This mine is mine!
How minerals fuel conflicts in Africa*

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Abstract. This paper studies empirically the impact of mining on conflicts in Africa. Using novel data, we combine geo-referenced information over the 1997-2010 period on the location and characteristics of violent events and mining extraction of 27 minerals. Working with a grid covering all African countries at a spatial resolution of 0.5 $\times$ 0.5 degree, we find a sizeable impact of mining activity on the probability/intensity of conflict at the local level. This is both true for low-level violence (riots, protests), as well as for organized violence (battles). Our main identification strategy exploits exogenous variations in the minerals' world prices; however the results are robust to various alternative strategies, both in the cross-section and panel dimensions. Our estimates suggest that the historical rise in mineral prices observed over the period has contributed to up to 21 percent of the average country-level violence in Africa. The second part of the paper investigates whether minerals, by increasing the financial capacities of fighting groups, contribute to diffuse violence over time and space, therefore affecting the intensity and duration of wars. We find direct evidence that the appropriation of a mining area by a group increases the probability that this group perpetrates future violence elsewhere. This is consistent with "feasibility" theories of conflict. We also find that secessionist insurgencies are more likely in mining areas, which is in line with recent theories of secessionist conflict.

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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, over the Jebel Amer gold mine near Kabkabiya in Sudan's North Darfur region, killing more than 800 people and displaced some 150,000 others since January 2013. 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.[1] 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" (cf. Campbell, 2002), Angola's rebels from "União Nacional para a Independência Total de Angola" (UNITA) that financed their armed struggle with diamond money (cf. Dietrich, 2000) or the case of several mines in Democratic Republic of Congo's Lunga region that are directly run by Mayi Mayi militias.[2]

The present paper investigates the impact of mining on conflict by using geolocalized data on conflict events and mining extraction of 27 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) 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 stage 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 when mines start to produce; (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 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 16.5% to a counterfactual 20.3%. When aggregated at the country level, the effect remains sizeable. Our estimates suggest that the contribution of the historical rise in mineral prices between 1997 and 2010 to the average violence observed across African countries over the period lies between 13 and 21%.

[1]Cf. 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]In addition, often armed groups control mines without directly managing them. For example in the DRC, the "plundering of mining communities – taking the form of brief visits to demand cash, goods or minerals with violence or the threat of violence – is a well-documented phenomenon, perpetrated by soldiers of all sides since during the recent conflict in the DRC" (De Koning, 2010: 13).

In a second stage 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 to regional or national wars. Looking at the nature of violent events, we first find that, beyond riots and protests, mining-induced violence is also composed of battles perpetrated by fighting groups, a form of organized violence that can lead to a change of territory. Then, we make use of the information contained in our data on the winners and losers of particular battle events. We show that the appropriation of a mining area by a fighting group increases the probability that this group perpetrates violence elsewhere in the rest of the country in the following years. We interpret this result as the fact that mines spread conflicts across space and time by making rebellions financially feasible. Finally, we use an additional dataset on the political exclusion of ethnic groups to study whether the effects of resource rents are particularly strong in regions with secessionist potential. We find indeed a particularly sizeable conflict potential in mineral-rich homelands of discriminated groups located in remote areas.

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 on various geographic, demographic, political and economic 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 (2011) 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, 2013).[5] 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 De Luca et al. (2013) on minerals in the DRC. However, there does

[3] Natural resources have also been found to empirically matter for homicides (Couttenier, Grosjean and Sangnier, 2014), for organized crime (Buonanno et al., 2012), for interstate wars (Caselli, Morelli and Rohner, 2013) and for mass killings of civilians (Esteban, Morelli and Rohner, 2013).

[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).

[5] Morelli and Rohner (2013) find – running fixed effects regressions with both a country and an ethnic group panel – that natural resource inequality is a major trigger of civil conflicts.

not exist so far a study of the nexus between natural resources and conflict with a panel of very disaggregated cells covering a whole continent, as we use in the current paper. In terms of the methodology, our paper is also related to the recent papers on conflict that exploit exogenous shocks and the geographical location of fighting events to identify the causes and consequences of violence, including Berman and Couttenier (2014), Cassar, Grosjean, and Whitt (2013), Michalopoulos and Papaioannou (2013), Rohner, Thoenig, and Zilibotti (2013b), Besley and Reynal-Querol (2013), and La Ferrara and Harari (2012).

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.[6] 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".[7] A second possibility is that natural resources make rebellion *feasible*, i.e. relax credit constraints and make it easier to set up and sustain a rebel movement (Fearon, 2004; Collier, Hoeffler and Rohner, 2009; Nunn and Qian, 2014; Dube and Naidu, 2014). A third channel, recently emphasized by Morelli and Rohner (2013), predicts that natural resources create incentives for separatism when they are unevenly spread in the country, as they provide perspectives of economically viable independence to resource rich regions with ethnic minorities. The other mechanisms that have been mentioned by the literature relate to state capacity (rentier states can rely on resource rents and do not build up enough state capacity, which makes them eventually more instable)[8] and grievances (natural resources can exacerbate grievances, due to frustrations from environmental degradation, or banned access to lucrative mining jobs)[9].

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 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.

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 time and space of mining-induced violence. Section 5 concludes.

[6] 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.

[7] 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).

[8] Fearon (2005), Besley and Persson (2011) and Bell and Wolford (2014).

[9] Le Billon (2001), Ross (2004), and Humphreys (2005).

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.[10] 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[11] (ACLED) (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 conflicts 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.[12] 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 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 from 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

[10] See e.g. La Ferrara and Harari (2013), Besley and Reynal-Querol (2013) or Berman and Couttenier (2014) for papers using similar grid-cell level data.

[11] See e.g. La Ferrara and Harari (2012), Michalopoulos and Papaioannou (2013), Rohner, Thoenig, and Zilibotti (2013b), Besley and Reynal-Querol (2013) and Berman and Couttenier (2014) for recent contributions using ACLED data.

[12] 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 an 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).

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.

Mines data. To each *cell-year*, we merge information on mines from *Raw Material Data* (RMD).[13] The data contain information on the location of mining companies around the world since 1980. 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[14] 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 compute 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. For cells with no active mines - the vast majority - we compute the distance between the cell's centroid and the closest mine. 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 period.

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. Firstly, 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. Secondly, 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), use 1×1 degree cells instead of 0.5×0.5, or use the distance to the closest active mine. As shown later, results are consistent across specifications.

