Dataset Codebook" (url).

[30] Grossman, Herschel and Juan Mendoza (2003): "Scarcity and appropriative competition," *European Journal of Political Economy* 19: 747-58.

[31] Guidolin, Massimo, and Eliana La Ferrara (2007): "Diamonds Are Forever, Wars Are Not. Is Conflict Bad for Private Firms?", *American Economic Review* 97: 1978-93.

[32] Hodler, Roland (2006): "The curse of natural resources in fractionalized countries," *European Economic Review* 50: 1367-86.

[33] Hsiang, Solomon, Kyle Meng, and Mark Cane (2011): "Civil Conflicts are Associated with the Global Climate", *Nature* 476: 438-441.

[34] Human Right Watch (2005) "The Curse of Gold: Democratic Republic of Congo", (url).

[35] Humphreys, David (2010): "The great metals boom: A retrospective", *Resources Policy* 35: 1-13.

[36] Humphreys, Macartan (2005): "Natural Resources, Conflict, and Conflict Resolution: Uncovering the Mechanisms," *Journal of Conflict Resolution* 49: 508-37.

[37] International Country Risk Guide (2013): "ICRG Indicator of Quality of Government", dataset (url).

[38] IntierraRMG (2013): "SNL Metals & Mining", dataset (url).

[39] Kaufmann, Daniel, Aart Kraay, and Massimo Mastruzzi (2013): "Worldwide Governance Indicators", dataset (url).

[40] Koenig, Michael, Dominic Rohner, Mathias Thoenig and Fabrizio Zilibotti (2015): "Networks in Conflict: Theory and Evidence from the Great War of Africa", CEPR DP 10348.

[41] Kotsadam, Andreas, Eivind Hammersmark Olsen, Carl Henrik Knutsen, and Tore Wig (2015): "Mining and local corruption in Africa", working paper, University of Oslo.

[42] Kotsadam, Andreas, and Anja Tolonen (2014): "African Mining, Gender, and Local Employment", working paper, University of Oslo.

[43] La Ferrara, Eliana, and Mariaflavia Harari (2014): "Conflict, Climate and Cells: A Disaggregated Analysis", mimeo, Bocconi University.

[44] Le Billon, Philippe (2001): "The political ecology of war: natural resources and armed conflicts," *Political Geography* 20: 561-584.

[45] Lei, Yu-Hsiang, and Guy Michaels (2014): "Do Giant Oil Field Discoveries Fuel Internal Armed Conflicts?", *Journal of Development Economics* 110: 139-157.

[46] Lujala, Paivi (2009): "Deadly Combat over Natural Resources: Gems, Petroleum, Drugs, and the Severity of Armed Civil Conflict", *Journal of Conflict Resolution* 53: 50-71.

[47] Lujala, Paivi (2010): "The Spoils of Nature: Armed Civil Conflict and Rebel Access to Natural Resources," *Journal of Peace Research* 47: 15-28.

[48] Lujala, Paivi, Nils Petter Gleditsch and Elisabeth Gilmore (2005): "A Diamond Curse? Civil War and a Lootable Resource," *Journal of Conflict Resolution* 49: 538-62.

[49] Maystadt, Jean-François, Giacomo De Luca, Petros G. Sekeris, and John Ulimwengu (2014): "Mineral resources and conflicts in DRC: a case of ecological fallacy?", *Oxford Economic Papers* 66: 721-749.

[50] Mehlum, Halvor, Karl Moene and Ragnar Torvik (2006): "Institutions and the Resource Curse", *Economic Journal* 116: 1-20.

[51] Michalopoulos, Stelios, and Elias Papaioannou (2013): "The Long-Run effects of the Scramble for Africa", mimeo, Brown University.

[52] Morelli, Massimo, and Dominic Rohner (2013): "Resource Concentration and Civil Wars", mimeo, Columbia University and University of Lausanne.

[53] National Oceanic and Atmospheric Administration (2010): "Version 4 DMSP-OLS Nighttime Lights Time Series." dataset (url).

[54] Nunn, Nathan, and Nancy Qian (2014): "U.S. Food Aid and Civil Conflict", *American Economic Review* 104: 1630-1666.

[55] Ploeg, Frederick van der and Dominic Rohner (2012): "War and Natural Resource Exploitation," *European Economic Review* 56: 1714-1729.

[56] Polity IV (2013): "Polity IV Individual Country Regime Trends, 1946-2013", dataset (url).

[57] PRIO (2013): PRIO-GRID, dataset (url).

[58] Reuveny, Rafael and John Maxwell (2001): "Conflict and Renewable Resources," *Journal of Conflict Resolution* 45: 719-42.

[59] Reynal-Querol, Marta (2014): "Data on ethnic and religious fractionalization and polarization", dataset (url).

[60] Rohner, Dominic, Mathias Thoenig, and Fabrizio Zilibotti (2013): "War Signals: A Theory of Trade, Trust and Conflict", *Review of Economic Studies* 80: 1114-1147.

[61] Ross, Michael (2004): "What Do We Know About Natural Resources and Civil War?" *Journal of Peace Research* 41: 337-56.

[62] Ross, Michael (2006): "A closer look at oil, diamonds, and civil war", *Annual Review of Political Science* 9: 265–300.

[63] Sanchez de la Sierra, Raul (2015): “On the Origin of States: Stationary Bandits and Taxation in Eastern Congo”, mimeo, UC Berkeley.

[64] Solt, Frederick (2014): “The Standardized World Income Inequality Database”, dataset (url).

[65] Transparency International (2012): “Corruption Perceptions Index”, , dataset (url)..

[66] Weidmann, Nils, Jan Ketil Rod, and Lars-Erik Cederman (2010): “Representing Ethnic Groups in Space: A New Dataset”, *Journal of Peace Research* 47: 491-499.

7 Appendix

Figure 5: Time trends of mines and conflict

(a) Number of conflict events (ACLED) | Number of active mines (RMD)

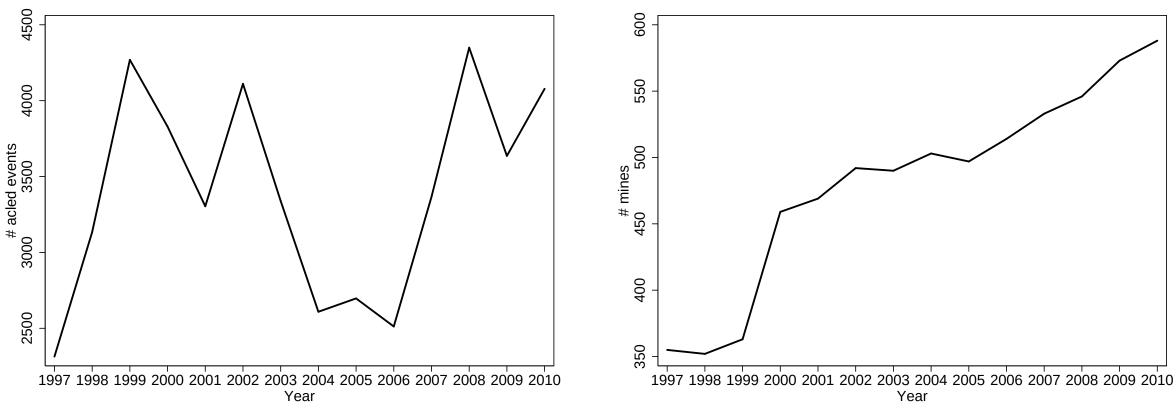
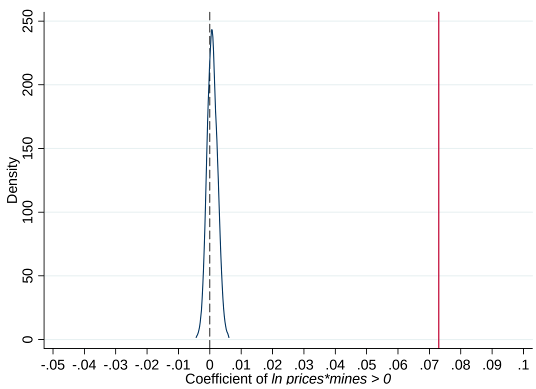


