Mining Competition and Violent Conflict in Africa: Pitting Against Each Other

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Abstract

Existing explanations for the well-established relationship between mining and conflict predominantly interpret violence near mines as conflict over territory or government. We provide evidence that competition between artisanal and industrial miners is also an important source of natural resources-related conflict, drawing on qualitative case studies at mining sites in the Democratic Republic of Congo and Zimbabwe, and a large-N analysis. For the latter, we use machine learning to estimate the feasibility of artisanal mining across the continent of Africa based on geological conditions. The impact of price shocks on violent conflict is over three times larger in locations with industrial mining where artisanal mining is feasible than in places with industrial mining unsuitable for artisanal mining. Our estimates suggest that 31 to 55% of the observed mining-conflict relationship is due to violent industrial-artisanal miner competition. This implies new avenues for conflict-mitigation as the clean energy transition increases demand for minerals.[1]

Keywords: Natural resources, violent conflict, artisanal mining, extractives industry.

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[1] Supplementary material for this article is available in the appendix in the online edition. Replication files are available in the JOP Data Archive on Dataverse (https://dataverse.harvard.edu/dataverse/jop). The empirical analysis has been successfully replicated by the JOP replication analyst.

Africa is mineral rich. The continent accounts for 30% of global mineral deposits – on average, mining composes more than two-thirds of total exports and over a quarter of gross domestic product (AfDB, 2016). A large literature finds that natural resource wealth in low-income countries is associated with increased violent conflict – a negative externality likely to rise as global demand surges for minerals associated with the clean energy transition (Blair et al., 2021; Hund et al., 2020). But while many explanations interpret violence near resource extraction sites as part of conflict over territory or government, less attention has been paid to competition between artisanal and industrial miners to extract deposits.

A substantial share of conflict associated with natural resource extraction happens in locations with no observed conflict over government or territorial control. According to the Armed Conflict Location and Event Dataset (ACLED), there have been approximately 4,721 violent events in the proximity of industrial mines on the continent between 1997 and 2020.[2] However, more than half of these events (52%) took place outside zones of conflict between government and rebel groups or among rebels.[3] Many of the incidents which do occur around mines in conflict zones have nothing to do with rebel forces fighting each other or the government: 44% of these events are riots, and 25% involve violence against civilians.

There are clearly other mechanisms at play. Drawing on qualitative case studies in Democratic Republic of the Congo (DRC) and Zimbabwe, we identify conflict between industrial mining operations and artisanal miners (LSM-ASM conflict) as an important source of mining-related conflict. Artisanal and small-scale mining (ASM) refers to mining by individuals or small groups using little or no capital-intensive equipment; the World Bank (2020) estimates ASM is the primary source of employment for nearly 45 million people in 80 countries. At our case study sites, industrial and artisanal miners compete directly to

[2]Proximity is defined as within a 5 kilometer radius of the mine extracting aluminum, coal, cobalt, coltan (tantalum), diamonds, gold, iron, lead, manganese, nickel, phosphate, platinum, silver, tin, tungsten or zinc.

[3]Kikuta (2022) uses a machine learning method to flexibly estimate geographic conflict zones at the actor-dyad level based on conflict event data.

extract minerals, leading to violent expulsions of artisanal miners, fights between miners and security forces, and violent protests. LSM-ASM conflict is distinct from frequently cited explanations of natural resource related conflict. It does not involve rebel groups, organized armed actors purporting to fight the state or each other over government or territory. As the state is no longer the object of contestation, state actors may strategically alternate between supporting both sides to the conflict.

Measuring the importance of this channel for mining-related conflict is challenging for two reasons. First, comprehensive data on artisanal mining operations are unavailable for much of Africa, the primary geography of study for most of the literature on mining-related conflict. Second, even if data were available, the presence of artisanal mining is an outcome of the negotiation process between mine owners and nearby communities, and can be correlated with the potential for other kinds of conflict.

We use a supervised machine learning classification to generate a measure of feasibility for artisanal mining across the continent of Africa based on geological conditions. Our approach is to learn the geological characteristics of areas which enable artisanal mining from three regions that have been comprehensively surveyed for such activity: Eastern DRC, Western Tanzania, and Burkina Faso. Drawing on geology literature, we identify several features that should predict feasibility and train multiple random forest models to predict the feasibility of artisanal mining of four sets of commodities in each cell of an arbitrary $.25^{\circ} \times .25^{\circ}$ grid (approximately 16 $\times$16 miles at the equator). The resulting machine learning model predicts artisanal mining in a test set with an accuracy of 72 to 93% – depending on commodity.

Using our model's prediction, we assess how the impact of commodity price shocks on conflict varies by the feasibility of artisanal mining. Extending a standard empirical specification, we show that the impact of price shocks on conflict is roughly three times as large in locations with industrial mining feasible for artisanal activity than in places with industrial mining but no such potential. A one standard deviation increase in resource price in a given year predicts a 0.81 standard deviation increase in the probability of conflict in grid cells with industrial mining which are suitable for artisanal mining, but only a 0.26 standard deviation increase in places with industrial mining where artisanal activity is not an option. Back-of-the-envelope calculations suggest that between 31 to 55% of conflict events estimated to be caused by price shocks are in places where industrial and artisanal mining overlap.

These results speak to three literatures. First, for the literature on extractive industries and conflict, they provide generalized empirical support for the importance of artisanal-industrial conflict as a key mechanism. Second, for those working to reduce extractives-related conflict, these results highlight the importance of finding ways to address conflicts between artisanal miners and industrial companies. Third, for the conflict studies literature, our analysis highlights the potential of using machine learning to bootstrap locality-specific measurements of key variables into gridded data for much larger areas. Such methods are no panacea: they require that the variable be predictable from readily observable features and that there is ground truth data on the variable being predicted, across the full distribution of features used in prediction (i.e. in our case geological characteristics). Where those conditions are met, there is tremendous potential for machine learning to enable scholars to extend insights from fieldwork to new locations, and thereby empower new analyses.

Literature

Numerous studies find an association between natural resources and violent conflict. This correlation is frequently interpreted as evidence that actors who fight over government or territory seek to control natural resource extraction sites.[4] However, this mechanism does not necessarily explain observed patterns of violence near industrial mining sites, which may reflect competition with artisanal miners.

[4]While prominent, this is not the only mechanism proposed, see e.g. Humphreys (2005).

Natural resources and conflict

An expansive literature investigates the association between natural resource extraction and violent conflict. Since resource extraction may be endogenous to conflict, more recent research designs leverage commodity price shocks as a natural experiment. Blair et al. (2021) conduct a meta-analysis of 46 such studies and find systematic evidence that increases in the price of oil, gas and artisanal minerals are associated with higher conflict risk.

Blair et al. (2021) note that few studies investigate industrial mining. Out of 46 studies considered, only 4 concern industrial mining, and half of these (Jensen et al., 2017; Rigterink, 2020) focus on diamonds only. Partially for this reason, Blair et al. (2021) are unable to draw a firm conclusion about the association between industrial mining and conflict.

The most prominent study that does find such an association is Berman et al. (2017). Focusing on African countries between 1997 and 2010, Berman et al. (2017) conclude that when the price of a given mineral increases, the risk of violent conflict in 0.5×0.5 degree grid cells with an industrial mine extracting this mineral increases, compared to cells with mines that extract minerals that have not increased in price.

Artisanal mining

Many industrially mined minerals can also be mined artisanally in the same location.[5] This includes prominent minerals such as gold, cobalt and copper ("2c" minerals), as well as tantalum, tungsten and tin ("3t" minerals) (Blair et al., 2021).

Artisanal mining has gained a negative reputation through its association with violent conflict, environmental degradation, and poor working conditions - including child labor. Nevertheless, research on artisanal mining highlights both its positive and negative impacts. On the one hand, artisanal mining is associated with increased risk of violent conflict (Blair

[5]We use "artisanal mining" and "ASM" (artisanal and small-scale mining) interchangeably. We abbreviate "conflict between industrial and artisanal miners" as LSM-ASM conflict, where LSM stands for Large-Scale Mining.

et al., 2021), and linked to pollution and consequent increased child mortality (Romero and Saavedra, 2019). On the other hand, artisanal mining contributes to households' livelihoods (Bazillier and Girard, 2020) - such that greater scrutiny of the use of artisanal minerals from DRC led to *greater* child mortality (Parker et al., 2016).

