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

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Abstract. We combine geo-referenced data on mining extraction of 14 minerals with information on conflict events at spatial resolution of $0.5^o \times 0.5^o$ for all Africa over 1997-2010. Exploiting exogenous variations in World prices, we find a positive impact of mining on conflict at the local level. Quantitatively, our estimates suggest that the historical rise in mineral prices (*commodity super-cycle*) might explain up to one fourth of average violence across African countries over the period. We then document how the appropriation of a mining area by a fighting group contributes to the escalation from local to global violence. Finally, we analyze the impact of corporate practices and transparency initiatives in the mining industry.

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1 Introduction

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

The present paper investigates the impact of mining on conflict by using geolocalized data on conflict events and mining extraction of 14 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, with the *Armed Conflict Location Events Data* (ACLED) that provides information on the location and type of conflict events and the involved actors. The units of analysis are cells of 0.5×0.5 degree latitude and longitude (approx. 55km $\times$ 55km at the equator) covering all Africa. The use of geo-referenced information enables causal identification: Including country$\times$year fixed-effects and cell fixed-effects, we exploit in most of our econometric specifications the within-mining area panel variations in violence due to changes in the World price of the main mineral extracted in the area.

In the first part of our analysis, we estimate the overall extent of mining-induced violence at the local level. We find a positive effect of mining activity on conflict probability: a spike of mineral prices increases conflict risk in cells producing these commodities. These results are robust to a variety of consistency checks. We also find that countries with less corrupt institutions and with lower religious fractionalization/polarization are less affected by mining-induced violence; however, we detect little effect of political institutions (e.g. democracy, rule of law, government effectiveness). Similarly we find that minerals associated with higher rents are particularly conflict-prone. We then perform several quantification exercises to gauge the magnitude of the effect: A one-standard deviation increase in the price of minerals translates into an increase in probability of violence *in mining areas* from the benchmark 16.9% to a counterfactual 22.5%. When aggregated at the country level, the effect remains sizeable. Indeed we quantify the effect

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

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

of the historical rise in mineral prices between 1997 and 2010, which according to most scholars was mainly due to the sharp increase in the demand for minerals by emerging market countries such as China and India (Humphreys, 2010; Carter, Rausser and Smith, 2011). Our estimates suggest that the contribution of this so-called *commodities super cycle* to the average violence observed across African countries over the period lies between 14% and 24%.

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

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

Our paper contributes to the literature in several ways. First, we study resource abundance and conflict i) for all major minerals; ii) using data at a high spatial resolution; iii) covering all Africa and iv) going beyond pooled panel regressions. Second, we 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 rebelion. Third, to the best of our knowledge we are the first ones to document how mining company characteristics and practices (e.g. size, location of headquarters, compliance to Corporate Social Responsibility) can contain or boost mining-induced violence.

The paper is organized as follows: Section 2 discusses the existing literature and the conceptual framework that underpins our empirical analysis. Section 3 presents the data. Section 4 displays the empirical analysis related to the local impact of mining activity on violence and how it varies with country and mineral characteristics. In section 5 we study the diffusion over space and time of mining-induced violence perpetrated by rebel groups. Section 6 studies the role of mining

companies and of transparency initiatives, and section 7 concludes.

2 Existing Evidence and Conceptual Framework

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 estimate pooled cross-country regressions finding that civil war onset and incidence correlate positively with natural resources, generally focusing on oil, diamonds or narcotics.[4] The main shortcoming of this "first generation" of papers is that resource-rich and resource-poor countries typically also differ in various geographic, demographic, political and economic dimensions, and the existence of unobserved heterogeneity makes it hard to give a causal interpretation to such cross-country correlations.

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

From a conceptual perspective, a rich theoretical literature has identified several major channels through which natural resources magnify the risk of conflict –a survey relevant for our analysis being provided by Bazzi and Blattman (2014). First, natural resources improve rebellion *feasability* i.e. looting and extortion relax financing constraints and make it easier to set up and sustain a rebel movement. Second, the presence of natural resources increases the "prize" that can be seized through the capture of the territory or the state – which has been referred to as *greed* or *rent-seeking*. Third, *weak state capacity and extractive institutions* may be a further consequence of resource wealth: Rentier states can rely on resource rents and do not build up enough state

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

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

capacity and good institutions, which makes them less effective in counterinsurgency and eventually more instable. Fourth, given that natural resource production is *capital intensive*, a resource price spike will boost capital-intensive production, and shrink labor-intensive sectors, which frees up cheap labor for rebellion. Fifth, natural resources can in addition exacerbate *grievances*, due to frustrations from environmental degradation or banned access to lucrative mining jobs. Sixth, mining booms could affect *migration* patterns and lead to changes in the size and composition of the local population in mining areas with respect to ethnicity, age and gender.[5] Finally, there is also a channel working in the opposite direction: *Higher local incomes* in mining areas may increase the opportunity cost of rebellion, which in turns decreases the likelihood of conflict.

The existing empirical literature has typically been unable to distinguish between these different theoretical mechanisms.[6] In the first part of the paper, we document a positive causal impact of mineral prices variations on conflicts which is consistent with all those mechanisms (except the last one). However, in the second part of the paper we focus specifically on the *feasability* channel. In particular, we find that territorial control of mining areas leads rebel groups to spread their fighting elsewhere in successive periods. We also find that foreign mining companies operating in corrupt environments trigger more conflict, which is a piece of suggestive evidence of the participation of these companies in the financing of rebel groups. Overall, we see these results as supporting the existence of the feasibility channel. But this does in no way preclude that other mechanisms are jointly at work.

3 Data

3.1 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.[7] Our unit of observation is therefore a *cell-year* in sections 4 and 6, i.e. we study how mineral resources affect the probability that a conflict takes place in a given cell, during a given year. In this section we provide information about the main datasets and variables used in the paper – more details appear in the online appendix, section A.

Conflict data. We use the Armed Conflict Location and Event dataset (Raleigh, Linke, and Dowd, 2014) which contains information on the geo-location of conflict events in all African countries. We focus on the 1997-2010 period which overlaps with our mines data. We have information about the date (precise day most of the time), longitude and latitude of conflict

[5] For *feasability* see Fearon (2004), Collier, Hoeffler and Rohner (2009), Nunn and Qian (2014), and Dube and Naidu (2015); for *greed* see Reuveny and Maxwell (2001), Grossman and Mendoza (2003), Hodler (2006), and Caselli and Coleman (2013); for *state capacity* see Fearon (2005), Besley and Persson (2011) and Bell and Wolford (2015); for *capital intensive* see Dal Bo and Dal Bo, (2011), Dube and Vargas, (2013); for *migration* see Le Billon (2001), Ross (2004), and Humphreys (2005).

[6] A notable exception is Humphreys (2005) who uses among others the distinction between production and reserves to distinguish between different channels, estimating pooled cross-country regressions, as well as Morelli and Rohner (2015) and Dube and Vargas (2013) documenting the role of secession, and capital-intensiveness, respectively.

[7] See e.g. Besley and Reynal-Querol (2014) or Michalopoulos and Papaioannou (2013) for papers using similar grid-cell level data combined with the same conflict data.

events within each country. These events are obtained from various sources, including press accounts from regional and local news, humanitarian agencies or research publications. A first unique feature of the ACLED dataset is that it records all political violence, including violence against civilians, rioting and protesting within and outside a civil conflict, without specifying a battle-related deaths threshold. Another is that it contains information on the type of events, their outcome, 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.[8] We shall make use of this information when testing for the channels of transmission.[9]

The latitude and longitude associated to 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. We keep only events which are geolocalized with the finer precision level for our analysis, and we drop duplicated events.[10]

The data is aggregated 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*. This is our main dependent variable throughout the paper. Alternatively, we compute a variable containing the number of events observed in the cell during the year, which we label *conflict intensity*. We also show that our results are robust to modeling cell-specific conflict onset and ending separately.

While the geo-coding of the events is cross-checked in the ACLED dataset, it is not immune to potential biases and measurement errors. We cannot rule out the possibility that the reporting of conflicts is biased towards certain types of countries, regions or events, as some regions might in particular have better media coverage. An event dataset such as ACLED cannot, by definition, be fully exhaustive. Our empirical methodology makes it however unlikely that this affects our results, as structural differences in media coverage or more generally in the reporting of events is captured by cell and country-year fixed-effects.[11]

Mines data. To each *cell-year*, we merge information on mines from *Raw Material Data* (RMD, IntierraRMG). The data contain information on the location of mines around the World since 1980.[12] For each year, we know whether a mine is active or not, the year production started,

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

[9]The presence of this detailed information as well as the more exhaustive character of the ACLED are the main reason why we chose to use this dataset, rather than the UCDP-GED dataset. The latter records only deadly events pertaining to conflicts reaching at least 25 battle-related deaths per year, and does not include information on battle events outcomes. We nevertheless also show and discuss the results obtained using the UCDP-GED dataset in the online appendix (Section E).

[10]This has no impact when considering conflict incidence, our main variable of interest, but reduces noise when looking at the number of events as we do in a robustness exercise.

[11]We also show that our results are obtained across events of different types (battles, riots, violence against civilians). Similarly, when considering jointly ACLED and UCDP-GED events, our coefficient of interest is similar for the two datasets, despite the fact that the UCDP-GED dataset is less exhaustive and records only large, deadly events which are arguably less likely to be affected by reporting bias.

[12]More information is available at http://www.snl.com/Sectors/metalsmining/Default.aspx. Other recent research using the RMD data includes Kotsadam and Tolonen (2016) who study gender and local labor market effects of mining, as well as Kotsadam, Olsen, Knutsen and Wig (2015) who assess the impact of mining on local corruption.

the specific minerals produced and the total production for each of them. We use this data to identify active mining areas, and the type of minerals they produce. The dataset also includes additional information about the ownership structure and characteristics of the mines, as well as some data about extraction methods - we come back to these variables in Sections 4.5 and 6 in which we study the role of minerals' and mining companies' characteristics.

For each cell k, we define M_{kt}, a dummy variable which equals one if a least one *active* mine is recorded in the cell during year t. We identify 25 minerals in our sample of African countries. In the rest of the analysis we focus on the cells producing one or several of the 14 minerals for which we have price data.[13] We define as the main mineral produced in the cell the mineral with the highest production over the entire period, evaluated at 1997 prices.[14] Among the 237 mining cells for which a main mineral is identified, 70% produce a single mineral, and the main mineral produced represents on average 96% of total production value. In the robustness section, we show a number of robustness checks related to the definition of the main mineral; in particular we restrict our sample to single-mineral cells or consider all the minerals produced in a price index instead of the main mineral only.

The RMD dataset collects information mostly for large-scale mines, usually operated by multinationals or the country's government. Hence small-scale mines, and those that are illegally operated, are not included in our sample. While these measurement errors could lead to some attenuation bias in our estimates, we believe that this concern is limited in practice, given our empirical strategy. First, our baseline specifications include time-invariant versions of M_{kt} and identify the effect of mining through variations in World mineral prices within cells; in other words, measurement errors are unlikely to attenuate our estimates given the inclusion of cell fixed effects. Second, our unit of analysis being an area (i.e. a 0.5×0.5 degree cell) where mining takes place, we interpret our 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 include all mines, including small ones. Note that we estimate a number of robustness tests to ensure that our results are not sensitive to changes in the definition of a mining area. In particular, we include the surrounding cells (first and second degrees) or use 1×1 degree units instead of 0.5×0.5. As shown later, results are consistent across specifications.

Other data. Information on the World price of the minerals is retrieved from the World Bank Commodities prices dataset. Real prices are measured in constant 2005 USD. We also add diamond prices from Rapaport. Diamond is problematic as its price varies importantly according to the quality and type of diamonds produced. There is a large heterogeneity in diamond quality across mines and the price series for different qualities can move in opposite directions. As the RMD dataset contains no information on diamond quality, we exclude diamonds from our baseline sample in order to limit measurement errors. We however show that our results are

[13] These minerals are: Bauxite (aluminum), Coal, Copper, Diamond, Gold, Iron, Lead, Nickel, Platinum (and Palladium/PGMs, i.e. Platinum Group Metals), Phosphate, Silver, Tantalum (Coltan), Tin and Zinc. These minerals are present in 92% of mining cells over our period of study. We do not consider the following minerals: Antimony, Chromite, Cobalt, Lithium, Manganese, Niobium, Rhodium, Tungsten, Uranium, Vanadium, Zirconium.

[14] For some cells minerals for which we have the price co-exist with minerals for which we do not, which complicates the identification of the main mineral. In most cases however, we can identify the main mineral produced by using additional information contained in the RMD data about the name of the mines. More details about the procedure are provided in the online appendix (Section A).

robust to the inclusion of this mineral. Similarly we add data on tantalum (coltan) price from the US Geological Survey. Unfortunately this series contains US unit values rather than a World price. To be consistent, we exclude tantalum from our baseline estimations and only keep the minerals for which World price data is available. Again, we show that adding coltan leaves our results largely unchanged. Finally, we add a number of cell-specific variables (distances, climate, ethnic homeland), country-specific data (institutions, social and ethnic cleavages, transparency initiatives) and mineral-specific information (extraction cost or method).

3.2 Descriptive statistics

Our final sample covers 52 countries and 14 minerals –see Section A in the online appendix for a visual representation of the geo-localization of both conflict events and mines. Only four countries display no conflict events over the entire period and there are 20 countries with no active mine recorded. The main minerals present in the dataset are gold (a third of mining cells), diamond, copper and coal (around 10-15% each). Note that, except in the case of South Africa, the countries contained in our sample are typically small producers of the minerals from a World perspective: the average market share of a country-mineral is around 6.5% (the median at 2.9%), and drops to 4.5% when we exclude South Africa (and the median to 1.6%).

Table 1: Descriptive statistics: cell-level

	Obs.	Mean	S.D.	Median
Pr(Conflict> 0)				
all cells	144690	0.06	0.23	0
if mines>0	2798	0.14	0.35	0
if mines = 0	141892	0.05	0.22	0
battles	144690	0.03	0.17	0
viol. against. civ.	144690	0.03	0.17	0
riots & protests	144690	0.02	0.12	0
# conflicts				
all cells	144690	0.25	3.41	0
if > 0	7980	4.61	13.79	2
Pr(Mine> 0)				
only cell	144594	0.02	0.14	0
incl. 1st *surrounding cells*	144690	0.09	0.29	0
incl. 1st *&* 2nd *surrounding cells*	144687	0.17	0.38	0
# mines				
all cells	144594	0.05	0.60	0
if > 0	2702	2.57	3.55	1
Pr(# mines > 2)				
all cells	144690	0.01	0.09	0
if mine> 0	2798	0.40	0.49	0

Source: Authors' computations from ACLED and RMD dataset.

Table 1 displays some descriptive statistics. Our sample consists in slightly more than 10,000 cells over 14 years. Several elements are worth mentioning. First, the unconditional probability of observing at least one conflict in a given cell and a given year is low, around 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 9% (respectively, 17%) when we consider the

neighboring cells (respectively, the first and second degree neighboring cells). Second, mines tend to be spatially clustered: conditional on observing at least one mine in a given cell, the average number of mines is 2.57. Finally, the conflict probability is much higher in cells with active mines, around 14%. Of course, this could be due to many unobserved cell characteristics, an issue we shall deal with in our estimations. In the online appendix (Section B) we document correlations between the presence of mining areas and the likelihood of violent events at the cell-level. We find that the presence of active mines is positively correlated with conflict incidence, both across and within cells.

4 Exogenous changes in the value of mines: Local impact

We turn now to our empirical analysis. First, our identification strategy is discussed and the baseline results are reported. Second, we provide a series of alternative specifications assessing the robustness of the results. Then we focus on heterogeneous effects. Finally, we perform various quantification exercises.

4.1 Methodological issues

Assessing the causal impact of mining on violence is subject to various methodological challenges. The most obvious one relates to the reverse causation from local violence to mine opening/closing. The direction of this bias is most likely negative, i.e. conflict incidence might impact negatively the likelihood of a mine being active. This should therefore work against our finding of a significant positive correlation between mining activity and conflict. However, we cannot rule out the possibility that conflicts affect the value of a mine in a non-trivial way, for instance if the state uses part of the mine production to fight insurgency.[15]

In order to address causality, we focus on exogenous variations in the economic value of mines. The idea is that more valuable mines increase local rent-seeking and, consequently, the likelihood of violence.[16] To abstract from local determinants of violence and guarantee exogeneity, we exploit the variations in the World prices of minerals. More precisely, we estimate a specification of the following form:

$$\text{CONFLICT}_{kt} = \alpha_1 M_{kt} + \alpha_2 \ln p_{kt}^W + \alpha_3 \left(M_{kt} \times \ln p_{kt}^W \right) + \mathbf{FE}_k + \mathbf{FE}_{it} + \varepsilon_{kt} \tag{1}$$

where (k, t, i) denote respectively cell, time and country, $\mathbf{FE}_k$ are cell fixed-effects and $\mathbf{FE}_{it}$ is an additional battery of fixed-effects that can vary at different levels depending on the specification (e.g. year, country×year). Note that border cells are assigned to the country that represents the largest share of their area. The dependent variable, CONFLICT_{kt}, corresponds to the observation of violent events at the cell-year level where violence is measured in terms of incidence, i.e. a binary variable coding for non-zero events in the ACLED dataset on civil conflicts. Alternative measures of

[15] Guidolin and La Ferrara (2007) actually find evidence that conflicts increase the value of extractive firms. They mention several reasons that might explain this finding: during conflict, (i) entry barriers might be higher; (ii) the bargaining power of governments might be lower and hence licensing cheaper; (iii) lower transparency leads to more unofficial deals which are profitable to the firms; (iv) the manufacturing sector leaves the country, forcing it to specialize in natural resources.

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

violence are considered in our sensitivity analysis in Section 4.3. The main explanatory variable, M_{kt} is a binary variable coding for the presence of at least one active mine at the cell-year level. The variable p^W_{kt} corresponds to the World price in year t of the main mineral produced by the mines present in cell k, i.e. the one with the highest total production (evaluated at 1997 prices) over the entire 1997-2010 period. For cells where no active mine ever produces over the period we set p^W_{kt} to zero; by contrast, it is non-zero for cells with a mine that is inactive only *temporarily*. Our sensitivity analysis investigates alternative coding rule for M_{kt} and p^W_{kt} (Section 4.3).

In equation (1) we are primarily interested in the estimates of α_3, the coefficient of the interaction term between the 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 fixed-effects at the country-year level, our identification strategy relies on the exogeneity of the interaction term, $M_{kt} \times \ln p^W_{kt}$, with respect to the local determinants of conflict. We discuss hereafter this identification assumption.

Exogeneity of prices. This seems a reasonable assumption for the World price of minerals, p^W_{kt}, as mentioned earlier. Still, one might argue that some mines are large enough to affect World prices, in which case the occurrence of conflict in these cells might also affect these prices. Although our sample contains only few countries with potentially large market power on the mineral market, we nevertheless test whether our results are robust to excluding from the sample all cells located in countries belonging to the top ten World producers of a specific mineral (see section H in the online appendix). Another possibility is that time-varying omitted variables could co-determine World prices and local violence in mining areas. The use of country×year fixed effects in our baseline specifications alleviates most of this problem, but we consider in our sensitivity analysis placebo exercises to ensure that our results are not driven by co-movements of the residual unobserved heterogeneity and the World prices of minerals.

Endogenous mining activity. As discussed above, potential reverse causation from conflicts to mining opening/closing is an important concern. As a consequence, our coefficient of interest, α_3, could be partly driven by conflict-induced shifts in the binary variable M_{kt}. To account for this issue, we first restrict the estimate of equation (1) to the sub-sample of cells for which mining activity always takes place during the period (i.e. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ 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 $\ln p^W_{kt}$ and $(M_k \times \ln p^W_{kt})$ become identical; we accordingly include only the interaction term and the specification takes the following simpler expression:

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

This specification ensures that our coefficient of interest, α_3, is identified within cells through the changes in World commodity prices conditional on having *permanently* active mining activity (i.e. $M_{kt} = 1$ for all t), and not through the potentially endogenous opening/closing of mines.

An alternative way to get rid of endogenous mining activity consists in defining as mining areas cells where a mine has *ever* been recorded as active over the 1997-2010 period.[17] Under

[17] In the same vein we consider alternative coding rules in Section 4.3. In particular, we code $M_k = 1$ if the cell had an active mine in the pre-sample period (i.e. in the five years prior to 1997).

this coding rule the mining activity dummy becomes time-invariant, $M_k \in \{0, 1\}$, such that the econometric specification is given by equation (2) and the coefficient of the interaction term α_3 keeps on being identified through changes in World mineral prices only. The advantage of this approach is that it can be estimated on the full sample of cells and not on a selected sub-sample as is the case with the estimation based on cells without opening/closing of mines. Its disadvantage is that a cell can be considered a mining area even when mining does not necessarily take place in a given year.

Estimation issues. Due to the inclusion of several dimensions of fixed effects, we estimate equations (1) and (2) using a Linear Probability Model in our baseline specifications. Non-linear estimators such as conditional logit or Poisson pseudo-maximum-likelihood estimator are implemented as robustness checks. Note also that with more than 900 country×year fixed effects in most specifications, estimating the large battery of fixed effects is very demanding from a data perspective. In this respect, keeping in the sample not only cells with mines but also the large number 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, specifications including the set of cells without mines, coding as zero the World price for these cells. Alternatively, we implement a neighbor-pair fixed effects methodology in the spirit of Acemoglu, Garcia-Jimeno and Robinson (2012) and Buonanno, Durante, Prarolo and Vanin (2015): Equation (2) is estimated on the sub-sample of mining cells and their immediate neighboring cells without mine. We define a neighborhood fixed effect that is specific to each (mine + neighbors) group. The price of the main mineral produced in the mining cell is also assigned to its neighbors. By contrast, the mining dummy can differ as it is set to zero in neighboring cells with no mine. Identification hence relies on relative variations in conflict incidence in the mining cell with respect to its neighboring cells when the World price of the main mineral changes. This approach is similar in spirit to a matching estimator. With a sample size reduction by a factor 10 this is a demanding specification. Its main benefit in our context is that it avoids coding to zero the log of mineral prices in cells with no mine.

Spatial correlation. Given the high spatial resolution of the data it is important to take into account spatial correlation as both conflict and mines are clustered in space. Henceforth in all specifications standard errors are estimated with a spatial HAC correction allowing for both cross-sectional spatial correlation and location-specific serial correlation applying the method developed by Conley (1999) and Hsiang, Meng and Cane (2011). Our treatment is quite demanding as we impose no constraint on the temporal decay for the Newey-West/Bartlett kernel that weights serial correlation across time periods: The horizon at which serial correlation is assumed to vanish can be infinite (i.e. 100,000 years). In the spatial dimension we retain a radius of 500km for the spatial kernel– close to the median internal distance in our sample of African countries according to the CEPII geodist dataset.[18]

[18] Robustness to alternative spatial and temporal kernels is explored in the online appendix, section F. We have created a new STATA routine based on the one from Hsiang, Meng and Cane (2011) (`ols_spatial_HAC.ado`) and its extension to multidimensional fixed effects by Thiemo Fetzer (`reg2hdfespatial.ado` – itself based on the work of Guimaraes and Portugal, 2010). Our routine also allows to perform 2SLS estimations (in samples of limited size given the current Stata limitations).

4.2 Baseline results

Table 2 reports the baseline results for various sample compositions and definitions of the variables. The dependent variable is conflict incidence. We see that in all columns, the interaction term between World price and local mining activity, our coefficient of interest, is positive and significant at the 1 or 5 percent level. Thus, a spike in mineral prices increases the conflict risk in cells producing these commodities. We estimate equation (1) on the full sample of cells. In column (1) mining activity (*mine*> 0) is measured with a dummy taking the value 1 if at least 1 mine is active in the cell in year t. Cell fixed effects are included with the purpose of controlling for time-invariant co-determinants of violence and mining at the local level – e.g. weak state capacity and property rights enforcement in remote places or latent political instability (e.g. ethnic cleavages). Country×year fixed effects are also included to filter out all countrywide time-varying characteristics affecting violence and activity of mines – e.g. a war-induced collapse of the central state and property rights.

Table 2: Conflicts and mineral prices

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Sample	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$		All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	
mine > 0	0.112^c					0.048
	(0.065)					(0.065)
ln price main mineral	-0.029					0.028
	(0.032)					(0.019)
ln price × mines > 0	0.086^b	0.072^a	0.060^a		0.085^a	0.108^a
	(0.034)	(0.020)	(0.021)		(0.024)	(0.041)
ln price × mines > 0 (neighbouring cells)			0.021^a			
			(0.006)			
ln price × mines > 0 (ever)				0.045^a		
				(0.014)		
Country×year FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	No
Neighborhood FE	No	No	No	No	No	Yes
Observations	143768	142296	127974	143864	142296	17360

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. *mine* > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. Column (6) is estimated on a sample containing only mining cells and their immediate neighboring cells. In columns (1) to (5), ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (6) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimations (1) and (6) include controls for the average level of mineral World price interacted with the mine dummy.

In column (2), we estimate equation (2) on the sub-sample of cells without mine opening/closing (i.e. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ for a given k). In column (3) we go beyond spatial clustering of standard errors for addressing spatial dependence in the data. To this purpose we allow for

spatial lags of our explanatory variable by including the interaction term between mineral price and mining activity in neighboring cells of degrees 1 and 2.[19] As shown by the coefficient of the second interaction term, we detect an impact on local conflict of mineral price shocks in neighboring cells. The effect is 60 percent lower than for the cell itself (i.e. the first interaction term) confirming that conflict tends to spill over with spatial decay, a feature that is likely to be driven by spatial diffusion of violence (e.g. rebels roaming around).[20] In column (4) we use the alternative definition of mining activity where the mining dummy ($mines > 0$ *ever*) is now equal to one for cells where at least a mine has been recorded as active at any point over the 1997-2010 period. The coefficient of interest is slightly lower, an expected feature given that in this specification we define as mining areas places where mining took place in at least one year during the sample period. This leads to cells with currently inactive mines being treated as mining areas, resulting in potential attenuation bias.

The last two columns deal with alternative sets of fixed effects. Column (5) replicates column (2) without the country×year fixed effects. Indeed, with 15 percent of the cells belonging to more than one country, the interpretation of the unobserved heterogeneity that is captured by those fixed effects is unclear for border cells. We consequently use year fixed effects only. In the sensitivity analysis of the online appendix, section L we explore a more radical approach by dropping border cells. Column (6) implements the neighborhood fixed effects described earlier. We concentrate on the sample of mining cells and their immediate neighbours, and estimate the differential effect of mineral price variations in mining areas compared to their immediate neighbours. Our findings are confirmed: variations in mineral prices have a significantly higher effect in mining cells.

4.3 Sensitivity Analysis

In this subsection we show that the baseline estimates of Table 2 are robust to a large battery of sensitivity checks.

4.3.1 Mining activity

We start by investigating the robustness of our results to alternative definitions of mining activity, to further ensure that our results are not driven by endogenous opening/closing of mines (i.e. variations in the mining dummy over time). Tables are relegated to the appendix.