Figure 6: Monte Carlo Sampling Distribution of (ln price × mines > 0)



We draw randomly 1,000 times a main mineral for mining cells and we run specification (2) of Table 4 with this fake $\left(M_{kt} \times \ln p_{kt}^{W}\right)$ variable.

Table 14: Descriptive statistics: country-level

	Obs.	Mean	S.D.	1^{st} Quartile	Median	3^{rd} Quartile
# conflicts / year	52	65.31	97.04	4.96	19.67	74.28
# mines / year	52	9.25	36.8	0.00	1.04	4.82

Table 15: Summary statistics

Country	Share of cells with		Average #		Country	Share of cells		Average # of	
	mines	conflicts	mines	conflicts		mines	conflicts	mines	conflicts
Algeria	0.01	0.04	11	134	Liberia	0.03	0.25	1	58
Angola	0.01	0.09	6	215	Libya	0	0	0	2
Benin	0	0.03	0	3	Madagascar	0.01	0.02	1	24
Botswana	0.04	0.01	14	3	Malawi	0.00	0.11	0	8
Burkina Faso	0.03	0.03	1	10	Mali	0.01	0.01	4	9
Burundi	0	0.89	0	220	Morocco	0.06	0.03	20	13
Cameroon	0	0.04	0	12	Mauritania	0.01	0	5	1
Cape Verde	0	0	0	0	Mauritius	0	0	0	0
Central Afr. Rep.	0	0.06	0	35	Mozambique	0.01	0.03	2	17
Chad	0	0.03	0	35	Namibia	0.03	0.02	20	15
Comoros	0	0	0	0	Niger	0.01	0.01	1	18
Congo. Dem. Rep.	0.01	0.08	20	336	Nigeria	0.01	0.17	2	180
Congo. Rep.	0	0.05	0	37	Rwanda	0.13	0.54	2	45
Djibouti	0	0.20	0	4	Senegal	0.02	0.11	2	31
Egypt	0	0.03	1	37	Sierra Leone	0.04	0.35	1	96
Equ. Guinea	0	0.11	0	2	Sao Tome and Pr.	0	0	0	0
Eritrea	0	0.11	0	32	Somalia	0	0.19	0	395
Ethiopia	0.01	0.10	1	115	South Afr.	0.15	0.06	263	76
Gabon	0.01	0.02	1	3	Sudan	0	0.07	2	225
Gambia	0	0.57	0	5	Swaziland	0.25	0.26	1	5
Ghana	0.10	0.05	16	7	Tanzania	0.01	0.02	5	22
Guinea	0.07	0.09	6	34	Togo	0.06	0.09	1	7
Guinea-Bissau	0	0.21	0	15	Tunisia	0.05	0.03	5	5
Ivory Coast	0.02	0.10	3	72	Uganda	0.01	0.44	1	264
Kenya	0.01	0.22	1	183	Zambia	0.03	0.03	13	47
Lesotho	0.08	0.10	1	1	Zimbabwe	0.16	0.24	50	288

Source: Authors computations from ACLED and RMD data from 1997 to 2010. *Share of cells* (with mines or conflicts) is the country average of yearly share of cells with active mines or conflict incidence, respectively. *Average #* (of mines or conflicts) is the country average number of active mines or conflict events, respectively.

Table 16: Companies characteristics

Type	# Companies	# Cells
Foreign owned	106	117
Former colonizer	*22*	*34*
Major company	*64*	*94*
Domestic - Publicly owned	19	27
Domestic - Privately owned	65	67
Total	190	211

This mine is mine! How minerals fuel conflicts in Africa

Online Appendix

June 16, 2015

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Contents

1 Minerals and conflict: more correlations

Table A.1: Conflicts and mines: between-cell results, cross-section

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator				OLS		
Dep. var.	Conflict incidence (Acled)	(Acled)	# events (Acled)	Fatalities (Acled)	Massacres (incidence)	Massacres (fatalities)
At least 1 mine over 1997-2010	0.175^a		0.126^b	0.058^a	0.030^c	0.028
	(0.034)		(0.051)	(0.020)	(0.016)	(0.024)
Average # mines		0.050^a				
		(0.013)				
Observations	10335	10335	10335	10335	10335	10335
R^2	0.210	0.209	0.206	0.220	0.103	0.241
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. $log(x+1)$ used for dependent variables in columns (3), (4), and (6).

Table A.2: Conflicts and mines: between-cell results, cross-section, NL estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	Logit	Logit	PPML	PPML	Logit	PPML
Dep. var.	Conflict incidence (Acled)	(Acled)	# events (Acled)	Fatalities (Acled)	Massacres (incidence)	Massacres (fatalities)
At least 1 mine over 1997-2010	0.918^a		0.868^a	0.713^a	0.705^b	0.531
	(0.209)		(0.113)	(0.152)	(0.293)	(0.369)
Average # mines		0.294^b				
		(0.135)				
Observations	10278	10278	10324	10324	8925	8934
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors, clustered by country in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. $log(x+1)$ used for dependent variables in columns (3), (4), and (6).

Table A.3: Conflicts and mines: between-cell results, panel, NL estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	Logit	Logit	PPML	PPML	Logit	PPML
Dep. var.	Conflict incidence (Acled)	(Acled)	# events (Acled)	Fatalities (Acled)	Massacres (incidence)	Massacres (fatalities)
mine > 0	1.096^{a}		0.981^{a}	0.841^{a}	0.809^{b}	0.650
	(0.150)		(0.100)	(0.184)	(0.314)	(0.406)
# mines		0.176^{a}				
		(0.051)				
Observations	139257	139257	139327	118713	109660	109577
Country × year FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors, clustered by country in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. $log(x+1)$ used for dependent variables in columns (3), (4), and (6).