The potential for conflict between industrial and artisanal miners has been noted in qualitative literature (e.g. Bush, 2009; Hilson and Carstens, 2009), but this has been studied mostly in isolation from other mining-related conflict. Stoop et al. (2019) do note that expansion of LSM into areas with ASM increases incidents of looting and violence against civilians. However, these authors interpret this result as rebel groups shifting to non-mining related revenue sources and their study covers selected areas of DRC where rebel violence is prominent. Our study seeks to add LSM-ASM conflict as a generalizable theoretical contribution to the "natural resource curse" literature.

Posited mechanisms

The correlation between natural resources and conflict is commonly interpreted as evidence that actors fighting over government or territory seek to control resource extraction sites. Initially, this was labelled as 'greed': rebels merely purporting to fight for political goals to cover profit-seeking (Collier and Hoeffler, 2004). Alternatively, capturing government and controlling resource revenue may constitute a *prize* for armed groups seeking to capture the state (Fearon and Laitin, 2003). As the unit of analysis increasingly shifted to the sub-national level, explanations shifted to emphasize the strategic value of controlling extraction sites in conflict over government or territory: controlling natural resource revenue can fund violent activity elsewhere, and denying such revenue to one's rival can bring a strategic advantage (e.g. Berman et al., 2017). The higher the price of the relevant natural resource, the greater the revenue, and the greater this incentive to fight to control extraction sites.[6]

[6]Of course, this is not the only proposed mechanism to explain the relationship between natural resources and conflict. An increase in the price of capital-intensive natural resources may depress wages, exacerbate grievances by local inhabitants against mining companies,

However, this mechanism does not explain several stylized facts about violence near industrial mining sites. It leads us to expect violence around mining sites in areas with disputes over government or territory, and to consist primarily of fighting between government and non-state armed groups, or among non-state armed groups. However, of the 4,721 violent events in ACLED that took place within 5 kilometers of a mining site in Africa between 1997 and 2020, 2,451 (52%) occurred outside conflict zones, either between a state and non-state armed group or between non-state armed groups (as per Kikuta, 2022).[7] Second, fighting between these armed actors accounts for only 21% of ACLED conflict events around industrial mining sites in Africa. The most prevalent types of violent events are riots (47%) and violence against civilians (31%). Given that civilians around industrial mining sites are not the principal economic beneficiaries, the prevalence of violence against civilians is puzzling.

Other studies note the frequency of other kinds of conflict around mining sites: e.g. Sexton (2020) and Christensen (2019) investigate the association between mining and protest.

Case studies and hypotheses

We explore mechanisms for the natural resources-conflict nexus through case studies of three mining sites each in DRC and Zimbabwe. We select two countries that vary in terms of central government's control over the mineral trade.[8] As the goal of the case studies was to inform theory development we focused on areas where activity by rebel groups was minimal. In each country, we selected three sites that vary in conflict outcomes, but share a common geography and mineral type. This allows us to hold constant physical and political context with each country, while illuminating processes that explain differing levels of violence.

Experts from International Crisis Group, an independent nongovernmental organization

induce migration, or diminish government incentives to develop 'good' state institutions (Humphreys, 2005; Berman et al., 2017).

[7]This analysis is restricted to mines extracting the commodities in footnote 2.

[8]At the time of the case studies, all gold mined in Zimbabwe had to be sold to the Zimbabwe Central Bank, while copper-cobalt mined in DRC could be bought and sold freely.

conducted interviews near these mining sites with residents, government officials, artisanal miners, community and civil society representatives and, where they were willing, representatives of mining companies.[9] These took place in Summer 2019 in DRC and early 2020 in Zimbabwe. We supplemented records of those interviews with a review of news articles, reports and ACLED events near the mining sites.

In DRC, we study three copper-cobalt mines in the former province of Katanga: Kipushi mine, Luiswishi mine and Tenke Fungurume Mine (TFM). Kipushi has no history of violent conflict, Luiswishi experienced a period of significant violence but had been peaceful for a decade, and TFM experienced frequent violent episodes. Rebel violence was not a factor at any of these sites.[10] Kipushi is majority-owned by a company registered in Canada, TFM and Luiswishi by two different Chinese-registered companies, though the latter was owned by a Belgian company when it experienced violence. All companies are publicly traded.

In Zimbabwe, we study three gold mines: Gaika, Giant, and Jumbo. Both Gaika and Jumbo were subject of frequent violence, whereas Giant experienced only a single violent event. As in our DRC case studies, rebel violence was not a factor at any of these sites. Giant and Jumbo are owned by companies registered in the United Kingdom, while Gaika's owning company is registered in Mauritius. None of these companies are publicly traded.

Table 1 summarizes key characteristics of the six case study mines.

Understanding LSM-ASM competition

Competition between artisanal and industrial miners led to violence in the vicinity of the case study sites through two main channels: (1) increases in efforts by artisanal miners to

[9]See: https://www.crisisgroup.org/africa/southern-africa/zimbabwe/294-all-glitters-not-gold-turmoil-zimbabwes-mining-sector and https://www.crisisgroup.org/africa/central-africa/democratic-republic-congo/290-mineral-concessions-avoiding-conflict-dr-congos-mining-heartland. These are distinct reports drawing on the same source material.

[10]Although independence of Katanga has been the object of violent contestation since the 1960s, rebel activity in Katanga was minimal in the period under investigation.

Table 1: Characteristics of case study mines

Mine	Mineral	Country	ASM?	Violence?	Violence Types
Panel A: Democratic Republic of the Congo					
Kipushi	Cobalt, Copper, Zinc	Canada	None	None	N/A
Luiswishi	Cobalt, Copper	China / Belgium	Limited	Infrequent	ASM - Police, ASM - Private security, ASM - Military, Riots
TFM	Cobalt, Copper	China	Intensive	Frequent	ASM - Police, ASM - Private security, ASM - Military, Police - Military, Riots
Panel B: Zimbabwe					
Gaika	Gold	Mauritius	Intensive	Frequent	ASM - ASM, ASM - Police, ASM - Military, ASM - Other civilians
Giant	Gold	UK	Intensive	Infrequent	ASM - Police, ASM - Military
Jumbo	Gold	UK	Intensive	Frequent	ASM - ASM, ASM - Police, ASM - Military, ASM - Other civilians, Riots

Based on International Crisis Group interview material (Summer 2019 in DRC, early-2020 in Zimbabwe) and secondary sources. "Country" refers to the country of registration of the company owning the majority stake in the mine. 'Riots' include demonstrations in which artisanal miners commit violence against property or clash with security forces.

enter industrial sites, and increases in industrial miners' efforts to keep artisanal miners out; (2) shifts in the political status of the operators or artisanal miners, which caused prior bargains to break down. Commodity price shocks exacerbate both channels by increasing the incentives to access industrial sites and the temptation to renege on bargains.

LSM-ASM competition and violence

In DRC, violent LSM-ASM competition tended to be over physical access to deposits.

At TFM, a short-lived pilot operation in the 1970s attracted tens of thousands of job-hopefuls to the area. Some migrants turned to artisanal mining, and their success attracted more artisanal miners. When industrial mining recommenced in 2005, the industrial operator found thousands of artisanal miners already mining on the site. The site saw periodic episodes of violence in 2005, 2009 and 2019. Notably, there were significant spikes in world cobalt prices beforehand in 2004, 2008, and 2018 .[11] Violent episodes followed a similar

[11] See `https://data.imf.org/?sk=9f7ae3b7-2599-457b-94f5-254c5f6475ea&_uv=1`, accessed 17 August 2022

pattern: expulsion of artisanal miners from TFM by the DRC army and/or mining police, violent protests by artisanal miners, and then clashes between artisanal miners and state armed forces. Expulsions were short-lived, partially because TFM's size makes it near-impossible to keep those encroaching out, and partially because military personnel deployed to secure the site repeatedly took bribes to allow artisanal miners access to TFM. This rent-seeking behavior also led to violent clashes between the mining police and DRC military.

Events at Luiswishi echo those at TFM, though less intensely. In 2009, hundreds of artisanal miners stormed the mining site. Members of the police and DRC armed forces violently expelled them in response, destroying hundreds of dwellings of artisanal miners.[12] After the 2009 violence and until a 2015 sale, the then-owner informally permitted some artisanal miners to access low-grade deposits on the mining site. While the current owner does not permit such access, there are off-site 'slag heaps' – left-over material from industrial mining operations – where artisanal miners can still prospect, helping to reduce tensions.