The first two columns of appendix Table 10 contain our two baseline ways of dealing with this potential reverse causation issue: considering only cells with permanently active mine (column (1), the same as column (2) in the Table 2), and using a time-invariant dummy for cells containing at least an active mine at any point over the 1997-2010 period (column (2), the same as column (4) in the Table 2). In column (3) of Table 10, we use a lagged mine dummy instead of the

[19] More precisely, we also impose the constraint of no closing/opening mines for neighboring cells. Therefore ln price × mines > 0 (neighboring cells) corresponds to the price of the main mineral produced among the neighboring cells with permanent mining activity.

[20] Our favorite interpretation of the results in column (3) is that violence diffuses in space. Henceforth this specification could be viewed as the reduced form of a TSLS estimate of a variant of equation (2) that would include on the RHS violence in neighboring cells instrumented by price shocks in neighboring cells. We do not want to push too far this interpretation as it could be that spatial dependence is simply driven by measurement errors on the actual surface of mining areas that are constrained by data construction to be contained in a 0.5 degree × 0.5 degree cell. Technically this additional channel could violate the exclusion restriction of the TSLS.

contemporaneous value. The estimated coefficient remains positive but becomes slightly insignificant – but this is not our preferred way of dealing with reverse causality, as mining activity can be affected by anticipation of future conflicts. In column (4), the mining variable is coded as 1 from the first year onwards when an active mine is observed over the 1997-2010 period, 0 if no active mine was ever recorded, and is coded as missing otherwise. Finally, we use mining activity at beginning of the period (column (5)) or in the pre-sample period (5 years in column (6) and entire pre-sample period covered by the RMD data in column (7)). Our coefficient of interest is always highly significant and quantitatively stable.[21]

We also inquire robustness to alternative size of the mining area. As discussed in Section 3, 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. But mining areas could on average be larger than our cells of a spatial resolution of 0.5×0.5 degree. 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 Table 11 in the appendix we broaden the scope of a mining area and we reproduce Table 2 for a grid of cells at a larger resolution (1 degree $\times$ 1 degree).

4.3.2 Main mineral and mineral prices

Another important element of our analysis is the way in which we define the main mineral produced in the cell. Note that this has no impact on cells producing a single mineral – which represent 70% of mining cells. For the others, we use the price of the mineral with the highest production over the period, evaluated at 1997 prices. In Table 12 in the appendix we show that alternative coding choices deliver similar results. We consider our preferred baseline specifications, columns (2) and (4) of Table 2. We keep our baseline definition of the main mineral but restrict the sample, either to mining cells producing a single mineral over the entire period (columns (1)-(2)) or to cells for which the main mineral is the same for each year of the sample (columns (3)-(4)). In columns (5) and (6), we replace the price variable by the average price of *all* the minerals produced in the cells (for which we have a price), with weights equals to the share of each mineral in total production value over the period.

We also perform a series of consistency checks on mineral prices. In particular, we want to rule out that time-varying omitted variables could co-determine World prices and local violence in mining areas. Indeed, it could be the case that the residual unobserved heterogeneity still co-moves with the World prices of minerals despite the wide array of fixed effects we include. We perform a placebo analysis to exclude this last concern and check the validity of our approach. Our idea is to replace the price of the mineral produced in the cell by the price of a mineral that is *not* produced in the cell. More precisely, we randomly assign a mineral to each of the mining cells and estimate specifications (2) and (4) of Table 2 with this fake $M_{kt} \times \ln p_{kt}^{W}$ variable. We repeat this Monte Carlo procedure in 1,000 draws. Figures 3.a and 3.b in the Appendix display the sampling distribution of the coefficient of the interaction term for each specification. Reassuringly, the Monte Carlo coefficients are distributed far from their baseline estimates and are

[21] An alternative way of considering this endogeneity issue is to instrument the mining dummy in the sample period by its pre-sample equivalent. This alternative is explored in the online appendix, section G and Table A.10. Very similar results emerge.

massively insignificant. This confirms that our baseline results are not driven by co-movements in mineral prices.

4.3.3 Alternative definitions of violence

In all tables we focus on conflict incidence, which reflects our interest in explaining the general presence of conflict. In this section we test for robustness to alternative measures of conflict in terms of intensity, onset and ending. We first look at intensity of violence as measured by the yearly number of ACLED events reported in a given cell. The results are displayed in appendix Table 13 where columns (2) and (4) of the baseline Table 2 are replicated in panels A and B, respectively. For each panel, column (1) reports the LPM estimation results for the full sample. The distribution of the number of events being right-skewed due to over-reporting of intense events in ACLED[22], we deal with outliers by winsorizing at top 5% in column (2) and at 2SD above the mean in column (3). We re-do the same exercises in columns (4)-(6) with a Poisson pseudo-maximum likelihood estimator – a well adapted procedure for count data. The results are again better estimated when extreme values are treated. This feature suggests that mineral prices impact violence intensity in a non-linear (concave) way. We investigate further this interpretation in the last two columns by estimating a LPM on the full sample with a $\log(1 + x)$ transformation of the LHS variable (column 7) and an inverse hyperbolic sine transformation (column 8). Finally we study cell-specific onsets and endings of conflict separately in the Section D of the online appendix, and in particular in Tables A.6 and A.7. Note that this exercise has a limited scope in the context of our spatial micro-data where, at the cell-level, the vast majority of events is short-lived.[23] Finally, we complement our sensitivity analysis on violence measurement by using an alternative conflict database with geo-coded information, namely the Conflict Data Program Geo-referenced Events Dataset (UCDP-GED). The UCDP-GED focuses on deadly incidents associated with civil wars, as identified by the UCDP-PRIO Armed Conflict Database. All these results are displayed and discussed in the section E of the online appendix.

4.3.4 Other robustness checks

We perform various additional sensitivity checks that are discussed in details in the online appendix. For the sake of brevity we only list them here: (i) we investigate alternative spatial and temporal kernels in the computation of standard errors (section F); (ii) we instrument World prices $\times$ actual mines, using World prices $\times$ historical mines as instrument (section G); (iii) we remove from the estimation sample all cells located in a top-10 World producer of the main mineral produced in the cell (i.e. countries that could have some influence on World prices) (section H); (iv) we show that our results are robust to the inclusion of diamond and coltan (tantalum) mines in the sample and we also show that they are not driven by any specific mineral, by excluding sequentially each mineral from the sample (section I); (v) we use a non-linear (logit)

[22]Take for example the following event: "CNDD rebels attacked Kazirabageni in Makamba Province. They clashed with security forces and 15 people were killed". It takes place from the 17 to the 22 April 2002 and each day is coded as separate event in ACLED.

[23]Indeed the potential issue with using conflict incidence as a dependent variable has been raised by the macro-level literature. Conflict being a persistent variable, one should estimate a dynamic model with the lagged conflict variable included on the right hand side, or equivalently, model onset and ending separately (Bazzi and Blattman, 2014). The problem is less clear in our case as local conflict incidence is much less persistent than country-specific incidence.

fixed-effects estimator instead of a LPM (section J); (vi) we use, instead of our binary mining variable, the number of mines or total production of the main mineral as measures of the intensity of mining activity in the cell (section K); (vii) border cells are removed from the sample to ease the interpretation of the country × year fixed effects (section L); (viii) we consider price shocks in log-differences rather than in levels (section M); (ix) we include time-varying climate variables (rainfall and temperature) which might be correlated with commodity price variations (section N); (x) We test for non-classical measurement errors affecting our mining data points following the approach by Koenig, Rohner, Thoenig and Zilibotti (2015) (section O).

4.4 Country characteristics and mining induced violence

Is the abundance of valuable mines always a curse for political stability? Countries' institutions and social characteristics may play a decisive role. In particular, minerals could exacerbate instability in countries where the conflict risk is already latently present due to social cleavages or weak institutions. This would be in line with the idea that minerals are not necessarily the deep cause of conflict but make them feasible – a mechanism we shall investigate in detail in the second part of the paper. In this sub-section we consider how country characteristics may modify the average effect of mineral price variations on local conflicts.

4.4.1 Domestic Institutions: Can Good Governance Stop the Guns?

While natural resources have often been thought of as affecting the nature and quality of institutions (e.g., as generating corruption, autocracies and more generally a weaker accountability of the state), only relatively little attention has been paid to the impact of the interaction between institutional quality and natural resource abundance on political stability and prosperity.[24] There are indeed reasons to expect natural resource extraction to have a stronger impact in weak states: it might for example be easier for local armed groups to extract rents from mining areas in such countries. Starting from our preferred specifications (columns (2) and (4) of Table 2) we now consider the triple interaction between our main explanatory variable ($M_k \times \ln p_{kt}^W$) and a country-level index of institutional quality IQ_i — a binary variable equal to 1 when a country's pre-sample (1996) institutional score is above the sample median.[25]

Table 3 displays the results. As our variable of interest varies across countries, we cluster standard errors at this level. In columns (1)-(2), the variable IQ_i corresponds to the ICRG Indicator of Quality of Government from the International Country Risk Guide, a standard and synthetic measure of institutional quality at the country-level. In both specifications, the coefficient of the triple interaction is far from statistical significance. This measure being very coarse, in the following specifications (3)-(4) we draw on four more specific indicators of institutional quality, making use of the WGI ("Worldwide Governance Indicators") dataset from Kaufmann, Kraay, and Mastruzzi (2013).[26] The coefficients of the triple interaction with Government Effectiveness

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

[25] We use pre-sample scores to mitigate endogeneity concerns. We focus on the year 1996 as many of the institutional variables are not available for earlier years.

[26] The indicators of this dataset are based on a great number of individual variables from 32 data sources.

Table 3: Heterogeneous effects: Institutional Quality

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Sample	$\mathbb{V}(M_{kt}) = 0$	All	$\mathbb{V}(M_{kt}) = 0$	All	$\mathbb{V}(M_{kt}) = 0$	All
ln price × mines > 0	0.077		0.039		0.090^b	
	(0.051)		(0.036)		(0.036)	
ln price × mines > 0 (ever)		0.032		0.053^c		0.050^b
		(0.029)		(0.028)		(0.024)
× ICRG	0.002	0.020				
	(0.059)	(0.033)				
× Gov. Effectiv.			-0.053	0.024		
			(0.046)	(0.034)		
× Rule of Law			0.027	0.030		
			(0.038)	(0.047)		
× Voice and Accoun.			0.107^b	0.004		
			(0.048)	(0.043)		
× Control of Corruption			-0.043	-0.064^b		
			(0.040)	(0.029)		
× Polity IV					-0.027	-0.008
					(0.045)	(0.027)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	115626	117082	131628	133126	131712	133210

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered by country in parentheses. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(M_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. Country-level variables are dummies taking the value 1 if the country is above the sample median of the corresponding variable before the start of the period.

and with Rule of Law are not statistically significant. In contrast, the coefficient of the triple interaction with Voice and Accountability is in both columns of positive sign, and significant in column (3) while not statistically significant in column (4). Taken at face value, this indicates that mining price shocks may have a stronger effect on civil conflict and unrest in places with greater voice and accountability. Further, the coefficient of the triple interaction with Control of Corruption has in both columns a negative sign, and is statistically significant in column (4), indicating that the impact of mining price spikes on conflict may be lower in

These four individual measures are mapped into clusters of key dimensions of government quality, with higher scores indicating better governance. Government Effectiveness captures "perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies". Rule of Law captures "perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence". Voice and Accountability measures "perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media". Control of Corruption is constructed based on "perceptions of corruption, conventionally defined as the exercise of public power for private gain."

countries putting in place better anti-corruption measures. Finally, in columns (5) and (6) we make use of the standard democracy score of Polity IV, which relates to governance and civil servant behavior, as well as political representation and free elections. The triple interaction has a negative sign but is not statistically significant.

In a nutshell, we do not detect strong heterogeneous effects for different institutional arrangements. Note that our country-level institutional measures are crude proxies, and our results may suffer from attenuation bias. Indeed, in the last section of the paper we show that anti-corruption and transparency measures have significant impact on specific types of events and mining companies.[27]

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

Social cleavages are considered in the literature as important sources of grievances and conflicts. A natural question consists in assessing whether they also amplify mining-induced violence.[28] In the following we consider a battery of alternative indicators of social cleavages at the country-level, namely economic inequality, ethnic and religious fractionalization and polarization, as well as indigenous groups presence. We follow the same methodology as in Table 3 by estimating the coefficient of the triple interaction between our main explanatory variable and each of these indicators.

The results are reported in Table 4. In columns (1) and (2) we focus on the Gini index of gross income distribution of the "Standardized World Income Inequality Database" (Solt, 2014). Higher Gini scores correspond to larger inequality. The coefficient of the triple interaction is positive but not statistically significant. Columns (3) to (6) study the heterogeneous effect of ethnic and religious fractionalization or polarization (all variables are from Reynal-Querol, 2014) on price spikes. The coefficients of the triple interactions with religious fractionalization (columns (3) and (4)) or polarization (columns (5) and (6)) have a positive sign and are statistically significant. Note that this result survives to including fractionalization and polarization variables simultaneously. On the other hand, no significant effect is found for ethnic fractionalization or polarization. Finally, we assess the heterogeneous effect of indigenous group presence. We build the binary variable INDIGENOUS that takes a value of 1 if all groups in a given cell are indigenous.[29] The coefficient of the triple interaction with this variable has a negative sign but is not statistically significant at conventional levels. Taken together, the results of this subsection suggest that mineral price increases have the strongest conflict-inducing effects in religiously divided places.

[27] In Section P in the online appendix we study how a specific type of corruption – at the port – affects the impact of mineral prices variations on conflict. We find evidence of a conflict inducing effect of our proxy of port-level corruption.

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

[29] By contrast, INDIGENOUS takes a value of 0 if there is at least one non-indigenous group in the cell. For the sake of statistical analysis we prefer this coding rule to the alternative option of coding for indigenous presence (i.e. at least one indigenous group in the cell) because in quasi all cells there is at least one indigenous group. The list of ethnic groups and information on their location is from Cederman, Buhaug and Rod (2009). Drawing on a variety of sources, we have coded for each ethnic group whether it is INDIGENOUS in a given country or not (i.e. settled in a place for several centuries).

Table 4: Heterogeneous effects: Cleavages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimator				LPM				
Dep. var.				Conflict incidence				
Sample	$\mathbb{V}(M_{kt}) = 0$	All	$\mathbb{V}(M_{kt}) = 0$	All	$\mathbb{V}(M_{kt}) = 0$	All	$\mathbb{V}(M_{kt}) = 0$	All
ln price × mines > 0	0.031		0.024		0.043		0.111^b	
	(0.026)		(0.028)		(0.032)		(0.054)	
ln price × mines > 0 (ever)		0.027		0.015		0.014		0.095^b
		(0.018)		(0.020)		(0.021)		(0.038)
× Gini	0.053	0.015						
	(0.043)	(0.022)						
× Ethnic Frac.			0.015	0.002				
			(0.040)	(0.025)				
× Religious Frac.			0.069^c	0.046^b				
			(0.038)	(0.023)				
× Ethnic Pol.					-0.017	0.015		
					(0.034)	(0.022)		
× Religious Pol.					0.081^b	0.042^b		
					(0.034)	(0.019)		
× Indigenous							-0.044	-0.060
							(0.058)	(0.041)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95494	96796	127666	129094	127666	129094	129290	130816

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered by country in columns (1) to (6); Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation in columns (7) 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 > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(M_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In columns (1) to (6), country-level variables are dummies taking the value 1 if the country is above the sample median of the corresponding variable before the start of the period. In columns (7) and (8) the "Indigenous" variable is a dummy taking a value of 1 if all groups in a given cell are indigenous.

4.5 Mineral characteristics

We now study whether our results generalize to all types of minerals or if some sub-group of minerals with specific characteristics are particularly conflict-prone.

Labor-versus capital-intensiveness. The labor-versus capital-intensiveness of a given commodity has been linked to conflict in the literature. In a general-equilibrium framework where (labor-intensive) appropriative activities compete for recruiting manpower with labor-intensive production, it has been shown that only a price spike in the capital-intensive sectors fuels conflict, while higher prices in labor-intensive sectors do not jeopardize peace (Dal Bo and Dal Bo, 2011). Dube and Vargas (2013) provide empirical evidence in line with this, comparing the effect of commodities price variations in coffee abundant versus oil abundant municipalities in Colombia.

To investigate this question, we have built a number of mineral-specific proxies of capital intensiveness (see data description in the online appendix, section A). It turns out that capital-intensiveness is difficult to measure because of the high within-mineral diversity in production

methods and types of mines and opaque communication of commodity firms. Note also that our exercise has limited comparability with Dube and Vargas (2013) because variation in capital intensiveness between coffee and oil productions is huge while in our case, cross-mineral variations in capital intensiveness is modest.

We consider three different proxies of capital intensiveness using data from RMD. For a given metal, OPEN CAST is defined as the average percentage of mines in Africa that use -at least for part of their extraction- the open-cast, resp. open-pit mining method. Open-cast is often argued to be a particularly capital-intense mining method.[30] The second proxy, ENERGY INTENSITY, corresponds to the ratio of ln(Energy/Production) over ln(Employees/Production). The third proxy, MINE AGE, is the number of years since mining activity started in a given cell with the assumption that older mines should on average be relatively less capital-intensive. Obviously mine age is a crude proxy of capital intensiveness and it may also correlate with other factors, such as e.g. environmental grievances of local stakeholders. Results are shown in Table 14 in the appendix. We focus on the triple interaction term between our main explanatory variable ($M_k \times \ln p_{kt}^W$) and each proxy of capital intensiveness. None of these coefficients is statistically significant. A possible interpretation is that all our minerals are capital intensive in absolute terms, and that they are not different enough in terms of technology to have detectable heterogeneous effects on conflicts.[31]

Lootability and bulkiness. The literature has argued that more precious commodities generating larger rents are more conducive to fighting. Larger rents do not only increase the "prize" to be appropriated in contest by the winner, but also constitute attractive opportunities for looting during the conflict, helping rebel groups to fund their activities. Further, the recent paper by Sanchez de la Sierra (2015) makes the point that bulky commodities leads violent actors to impose monopolies of violence and sustain taxation.

We consider three different proxies of mineral lootability to study how proxies for minerals' lootability/bulkiness may affect the nexus between price spikes and fighting (see Table 15 in the appendix and Section A in the online appendix for data information). First, we split the set of minerals into high vs low value-to-weight minerals. We interact our main explanatory variable with two mutually exclusive dummies coding for minerals with a 1997 price (in USD per ton) above or below the sample median. We find that the coefficient of interest is equal to 0.046 for minerals BELOW MEDIAN PRICE, while for minerals ABOVE MEDIAN PRICE the analogous coefficient is almost twice as large (column (1)). A similar picture emerges in column (2). This suggests that price spikes of more precious metals have a stronger conflict-inducing effect – consistent with recent evidence on mineral discoveries from Smits, Tessema, Sakamoto and Schodde (2016). Second, we interact the mining price shock with the variable RENTS that corresponds to the mineral-specific ratio of price over cost for all African mines. The coefficient of the triple

[30] Open-cast is often argued to be less labor intensive than underground mining: "Underground methods from deep deposits (which) are generally more labor-intensive and expensive to mine than deposits mined by open-pit methods."(ILO, 1990: 18).

[31] We have also looked at the following additional proxies of capital intensiveness: alternative measures of open-cast mining (average percentage of mines using open-cast technologies for a given mineral computed at the country, or cell level); alternative measure of open-cast mining using alternative data from Hargreaves and Fromson (1983); production-function-based estimates of capital-intensiveness; measures of average lead time to setup a mining site; share of artisan production for particular minerals. All those proxies delivered similar results with a coefficient of the triple interaction that is non significantly different from zero. Section Q in online appendix provides the results for some of these variables.

interaction is non-significant (columns (3) and (4)). Last, we interact our price shock variable with a measure of average metal concentration in its corresponding ore. Bulky metals like e.g. platinum, are usually very diluted in the stone, which is why they are so expensive, while cheaper ones like iron have a larger ore grade.[32] We find that the coefficient of the triple interaction is negative and significant (columns (5) and (6)), suggesting that bulky/diluted metals entail a larger conflict risk when prices spike. This could be driven by the fact that they are more valuable, increasing the potential for looting. Moreover mining companies extracting bulky minerals have also a hard time to hide production, making it easier for armed groups to control the mining site and engage in extortion.

4.6 Quantification

How large is the effect of mineral price variations on the conflict probability? Taking the baseline specification of Table 2, column (2), a one SD increase in the price of all minerals from their mean translates into an increase in probability of violence from 0.169 to 0.225. This is of sizeable magnitude, but concerns only the cells where active mining takes place. When we also consider the surrounding cells (Table 2, column (3)), conflict probability rises from 0.197 to 0.253.

Over the period of our study mineral prices more than doubled on average.[33] For instance, in constant 2005 USD, the ounce of gold was valued at $338 in 1997, and reached $1084 in 2010. This spectacular rise of mineral prices over the 2000-2009 period, known as the *2000s commodity boom* or *commodities super cycle* has attracted quite a lot of attention. There is a consensus among scholars that no contraction of resource supply is to blame, but rather a rapid and substantial increase in demand, particularly so from the BRICS countries. As pointed out by Carter, Rausser and Smith (2011), "strong global demand, especially in lower-middle-income countries" helped set the stage for this commodity price boom, and "this strong demand was reflected in low real interest rates, a declining U.S. dollar, and strong GDP growth, and it contributed to the reduction in inventory levels that made commodity markets vulnerable to supply and demand shocks" (2011: 107). Similarly, Humphreys (2010) points out that the great metals boom between 2003 and 2008 "can be readily explained by the unusual strength of the demand shock and the lagged response of the supplying industry, with prices receiving an additional boost from the activities of commodity investors" (2010: 1).

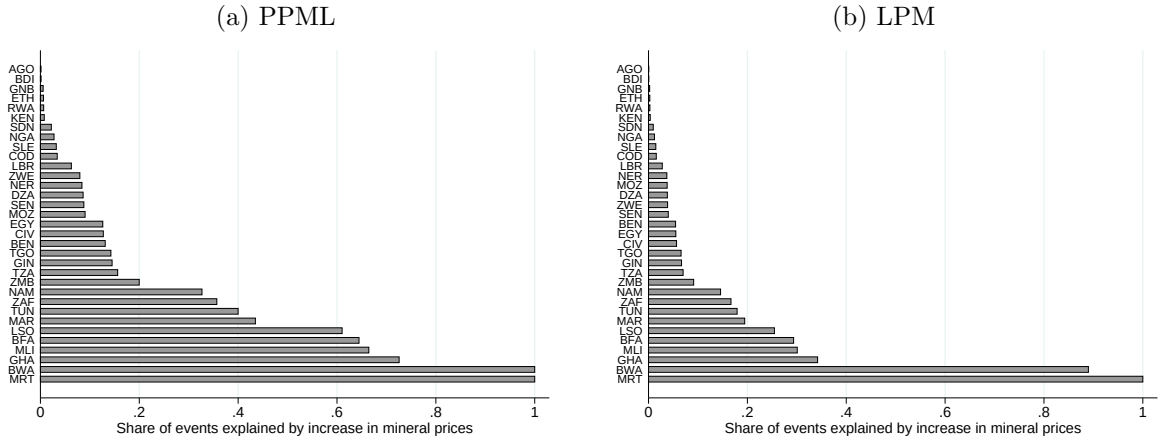
What has been the effect of the commodity super cycle on conflicts in Africa? In Figure 1, we compute, for each country with recorded mines, the contribution to the observed violence of this historical rise in mineral prices (see Figures A.7 and A.8 in the online appendix for the map equivalent). The quantification being related to the number of conflict events, our exercise (left panel) is based on the PPML estimates from Table 13. Nevertheless we also include the quantification based on LPM estimates from Table 13 for the sake of robustness (right panel).[34]

[32] It is important to keep in mind that we focus here on large-scale industrial mining production. Some precious, very diluted metals like gold may be "bulky" in industrial production yet much less bulky when extracted in artisan, alluvial depletion

[33] Prices have been multiplied by 2.8 in constant USD. Figure A.4 in the online appendix, section A shows the evolution of the price of each of the minerals.

[34] More precisely, we compute the counterfactual share of events that would not have happened if prices had stayed stable across the entire period. The PPML estimator is our preferred one given the nature of the data. However, we cannot include country×year in these estimations. For this reason we complement these results with LPM estimates because LPM allows the inclusion of two large sets of fixed effects. In both cases we use as baseline sample B of Table 13 (i.e. define a mining areas as cells in which a mine was active at some point), which allows

Figure 1: The contribution of rising mineral prices to violence in Africa



Note: These figures represent for each country the counterfactual share of events that would not have happened if prices had stayed stable at their 1997 level across the entire period. Predictions are based on an estimation similar to Table 13, Panel B, column (5) and (2) except that we also include the interaction term between mineral prices and the mining dummy for neighbouring cells.

In both cases the effect is highly heterogeneous across countries. Averaging across all countries with at least one recorded mine, we find that the historical rise in mineral prices contributed on average to 24% of the observed country-level violence using PPML estimates (14% using LPM). As is apparent in Figure 1, this number is however inflated by countries, such as Mauritania, in which only few conflict events are recorded (see online appendix Table A.3).[35] Effects are on average larger when computations are based on the sample with permanently active mines (see Table A.9 in the online appendix).

We have several reasons to believe that these numbers are conservative estimates. First, our dataset is not exhaustive: only two percent of the cells contain active mines; we consider surrounding cells as well, but many small-scale mines are not included, although they may have a significant impact on violence, adding up to the one we identify here; further, not all minerals are taken into account in these estimations. 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.

keeping all cells in the sample and taking into account the effect of mineral price variations in both mining cells and their neighbours. Here is the detail of our quantification procedure: (step 1) We estimate specifications similar to columns (5) and (2) of Table 13 where we add the price of the main mineral in neighbouring cells of degree 1 and 2; (step 2) we compare for each year and cell the predicted number of events for the observed prices with the counterfactual prediction when prices are set at their 1997 level; (step 3) we sum events across cells and years for each country; (step 4) we take the ratio of these counterfactual "prevented" events over the total number of events observed in the country during the 1998-2010 period.

Figures A.5 and A.6 in the on-line appendix show, by cell, the predicted decrease in the conflict probability that would be observed in 2010 if the prices were the same as in 1997. When aggregated at the country level as in Figure 1, the magnitude of the effect obviously varies with the number of mining areas in the country.

[35] 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 16% of the observed violence (8% in LPM estimations). Alternatively we can aggregate violence *at the continental level.* In that case the contribution of mineral prices to violence ranges from 7.7% in PPML estimations to 3.5% in LPM estimations, 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).

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

So far our empirical analysis has focused on local violence, i.e. in the immediate surroundings of mining areas. As mentioned in the introduction, several mechanisms may be at play and explain our findings: rebel finance/feasibility; greed/rent-seeking and secessionism; weak state capacity and extractive institutions; grievances; or migration/population changes.[36] In this section and in section 6, we focus specifically on the feasibility channel, and provide various pieces of evidence suggesting that it is empirically relevant.