Table A.4: Conflicts and mines: within-cell results, NL estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimator	Logit				PPML		Log	PPML
Dep. var.	Conflict incidence (Acled)				# events (Acled)	Fatalities (Acled)	Massacres (incidence)	Massacres (fatalities)
mine > 0	0.458	0.612^{c}	0.915^{a}		0.271^{c}	-0.098	-0.676	-0.033
	(0.333)	(0.371)	(0.264)		(0.140)	(0.522)	(0.766)	(0.297)
log rainfall		-0.044	-0.112	-0.110	-0.061	-0.038	0.006	-0.102
		(0.207)	(0.124)	(0.125)	(0.098)	(0.148)	(0.386)	(0.089)
average temperature		0.362^{b}	0.175^{c}	0.176^{c}	0.120^{c}	0.198	-0.348	-0.063
		(0.144)	(0.100)	(0.100)	(0.062)	(0.131)	(0.218)	(0.085)
# neighbouring cells in conflict			0.595^{a}	0.594^{a}	0.335^{a}	0.321^{a}	0.261^{a}	0.090^{a}
			(0.049)	(0.049)	(0.028)	(0.024)	(0.070)	(0.021)
# mines				0.160^{b}				
				(0.078)				
Observations	38066	28920	27948	27948	28344	18264	3480	4980
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors, clustered by country in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. $log(x+1)$ used for dependent variables in columns (5), (6), and (8). mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell in year t. # neighbouring cells in conflict is the number of neighbouring cells, among the 8 surrounding cells, in which at least a conflict event occurs in year t.

2 Conflicts, minerals and prices: additional robustness tests

2.1 Exogenous World Prices

Table A.5: Conflicts and mineral prices: dropping large producers

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator				OLS		
Sample	All	$\text{Var}(M_{kt}) = 0$	All	$\text{Var}(M_{kt}) = 0$	All	$\text{Var}(M_{kt}) = 0$
Dep. var.	Conflict incidence		# conflicts		Conflict incidence	
mine > 0	0.044		-0.001			
	(0.068)		(0.091)			
ln price main mineral	-0.074^a		-0.134^a		-0.030^c	
	(0.021)		(0.042)		(0.017)	
ln price × mines > 0	0.132^a	0.061^b	0.216^a	0.052^a		
	(0.038)	(0.027)	(0.056)	(0.019)		
# mines					0.029	
					(0.036)	
ln price × # mines					0.065^a	0.039^a
					(0.012)	(0.014)
Observations	142772	141851	142772	141851	143038	141974
R^2	0.446	0.445	0.561	0.562	0.447	0.446
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. This table is the same as Table 4 from the main text, except that cells producing minerals for which the country is among the top 10 of world producers are removed from the sample. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell producing the main mineral in year t. $\text{Var}(M_{kt}) = 0$ means that we consider only cells in which the mine variable (the binary version or the number of mines) takes always the same value over the period. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period. Estimations (1), (3) and (5) include controls for the average level of mineral world price interacted with the mines variables.

2.2 Alternative definitions of a mining area

Table A.6: Mineral and price: 1×1 degrees cells

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			OLS			
Dep. var.	Conflict incidence		# conflicts		Conflict incidence	
Sample	All	$\text{Var}(M_{kt})=0$	All	$\text{Var}(M_{kt})=0$	All	$\text{Var}(M_{kt})=0$
mine > 0	-0.027		-0.035			
	(0.089)		(0.157)			
ln price main mineral	-0.003		0.027		0.042^b	
	(0.032)		(0.081)		(0.019)	
ln price × mines > 0	0.089^b	0.098^a	0.105	0.122^b		
	(0.043)	(0.032)	(0.096)	(0.057)		
# mines					0.043^b	
					(0.019)	
ln price × # mines					0.009^a	0.002
					(0.003)	(0.002)
Observations	36515	35826	36515	35826	36624	35672
R^2	0.522	0.521	0.639	0.639	0.525	0.525
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. This table is the same as Table 4 from the main text, except that we consider 1×1 instead of 0.5×0.5 degree cells. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell producing the main mineral in year t. $\text{Var}(M_{kt}) = 0$ means that we consider only cells in which the mine variable (the binary version or the number of mines) takes always the same value over the period. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period. Estimations (1), (3) and (5) include controls for the average level of mineral world price interacted with the mines variables.

Table A.7: Conflicts and mineral prices: alternative area definitions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimator				OLS				
Sample		$\text{Var}(M_{kt})=0$				$\text{Var}(M_{kt})=0$		
Dep. var.		Incidence				# conflicts		
mine > 0 (a)	0.042				0.025			
	(0.028)				(0.039)			
ln price main mineral	-0.042		0.046^a	0.053^a	-0.090^b		0.063^a	0.076^a
	(0.027)		(0.010)	(0.014)	(0.044)		(0.018)	(0.023)
ln price × mines > 0	0.109^a	0.076^a			0.197^a	0.101^a		
	(0.037)	(0.022)			(0.057)	(0.032)		
Observations	143775	142257	143775	143297	143775	142257	143775	143297
R^2	0.446	0.446	0.445	0.446	0.562	0.563	0.562	0.563
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Columns (1) and (2) and (5) and (6) are our baseline estimations (columns (1) to (4) of Table 4 in the main text), where mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. (a) In columns (3) and (7) the variable mine > 0 is equal to 1 in year t if an active mine has been observed in the cell at least once *over the entire period*; in columns (4) and (8) it equals 1 in year t if an active mine has been observed at some point *since the start of our sample*. # mines is the number of active mines in the cell producing the main mineral in year t. $\text{Var}(M_{kt}) = 0$ means that we consider only cells in which the mine variable (the binary version or the number of mines) takes always the same value over the period. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period. Estimations (1) and (5) include controls for the average level of mineral world price interacted with the mines variables.

2.3 Measurement errors

Table A.8: Conflicts and mineral prices: ACLED reporting bias

	(1)	(2)	(3)	(4)
Estimator	OLS			
Dep. var.	Conflict incidence			
	$\text{Var}(M_{kt}) = 0$			
Sample	Severity (fatalities quartile)			
	Q1	Q2	Q3	Q4
ln price × mines > 0	0.069^a	0.060^b	0.062^c	0.058^c
	(0.026)	(0.027)	(0.032)	(0.033)
Observations	138812	139180	138901	138783
R^2	0.371	0.378	0.367	0.386
Country×year FE	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Each column keeps only events belonging to a different quartile of the sample in terms of number of fatalities of the event. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. $\text{Var}(M_{kt}) = 0$ means that we consider only cells in which the mine variable (the binary version or the number of mines) takes always the same value over the period. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period.

As for gauging the impact of potential non-classical measurement errors the basic idea consists in regressing a subsample of our RMD mining data on a quasi-exhaustive list of mines and to see whether the residual variation in RMD coverage can be significantly explained by conflict. Unsurprisingly, for most types of minerals no alternative data sources are available that capture a broader range of mines than RMD. However, luckily, there exists one dataset on diamonds, DIADATA, from Gilmore et al. (2005), which is extremely fine-grained and aims to include not only big, industrial mining sites, but also small, artisanal exploitations. Further, it does not only include sites with production, but also mining areas with confirmed diamond presence where production has not started yet. They stress that "DIADATA is a comprehensive list of diamond occurrences throughout the world. (...) A diamond occurrence is broadly defined as any site with known activity, meaning production (either commercial or artisan) or confirmed discovery. The list of sites was compiled through an intensive literature search of academic databases and journals, national geological survey reports, and industry databases and reports" (2005: 5).

To see whether the RMD diamonds data are biased, consider the following simple model:

$$\text{DIAMONDS}_{ct}^{\text{DIADATA}} = \text{DIAMONDS}_{ct} + v_{ct}^{\text{DIADATA}} \quad (5)$$

$$\text{DIAMONDS}_{ct}^{\text{RMD}} = \text{DIAMONDS}_{ct} + \tilde{v}_{ct}^{\text{RMD}} \quad (6)$$

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

$$\text{DIAMONDS}_{ct}^{\text{RMD}} = \text{DIAMONDS}_{ct}^{\text{DIADATA}} + \xi \times \text{VIOLENCE}_{ct} + \nu_{ct} \tag{7}$$

where $\nu_{ct} = v_{ct}^{\text{RMD}} - v_{ct}^{\text{DIADATA}}$ is an i.i.d. disturbance. Our null hypothesis is that $\xi = 0$. If $\xi \neq 0$, the RMD measure suffers from non-classical measurement error.