At Kipushi mine, by contrast, there has been no significant violence. Part of the reason is that, unlike at Kipushi and TFM, most of Kipushi's deposits are deep underground, and thus not accessible to artisanal mining. But the decision by local site operators to allow artisanal miners access to slag heaps and low-grade deposits also plays a role. Finally, owning and operating company, Canadian firm Ivanhoe, has invested in livelihood programs and community relations projects, which appear to have helped forestall conflict.

In Zimbabwe, shifts in the political bargains facilitating extraction often lead to violence. Violence increased during a rise in world gold prices from 2018 to 2021.[13]

Jumbo mine tells a complex story of competition between industrial and artisanal mining, fighting among artisanal miners, and political interference by the ruling ZANU-PF party. Jumbo mine was owned by UK-registered Metallon Corporation, which fell out of politi-

[12] See: https://www.amnesty.eu/news/bulldozed-how-a-mining-company-buried-the-truth-about-forced-evictions/, accessed 11 August 2022

[13] See `https://data.imf.org/?sk=d6587245-00fa-4728-b6d2-ccbbf5265e4d&hide_uv=1`, accessed 17 August 2022

cal favour in 2018. This coincided with the onset of financial problems for the company, which alleged that the subsidiary of the Zimbabwe Central Bank which by law buys all gold produced in Zimbabwe neglected to pay on time for gold deliveries.[14] When production at Jumbo mine halted due to these financial issues, thousands of artisanal miners started working the site. Artisanal miners gained access through ventilation shafts or by paying off guards to access lifts. Underground and in areas surrounding Jumbo mine, fights broke out between artisanal miners organized into armed gangs and allegedly sponsored by different ZANU-PF politicians. In 2021, after the mine was sold to a prominent ZANU-PF supporter, artisanal miners were violently expelled from Jumbo by police, as part of a large operation that saw 25,000 artisanal miners arrested across the country.[15]

Violence at Gaika mine in Zimbabwe also speaks to the intersection of industrial-artisanal competition and politics. The gold mine was invaded by artisanal miners in 2018, encouraged by a local ZANU-PF aligned politician.[16] This politician allegedly assured artisanal miners police would not take action against them, and attempted to pressure the industrial mine owner to grant invading artisanal miners a tribute, a form of subcontract. Different groups of miners claimed territory within the mine and fought to expand their claims. Although Duration Gold, the Mauritius-registered company that owns the mine, obtained multiple court orders for the expulsion of the artisanal miners, as well as for the arrest of the local politician supporting them, the police and armed forces failed to take action for over a year. They did eventually expel artisanal miners in April 2019, but only after expulsion had become inevitable since the company had hired private security contractors to do so.

Giant mine in Zimbabwe provides clear evidence that long-term accommodation between industrial and artisanal miners is possible, at least when the artisanal miners have strong

[14]See for example: "Metallon Corporation Sues the Government of Zimbabwe for US$132M for Failing to Pay for Gold", Metallon Corporation, 16 May 2019.

[15]See: "25K illegal artisanal mining nabbed", Daily News, 15 March 2021.

[16]See: "Chief Justice Malaba orders the arrest of ZANU-PF stalwart for Gaika mine invasion", Nehanda Radio, 6 April 2019.

political backing. When the current operator, UK-registered Breckridge Investments, took over the site in 2015, it negotiated a tribute agreement with the politically-connected artisanal mining cooperative working the site since 2012. That cooperative, closely linked to the Mugabe government, reached a formal revenue-sharing agreement with Breckridge in 2016. In late-2017 Mugabe was ousted, and the cooperative's local sponsor lost his influence. In 2018 Breckridge did not extend the agreement and obtained a court order to expel the artisanal miners, which was carried out by police in April 2019 with one casualty.

Violence patterns across sites and over time

Competition between industrial and artisanal miners (or lack thereof), can explain part of the variation in violence across case study sites. Copper-cobalt deposits at Kipushi mine, the DRC case study not associated with any violent conflict, lie deep underground and can only be accessed using industrial methods. Unlike the other case study sites in DRC, it would be virtually impossible for artisanal miners to derive a livelihood at Kipushi, and direct competition between artisanal and industrial mining is minimal. This is reflected in conflict event data: ACLED refers to artisanal miners in the description of 78% of violent events near TFM and 33% of events near Luiswishi, but 0% of events near Kipushi.[17]

Industrial and artisanal miner competition is possible at all Zimbabwe case study mines, but was mitigated by agreements between industrial and artisanal miners. At Giant mine in Zimbabwe, the mining cooperative had a formal agreement with the industrial mine operator that limited direct competition for several years. Data reflect the possibility of LSM-ASM competition at all Zimbabwean sites, as well as variation between them: the percentage of ACLED events mentioning artisanal miners varies between 5% at Giant and 14% at Gaika.[18]

[17] An event is 'near' a case study mine if it takes place within 27.5 kilometers, which mathces the unit of analysis for the large-N results in this paper.

[18] These percentages are substantially lower than in the DRC, but not indicative of rebel activity. ACLED records many instances of ZANU-PF violence against individual political opponents across Zimbabwe, including around the case study mines.

Industrial-artisanal miner competition can also explain some of the variation over time in violence within case study sites. Giant mine, where violence followed directly from a break-down in cooperation between industrial and artisanal miners, is an obvious example. Elsewhere, violence increased after commodity prices rose or risks of artisanal mining varied. As noted above, violent episodes at TFM and Luiswishi occurred in the year of or after cobalt price spikes and increased in the Zimbabwe sites when gold prices rose after 2018.

At Luiswishi, violence has decreased since 2009 as the costs to artisanal mining there increased and alternative livelihood options improved. Specifically, after 2009, it became clear that radiation levels in the mine are elevated, which is harmful to artisanal miners' health. After 2009, the company operating the mine began informally allowing artisanal miners to exploit slag heaps and other low-grade deposits.

At Jumbo mine, violence occurred when the cost to artisanal miners of encroaching on the industrial site were particularly low. As Jumbo is an underground mine, it would have been prohibitively difficult for artisanal miners to gain access to the industrial shafts or mine its gold under normal circumstances. However, the costs of doing so decreased when the mine became inactive in 2018. Similarly, at Gaika mine, violence occurred when a local politician encouraged artisanal miners to invade the site in 2018, ensuring them the police would not act to prevent the invasion.

Hypotheses

Informed by our comparative case studies, we hypothesize that the probability of violence is higher at industrial mining sites that are suitable for artisanal mining, compared to industrial mining sites unsuitable for artisanal mining. Following the literature in exploiting plausibly exogenous variation in commodity prices, we arrive at the following hypothesis:

Hypothesis 1 (H1) *An increase in the international price of a commodity will lead to a greater increase in the probability of violence around industrial sites extracting that commodity that are also suitable for artisanal mining, compared to industrial sites extracting that* *commodity but that are unsuitable for artisanal mining.*

Sites where both industrial and artisanal mining are feasible are possible sites of competition between industrial and artisanal miners. LSM-ASM conflict therefore poses a risk of conflict over and above conflict risks associated with industrial or artisanal mining alone.

LSM-ASM competition is likely to intensify as commodity prices increase. As the price of a commodity increases, this increases the incentive of both industrial and artisanal miners to obtain access to mining sites, and to prevent the other party from doing so. Multiple micro-mechanisms may be at work. For instance, bargains that may have prevented conflict in the past may break down as the benefits to industrial owners of reneging increase but costs stay constant. Alternatively, as artisanal miners have lower fixed costs and are thus more elastic than industrial miners, they may intensify efforts to access sites when commodity prices increase. Finally, commodity price shocks may increase the attractiveness of participating in artisanal mining and thus the volume of miners attempting to access industrial sites.

Measurement

Quantitative analysis of mining and conflict has been hampered by the lack of comprehensive data on artisanal mining, and the endogeneity of the presence of artisanal mining to conflict.

Currently available datasets record the presence of selected minerals that can be artisanally mined - mainly diamonds and gemstones (Gilmore et al., 2005) - or the presence of artisanal mining sites of any mineral in (small parts of) a few countries - mainly Burkina Faso and DRC (Bazillier and Girard, 2020; Stoop et al., 2019).

