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Nothing Gold Can Stay: Artisanal Mine Certifications and Conflict Dynamics in the Congo

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Nothing Gold Can Stay: Artisanal Mine Certifications and Conflict Dynamics in the Congo

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Abstract: We examine how conflict-free certifications for artisanal mines—used to comply with provision 1502 of the Dodd-Frank Act—affect conflict dynamics in the Eastern Democratic Republic of the Congo (DRC). Certifications are associated with a 9.4% (16.3%) reduction in armed group–initiated conflicts (fatalities) within a 10-kilometer radius of gold mines. After certifications, there is no aggregate reduction in conflict intensity in Eastern DRC territories, but conflicts intensify further away from certified mines, consistent with certifications displacing, not reducing, conflicts. These findings caution that, rather than being relied on as an exclusive solution, certification programs must be part of a concerted effort toward resolving complex geopolitical challenges, such as the humanitarian crisis in the DRC.

Keywords: Conflict-free certification, conflict, armed groups, artisanal mining, mineral supply chain, supply chain due diligence, Democratic Republic of the Congo, DRC, Dodd-Frank Act Provision 1502.

JEL Classification: D74; E26; G18; G38; K22; K23; M42; M48; N47; N57; O13; Q34; Q38

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1. Introduction

Mineral purchases by multinational corporations from artisanal and small-scale mining operations have long been accused of financing armed groups in conflict-affected regions (Berman et al., 2017; Christensen, 2019).[1] The Eastern Democratic Republic of the Congo (DRC) serves as a prominent example, with an artisanal mining sector employing over two million individuals and a decades-long conflict regarded as the bloodiest since World War II. Both policy efforts within the DRC and diplomatic efforts supported by the international community have seen limited success in resolving the conflict and attenuating the unfolding humanitarian tragedy. In response to this impasse, Western powers recently introduced supply-chain due-diligence requirements for corporate mineral users in an effort to curtail the flow of money to armed groups.[2] These programs attempt to "trace the origins of minerals, certify minerals as conflict-free, and to improve mining communities' livelihoods while reducing human rights abuses in conflict affected and high-risk areas" (Jaillon et al., 2019, p. 5). A crucial component of these initiatives involves the certification of mines in the African Great Lakes Region, specifically in the Eastern DRC, as conflict-free (Schütte, 2018). This paper examines the impact of artisanal and small-scale mine conflict-free certifications on conflict dynamics in the Eastern DRC.

Whether artisanal and small-scale mine certifications reduce or increase conflict is conceptually unclear. A certification scheme holds the potential to mitigate conflicts by guaranteeing regular audit visits for certified mines. Mines lose their certified status if armed groups are detected at or around the mine site,

[1] For additional institutional details on artisanal mining and its role in financing militant group operations, see (Internet Appendix) Section IA2.

[2] These Western initiatives include the Dodd-Frank Act Provision 1502 in the United States and Regulation (EU) 2017/821 in the European Economic Area. The minerals covered by these regulations (i.e., gold, tin, tantalum, and tungsten) are used in everyday products such as mobile phones, cars, and jewelry.

forcing them to illegally sell minerals at a lower price (Alusala, 2017; Childs, 2014). Since armed groups attain income from taxing mine proceeds, certifications create an incentive for a local reduction in conflict.

Even if the certification scheme is effective in reducing conflict intensity around mines, armed groups can relocate, raising concerns that even an effective conflict-mineral certification scheme may simply displace the conflict to uncertified areas. This displacement is likely because minerals are not the underlying source of the conflict (Jaillon et al., 2019; Hanai, 2021). The political, ethnic, and institutional reasons for the ongoing conflict will likely persist even if the artisanal mining sector ceases to provide direct financing to armed groups (Laudati, 2013). We formalize the intuition for this argument using a stylized model, discussed in Section 2.3 and presented in (Internet Appendix) Section IA1. The conceptually unclear implications of certifications should make empirical evidence of interest to policymakers, as shifting conflicts away from mining areas and more broadly reducing conflicts have distinct political and economic implications.[3]

To assess the impact of mine certification, we examine the effect of artisanal mine certifications on conflict intensity in the vicinity of certified mines and on the geographic displacement of conflicts. We first focus on conflicts (i.e., battles, violence against civilians, and riots) in the 10-kilometer area immediately surrounding certified mines as well as around villages within 10 kilometers of certified mines. Then, we expand our analysis by examining potential conflict displacement from certified mining areas toward uncertified and non-mining areas.