We run a regression based on equation (7), measuring violence by the number of conflicts in ACLED. Table A.9 summarizes the results. Column (1) is a cross-sectional specification; Column (2) includes annual year fixed effects, while Columns (3) includes country fixed effects. Finally, Column (4) includes Country x year fixed effects. Note that the DIADATA dataset does not contain time variation for the period we study, which excludes any specifications with cell fixed effects. We allow for robust standard errors to be clustered at the country level.

As expected, there is a highly significant positive correlation between the RMD and the DIADATA diamond measures. Most important, all estimates of ξ are tiny and not significantly different from zero, with its point estimates switching sign across specifications. We conclude that there is no evidence that the RMD diamond data are subject to non-classical measurement error in our sample.

Table A.9: Mines data: non classical measurement errors

	(1)	(2)	(3)	(4)
Dep. var.	Number of RMD mines			
Number of mines Lujala	0.068^b	0.068^b	0.068^b	0.068^b
	(0.032)	(0.032)	(0.033)	(0.033)
Number of events (ACLED)	-0.001	-0.001	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Fixed effects	No	Year	Country	Country-year
Observation	144690	144690	144690	144690
R-squared	0.136	0.136	0.151	0.153

Standard errors, clustered by country, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

2.4 Additional controls

Table A.10: Conflicts and mineral prices: controlling for luminosity

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator				OLS		
Sample	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0
Dep. var.	Conflict incidence		# conflicts		Conflict incidence	
mine > 0	0.042		0.027			
	(0.028)		(0.038)			
ln price main mineral	-0.032		-0.093[c]		0.028[c]	
	(0.032)		(0.047)		(0.014)	
ln price × mines > 0	0.109[a]	0.090[a]	0.196[a]	0.105[a]		
	(0.038)	(0.019)	(0.057)	(0.026)		
luminosity	0.002	0.002	0.001	0.001	0.002	0.002
	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
ln price × luminosity	-0.001	-0.001[b]	0.000	-0.000	-0.001	-0.001[b]
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
# mines (main mineral)					0.009[a]	
					(0.003)	
ln price × # mines					0.019[a]	0.029[c]
					(0.006)	(0.016)
Observations	140558	139047	140558	139047	140836	138974
R^2	0.438	0.438	0.555	0.556	0.440	0.438
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. This table is the same as Table 4 from the main text, with additional controls. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell producing the main mineral in year t. Var(M_{kt}) = 0 means that we consider only cells in which the mine variable (the binary version or the number of mines) takes always the same value over the period. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period. Estimations (1), (3) and (5) include controls for the average level of mineral world price interacted with the mines variables.

Table A.11: Conflicts and mineral prices: additional controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimator					OLS				
Sample		$\text{Var}(M_{kt}) = 0$			$\text{Var}(M_{kt}) = 0$			$\text{Var}(M_{kt}) = 0$	
Dep. var.	Incidence	# conflicts	Incidence	Incidence	# conflicts	Incidence	Incidence	# conflicts	Incidence
ln price × mines > 0	0.113^a	0.136^a		0.067^a	0.069^b		0.069^a	0.086^a	
	(0.024)	(0.040)		(0.022)	(0.033)		(0.021)	(0.027)	
ln price × # mines			0.042^b			0.021^c			0.023
			(0.017)			(0.012)			(0.014)
temperature × mines > 0	0.019	0.011	0.028						
	(0.016)	(0.024)	(0.018)						
rainfall × mines > 0	-0.027	-0.140	-0.048						
	(0.076)	(0.146)	(0.059)						
ln price × # neighb. cells in conflict				0.000	0.004^c	-0.000			
				(0.001)	(0.002)	(0.001)			
# neighbouring cells in conflict				0.037^a	0.067^a	0.037^a			
				(0.004)	(0.008)	(0.004)			
ln price × # past conflicts in cell							-0.003^c	-0.008	-0.002
							(0.002)	(0.007)	(0.003)
Observations	119189	119189	119124	138239	138239	138180	142257	142257	142184
R^2	0.447	0.568	0.447	0.448	0.563	0.448	0.446	0.563	0.446
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell producing the main mineral in year t. $\text{Var}(M_{kt}) = 0$ means that we consider only cells in which the mine variable (the binary version or the number of mines) takes always the same value over the period. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period. Non interacted variables included but coefficients not reported.

2.5 Alternative price data

Table A.12: Conflicts and mineral prices: alternative price data

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			OLS			
Sample	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0
Dep. var.	Conflict incidence		Conflict incidence		Conflict incidence	
Robustness	World Bank prices (nom.)		UNCTAD prices		Prices indexes	
mine > 0	0.041		-1.778		0.028	
	(0.028)		(1.299)		(0.026)	
ln price main mineral	-0.037		-0.043^c		-0.067^b	
	(0.023)		(0.022)		(0.026)	
ln nominal price × mines > 0	0.094^a	0.066^a	0.095^a	0.061^a	0.072^a	0.076^a
	(0.030)	(0.017)	(0.031)	(0.017)	(0.016)	(0.022)
Observations	143775	142257	143314	142277	105658	104104
R^2	0.446	0.446	0.447	0.446	0.440	0.440
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell producing the main mineral in year t. Var(M_{kt}) = 0 means that we consider only cells in which the mine variable (the binary version or the number of mines) takes always the same value over the period. $log(x+1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period. In columns (5) and (6), if no mine is recorded the variable is replaced by a price index computed as the average price of the mineral produced by the country, weighted by the average share of the mineral in the country's total production.

2.6 Sets of minerals

Table A.13: Conflicts and mineral prices: robustness (adding diamonds)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator				OLS		
Sample	All	$\text{Var}(M_{kt}) = 0$	All	$\text{Var}(M_{kt}) = 0$	All	$\text{Var}(M_{kt}) = 0$
Dep. var.	Conflict incidence		# conflicts		Conflict incidence	
mine > 0	0.020		-0.008			
	(0.027)		(0.051)			
ln price main mineral	-0.037		-0.082^c		0.011	
	(0.027)		(0.043)		(0.012)	
ln price × mines > 0	0.094^b	0.064^b	0.173^a	0.082^b		
	(0.039)	(0.024)	(0.057)	(0.035)		
# mines					0.008^b	
					(0.003)	
ln price × # mines					0.019^a	0.023
					(0.006)	(0.014)
Observations	144300	142607	144300	142607	144592	142464
R^2	0.445	0.445	0.562	0.563	0.447	0.446
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. This table is the same as Table 4 from the main text, except that we add diamond producing cells. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell producing the main mineral in year t. $\text{Var}(M_{kt}) = 0$ means that we consider only cells in which the mine variable (the binary version or the number of mines) takes always the same value over the period. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period. Estimations (1), (3) and (5) include controls for the average level of mineral world price interacted with the mines variables.