In addition, the *presence* of artisanal mining might be endogenous to violent conflict. This could bias analyses of the relationship between artisanal mining and conflict in an unknown direction. On the one hand, artisanal miners might avoid conflict areas. On the other hand, conflict frequently disrupts alternative livelihood options, making individuals more reliant on artisanal mining (see for example Hilson, 2016).

Furthermore, the *presence* of artisanal mining around industrial mining sites might be endogenous to the operating company's standing with government. A company's political connections can affect its ability to prevent artisanal miners from accessing it mining sites. Political connections of the operating company might also be related to the probability of violence around the mining site (e.g. because politically connected companies receive protection against other threats or because they operate more desirable sites).

To overcome these concerns we employ machine-learning to predict the *suitability* of an area to artisanal mining based on geological characteristics. Geological characteristics are plausibly exogenous to conflict. Though we use data on observed artisanal mining to train our machine learning classifier, our predictions of artisanal suitability are constructed using only information on a location's geology. For example, if artisanal mining occurs in a location with unsuitable geology but favourable economic or political conditions – as it did at Jumbo mine – our machine learning classifier would predict no artisanal mining there. This worsens classifier performance, but the resulting prediction is plausibly exogenous to conflict.

Predicting artisanal mining using geology

Literature in geology suggests it is possible to predict the presence of mineral deposits using geological characteristics such as the age of the bedrock, presence of particular stone types, and indicators of past tectonic activity such as fault lines (see Cox et al., 2007; Marshall and Baxter-Brown, 1995; Kamilli et al., 2017; Green et al., 2020; Bradley et al., 2010, on gold, diamonds, copper, tin, tungsten and coltan respectively). Such 'deposit models' are commonly used in mineral exploration (Cox et al., 2007), along with readings of the electromagnetism of an area, commonly taken by satellite or planes (Maus, 2009). The use of the age of the bedrock to predict the presence of diamonds (Rigterink, 2020) and gold (Bazillier and Girard, 2020) that can be artisanally mined has precedent in the literature.

Geological characteristics can also predict the depth at which minerals are found, and therefore whether they can feasibly be mined artisanally. Many minerals, including gold, diamonds, copper, tin and tungsten (Gosselin and Dubé, 2005; Cox et al., 2007; Marshall and

Baxter-Brown, 1995; Kamilli et al., 2017; Green et al., 2020) can occur as different deposit types, some found at the surface, others deeper – up to 10 kilometers – underground (e.g. Gosselin and Dubé, 2005). Surface deposits of a mineral can feasibly be mined artisanally, whereas deeper lying deposits of the same mineral are inaccessible to artisanal miners.

Random Forest Predictions of Artisanal Suitability

We construct binary classifiers to predict the suitability of an area to artisanal mining of all main artisanal commodities, based on geological characteristics for each arbitrary $.25^{\circ} \times .25^{\circ}$ square on the continent of Africa. We train on comprehensive artisanal mining data for three important regions: Eastern Democratic Republic of the Congo, Western Tanzania, and Burkina Faso. Trained classifiers predict artisanal mining in a test set with 72 to 93% accuracy – depending on commodity. We predict out to other areas of the African continent whose geology is represented in the training sample, roughly 78% of Africa's surface area.

Features

Data on artisanal mines comes from the International Peace Information Service (IPIS) for Eastern DRC and Western Tanzania, and the Government of Burkina Faso (Effigis, 2018).[19] IPIS contains data on artisanal mining of cobalt, coltan, copper, diamond, gold, lead, manganese, tin and tungsten. The Burkina Faso data only cover gold.

IPIS data on artisanal mining was gathered through on-the-ground surveys across a range of different research projects employing a snowball sampling method with seed sites chosen based on mapping of known mining sites. After choosing the specific mining zone for a given project (e.g. an impact evaluation of a miner welfare program), IPIS contacts the network of stakeholder in that mining zone, map existing mines, and draft a provisional itinerary (in-

[19]Available here: https://ipisresearch.be/home/maps-data/open-data/, accessed 19 August 2021. We opt to not use data on artisanal mining in Zimbabwe, Central African Republic as IPIS judges these are not (yet) comprehensive. Appendix section A.2.2 details DRC provinces and Tanzanian regions where IPIS considers data comprehensive.

cluding a selection of mines to be prioritized). Once in the field IPIS tries to be as exhaustive as possible (within the limits of the project budget) starting with visits to artisanal mining sites and asking miners at each one to identify other sites. As artisanal miners frequently move between different sites, this is likely to have resulted in a comprehensive set of mines in the areas covered.[20] The aggregate data we use are the union of all mines identified across 11 data collection waves. Data on Burkina Faso were gathered by a government contractor by first manually assessing satellite imagery and then following up with on-the-ground surveys at a selection of artisanal mining sites (Effigis, 2018). Appendix A.2.2 provides diagnostics on the quality and comprehensiveness of the training data.

Data on age and type of bedrock was compiled by the Geological Survey of Canada (Chorlton, 2007) and on presence of different surface rock types by the GLiM database (Hartmann and Moosdorf, 2012). Faults lines are from the Global Faults layer in ArcAtlas (Finko and Liouty, 2014). Electromagnetism is from the EMAG2 database (Maus, 2009).

We can only predict the feasibility of artisanal mining in areas on the 'common support': areas that have geological characteristics that also occur in areas where we have data on ASM. This holds for 78% of the continent of Africa: bedrock ages occurring in areas with ASM data cover 91% of the continent, bedrock type 98%, fault lines 100%, surface rock types 82%, and electromagnetism 89% the latter due to non-comprehensive flight paths of recording planes. See Appendix section A.1 for more detail.

Classifier

We split the ASM prediction problem into four independent prediction problems, one for each major commodity group extracted by artisanal miners: 2c (copper and cobalt), 3t (tin, tungsten and tantalum/coltan), gold and diamonds. For each commodity group an ensemble of random forest classifiers was trained using a two-step cross validation procedure which split

[20]IPIS does prioritize the most productive mines (e.g. those mines hosting the most workers if worker welfare is a key focus), and take accessibility into account.

the training by geography and stratified sampling, and optimized on F_1.[21] The procedure consisted of splitting the data into on several overlapping subsamples of the training data restricted to one side of a random latitude between the northernmost and southernmost points of our sample, and then selecting the best models for each subsample according to a simple cross-validation procedure on the sub-sample, and finally choosing the best performing model across subsamples (see Appendix section A.2). We employ this two-step cross validation to select a classifier that performs well when predicting out-of-latitude (see Appendix section A.3). The predictions from these models are aggregated so that a cell is classified as suitable for ASM if it is predicted to be so for any individual commodity group.[22]

Classification Performance

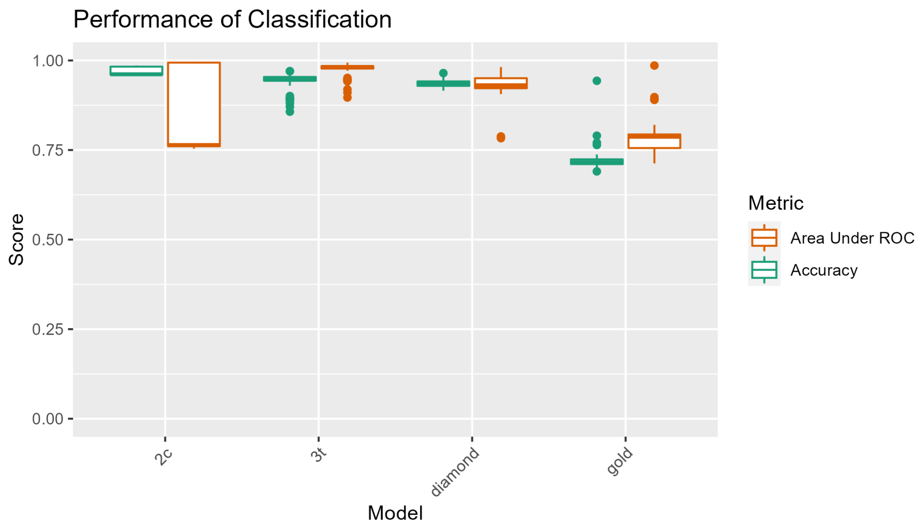
We reserve a 50% sample of the training cells stratified on our outcome variable to test the performance of the model out of sample. Figure 1 shows that all of the models except gold have a mean accuracy $\geq .93$. The mean area under the receiver operating curve (ROC-AUC) is similarly high. Gold is the lowest performing classifier, with accuracy of 0.72 (*s.d.* 0.04) and an ROC-AUC of 0.79 (*s.d.* 0.05). This is likely because there are multiple geological mechanisms which affect gold mining, making the prediction problem more difficult (Gosselin and Dubé, 2005). Inaccuracy should conform to standard measurement error and only bias against finding a treatment effect.