More precisely, this section aims to investigating the diffusion over space and time of mining-induced violence. Our objective 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, geo-location, information on the outcome of the violent events, their type, and the identity of the perpetrators.

5.1 The nature of mining-induced violence

From the Wild West to South Africa, there is an abundance of narratives about how dangerous and lawless the mining areas are. They attract a selected sub-sample 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 (2016) for statistical evidence on homicide rates in US mining areas). By nature, such violence, rooted in riots and protests, is likely to be spatially concentrated around mining areas. By contrast, battles between fighting groups over the control of mines can spread over space as appropriation relaxes the financing constraints of future fighting capacity. Uncovering the nature of mining-induced violence is thus crucial for understanding whether it can escalate from the local to the global level. Here we provide evidence that different types of events (in terms of scale and objectives) are affected by changes in mineral prices.

In Table 5 we replicate our baseline specifications (columns (2) and (4) of Table 2) for each of the three categories of violent events covered by the ACLED dataset: battles between fighting groups, violence against civilians, and riots/protests. As expected, we find that an increase in mineral prices leads to more riots/protests (columns (5) and (6)) and more violence against civilians (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 column (1), confirming that the appropriation of mines is a key driver of violence.[37] In the specification of column (2) the coefficient of battles now loses statistical significance. In section T of the online appendix, we

[36] The opportunity cost channel – spikes in mineral prices generate increases in income and in the opportunity cost of rebelion – would go in the direction opposite to our findings. Section S in the online appendix specifically consider the migration channel. More precisely, we try to determine whether our results are driven by population changes / migration into mining areas caused by increases in prices. We fail to find significant effects of our mining price shocks on local population or nighttime lights. Similarly, the effect of mining prices on conflicts is not larger in cells located close to the capital city which have lower migration costs.

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

Table 5: Minerals price and types of conflict events

	(1)	(2)	(3)	(4)	(5)	(6)
			LPM			
Sample	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All
Conflict incidence var.	Battles		Violence against civ.		Riots / Protests	
ln price × mines > 0	0.016^b		0.040^a		0.044^b	
	(0.008)		(0.014)		(0.018)	
ln price × mines > 0 (ever)		0.002		0.034^a		0.038^a
		(0.006)		(0.010)		(0.011)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142296	143864	142296	143864	142296	143864

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells.

display the full set of results by replicating for each category of violent events all specifications of the baseline Table 2. As shown in Table A.26 for battles, with the exception of column (4), the coefficient of interest is positive and statistically significant throughout in all columns. Similarly, Tables A.27 and A.28 replicate the baseline Table 2 for violence against civilians and for riots, respectively. In both tables the coefficient of interest is statistically significant in 5 out of 6 columns.

5.2 Feasibility and the diffusion of violence

We now focus our empirical analysis on the channel of feasibility. The logic is that rebel groups, by controlling mining areas, can step up their military capacity and enlarge the scope of their operations. This can result in spatial diffusion and escalation of the conflict. Rebel groups do not need to operate the mines themselves; they can also extract rents from mining areas through bribing/extortion, as discussed earlier.

The main empirical challenge consists in retrieving information on the effective presence and influence of groups in mining territories. We follow two different approaches. First, we assume that rebel groups benefit relatively more from the extractive rents of mines that are located in their ethnic homeland. This has the statistical virtue of leading to a relatively large sample of mine-group combinations. Still, the match between ethnic affiliation and effective control of mining rents may not always be fully accurate, as some groups operate far beyond their group homelands. Hence, we also follow a second approach where we use unique ACLED information on battle-induced territorial changes in areas with or without mines. This second approach is more precise, but is based on a relatively small number of events.

In the following, we extend our dataset in a new dimension, namely the fighting group operating in each grid cell. We restrict our analysis to the 148 rebel groups that are active in our sample period, ignoring other types of fighting groups. ACLED considers as rebel groups "political organizations whose goal is to counter an established national governing regime by violent acts."

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.[38]

5.2.1 Mines located in ethnic homelands

We first test whether positive price shocks on the minerals extracted in the ethnic homeland of a rebel group boost its fighting operations. Exploiting ACLED information on the identity of the rebel groups, we assign to each group a main ethnic affiliation, based on the ethnicity of the group's leaders and troops. Out of the 148 rebel groups of our sample, we are able to identify the presence or the absence of an ethnic affiliation for 109 groups (74%); the remaining groups are dropped from the analysis.[39] Then we use the geo-coordinates of ethnic homelands from the "Georeferencing of ethnic groups" (GREG) dataset (Weidmann, Rod and Cederman, 2010) to build the number of mines and main minerals produced in the ethnic homeland of each armed group at the beginning of the sample period.[40] We use a balanced dataset containing, for each rebel group, all combinations of countries × years where the group can potentially be active. Here we allow each rebel group to be potentially present in all the countries in which it has been involved in at least one event over the period.[41] Therefore, our unit of analysis is a rebel group×country of operation×year triplet (g, i, t). Table A.32 in the online appendix contains some descriptive statistics on the sample used in this section. The unconditional probability of conflict incidence – 0.21 – is logically higher than at the cell-level. Conflict is also more likely within the boundaries of the rebel group's homeland, and in ethnic homelands containing mining areas.

We now study how conflict incidence at the rebel group-country level is affected by mineral prices in the ethnic homeland of the group and we estimate the following specification:

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

where $\textsc{Conflict}_{git}$ is a dummy coding for the incidence of a conflict involving group g in country of operation i during year t. The variable $\ln p^W_{gt}$ is the World price of the main mineral produced by mines located in the homeland of the main ethnicity of rebel group g (the mineral observed in the largest number of cells – robustness results using the prices of all minerals aggregated into a price index are discussed below) and M_g is the number of mines producing this mineral in the homeland at the beginning of the period. The coefficient of interest, β_2, is a proxy for the mining-related financial capacity of the group. We expect it to have a positive sign, as

[38] 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."

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

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

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

better funded groups are able to extend their fighting operations. Note that this is a somewhat imprecise proxy of effective control of the mining rents – subject to measurement errors – as the historical ethnic homelands information corresponds to a snapshot of the 1960's.

Table 6: Feasibility - Mines in ethnic homelands

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator				LPM		
Dep. var.				Conflict incidence		
Conflict zone	Unrestricted		Outside ethnic homelands		Unrestr.	Outside ethn. homel.
ln price main mineral (homeland in country)						
× # mines	0.562^a	0.284^b	0.374^a	0.141	0.979^a	0.717^a
	(0.012)	(0.119)	(0.091)	(0.111)	(0.167)	(0.212)
ln price main mineral (entire homeland)						
× # mines					-0.107^b	-0.096^a
					(0.047)	(0.034)
ln price main mineral (in country outside homeland)						
× # mines					0.034^c	0.031
					(0.020)	(0.020)
Group×country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	Yes
Country×year FE	No	Yes	No	Yes	No	No
Observations	2352	2226	2352	2226	2352	2352

LPM estimations. Standard errors, clustered by group in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. The unit of observation is the rebel group-country-year. Cols. 3, 4 and 6 keep in the sample only cells which are located outside the ethnic homeland associated with the rebel group. ln price main mineral (homeland in country) is the price of the main mineral produced in the ethnic homeland of the rebel group and in the considered country. ln price main mineral (entire homeland) is the price of the main mineral produced in the ethnic homeland of the rebel group, inside or outside the considered country. ln price main mineral (in country outside homeland) is the price of the main mineral produced inside the considered country but outside the ethnic homeland of the rebel group. Main minerals are defined as the mineral produced in the largest number of cells at the beginning of the period. For each price variable the associated # mines variable denotes the number of mines producing the mineral in each respective area. All specifications include linear terms and interaction terms but only the coefficients of the interactions are displayed.

Table 6 displays the estimation results (only interaction terms being reported). In column (1) the dependent variable is (unrestricted) conflict incidence accounting for violence involving the rebel group g within country of operation i inside and outside its ethnic homeland. We control for group-country fixed effects as well as year fixed effects. As expected, the coefficient of the interaction term is positive and statistically significant. Column (2) shows that the results of column (1) are robust to controlling for country-year fixed effects instead of year fixed effects.[42] In columns (3) and (4) we replicate the specifications of col.(1)-(2) with a restricted definition of the dependent variable that now accounts for conflict incidence involving g in country i but only *outside* the ethnic homelands of the rebel group. The estimates are similar (although below

[42]The reason why we favor year fixed effects in this table is twofold. First, given the small number of observations, country×year results in a massive loss of degrees of freedom. Second, in columns (5) and (6) where we split price variations in several components – in the country, inside and outside homelands – the inclusion of country×year dummies would lead to a collinearity problem.

conventional statistical significance in column (4)). This finding suggests that a rise in the price of minerals extracted in their ethnic homelands enables groups to increase their fighting activity out of their homeland. This is a first piece of evidence documenting the spatial diffusion of mining-induced violence.

In columns (5) and (6) we assess the role of international/ethnic borders by building an additional set of variables coding for minerals extracted in different geographic areas. More specifically for a given group×country of operation×year triplet, (g, i, t), we consider a second interaction term between log prices and the number of mines in the entire homeland of g (inside or outside i) and a third interaction term between log prices and the number of mines located in i but outside the homeland of g; note that all the linear terms are also included (their point estimates are unreported). Column (5) displays the results for the unrestricted definition of conflict incidence and the column (6) for the restricted one. As for the role of international borders, we find that the estimated coefficient of the second interaction term is negative (-0.107) and significant at the 5% level. Together with the positive coefficient (0.979) of the first interaction term (price shocks impacting only the ethnic homeland of g in i), this finding suggests that international borders affect how price shocks translate into additional funding for rebel groups: Following an increase in mineral prices in the part of the ethnic homeland located abroad, an armed group g operating in country i tends to experience a reduction in its fighting activity. Our interpretation is that the now richer co-ethnics abroad may prefer to fund local rebels who may be better placed to get their hands on the now more lucrative resource rents in the foreign country. Note that the sum of the two coefficients is positive (0.979 - 0.107 = 0.872), which implies that the overall conflict probability increases after a price shock in the ethnic homeland; but the conflict tends to relocate in the country where the mines are. As for the role of ethnic borders, we find that the estimated coefficient of the third interaction term is positive, but thirty times smaller than the coefficient of the first interaction term. This evidence supports our hypothesis that rebel groups benefit relatively more from the extractive rents of mines that are located in their ethnic homeland. Finally it is worth mentioning that these results are to be taken with caution: The main coefficients are identified thanks to the few rebel groups whose ethnic homeland is spread over several countries and contain mines producing distinct minerals.[43]

5.2.2 Changes in territory

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

We build a balanced dataset containing, for each rebel group, all combinations of grid cells × years where the group can potentially be active (i.e. all cells located in the countries of operation of the group). Therefore, our unit of observation is now a grid cell × year × rebel group. Our

[43]The online appendix, section U contains supplementary material. In particular we replicate in Table A.30 the results of Table 6, but using a weighted price index of all minerals present instead of the price of the main mineral. To capture the diffusion of violence from mining areas to non-mining areas, we replicate in Table A.31 the results of Table 6 when restricting the dependent variable to conflicts occurring in cells located outside mining areas.

idea is to test wether a change in territory has more effect on future rebel activity elsewhere if the territory is a mining area. To test for this diffusion over space and time of mining-induced battles, we restrict our analysis to rebel groups that have been active in period $t-1$ and estimate a LPM of the probability of outbreak of a *new* event involving a group g in cell k in year t:

$$\text{ONSET}_{gkt} = \alpha \times \text{BATTLE}^{0}_{gt-1} + \beta \times \text{BATTLE}^{\mathbf{m}}_{gt-1} + \mathbf{FE}_{gk} + \mathbf{FE}_{it} + \varepsilon_{gkt}, \tag{3}$$

where $\mathbf{FE}_{gk}$ are group×cell fixed-effects, and $\mathbf{FE}_{it}$ are country of operation×year fixed effects. $\text{ONSET}_{gk,t}$ is a binary variable equal to one if group g is involved in an event in year t in a cell k that was at peace in $t-1$; it is zero if the cell is still in peace in year t. Notice that we deliberately focus on event outbreak and not on incidence; henceforth the observation is dropped out of the sample if g perpetrates violence in k in $t-1$. Our main explanatory variables are $\text{BATTLE}^{\mathbf{m}}_{g,t-1}$ and $\text{BATTLE}^{0}_{g,t-1}$. The first one corresponds to the total number of battles won by group g in $t-1$ in mining areas; the second one is the number of battles won in $t-1$ in non-mining areas.[44] The two coefficients α and β could be either positive or negative depending on the underlying process governing the dynamics of battles: negative if battle occurrence is mean reverting; positive in presence of unobserved transient shocks that, for example, impact the fighting capacity of a group. However, our test of the spatial and time diffusion of mining-induced violence does not rest upon the absolute level of these coefficients but on their relative value as we expect $\beta > \alpha$: winning in $t-1$ a territory containing active mining increases the probability of battle onset *in other cells* in t more than winning a territory with no active mine. The implicit assumption here is that winning a battle on a mining area enables the rebel groups to appropriate mining rents. In all specifications, the standard errors are clustered at the same level than our main explanatory variables, namely at the rebel group level (we explore other levels of clustering in the robustness analysis).

Before turning to regression results, we first report some simple statistics (see also Table A.32 in online appendix). The sample size is larger (204,402 observations) as the unit of observation is now a grid cell × year × group. It contains 126 groups operating in 32 countries. Each group operates in 1.7 countries on average (with a maximum of 6 countries). The dependent variable $\text{ONSET}_{gk,t}$ is equal to one for 2,019 observations (0.99% of the observations). The number of battles won in $t-1$ is positive for 42% of observations. Among these, 4% correspond to battles won in mining areas (2940 observations). This may seem to be a large amount of observations, but it actually represents only 1.4% of the sample size and 54 events. This data limitation prevents us from including an interaction term with the World price of minerals.

Table 7 displays the regression results. Only the subsample of rebel groups active in $t-1$ is considered. In column (1) the explanatory variable corresponds to the total number of battles won by a rebel group in the previous period. From column (2) onwards, we estimate equation (3) where battles won in mining areas are accounted separately from battles won in non-mining areas. While in column (2) the two variables of battles won are binarized, in column (3) we look at the number of battles won. In both cases, we find that β is statistically significantly larger than α. 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

[44] We include the establishment of headquarters in the battles won, as it is also a case of rebel groups gaining the territory.

Table 7: Feasibility and the diffusion of war

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Conflict onset				
Estimator				LPM				
# battles$_{g,t-1}$	0.002						0.033^b	
	(0.002)						(0.015)	
Battle$^0_{g,t-1}$		0.000						
		(0.002)						
Battle$^m_{g,t-1}$		0.040^a						
		(0.012)						
# battles$^0_{g,t-1}$			0.001	-0.001	0.000	0.000		0.029^c
			(0.002)	(0.002)	(0.002)	(0.002)		(0.014)
# battles$^m_{g,t-1}$			0.053^a	0.041^b	0.062^a	0.054^a		0.600^a
			(0.016)	(0.017)	(0.013)	(0.013)		(0.184)
# battles$^0_{g,t-1}$ (no change of terr.)				0.001^c				
				(0.001)				
# battles$^m_{g,t-1}$ (no change of terr.)				0.008^a				
				(0.003)				
# battles$^0_{g,t-2}$					-0.000	0.000		
					(0.001)	(0.001)		
# battles$^m_{g,t-2}$					0.023^b	0.021^a		
					(0.009)	(0.008)		
# battles$^0_{g,t-3}$						-0.004^a		
						(0.001)		
# battles$^m_{g,t-3}$						0.030^c		
						(0.016)		
ln average distance to battles$_{t-1}$							-0.001	-0.001
							(0.003)	(0.003)
# battles$_{g,t-1}$× ln av. dist.							-0.005^b	
							(0.002)	
# battles$^0_{g,t-1}$ × ln av. dist								-0.004^b
								(0.002)
# battles$^m_{g,t-1}$ × ln av. dist								-0.084^a
								(0.027)
Difference in coefs.								
# battles$^m_{g,t-1}$–# battles$^0_{g,t-1}$		0.039^a	0.056^a	0.042^b	0.061^a	0.053^a		
		(0.012)	(0.016)	(0.016)	(0.014)	(0.013)		
– no change of terr.				0.007^b				
				(0.003)				
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group×Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	168887	168887	168887	168887	168887	158040	168887	168887

LPM estimations. Standard errors, clustered by group, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. The unit of observation is the cell-rebel group-year. Only the sample of rebel groups active in $t-1$ is considered. Singletons are dropped. # battles$_{g,t-1}$, # battles$^o_{g,t-1}$ and # battles$^m_{g,t-1}$ are the number of battles won in t-1, respectively in total, in non mining areas and in mining areas. "No change of terr." means that the number of battles with no change in territory in considered. # battles variables are expressed as $\log(x+1)$. ln average distance to battles$_{t-1}$ is the average distance between the cell and all previous year's battles.

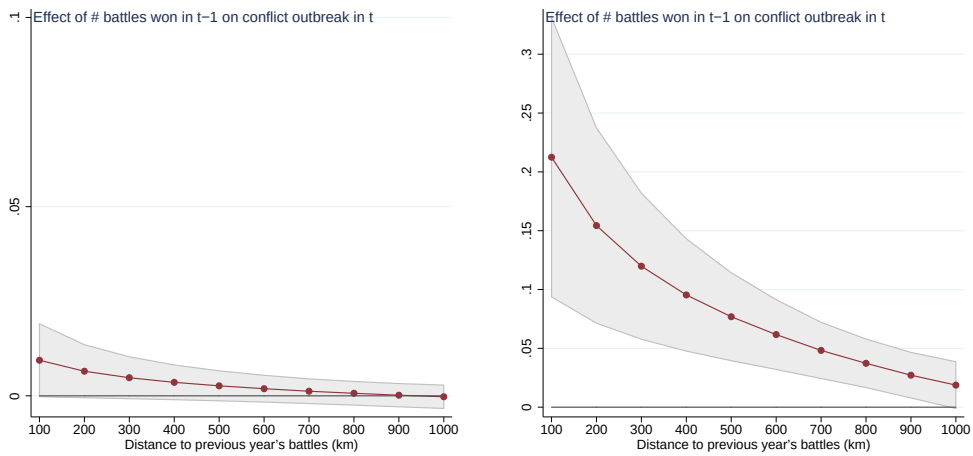
the view that mineral rents finance rebellions.

One potential selection bias in our estimation could arise if groups attacking mines have different unobserved characteristics than the groups engaged in battles in non-mining areas. Note, however, that time-invariant group differences are filtered out by group×cell fixed-effects. Still, time-varying group characteristics could correlate with the decision to fight in mining areas, e.g. a situation where groups get stronger or weaker over time and only dare attacking a mine when they are strong. With the idea of testing that our results are not driven by such unobserved transient shocks affecting groups' fighting capacity we include in column (4) measures of battles fought inside/outside mining areas that did not result in a change of territory. The absence of territorial change does not necessarily mean that the rebels lost, but could also indicate an indecisive battle or a situation where rebels successfully managed to keep control of previously conquered territory. Still, we expect the effect to be larger when rebels manage to conquer the mining territory. The estimation results confirm our previous finding that β is statistically significantly larger than α. Interestingly, for battles in mining areas, the coefficient associated with the absence of territorial change is five times smaller than the one associated with winning a battle, in line with the logic described above.

We now document the time and spatial decays. In columns (5) and (6) we include battles won in $t-2$ and in $t-3$ and our main finding can be observed at different time lag (i.e. $\beta > \alpha$). Columns (7)-(8) start from specifications of columns (1) and (3) and add interaction terms between the lagged battles variables and their average distance to the cell's centroid. A clear pattern of spatial decay emerges. This evidence can be seen in more details in Figure 2 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 (based on the estimates of column (8)). The change in conflict probability is small and non-significant if a territory containing no mine was won (left panel). In cases where battles happened in mining areas (right panel), the probability increases by up to 20 percentage points in the close surroundings of the battles and remains significant up to 1000 kilometers around. This clearly suggests that mining-induced violence diffuses across space.

Figure 2: Feasibility and the spatial diffusion of conflicts

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



Finally we can quantify in a simple way the extent to which the conquest of a mining area exacerbates future violence. The appropriation of a mining area in year t increases by 4 percentage points the cell-level probability of an event occurring in year $t+1$. Given that a rebel group is active in 335 cells on average, this leads to $0.040 \times 335 = 13.4$ additional events (Table 7, column 2). This represents a tripling in rebel fighting activity (average number of events by group-year being 3.78). Admittedly this back-of-the-envelop calculation is very rough. But it supports the view that mining activity, through the feasibility channel, is an important driver of escalation from local violence to large-scale conflict.[45]

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

The previous section has focused on the role of fighting groups in mining-induced violence. But the behavior of mining companies may also play an important part. In this section, we study specifically the role of companies' characteristics and management practices on the presence of violence. A recent case reported by the NGO Global Witness (2016) illustrates well our approach. A Chinese mining company, Kun Hou Mining, is accused of having extracted gold from the Ulindi River in South Kivu (DRC) between 2013 and 2015 with the support of both local corrupt authorities and armed groups. To operate in the area and secure access, the company provided the armed groups operating on the banks of the river (the Raia Mutumboki militias) with money, rations, AK-47 rifles and other items which allowed the militias to extort gold from artisanal miners extracting minerals in the same area. These activities have been in place thanks to the cooperation of the local authorities of South-Kivu, which covered up the presence of Kun Hou Mining in the region and its links with local armed groups. Similarly, the governmental agency in charge of protecting local small-scale miners cooperated with the local militias to collect illegal taxes from the miners. No formal fiscal revenue from alluvial gold mining was recorded in the South-Kivu province over the period. Meanwhile, the gold was sold and smuggled to Dubai by a trader from Bukavu, Alpha Gold. This story fits perfectly the main findings discussed below: The extraction by a foreign-owned company of a precious and easy-to-smuggle mineral has fueled conflicts by providing local armed groups with financial and material means to sustain and enlarge their activities. Both bribing by the company and extortion by rebel groups were observed. Local corruption –in the extraction area and along the trading routes– played its part by facilitating and participating to the entire process. Global regulations on transparency and traceability were ignored.

6.1 Companies' Characteristics: Does Mine Ownership Matter?

By operating mines in conflict-prone environments, companies potentially play a central role in the logic of violence: At the local level they could be more or less willing to secure mining areas where they plan to operate (e.g. with the help of governmental troops or private militias).

[45] Section V in the online appendix contains additional results. Table A.33 uses spatially clustered standard errors and Table A.34 allows for two-way clustering of standard errors by group and cells. The significance levels are very similar to the ones reported in Table 7. Finally, in Table A.35 the dependent variable is outbreak of battle events only (instead of all events).

And even more importantly, the escalation of conflict may be impacted by their propensity to finance/bribe, often in an illegal and opaque way, the rebel groups that control the territories surroundings the mines – the terms of the implicit agreement being bribes in exchange of "protection" by rebel groups in order to guarantee companies' efficiency in large-scale extraction. Hence, understanding the role of firms' behavior is clearly of foremost importance, both from a positive and policy perspective.[46] For this purpose we exploit a unique feature of our dataset, i.e. that it contains information on the identity of the owning company and the country of its headquarter.

Let us start first with a short overview of the companies that are present in our dataset (Table A.36 in the online appendix displays more detailed descriptive statistics). Foreign owned firms represent on average 60% of the companies. 12% of mines are publicly owned by the domestic government and the residual category is composed of domestic private firms. We should typically expect that not all foreign firms benefit from the same level of protection by the domestic government. As discussed in more detail below, there is a vast literature showing that firms from the ex-colonizing power continue to benefit from privileged relationships with the new rulers after decolonization (see e.g. Stockwell, 2000; White, 2000; Cain and Hopkins, 2016). Henceforth, we distinguish between firms from a foreign colonizer country versus firms from a foreign country with no colonial ties to the country where the mine is located. Among foreign firms, roughly a fifth have their headquarter located in the country that was the former colonizer.

In Table 8 we investigate how the type of ownership impacts mining-induced violence. We start from the specification of column (2) of baseline Table 2.[47] Mutually exclusive categories of ownership, FOREIGN FIRMS, DOMESTIC PUBLIC FIRMS and DOMESTIC PRIVATE FIRMS are coded as the share of firms in a given cell belonging to this given category, and is interacted with our main effect ($M_k \times \ln p_{kt}^W$). We retain the ownership status at the beginning of the sample period for the sake of exogeneity (i.e. self-selection). As these three shares sum up to one, the baseline interaction term ($M_k \times \ln p_{kt}^W$) is dropped from the specification to avoid collinearity. In all odd numbered columns the dependent variable is conflict incidence, while in all even columns the dependent variable is restricted to incidence of battles only, for which the role of political protection and connections are arguably particularly salient.

Columns (1)-(2) of Table 8 display the coefficients of the interaction term for each category of ownership. In both columns the share of foreign firms has a positive and statistically significant impact, meaning that a larger presence of foreign firms magnifies the impact of mineral price shocks on conflict. In contrast, we do not detect any statistically significant effect for domestic firms. This finding is consistent with at least two explanations: First, it could be that domestically owned companies are better protected by the national army and hence harder to capture by rebels (who are deterred to attack them), and/or second, it could be that domestic firms are more reluctant to pay bribes and extortion money, which would make indirect control of the mining area by rebel forces less lucrative. Of course, the two explanations may well be inter-twined: A firm that is better protected by the state is less willing to give in to demands for "protection money" by rebels operating in a given area. By analogy, the fact that we find strongly significant

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

[47] We replicate in the Appendix Table 16 the analogous analysis, but focusing on the second baseline specification from the benchmark Table 2, namely column (4). The results are very similar for overall conflict incidence, but become weaker for battles (missing the conventional threshold for significance).

Table 8: Mineral price, firm ownership and conflicts

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Sample			$\mathbb{V}(\mathrm{M}_{kt}) = 0$			
Dep. var.			Conflict incidence			
Events	All	Battles	All	Battles	All	Battles
ln price × mines > 0 × Foreign Firms	0.101[a]	0.030[c]				
	(0.038)	(0.016)				
ln price × mines > 0 × Dom. Private Firms	0.035	-0.002	0.034	-0.002	0.047	-0.007
	(0.030)	(0.006)	(0.030)	(0.006)	(0.052)	(0.017)
ln price × mines > 0 × Dom. Public Firms	0.027	-0.006	0.026	-0.007	0.026	-0.006
	(0.037)	(0.011)	(0.036)	(0.011)	(0.036)	(0.011)
ln price × mines > 0 × Fgn Firms (col.)			0.022	-0.008	0.035	-0.012
			(0.037)	(0.026)	(0.048)	(0.025)
ln price × mines > 0 × Fgn Firms (non col.)			0.150[a]	0.053[a]	0.159[a]	0.050[b]
			(0.052)	(0.020)	(0.047)	(0.022)
ln price × mines > 0 × Large Firms					-0.018	0.006
					(0.054)	(0.022)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142072	142072	142072	142072	142072	142072

LPM estimations. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. The company characteristics (foreign, domestic public, domestic private, etc) denote the share of mine owned by a given category at the beginning of the period. Cells containing only mines with missing ownership information are dropped.

effects for foreign firms is consistent with either the view that mining areas operated by foreign firms are less well protected and/or the view that foreign firms are more easily willing to pay extortion money to rebels.