Table A.14: Conflicts and mineral prices: dropping gold, diamond and silver mines

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator				OLS		
Sample	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0
Dep. var.	Conflict incidence		# conflicts		Conflict incidence	
mine > 0	0.044^a		0.035^b			
	(0.016)		(0.016)			
ln price main mineral	-0.060^b		-0.092^b		0.018	
	(0.027)		(0.042)		(0.016)	
ln price × mines > 0	0.127^a	0.076^b	0.194^a	0.100^c		
	(0.040)	(0.033)	(0.071)	(0.054)		
# mines					0.004^a	
					(0.001)	
ln price × # mines					0.014	0.028
					(0.009)	(0.018)
Observations	142561	141682	142561	141682	142772	141722
R^2	0.443	0.443	0.556	0.556	0.445	0.444
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. This table is the same as Table 4 from the main text, except that we drop gold, silver and producing cells. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell producing the main mineral in year t. Var(M_{kt}) = 0 means that we consider only cells in which the mine variable (the binary version or the number of mines) takes always the same value over the period. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period. Estimations (1), (3) and (5) include controls for the average level of mineral world price interacted with the mines variables.

2.7 Sample restrictions

Table A.15: Conflicts and mineral prices: cells with permanent active mine(s)

	(1)	(2)	(3)	(4)
Estimator	OLS			
	Conflict incidence			
Sample	Var(M_{kt}) = 0	Permanent active mine(s)	Var(M_{kt}) = 0	Permanent active mine(s)
ln price × mines > 0	0.076[a]	0.016	0.094[a]	0.094[a]
	(0.022)	(0.076)	(0.031)	(0.032)
Observations	142257	1078	142257	1078
Country×year FE	Yes	Yes	No	No
Cell FE	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Var(M_{kt}) = 0: only cells in which the mine variable takes always the same value over the period. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. ln price main mineral is the world price of the mineral with the highest average production in the cell over the period.

2.8 Conflict onset and ending

Table A.16: Conflicts and mineral prices: conflict onset and ending

	(1)	(2)	(3)	(4)
	Onset		Ending	
Estimator	OLS			
Sample	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0
mine > 0	0.028		-0.038	
	(0.017)		(0.063)	
ln price main mineral	-0.018		0.106[c]	
	(0.028)		(0.060)	
ln price × mines > 0	0.053	0.058[a]	-0.178[a]	-0.069
	(0.035)	(0.016)	(0.066)	(0.043)
Observations	139685	138253	22840	22445
R^2	0.201	0.200	0.387	0.389
Country×year FE	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. In columns (1) and (2) the dependent variable equals 1 is a conflict event is recorded in year t in the cell, but no conflict event is recorded in $t-1$ (the variable is coded as missing for ongoing conflicts); in columns (3) and (4) the dependent variable equals 1 is no conflict is recorded in year t but a conflict was recorded in year $t-1$. mine >0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. Var(M_{kt}) = 0 means that we consider only cells in which the mine variable takes always the same value over the period. ln price main mineral is the world price of the mineral with the highest average production in the cell over the period.

2.9 Non-linear estimators

Table A.17: Conflicts and mineral prices: non linear estimators

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	FE-Logit		PPML		FE-Logit	
Sample	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0
Dep. var.	Conflict incidence		# conflicts		Conflict incidence	
mine > 0	0.539		0.121			
	(0.637)		(0.478)			
ln price main mineral	-0.512		-0.478[b]		0.330	
	(0.372)		(0.241)		(0.299)	
ln price × mines > 0	1.494[a]	1.146[a]	0.876[a]	0.304[c]		
	(0.350)	(0.317)	(0.228)	(0.183)		
# mines					0.296	
					(0.201)	
ln price × # mines					0.165[b]	0.509[c]
					(0.072)	(0.304)
Observations	37714	36974	38263	37523	37814	36834
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors, clustered by country, in parentheses. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. This table is the same as Table 4 from the main text, except that we use different estimators. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell producing the main mineral in year t. Var(M_{kt}) = 0 means that we consider only cells in which the mine variable (the binary version or the number of mines) takes always the same value over the period. $log(x+1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period. Estimations (1), (3) and (5) include controls for the average level of mineral world price interacted with the mines variables.

2.10 Standard-errors

Table A.18: Conflicts and mineral prices: spatial correlation

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator				OLS		
Sample	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0
Dep. var.	Conflict incidence		# conflicts		Conflict incidence	
ln price × mines > 0	0.104	0.076	0.187	0.101		
Spatial: 100km; Time: 1 year	(0.029)	(0.017)	(0.047)	(0.029)		
Spatial: 100km; Time: 5 years	(0.029)	(0.018)	(0.047)	(0.029)		
Spatial: 1000km; Time: 1 year	(0.031)	(0.021)	(0.046)	(0.030)		
Spatial: 1000km; Time: 5 years	(0.031)	(0.021)	(0.046)	(0.030)		
ln price × # mines					0.019	0.026
Spatial: 100km; Time: 1 year					(0.007)	(0.012)
Spatial: 100km; Time: 5 years					(0.006)	(0.012)
Spatial: 1000km; Time: 1 year					(0.006)	(0.011)
Spatial: 1000km; Time: 5 years					(0.006)	(0.011)
Observations	143775	142257	143775	142257	144046	142184
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, adjusted for various levels of spatial and serial correlation, in parentheses. This table is the same as Table 4 from the main text, except that we allow the spatial and serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell producing the main mineral in year t. Var(M_{kt}) = 0 means that we consider only cells in which the mine variable (the binary version or the number of mines) takes always the same value over the period. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period. Estimations (1), (3) and (5) include the non interacted variables and the average level of mineral world price interacted with the mines variables.