Our model's predictions of ASM suitability correlate to country-level data on ASM employment and production (see Appendix section A.4). Estimated correlation coefficients are between 0.59 and 0.69 and statistically significant at the 5% level or stricter.

[21] F_1 is the harmonic mean of precision and recall, written in terms of true-positive (TP), false-negative (FN) and false-positive (FP) rates as $\frac{TP}{TP+\frac{FP+FN}{2}}$. An ensemble was used to ensure the classification did not depend on the initial random state. See Section A.6.

[22] The splitting of the problem into individual subproblems and then aggregating via the maximum is a particularly simple version of a Mixture of Explicitly Localized Experts approach (Masoudnia and Ebrahimpour, 2014).

Figure 1: The performance of the individual commodity classifiers on test sets



Notes: Distribution of accuracy and ROC-AUC of commodity classification model on 50% test set across 50 different seed values. 2c represents copper and cobalt. 3t represents coltan (tantalum), tin, and tungsten.

Prices

We obtain data on the price of most commodities from the World Bank Commodity Markets Outlook. These data contains real year-average commodity prices for most commodities .[23] Data on the cobalt price stems from the IMF Primary Commodity Price System, unit values per ton for tungsten, manganese and coltan from the US Geological Survey (USGS), and a rough diamond price index from Bloomberg. These prices are converted to real prices using the weighting used in the World Bank data, and logged. Tungsten, manganese, tantalum and diamond prices are available for fewer years than other commodity prices.[24]

We assign to each $.25^{\circ} \times .25^{\circ}$ grid cell across the continent of Africa the price of the modal commodity mined in this cell, or zero if no mining takes place. Modal commodity mined by LSM is the commodity mined by the largest number of mines in the cell. The modal commodity mined by ASM is that commodity for which the cell as the highest suitability, as predicted by our machine learning classifier. In cells with LSM and ASM suitability, there

[23]Aluminum, coal, copper, gold, iron lead, nickel, phosphorus, platinum, tin, silver, zinc.

[24]Diamonds: 2004-2020, manganese: 1997-2014, coltan and tungsten: 1997-2016.

are two modal commodity prices if LSM and ASM do not mine the same modal commodity.

Figure B.1 displays commodity prices. While there are some shocks that affect multiple commodities simultaneously (e.g. around 2005-2006), many price shocks are idiosyncratic to individual commodities. Table B.1 gives summary statistics for commodity prices.

Other data

Data on industrial mining stems from the SNL Metals & Mining dataset, the successor to data used by Berman et al. (2017). This dataset records the location of known industrial mines, minerals mined, and (often) the name and country of registration of the most recent owner and operator of the site.[25] We aggregate mines to $.25^{\circ} \times .25^{\circ}$ degree grid cells. A grid cell is considered to contain a mine if there ever was an mine in the cell.

Conflict data stems from the Armed Conflict Location and Event Dataset (ACLED). Our main dependent variable is an indicator equalling one if there is any violent ACLED event in a given cell-year. We include all types of ACLED events except strategic developments: battles, violence against civilians, protests and remote violence.[26] We distinguish between ACLED events involving and not involving non-state armed groups.[27]

We capture heterogeneity of operator and owner companies, conditional on company name or country of registration being non-missing. We construct a proxy for company size, equal to the number of mines a named company owns on the African continent, and an indicator for a large company if this number is 10 or more. A number of variables capture the level of scrutiny a company is plausibly subject to. We fuzzy text-match company names to the BvD Orbis company database, and construct an indicator for whether a company is publicly traded. For companies with a non-missing country of registration, we construct the following indicators: registered in China, local – only registered in the same country as the

[25]Copyright © 2020, S&P Global Market Intelligence (and its affiliates, as applicable).

[26]We omit ACLED events with low levels of geographic precision (i.e. precision level 3).

[27]A non-stated armed group is any actor that is not "Civilians", "Rioters", "Protestors", "Military forces of [country]", "Police forces of [country]" or "Government of [country]".

mine –, registered in a tax haven according to the OECD Inclusive Framework against tax avoidance (BEPS)[28], and registered in a country adhering to the OECD Due Diligence Guidance for Responsible Supply Chains of Minerals from Conflict-Affected Areas(OECD+9).[29]

The level of analysis is the grid cell-year, between 1997 and 2020. Table B.2 presents summary statistics for all variables at the cell-year level.

Estimation

Our main estimation approach introduces our measure of the suitability of a cell for artisanal mining into a standard specification used to investigate the relationship between natural resources and conflict. The most broadly cited pieces in the literature estimate variations on this Linear Probability Model:

$$Y_{it} = \beta_1 \ln(LSMp_{it}) \times LSM_i + \gamma_i + \phi_{ct} + \epsilon_{it} \tag{1}$$

where Y_{it} is an indicator equalling one if there is violence in cell i in year t, LSM_i equals one if the cell has ever contained an industrial mine, and $\ln(LSMp_{it})$ equals the natural log of the price of the modal LSM commodity mined in the cell if it contains a mine, and zero otherwise. γ_i and ϕ_{ct} indicate cell and country-year fixed effects respectively. β_1 captures the effect of a commodity price increase on the probability that violence takes place in cells with a mine extracting that commodity, relative to cells mining other commodities.

However, if artisanal and industrial mining are spatially correlated, β_1 might be biased upwards. We therefore expand specification 1 as follows:

$$Y_{it} = \beta_1 \ln(LSMp_{it}) \times LSM_i + \beta_2 \ln(ASMp_{it}) \times ASM_i + \beta_3 \ln(p_{it}) \times LSM_i \times ASM_i + \gamma_i + \phi_{ct} + \epsilon_{it} \tag{2}$$

where ASM_i is an indicator equalling one if cell i is suitable for artisanal mining of one

[28] https://www.oecd.org/tax/beps/

[29] https://www.oecd.org/corporate/mne/mining.htm

or more of gold, diamond, 2c or 3t, as predicted by our machine learning classifier described in section . $LSMp_{it}$ ($ASMp_{it}$) is the price of the modal LSM (ASM) commodity in cell i (we show robustness to assigning the LSM price or ASM price to cells with both types of mining). We estimate Conley standard errors to account for potential spatial autocorrelation.

We hypothesize that β_3 is positive: a commodity price shock increases the probability of violent conflict more strongly in cells with both LSM and ASM, compared to cells LSM or ASM only, potentially reflecting violent LSM-ASM competition.

Results

Overlap between artisanal and industrial mining

There is substantial overlap between suitability for artisanal mining and the presence of industrial mining, and between the minerals mined by both where they co-occur (Appendix section B.3). Out of 31,959 cells across the African continent, 1,856 contain an industrial mine extracting one of the commodities we have price data for. Of cells with an industrial mine, 762 (41%) are also suitable for artisanal mining (Table 2).

Cells with industrial mining only are not just those cells in which some commodity other than gold, diamonds, 3T or 2C is mined. As we know from geology, these minerals can occur at different depths, so they might be accessible to artisanal miners in one cell, but inaccessible in another. Table 2 illustrates that over half of cells with industrial mining of gold, diamonds, 3T or 2C is not suitable for ASM.

Among cell-years with an industrial mine, conflict is more likely in those that are suitable for artisanal mining than in those that are not. The probability of conflict is 7.8% in the former, and 9.1% in the latter. The difference is strongly statistically significant ($t = 5.02$).