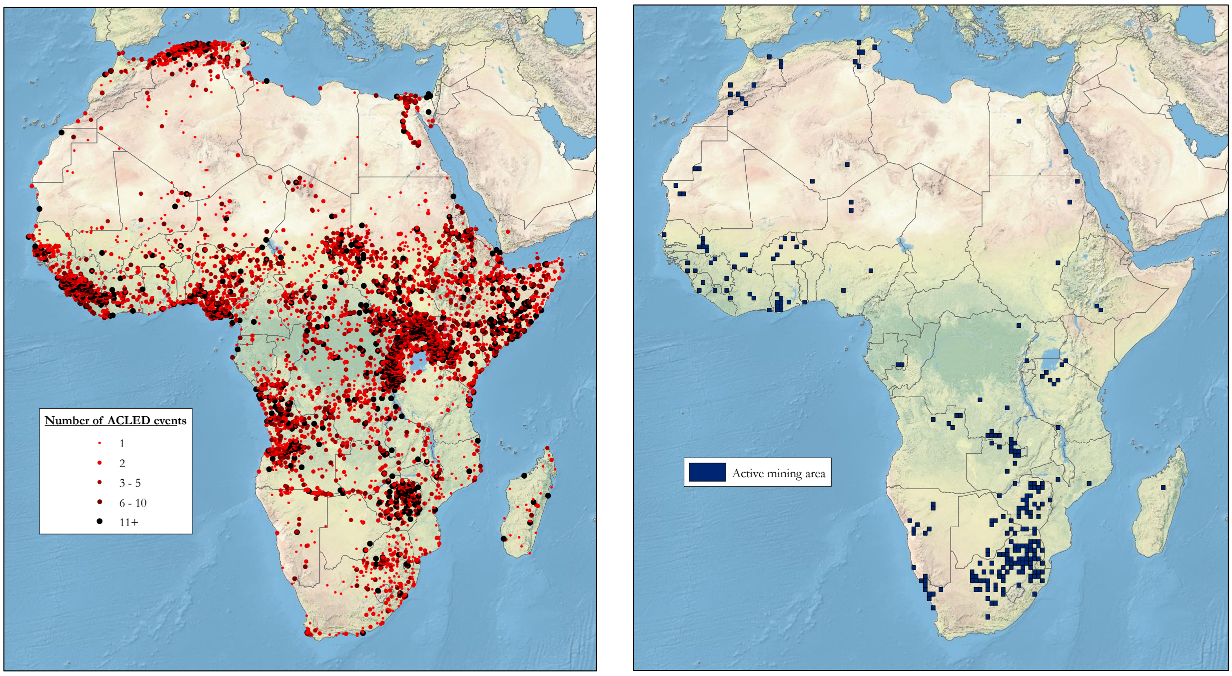
Other data. Our final dataset contains a number of additional variables. The appendix contains more details on the data construction and sources. We complement the conflict data with geo-localized data on massacres from the "Political Instability Task Force Worldwide Atrocities Event Data" (PITF, 2013) and with country-level information on conflict incidence from UCDP/PRIO Armed Conflict Dataset. We use data on mineral prices from the World Bank Commodities prices dataset. Finally, we include a number of cell-specific information, including the distance between the cell's centroid and international borders and to capital city (from PRIO-GRID), 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 (Henderson *et al.*, 2012).

[13]This dataset comes from IntierraRMG (2013): http://www.intierrarmg.com/Homepage.aspx

[14]27 minerals are included for African mines: Antimony, Bauxite, Chromite, Coal, Cobalt, Copper, Diamond, Gold, Iron, Lead, Lithium, Manganese, Nickel, Niobium, PGMs, Palladium, Phosphate, Platinum, Rhodium, Silver, Tantalum, Tin, Tungsten, Uranium oxide, Vanadium, Zinc, Zirconium.

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.

2.2 Descriptive statistics

Figure 2.1 contains a visual representation of both the geolocalisation 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 conflicts events does not follow a specific trend over time, while the 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).

Our sample contains 52 countries and 27 minerals. Tables 10 and 11 in the appendix contain additional country-level descriptive statistics. On average, 15 conflicts events and 10 active mines are recorded each year in each country. Only four countries display no conflict events over the entire period[15], Somalia being 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.[16] 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

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

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

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)	144690	0.06	0.24	0.00
Pr(Mine> 0)	144690	0.02	0.14	0.00
Pr(Mine> 0) (incl. 1^{st} surrounding cells)	144690	0.13	0.34	0.00
Pr(Mine> 0) (incl. 1^{st} & 2^{nd} surrounding cells)	144690	0.21	0.41	0.00
# conflicts (if > 0)	9098	1.32	0.79	1.10
# mines	144690	0.06	0.71	0.00
# mines (if > 0)	2985	2.78	4.12	1.00
Pr(# mines > 2)	144690	0.01	0.09	0.00
Pr(# mines > 2 | Mine> 0)	2985	0.43	0.50	0.00
Pr(Conflict> 0) if mines>0	2985	0.15	0.36	0.00
Pr(Conflict> 0) if mines = 0	141705	0.06	0.24	0.00
Distance to closest mine (km)	118384	353.08	232.45	317.12

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

Table 1 contains descriptive statistics on our final sample, which contains 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 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 13% (respectively 21%) when we consider the neighboring cells (resp. the first and second degree neighboring cells). On average, the distance between the cells' centroid and the closest mine is around 350 kilometers. Second, mines tend to be spatially clustered: conditional on observing at least mine in a given cell, the number of mines is 2.78. 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 (43%). Finally, 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 the following specification:

$$\text{CONFLICT}_{kt} = \alpha \times \mathrm{M}_{kt} + \mathbf{FE}_{it} + \varepsilon_{kt} \qquad (1)$$

where (k, t, i) denote respectively cell, time and country. The dependent variable, CONFLICT_{kt}, corresponds to the observation of violent events at the cell-year level where violence is measured either in term of intensity (i.e. number of events) or in term of incidence (i.e. a binary variable coding for non-zero events). Information on violent events is retrieved from the ACLED dataset on civil conflicts or alternatively from data on massacres from the Political Instability Task Force (PITF). 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. Finally, 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.

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 PPML estimator (Tables A.2 and A.3 in the online appendix). 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) (see Table A.11).

Results are displayed in Table 2. Columns (1) and (2) show that our two measures of mining activity (presence and number) correlate positively and significantly (at the 1 percent level) with the incidence of ACLED conflict events at the cell-level. The presence of one or more mines is associated with a 8.5 percentage points increase in conflict probability. Given the similarity of the results, in the rest of our empirical analysis, we report the results mostly for the binary version of mining activity (i.e. presence) estimated with LPM. Columns (3) to (6) consider several alternatives for the dependent variable with violence being measured, respectively, by the number of ACLED events, by the violence-induced fatalities (as reported in ACLED), by the incidence of massacres and by the massacre-induced fatalities. Our point estimates are systematically positive and, except in the last specification, statistically significant at the 5 percent threshold.[17]

The main source of identification in specification (1) corresponds to the between-cell variations in mining activity and violence, for a given country in a given year. Part of the correlation could be spuriously driven by omitted time-invariant cell-specific characteristics such as the local

[17] In the online appendix we consider pure cross-sectional specifications that replicate Table 2 with all variables being averaged in the time dimension (see Table A.1).

Table 2: Conflicts and mines: between-cell results, panel

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator				LPM		
Dep. var.	Conflict incidence (Acled)	(Acled)	# events (Acled)	Fatalities (Acled)	Massacres (incidence)	Massacres (fatalities)
mine > 0	0.085^a		0.136^b	0.059^b	0.027^b	0.032
	(0.026)		(0.056)	(0.025)	(0.011)	(0.025)
# mines		0.016^a				
		(0.005)				
Observations	144690	144690	144690	144690	144690	144690
R^2	0.123	0.123	0.153	0.114	0.108	0.194
Country × year dummies	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimations with country × year dummies. 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). 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.

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 amend (1) and estimate the following within-cell specification:

$$\text{CONFLICT}_{kt} = \alpha \times M_{kt} + \mathbf{C_{kt}}'\beta + \mathbf{FE}_k + \mathbf{FE}_{it} + \varepsilon_{kt} \quad (2)$$

where $\mathbf{FE}_k$ 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. Table 3 reports the results for a LPM estimator, non-linear estimates being relegated to Table A.4 in the online appendix. Column (1) replicates the first column of Table 2 with the additional inclusion of cell fixed effects. Though this specification is very demanding, we obtain a positive and significant (5 percent) coefficient. In term of magnitude, the within estimate represents half of its between-cell counterpart confirming that part of the correlation in Table 2 is driven by time-invariant cell characteristics. Columns (2) and (3) gradually include time-varying cell-specific controls. Despite a substantial reduction in the sample size, our coefficient of interest remains stable and significant. The opening of a mine in a given cell is associated with a 4.5 percentage points increase in conflict probability in this cell. Columns (5) to (9) replicate columns (2) to (6) of Table 2 with the full set of cell fixed-effects and time varying controls. The coefficient of mining activity remains positive but statistical significance is unstable for these alternative dependent variables.