3 Additional quantifications

Figure A.1: Counterfactuals: share of events due to increasing prices

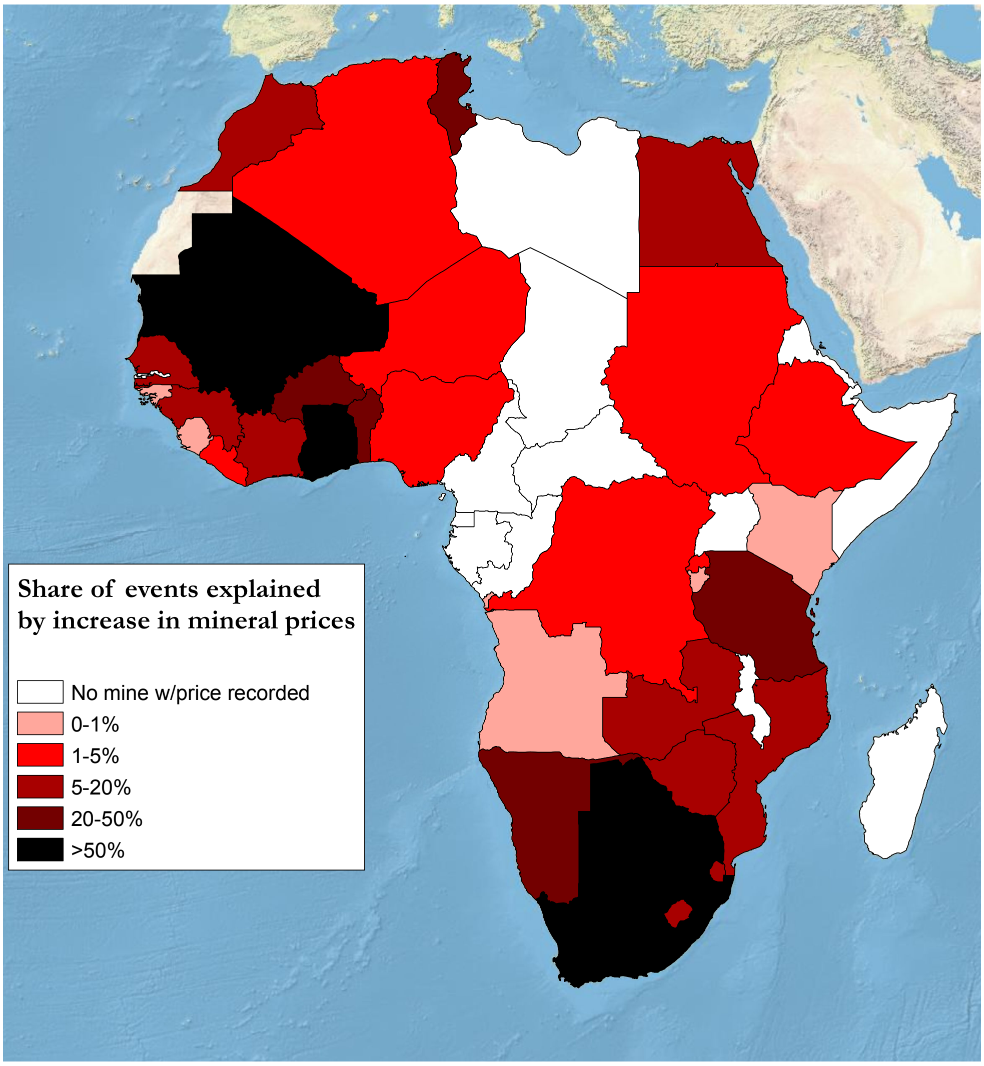


Figure A.2: Counterfactuals: share of events due to increasing prices

(a) In sample cells (b) Excluding surrounding cells

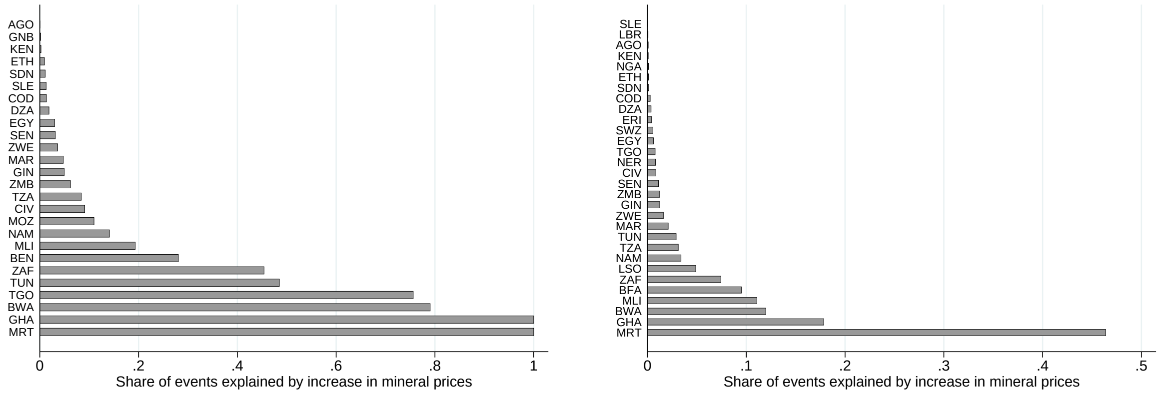
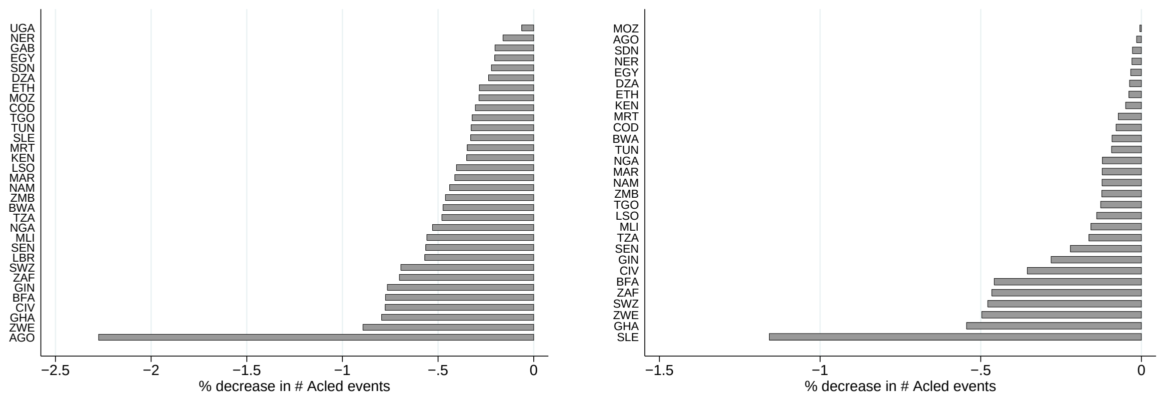


Figure A.3: Counterfactuals: closing all mines

(a) Including surrounding cells (b) Excluding surrounding cells



3.1 Sample restrictions

Table A.19: Baseline results, excluding conflicts involving civilians, rioters or protesters

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			OLS			
Dep. var.	Conflict incidence		# conflicts		Conflict incidence	
Sample	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0
mine > 0	0.009		0.021			
	(0.020)		(0.025)			
ln price main mineral	-0.074^b		-0.095^b		-0.012	
	(0.029)		(0.045)		(0.008)	
ln price × mines > 0	0.095^b	0.024^a	0.118^b	0.021^a		
	(0.036)	(0.006)	(0.051)	(0.008)		
# mines					-0.002	
					(0.002)	
ln price × # mines					0.009	0.012^c
					(0.007)	(0.007)
Observations	143775	142257	143775	142257	144060	142184
R^2	0.367	0.366	0.456	0.456	0.367	0.367
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by country, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Var(M_{kt}) = 0 means that we include only cells in which the mine variable takes always the same value over the period. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell in year t. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period.

4 Group-level estimations

We replicate our baseline results (in Table 3) at the group-cell level. With respect to the cell-level data used for our baseline estimates, the unconditional conflict probability in the group-cell dataset is very low, at 0.2%, and we therefore expect the estimated coefficients to be quantitatively small. More precisely, we estimate:

$$\text{Conflict}_{gkt} = \alpha_1 M_{kt} + \alpha_2 \ln p_{kt}^W + \alpha_3 \left(M_{kt} \times \ln p_{kt}^W \right) + \mathbf{FE}_{gk} + \mathbf{FE}_{it} + \varepsilon_{gkt}, \tag{8}$$

where g denotes a fighting group and $\mathbf{FE}_{gk}$ are group $\times$ cell fixed effects. Standard errors are clustered at the group-level.