As mentioned above, it is reasonable to expect firms from former colonizers to have privileged access to government circles and benefit from similar "insider" protection as domestic firms. For example, a US firm operating in a country with a traditionally left-leaning government may not be as well protected as a firm belonging to a country with strong connections to the local elite, such as, say, a Belgian company operating in the Democratic Republic of Congo, or a British firm doing business in Ghana.[48]

In columns (3)-(4) we replicate columns (1)-(2) with the foreign firms category that is now

[48] Indeed, there is a vast literature on the persistence of economic ties in the post-colonial era (see Cain and Hopkins, 2016). For example, for the case of British companies in Ghana, Stockwell (2000: 237) points out that "businessmen, like other non-officials, experienced decolonization not just as passive observers of a constitutional readjustment, but as active participants in a complicated process involving the reorganization and adaptation of their activities, a re-examination of their employment policies, and a renegotiation of their relationships with a changing pattern of state structures and political forces" and that "established British companies continue to retain a strong presence in Ghana today". Also White (2000: 545) concludes that British firms managed to maintain their influence after decolonization, and that "the transfer of political power for British firms in territories such as Malaya, the Gold Coast, and Kenya was favourable as independent regimes remained in the sterling area and chose development strategies heavily reliant on foreign investment. Even for territories where more statist development models were followed, such as Nigeria, British commercial banks, shipping lines, and import-export firms were remarkably successful in maintaining their positions".

split into foreign firms from former colonizer country (FGN FIRMS (COL.)) and foreign firms without colonial ties (FGN FIRMS (NON COL.)). We find striking differences: Foreign firms with a headquarter in the former colonizer country are very comparable to domestic state-owned firms as they are not associated to any political instability after mineral price shocks. In contrast, mines owned by foreign firms without colonial ties experience a quantitatively large, statistically significant effect on boosting the conflict potential when mineral prices rise.[49] Again, this finding could be due to greater vulnerability of mining firms in the absence of state protection, and/or to "dirty" business practices such as paying bribes and extortion money that could invite mining area takeovers by rebels. In columns (5)-(6) we replicate the columns (3)-(4) and in addition control for the interaction with LARGE FIRM, a dummy variable coding for large firms.[50] The results are unchanged, meaning that the previous finding is not a sheer size effect.

6.2 Promoting Good Practices: Does Transparency Matter?

A government that is respectful of property rights may find it difficult to engineer the ownership status of mining companies operating in its national territory. Yet, policy interventions targeting bribing practices of mining companies might be able to curb conflict. International policy makers have recently started to promote transparency and traceability in the mining industry. Examples include the US legislation requiring US firms to certify that their purchases of particular minerals are "DRC conflict free", or the recent framework adopted by the EU commission (on June 16, 2016) to force companies to track the origin of minerals produced in conflict-prone areas. In the same vein, several international initiatives aiming at encouraging good practices among extractive companies and tracking the origins of minerals are underway. For instance, the "Mineral Certification Scheme of the International Conference on the Great Lakes Region (ICGLR)" tracks the sales of gold, cassiterite, wolframite, and coltan. Similar certification efforts are observed in the tin and tantalum industries. Several countries have adopted international standards for managing in an open and accountable way the extractive rent, e.g. by fully disclosing royalties.

While many conceptual policy memos have been written on transparency and certification schemes, there is virtually no hard evidence so far on the conflict-decreasing impact of these schemes in reality.[51] We address this issue in Table 9. We take as starting point column (2) of the baseline Table 2 and focus on a battery of triple interactions. As before, all uneven columns have as dependent variable conflict incidence, while the even columns restrict attention to battle incidence only. The analysis is restricted to foreign firms, which is the category of firms that drive most of the conflict-fueling effect of mining price spikes (see Table 8), that are likely to benefit from lower government protection and that may be more likely to be vulnerable to corruption and extortion, as discussed in the previous subsection. We exclude from the sample all mines that are not foreign owned. Note also that in all columns we control for the triple interaction with the dummy for large firms to account for scale effects.

[49] The difference between the triple interaction coefficients of FOREIGN FIRMS (COLONIZER) and FOREIGN FIRMS (NON COLONIZER) misses the conventional threshold for statistical significance in column (3) but is statistically significant in column (4).

[50] We use information provided by the RMD dataset about whether the owner of the mine is a "major company", i.e. if the corresponding company belongs to the World top ten in terms of production of the corresponding mineral in a given year. About 60 percent or foreign firms belong to the group of these large multinational firms.

[51] With the notable recent exception of Heffernan (2016) who look at the effect of the Kimberley Process using cross-country panel data and finds a conflict-reducing effect.

In Table 3 presented earlier, we found on the whole sample of mining companies and conflict events that mining price spikes had a somewhat attenuated impact in countries with a powerful control of corruption. In columns (1) and (2) we show that this results is reinforced in the case of foreign firms and battle events: the interaction of mining price shocks with CONTROL OF CORRUPTION, the measure already used in Table 3, is negative and significant at the 1 or 5% level. In columns (3) and (4) we interact mining price shocks with a variable representing the share of companies which are members of the "International Council on Mining and Metals" (ICMM) — a network of companies promoting Corporate Social Responsibility in the mining industry.[52] In both columns the coefficient of the triple interaction with CSR practices has the expected negative sign and is statistically significant, suggesting that corporate social responsibility can indeed build powerful ramparts against the resource curse.

Table 9: Heterogeneous effects: The Role of Transparency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Estimator					LPM					
Sample					$\mathbb{V}(\mathrm{M}_{kt}) = 0$					
Dep. var.					Conflict incidence					
Events	All	Battles	All	Battles	All	Battles	All	Battles	All	Battles
ln price × mines > 0	0.002	0.028	0.045^c	0.043^c	0.066	0.048	0.045^c	0.043	0.062^c	0.025
	(0.057)	(0.036)	(0.024)	(0.025)	(0.047)	(0.038)	(0.025)	(0.026)	(0.034)	(0.021)
× Large Firms	0.130^c	-0.013	0.120^c	-0.008	0.076	-0.023	0.092	-0.020	0.069	-0.003
	(0.069)	(0.039)	(0.064)	(0.032)	(0.066)	(0.039)	(0.059)	(0.034)	(0.061)	(0.028)
× Control of Corruption	-0.105^a	-0.041^b								
	(0.038)	(0.016)								
× Firm CSR (ICMM)			-0.224^a	-0.085^b						
			(0.067)	(0.038)						
× Tracea. Init. (EITI, request)					-0.004	-0.001				
					(0.004)	(0.002)				
× Tracea. Init. (EITI, compliance)							-0.007^b	-0.001		
							(0.003)	(0.001)		
× Tracea. Init. (GLR)									-0.004^c	0.005
									(0.002)	(0.004)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	131026	131026	141624	141624	141610	141610	141610	141610	141610	141610

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. Sample restricted to non mining cells and cells for which foreign owned mines represent the largest share. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. See main text for a description of the various transparency variables.

Could it be that also top-down initiatives at the country level aiming at imposing good practices can have such as a dampening effect? In columns (5)-(10) we look at two country-level transparency initiatives, the "Extractive Industries Transparency Initiative" (EITI) and the "Mineral Certification Scheme of the International Conference on the Great Lakes Region (GLR)".

[52] See http://www.icmm.com. It is important to note that membership to ICMM is endogenous to a variety of factors, and hence the results presented here should be taken with a grain of salt. In particular, it may be the case that companies deciding to join the ICMM are located in more stable areas which makes it less costly for them to join the ICMM. Indeed, in our data the conflict probability is twice lower in areas in which ICMM companies are present, even before the creation of ICMM in 2001.

The former initiative imposes to its member countries to fully disclose taxes and payments made by mining companies to their governments; the latter tracks the origin of a number of metals. The ICGLR aims – among others - at identifying mines which are related to conflicts, e.g. through illegal control, taxation, or extortion.[53]

In each specification we interact mineral prices with a dummy coding for country membership (for the relevant minerals in the case of ICGLR). For the EITI initiative we use data on the country-specific dates of EITI membership from Papyrakis, Rieger and Gilberthorpe (2016). We first use the date at which the country becomes a candidate country. The application process generally lasts several years, at the end of which the country produces and submits a "validation report" that shows compliance to the EITI criteria and grants the country membership to the initiative. As a second indicator, we use the year during which the validation report was submitted.[54] In columns (5)-(6) we code a country as EITI member from the date on when it has requested adhesion. The triple interaction of interest has the expected sign but is not statistically significant. In column (7)-(8) we take an alternative stand and code a given country as EITI member only when it has submitted the final validation report. With this more restrictive definition of membership we now detect a conflict-dampening effect of EITI membership in column (7) (which turns insignificant for battles in column (8)). In sum, mining price spikes tend to have a less detrimental effect in EITI countries, provided that they have already started complying to EITI rules. Note however that compliance to EITI standards occurred only in few countries in our sample period. Finally, column (9) shows that the conflict-inducing effect of mineral price rises is less severe in countries that have adhered to the GLR mineral certification scheme, while in column (10) no effect is detected for battle incidence.[55]

7 Conclusion

In this paper we provide a systematic analysis of the impact of all major mineral extraction on the likelihood of armed conflict in Africa, using novel and fine-grained panel data with a spatial resolution of 0.5×0.5 degree latitude and longitude and covering the 1997-2010 period. We find a strongly significant and quantitatively large impact of mining activities on the likelihood of conflict incidence. We perform numerous sensitivity tests and show that the results are robust to a variety of alternative specifications. According to our estimates, the *commodities super cycle*

[53]For the the "Extractive Industries Transparency Initiative" (EITI) see https://eiti.org/eiti. and http://www.pacweb.org/en/regional-certification. For the "Mineral Certification Scheme of the International Conference on the Great Lakes Region (GLR)" see http://www.oecd.org/investment/mne/49111368.pdf.

[54]The country is generally granted membership during the same year or in the year after submitting the report. We chose to use the date at which the report was submitted rather than the date at which membership was granted because of data limitations: our period of study ends in 2010, and only three countries were granted membership at this date (Ghana, Niger and Liberia), two of which are very small. Considering the date at which the report was submitted allows to consider the effect on three (large) additional countries (Nigeria, Mauritania and Mali).

[55]In the Appendix Table 17 we carry out the analogous analysis, but focusing on the specification of column (4) of the baseline Table 2. We also find that control of corruption, Corporate Social Responsibility and the Great Lakes Region certification scheme tend to decrease the conflict-boosting effect of mineral price shocks, although the results are somewhat weaker than in Table 9. Further, we replicate in Table A.37 in the online appendix the regressions of Table 9 but for domestic firms. Interestingly, we find that the detrimental effect of mining price spikes as well as the virtues of transparency are confined to foreign firms. Finally, Table A.38 in the online appendix studies the effect of the Kimberley initiative on war diamonds. We find either no effect or a marginally significant conflict-reducing effect. These results are to be interpreted with caution given the limited source of identification and the drawbacks of the diamond price data mentioned previously.

(i.e. steep increase in mineral prices during the 2000s) accounts for 14% to 24% of the average violence observed in African countries over 1997-2010.

This 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 a possible mechanism through which mineral rents could fuel fighting efforts and lead to the escalation of violence over space and time. In particular, we find that mining activity does not only increase the scope for localized protests and riots, but that it also systematically fuels larger-scale battles. Importantly, we document that gaining the territorial control of a mining area leads rebel groups to intensify and spread their fighting activity elsewhere in the territory in the successive periods, while winning a battle outside a mining area does not have such a conflict diffusion effect. In the same way, variations in the prices of mines located in the ethnic homelands of rebel groups have a strong effect of conflicts involving this group elsewhere.

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

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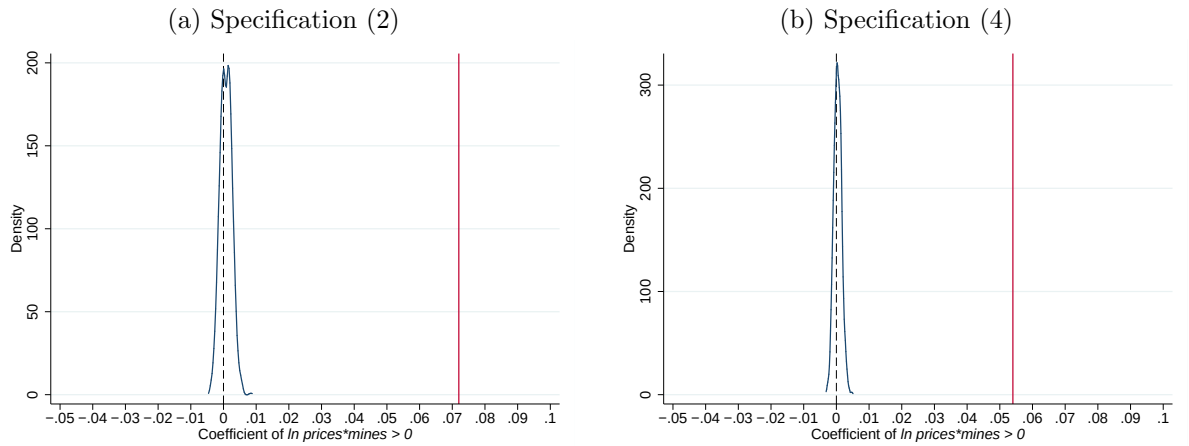
8 Appendix – additional results

Figure 3: Monte Carlo Sampling Distribution of (ln price × mines > 0)



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

Table 10: Robustness: alternative definitions of mining areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimator				LPM			
Dep. var.				Conflict incidence			
Def. mining area	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	Ever 1997-2010	Mine$(t-1)$	1 from opening onwards	Mine in 1997	Mine over 1992-1996	Mine over 1980-1996
ln price × mines > 0	0.072^a	0.043^a	0.033	0.050^a	0.056^a	0.056^a	0.050^a
	(0.020)	(0.014)	(0.032)	(0.016)	(0.019)	(0.020)	(0.019)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142296	143768	133492	143375	143768	143768	143768

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. In columns (1) to (5), ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. Column 1: mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t, and we consider only cells in which the mine dummy takes always the same value over the period. Column 2: mine take the value 1 if the an active mine was observed in the cell at any point over the 1997-2010 period. Column 3: mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year $t-1$ (coefficients on non interacted variables non reported). Column 4: mine > 0 is a dummy taking the value 1 from the first year an active mine is observed over the 1997-2010 period onwards, 0 if no active mine was ever recorded, and is coded as missing otherwise. Column 5: mine > 0 is a dummy taking the value 1 if at least 1 active mine was recorded in the cell in 1997. Column 6: mine > 0 is a dummy taking the value 1 if at least 1 active mine was recorded in the cell over the 5-year pre-sample period 1992-1996. Column 7: mine > 0 is a dummy taking the value 1 if at least 1 active mine was ever recorded in the cell in the RMD data (period 1980-1996).

Table 11: Conflicts and mineral prices: 1×1 degree cells

	(1)	(2)	(3)	(4)	(5)
Estimator			LPM		
Dep. var.			Conflict incidence		
Sample	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$		All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$
mine > 0	0.159^b				0.221^b
	(0.068)				(0.108)
ln price main mineral	-0.043				-0.049^b
	(0.036)				(0.021)
ln price × mines > 0	0.130^a	0.104^a		0.118^a	0.154^a
	(0.042)	(0.036)		(0.037)	(0.041)
ln price × mines > 0 (ever)			0.068^a		
			(0.022)		
Country×year FE	Yes	Yes	Yes	No	No
Year FE	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	No
Neighbour-pairs FE	No	No	No	No	Yes
Observations	37198	36120	37198	36120	9394

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. In all columns, ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. Estimation (1) includes controls for the average level of mineral World price interacted with the mine dummy.

Table 12: Main Mineral Price

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Robustness	Single mineral		Stable main mineral		Price index	
Sample	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	None	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	None	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	None
main_lprice_mines	0.046^b		0.068^a		0.065^a	
	(0.019)		(0.020)		(0.020)	
main_lprice_hist0		0.040^b		0.048^a		0.039^a
		(0.016)		(0.015)		(0.013)
Country×year FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	No
Neighbour-pairs FE	No	No	No	No	No	Yes
Observations	141960	143136	142212	143542	142464	144452

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. In columns (1) and (2), ln price mineral is the average price of the minerals produced in the cells, with weights equals to the share of each mineral in total production value over the period. In columns (3) to (6), ln price mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. Columns (4) and (5) include only mining cells producing a single mineral over the entire period. Columns (5) and (6) include only cells for which the main mineral is the same for each year of the sample.

Table 13: Number of Events

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimator		LPM			PPML			LPM
Dep. var.				Number of events				
	All	Dropping top 5%	Dropping 2SD	All	Dropping top 5%	Dropping 2SD	log(x+1)	Inverse hyperbolic
Sample A					$\mathbb{V}(\mathrm{M}_{kt}) = 0$			
ln price × mines > 0	0.249	0.263[a]	0.256[c]	0.195	0.440[b]	0.301	0.094[a]	0.121[a]
	(0.240)	(0.100)	(0.155)	(0.283)	(0.197)	(0.239)	(0.032)	(0.040)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×year FE	Yes	Yes	Yes	No	No	No	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes	No	No
Observations	142296	141894	142163	35210	34769	35064	142296	142296
Sample B					All			
ln price × mines > 0 (ever)	0.245[c]	0.216[a]	0.217[b]	0.253	0.395[b]	0.289	0.070[a]	0.089[a]
	(0.136)	(0.079)	(0.100)	(0.264)	(0.172)	(0.194)	(0.022)	(0.028)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×year FE	Yes	Yes	Yes	No	No	No	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes	No	No
Observations	143864	143361	143634	35980	35472	35771	143864	143864

LPM estimations. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation in columns (1) to (3) and (7) to (8). Standard errors clustered by country in columns (4) to (6). mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells.

Table 14: Heterogeneous effects: minerals' capital intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Sample	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All
ln price × mines > 0	0.119		0.089^a		0.069^a	
	(0.119)		(0.026)		(0.022)	
ln price × mines > 0 (ever)		0.087^c		0.078^a		0.041^a
		(0.048)		(0.023)		(0.014)
× Open Cast	0.078	-0.042				
	(0.650)	(0.119)				
× Energy intensity			-0.000	-0.000		
			(0.000)	(0.000)		
× Mine age					0.001	0.002
					(0.002)	(0.002)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	141344	141946	141782	142192	142221	143789

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. Open Cast is the average percentage of mines using open-pit mining method in Africa over the period. Energy intensity is the ratio of ln(energy/production) over ln(employees/production). Mine age is the number of years since the first mining activity was observed.

Table 15: Heterogeneous effects: minerals' lootability

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Sample	$\mathbb{V}(M_{kt}) = 0$	All	$\mathbb{V}(M_{kt}) = 0$	All	$\mathbb{V}(M_{kt}) = 0$	All
ln price × mines > 0: low price	0.046^c					
	(0.027)					
ln price × mines > 0: high price	0.084^a					
	(0.025)					
ln price × mines > 0 (ever): low price		0.020				
		(0.020)				
ln price × mines > 0 (ever): high price		0.054^a				
		(0.018)				
ln price × mines > 0			0.093		0.088^a	
			(0.066)		(0.024)	
ln price × mines > 0 (ever)				-0.001		0.054^a
				(0.058)		(0.017)
× Rents			0.022	0.072		
			(0.072)	(0.061)		
× Ore concentration					-0.174^a	-0.166^a
					(0.059)	(0.056)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142296	143768	141498	141876	142170	143262

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(M_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. High (respectively low) price means above (resp. below) the sample median of prices in USD per ton in 1997. Rents is the ratio of mineral price over mineral-specific average costs for all African mines. Ore concentration is the average concentration of the metal in the corresponding ore.

Table 16: Mineral price, firm ownership and conflicts: robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Events	All	Battles	All	Battles	All	Battles
ln price × mines > 0 × Foreign Firms	0.058[a]	0.010				
	(0.021)	(0.009)				
ln price × mines > 0 × Dom. Private Firms	0.018	-0.001	0.018	-0.001	-0.011	-0.004
	(0.014)	(0.003)	(0.014)	(0.003)	(0.024)	(0.007)
ln price × mines > 0 × Dom. Public Firms	0.032	-0.005	0.031	-0.006	0.032	-0.005
	(0.034)	(0.019)	(0.034)	(0.019)	(0.034)	(0.019)
ln price × mines > 0 × Fgn Firms (col.)			0.007	-0.012	-0.034	-0.016
			(0.031)	(0.017)	(0.037)	(0.018)
ln price × mines > 0 × Fgn Firms (non col.)			0.071[a]	0.015	0.043[b]	0.013
			(0.024)	(0.010)	(0.020)	(0.009)
ln price × mines > 0 × Large Firms					0.061[c]	0.006
					(0.033)	(0.013)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143542	143542	143542	143542	143542	143542

LPM estimations. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. The company characteristics (foreign, domestic public, domestic private, etc) denote the share of mines owned by a given category at the beginning of the period. Cells containing only mines with missing ownership information are dropped.

Table 17: Heterogeneous effects: The Role of Transparency (robustness)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Estimator					LPM					
Dep. var.					Conflict incidence					
Events	All	Battles	All	Battles	All	Battles	All	Battles	All	Battles
ln price × mines > 0 (ever)	-0.022	-0.002	-0.001	0.011	-0.014	0.006	-0.008	0.002	-0.005	0.006
	(0.015)	(0.010)	(0.018)	(0.010)	(0.016)	(0.010)	(0.013)	(0.007)	(0.012)	(0.007)
× Large Firms	0.137[a]	0.010	0.155[a]	0.011	0.136[a]	0.004	0.133[a]	0.004	0.133[a]	0.003
	(0.031)	(0.016)	(0.044)	(0.018)	(0.032)	(0.017)	(0.032)	(0.016)	(0.032)	(0.016)
× Control of Corruption	-0.044[b]	-0.035[b]								
	(0.022)	(0.017)								
× Firm CSR (ICMM)			-0.102[c]	-0.040[b]						
			(0.056)	(0.020)						
× Tracea. Init. (EITI, request)					0.001	0.000				
					(0.002)	(0.001)				
× Tracea. Init. (EITI, compliance)							0.001	0.006		
							(0.003)	(0.005)		
× Tracea. Init. (GLR)									-0.002[b]	0.001
									(0.001)	(0.002)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	131908	131908	142562	142562	142548	142548	142548	142548	142548	142548

LPM estimations. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. Sample restricted to non mining cells and cells for which foreign owned mines represent the largest share. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(M_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the World price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. See main text for a description of the various transparency variables.

This mine is mine!
How minerals fuel conflicts in Africa

Online Appendix

August 4, 2016

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A Additional data description

A.1 Additional information on variables used

Structure of the dataset. The structure of the dataset we use in Sections 4 and Section 6 of the manuscript 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). This is the exact same level of aggregation as the one used in the PRIO-GRID, which allows us to easily include cell-specific information from this dataset. We use this level of aggregation rather than administrative boundaries to ensure that our unit of observation is not endogenous to conflict events. To each cell we assign a country based on the end-of-the-period boundaries. The country which represents the largest share of the cell's area is assigned to this cell.

Conflict Data. We use the Armed Conflict Location and Event dataset (Raleigh, Linke and Dowd, 2014) which contains information on the geo-location of conflict events in all African countries. We focus on the 1997-2010 period which overlaps with our mines data. We use ACLED v3 (http://www.acleddata.com/wp-content/uploads/2014/acled_with_prio.zip) as it contains cells identifiers which allows to directly match the data with PRIO-GRID and to use its standard grid of 0.5×0.5 degree cells. In ACLED data, the unit of observation is the "event". We have information about the date (precise day most of the time), longitude and latitude of conflict events within each country. These events are obtained from various sources, including press accounts from regional and local news, humanitarian agencies or research publications. ACLED records all political violence, including violence against civilians, rioting and protesting within and outside a civil conflict, without specifying a battle-related deaths threshold.

A unique feature of the ACLED dataset is that it contains information about the type of events, about the characteristics of the actors on both sides of the conflicts, and about the outcome of conflicts. For instance, we know in particular if the event was a battle, the names of the groups involved, and who won the battle.[5] We shall make use of this information when testing for the channels of transmission. The presence of this detailed information as well as the more exhaustive character of the ACLED are the main reason why we chose to use this dataset, rather than the UCDP-GED dataset. The latter records only events pertaining to conflicts reaching at least 25 battle-related deaths per year, and does not include information on battle events outcomes. We however use this alternative dataset in our robustness analysis.

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

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. We keep only events which are geolocalized with the finer precision level for our analysis. We also drop duplicated events, i.e. events for which all the ACLED variables' content (precise date, location, actors, description, etc.) is the same for several observations – in this case we keep only one observation for the event. This drops 1.7% of events.

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*. This is our main dependent variable throughout the paper. Alternatively, we compute a variable containing the number of events observed in the cell during the year, which we label *conflict intensity*. We also show that our results are robust to modeling cell-specific conflict onset and ending separately.

Mines data. To each *cell-year*, we merge information on mines from *Raw Material Data* (RMD – IntierraRMG). For more information see http://www.snl.com/Sectors/metalsmining/Default.aspx. The data contain information on the location of mining companies around the world since 1980. For each year, we know the name of the mine, whether it is active or not, the specific minerals produced and the total production (in volume) for each of them. In some case the production data is missing but we nevertheless know if the mine is active or not. We also have information on the type of extraction method (open cast, underground, alluvial), the end-of-period number of employees (which contains many missing values), and the age of the mine. All this information is used in section 4.5 of the paper. Finally, we also know the names and types (foreign, domestic, public or private owned) of the companies owning the mines. This information is used in the last section of the paper.

Main minerals. We use the RMD data to identify active mining areas, and the type of minerals they produce. For each cell k, we define M_{kt}, a dummy variable which equals one if a least one *active* mine is recorded in the cell during year t. As an alternative measure we also compute the number of mines. To determine the main mineral produced by the cell we make use of the information on production by mine and mineral provided in the RMD dataset. First, given that production is provided in volumes with different units of measurement, we convert it into tons and then to value using 1997 prices to avoid endogeneity. Second, we compute the total production value of the minerals produced in the cell over the 1997-2010 period. In our data, 280 cells contain mines producing one or several minerals. For 21 of them we do not have price data for any of the

minerals and therefore cannot define a main mineral.[6] For 215 cells, we have price data for all minerals, and the main mineral can be straightforwardly defined as the mineral with the highest production value. In the remaining 44 cells, minerals for which we have the price co-exist with minerals for which we do not. In most cases however, we can identify the main mineral produced by looking at the names of the mines. For instance, the cell with the PRIO-GRID identifier 88974 produces both gold (price data available) and uranium oxide (price data unavailable) but the latter is produced only in mines named "Freegold Gold mine" and "Harmony/Free Stage UG Gold mine", which main mineral is clearly gold. Therefore, whenever the name of a mine producing a mineral for which we do not have price data contains the name of a mineral for which we do have price data, we define the mineral contained in the name of the mine as the main mineral produced by the mine. This allows us to identify the main mineral even in some cells for which we do not have price data for some mines. In total, we are able to identify the main mineral in 237 cells out of 280 (85%). The table below summarizes the share of cells producing each of the main minerals.