3.2 Exogenous changes in the value of mines – Baseline Results

Though demanding, the within-cell identification of Table 3 is not immune to endogeneity issues. Besides unobserved heterogeneity, 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

Table 3: Conflicts and mines: within-cell results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimator	LPM				LPM			
Dep. var.	Conflict incidence (Acled)				# events (Acled)	Fatalities (Acled)	Massacres (incidence)	Massacres (fatalities)
mine > 0	0.040^b	0.044^b	0.046^b		0.020	0.005	0.012^b	0.010
	(0.019)	(0.020)	(0.020)		(0.032)	(0.060)	(0.006)	(0.011)
log rainfall		0.002	0.001	0.001	0.001	0.006	-0.000	0.001
		(0.004)	(0.003)	(0.003)	(0.004)	(0.006)	(0.002)	(0.003)
average temperature		0.016^b	0.011^b	0.011^b	0.012^c	0.020	0.002	0.005
		(0.007)	(0.005)	(0.005)	(0.007)	(0.014)	(0.002)	(0.004)
# neighbouring cells in conflict			0.035^a	0.035^a	0.065^a	0.079^a	0.002	0.008^a
			(0.005)	(0.005)	(0.009)	(0.014)	(0.002)	(0.003)
# mines				0.008^b				
				(0.003)				
Observations	144690	121236	119016	119016	119016	119016	119016	119016
R^2	0.447	0.448	0.451	0.451	0.568	0.394	0.815	0.773
Country×year dummies	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.

therefore work against our findings of a significant positive correlation between mining activity and conflict (Table 3). 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. La Ferrara and Guidolin (2007, 2010) actually find evidence that conflicts increase the value of extractive firms.[18]

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.[19] 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:

$$\text{CONFLICT}_{kt} = \alpha_1 M_{kt} + \alpha_2 \ln p^W_{kt} + \alpha_3 \left(M_{kt} \times \ln p^W_{kt} \right) + \mathbf{FE}_k + \mathbf{FE}_{it} + \varepsilon_{kt}. \quad (3)$$

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 *full* 1997-2010 period.[20] We code p^W_{kt} as a zero for the cells where no

[18]Several reasons 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.

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

[20]Price data are available for the ten following minerals: aluminum, copper, gold, iron, lead, nickel, platinum, silver, tin and zinc, and diamond. 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

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.[21] 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 estimate 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 $\times$year fixed-effects in all specifications, our identification strategy relies on the exogeneity of the interaction term, $M_{kt} \times \ln p_{kt}^W$, 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_{kt}^W, 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 (3) to the sub-sample of cells without opening/closing of mine over the period (i.e. $\mathrm{Var}(M_{kt}) = 0$ for 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 $\ln p_{kt}^W$ and $(M_{kt} \times \ln p_{kt}^W)$ become identical; we accordingly include only the interaction term and the specification takes the following simpler expression:

$$\textsc{conflict}_{kt} = \alpha_3 \left(M_{kt} \times \ln p_{kt}^W\right) + \mathbf{FE}_k + \mathbf{FE}_{it} + \varepsilon_{kt} \tag{4}$$

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$\times$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. With this respect,

from our baseline estimations. We however show that our results are robust to the inclusion of this mineral (see Table A.6).

[21] We also run robustness checks where instead of replacing p_{kt}^W 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.

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, we report the estimates when the sample is restricted to cells with a permanent active mine (see subsection 3.3.4).

Table 4 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. Columns (1), (3) and (5) are estimated on the full sample (specification 3); while columns (2), (4) and (6) are restricted on the subsample of cells without mine opening/closing (specification 4). We see that in all columns, our coefficient of interest is positive and significant at the 1 percent level. Columns (2) and (4) are our preferred regressions.

Table 4: Conflicts and mineral prices

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	LPM		LPM		LPM	
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	0.055		0.043			
	(0.094)		(0.111)			
ln price main mineral	-0.029		-0.045^c		0.010	
	(0.019)		(0.024)		(0.012)	
ln price × mines > 0	0.093^a	0.073^a	0.148^a	0.099^a		
	(0.027)	(0.020)	(0.035)	(0.033)		
# mines					0.036^b	
					(0.015)	
ln price × # mines					0.017^a	0.004^a
					(0.004)	(0.001)
Observations	142817	141890	142817	141890	142926	141568
R^2	0.445	0.445	0.562	0.563	0.447	0.446
Country×year dummies	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%. $\text{Var}(M_{kt}) = 0$ means that we consider 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. $log(x + 1)$ used for dependent variable in columns (3) and (4). # mines is the number of active mines 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.

3.3 Robustness

Our results shown in Table 4 are robust to a battery of sensitivity checks. We present below several types of robustness exercises. First, we address further concerns with reversed causality, and second, further concerns with omitted variable bias. Third, we consider alternative cell sizes, and fourth, a variety of further robustness checks.

3.3.1 Reversed causality

Reversed causality is a potential concern. In particular, it could be conceivable that mining prices do not affect conflict, but that on the contrary the occurrence or the anticipation of a conflict in a major producer country leads to an increase in the mineral prices. To address this concern, we include additional interaction terms between world prices of minerals and a dummy which equals 1 if the country belongs to the top-10 world producer in the mineral produced by the cell, and therefore could influence world prices (Table 12 in the appendix). Our result still holds for the rest of the cells, and we cannot find robust evidence of market power influencing our results (the interaction terms with the large producer dummy is insignificant or negative in all but one specification). Alternatively, we drop all country-minerals which belong to the top-10 world producers (Table A.5 of the online appendix). The results are again similar.

3.3.2 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 13 (see appendix) 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 14 of the appendix goes further and includes a number of alternative cell-specific, time-varying controls which might be correlated with commodity price variations (climate variables) 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.

3.3.3 Alternative cell sizes

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.

In Table 5 below 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).

Table 5: Conflicts and mineral prices, including neighboring cells

	(1)	(2)	(3)	(4)
Estimator	LPM		LPM	
Dep. var.	Conflict incidence		# conflicts	
Sample	All	Var(M_{kt}) = 0	All	Var(M_{kt}) = 0
mine > 0	0.056		0.040	
	(0.096)		(0.113)	
ln price main mineral	-0.041^b		-0.065^b	
	(0.019)		(0.026)	
ln price × mines > 0	0.094^a	0.059^b	0.152^a	0.087^c
	(0.028)	(0.026)	(0.034)	(0.048)
mine > 0 (neighboring cells)	-0.023		-0.037	
	(0.016)		(0.026)	
ln price × mine > 0 (neighbouring cells)	0.024^a	0.028^a	0.041^b	0.052^a
	(0.008)	(0.010)	(0.016)	(0.019)
Observations	134899	123466	134899	123466
R^2	0.442	0.440	0.554	0.557
Country×year dummies	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes

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 consider only cells in which the mine variables (including the one for surrounding cells) take 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. $log(x + 1)$ 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. Neighboring cells include the first degree neighboring cells (8 cells) as well as the second degree (16 cells).

Alternatively, in Table 16 in the appendix we reproduce our baseline table for a grid of cells at a larger resolution (1 degree × 1 degree). In all columns, the coefficient of interest has the expected positive sign and is often statistically significant at the 5 or 1 percent level. The slightly weaker results for the 1 × 1 resolution than in the baseline table may indicate that many mining zones are of relatively limited size and that the baseline resolution of 0.5 × 0.5 is indeed the appropriate level of disaggregation.