The results are displayed in Table A.20. The main coefficient of interest has the expected sign and is statistically significant in columns (1) to (4), but insignificant when considering the interaction of the price with the number of mines in columns (5) and (6).[5]

Table A.20: Conflicts and mineral prices (actor-level)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			OLS			
Dep. var.	Conflict incidence		# conflicts		Conflict incidence	
Sample	All	$\text{Var}(M_{kt}) = 0$	All	$\text{Var}(M_{kt}) = 0$	All	$\text{Var}(M_{kt}) = 0$
mine > 0	0.001		0.001		0.000	
	(0.002)		(0.001)		(0.002)	
ln price main mineral	-0.006^b		-0.007^b		-0.001	
	(0.002)		(0.003)		(0.001)	
ln price × mines > 0	0.007^a	0.001^a	0.009^a	0.001^b		
	(0.003)	(0.001)	(0.003)	(0.001)		
ln price × # mines					0.001^b	0.001^c
					(0.000)	(0.000)
Observations	3611364	3594022	3611364	3594022	3614604	3591826
R^2	0.193	0.193	0.237	0.237	0.193	0.193
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Actor-Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by actor, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. $\text{Var}(M_{kt}) = 0$ means that we include only cells in which the mine variable takes always the same value over the period. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. # mines is the number of active mines in the cell in year t. $log(x + 1)$ used for dependent variable in columns (3) and (4). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period.

[5] The coefficient on the interaction term in columns (5) and (6) turns significant when we use the log of the number of mines plus one instead of the number of mines, which suggests that outliers might drive the insignificant estimates.

5 Battles won: robustness

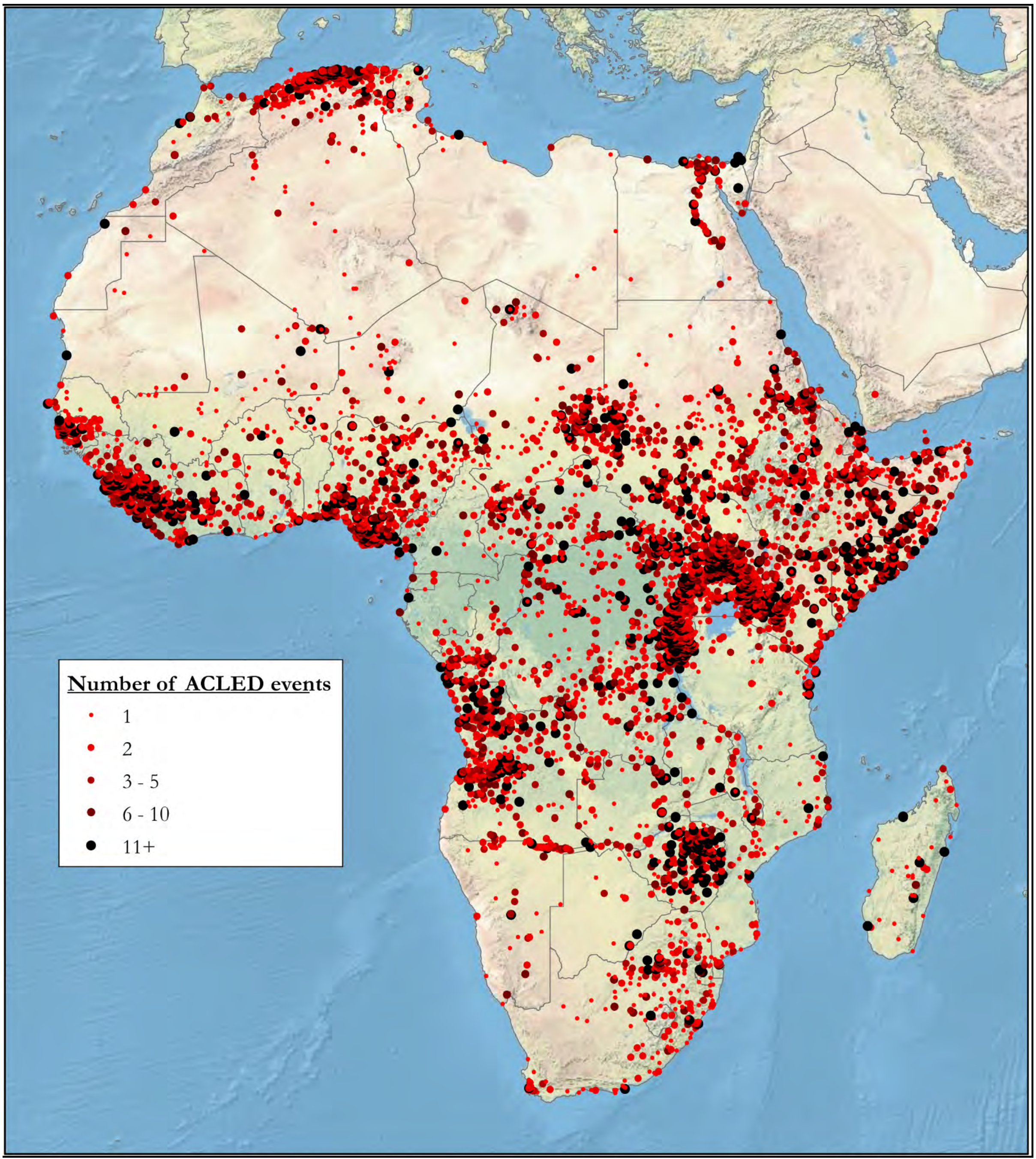
Table A.21: Feasibility and the diffusion of war: actor-specific trends

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Conflict onset				Conflict onset
Estimator			OLS				OLS
Battle_{at-1} outcome			Rebels won territory				No change
Battle_{at-1} (dummy)	0.002^a						
	(0.001)						
# battles_{at-1}		0.001^b					
		(0.000)					
Battle_{at-1} (dummy, no mine)			0.001^b		0.001^b		
			(0.001)		(0.001)		
Battle_{at-1} (dummy, mine)			0.013^a		0.013^a		
			(0.002)		(0.003)		
# battles_{at-1} (no mine)				0.001		0.001^c	0.001^a
				(0.000)		(0.000)	(0.000)
# battles_{at-1} (mine)				0.004^a		0.004^a	0.001
				(0.001)		(0.001)	(0.000)
Difference in coefs.			0.011^a	0.003^a	0.012^a	0.003^b	0.000
			(0.002)	(0.001)	(0.003)	(0.001)	(0.000)
Observations	1942340	1942340	1942340	1942340	1942340	1942340	1942340
Year dummies	Yes	Yes	Yes	Yes	No	No	Yes
Actor-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×year FE	No	No	No	No	Yes	Yes	No
Actor-Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations (LPM for conflict incidence columns). Standard errors, clustered by actor, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. # battles variables are expressed as $\log(x+1)$.