Table A.1: Main minerals

Main mineral	# cells	Share cells (%)
aluminum	4	1.69
coal	32	13.50
copper	27	11.39
diamond	40	16.88
gold	83	35.02
iron	14	5.91
lead	2	0.84
nickel	5	2.11
phosphate	7	2.95
platinum	10	4.22
silver	1	0.42
tantalum	2	0.84
tin	2	0.84
zinc	8	3.38
All	237	100

Some statistics about the main minerals. First, for 70% of the cells only one mineral is produced over our period of study. Second, for 85% of the cells, the main mineral is stable over the entire period. Third, the main mineral represents 96% of the total production over the period on average (84% when excluding single mineral cells).

[6] We have price data for 14 minerals: Bauxite (aluminum), Coal, Copper, Diamond, Gold, Iron, Lead, Nickel, Platinum (and Palladium/PGMs, i.e. Platinum Group Metals), Phosphate, Silver, Tantalum (Coltan), Tin and Zinc. We do not have price data for the following minerals: Antimony, Chromite, Cobalt, Lithium, Manganese, Tungsten, Uranium, Zirconium.

Mineral prices. For all commodities but diamond and coltan, we use information on the world price of the minerals from the World Bank Commodities prices dataset (http://databank.worldbank.org/data/databases/commodity-price-data). Real prices are measured in constant 2005 USD. We also add composite diamond prices from Rapaport (http://www.diamonds.net/Reports/) and tantalum (coltan) US market unit values from the U.S. geological survey (http://minerals.usgs.gov/minerals/pubs/historical-statistics/#tantalum).

Other mineral-specific data. In section 4.5 we use Energy requirements in kWh/t by mineral from USGS (2011), employees and production figures are from RMD (IntierraRMG, 2013) and an alternative measure of open-cast mining using alternative data from Hargreaves and Fromson (1983). We also add data on metal-specific average cost data for all African mines from http://www.minecost.com and metal-specific concentration in ore from Philipps and Edwards (1976).

Other cell-specific variables. Our dataset is merged with PRIO-GRID v2 (Tolefsen, Strand and Buhaug, 2012, found at http://grid.prio.org) which contains a number of additional cell-specific variables which we use in our robustness analysis. These include in particular information on climate (temperature and rainfall), GDP and population (included in PRIO-GRID but originally from G-econ), as well as distances between the cell's centroid and international borders and to the capital city. Finally, we add information on satellite nighttime lights data from the National Oceanic and Atmospheric Administration (2010) (http://ngdc.noaa.gov/eog/) and data on the presence of non-indigenous groups in the cell from Cederman, Buhaug and Rod (2009) (in particular, we use the list of ethnic groups and information on their location from Cederman, Buhaug and Rod (2009), and drawing on a variety of sources, we code for each ethnic group whether it is INDIGENOUS in a given country or not, i.e. settled in a place for several centuries).

Country-specific data. In section 4.4 we study how the effect of mineral price variations on conflict varies with countries' characteristics. We use the *ICRG Indicator of Quality of Government* from International Country Risk Guide (2013); the *Government Effectiveness*, *Rule of Law*, *Control of Corruption*, *Voice and Accountability* indexes from the WGI ("Worldwide Governance Indicators") dataset (Kaufmann, Kraay, and Mastruzzi, 2013); and the GINI index from the Standardized World Income Inequality Database (Solt, 2014). All these variables are taken from the Quality of Governance (QOG) dataset (Dahlberg, Dahlstrom, Petrus and Teorell, 2013, available at http://www.qog.pol.gu.se). Finally, ethnic and religious fractionalization or polarization are

from Reynal-Querol (2014) (www.econ.upf.edu/~reynal/data_web.htm). In section 6 we use data on colonial links between countries from the CEPII gravity dataset (http://www.cepii.fr).

Ethnic homelands. In section 5.2.1 we use the geo-coordinates of ethnic homelands from the "Georeferencing of ethnic groups" (GREG) dataset (Weidmann, Rod and Cederman, 2010). GREG includes the geographical location of ethnic groups, based on the "Soviet Atlas Narodov Mira" from 1964.

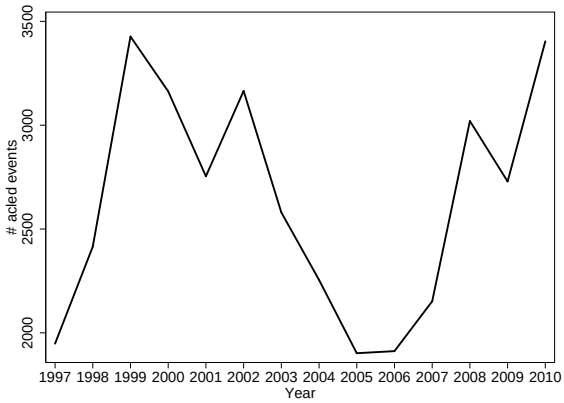
Port-level corruption. In the online appendix, section P, we use a proxy of port-level corruption constructed from bilateral trade data. More precisely, we compute the ratio of the import quantities declared by the country over the quantities declared by the rest of the World as exports to that country in the 5 years before the start of the period (1992-1996). The data on imports and exporters quantities declarations come from UN-COMTRADE (http://comtrade.un.org/).

Transparency initiative. In section 6, data on firms' membership to the "International Council on Mining and Metals" (ICMM) come from the ICMM website (http://www.icmm.com). Data on countries' membership to the "Extractive Industries Transparency Initiative" (EITI) come from Papyrakis, Rieger and Gilberthorpe (2016). Finally, countries' and minerals' membership to the "Mineral Certification Scheme of the International Conference on the Great Lakes Region (GLR)" come from http://www.pacweb.org/en/regional-certification.

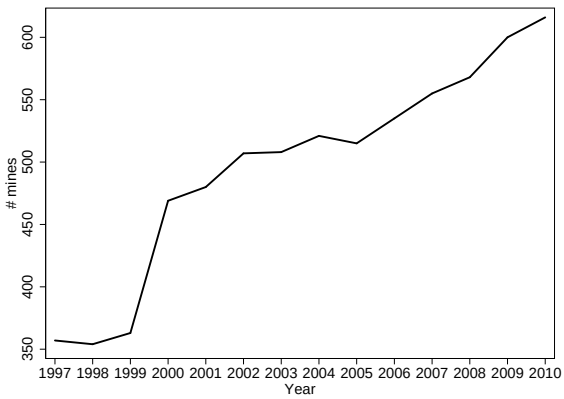
A.2 Trends in conflict and mining

Figure A.1: Time trends of mining and conflict

(a) Number of conflict events (ACLED)

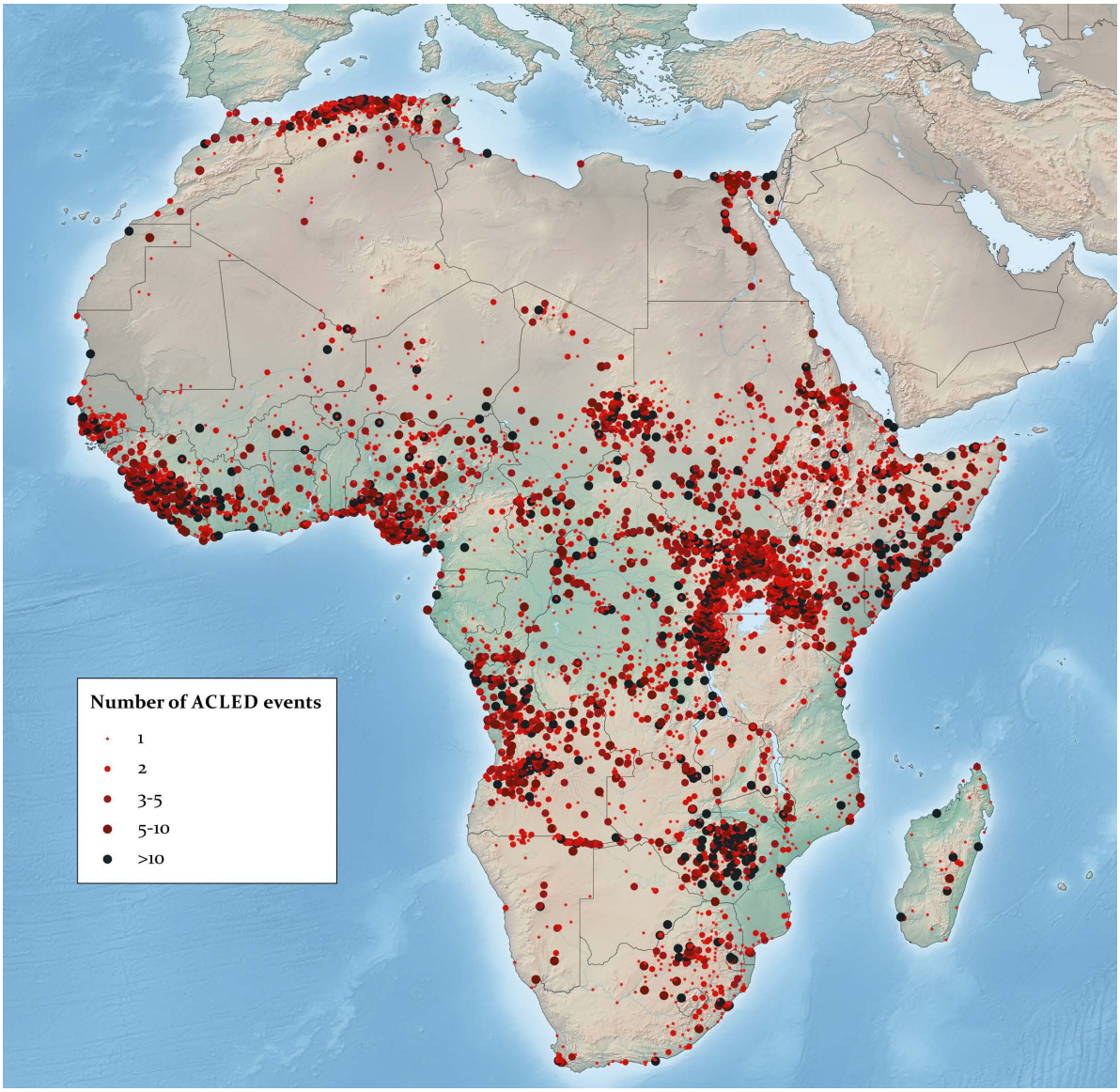


(b) Number of active mines (RMD)



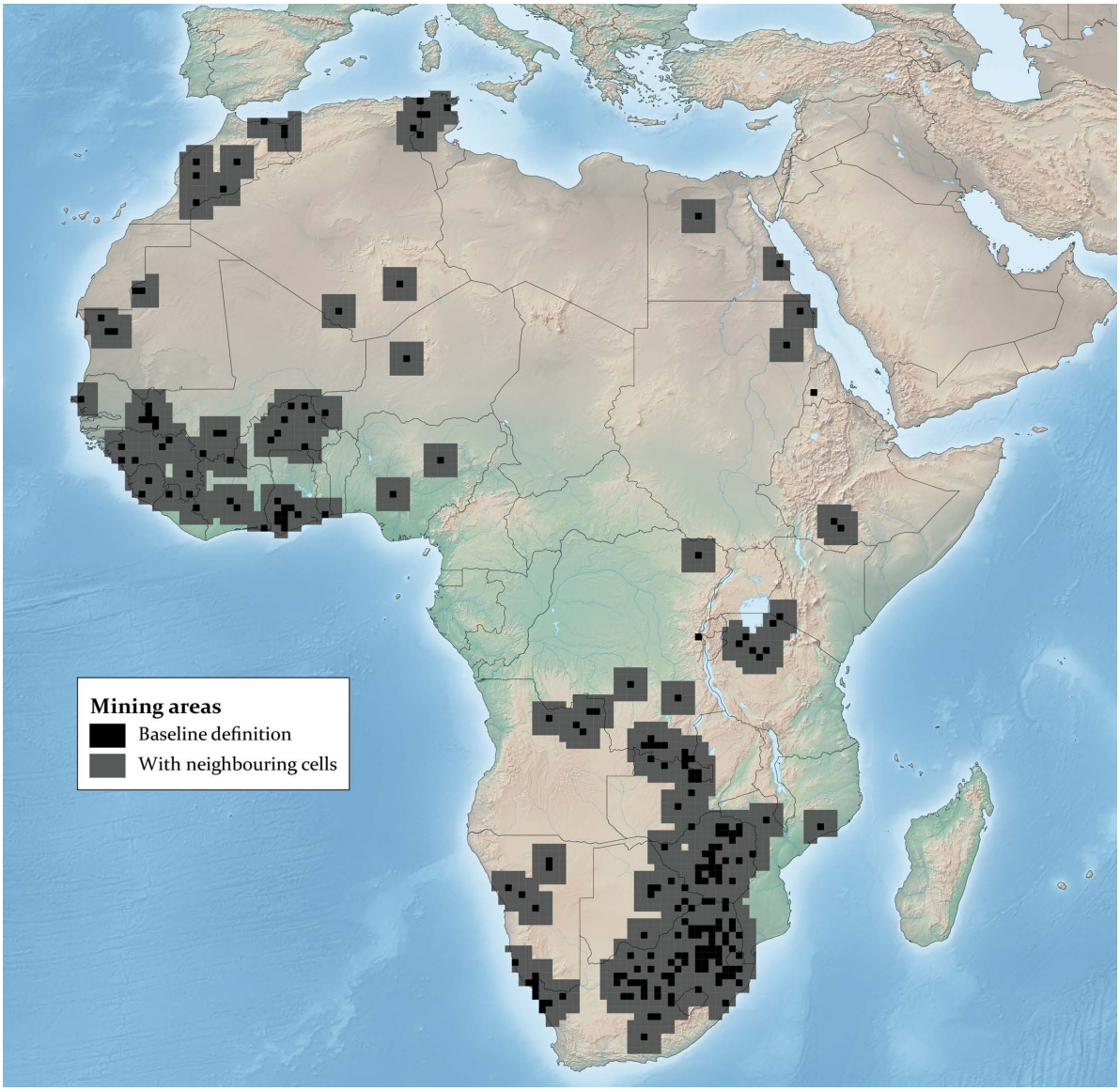
A.3 Maps

Figure A.2: Conflict events



Geo-location of conflict from the Armed Conflict Location and Event dataset (ACLED, 2014).

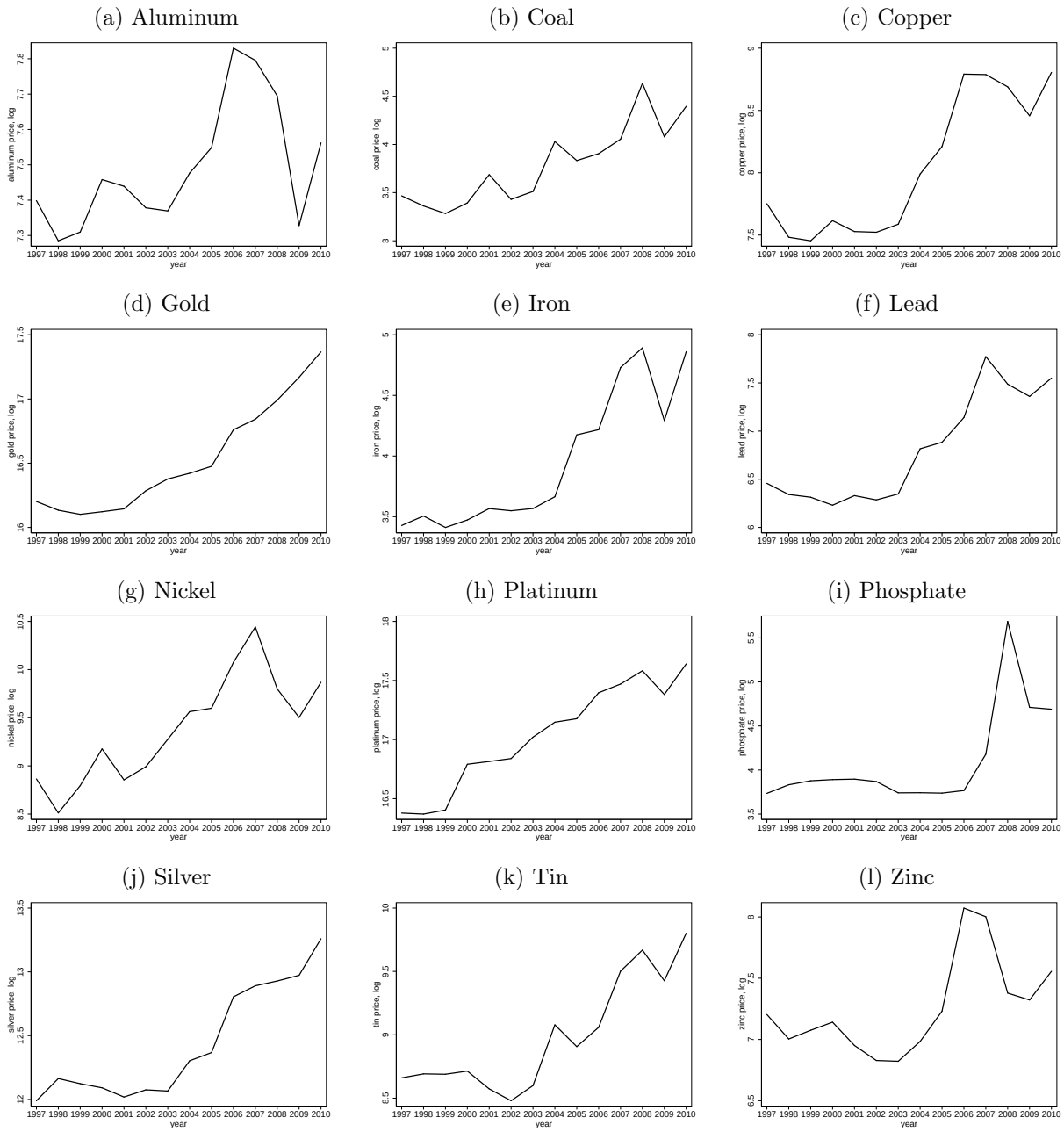
Figure A.3: Mining areas



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

A.4 Mineral prices

Figure A.4: Mineral prices (log scale)



Source: World Bank.

A.5 Country-level descriptive statistics

Our final sample contains 52 countries and 14 minerals. Tables A.2 and A.3 contain additional country-level descriptive statistics. On average, around 50 conflict events and 10 active mines are recorded each year in each country. Only four countries display no conflict events over the entire period, the Republic Democratic of Congo is the country with the highest number of events (almost 300 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 20 countries no active mine is recorded. The highest numbers of mines are recorded in South Africa and Zimbabwe, but these are highly concentrated, as in both cases mining areas represent less than 20% of the cells. Note that – except in the case of South Africa – the countries contained in our sample are typically small producers of the minerals from a world perspective: the average market share of a country-mineral is around 6.5% (the median at 2.9%), and drops to 4.5% when we exclude South Africa (and the median to 1.6%).

Table A.2: Descriptive statistics: country-level

	Obs.	Mean	S.D.	1st Quartile	Median	3rd Quartile
# conflicts / year	53	49.63	72.40	4.5	17.42	61.92
# mines / year	53	9.36	38.44	0.00	1	4.64

Source: Authors' computations from ACLED and RMD data from 1997 to 2010.

Table A.3: 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	103	Liberia	0.03	0.23	0	53
Angola	0.01	0.08	6	172	Libya	0	0.00	0	2
Benin	0	0.03	0	2	Madagascar	0.00	0.02	1	24
Botswana	0.03	0.01	14	3	Malawi	0	0.10	0	7
Brukina Faso	0.03	0.03	1	9	Mali	0.01	0.01	4	7
Burundi	0	0.89	0	211	Marocco	0.05	0.03	19	10
Cameroon	0	0.03	0	10	Mauritania	0.01	0.00	5	1
Cape Verde	0	0	0	0	Mauritius	0	0	0	0
Central African Rep.	0	0.06	0	29	Mozambique	0.01	0.03	3	18
Chad	0	0.03	0	28	Namibia	0.03	0.02	20	13
Comoros	0	0	0	0	Niger	0.00	0.01	1	17
Congo, Dem. Rep.	0.01	0.08	20	278	Nigeria	0.01	0.15	2	145
Congo, Rep.	0	0.05	0	33	Rwanda	0.13	0.52	1	40
Djibouti	0	0.15	0	3	Senegal	0.02	0.11	2	28
Egypt	0.00	0.03	1	37	Sierra Leone	0.04	0.34	1	90
Equatorial Guinea	0	0.10	0	2	Soa Tome and Principe	0	0	0	0
Eritrea	0	0.09	0	15	Somalia	0	0.14	0	257
Ethiopia	0.01	0.08	2	72	South Africa	0.15	0.05	277	74
Gabon	0	0.02	0	3	Sudan	0.00	0.05	2	118
Gambia. The	0	0.58	0	5	Swaziland	0.25	0.27	1	5
Ghana	0.10	0.04	15	7	Tanzania	0.01	0.02	5	21
Guinea	0.07	0.09	6	32	Togo	0.06	0.09	1	7
Guinea-Bissau	0	0.23	0	14	Tunisia	0.05	0.03	5	5
Ivory Coast	0.02	0.09	3	62	Uganda	0	0.34	0	112
Kenya	0.01	0.18	1	136	Zambia	0.03	0.03	12	44
Lesotho	0.08	0.10	1	1	Zimbabwe	0.16	0.23	55	268

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.

B Minerals and conflicts: Correlations

Table A.4 displays the results of the correlation between mining and conflict at the local level. In columns (1)-(2), we consider a pure cross-sectional specifications. The dependent variable takes the value 1 if at least 1 conflict event is observed in the cell over the period. The explanatory variable is either a dummy coding for the presence of at least 1 mine in the cell over the period (col. 1), or the average number of mines observed in the cell during the period (col. 2). In both cases, a positive association with conflict is found.

In columns (3) to (6) we use the full panel. The dependent variable is cell-level conflict incidence, and the mining variable is either a discrete variable equal to the number of *active* mines, or a binary variable coding for the presence of at least one active mine. Column (3) includes a vector 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. We find that in a given country-year, conflict is more likely to occur in mining areas. The presence of one or more mines is associated with a 8.2 percentage points increase in conflict probability.

Part of the correlation could be spuriously driven by omitted time-invariant cell-specific characteristics such as the local determinants of state capacity, property rights enforcement or political instability (e.g. ethnic cleavages). In order to control for this source of unobserved heterogeneity, we include cell fixed-effects in the remaining columns. Estimates are still positive and significant at the 10% level. In term of magnitude, the within-cell estimates correspond to half of their between-cell counterparts confirming that part of the correlation in column (3) is driven by time-invariant cell characteristics. The opening of a mine in a given cell is associated with a 3.4 percentage points increase in conflict probability in this cell.

Table A.4: Conflicts and mines: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	LPM					
Dep. var.	Conflict Incidence					
Sample	Cross-section		Panel			
At least 1 mine over 1997-2010	0.178[a]					
	(0.021)					
average # mines		0.043[a]				
		(0.014)				
mine > 0			0.082[a]	0.034[c]	0.034[c]	
			(0.007)	(0.019)	(0.019)	
# mines						0.007[a]
						(0.003)
ln precipitation					0.000	0.000
					(0.001)	(0.001)
average temperature					0.001	0.001
					(0.002)	(0.002)
Country FE	Yes	Yes	No	No	No	No
Country×year FE	No	No	Yes	Yes	Yes	Yes
Cell FE	No	No	No	Yes	Yes	Yes
Observations	10335	10335	144594	144594	144481	144481

LPM estimations. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Dependent variable is conflict incidence, which takes the value 1 in columns (1)-(2) if at least one conflict event is observed in the cell over the period (during the year in columns (3)-(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.

C Spatial spillovers

This section provides some additional evidence that conflicts diffuse spatially following mining shocks. In columns (1) and (2) of Table A.5, we include the number of neighbouring cells in conflict in our baseline estimations (Table 2, columns (2) and (4)) without instrumenting. We find positive spillovers of conflicts. This variable is however endogeneous, as jointly determined with the LHS variable (the "Manski" reflection problem).

We therefore perform 2SLS estimations following Bramoulle, Djebbari and Fortin (2009). In columns (3) to (6), we instrument the neighbouring cells in conflict term, either with the mineral shocks in the neighbouring cells of degrees 1 and 2 (columns (3) and (4)) or with conflicts in neighbours of degree 2 (columns (5) and (6)). In all cases the local effect of mineral price variations survives, and spatial spillovers from neighbouring cells are found to be strongly significant. However, results of columns (3) and (4) need to be interpreted with caution as the validity condition of the 2SLS is likely to be violated: mineral price variations in neighbouring cells could have a direct effect on conflict, for instance if there is measurement error in the actual surface of mining areas. The results of columns (5) and (6) are suggestive of the presence of spatial spillovers of conflicts, but they are not directly related to mineral extraction. For these reasons, the methodologies presented in section 5.2.1 (based on ethnic homelands of rebel groups and changes in territories) are our preferred ways of looking at the spatial diffusion of conflicts through mineral extraction.

Table A.5: Conflicts and mineral prices: conflicts in neighbouring cells

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			Conflict incidence			
Sample	$\mathbb{V}(M_{kt}) = 0$	All	$\mathbb{V}(M_{kt}) = 0$	All	$\mathbb{V}(M_{kt}) = 0$	All
Estimator	OLS		2SLS			
Instrument			Prices of main mineral of neighbouring cells		Conflicts in neighbours of degree 2	
ln price × mines > 0	0.057^a		0.041^c		0.032^c	
	(0.020)		(0.024)		(0.018)	
ln price × mines > 0 (ever)		0.035^a		0.026^c		0.019^c
		(0.011)		(0.014)		(0.011)
# neighbouring cells in conflict (1 degree)	0.047^a	0.046^a			0.124^a	0.125^a
	(0.005)	(0.005)			(0.005)	(0.005)
# neighbouring cells in conflict (2 degrees)			0.046^a	0.043^a		
			(0.007)	(0.007)		
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	137914	139412	137914	139412	137914	139412

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered by country in parentheses. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(M_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In columns (3) to (4) # neighbouring cells of degree 2 in conflict is instrumented by the prices of the main minerals produced in the first and second degree neighbouring cells. In columns (5) and (6) # neighbouring cells of degree 1 in conflict is instrumented by # neighbouring cells of degree 2 in conflict.