A further sensitivity test relates to taking into account actual distances from the closest mines. As mentioned above, the observation of a mine acts as a proxy for the existence of a wider mining area, given that some smaller non-industrial mines are unobserved. However, the spatial extension of the extraction areas may clearly vary across minerals and across deposits, an issue that we ignore in our baseline estimates where the grid scaling imposes all mining areas to be limited to a 0.5 × 0.5 degree cell. We consequently adopt a more flexible approach here by using information on the precise location of mines to compute the distance between each cell and the closest mine. We consequently estimate:

$$\textsc{conflict}_{kt} = \beta_1 \ln D_{kt} + \beta_2 \ln D_{kt} \times \ln p^W_{kt} + \ln p^W_{kt} \times \gamma_i + \mathbf{FE}_k + \mathbf{FE}_{it} + \varepsilon_{kt} \tag{5}$$

where D_{kt} is the distance in kilometers between the centroid of the cell and the closest active mine in the country during year t. p^W_{kt} is the world price of the mineral produced by the closest mine. We include a set of interaction terms between the price variable and country dummies to control for country-specific heterogeneity such as country size, which can be correlated with conflicts and affect the value of D_{kt}. If mining fuels conflicts, we expect both β_1 and β_2 to be negative. The results are provided in the appendix, in Table 17. In column (1), we include only the log of distance to the closest mine.[22] In column (2) we add the interaction with mineral prices. Column (3) restricts the sample to the cell in which distance to mines is fixed over the period. Finally, in column (4) we include additional interactions with cell-specific variables which could be correlated with the distance to the closest mine: distance to the capital city and to the nearest international border. The results are consistent with our baseline estimates: cells located further away from opening mines have a significantly lower conflict probability in column (1), and variations in mineral prices have a significantly lower effect in cells located away from mines (columns (2) to (4)).

3.3.4 Other robustness checks

Placebo – We perform a placebo test with the idea of testing the consistency of our empirical strategy that is based on exogenous variations in mineral prices. In particular, we want to exclude the fact that comovements in the World price of minerals could drive our results. The logic 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 4 with this fake $M_{kt} \times \ln p_{kt}^{W}$ variable. We repeat the procedure in 1,000 draws. Figure A.1 in the online appendix displays the results. Reassuringly, the Monte Carlo coefficients are distributed far from our baseline estimate (0.073) and are massively insignificant.

Alternative price data – An important variable in our analysis are the mineral prices. We hence investigate robustness to alternative definition of prices (Table A.9 in the appendix). In particular, we use second-differences in prices instead of levels in columns (1) and (2), real prices instead of nominal prices 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). In all columns the coefficient of interest is still highly significant.

Sample restrictions – Another issue that arises for our interaction with mineral prices is how to treat cells that do not have any mines. In Table 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 (925 observations) with a set of country×year dummies remaining large (221). 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.

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

[22] This coefficient can be identified despite the cell fixed effects as distance can vary over time when mines open or close in the country.

of minerals (Tables A.6 and A.7 of the online appendix).[23] 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.

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 beginnings (onsets) and endings separately. In Table A.8 of the online appendix, we study cell-specific conflict onsets and endings of conflict separately. We find that our variable of interest, the interaction of mining dummy times price, both significantly increases the risk of conflict onset, and significantly reduces the likelihood of conflict ending. This implies that the higher conflict incidence due to mines is both due to more conflicts breaking out and to existing conflicts lasting longer.

Alternative estimators – Table A.10 of the online appendix reproduces our baseline results using 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). With the exception of column (4) where the coefficient on the interaction term between the world price and the dummy for mining activity is marginally insignificant, 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.[24]

Statistical inference – Another econometric issue to consider is statistical inference. As mentioned, 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 Hsiang (2010). 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.11 of the online appendix). For all combinations of spatial and serial correlation considered, the standard errors are such that our coefficients of interest are still statistically significant.

3.4 Quantification

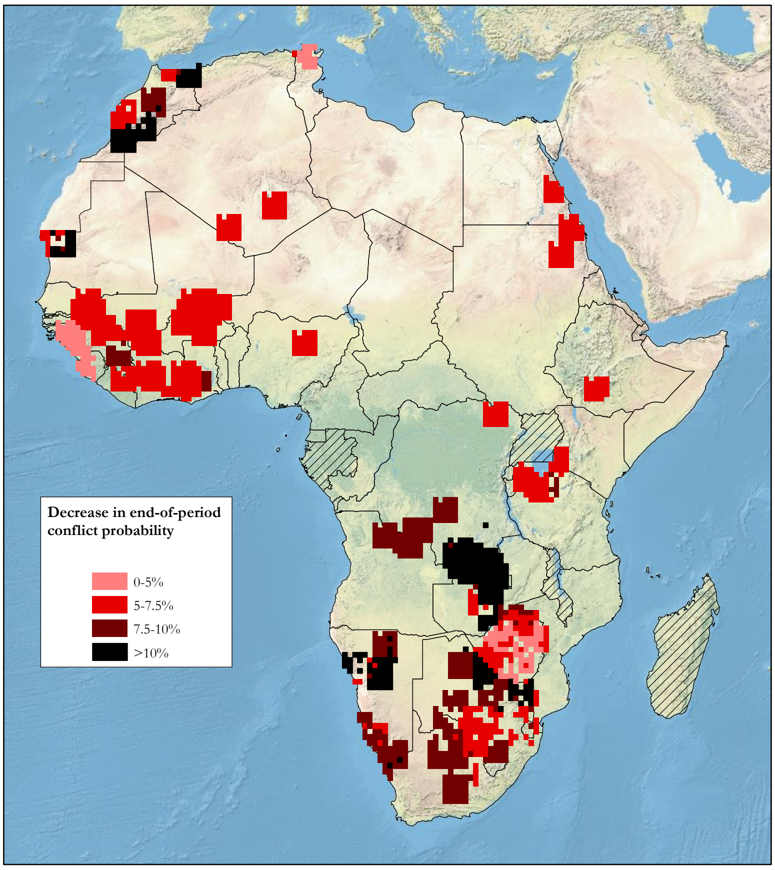
How large is the effect of mineral price variations on the conflict probability? In our preferred specification (Table 4, column (2)) a standard-deviation increase in the price of all minerals from their mean translates into an increase in probability of violence from 0.165 to 0.203. This is of non negligible magnitude, but of course concerns only the cells where active mining takes

[23]There is large heterogeneity in diamond quality in different mines and price shocks for different categories of diamonds can go in different directions. As we do not have information of the type of diamonds produced by each cell, we ignore this heterogeneity, which might add statistical noise and lead to attenuation bias; this is why our preferred estimations do not consider diamond mines.

[24]The estimations shown in Table A.10 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 dimensions of fixed effects in logit and Poisson models might lead to an incidental parameter problem (Charbonneau, 2012).

place. When we also consider the surrounding cells (Table 5, column (2)), conflict probability rises from 0.169 to 0.212.

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



Over the period of our study mineral prices more than doubled on average.[25] The ounce of gold, for instance, was valued at \$331 in 1997, and reached \$1226 in 2010.[26] What effect did this surge in mineral prices have on conflicts? 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 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 6.2 in the appendix for the map equivalent).[28] The effect is highly heterogeneous

[25] Figure A.6 in the online appendix shows the evolution of the price of each of the minerals.

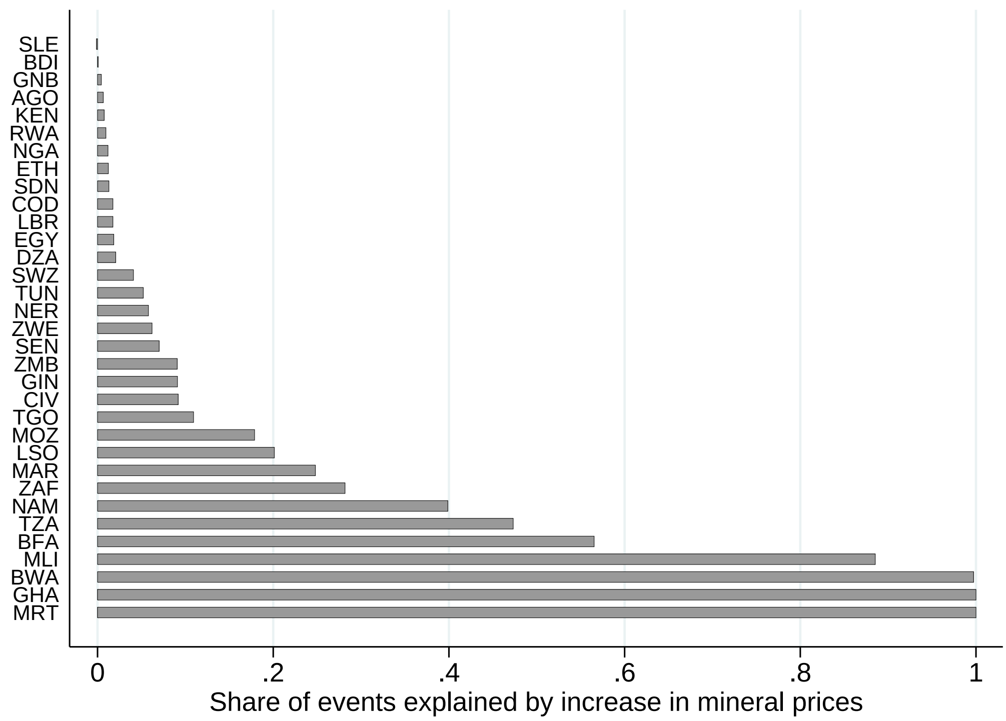
[26] In real 2005 USD, prices have been multiplied by 2.8. Gold was valued at \$338 in 1997, and reached \$1084 in 2010.