To examine changes in conflict incidences near artisanal mines, we exploit the fact that only a subset of artisanal mines in the DRC is certified. An empirical

[3] There is also an argument that increased regulation could plausibly increase the need for "protection," a major source of revenue for many armed groups including the armed forces of the DRC (Laudati, 2013). In this case, the overall conflict level in the DRC could increase due to conflict minerals regulation.

challenge is that, even though mines are selected for certification by the provincial government as opposed to mine owners, selection is not random. We address this issue by showing that prior conflict levels and local economic characteristics do not explain certification selection within territory.

We first estimate the treatment effect for areas around a certified mine benchmarked against a control sample of non-certified mining areas in the same territory. Over a six-year period following the initial certification visit, we find a gradual decrease in conflict incidence at both the mine and village level for gold mines.[4] This decrease amounts to a 9.4% decline in the probability of conflict in the 10-kilometer radius around a certified gold mine and a 2.6% decline in the probability of conflict in a village within 10 kilometers of a certified gold mine, though the latter effect is statistically insignificant. Although we find an effect for gold mines and villages close to gold mines, we find no corresponding decrease for tin, tantalum, and tungsten (3T) mines and villages close to 3T mines. One potential explanation is that several private certification schemes (e.g., CFSI, CTC, and iTSCi) existed for 3T minerals prior to the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act), which may have been successful in reducing conflict around 3T mining areas.[5] However, regulation of gold mining and exports is more difficult due to the elevated opportunity for smuggling, taxation, and other illicit activity (Lezhnev & Prendergast, 2009; Parker & Vadheim, 2017).

Because we anticipate that the reduction in conflict near gold mines is caused by the diminished ability of armed groups to obtain revenue from

[4] Assuming that provincial governments cannot predict future changes in local conflict, the timing of the treatment effect is inconsistent with selection explaining our results. Given the logistical challenges of carrying out inspection missions, there is likely a significant delay between provincial government selection and inspections. Yet, none of our results materialize prior to the initial inspection.

[5] These certification schemes are documented in detail in Baik et al. (2023). They are each schemes run by private research or nonprofit organizations with various due-diligence objectives.

controlling mines, we expect that the greatest reduction occurs for conflict types originating in armed-group activity. Following the extant literature, we separate conflicts into battles and violence against civilians, which are initiated by armed groups, and riots, which are initiated by civilians (Berman et al. 2017; Stoop et al., 2018; Christensen, 2019). Over a six-year period after the initial certification visit, we find a gradual decrease in both battles and violence against civilians around gold mines, though the effect is stronger for battles. The estimated effect amounts to a 7.5% decline in the probability of battles in the 10-kilometer radius around a certified gold mine and a 3.0% decline in the probability of battles in a village within 10 kilometers of a certified gold mine, though the latter effect is statistically insignificant. Additionally, around gold mines we find a 16.3% decrease in deaths from all conflicts and a 14.2% decrease in deaths from battles, corresponding to effect sizes of 0.39 and 0.20 deaths per certified mine-year, respectively.[6]

To triangulate the potential geographic displacement of conflict, we explore (1) territory-level aggregated data, (2) distance between a mine and the closest conflict, and (3) conflicts farther from certified mines. For the territory-level analysis, we aggregate mine certifications and conflicts to the territory level and show that a higher count or proportion of mines certified in a territory does not decrease any type of conflict or fatalities. Instead, we find weak evidence of a small increase for territories with a higher count or proportion of certified gold mines. Consistent with reduced conflicts around certified mines but no effect at the territorial level, we find evidence of an 18.3% increase in the distance from a certified mine to the nearest conflict and a 12.1% increase in the distance to the nearest battle, corresponding to effect sizes of 8.98 and 8.04 kilometers, respectively. Next, directly supporting the displacement hypothesis, we document

[6] Using deaths as a dependent variable alleviates concerns of reporting bias, as conflicts involving one or more deaths are more likely to be consistently and comprehensively reported by local media, from which our data is compiled.

a 2.6% increase in the probability of conflict and a 2.7% increase in the probability of battles after certification for uncertified mining villages 50 to 100 kilometers from certified villages but no such increase for non-mining villages.