D Mineral prices and conflicts: onset and ending

Our focus on conflict incidence reflects our interest in explaining the general presence of conflict. A higher conflict incidence can be due to either more conflicts breaking out or due to existing conflicts lasting longer. Hence, in the civil war literature, a number of papers focus on civil war outbreaks (onsets) and endings separately. In the context of our spatially disaggregated data, conflict exhibits only little persistence (more than 75% of events do not last more than two years) and therefore this exercise has a limited scope. Tables A.6 and A.7 displays the results. We find that our variable of interest both significantly increases the risk of conflict onset, and reduces the likelihood of conflict ending, although the coefficient is less precisely estimated for conflict ending. This suggests that the higher conflict incidence due to mines is both due to more local conflicts breaking out and to existing conflicts lasting longer.

Table A.6: Conflicts and mineral prices: conflict onset

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict onset			
Sample	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$		All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	
mine > 0	0.059					0.028
	(0.063)					(0.026)
ln price main mineral	-0.014					0.024^b
	(0.023)					(0.011)
ln price × mines > 0	0.060^b	0.066^a	0.047^b		0.075^a	0.028
	(0.029)	(0.022)	(0.023)		(0.024)	(0.018)
ln price × mines > 0 (neighbouring cells)			0.018^a			
			(0.005)			
ln price × mines > 0 (ever)				0.038^a		
				(0.013)		
Country×year FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	No
Neighbour-pairs FE	No	No	No	No	No	Yes
Observations	136565	135268	121742	136658	135268	16515

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. Conflict onset is a dummy taking the value 1 if the cell experiences a conflict event in t conditional on no conflict occurring in $t-1$, and is coded as missing if a conflict occurred in $t-1$. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. Column (6) is run on a sample containing only mining cells and their immediate neighbouring cells. In columns (1) to (5), ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (6) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimations (1) and (6) include controls for the average level of mineral world price interacted with the mine dummy.

Table A.7: Conflicts and mineral prices: conflict ending

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict ending			
Sample	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$		All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	
mine > 0	-0.008					-0.016
	(0.179)					(0.082)
ln price main mineral	0.027					-0.000
	(0.118)					(0.049)
ln price × mines > 0	-0.176	-0.120^c	-0.159^b		-0.086	-0.066
	(0.120)	(0.064)	(0.067)		(0.057)	(0.045)
ln price × mines > 0 (neighbouring cells)			-0.019			
			(0.048)			
ln price × mines > 0 (ever)				-0.120^b		
				(0.051)		
Country×year FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	No
Neighbour-pairs FE	No	No	No	No	No	Yes
Observations	17447	17192	15373	17482	17192	3668

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. Conflict ending is a dummy taking the value 1 if the cell experiences no conflict event in t conditional on a conflict occurring in $t-1$, and is coded as missing if no conflict occurred in $t-1$. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. Column (6) is run on a sample containing only mining cells and their immediate neighbouring cells. In columns (1) to (5), ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (6) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimations (1) and (6) include controls for the average level of mineral world price interacted with the mine dummy.

E Alternative Dataset on Violence: UCDP-GED

We complement our sensitivity analysis on violence measurement using an alternative conflict database with geo-coded information from UCDP-GED, namely the Conflict Data Program Geo-referenced Events Dataset (Sundberg, Lindgren, and Padskocimaite (2010)). The UCDP-GED focuses on deadly incidents associated with civil wars (i.e. more than 25 conflict-related casualties in a given year), as identified by the UCDP-PRIO Armed Conflict Database.

The results are displayed in Table A.8. In Columns (1) and (2) we replicate with our baseline specifications (col. (2) and (4) of Table 2) with a measure of conflict incidence based on UCDP-GED events. A striking feature relates to the dramatic sample size reduction by nearly one half, the reason being that only countries experiencing more than 25 conflict-related casualties in a given year are included in the UCDP-GED sample. Unsurprisingly, the coefficients of interest loose their statistical significance. For the sake of comparison we replicate in columns (3) and (4) the baseline specifications (with ACLED events) on the same subsample of countries. Here too we observe a deterioration of statistical significance confirming that it relates to the drastic sample size reduction and not to the nature of the UCDP-GED events. To alleviate this problem we combine the two datasets in columns (5)-(6). More precisely, we code violent events with UCDP-GED for country-year cells that are covered by this dataset and for other country-year cells, we use ACLED events. This coding procedure restores the initial sample size. Statistical significance is also restored. In columns (7) and (8) we check that the previous finding is not entirely driven by ACLED events. For this purpose we create two mutually exclusive dummies coding for country-year cells covered respectively by UCDP-GED and ACLED that we interact with our main explanatory variable. Reassuringly, the two coefficients of the triple interaction terms are positive, statistically significant and of similar magnitudes, showing that the results of the two previous columns are not solely driven by ACLED events. In sum, this indicates that our main findings are robust to the use of the alternative UCDP-GED dataset.

Table A.8: Robustness: UCDP-GED dataset

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimator				LPM				
Conflict (dep. var.)	UCDP		ACLED		Combined			
Sample	UCDP		UCDP		All		All	
Condition	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	None	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	None	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	None	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	None
ln price × mines > 0	-0.009		0.042^c		0.053^b			
	(0.025)		(0.024)		(0.022)			
× ACLED sample							0.049^b	
							(0.022)	
× UCDP sample							0.041^c	
							(0.022)	
ln price × mines > 0 (ever)		0.005		0.035^c		0.032^b		
		(0.016)		(0.021)		(0.013)		
× ACLED sample								0.030^b
								(0.013)
× UCDP sample								0.027^b
								(0.013)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91849	92636	91849	92636	142296	143864	142296	143864

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. Estimations (1)-(4) are run on the sub-sample of country-years covered in UCDP-GED. In columns (5)-(8), the dependent variable is conflict incidence from UCDP-GED for the countries covered by this dataset and conflict incidence from ACLED for the rest of the sample. The ACLED sample variable is a dummy which equals 0 if an observation is in the UCDP-GED sample, and 1 otherwise. The UCDP sample variable is 0 when the ACLED sample variable is 1, and vice versa.

F Standard-errors

In this section we allow for various levels of cross-sectional spatial correlation and cell-specific serial correlation. Remember that in all tables of the manuscript we allow as benchmark the serial correlation to be present for an infinite horizon (i.e. 100,000 years), and a spatial radius of 500 kilometers. In Table A.9, we replicate Table 2 but allow alternatively for spatial correlation of 100 or 1000 kilometers, and for a serial correlation over 1 or 5 years or an infinite horizon. We also provide an alternative treatment, where we simply cluster the standard errors at the country-level. In all cases, the standard errors are such that our coefficients of interest remain statistically significant at conventional levels.

Table A.9: Standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Sample	All	$\mathbb{V}(M_{kt}) = 0$		All	$\mathbb{V}(M_{kt}) = 0$	
mine > 0	0.112					0.048
Spatial: 100km; Time: Infinite	(0.062)					(0.064)
Spatial: 1000km; Time: Infinite	(0.065)					(0.064)
Spatial: 100km; Time: 1 year	(0.055)					(0.030)
Spatial: 100km; Time: 5 years	(0.056)					(0.043)
Country level	(0.066)					(0.063)
ln price main mineral	-0.029					0.028
Spatial: 100km; Time: Infinite	(0.032)					(0.018)
Spatial: 1000km; Time: Infinite	(0.032)					(0.019)
Spatial: 100km; Time: 1 year	(0.026)					(0.016)
Spatial: 100km; Time: 5 years	(0.026)					(0.019)
Country level	(0.017)					(0.015)
ln price × mines > 0	0.086	0.072	0.060		0.085	0.108
Spatial: 100km; Time: Infinite	(0.035)	(0.019)	(0.022)		(0.021)	(0.041)
Spatial: 1000km; Time: Infinite	(0.035)	(0.020)	(0.021)		(0.025)	(0.041)
Spatial: 100km; Time: 1 year	(0.029)	(0.017)	(0.019)		(0.018)	(0.026)
Spatial: 100km; Time: 5 years	(0.029)	(0.017)	(0.018)		(0.022)	(0.035)
Country level	(0.016)	(0.022)	(0.024)		(0.022)	(0.050)
ln price × mines > 0 (neighbouring cells)			0.021			
Spatial: 100km; Time: Infinite			(0.006)			
Spatial: 1000km; Time: Infinite			(0.006)			
Spatial: 100km; Time: 1 year			(0.005)			
Spatial: 100km; Time: 5 years			(0.006)			
Country level			(0.009)			
ln price × mines > 0 (ever)				0.045		
Spatial: 100km; Time: Infinite				(0.013)		
Spatial: 1000km; Time: Infinite				(0.014)		
Spatial: 100km; Time: 1 year				(0.011)		
Spatial: 100km; Time: 5 years				(0.011)		
Country level				(0.011)		
Country×year FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	No
Neighbour-pairs FE	No	No	No	No	No	Yes
Observations	143754	142282	124474	143850	142282	17360

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(M_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. Column (6) is run on a sample containing only mining cells and their immediate neighbouring cells. In columns (1) to (5), ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (6) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimations (1) and (6) include controls for the average level of mineral world price interacted with the mine dummy.

G Instrumenting mining activity

In the baseline, to address endogenous mining openings and closings, we restrict the sample to cells with either permanently active mine over the sample period or, alternatively, to cells where at least in one year a mine was active during the sample period. In the appendix of the manuscript, Table 10 displays alternative definitions of mining activity, to further ensure that our results are not driven by endogenous opening/closing of mines (i.e. variations in the mining dummy over time). An alternative methodology to address these endogeneity concerns is to instrument world prices $\times$ actual mines, using world prices $\times$ historical mines as instrument, which is what we do in the current online appendix, section G.

Table A.10 displays the results. In the first panel the first stage results are displayed while in the second panel the second stage coefficients are reported. Column (1) corresponds to the baseline specification of column (2) of Table 2. The interaction of current price times the presence of a historical mine (before 1997) is an extremely strong predictor of the interaction of the current price times the actual permanent presence of a mine, yielding a coefficient of close to 1, significant at the 1 percent level. The instrumented world prices $\times$ actual mines variable of interest is highly significant in the second stage with a coefficient close to the one in the benchmark of Table 2. Column (2) of Table A.10 similarly corresponds to column (4) of Table 2, while column (3) of Table A.10 instruments the variable of interest of column (6) of the baseline Table 2. In both of these columns of Table A.10 the results of the corresponding columns of Table 2 continue to hold.

Column (4) of Table A.10 follows an alternative and complementary approach. Here we use the price of a given main mineral as instrument for the opening of a mine in a given cell. The underlying logic is that when a mineral yields a higher price on international markets it is more worthwhile to exploit a given mining site that otherwise may not be economically viable. In the second stage, the impact of an open mine on conflict is investigated. All coefficients have the expected sign: In the first stage a higher price of a mineral indeed strongly predicts the likelihood of having an open mine, while in the second stage an active mine tends to increase the conflict incidence (missing, however, conventional thresholds of statistical significance). While the result of column (4) constitutes a useful robustness check, it has to be taken with a grain of salt, as the exclusion restriction imposes that price shocks should only affect the conflict incidence through the mechanism of greater likelihood of an operating mine (i.e. the extensive margin). To the extent that the amount produced (i.e. the intensive margin) may also be impacted by prices and may also affect conflict, one could think of challenges to the exclusion restriction.

Table A.10: Alternative definitions of mining areas: 2SLS

	(1)	(2)	(3)	(4)
Estimator		2SLS		
Sample	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All
First stage	ln **price** × **mines** > 0			**mines** > 0
ln price × mines > 0 (before 1997)	0.999^a	0.981^a	0.939^b	
	(0.002)	(0.006)	(0.454)	
ln price main mineral				0.106^b
				(0.049)
Second stage		**Conflict incidence**		
mine > 0			0.046	0.409
			(0.067)	(0.254)
ln price main mineral			0.029	
			(0.020)	
ln price × mines > 0	0.074^a		0.105^c	
	(0.023)		(0.061)	
ln price × mines > 0 (ever)		0.051^b		
		(0.020)		
Cell FE	Yes	Yes	No	Yes
Neighbourhood FE	No	No	Yes	No
Country×year FE	Yes	Yes	No	Yes
Year FE	No	No	Yes	No
Observations	142282	143754	17346	143754

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation in column (3), and clustered by country otherwise. Columns (1), (2) and (3) are the equivalent of columns (2), (4) and (6) of our baseline Table 2, except that the interaction term between the mine dummy and the price of the mineral is instrumented by an interaction term between a pre-period mine dummy and mineral prices. Column (1): mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t, and we consider only cells in which the mine dummy takes always the same value over the period. Column (2): mine takes the value 1 if an active mine was observed in the cell at any point over the 1997-2010 period. Column (3) is run on a sample containing only mining cells and their immediate neighbouring cells. In columns (1) and (2), ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (3) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimation (3) include controls for the average level of mineral world price interacted with the mine dummy. Column (4) instruments the time-varying, contemporaneous mine dummy with the world price of the main mineral produced in the cell.

H Mineral prices and conflicts: dropping large players

A threat to our identification strategy could consist in potential reverse causality from local violence to world prices. In particular, it is conceivable that the occurrence or the anticipation of a conflict in a major producer country could lead to an increase in the world prices of the relevant minerals. To address this concern, we drop mining cells belonging to countries that are top-10 world producers of the main mineral produced in the cell. In Table A.11 below we replicate our baseline Table 2 on this restricted sample with no large producer countries. The baseline results prove robust to removing large players, with the coefficient of interest being statistically significant in all columns, and quantitatively close to our baseline estimates.

Table A.11: Conflicts and mineral prices: dropping large players

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Sample	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$		All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	
mine > 0	0.138					0.004
	(0.088)					(0.081)
ln price main mineral	-0.025					0.028
	(0.040)					(0.019)
ln price × mines > 0	0.076[c]	0.057[a]	0.044[c]		0.071[a]	0.117[b]
	(0.042)	(0.020)	(0.023)		(0.027)	(0.055)
ln price × mines > 0 (neighbouring cells)			0.020[a]			
			(0.006)			
ln price × mines > 0 (ever)				0.034[b]		
				(0.017)		
Country×year FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	No
Neighbour-pairs FE	No	No	No	No	No	Yes
Observations	142784	141846	127656	142880	141846	16770

LPM estimations. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. Column (6) is run on a sample containing only mining cells and their immediate neighbouring cells. In columns (1) to (5), ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (6) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimations (1) and (6) include controls for the average level of mineral world price interacted with the mine dummy.

I Mineral prices and conflicts: subsets of minerals

In our baseline results, we exclude diamonds due to the impossibility of assigning a reliable world price in this case. Indeed, there is a large heterogeneity in diamond quality across mines and the price series for different qualities can move in opposite directions over time. Having no information on the quality of diamonds, we preferred to exclude diamonds from our baseline estimates in order to limit measurement error. We also excluded coltan (tantalum), as no world price was available – only a price based on the US market. In Table A.12 we include back these minerals as a robustness check. For diamonds we use a generic price index from Rapaport (2012), while for coltan we use data from the US Geological survey. The results are very close to our baseline estimates, with our coefficient of interest being statistically significant in all columns, and of a similar size as in the baseline Table 2.

Further, in Table A.13 we show more generally that our results are not driven by a particular subset of minerals. We exclude each mineral separately from our set of minerals and we replicate the estimate of column (2) of Table 2. The coefficient of interest is positive and significant at the 1 percent level in all columns, and is of similar magnitude throughout the table.

Table A.12: Conflicts and mineral prices: adding diamonds and tantalum

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Sample	All	$\mathbb{V}(M_{kt}) = 0$		All	$\mathbb{V}(M_{kt}) = 0$	
mine > 0	0.043					0.048
	(0.046)					(0.065)
ln price main mineral	-0.025					0.028
	(0.032)					(0.019)
ln price × mines > 0	0.072^b	0.059^a	0.060^a		0.069^a	0.108^a
	(0.035)	(0.019)	(0.021)		(0.023)	(0.041)
ln price × mines > 0 (neighbouring cells)			0.021^a			
			(0.006)			
ln price × mines > 0 (ever)				0.039^a		
				(0.013)		
Country×year FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	No
Neighbour-pairs FE	No	No	No	No	No	Yes
Observations	144452	142674	127974	144452	142674	17360

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(M_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. Column (6) is run on a sample containing only mining cells and their immediate neighbouring cells. In columns (1) to (5), ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (6) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimations (1) and (6) include controls for the average level of mineral world price interacted with the mine dummy.

Table A.13: Conflicts and mineral prices: dropping each mineral separately

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Estimator							LPM					
Dep. var.							Conflict incidence					
Sample							$\mathbb{V}(\mathrm{M}_{kt}) = 0$					
Mineral dropped	aluminum	coal	copper	gold	iron	lead	nickel	phosphate	platinum	silver	tin	zinc
ln price × mines > 0	0.073^a	0.072^a	0.066^a	0.076^a	0.082^a	0.071^a	0.064^a	0.073^a	0.069^a	0.072^a	0.074^a	0.070^a
	(0.020)	(0.020)	(0.020)	(0.025)	(0.022)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142268	142296	142142	141764	142184	142282	142240	142198	142226	142282	142268	142240

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. These estimations are analogous of columns (2) of table 2 but exclude each mineral separately from the regressions. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells.

J Mineral prices and conflicts: Fixed effects logit estimator

Table A.14 replicates our baseline specifications using a fixed effects logit estimator. 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. Note that the estimations displayed in Table A.14 include year dummies instead of country×year dummies for two reasons: First, because the logit estimator fails to reach convergence when including country×year dummies; second, because the inclusion of two different large sets of fixed effects in logit models may lead to an incidental parameter problem (Charbonneau, 2012).

Table A.14: Conflicts and mineral prices: Fixed effects logit estimator

	(1)	(2)	(3)	(4)	(5)
Estimator			FE logit		
Dep. var.			Conflict incidence		
Sample	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$		All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$
mine > 0	0.708				
	(1.065)				
ln price main mineral	-0.460				0.010^b
	(0.480)				(0.005)
ln price × mines > 0	1.375^a	1.173^a	0.746^a		1.222^a
	(0.404)	(0.311)	(0.274)		(0.262)
ln price × mines > 0 (neighbouring cells)			0.600^b		
			(0.237)		
ln price × mines > 0 (ever)				0.689^a	
				(0.260)	
Year FE	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	No
Neighbour-pairs FE	No	No	No	No	Yes
Observations	35470	34762	30604	35532	6650

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors clustered by country in parentheses. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. Column (5) is run on a sample containing only mining cells and their immediate neighbouring cells. In columns (1) to (4), ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (5) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimations (1) and (5) include controls for the average level of mineral world price interacted with the mine dummy.

K Mining intensity

In the baseline analysis of the paper we do not exploit information about the intensive margin, i.e. the *volume* or *scale* of production. One of the reasons for this is the concern about exogeneity. In the current section we shall investigate robustness to taking into account this intensive margin.

Table A.15 displays the results. In column (1), we estimate the effect of the interaction of the mining price times the *number* of mines in a given cell. To avoid picking up endogenous opening and closing of mines, we limit the sample to cells with a constant number of mines over the period. While the coefficient of interest has the expected sign, it is not statistically significant at conventional levels. This is unsurprising given the big drop in mines contained in our sample. To address this loss of information, we keep in column (2) all cells in the sample, and define the variable of interest as the interaction of the mining price times the *average* number of mines in a cell over the sample period. This allows us to attenuate concerns about endogenous opening and closing of mines, while keeping all cells in the sample. The coefficient of interest is now positive and significant at the 1 percent level. In columns (3) and (4), our variable of interest is the average production value of the main mineral. It turns out that the coefficient of interest is positive and significant at the 1 percent level both in column (3) (where the sample is restricted to cells with permanently active mines) and in column (4) (mining activity is defined as cells where at least a mine has been recorded as active at any point over the 1997-2010 period). Columns (5) and (6) replicate the columns (3) and (4), but replace current production with the production in 1997, serving the purpose of addressing concerns about the endogeneity of production levels. The coefficients of interest remain positive and highly significant.

Table A.15: Robustness: intensity of mining production

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Sample	$\mathbb{V}(\#\ \text{mines}_{kt}) = 0$	All	$\mathbb{V}(\text{M}_{kt}) = 0$	All	$\mathbb{V}(\text{M}_{kt}) = 0$	All
ln price × # mines	0.018					
	(0.013)					
ln price × # mines (average)		0.023^b				
		(0.009)				
ln total value main mineral			0.074^a	0.048^a		
			(0.021)	(0.014)		
ln total value main min. (at 1997 prod.)					0.075^a	0.047^b
					(0.022)	(0.019)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142016	144102	142534	143864	142534	143864

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. # mines is the number of active mines observed in the cell in year t. # mines (average) is the number of mines observed on average in the cell over the period. ln total value main mineral is the value of the main mineral computed using the contemporaneous world price and the average production volume. ln total value main mineral (at 1997 production) is the value of the main mineral computed using the contemporaneous world price and the production volume in 1997. $\mathbb{V}(\text{M}_{kt}) = 0$ means that we consider only cells in which the mine variable (number of mine in column (1), mine dummy in columns (3) and (5)) always takes the same value over the period.

L Excluding border cells

One potential worry with our econometric specification, and in particular with the use of the country × year fixed effects, is that a cell may belong to more than one country, which is the case for 15 percent of the cells. In order to address this concern, we replicate below our baseline Table 2, but excluding from the sample all border cells for which the distance between the cell's centroid and the closest international border is smaller than 30 kilometers. Table A.16 displays the results. The coefficients of interest are positive and statistically significant in all columns, and are similar in magnitude to those of the baseline Table 2.

Table A.16: Robustness: excluding cells in multiple countries

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Sample	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$		All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	
mine > 0	0.040					-0.048
	(0.060)					(0.048)
ln price main mineral	-0.042					0.035
	(0.034)					(0.023)
ln price × mines > 0	0.094^b	0.063^a	0.049^b		0.081^a	0.114^c
	(0.037)	(0.023)	(0.024)		(0.027)	(0.059)
ln price × mines > 0 (neighbouring cells)			0.018^a			
			(0.006)			
ln price × mines > 0 (ever)				0.039^a		
				(0.014)		
Country×year FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	No
Neighbour-pairs FE	No	No	No	No	No	Yes
Observations	123088	121786	110390	123088	121786	11634

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. These estimations exclude from the sample cells for which the distance between the cell's centroid and the closest international border is larger than 30km. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. Column (6) is run on a sample containing only mining cells and their immediate neighbouring cells. In columns (1) to (5), ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (6) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimations (1) and (6) include controls for the average level of mineral world price interacted with the mine dummy.

M Prices: Levels vs Differences

In our main analysis we interact mining activity with the *level* of mineral log-prices. An alternative approach would be to focus on price growth over time (i.e. *difference* in log-prices). A theoretical reason for focusing on levels is that the typical workhorse model of conflict (Contest Success Function) would predict the mineral price level and not changes to affect conflict incentives. Moreover, when taking such a model to the data, Ciccone (2011) shows (in the context of rainfall-induced income shocks) that the correct specification of the econometric model involves levels rather than differences: Only in the presence of non-stationary price series can the effect of shocks on conflict be uncovered using a specification in differences. To assess stationarity, we display below in Tables A.17 and A.18 the results from various variants of unit root tests. We purge the price series of a potential common trend by including year fixed effects (as we do in the main regressions). The unit root tests are either performed on each series separately (i.e. augmented Dickey-Fuller tests in Table A.17) or jointly on all series (i.e. the panel version of Im-Pesaran-Shin and variants in Table A.18). In the vast majority of cases the null hypothesis of a presence of unit root is clearly rejected. In a nutshell, when de-trended, the time series of the mineral prices turn out to be stationary. This result is consistent with the finding of Bazzi and Blattman (2014) who show that the persistence of most commodity prices tend to be short (see their discussion in Section 1.A and their online Appendix).

Moreover, as shown below in Table A.19, our results continue to hold when focusing on price differences rather than levels. Note that the specifications in price differences also include cell fixed effects in order to capture cell-specific unobservables: Hence, our coefficients of interest pick up the impact on conflict probability of a deviation of price growth from their average growth rate –the interpretation of such an effect is less straightforward than in the case of our baseline estimations specified in levels. More precisely column (1) displays for the purpose of comparison the baseline estimate of column (2) of the benchmark Table 2. In column (2) the price variable is defined as the change in mineral prices between period t-1 and the current period t. The variable of interest hence becomes the interaction of the price difference with active mine. While the coefficient of interest is still of the expected positive sign its magnitude is now considerably smaller and it loses significance. One downside of focusing on short-term price movements is the risk of picking up much random noise, leading to attenuation bias. Hence, in column (3) we focus on the price difference over a longer period, i.e. between t-2 and t. The coefficient of interest continues to be of positive sign, but now is again of similar magnitude as in the baseline regression and becomes significant again at the 1 percent level. Similarly, column (4) shows that the results also hold for price changes over an even longer period, i.e. between t-3 and t. This corresponds to the baseline specification of Bruckner and Ciccone (2010) who estimate the country-level impact of a 3-year commodity price growth on civil war.

Finally, we address further the question of the time response of conflict to variations in price shocks in Table A.20 by looking at the delay in response (lagged prices) and the role of expectations (leads prices). In column (1) the price variable is lagged by one year. The coefficient of interest is very close to the baseline point estimate of Table 2, col. (2) (0.078 vs 0.072). Nevertheless, statistical significance is lost when including both current and lagged prices in column (2). The same pattern emerges in columns (3) and (4) where we replicate the exercise with a one year lead in prices. The overall interpretation of these findings is unclear given that the

levels of current and lagged (or leads) prices are highly correlated (close to 0.98). To circumvent this problem, we implement in columns (5) and (6) a dynamic OLS (Stock and Watson, 1993) where the current level of log-price is included together with the leads and lags of the log-price first differences. Given the inclusion of cell-fixed effects, the log-price level can be interpreted as long run deviations, whereas the first differences can be interpreted as short-run variations. We see that the coefficient of current price level retains its statistical significance, while the coefficients of price differences are not significant anymore. This result indicates that long-run shifts in prices tend to impact conflicts while short-run variations do not. To the extent that the expected value of future prices is captured by current price, this also indicates that unexpected shifts in prices do not affect conflicts. All in all this evidence supports the theoretical view that the decision to fight and to conquer mining areas is not a short run decision based on transitory shocks in mineral values.

Table A.17: Dickey-Fuller Unit root tests

Mineral	**Augmented Dickey Fuller** (p-value)
Aluminum	0.220
Coal	0.000
Copper	0.035
Gold	0.178
Iron	0.009
Lead	0.000
Nickel	0.004
Phosphate	0.000
Platinum	0.063
Silver	0.017
Tin	0.043
Zinc	0.005

Dickey-Fuller test is based on the log of each mineral's series, over the entire 1960-2012 period. The null hypothesis (rejected here in most case) is that the variable follows a random walk with non zero drift. Prices series have been purged from their common time components (i.e. we use the residuals from a regression of the log price on year dummies).

Table A.18: Panel unit root tests

Test	**p-value**
Im-Pesaran-Shin	0.001
Levin-Lin-Chu	0.011
Harris-Tzavalis	0.000
Combined Dickey Fuller	0.001
Breitung	0.001
Hadri	0.000

Tests is based on the log of all minerals' series together, over the entire 1960-2012 period. The null hypothesis is that all the panels contain a unit root. Price series have been purged from their common time components (i.e. we use the residuals from a regression of the log price on year dummies).