[27] This counterfactual exercise is based on the estimated coefficients of Table 5, column (2), a specification 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 our preferred estimation, Table 5, column (2), to all cells contained in Table 5, 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

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 21% 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 11). 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 contributed to a 13.6% of the observed violence.[29] In the online appendix (Figures 4.a and 4.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 Ghana or Zimbabwe; and in most countries, the number of conflicts decreases by more than 20%.

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



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

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 5, 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 5, see online appendix, Figure A.3.a. Also in the online appendix, Figure A.3.b contains a similar quantification but based on column (2) of Table 4, i.e. it does not take into account the mines active in surrounding cells. As expected, the effects are smaller.

[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).

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 been performed at the local level: Our baseline results show that mining areas generate violence. 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 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, geolocalization, information on the outcome of the violent events, their type, and the identity of the perpetrators.

4.1 The nature of mining-induced violence

Uncovering the nature of mining-induced violence is crucial for understanding whether it can escalate from the local level to the global scale. 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). Such violence, rooted in riots and protests, is driven by the characteristics of the mining areas that are local and immobile. 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.

In Table 6 we replicate our baseline specifications (columns (2) and (4) of Table 4) for each of the three categories of violent events covered by the ACLED dataset: battles between fighting groups, protests/riots, and violence against civilians.[30] 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.[31]

[30] The data also contains non violent events. We do not consider them in this section.

[31] We have also reproduced our baseline estimations excluding all events that involved civilians, protesters or rioters. These results are very similar to our baseline estimates (Table 18).

Table 6: Minerals price and types of conflict events

	(1)	(2)	(3)	(4)	(5)	(6)
			LPM			
Sample	Var(M_{kt}) = 0		Var(M_{kt}) = 0		Var(M_{kt}) = 0	
Dependent conflict var.	Battles		Violence against civ.		Riots / Protests	
	Incidence	# events	Incidence	# events	Incidence	# events
ln price × mines > 0	0.020^a	0.017^a	0.037^b	0.021	0.040^b	0.079^b
	(0.006)	(0.006)	(0.019)	(0.013)	(0.016)	(0.034)
Observations	141890	141890	141890	141890	141890	141890
R^2	0.357	0.447	0.383	0.498	0.399	0.541
Country×year dummies	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%. $log(x+1)$ used for dependent variable in columns (2), (4) and (6). 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.

4.2 Feasibility and the diffusion of violence

We now focus specifically on mining-induced battles and study how they can diffuse throughout the territory. For each battle, our data detail the name and type of fighting groups on each side – government, rebel group, militias, foreign power, civilians – and the outcome of the battle – who won and gained (or kept) the territory. This information is at the core of our strategy to identify the feasibility mechanism.

More precisely, we extend our dataset in a new dimension, namely the fighting group operating in the cell. We keep two types of fighting groups: governments (and government-related parties such as police or military forces) and rebel groups. ACLED considers as rebel groups "political organizations whose goal is to counter an established national governing regime by violent acts."[32] 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.[33] In the absence of more precise information on their location, we allow each fighting 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.[34] We therefore use a balanced dataset containing, for each fighting group, all combinations of grid cells × years where the group can potentially be active. Our final sample includes 560 distinct groups in addition to the observable characteristics used in our baseline specifications, i.e. presence of mines and occurrence of battle events. The unit of observation is now a grid cell × *year* × *group*. In the section 6.4 in the Appendix we check that our baseline results are robust to this data reshuffling

[32] 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."

[33] 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."

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

and to restricting violence to battle events only.

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* battle perpetrated by a group g in cell k in year t:

$$\text{ONSET}_{gk,t} = \alpha \times \text{BATTLE}^{0}_{g,t-1} + \beta \times \text{BATTLE}^{\mathbf{m}}_{g,t-1} + \mathbf{FE}_{gk} + \mathbf{FE}_{it} + \varepsilon_{gkt}, \tag{6}$$

where $\mathbf{FE}_{gk}$ are group $\times$ cell fixed effects. $\text{ONSET}_{gk,t}$ is a binary variable equal to one if a battle is initiated by group g 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 battle 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.[35] 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* the following year more than winning a territory where no active mining is taking place. The implicit assumption here is that winning a battle on a mining area enables the fighting groups to appropriate the mining rents. In all specifications, the standard errors are clustered at the same level than our main explanatory variables, namely the fighting 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 $\times$ year $\times$ group. It contains 560 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 (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 7 displays the results. In columns (1) and (2), the explanatory variable corresponds to the total number of battles won by the group in $t-1$ (column (2)) and its binary version (column (1)). 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 6 where battles

[35] 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 extremely similar if we exclude these.

Table 7: Feasibility and the diffusion of war (1/2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Conflict onset				Conflict onset
Estimator			LPM				LPM
Battle_{at-1} outcome			Rebels won territory				No change
Battle_{at-1} (dummy)	0.005^{a}						
	(0.001)						
# battles_{at-1}		0.003^{a}					
		(0.001)					
Battle_{at-1} (dummy, no mine)			0.004^{a}		0.004^{a}		
			(0.001)		(0.001)		
Battle_{at-1} (dummy, mine)			0.022^{a}		0.023^{a}		
			(0.004)		(0.005)		
# battles_{at-1} (no mine)				0.002^{a}		0.002^{a}	0.001^{a}
				(0.000)		(0.000)	(0.000)
# battles_{at-1} (mine)				0.007^{a}		0.007^{a}	0.003^{a}
				(0.002)		(0.003)	(0.001)
<u>Difference in coefs.</u>			0.018^{a}	0.005^{b}	0.020^{a}	0.005^{b}	0.001
			(0.003)	(0.002)	(0.005)	(0.003)	(0.001)
Observations	1930160	1930160	1930160	1930160	1930160	1930160	1930160
Year dummies	Yes	Yes	Yes	Yes	No	No	Yes
Country×year dummies	No	No	No	No	Yes	Yes	No
Actor-Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

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. In column (7), we implement a simple placebo test with the idea of testing our identifying assumption that winning a battle on a mining area enables the fighting groups to appropriate the mining rents. To this purpose, we estimate equation (6) 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 now document the spatial and time decays of this process of diffusion of mining-induced violence. In Table 8 we restrict our analysis to the groups that were active in $t-1$. Columns (1) and (2) reproduce the estimations of Table 7, 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; we indeed find that winning battles in $t-1$