Main results

We first reproduce a now-standard analysis of the effect of industrial mining on conflict (specification 1), which suggests that an increase in the price of a given commodity is as-

Table 2: Overlap between presence LSM and ASM suitability

ASM suitable?	LSM present? Yes	LSM present? No	LSM modal mineral gold, diam., 2c or 3t? Yes	LSM modal mineral gold, diam., 2c or 3t? No	LSM of gold, diam., 2c or 3t present? Yes	LSM of gold, diam., 2c or 3t present? No
Yes	762	4529	601	161	615	147
No	1094	25574	713	381	742	352

Notes: unit of analysis is the cell level (N=31,959). Modal LSM mineral in a cell the mineral mined by the largest number of mines. LSM mining of a mineral is present in a cell if at least one LSM mine extracts this mineral.

sociated with an increase in conflict incidence in cells where this commodity is industrially mined. Column 1 of Table 3 shows that the interaction between modal commodity price and the presence of industrial mining is positively and significantly related to conflict risk. This effect is substantial in size: results in column 1 suggest that a one standard deviation increase in commodity price is associated with a 0.43 standard deviation increase in the probability of conflict in cells with an industrial mine extracting this commodity.

The association between industrial mining and conflict risk holds for the sub-sample of cells with requisite data on geology to support our ASM predictions (Table 3, column 2).

A large share of the association between industrial mining and conflict is driven by cells that are *also* suitable for artisanal mining. When estimating specification 2, the coefficient on ln LSM price $\times$ LSM almost halves: from 0.023 in column 2 to 0.012 in column 3 of Table 3. Column 3 suggests that a commodity price increase raises conflict incidence in cells with an industrial mine *and* potential for artisanal mining by more than three times as much as in cells with an industrial mine only: the effect of a one standard deviation commodity price increase on the probability of conflict is 0.81 standard deviations for cells with both types of mining, compared to 0.26 in cells with only industrial mining.

Column 3 of Table 3 suggest that a commodity price increase is not statistically significantly related to conflict risk in cells without an industrial mine, yet suitable for artisanal mining. The coefficient on ln ASM price $\times$ ASM is not statistically significant. However, the estimated effect is roughly commensurate with that observed in the literature, at 0.05 standard deviations (Blair et al., 2021).

We replicate Table 3 using data by Berman et al. (2017) (Appendix section D.7). Adding the indicator for ASM suitability roughly halves the predicted effect of a commodity price increase on the probability of conflict in cells with LSM only, and the effect on conflict in cells with both LSM and ASM suitability is 2.2 times as large. Although effects are not statistically significant, and should be taken with great caution given the small number of cells with LSM, they are consistent with our main results.

The result in column 3 is robust to assigning cells with LSM and ASM the modal ASM commodity price instead of the modal LSM commodity price (column 4).

Furthermore, we show that the effect of a commodity price increase on conflict risk is strongest for those cells where LSM and ASM mine the same commodity, as we would expect if this effect is driven by LSM-ASM conflict. Column 5 of Table 3 suggests that a one standard deviation increase in the commodity price is associated with a 0.97 standard deviation increase in the probability of conflict in cells where LSM and ASM mine the same mineral. By contrast, the same increase in the price of the modal ASM mineral is associated with a 0.64 standard deviation increase in conflict risk when modal minerals differ. The effect of an increase in the price of the modal LSM mineral on conflict in cells where LSM and ASM mine different minerals is not meaningfully different from that in LSM-only cells. These contrasting effects of an increase in the modal LSM and ASM mineral could be explained if ASM can more easily expand into territory covered by LSM than the other way around.

A back-of-the-envelope calculation suggests that artisanal-industrial mining conflict explains between 31 and 55% of the total observed effect of industrial mining on conflict. Let the model in Table 3 column 3 predict conflict in a cell-year if its predicted probability of conflict is higher than a cut-off, setting this cut-off such that the total predicted number of cell-years in conflict approximately equals the total according to ACLED. Given commodity prices between 1997 and 2020, the model predicts that 36,076 (out of 62,785) cell-years with an industrial mine experience conflict, of which 20,037 (out of 21,902) are cell-years also suitable for artisanal mining. If we ascribe all the latter conflict events to LSM-ASM conflict, this mechanism explains an upper bound of 55.4% of conflict in industrial mining cells. To get a lower-bound on the impact of LSM-ASM conflict, we can assume that the effect of industrial mining is the same in cells with and without artisanal mining. Using that approach, industrial mining can account for an estimated total of 8,648 of conflict cell-years with both types of mining.[30] This leaves a lower bound of 11,389 cell-years with conflict explained by LSM-ASM conflict, or 31.5% of cell-years with industrial mining and conflict. This range is the same regardless of whether we subtract conflict cell-years accounted for by cell and country-year fixed effects.

Heterogeneous effects

Heterogeneity by involvement of non-state armed groups

We have so far presented LSM-ASM conflict as an *alternative* mechanism which can help explain the observed correlation between natural resources and conflict, contrasting it with conflict relating to non-state armed groups. It seems plausible that the two mechanisms are distinct, as 85% of industrial mines suitable for artisanal mining are located outside of 'conflict zones' where non-state armed groups are active (Kikuta, 2022). But it is also possible that non-state armed groups play a role in LSM-ASM conflict. They could mine on industrial sites, facilitate access to such sites, or tax artisanal miners operating such sites.

Table 4 distinguishes between violent events that do and do not involve a non-state armed group. Results suggest that a one standard deviation commodity price increase in LSM-ASM cells has a greater effect on the probability of conflict *without* non-state armed actors – an increase of more than a full standard deviation (columns 1 and 2) – compared to conflict *with* non-state armed actors – an increase of between 0.36 and 0.40 standard deviations (columns 3 and 4). This holds regardless of whether we investigate a price shock to the modal mineral mined by ASM or LSM. Although the effect sizes are smaller, commodity price shocks do statistically significantly affect the probability of conflict with non-state armed groups. This may indicate armed group involvement in LSM-ASM conflict, or reflect

[30] Artisanal mining by itself does not account for any cells in conflict using this approach.

Table 3: Main results

	(1) acled>0	(2) acled>0	(3) acled>0	(4) acled>0	(5) acled>0
ln LSM price × LSM	0.021***	0.023***	0.012***	0.015***	0.012***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
ln ASM price × ASM			0.002	0.002	0.002
			(0.002)	(0.002)	(0.002)
ln LSM price × LSM × ASM			0.024***		
			(0.007)		
ln ASM price × LSM × ASM				0.019***	
				(0.006)	
ln ASM price × LSM × diff. ASM					0.012
					(0.009)
ln LSM price × LSM × diff. ASM					-0.001
					(0.011)
ln price × LSM × same ASM					0.032***
					(0.008)
Country-year FEs	Yes	Yes	Yes	Yes	Yes
Grid FEs	Yes	Yes	Yes	Yes	Yes
Control mean	0.039	0.039	0.039	0.039	0.039
Total stand. effect	0.432	0.487	0.813	0.880	0.969
Sample	All	\w geo data	\w geo data	\w geo data	\w geo data
Observations	1080328	825583	823469	823469	823469

Notes: Dependent variable in all columns is an indicator equalling one if there is one or more ACLED violent events in a cell-year. "ln LSM price" ("ln ASM price") is the natural log of the price of the modal LSM (ASM) commodity in the a cell, and equals zero if there is no LSM (ASM) in the cell. Modal LSM commodity is the commodity mined by the greatest number of mines in a cell. Modal ASM commodity is the commodity (gold, diamonds, 3t or 2c) with the highest predicted ASM suitability. For 3t and 2c minerals, price is the simple average of prices of tin, tantalum and tungsten, and copper and cobalt respectively. "LSM" is an indicator equalling one if there was ever LSM in a cell, and "ASM" equals one if the cell is predicted to be suitable for ASM mining of one or more of gold, diamonds, 3t or 2c minerals. "diff. ASM" ("same ASM") is an indicator equalling one if ASM mines a different (the same) modal commodity than LSM. "Total stand. effect" is the effect of a one standard deviation increase in commodity price on the probability of conflict in cells with LSM and ASM (in cells with LSM for columns 1 and 2), expressed in standard deviations of the probability of conflict in cells without mining. This aggregates effects captured by all coefficients in each regression, except for column 5, which aggregates the effects captured by "ln LSM price × LSM", "ln ASM price × ASM" and "ln price × LSM × same ASM". Columns 2-5 restrict the sample to cells with geological data, allowing prediction of ASM suitability. Sample size is smaller in columns 3-5 than in column 2, as more cells are assigned a commodity price, which may be missing for some years. This does not drive the main results (see Appendix Table **??**). Conley standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

(mis)coding of groups of artisanal miners as organized armed actors. Appendix Tables C.11 and C.12 explore further heterogeneity by ACLED event type.