Table A.19: Robustness: log differences

	(1)	(2)	(3)	(4)
Estimator		LPM		
Dep. var.		Conflict incidence		
Sample		$\mathbb{V}(\mathrm{M}_{kt}) = 0$		
ln price × mines > 0	0.072^a			
	(0.020)			
$\Delta_t, t-1$ ln price × mines > 0		0.017		
		(0.042)		
$\Delta_t, t-2$ ln price × mines > 0			0.078^a	
			(0.029)	
$\Delta_t, t-3$ ln price × mines > 0				0.061^b
				(0.026)
Country×year FE	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes
Observations	142296	142296	142296	142296

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells.

Table A.20: Robustness: short-run versus medium-run effect

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Sample			$\mathbb{V}(\mathrm{M}_{kt}) = 0$			
ln price_{t-1} × mines > 0	0.078^a	0.052				
	(0.024)	(0.051)				
ln price_t × mines > 0		0.028		0.057	0.080^a	0.100^a
		(0.044)		(0.045)	(0.023)	(0.027)
ln price_{t+1} × mines > 0			0.080^a	0.035		
			(0.022)	(0.042)		
$\Delta_{t,t-1}$ ln price × mines > 0					-0.052	-0.053
					(0.051)	(0.049)
$\Delta_{t,t+1}$ ln price × mines > 0						0.020
						(0.043)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132132	132132	132132	132132	132132	121968

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells.

N Time-varying controls

While our identification strategy manages to filter out time-invariant factors at the cell-level (through the cell fixed effects) and country-level shocks (through the country × year fixed effects), our results could potentially be biased by cell-level shocks. To address this concern, we control in this section for variables that are time-varying at the cell-level.

Table A.21 replicates the baseline Table 2, but adding cell-specific, time-varying controls which may be correlated with commodity price variations. In particular, we control for rainfall and temperature, both as levels and interacted with the presence of mines. In all columns, our coefficients of interest remain stable and highly significant.

Table A.21: Robustness: additional time-varying controls

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Sample	All	$\mathbb{V}(M_{kt}) = 0$		All	$\mathbb{V}(M_{kt}) = 0$	
mine > 0	0.135[c]					0.071
	(0.072)					(0.074)
ln price main mineral	-0.032					0.028
	(0.033)					(0.019)
ln price × mines > 0	0.088[b]	0.067[a]	0.053[a]		0.081[a]	0.107[a]
	(0.035)	(0.019)	(0.020)		(0.023)	(0.041)
ln price × mines > 0 (neighbouring cells)			0.021[a]			
			(0.006)			
ln price × mines > 0 (ever)				0.042[a]		
				(0.014)		
Temperature × mines > 0	0.003	0.018	0.031[c]	-0.000	0.017	0.006
	(0.004)	(0.016)	(0.018)	(0.004)	(0.019)	(0.006)
Rainfall × mines > 0	-0.002	-0.029	-0.019	0.009	-0.037	0.019
	(0.011)	(0.021)	(0.022)	(0.013)	(0.024)	(0.014)
Temperature	0.001	-0.000	-0.000	0.001	0.006[a]	-0.007[c]
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)
Rainfall	0.001	0.001	0.001	0.001	0.000	0.015
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)
Country×year FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	No
Neighborhood FE	No	No	No	No	No	Yes
Observations	143655	142183	127875	143655	142183	17360

LPM estimations. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(M_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. Column (6) is run on a sample containing only mining cells and their immediate neighboring cells. In columns (1) to (5), ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (6) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimations (1) and (6) include controls for the average level of mineral world price interacted with the mine dummy.

O Mines data: measurement error

The RMD data only includes big, industrially operated mines, and hence do not report direct information on small-scale artisanal production sites. In presence of classical measurement errors, our empirical strategy that is based on spatial clustering of deposits and variations in prices, limits the extent of the attenuation bias (see our discussion in Section 3 of the main text). However, the scale of operation of extractive activity— big industrial mines or small artisanal sites – does not only depend on geographical features; it may also be correlated with the presence of conflict. Hence, there could be non-classical measurement errors affecting our mining data points and the resulting estimation bias is unclear.

Suppose for example that multinationals only go to places with low political risk. In this case there would be more missing mines in high-risk areas, and focusing on industrial mines could bias downward the effect we find. On the contrary, if big mining companies were to benefit from political instability (which could make the bribing of officials easier), in this case there could be more missing mines in peaceful zones and our analysis could suffer from over-stated estimates of the effect of mining extraction on conflict. Notice that, in both cases, the inclusion of cell and country×year fixed-effects alleviates most of our concern. The only estimation bias that would be problematic could arise in case these non-classical measurement errors were more likely in periods of high prices. Here we study this potential problem, following a recent approach developed by Koenig *et al.* (2015).

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

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

$$\text{DIAMONDS}_{ct}^{\text{DIADATA}} = \text{DIAMONDS}_{ct} + v_{ct}^{\text{DIADATA}} \tag{4}$$

$$\text{DIAMONDS}_{ct}^{\text{RMD}} = \text{DIAMONDS}_{ct} + \tilde{v}_{ct}^{\text{RMD}} \tag{5}$$

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

equations and obtain:

$$\text{DIAMONDS}_{ct}^{\text{RMD}} = \text{DIAMONDS}_{ct}^{\text{DIADATA}} + \xi \times \text{VIOLENCE}_{ct} + \nu_{ct} \tag{6}$$

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

We run a regression based on equation (6), measuring violence by the number of conflicts in ACLED. Table A.22 summarizes the results. Column (1) is a cross-sectional specification; column (2) includes annual year fixed effects, while column (3) includes country fixed effects. Finally, column (4) includes country x year fixed effects. Note that the DIADATA dataset does not contain time variation for the period we study, which excludes any specifications with cell fixed effects. We allow for robust standard errors to be clustered at the country level.

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

Table A.22: Mines data: non classical measurement errors

	(1)	(2)	(3)	(4)
Dep. var.		Number of RMD mines		
Nb of mines by grid (DIADATA)	0.095^a	0.095^a	0.096^a	0.096^a
	(0.033)	(0.033)	(0.032)	(0.032)
Number of events (ACLED)	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects	No	Year	Country	Country-year
Observations	144690	144690	144690	144690
R-squared	0.136	0.136	0.151	0.153

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

P Port-level corruption

In this section, we study how a specific type of corruption – at the port – affects the impact of mineral price variations on conflict. We follow the trade literature (e.g. Sequeira, 2016; Fisman and Wei, 2004; Javorcik and Narciso, 2007) and use the gaps in the declarations of importers and exporters as a proxy for port-level corruption. More precisely, we use the ratio of the import quantities declared by the country over the quantities declared by the rest of the World as exports to the country (in the 5 years before the start of the period). Because of import tariffs, importers have strong incentives to under-report trade quantities, and under-reporting is easier in corrupt environments. Starting from our preferred specifications (columns (2) and (4) of Table 2) we now consider the triple interaction between our main explanatory variable ($M_k \times \ln p_{kt}^W$) with either this trade gap ratio (Trade Gap Ratio) or with a dummy taking the value 1 whenever imports declared are lower than exports at the port-level (Trade Gap < 1). Table A.23 displays the results. We find evidence of a conflict inducing effect of our proxy of port-level corruption. Interestingly, this result continues to hold controlling for our more global measure of corruption (columns (3)-(4), (7)-(8)).

Table A.23: Conflicts and mineral prices: port-level corruption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimator				LPM				
Dep. var.				Conflict incidence				
Sample	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All
ln price × mines > 0	0.074^a		0.077^a		0.006		-0.002	
	(0.025)		(0.021)		(0.018)		(0.008)	
× Trade Gap Ratio	-0.001^c		-0.001^b					
	(0.000)		(0.001)					
× Trade Gap < 1					0.072^b		0.083^a	
					(0.031)		(0.025)	
× Anti-corruption index			-0.048^c				-0.045^c	
			(0.027)				(0.025)	
ln price × mines > 0 (ever)		0.049^a		0.049^a		-0.016^a		-0.017^c
		(0.012)		(0.012)		(0.005)		(0.008)
× Trade Gap Ratio		-0.001^a		-0.001^a				
		(0.000)		(0.000)				
× Trade Gap < 1						0.068^a		0.069^a
						(0.013)		(0.015)
× Anti-corruption index				-0.017				-0.014
				(0.015)				(0.014)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135268	136752	124614	125938	135268	136752	124614	126028

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Standard errors in parentheses, clustered by country. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. Trade Gap Ratio is the ratio of quantities imported from the rest of the world declared by the country over the quantities exported by the rest of the world to the country (declared by the rest of the world), computed over the period 1992-1996. Trade Gap <1 is a dummy which equals 1 if the trade gap ratio is lower than 1. Anti-corruption index is the anti-corruption index from the WGI ("Worldwide Governance Indicators") dataset from Kaufmann, Kraay, and Mastruzzi (2013), taken at the beginning of the period.

Q Additional results: mineral characteristics

In section 4.5 of the main text, and in particular in Table 14 in the appendix we display results on how the relative capital versus labor intensiveness of mining production affects the impact of mineral price spikes on the conflict risk. We are not able to detect any effect of relative capital intensiveness, which may well be due to the fact that the variation in relative capital intensiveness among the minerals studied is not very large.

We display further results on the impact of relative capital intensiveness in Table A.24. This Table is constructed identically to appendix Table 14, simply focusing on three other capital intensiveness measures for the triple interactions.

In columns (1)-(2), capital intensiveness is measured using production functions. In particular, we take as starting point a Cobb-Douglas production function of $Y = K^{\alpha}L^{\beta}$ with K=capital, L=labor. For each mineral separately, we regress on the firm level the ln(production) on ln(capital) and ln(employees) to obtain estimates of α and β, and to define as relative capital intensiveness the ratio of $\alpha/(\alpha+\beta)$. All data on production, capital and employees are from RMD.[7] The coefficient of the triple interaction of the main explanatory variable ($M_k \times \ln p_{kt}^W$) with our measure of $\alpha/(\alpha+\beta)$ is not statistically significant. The reason why we prefer the variables used in the appendix Table 14 is that for estimating our production functions we need to proxy capital very crudely with project cost estimates, and face many missing observations.

Columns (3)-(4) focus on using mean lead (i.e. development) times until a newly opened mine of a given mineral is up and running. This measure varying at the mineral-level is from Hargreaves and Fromson (1983). A longer lead / development time can be thought of indicating greater capital intensiveness. The triple interaction with this variable is not statistically significant. Finally, columns (5)-(6) interact our variable of mining price shocks with the artisan and small scale mining proportion of world production of various metals, collected by ICMM (2012). The triple interaction with this variable is non-significant. Again, the reason we do not prefer these specifications is that lead times and artisan mining proportion are only crude proxies.

In a nutshell, these additional results confirm our earlier conclusion that we are unable to detect an effect of capital intensiveness on the magnitude of price shock impact on conflict.

[7] To measure production value we use end of period production amounts multiplied with pre-period prices. Capital is proxied (very crudely) by project cost estimates (no actual capital figures are available). Both the project cost and number of employees information is time invariant and corresponds to end of period numbers. We only include firms with non-zero amounts for Y, K and L, and only keep minerals with at least 15 firm observations.

Table A.24: Heterogeneous effects: minerals' capital intensity (additional results)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence			
Sample	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All
ln price × mines > 0	0.069^b		0.052		0.071^b	
	(0.035)		(0.058)		(0.036)	
ln price × mines > 0 (ever)		0.043^c		0.055		0.031
		(0.026)		(0.043)		(0.026)
× Capital intensiveness	0.067	0.028				
	(0.124)	(0.085)				
× Lead time			0.003	-0.002		
			(0.008)	(0.006)		
× Artisanal					-0.001	0.000
					(0.002)	(0.001)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	141946	142870	142296	143768	142030	143038

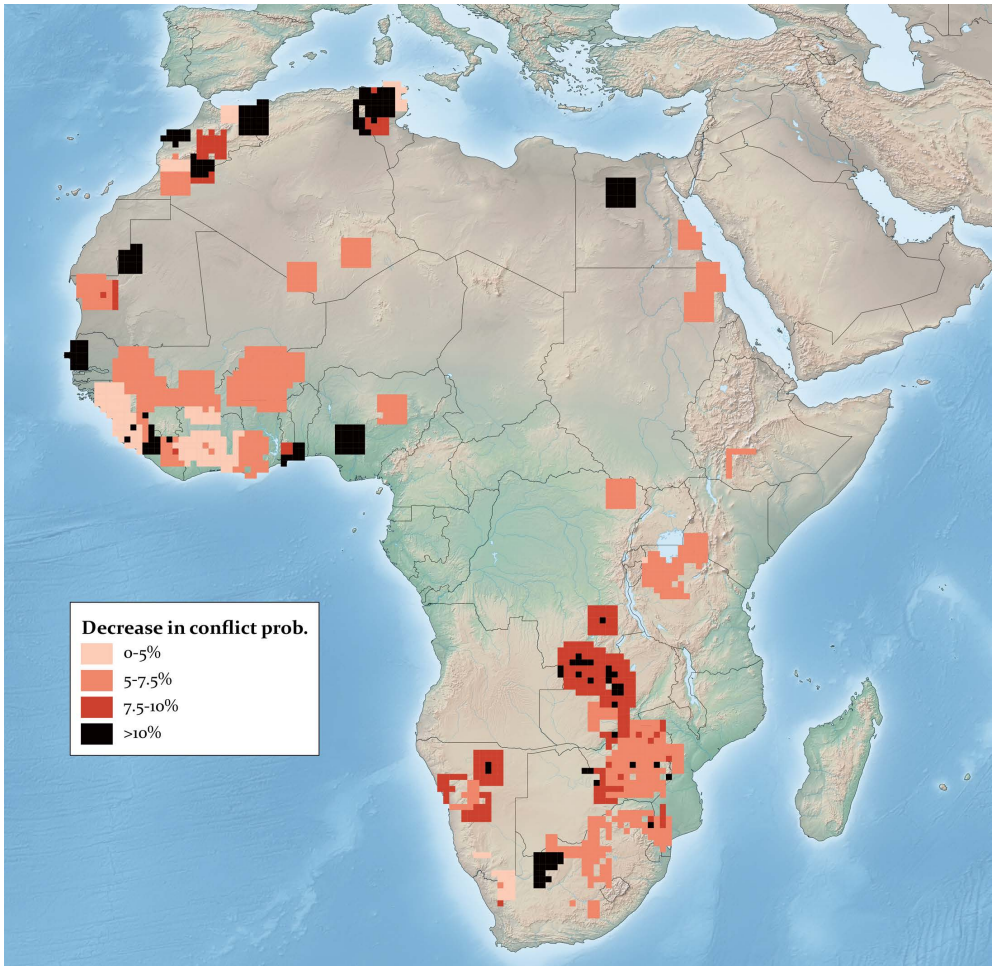
LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. See the text of the current online appendix, section Q for details on the construction of the mineral-specific variables.

R Additional quantifications

R.1 Cell-level

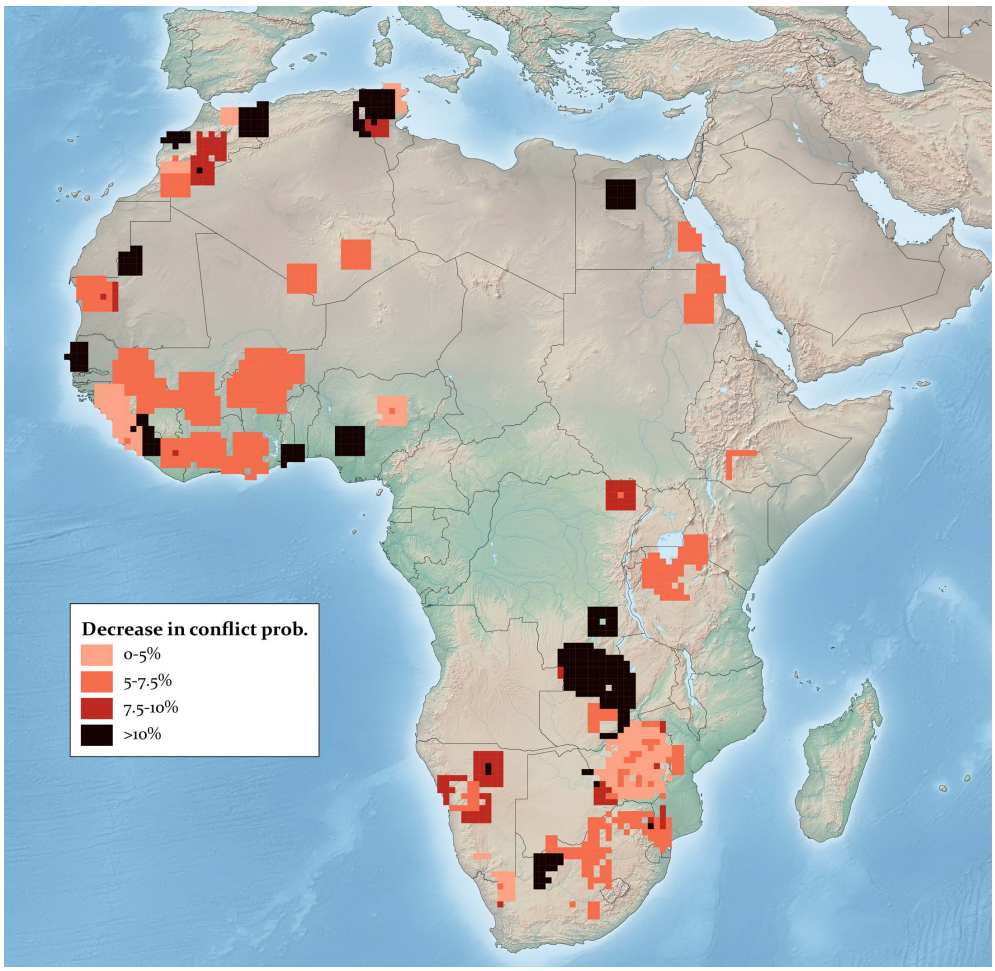
Figure A.5 shows, by cell, the predicted decrease in the conflict probability that would be observed in 2010 if the prices were the same as in 1997. This counterfactual exercise is based on the estimated coefficients of a regression similar to column (4) of Table 2, except that we also include the interaction term between mineral prices and the mining dummy for neighbouring cells of degrees 1 and 2. This is our preferred specification for this type of exercise as it allows performing in-sample predictions for all cells in which a mine is opened at some point. Note that a number of mining cells do not appear in these maps as price data is not available for all minerals. Figure A.6 performs the same exercise based on the coefficients of column (3) of Table 2, which is restricted to cells with permanently active mines.

Figure A.5: The contribution of rising mineral prices to the probability of conflict in Africa



Note: This figure represents for each mining cell the decrease in conflict probability that would have occurred in 2010 if mineral prices had stayed at their 1997 level. Predictions are based on the coefficients of a regression similar to column (4) of Table 2, except that we also include the interaction term between mineral prices and the mining dummy for neighbouring cells.

Figure A.6: The contribution of rising mineral prices to the probability of conflict in Africa (alternative specification)

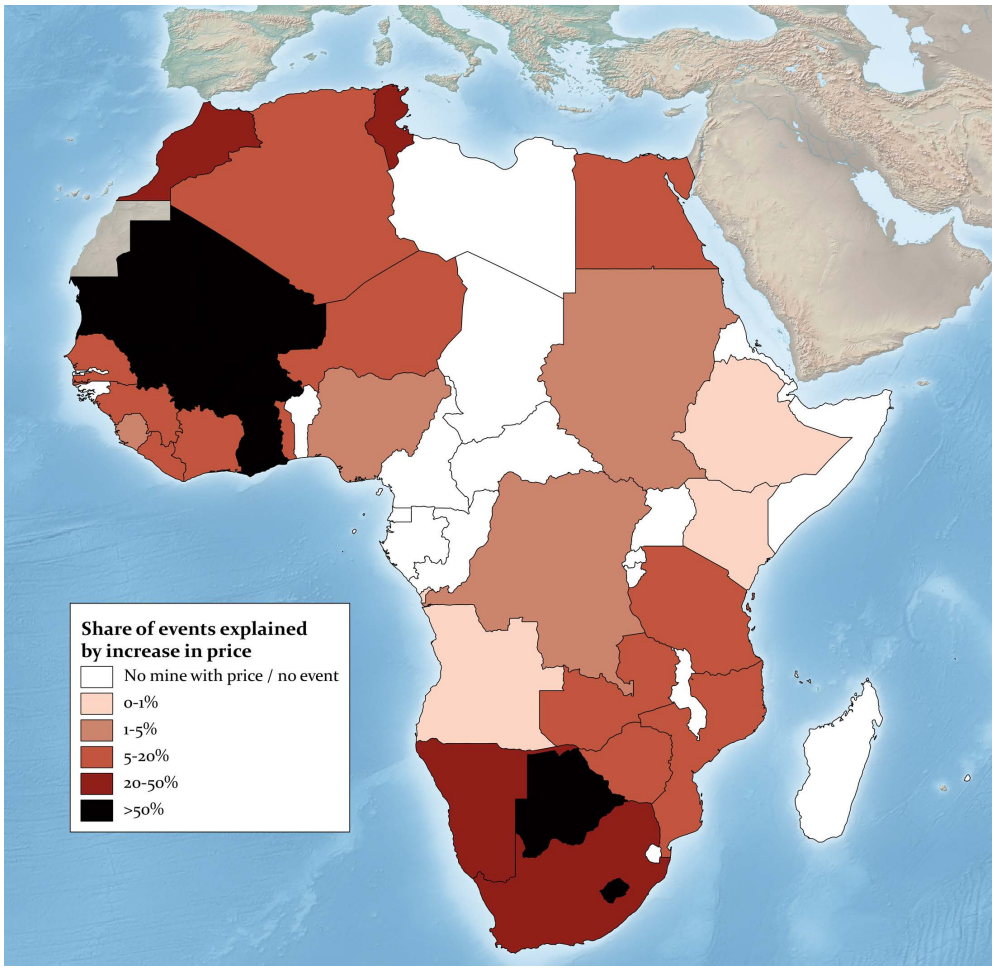


Note: This figure represents for each mining cell the decrease in conflict probability that would have occurred in 2010 if mineral prices had stayed at their 1997 level. Predictions are based on the coefficients of Table 2, column (3). As this specification is restricted to cells with a permanently active mine over the entire period ($\text{Var}(M_{kt}) = 0$), we complement the in-sample predictions for those cells with the out-of-sample predictions for cells that have a transiently active mine for which price data is available. Put differently, we apply the estimated coefficients of Table 2, column (3), to all cells contained in Table 2, column (1).

R.2 Country-level

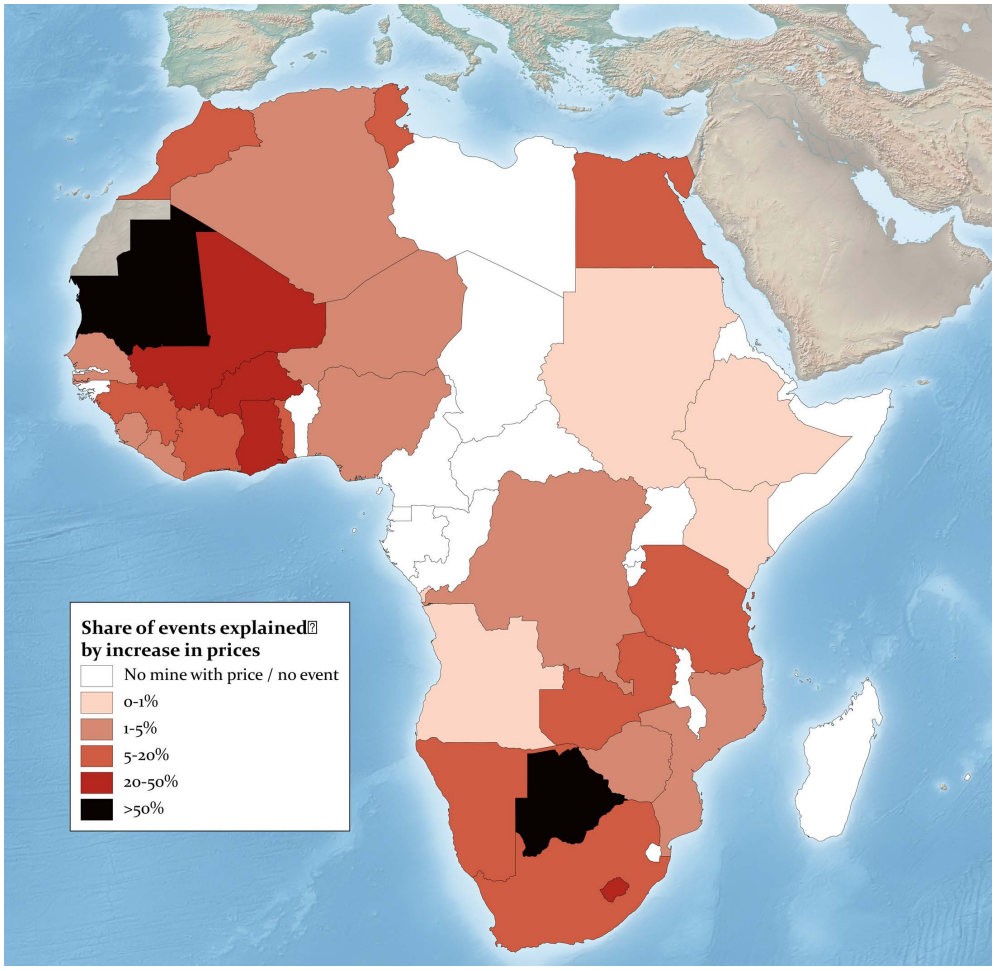
Figures A.7 and A.8 are map-equivalents of Figure 1 (main text). Figure A.9 performs the same exercise as Figure 1 (main text), except that coefficients are based on estimations similar to Panel A of Table 13, which is restricted to cells with permanently active mines.

Figure A.7: Counterfactuals: share of events due to increasing prices (PPML)



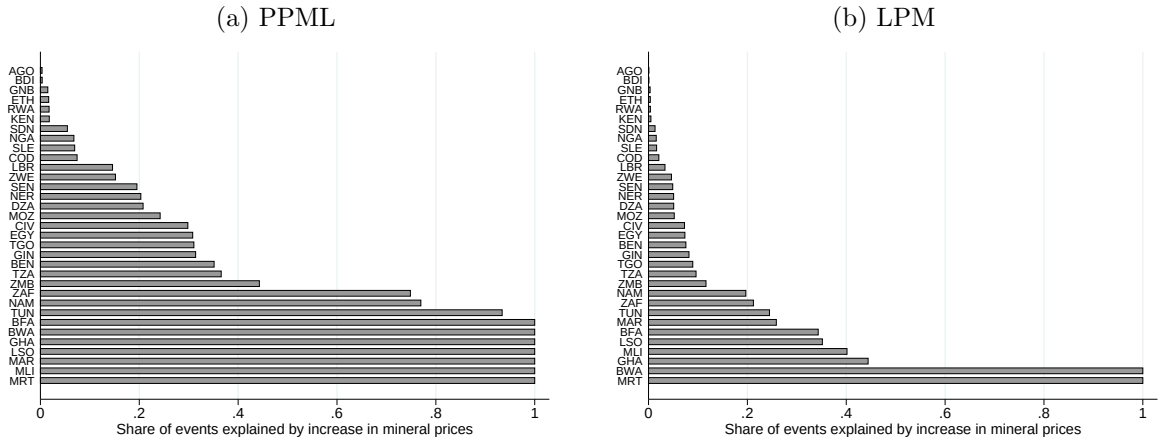
Note: This figure represents for each country the counterfactual share of events that would not have happened if prices had stayed stable at their 1997 level across the entire period. Predictions are based on an estimation similar to Table 13, Panel B, column (5) except that we also include the interaction term between mineral prices and the mining dummy for neighbouring cells.