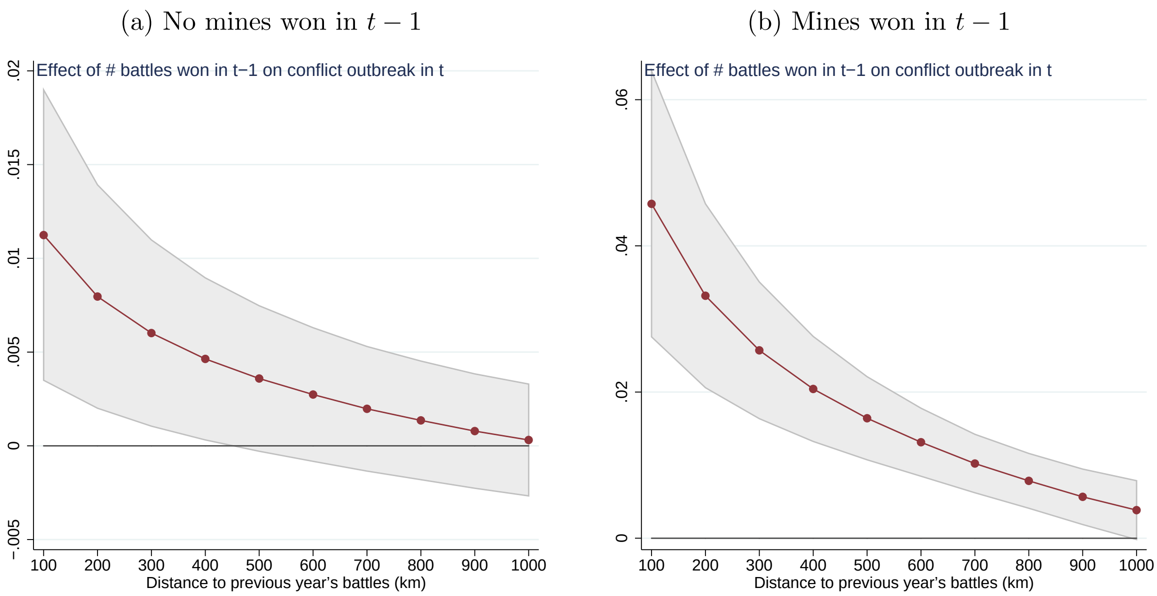
Table 8: Feasibility and the diffusion of war (2/2)

	(1)	(2)	(3)	(4)	(5)	(6)
			Conflict onset			
Estimator			LPM			
Sample			Groups active in $t-1$			
# battles$_{at-1}$	0.002				0.036^{a}	
	(0.002)				(0.012)	
# battles$_{at-1}$ (no mine)		0.002	0.001	0.001		0.033^{a}
		(0.002)	(0.002)	(0.002)		(0.013)
# battles$_{at-1}$ (mine)		0.007^{a}	0.008^{a}	0.010^{a}		0.130^{a}
		(0.002)	(0.002)	(0.003)		(0.034)
# battles$_{at-2}$ (no mine)			-0.001	-0.000		
			(0.001)	(0.001)		
# battles$_{at-2}$ (mine)			0.004^{b}	0.006^{b}		
			(0.002)	(0.002)		
# battles$_{at-3}$ (no mine)				-0.002^{c}		
				(0.001)		
# battles$_{at-3}$ (mine)				0.004		
				(0.006)		
ln average distance to battles$_{t-1}$					0.003	0.003
					(0.004)	(0.004)
# battles$_{at-1}\times$ ln av. dist.					-0.005^{a}	
					(0.002)	
# battles$_{at-1}$ (no mine) $\times$ ln av. dist.						-0.005^{a}
						(0.002)
# battles$_{at-1}$ (mine)$\times$ ln av. dist.						-0.018^{a}
						(0.005)
Observations	215466	215466	215466	199741	215466	215466
Country$\times$year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Actor-Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

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

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 neighbouring 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)). 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, on the other hand, the probability increases by up to 5 percentage points in the close surroundings of the battles but remains significant up to 1000 kilometers around. This clearly suggests that mining diffuses conflict across space.

Figure 4: Feasibility and the spatial diffusion of conflicts



4.3 Minerals and separatism

As shown in Fearon (2004), "sons of the soil" wars that typically involve land conflict between a peripheral ethnic minority and state-supported migrants of a dominant ethnic group are on average quite long-lived. In this category of wars secessionist rebel groups have the strongest need for cash to sustain their armed struggle. Hence, we expect the relaxation of *feasibility* constraints due to controlling mining revenues to play a particularly major role in separatist conflicts.

Hence, in this subsection we study whether mines have a stronger impact on the conflict risk in the homelands of discriminated groups. For this purpose we make use of the "Geo-referencing Ethnic Power Relations" (GeoEPR) dataset (Wucherpfennig et al., 2011). This provides geo-referenced settlement patterns of a global sample of ethnic groups. The underlying Ethnic Power Relations (EPR) data allows in addition to classify groups according to access to political power. The least favorable category of power status is called "Discrimination", which is defined as "Group members are subjected to active, intentional, and targeted discrimination, with the intent of excluding them from both regional and national power. Such active discrimination can be either formal or informal." We create a variable of "discriminated group" (DG) taking a value of 1 if a cell contained a discriminated group during the pre-sample period 1992-1996 to alleviate concerns of reversed causality.

The results are shown in Table 9. We carry out the usual interactions with mineral prices. In column (1), we find that while increases in the price of the main mineral produced by a given cell tend in general to increase the risk of conflict incidence, this effect is much stronger when a mine is located in the ethnic homelands of a discriminated group. Further, columns (2) and (3) show that the effects of interest are much more substantial when the mineral-rich homelands of

Table 9: Minerals and separatism

	(1)	(2)	(3)
Estimator		LPM	
Dep. var.		Conflict incidence (Acled)	
DG[1] × ln price	0.164^c	0.055^b	0.083^a
	(0.099)	(0.022)	(0.019)
ln price main mineral	0.064^a	0.061^a	0.040^b
	(0.021)	(0.022)	(0.019)
DG[1] × ln price × ln distance to border		-0.163^a	-0.158^a
		(0.011)	(0.011)
DG[1] × ln price × ln distance to capital			0.061^a
			(0.012)
Observations	137648	137648	137648
R^2	0.445	0.445	0.445
Country×year dummies	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes

Standard errors, clustered by country in parentheses. The sample includes only cells with always at least an active mine, or no mine over the period. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. [1] Dummy taking the value 1 if the cell contains a discriminated group (in year t in columns (1) and (2) over the period 1992-1996. Columns (2) and (3) include interactions between prices and distance variables, and between DG and distance variables. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t.

a discriminated group are located far from the capital and close to the country border. Taken together, these findings are in line with the view that mining income can play a major role to finance and hence sustain the insurgency of separatist ethnic groups, by making their armed struggle feasible.

5 Conclusion

In this paper we provide a systematic analysis of the impact of all major mineral mines 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 analysed the within-cell variations in violence driven by the opening and closing of mines. After this preliminary benchmark analysis we have moved to an even tighter identification strategy where we can restrict the sample to only cells without opening and closing of mines and where the identifying variation comes from exogenous price shocks for different minerals produced by the cell or the region around it. We find a strongly significant and quantitatively large impact of mining activities on the likelihood of conflict incidence. According to our estimates, the steep increase in mineral prices between 1997 and 2010 accounts for 13 to 21% of the average violence observed in African countries over this time period. We perform numerous sensitivity tests and show that the results are robust to a variety of alternative specifications, addressing concerns related to reversed causality, omitted variable bias and the appropriate level of aggregation.

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 diffusion of violence over space and time. In particular, we have found that mining activity does not only increase the scope for localised protests and riots, but that it also systematically fuels larger-scale battles. Importantly, we have been able to show that winning a battle involving a mine empowers rebel groups and leads them to intensify and spread their fighting activity in the successive periods, while winning a battle outside a mining area does not have such a conflict diffusion effect. Our findings are consistent with the view that rents from looted minerals can make it financially feasible for the rebels to sustain insurgency over a longer period, which can result in longer-lasting wars. We also find that the presence of mines has the strongest conflict inducing effect in the homelands of discriminated ethnic groups being located in peripheral areas of the country, which is consistent with recent theories of separatist warfare.