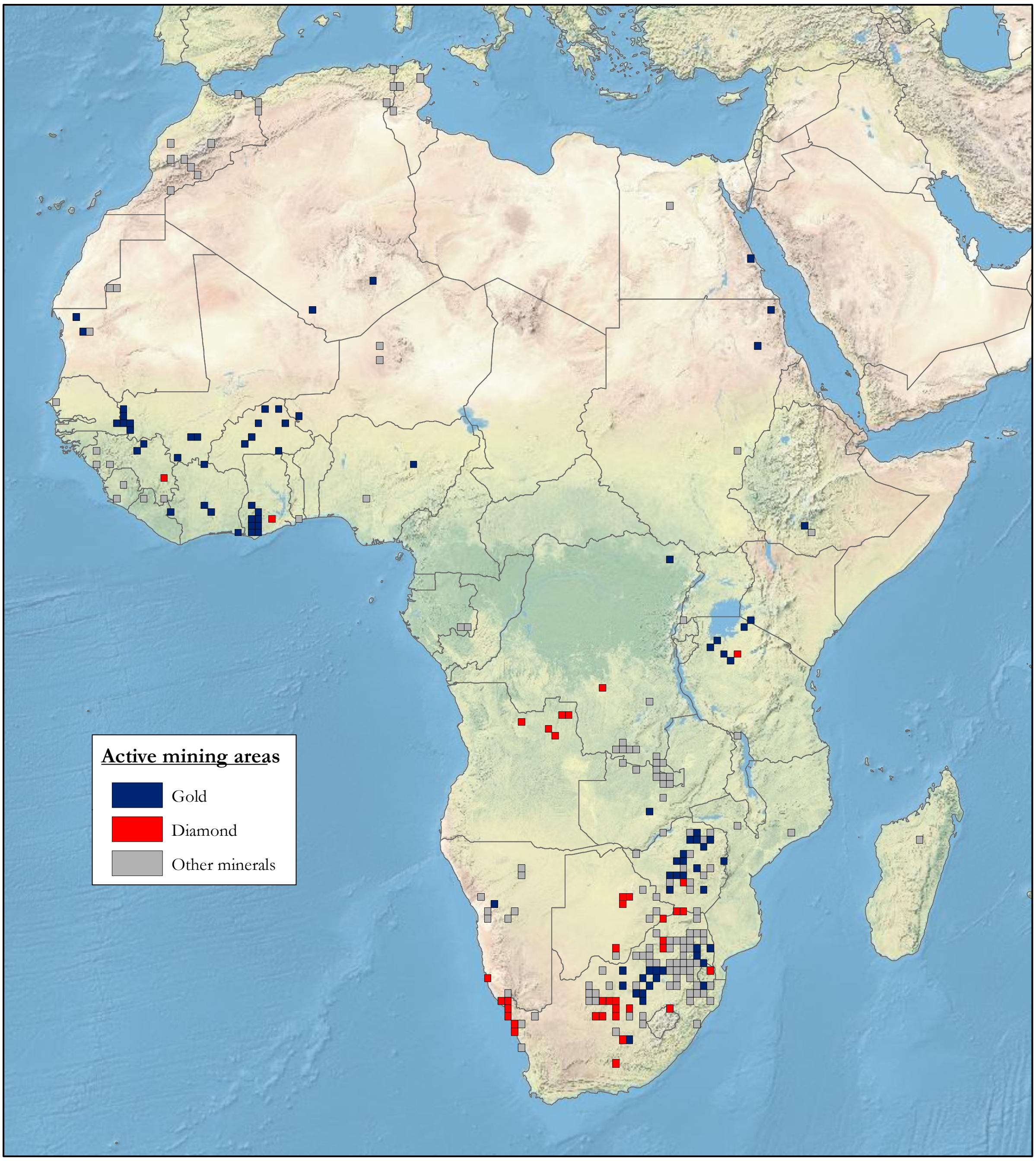
6 Maps

Figure A.4: Conflict events



Geo-location of conflict from the Armed Conflict Location and Event dataset (ACLED, 2013).

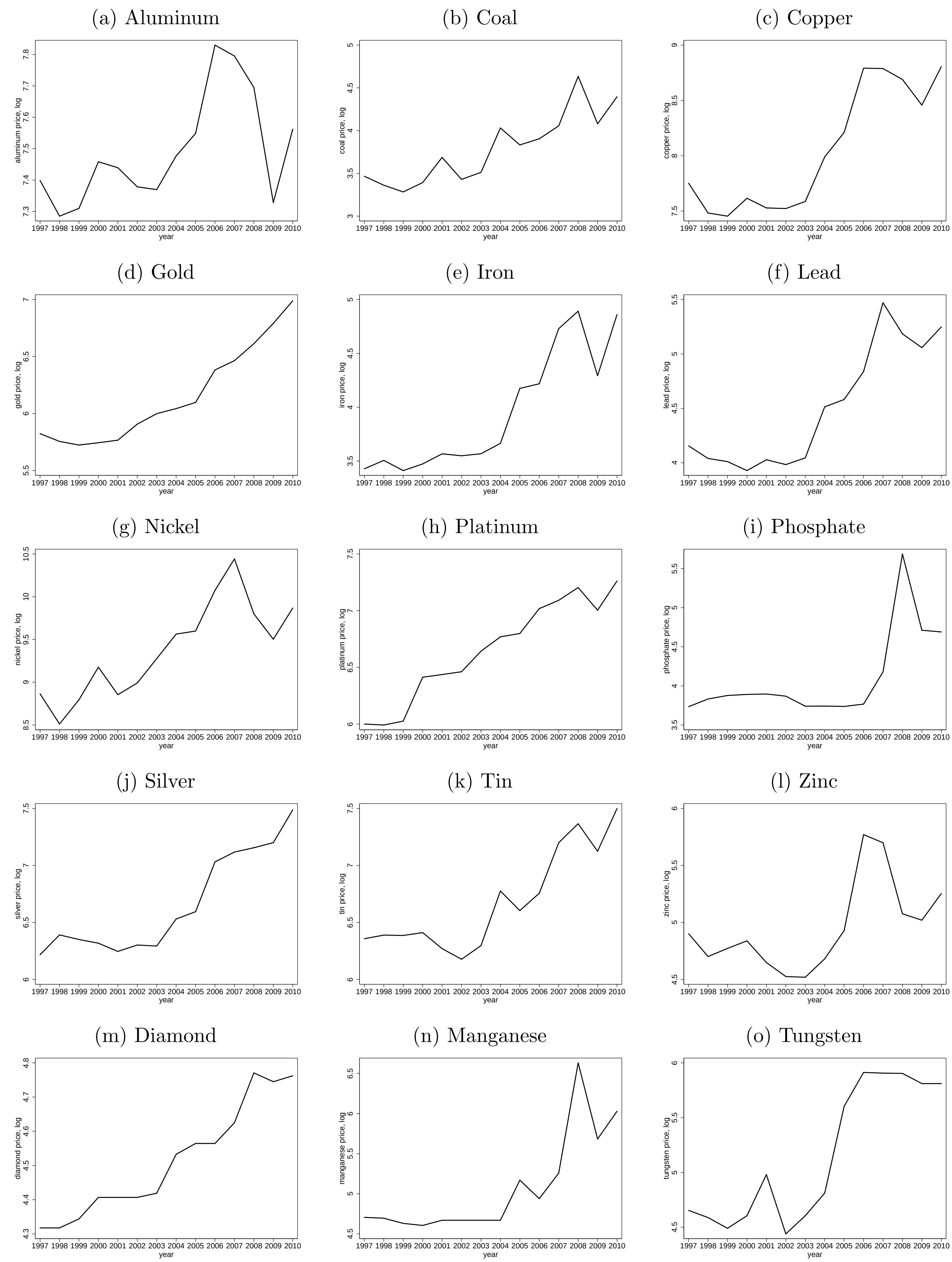
Figure A.5: Mining areas



Geo-location of active mining areas from *Raw Material Data*.

7 Mineral prices

Figure A.6: Mineral prices (log scale)



Source: (a) to (l): World Bank; (m) Rapaport (2012); (n) and (o): UNCTAD.