Overall, our results show that artisanal gold mine certifications in the Eastern DRC are associated with a decrease in conflict intensity in the area immediately surrounding the certified mine and in villages proximal to certified gold mines, but there is no effect for 3T mines. This decrease in conflict near gold mines comes not from an overall improvement in safety within the Eastern DRC but rather from a displacement of conflict from certified mines toward surrounding uncertified mining areas.

These findings contribute most directly to the literature on the impact of Dodd-Frank Provision 1502 on conflict in the DRC. Current scholarship on the effects of this provision on conflicts has arrived at mixed conclusions. On the one hand, Parker and Vadheim (2017) and Stoop et al. (2018), focusing on Eastern DRC after the enactment of Dodd-Frank in 2010, observe an increase in conflict incidents in mining areas subject to Provision 1502. On the other hand, Baik et al. (2023) attend to the SEC's implementation of Dodd-Frank Provision 1502 in 2014 (rather than its enactment in 2010), finding conflict reduction in areas with 3T mines and increase in areas with gold mines.[7] The authors suggest that the dispersed gold market and the potential for gold smuggling might explain the opposing trends. Our research focuses on the certification of mines between 2011 and 2019 rather than on the enactment in 2010 or implementation in 2014 of Provision 1502. SEC registrants use the certification program to fulfill the due-diligence requirements stipulated by Dodd-Frank, but certifications provide a much narrower context with which to pinpoint the conflict dynamics. Rather than contradicting prior findings

[7] Baik et al.'s (2023) main analysis focuses on a broader geographical area and finds evidence of a decrease in conflict incidents in extraction areas within the DRC and neighboring countries (which are subject to Provision 1502) compared to other African extraction areas.

for 3T mines, our results represent an additional improvement for gold mines realized from the local certification system, which is better equipped to capture local conditions and regulate illicit behavior. Conversely, the null effect we find for 3T mines could be due to the success of past endeavors for areas surrounding 3T mines, some documented in the studies above, leaving limited potential for improvement at the time of the certification visit.[8] We also provide evidence of the geographic displacement of conflicts, which sheds light on the limited success of local and global due-diligence requirements in resolving the ongoing conflict.

We also contribute to the literature on mineral-certification schemes in developing nations. Martinez et al. (2022) explore voluntary artisanal gold certifications in Peru, and Binzel et al. (2023) examine large-scale diamond certification and armed conflicts in Africa. Similar to us, they find improvements in mining practices and reductions in conflict after certification schemes.[9] However, we also uncover the displacement of conflicts toward surrounding areas, which raises concerns about the overall impact of certification on conflict intensity in the DRC. Mineral extraction may be a source of financing for some armed groups in the DRC, but it is not the ultimate reason for the long-standing conflict. Although certification schemes have been successful in previously studied settings, our results illustrate that certifications may displace conflict away from certified mining areas toward non-certified areas rather than reducing aggregate conflict. From a

[8] Supporting our mineral type hypothesis, a recent IPIS report (Matthysen & Gobbers, 2022, p. 30) states the following: "Most stakeholders agree that responsible sourcing efforts have achieved considerable progress, and that the security situation in 3T mining has improved. But more isolated zones, and gold mining remain problematic."