In future work, we plan to extend the approach in this paper to the study of how multinational mining companies adapt to the conflict risk in mining areas. Other interesting research questions include the impact of trade embargoes on particular mineral types (e.g. "blood diamonds") and the impact of the (public or private) ownership of mines on the conflict risk.

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6 Appendix

6.1 Additional data information

Massacre data: We rely on the "Political Instability Task Force Worldwide Atrocities Event Data" (PITF, 2013), put together by the "Political Instability Task Force", which has under the direction of Barbara Harff provided the most widely used datasets on mass killings. PITF's Atrocities Event Data contains information on geo-referenced events of atrocities committed, where "atrocities" are defined as "as implicitly or explicitly political, direct, and deliberate violent action resulting in the death of noncombatant civilians".

The Ethnic Power Relations Dataset: Further, we use the "Geo-referencing Ethnic Power Relations" (GeoEPR) dataset (Wucherpfennig et al., 2011). This provides geo-referenced settlement patterns of a global sample of ethnic groups. The underlying Ethnic Power Relations (EPR) data allows in addition to classify groups according to access to political power. The least favorable category of power status is called "Discrimination", which is defined as "Group members are subjected to active, intentional, and targeted discrimination, with the intent of excluding them from both regional and national power. Such active discrimination can be either formal or informal." We create a variable of "discriminated group" (DG) taking a value of 1 if a cell contains a discriminated group.

Country level conflict data: We use also information from the UCDP/PRIO Armed Conflict Dataset (v4-2013) to measure the incidence of conflict at the country level. We use the civil war incidence dummy variable, which is equal to 1 for years with a number of battle deaths greater than 1000, and 0 otherwise; and civil conflict dummy which is equal to 1 for years with a number of battle deaths greater than 25, and 0 otherwise.

Other location-specific data. Distance between the cell's centroid and international borders and to capital city are taken directly from PRIO-GRID. Cell-specific GDP and population data are also available in PRIO-GRID, and originally come from G-econ 4.0 data (Nordhaus, 2006). We proxy the level of economic activity with data on *Satellite nightlight.* This data comes from the National Oceanic and Atmospheric Administration (2010). We use their data on Average Visible, Stable Light & Cloud Free Coverages. In particular, we use their "cleaned" and "filtered" version of the data, which "contains the lights from cities, towns, and other sites with persistent lighting, including gas flares. Ephemeral events, such as fires have been discarded. Then the background noise was identified and replaced with values of zero. Data values range from 1-63." Using ArcGIS we generate the average at cell-year level.

Price data. The data on mineral prices comes from the World Bank Commodity Prices dataset. Data is available for the ten following minerals: aluminum, copper, diamond, gold, iron, lead, nickel, platinum, silver, tin and zinc.

6.2 Additional Figures

Figure 5: Time trends of mines and conflict

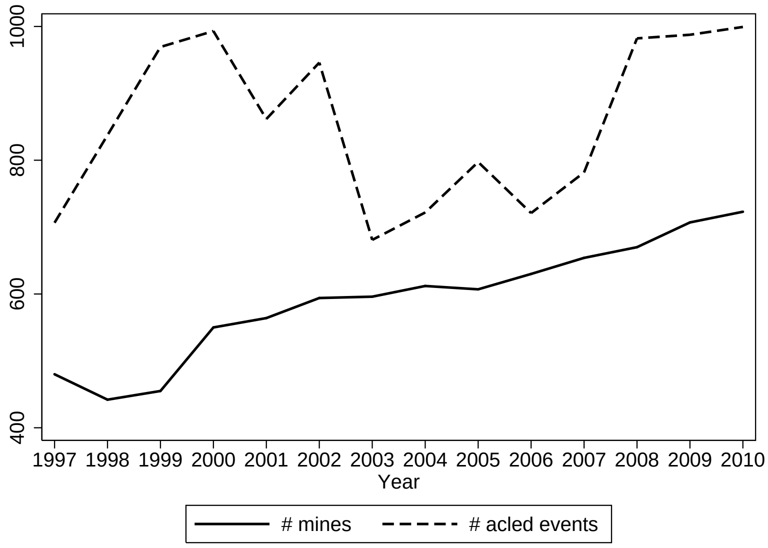
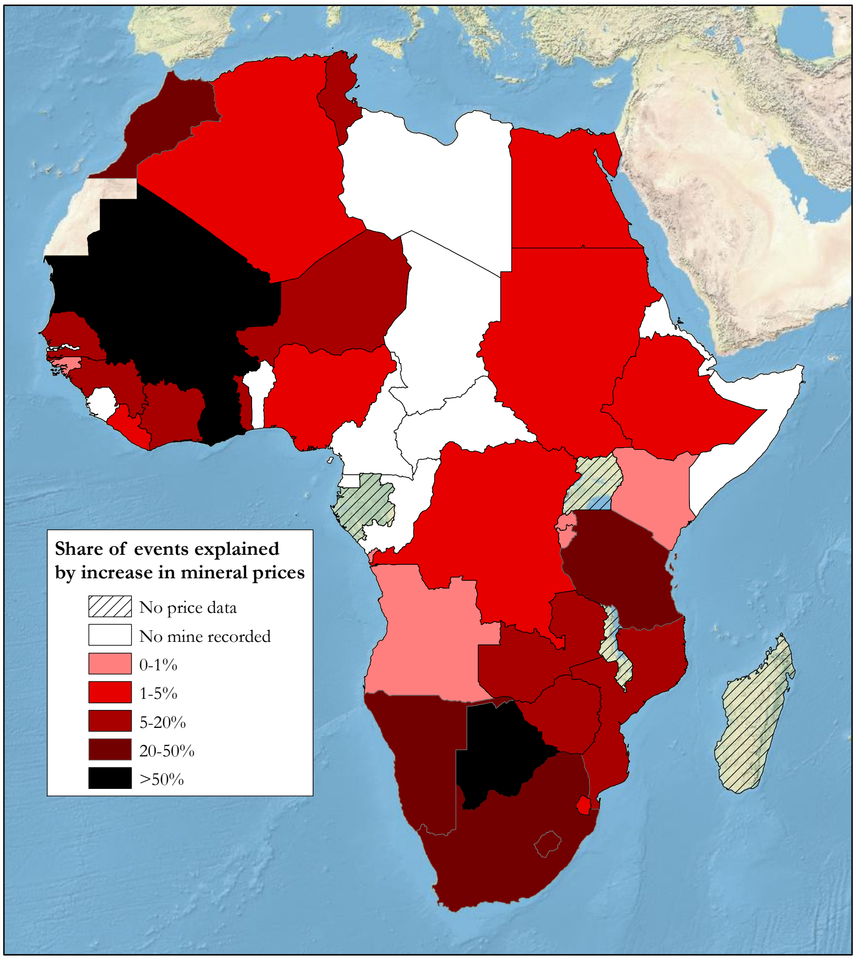


Figure 6: Counterfactuals: share of events due to increasing prices



6.3 Additional tables

Table 10: Descriptive statistics: country-level

	Obs.	Mean	S.D.	1st Quartile	Median	3rd Quartile
# conflicts / year	52	16.46	22.10	1.78	7.17	17.08
# mines / year	52	11.37	47.10	0.00	1.32	4.82

Table 11: 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	3	24
Botswana	0.04	0.01	17	3	Malawi	0.03	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	21	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	3	17
Chad	0	0.03	0	35	Namibia	0.03	0.02	21	15
Comoros	0	0	0	0	Niger	0.01	0.01	3	18
Congo. Dem. Rep.	0.01	0.08	28	336	Nigeria	0.01	0.17	3	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	2	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	2	115	South Afr.	0.17	0.06	337	76
Gabon	0.01	0.02	1	3	Sudan	0	0.07	3	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	14	47
Lesotho	0.08	0.10	1	1	Zimbabwe	0.17	0.24	62	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 12: Conflicts and mineral prices: robustness (controlling for large players)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	LPM		LPM		LPM	
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	0.060		0.050			
	(0.095)		(0.115)			
ln price main mineral	-0.026		-0.042[c]		0.013	
	(0.018)		(0.025)		(0.012)	
ln price × mines > 0	0.091[a]	0.058[b]	0.144[a]	0.048[a]		
	(0.028)	(0.023)	(0.036)	(0.017)		
ln price × mines > 0 × large player	0.004	0.053	0.006	0.178[b]		
	(0.004)	(0.040)	(0.004)	(0.084)		
# mines					0.045[b]	
					(0.019)	
ln price × # mines					0.016[a]	0.004[a]
					(0.003)	(0.001)
ln price × # mines × large player					0.001	-0.034[a]
					(0.002)	(0.010)
Observations	142817	141890	142817	141890	142926	141568
R^2	0.445	0.445	0.562	0.563	0.447	0.446
Country×year dummies	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, except that cells producing minerals for which the country is among the top 10 of world producers are removed from the sample. Var(M_{kt}) = 0: only cells in which the mine variable takes always the same value over the period. All estimations include controls for the average level of mineral world price interacted with the mines variables. 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.