Figure A.8: Counterfactuals: share of events due to increasing prices (LPM)



Note: This figure represents for each country the counterfactual share of events that would not have happened if prices had stayed stable at their 1997 level across the entire period. Predictions are based on an estimation similar to Table 13, Panel B, column (2) except that we also include the interaction term between mineral prices and the mining dummy for neighbouring cells.

Figure A.9: The contribution of rising mineral prices to violence in Africa (alternative specification)



Note: These figures represent for each country the counterfactual share of events that would not have happened if prices had stayed stable at their 1997 level across the entire period. Predictions are based on an estimation similar to Table 13, Panel A, columns (5) and (2) except that we also include the interaction term between mineral prices and the mining dummy for neighbouring cells. As this specification is restricted to cells with a permanently active mine over the entire period ($\text{Var}(M_{kt}) = 0$), we complement the in-sample predictions for those cells with the out-of-sample predictions for cells that have a transiently active mine for which price data is available.

S The role of population changes

In this section, we aim to mitigate the concern that our results could be entirely driven by migration-related violence due to population inflows into mining areas when mineral prices increase. To this purpose we investigate whether mineral price shocks have a systematic impact on total population size. In Table A.25 we consider two different proxies of population size at the local level, the first one being nighttime lights from NOAA (columns (1) and (2)), the second one being a fine-grained measure of population retrieved from prio-grid but originally from G-econ (columns (3)-(6)). The effect of mineral price variations is positive and significant only in column (2); in all other columns, no significant effect can be detected, suggesting that the impact of mining shocks on population changes are limited.

Finally, we perform a different exercise by looking at potential heterogeneous effects. The idea is that, in the presence of a pervasive migration channel, we should observe larger effects for mining areas close to big population centers, such as the capital city. The underlying assumption is that population inflows/outflows should be larger when mobility costs are low. Hence, in columns (7) and (8), we return to our baseline specifications and estimate the interaction term between mineral price shocks and the distance to the capital city of the cells' centroids (controlling for equivalent interaction terms with distance to the closest international border). We detect no significant heterogeneous effect, suggesting again that migration does not play a key role in explaining our findings on mining-induced violence.

Table A.25: Conflicts and mineral prices, and population

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimator				LPM				
Sample	$\mathbb{V}(M_{kt}) = 0$	All	$\mathbb{V}(M_{kt}) = 0$	All	$\mathbb{V}(M_{kt}) = 0$	All	$\mathbb{V}(M_{kt}) = 0$	All
Dep. var.	Nighttime lights		log population (interpolated)				Conflict Incidence	
ln price × mines > 0	0.095		0.002		0.002		0.345^b	
	(0.063)		(0.017)		(0.011)		(0.153)	
× ln dist. to capital							-0.037	
							(0.024)	
ln price × mines > 0 (ever)		0.130^a		0.008		0.005		0.258^b
		(0.047)		(0.012)		(0.008)		(0.130)
× ln dist. to capital								-0.026
								(0.021)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142296	143864	30396	30732	30396	30732	138908	140476

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(M_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. Missing values of the population variable (the dependent variable) are interpolated in columns (5) and (6). Estimations (7) and (8) also include interaction terms between the mining price shock variables and distance to the closest international border. ln dist. to capital is demeaned.

T Types of events – full results

We replicate our baseline Table 2 for each of the three categories of violent events covered by the ACLED dataset: battles between fighting groups, violence against civilians, and riots/protests. The occurrence of battles is significantly affected by changes in the value of mines, except in column (4), confirming that the appropriation of mines is a key driver of violence (Table A.26). We find also that an increase in mineral prices leads to more violence against civilians (Table A.27) and more riots/protests (Table A.28).

Table A.26: Conflicts and mineral prices: Battles

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence – battles only			
Sample	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$		All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	
mine > 0	0.011					0.007
	(0.036)					(0.020)
ln price main mineral	-0.030^b					0.009
	(0.013)					(0.015)
ln price × mines > 0	0.040^a	0.016^b	0.006		0.018^b	0.022^c
	(0.014)	(0.008)	(0.008)		(0.008)	(0.012)
ln price × mines > 0 (neighbouring cells)			0.010^a			
			(0.005)			
ln price × mines > 0 (ever)				0.002		
				(0.006)		
Country×year FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	No
Neighborhood FE	No	No	No	No	No	Yes
Observations	143768	142296	127974	143864	142296	17360

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. Column (6) is estimated on a sample containing only mining cells and their immediate neighboring cells. In columns (1) to (5), ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (6) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimations (1) and (6) include controls for the average level of mineral world price interacted with the mine dummy.

Table A.27: Conflicts and mineral prices: Violence against civilians

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.	Conflict incidence – violence against civilians only					
Sample	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$		All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	
mine > 0	0.030					-0.010
	(0.044)					(0.037)
ln price main mineral	0.008					0.011
	(0.023)					(0.012)
ln price × mines > 0	0.035	0.040^a	0.041^a		0.051^a	0.088^c
	(0.025)	(0.014)	(0.016)		(0.018)	(0.046)
ln price × mines > 0 (neighbouring cells)			0.011^b			
			(0.005)			
ln price × mines > 0 (ever)				0.034^a		
				(0.010)		
Country×year FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	No
Neighborhood FE	No	No	No	No	No	Yes
Observations	143768	142296	127974	143864	142296	17360

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. Column (6) is estimated on a sample containing only mining cells and their immediate neighboring cells. In columns (1) to (5), ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (6) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimations (1) and (6) include controls for the average level of mineral world price interacted with the mine dummy.

Table A.28: Conflicts and mineral prices: Riots

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator			LPM			
Dep. var.			Conflict incidence – riots only			
Sample	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$		All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	
mine > 0	-0.018					0.071
	(0.077)					(0.057)
ln price main mineral	0.029					0.004
	(0.025)					(0.009)
ln price × mines > 0	0.004	0.044^b	0.046^b		0.047^b	0.087^c
	(0.028)	(0.018)	(0.019)		(0.018)	(0.048)
ln price × mines > 0 (neighbouring cells)			0.004			
			(0.003)			
ln price × mines > 0 (ever)				0.038^a		
				(0.011)		
Country×year FE	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	No
Neighborhood FE	No	No	No	No	No	Yes
Observations	143768	142296	127974	143864	142296	17360

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. mines > 0 (neighbouring cells) is a dummy taking the value 1 if at least 1 mine is recorded in neighbouring cells of degree 1 and 2 in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy (or dummies in column (3)) takes always the same value over the period. Column (6) is estimated on a sample containing only mining cells and their immediate neighboring cells. In columns (1) to (5), ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. In column (6) ln price main mineral takes the same value for the mining cell and its immediate neighbours. Estimations (1) and (6) include controls for the average level of mineral world price interacted with the mine dummy.

U Mines in ethnic homelands – robustness

We include supplementary material and further robustness checks on the regressions of section 5.2.1 of the main text. In particular, we start by displaying descriptive statistics (Table A.29). Then, we replicate in Table A.30 the results of Table 6, but using a weighted price index of all minerals present instead of the price of the main mineral. Further, to capture the diffusion of violence from mining areas to non-mining areas, we replicate in Table A.31 the results of Table 6 when restricting the dependent variable to conflicts occurring in cells located outside mining areas. Overall, the results of the robustness tables presented here are consistent with the ones displayed in section 5.2.1 of the main text.

Table A.29: Descriptive statistics: ethnic homeland

	Obs.	Mean	S.D.	Median
Pr(Conflict> 0)				
all	2548	0.21	0.41	0.00
outside ethnic homeland	2548	0.13	0.34	0.00
excluding mining areas	2506	0.19	0.40	0.00
excluding mining areas and ethnic hom.	2506	0.12	0.32	0.00
if at least 1 mine in homeland	126	0.27	0.45	0.00
if no mine in homeland	2422	0.21	0.41	0.00
# conflicts				
all	2548	4.32	31.86	0.00
# mines (beginning-of-period)				
in homeland, in country	2548	0.05	0.25	0.00
in homeland, all countries	2548	0.36	0.88	0.00
outside homeland, in country	2548	0.43	1.16	0.00

Source: Statistics on the sample of 109 rebel groups contained in ACLED that could be matched with 35 ethnic groups. Each observation is a rebel group-country-year triplet.

Table A.30: Feasibility - Mines in ethnic homelands (price index)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator				LPM		
Dep. var.				Conflict incidence		
Conflict zone	Unrestricted		Outside ethnic homelands		Unrestr.	Outside ethn. homel.
ln price index minerals (homeland in country)	-0.479[b]	-0.178	-0.549[a]	-0.234	-1.307[b]	-1.464[a]
	(0.203)	(0.298)	(0.098)	(0.278)	(0.510)	(0.335)
× # mines	0.307	0.096	0.379[a]	0.152	0.719[b]	0.856[a]
	(0.194)	(0.194)	(0.088)	(0.162)	(0.324)	(0.199)
ln price index minerals (entire homeland)					0.138	0.051
					(0.116)	(0.074)
× # mines					-0.091[a]	-0.066[a]
					(0.031)	(0.022)
ln price index minerals (in country outside homeland)					0.104	0.043
					(0.095)	(0.078)
× # mines					0.021	0.032[b]
					(0.020)	(0.015)
Actor-country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	Yes
Country×year FE	No	Yes	No	Yes	No	No
Observations	2352	2226	2352	2226	2352	2352

LPM estimations. Standard errors, clustered by actor in parentheses. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Estimations are run at the rebel group-country-year level. Cols. 3, 4 and 6 keep in the sample only cells which are located outside the ethnic homeland associated with the rebel group. ln price index minerals (homeland in country) is the sum of prices of the all main minerals produced in the cells belonging to the ethnic homeland of the rebel group and in the considered country, weighted by the share in total production at 1997 prices. ln price index minerals (entire homeland) and ln price main mineral (in country outside homeland) are the equivalent for the minerals produced in the ethnic homeland of the rebel group inside or outside the considered country and for the minerals produced inside the considered country but outside the ethnic homeland of the rebel group. For each price variable the associated # mines variable denotes the number of mines in each respective area. All specifications include linear terms and interaction terms but only the coefficients of the interactions are displayed.

Table A.31: Feasibility - Mines in ethnic homelands, excluding mining areas

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator				LPM		
Dep. var.				Conflict incidence		
Conflict zone	Unrestricted		Outside ethnic homelands		Unrestr.	Outside ethn. homel.
ln price main mineral (homeland in country)	-0.730^a	-0.412^b	-0.431^b	-0.183	-1.388^a	-0.876^b
	(0.056)	(0.191)	(0.188)	(0.195)	(0.316)	(0.385)
× # mines	0.562^a	0.289^b	0.374^a	0.146	0.944^a	0.663^a
	(0.012)	(0.118)	(0.091)	(0.112)	(0.152)	(0.189)
ln price main mineral (entire homeland)					0.098	-0.001
					(0.106)	(0.063)
× # mines					-0.085^b	-0.056^a
					(0.033)	(0.019)
ln price main mineral (in country outside homeland)					0.116	0.092
					(0.083)	(0.063)
× # mines					0.029	0.023
					(0.018)	(0.019)
Actor-country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	Yes
Country×year FE	No	Yes	No	Yes	No	No
Observations	2352	2226	2352	2226	2352	2352

LPM estimations. Standard errors, clustered by actor in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Estimations are run at the rebel group-country-year level. When aggregating the data all cells containing a mine at some point, or surrounded by cells containing a mine at some point over the period are excluded. Cols. 3, 4 and 6 keep in the sample only cells which are located outside the ethnic homeland associated with the rebel group. ln price main mineral (homeland in country) is the price of the main mineral produced in the ethnic homeland of the rebel group and in the considered country. ln price main mineral (entire homeland) is the price of the main mineral produced in the ethnic homeland of the rebel group, inside or outside the considered country. ln price main mineral (in country outside homeland) is the price of the main mineral produced inside the considered country but outside the ethnic homeland of the rebel group. Main minerals are defined as the mineral produced in the largest number of cells at the beginning of the period. For each price variable the associated # mines variable denotes the number of mines producing the mineral in each respective area. All specifications include linear terms and interaction terms but only the coefficients of the interactions are displayed.

V Changes in territory – robustness

We display summary statistics and additional robustness results for the section 5.2.2. In particular, Table A.32 presents the descriptive statistics for this section, followed by Table A.33 that uses spatially clustered standard errors and Table A.34 that allows for two-way clustering of standard errors by group and cells. Finally, in Table A.35 the dependent variable is outbreak of battle events only (instead of all events). The significance levels of all robustness tables presented here are very similar to the ones reported in Table 7.

Table A.32: Descriptive statistics: battle won

	Obs.	Mean	S.D.	Median
Pr(Conflict> 0)	204402	0.01	0.11	0.00
# conflicts	204402	0.06	1.48	0.00
$\text{Battle}^0_{g,t-1}$	204402	0.41	0.49	0.00
$\text{Battle}^m_{g,t-1}$	204402	0.01	0.12	0.00
# $\text{battles}_{g,t-1}$	204402	2.61	6.94	0.00
# $\text{battles}^0_{g,t-1}$	204402	2.58	6.81	0.00
# $\text{battles}^m_{g,t-1}$	204402	0.03	0.24	0.00
# $\text{battles}^0_{g,t-1}$ (no change of terr.)	204402	30.31	99.77	8
# $\text{battles}^m_{g,t-1}$ (no change of terr.)	204402	0.17	0.71	0.00
ln average distance to battles_{t-1}	204402	790.48	404.31	748.52

Statistics on the sample of 126 rebel groups contained in ACLED that were active in year $t-1$. Each observation is a rebel group-cell-year triplet. # $\text{battles}_{g,t-1}$, # $\text{battles}^o_{g,t-1}$ and # $\text{battles}^m_{g,t-1}$ are the number of battles won in t-1, respectively in total, in non mining areas and in mining areas. "No change of terr." means that the number of battles with no change in territory. # battles variables are expressed as $\log(x+1)$. ln average distance to battles_{t-1} is the average distance between the cell and all previous year's battles.

Table A.33: Feasibility and the diffusion of war: Conley standard errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Conflict onset				
Estimator				LPM				
# battles$_{g,t-1}$	0.002^a						0.033^a	
	(0.001)						(0.010)	
Battle$^0_{g,t-1}$		0.000						
		(0.001)						
Battle$^m_{g,t-1}$		0.040^a						
		(0.010)						
# battles$^0_{g,t-1}$			0.001	-0.001	0.000	0.000		0.029^a
			(0.001)	(0.001)	(0.001)	(0.001)		(0.010)
# battles$^m_{g,t-1}$			0.053^a	0.041^a	0.062^a	0.054^a		0.600^a
			(0.015)	(0.015)	(0.016)	(0.015)		(0.214)
# battles$^0_{g,t-1}$ (no change of terr.)				0.001^b				
				(0.001)				
# battles$^m_{g,t-1}$ (no change of terr.)				0.008^b				
				(0.003)				
# battles$^0_{g,t-2}$					-0.000	0.000		
					(0.001)	(0.001)		
# battles$^m_{g,t-2}$					0.023^a	0.021^b		
					(0.008)	(0.008)		
# battles$^0_{g,t-3}$						-0.004^a		
						(0.001)		
# battles$^m_{g,t-3}$						0.030		
						(0.023)		
ln average distance to battles$_{t-1}$							-0.001	-0.001
							(0.002)	(0.002)
# battles$_{g,t-1}$× ln av. dist.							-0.005^a	
							(0.001)	
# battles$^0_{g,t-1}$ × ln av. dist								-0.004^a
								(0.001)
# battles$^m_{g,t-1}$ × ln av. dist								-0.084^a
								(0.032)
Difference in coefs.								
# battles$^m_{g,t-1}$–# battles$^0_{g,t-1}$		0.039^a	0.056^a	0.042^a	0.061^a	0.053^a		
		(0.011)	(0.015)	(0.015)	(0.016)	(0.015)		
– no change of terr.				0.007^c				
				(0.004)				
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Actor-Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	201352	201352	201352	201352	201352	189444	201352	201352

LPM estimations. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. This estimations are run at the cell-rebel group-year level. Only the sample of rebel groups active in $t-1$ is considered. Singletons are dropped. # battles$_{g,t-1}$, # battles$^o_{g,t-1}$ and # battles$^m_{g,t-1}$ are the number of battles won in t-1, respectively in total, in non mining areas and in mining areas. "No change of terr." means that the number of battles with no change in territory. # battles variables are expressed as $\log(x+1)$. ln average distance to battles$_{t-1}$ is the average distance between the cell and all previous year's battles.

Table A.34: Feasibility and the diffusion of war: multi-way clustering

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Conflict onset				
Estimator				LPM				
# battles$_{g,t-1}$	0.002						0.033^b	
	(0.002)						(0.015)	
Battle$^0_{g,t-1}$		0.000						
		(0.002)						
Battle$^m_{g,t-1}$		0.040^a						
		(0.012)						
# battles$^0_{g,t-1}$			0.001	-0.001	0.000	0.000		0.029^b
			(0.002)	(0.002)	(0.002)	(0.002)		(0.014)
# battles$^m_{g,t-1}$			0.053^a	0.041^b	0.062^a	0.054^a		0.600^a
			(0.016)	(0.017)	(0.013)	(0.013)		(0.184)
# battles$^0_{g,t-1}$ (no change of terr.)				0.001^c				
				(0.001)				
# battles$^m_{g,t-1}$ (no change of terr.)				0.008^a				
				(0.003)				
# battles$^0_{g,t-2}$					-0.000	0.000		
					(0.001)	(0.001)		
# battles$^m_{g,t-2}$					0.023^b	0.021^a		
					(0.009)	(0.008)		
# battles$^0_{g,t-3}$						-0.004^a		
						(0.001)		
# battles$^m_{g,t-3}$						0.030^c		
						(0.016)		
ln average distance to battles$_{t-1}$							-0.001	-0.001
							(0.003)	(0.003)
# battles$_{g,t-1}$× ln av. dist.							-0.005^b	
							(0.002)	
# battles$^0_{g,t-1}$ × ln av. dist								-0.004^b
								(0.002)
# battles$^m_{g,t-1}$ × ln av. dist								-0.084^a
								(0.027)
Difference in coefs.								
# battles$^m_{g,t-1}$–# battles$^0_{g,t-1}$		0.039^a	0.056^a	0.042^a	0.061^a	0.053^a		
		(0.012)	(0.016)	(0.016)	(0.013)	(0.013)		
– no change of terr.				0.007^b				
				(0.003)				
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Actor-Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	168887	168887	168887	168887	168887	158040	168887	168887

LPM estimations. Standard errors, clustered two-ways by actor and cells, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. This estimations are run at the cell-rebel group-year level. Only the sample of rebel groups active in $t-1$ is considered. Singletons are dropped. # battles$_{g,t-1}$, # battles$^o_{g,t-1}$ and # battles$^m_{g,t-1}$ are the number of battles won in t-1, respectively in total, in non mining areas and in mining areas. "No change of terr." means that the number of battles with no change in territory. # battles variables are expressed as $\log(x+1)$. ln average distance to battles$_{t-1}$ is the average distance between the cell and all previous year's battles.

Table A.35: Feasibility and the diffusion of war: battles only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Conflict onset (battles only)							
Estimator	LPM							
# battles$_{g,t-1}$	0.002						0.034^a	
	(0.001)						(0.012)	
Battle$^0_{g,t-1}$		0.000						
		(0.001)						
Battle$^m_{g,t-1}$		0.040^a						
		(0.010)						
# battles$^0_{g,t-1}$			0.001	-0.001	0.000	0.001		0.030^b
			(0.001)	(0.001)	(0.001)	(0.001)		(0.011)
# battles$^m_{g,t-1}$			0.053^a	0.044^a	0.060^a	0.052^a		0.555^a
			(0.015)	(0.014)	(0.012)	(0.011)		(0.135)
# battles$^0_{g,t-1}$ (no change of terr.)				0.002^b				
				(0.001)				
# battles$^m_{g,t-1}$ (no change of terr.)				0.006^a				
				(0.003)				
# battles$^0_{g,t-2}$					-0.001	0.000		
					(0.001)	(0.001)		
# battles$^m_{g,t-2}$					0.019^a	0.017^a		
					(0.007)	(0.006)		
# battles$^0_{g,t-3}$						-0.003^a		
						(0.001)		
# battles$^m_{g,t-3}$						0.014		
						(0.011)		
ln average distance to battles$_{t-1}$							0.000	0.000
							(0.002)	(0.002)
# battles$_{g,t-1}$× ln av. dist.							-0.005^a	
							(0.002)	
# battles$^0_{g,t-1}$ × ln av. dist								-0.004^b
								(0.002)
# battles$^m_{g,t-1}$ × ln av. dist								-0.077^a
								(0.019)
Difference in coefs.								
# battles$^m_{g,t-1}$–# battles$^0_{g,t-1}$		0.039^a	0.052^a	0.045^a	0.059^a	0.051^a		
		(0.011)	(0.014)	(0.014)	(0.012)	(0.011)		
– no change of terr.				0.004^c				
				(0.004)				
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Actor-Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	168887	168887	168887	168887	168887	158040	168887	168887

LPM estimations. Standard errors, clustered by group, in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. This estimations are run at the cell-rebel group-year level. Only the sample of rebel groups active in $t-1$ is considered. Singletons are dropped. # battles$_{g,t-1}$, # battles$^o_{g,t-1}$ and # battles$^m_{g,t-1}$ are the number of battles won in t-1, respectively in total, in non mining areas and in mining areas. "No change of terr." means that the number of battles with no change in territory. # battles variables are expressed as $\log(x+1)$. ln average distance to battles$_{t-1}$ is the average distance between the cell and all previous year's battles.

W Company ownership – some descriptive statistics

Table A.36 displays descriptive statistics on the company characteristics, of which we make use in section 6.1 of the main text.

Table A.36: Company characteristics

	Obs.	Mean	S.D.	Median
Share				
Domestic - Publicly owned	2310	0.12	0.32	0
Domestic - Privately owned	2310	0.27	0.42	0
Foreign owned	2310	0.60	0.46	1
Former colonizer	2310	0.14	0.32	0
Other	2310	0.47	0.48	0.33
Major company	2310	0.43	0.47	0
Full ownership				
Domestic - Publicly owned	2310	0.12	0.32	0
Domestic - Privately owned	2310	0.22	0.41	0
Foreign owned	2310	0.55	0.50	1
Former colonizer	2310	0.11	0.31	0
Other	2310	0.42	0.49	0

Statistics on the sample of mining cells. Shares are shares of mines with a given ownership type in the cell at the beginning of the period. Full ownership is a dummy which equals 1 when all mines in a given cell are of a given type at the beginning of the period.

X The role of transparency – robustness

We present additional results for the analysis of section 6.2 of the main text. First, we replicate in Table A.37 the regressions of Table 9 but for domestic firms. The effects found for foreign firms do not carry over to domestic firms, suggesting hence that the detrimental effect of mining price spikes as well as the virtues of transparency are confined to foreign firms only. Second, Table A.38 studies the impact of the Kimberley initiative on war diamonds, finding either no effect or a marginally significant conflict-reducing effect (caution is however required for the interpretation of the results, given the limited source of identification and the drawbacks of the diamond price data discussed in the main text).

Table A.37: Heterogeneous effects: The Role of Transparency (other types of companies)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Estimator					LPM					
Sample					$\mathbb{V}(\mathrm{M}_{kt}) = 0$					
Dep. var.					Conflict incidence					
Events	All	Battles	All	Battles	All	Battles	All	Battles	All	Battles
ln price × mines > 0	0.025	-0.009	0.040	-0.007	0.033	-0.018^b	0.046	-0.006	0.047	-0.006
	(0.035)	(0.005)	(0.035)	(0.007)	(0.039)	(0.008)	(0.038)	(0.008)	(0.038)	(0.008)
× Large Firms	0.026	-0.005	-0.029	0.010	-0.024	0.002	-0.014	0.014	-0.015	0.013
	(0.030)	(0.006)	(0.053)	(0.011)	(0.051)	(0.015)	(0.041)	(0.008)	(0.041)	(0.008)
× Control of Corruption	-0.023	0.021								
	(0.027)	(0.013)								
× Firm CSR (ICMM)			0.064	0.016						
			(0.072)	(0.018)						
× Tracea. Init. (EITI, request)					0.014^a	0.014^c				
					(0.005)	(0.007)				
× Tracea. Init. (EITI, compliance)							-0.009	0.001		
							(0.008)	(0.002)		
× Tracea. Init. (GLR)									-0.003	-0.000
									(0.002)	(0.000)
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130998	130998	141610	141610	141596	141596	141596	141596	141596	141596

LPM estimations. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. Sample restricted to non mining cells and cells for which domestic (private and public owned) represent the largest share. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. See main text for a description of the various transparency variables.

Table A.38: Conflicts and mineral prices: the Kimberley process

	(1)	(2)	(3)	(4)
Estimator	LPM			
Dep. var.	Conflict incidence			
Conflicts	All events		Battles only	
Sample	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All	$\mathbb{V}(\mathrm{M}_{kt}) = 0$	All
ln price × mines > 0	0.036		0.010	
	(0.025)		(0.009)	
× Kimberley	0.007		-0.005[c]	
	(0.010)		(0.003)	
ln price × mines > 0 (ever)		0.026		0.003
		(0.016)		(0.007)
× Kimberley		-0.009		-0.008
		(0.010)		(0.005)
Country×year FE	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes
Observations	142646	144424	142646	144424

LPM estimations. [c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. mine > 0 is a dummy taking the value 1 if at least 1 mine is active in the cell in year t. mines > 0 (ever) is a dummy taking the value 1 if at least 1 mine is recorded in the cell at any point over the 1997-2010 period. $\mathbb{V}(\mathrm{M}_{kt}) = 0$ means that we consider only cells in which the mine dummy takes always the same value over the period. ln price main mineral is the world price of the mineral with the highest production over the period (evaluated at 1997 prices) for mining cells, and zero for non-mining cells. Kimberley is a dummy taking the value 1 after 2002 for mining cells whose main mineral is diamond. The estimations also include interaction terms between the price×mines variables and a diamond dummy, as well as between the price×mines variables and a post-2002 dummy.

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