[9] There is a broader certification literature that primarily focuses on the verification of corporate information through financial audits (see review by DeFond & Zhang, 2014) and disclosure certification (Jiang et al., 2023), but the economics and accounting literatures have also explored different contexts such as environmental information (Choy et al., 2023), restaurant hygiene (Jin & Leslie, 2003), crowdfunded projects (Yu & Xiao, 2023), and forestry (Bocci & Fortmann, 2023). These studies generally indicate that certifications have a positive effect on the observed outcomes, either financially or operationally, but it is a priori unclear whether such findings extend to conflict-free certifications of mines.

policy perspective, we caution that, rather than being relied on as an exclusive solution, certification programs must be part of a concerted effort toward resolving complex geopolitical challenges.

2. Institutional Details and Their Connection to the Research Design

Estimating the local impact of conflict-free mine certifications on conflict intensity is challenging because of numerous concurrent events and the potential for conflict displacement rather than resolution. We address these challenges by exploiting highly geographically localized variation in conflict intensity in mining areas purged for aggregate effects and, in separate analyses, variation in conflict intensity at the more aggregated territorial level. In this section, we lay out the institutional details that support our identification assumptions and provide a context in which to interpret our evidence.

2.1 History of Conflict in the DRC

With a land area of almost 2.35 million square kilometers, the DRC is more than three times the size of Texas and approximately the size of Western Europe. Boasting 80 million hectares of arable land and a diverse range of valuable minerals such as diamonds, gold, copper, coltan (tantalum), tin, and lithium, the DRC possesses the potential to be a prosperous nation. However, in contrast to such wealth, the DRC is home to an estimated 90 million individuals who are among the world's poorest and have endured unimaginable suffering for several decades. Termed in the literature (Auty, 1993; Sachs & Warner, 1995) as "the resource curse," weak political institutions, flagrant corruption, and active armed groups have been blamed for the inconsistency between natural endowments and living conditions (e.g., Mehlum et al., 2006; Robinson et al., 2006; Humphreys et al., 2007; Sarr et al., 2011). At the center of the conflict in the DRC are the six far eastern provinces (Haut-Uele, Ituri, North Kivu, South Kivu, Tanganyika, and Haut Katanga) and, to a lesser extent, the five neighboring provinces (Bas-Uele, Tshopo, Maniema, Haut-

Lomami, and Lualaba). These areas are mostly under shifting control by various warlords, and the DRC government located in the far western capital of Kinshasa has little control over the territory or even its own federal military personnel stationed in the area. Figure 1 Panel A shows the geographic intensity of conflict across DRC provinces measured as the total number of conflict incidences from 2004 through 2022. This figure illustrates that the conflict is most intense in the eleven provinces in the eastern DRC and, even within these provinces, is clustered in the easternmost territories.

Complicating any resolution of the conflict, neighboring countries to the east have repeatedly interfered in the DRC conflict—meddling that climaxed with the presence of military factions associated with nine countries during the Second Congo War (a.k.a., Africa's Great War), which officially ended with a ceasefire in 1996. Despite this ceasefire, however, conflict and political unrest have continued without any credible evidence of diminishing intensity. Recognizing the unfolding humanitarian catastrophe, Western powers—led by the United States, France, and the United Kingdom—have taken various initiatives to pacify the conflict. These initiatives include providing humanitarian aid, diplomatically supporting peace negotiations, advocating for political stability in the region, maintaining one of the largest UN peacekeeping operations in the world, and imposing sanctions on individuals counteracting peace efforts. These initiatives have all had limited and/or short-lived success and seen no permanent improvements.

Though mining operations have been shown to increase conflict in Africa (Berman et al., 2017; Christensen, 2019), most observers and researchers agree that the persistent conflict in the DRC is not solely caused by its mineral endowment (e.g., Laudati, 2013; Hanai, 2021). Indeed, the causes are myriad and complex, including issues such as land rights (ownership and access), ethnic conflicts, and political struggles for power and influence (e.g., Vlassenroot & Raeymaekers, 2004;

Verweijen & Brabant, 2017).[10] While mineral extraction is a source of financing for some of the estimated 120 armed groups, other sources of income include illegal taxation at roadblocks, taxation of fishing and agriculture, kidnapping for ransom, illicit logging of redwood, and leasing agricultural land (Matthysen & Gobbers, 2022). However, advocacy groups have made conflict minerals a central issue in their efforts to stop human rights abuses in the DRC, and some politicians and lobbying groups in the United States and Europe have embraced this narrative (see Vogel & Musamba, 2017; Christensen, 2022). In the past ten years, emphasis by developed nations, global dialogue, and humanitarian initiatives have largely concentrated on mining operations in the Eastern DRC.