Table 13: Conflicts and mineral prices: controlling for luminosity

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	LPM		LPM		LPM	
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	0.052		0.045			
	(0.093)		(0.112)			
ln price main mineral	-0.024		-0.051^c		0.018	
	(0.021)		(0.028)		(0.014)	
ln price × mines > 0	0.097^a	0.089^a	0.146^a	0.102^a		
	(0.026)	(0.017)	(0.034)	(0.031)		
luminosity	0.002	0.002	0.001	0.001	0.002	0.002
	(0.002)	(0.002)	(0.005)	(0.005)	(0.002)	(0.002)
ln price × luminosity	-0.001	-0.001^b	0.001	-0.000	-0.001	-0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
# mines					0.037^a	
					(0.014)	
ln price × # mines					0.017^a	0.004^a
					(0.004)	(0.001)
Observations	139607	138680	139607	138680	139702	138372
R^2	0.437	0.437	0.554	0.555	0.439	0.438
Country×year dummies	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%. Var(M_{kt}) = 0 means that we include only cells in which the mine variable takes always the same value over the period. All estimations include controls for the average level of mineral world price interacted with the mines variables. 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.

Table 14: Conflicts and mineral prices: additional controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimator		LPM			LPM			LPM	
Sample		Var$(M_{kt}) = 0$			Var$(M_{kt}) = 0$			Var$(M_{kt}) = 0$	
Dep. var.	Incidence	# conflicts	Incidence	Incidence	# conflicts	Incidence	Incidence	# conflicts	Incidence
ln price × mines > 0	0.105^a	0.151^a		0.064^a	0.067^b		0.071^a	0.084^b	
	(0.022)	(0.047)		(0.020)	(0.034)		(0.022)	(0.034)	
ln price × # mines			0.005^a			0.004^a			0.004^a
			(0.001)			(0.001)			(0.001)
temperature × mines > 0	0.028	0.027	0.024						
	(0.018)	(0.035)	(0.015)						
rainfall × mines > 0	-0.014	-0.141	-0.056						
	(0.066)	(0.163)	(0.040)						
ln price × # neighb. cells in conflict				0.000	0.004^b	-0.001			
				(0.001)	(0.002)	(0.001)			
ln price × # past conflicts in cell							0.004	0.019^b	0.004^a
							(0.003)	(0.008)	(0.001)
Observations	118884	118884	118608	137900	137900	137578	141890	141890	141568
R^2	0.446	0.567	0.446	0.448	0.563	0.448	0.445	0.563	0.446
Country×year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	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%. Var$(M_{kt}) = 0$ means that we include only cells in which the mine variable takes always the same value over the period. All estimations include controls for the average level of mineral world price interacted with the mines variables. 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 (2) and (5) and (8). ln price main mineral is the world price of the mineral with the highest average production in the cell over the period.

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

	(1)	(2)	(3)	(4)
Estimator	LPM		LPM	
	Conflict incidence			
Sample	Var(M_{kt}) = 0	Permanent active mine(s)	Var(M_{kt}) = 0	Permanent active mine(s)
ln price × mines > 0	0.073^{a}	0.049	0.082^{a}	0.082^{a}
	(0.020)	(0.102)	(0.025)	(0.026)
Observations	141890	952	141890	952
Country×year dummies	Yes	Yes	No	No
Cell FE	Yes	Yes	Yes	Yes

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. All estimations include controls for the average level of mineral world price interacted with the mines variables. 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.

Table 16: Mineral and price: 1×1 degrees cells

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	LPM		LPM		LPM	
Dep. var.	Conflict incidence		# conflicts		Conflict incidence	
Sample	All	$\mathrm{Var}(M_{kt}) = 0$	All	$\mathrm{Var}(M_{kt}) = 0$	All	$\mathrm{Var}(M_{kt}) = 0$
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 dummies	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%. $\mathrm{Var}(M_{kt}) = 0$: 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. $log(x + 1)$ used for dependent variable in columns (3) and (4). # mines is the number of active mines 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.

Table 17: Conflicts, mineral prices and distance to mines

	(1)	(2)	(3)	(4)
Estimator		LPM		
Dep. var.		Conflict incidence (Acled)		
Sample	All	All	$Var(dist\_mine) = 0$	
log distance to closest mine	-0.010^b	0.004		
	(0.005)	(0.023)		
ln price × ln dist. closest mine		-0.001^b	-0.003^b	-0.004^b
		(0.001)	(0.001)	(0.002)
ln price × ln dist. capital city				0.003
				(0.003)
ln price × ln dist. border				0.001
				(0.002)
Observations	118343	73136	40200	34304
R^2	0.438	0.448	0.446	0.457
Country×year dummies	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes

Standard errors, clustered by country in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. In col. 3 no opening / closing of mines. Distance to closest mine is the distance to the closest mine within the same country. Estimations (2) to (4) include interaction terms between price variations and country dummies.

Table 18: Baseline results, excluding conflicts involving civilians, rioters or protesters

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	LPM		LPM		LPM	
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	0.012		0.022			
	(0.043)		(0.036)			
ln price main mineral	-0.063^b		-0.068^b		-0.015^c	
	(0.028)		(0.032)		(0.009)	
ln price × mines > 0	0.082^a	0.023^a	0.089^b	0.021^b		
	(0.030)	(0.008)	(0.035)	(0.008)		
# mines					-0.032	
					(0.027)	
ln price × # mines					0.007^b	-0.000
					(0.003)	(0.001)
Observations	142817	141890	142817	141890	142926	141568
R^2	0.366	0.367	0.456	0.457	0.367	0.368
Country×year dummies	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%. 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.

6.4 Group-level estimations

We replicate our baseline results (in Table 4) 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:

$$\text{Conflict}_{gkt} = \alpha_1 M_{kt} + \alpha_2 \ln p^W_{kt} + \alpha_3 \left(M_{kt} \times \ln p^W_{kt}\right) + \mathbf{FE}_{gk} + \mathbf{FE}_{it} + \varepsilon_{gkt}, \tag{7}$$

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 19. 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).[36]

Table 19: Conflicts and mineral prices (actor-level)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	LPM		LPM		LPM	
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	0.003		0.002		-0.001	
	(0.003)		(0.002)		(0.001)	
ln price main mineral	-0.003^a		-0.004^b		-0.000	
	(0.001)		(0.002)		(0.001)	
ln price × mines > 0	0.005^a	0.001^b	0.005^a	0.001^c		
	(0.002)	(0.000)	(0.002)	(0.001)		
ln price × # mines					0.000	0.000
					(0.000)	(0.000)
Observations	3603632	3590734	3603632	3590734	3604846	3583202
R^2	0.193	0.194	0.237	0.237	0.193	0.194
Country×year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Actor-Cell FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors, clustered by actor, 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.

[36] 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.