Heterogeneity by company type

An important question for policy is whether certain kinds of companies experience higher levels of industrial-artisanal miner conflict than others. We may think, for example, that industrial mining companies that are more subject to scrutiny have a greater incentive to manage conflict with artisanal miners peacefully. We find some evidence for this supposition.

Table 4: Heterogeneity by involvement non-state armed groups in violent events

	Without non-state armed actors		With non-state armed actors	
	(1)	(2)	(3)	(4)
	acled>0	acled>0	acled>0	acled>0
ln LSM price × LSM	0.018***	0.020***	0.002	0.003
	(0.004)	(0.003)	(0.003)	(0.003)
ln ASM price × ASM	0	0	0.002	0.002
	(0.002)	(0.001)	(0.002)	(0.002)
ln LSM price × LSM × ASM	0.017***		0.011**	
	(0.006)		(0.005)	
ln ASM price × LSM × ASM		0.013**		0.009*
		(0.005)		(0.004)
Country-year FEs	Yes	Yes	Yes	Yes
Grid FEs	Yes	Yes	Yes	Yes
Control mean	0.019	0.019	0.026	0.026
Total stand. effect	1.016	1.077	0.364	0.404
Sample	\w geo data	\w geo data	\w geo data	\w geo data
Observations	823469	823469	823469	823469

Notes: Non-state actors are all actors that are not “Civilians”, “Rioters”, “Protesters”, “Military forces of [country]”, “Police forces of [country]” and “Government of [country]”. Otherwise as Table 3. Conley standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

For example, publicly traded companies could be subject to scrutiny from shareholders, and companies in countries adhering to the OECD Due Diligence Guidance for Responsible Supply Chains of Minerals from Conflict-Affected Areas might also face stronger scrutiny compared to companies elsewhere. Conversely, Chinese companies, companies in tax havens or local companies may be subject to less scrutiny.[31]

Table 5 investigates whether the effect of a commodity price increase on violence in cells with potential for LSM-ASM conflict is stronger for certain types of industrial mine owners. Since proxies for scrutiny can only be constructed for companies with a non-missing name (for publicly traded) and country of registration (for all other indicators), we add interactions with a dummy variable indicating the relevant information is non-missing, in addition to interactions with an indicator whether a given company type is present in each cell.[32] As

[31]Chinese companies are frequently scrutinized for lack of Corporate Social Responsibility reporting (Dong et al., 2014). Local companies are subject to scrutiny in only one jurisdiction, as opposed to at least two for foreign companies.

[32]Of our 1,856 cells with industrial mining activity and ASM predictions, 65.9% have a

companies may endogenously seek out more peaceful or violent places, these results should not be directly interpreted as causal evidence.

Table 5: Heterogeneity by company owner type

	(1) public	(2) tax haven	(3) local	(4) Chinese	(5) OECD+9
ln LSM price × LSM	0.006	0.004	0.004	0.004	0.004
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
ln LSM price × LSM × non-miss	0.006	0.018**	0.019**	0.018**	-0.006
	(0.009)	(0.008)	(0.009)	(0.008)	(0.011)
ln LSM price × LSM × non-miss & ...	0.007	0.002	-0.006	0.010	0.031***
	(0.010)	(0.028)	(0.014)	(0.024)	(0.012)
ln ASM price × ASM	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln LSM price × LSM × ASM	0.023**	0.031***	0.030***	0.031***	0.031***
	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)
ln LSM price × LSM × ASM × non-miss	0.007	-0.018	-0.031**	-0.019	0.038*
	(0.016)	(0.013)	(0.014)	(0.013)	(0.022)
ln LSM price × LSM × ASM × non-miss & ...	-0.011	0.040	0.105***	0.111**	-0.068***
	(0.017)	(0.041)	(0.032)	(0.053)	(0.024)
Country-year FEs	Yes	Yes	Yes	Yes	Yes
Grid FEs	Yes	Yes	Yes	Yes	Yes
Control mean	0.039	0.039	0.039	0.039	0.039
Sample	\w geo data	\w geo data	\w geo data	\w geo data	\w geo data
Observations	823469	823469	823469	823469	823469

Note: "public" indicates that at least one company owning a mine in the cell is publicly traded, "tax haven" – registered in a country with tax avoidance according to the OECD BEPS, "local" – exclusively registered in the country in which the mine it owns is located, "Chinese" – registered in China, "OECD+9" – registered in a country signatory to the OECD Due Diligence Guidance for Responsible Supply Chains of Minerals from Conflict-Affected Areas. Note that "public" is only available if company name is non-missing in SNL, and the remaining variables are only available if the country of registration is non-missing - "non-miss." equals one if this is the case in the respective columns. Otherwise as Table 3. Conley standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

More intensely scrutinized companies appear to be associated with less LSM-ASM conflict. While the quadruple interaction term in column (1) of Table 5 is not statistically significant, coefficient sizes imply that a commodity price increase leads to 2.5 times more conflict in LSM-ASM cells with non publicly traded named companies, compared to publicly traded named companies.[33] The effect size for named companies in tax havens is 5.5 times

named owner, of which 54% is publicly traded. 48.6% of owners have a non-missing country of registration, of which 5.1% is in a tax haven, 21.8% is local, 3.1% is in China and 74.3% in an OECD+9 country.

[33] The relevant comparison is: $\frac{\text{ln LSM price}\times\text{LSM}\times\text{ASM}+\text{ln LSM price}\times\text{LSM}\times\text{ASM}\times\text{non-miss}}{\text{ln LSM price}\times\text{LSM}\times\text{ASM}+\text{ln LSM price}\times\text{LSM}\times\text{ASM}\times\text{non-miss \& public}}$.

as large (column 2, not statistically significant), and 11.8 times as large for Chinese companies (column 4, statistically significant). From columns (3) and (5), which show statistically significant results, LSM-ASM conflict upon an increase in the resource price appears to be entirely driven by local, and non-OECD+9 registered companies respectively.

Results for publicly traded, tax haven-registered, Chinese and local companies are unlikely to be driven by endogenous company sorting. There is no evidence that publicly traded or Chinese companies seek out more violent mines on average, and if anything, tax haven-registered and locally-registered companies seek out less violent mines. Results for OECD+9 companies may be driven by endogenous company sorting however.[34]

Appendix section C.1 provides robustness checks. We observe heterogeneous effects for operators in similar directions as for owners (Appendix table C.1) but coefficients are not statistically significant and results do not hold for OECD+9 companies. Results are similar or stronger when assigning the ASM price to cells with both types of mining, and when controlling for company size (Appendix tables C.2, C.3, C.6, C.7). We observe no heterogeneity by company size or by companies having a non-missing name or country of registration (Appendix tables C.4, C.5, C.8, C.9).

Heterogeneity by commodity type

We also explore heterogeneity by commodity type. The effect of a commodity price increase on violence in cells with an industrial mine and suitable for artisanal mining is primarily driven by gold, 2c and 3t minerals. This corroborates case study evidence of industrial-artisanal miner conflict over gold and copper-cobalt, and is noteworthy given the International Energy Agency (2021) estimates that from 2020 to 2040, the clean energy transition will increase demand for copper by 1.3-2.7 times and cobalt by 6.3-30.9 times. It further

[34] The average number of violent events within a 5 kilometer radius is 0.42 (0.48) for publicly registered (non-publicly registered), 0.25 (0.46) for tax haven-registered (non-tax haven-registered), 0.28 (0.43) for locally-registered (foreign-registered), 0.48 (0.45) for Chinese (non-Chinese) and 0.38 (0.52) for OECD+9-registered (non-OECD+9) companies.

suggests that there is little LSM-ASM conflict over diamonds, consistent with the stylized fact that industrial mining focuses on primary diamonds and artisanal miners on secondary diamonds, which rarely co-occur geographically (Rigterink, 2020) (see Appendix section C.2).

Robustness

Appendix D shows that main results survive an array of robustness checks to address potential concerns about endogenous prices or the construction choices of key variables.

Conclusion

In this paper, we identify a new mechanism which contributes to the commonly observed correlation between industrial mining and conflict: violent competition between industrial and artisanal miners. Our methodology combines qualitative-based theory building with quantitative hypothesis testing in collaboration with civil society researchers. Using case studies, we illustrate how such competition can lead to violence. Results from a large-N analysis across the continent of Africa suggest that, when the price of a commodity increases, violence increases significantly more in cells with an industrial mine which are suitable for artisanal mining than in cells with only artisanal or only industrial mining. This suggests that artisanal-industrial conflict is an important driver of extractives-related violence.

Our results have implications for research on mining and violent conflict. First, results suggest that such studies should control for artisanal mining, as this is a potential omitted variable. Second, we should be careful to interpret a correlation between an increase in the price of an industrially mined commodities and violent conflict as evidence that rebel groups fight each other or the government over control of mining sites. A substantial share of this correlation may in fact be due to industrial-artisanal miner conflict.

If competition between industrial and artisanal miners is behind some of the conflict around mining sites, this offers new avenues for conflict-mitigation. Thus far, the most prominent conflict-mitigation tool has been to restrict or create transparency around the sale of commodities that are suspected of funding rebel groups (e.g. The Kimberley Process Certification Scheme and the Dodd-Frank act section 1502). LSM-ASM competition however, adds a different set of tools to the conflict-mitigation toolbox.

First, national governments may try and diminish direct competition by reserving separate zones for artisanal miners. For these to successfully mitigate violent conflict, mining in these zones needs to be more attractive to artisanal miners than mining on industrial mining sites. Second, peaceful cooperation between industrial and artisanal miners may be possible. Giant mine in Zimbabwe is an example of such a cooperation that was at least temporarily successful, and it has been successful elsewhere, e.g. in Colombia (OECD, 2017). Industrial mining sites are often extremely large, and not all parts of it viable for industrial mining, allowing for 'ASM-tolerant zones' (Stoop and Verpoorten, 2021). It may even be profitable for industrial mining companies to subcontract to artisanal miners. A major barrier to such cooperation is the bad reputation of artisanal mining. Hence, industrial mining corporations are rightfully weary of damage to their reputation if they were to cooperate with artisanal miners, or alternatively, of high costs of enforcing labour and environmental standards. A combination of measures might lower this barrier: organization of artisanal miners into cooperatives that are easier to monitor; regulation and scrutiny of such cooperatives by governments and NGOs; and more public awareness of the positive contribution that artisanal mining makes to livelihoods in developing countries.

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References

AfDB, African Natural Resources Center (2016). Catalysing growth and development through effective natural resources management.

Agency, International Energy (2021). *The role of critical minerals in clean energy transitions.* OECD Publishing.

Bazillier, Remi and Victoire Girard (2020). The gold digger and the machine. Evidence on the distributive effect of the artisanal and industrial gold rushes in Burkina Faso. *Journal of Development Economics 143*(August 2019), 102411.

Berman, Nicolas , Mathieu Couttenier, Dominic Rohner, and Mathias Thoenig (2017). This mine is mine! How minerals fuel conflicts in Africa. *American Economic Review 107*(6), 1564–1610.

Blair, Graeme , Darin Christensen, and Aaron Rudkin (2021). Do Commodity Price Shocks Cause Armed Conflict? A Meta-Analysis of Natural Experiments. *American Political Science Review 115*(2), 709–716.

Bradley, Dwight C. , Andrew D. McCauley, and Lisa M. Stillings (2010). Mineral-Deposit Model for Lithium-Cesium- Tantalum Pegmatites.

Bush, Ray (2009, 3). 'soon there will be no-one left to take the corpses to the morgue': Accumulation and abjection in ghana's mining communities. *Resources Policy 34*, 57–63.

Chorlton, L.B. (2007). Generalized geology of the world. Bedrock domains and major faults in GIS formate.

Christensen, Darin (2019). Concession Stands: How Mining Investments Incite Protest in Africa. *International Organization 73*(1), 65–101.

Collier, Paul and Anke Hoeffler (2004). Greed and grievance in civil war. *Oxford Economic Papers 56*(4), 563–595.

Cox, Dennis P , David A Lindsey, Donald A Singer, Barry C Moring, and Michael F Diggles (2007). Sediment-Hosted Copper Deposits of the World: Deposit Models and Database.

Dong, Shidi , Roger Burritt, and Wei Qian (2014). Salient stakeholders in corporate social responsibility reporting by chinese mining and minerals companies. *Journal of Cleaner Production 84*, 59–69.

Effigis (2018). Cartographie des principaux sites miniers artisanaux. Technical report, Projet d'Appui au Developpement du secteur minier du Burkina Faso (PADSEM).

Fearon, James D. and David D. Laitin (2003). Ethnicity, insurgency, and civil war. *American Political Science Review 97*(1), 75–90.

Finko, E.A. and A. A. Liouty (2014). Global Faults layer from ArcAtlas (ESRI).

Gilmore, Elisabeth , Nils Petter Gleditsch, Päivi Lujala, and Jan Ketil Rød (2005). Conflict diamonds: A new dataset. *Conflict Management and Peace Science 22*(3), 257–272.

Gosselin, P and B Dubé (2005). Gold deposits of the world: distribution, geological parameters and gold content.

Green, Carlin J. , Graham W. Lederer, Heather L. Parks, and Michael L. Zientek (2020). Grade and Tonnage Model for Tungsten Skarn Deposits.

Hartmann, Jens and Nils Moosdorf (2012). The new global lithological map database GLiM: A representation of rock properties at the Earth surface. *Geochemistry, Geophysics, Geosystems 13*(12), 1–37.

Hilson, Gavin (2016). Farming, small-scale mining and rural livelihoods in Sub-Saharan Africa: A critical overview. *Extractive Industries and Society 3*(2), 547–563.

Hilson, Gavin and Johanna Carstens (2009). Mining, grievance and conflict in rural tanzania. *International Development Planning Review 31*, 301–326.

Humphreys, Macartan (2005). Natural resources, conflict, and conflict resolution: Uncovering the mechanisms. *Journal of Conflict Resolution 49*(4), 508–537.

Hund, Kirsten , Daniele La Porta, Thao P Fabregas, Tim Laing, and John Drexhage (2020). Minerals for climate action: the mineral intensity of the clean energy transition. Technical report, The World Bank.

Jensen, Christian , Michelle Kuenzi, and Moritz Rissman (2017). Does crime pay enough? Diamond prices, lootability and ethnic war. *Journal of Conflict Management 5*(1), 6–23.

Kamilli, Robert J. , Bryn E. Kimball, and James F. Carlin Jr. (2017). Tin.

Kikuta, Kyosuke (2022). A new geography of civil war: A machine learning approach to measuring the zones of armed conflicts. *Political Science Research and Methods 10*(1), 97–115.

Marshall, T. R. and R. Baxter-Brown (1995). Basic principles of alluvial diamond exploration. *Journal of Geochemical Exploration 53*(1-3), 277–292.

Masoudnia, Saeed and Reza Ebrahimpour (2014). Mixture of experts: A literature survey. *42*(2), 275–293.

Maus, S., et al. (2009). EMAG2: A 2-arc min resolution Earth Magnetic Anomaly Grid compiled from satellite, airborne, and marine magnetic measurements. *Geochemistry, Geophysics, Geosystems 10*(8).

OECD (2017). Due Diligence in Colombia's Gold Supply Chain. Technical report, OECD.

Parker, Dominic P. , Jeremy D. Foltz, and David Elsea (2016). Unintended Consequences of Sanctions for Human Rights: Conflict Minerals and Infant Mortality. *The Journal of Law and Economics 59*(4), 731–774.

Rigterink, A.S. (2020). Diamonds, Rebel's and Farmer's Best Friend: Impact of Variation in the Price of a Lootable, Labor-intensive Natural Resource on the Intensity of Violent Conflict. *Journal of Conflict Resolution 64*(1), 90–126.

Romero, Mauricio and Santiago Saavedra (2019). The effects of gold mining on Newborns' Health.

Sexton, Renard (2020). Unpacking the Local Resource Curse: How Externalities and Governance Shape Social Conflict. *Journal of Conflict Resolution 64*(4), 640–673.

Stoop, Nik and Marijke Verpoorten (2021, 7). Would you fight? we asked aggrieved artisanal miners in eastern congo. *Journal of Conflict Resolution 65*, 1159–1186.

Stoop, Nik , Marijke Verpoorten, and Peter van der Windt (2019). Artisanal or industrial conflict minerals? Evidence from Eastern Congo. *World Development 122*, 660–674.

World Bank, DC (2020). *2020 State of the Artisanal and Small-scale Mining Sector*.

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