Inspired by the Kimberley Process Certification Scheme established in 2003, which currently governs the global diamond trade (Cuvelier et al. 2014), several private mineral-certification schemes were created in the first decade of the 2000s. These initiatives were predominantly focused on 3T minerals, the most prominent example being iTSCi certifications initiated in 2009. After several failed attempts by US lawmakers at imposing a certification requirement, Provision 1502 was introduced to the draft of the Dodd-Frank Act in May 2010, two months before its ultimate enactment in July 2010. Provision 1502 requires that SEC-registrants perform supply-chain due diligence and disclose the steps they have taken to avoid purchasing minerals that finance armed groups. These due-diligence requirements are limited to 3T and gold (3TG) sourced from the DRC and neighboring countries.[11] Further, as outlined in Figure 3, companies are only required to audit

[10] For instance, see the 2014 open letter from seventy policy experts that highlights concerns about the focus on conflict minerals (https://ethuin.files.wordpress.com/2014/09/09092014-open-letter-final-and-list.pdf).

[11] The European Union has enacted similar regulation for 3TG minerals in 2017 (Regulation (EU) 2017/821). However, unlike the Dodd-Frank Act, the EU regulation focuses on mineral importers, regardless of public listing status, and it is not limited to minerals from the DRC and neighboring countries. The EU regulation became effective on January 1, 2021, toward the end of our sample period. The objective of focusing on tin, tantalum, tungsten, and gold is that these minerals are most

smelters to ensure that they (1) only buy from certified mines, and (2) trace the country of origin. Motivated by the need for smelters to trace minerals further up the supply chain, the International Conference on the Great Lakes Region (ICGLR) adopted a conflict-free certification framework for artisanal and small-scale mining in 2011 covering mining areas in member states, including the DRC.[12] The certification scheme was initially financed and logistically supported by the German Institute for Geosciences and Natural Resources (BGR), a German governmental agency that committed to sharing technology and supporting certification programs with the ICGLR. Also shown in Figure 3, this scheme certifies the artisanal mine sites, with the aim of verifying that there is no armed presence on the ground and thereby transforming the smelter-audit requirements under Dodd-Frank into physical operations in artisanal mining regions.

2.2 Certification Procedures and Armed Group Incentives

Under the Pact on Security, Stability and Development in the Great Lakes Region which establishes the ICGLR, the DRC is legally obligated to implement ICGLR declarations including the mineral certification scheme. The ICGLR Certification Manual (ICGLR, 2011) requires the DRC Ministry of Mines to select mines for certification and reinspect the same mines no less than once per year. Hence, the likelihood of mine inspection within one year increases from 2% to 100% after the initial visit.[13]

often linked to armed-conflicts and related human rights abuses (see Dodd-Frank Act Provision 1502 and Regulation (EU) 2017/821).

[12] The ICGLR member states are Angola, Burundi, the Central African Republic, the Republic of the Congo, the DRC, Kenya, Rwanda, Sudan, South Sudan (since its independence in 2011), Tanzania, Uganda, and Zambia.

[13] The selection model in (Internet Appendix) Section IA3.2 indicates that, on average, 2.1% of previously uncertified mines are selected for certification each year.

The mine inspector must visit the artisanal mine site and ensure that there is no armed presence at the mine site or in the surrounding area.[14] If these requirements are not met, a mine may not be certified "green," but instead receives a "yellow" or "red" designation. Yellow-rated mines can be reevaluated for green status after six months while continuing operations. Red-rated mines maintain uncertified status for a minimum of six months and may then be reevaluated for a higher status. Of certified mines, nearly 90% of mines are rated green on the initial visit (see Table 1 Panel A). Mines that are certified green receive an ICGLR Certificate, allowing them to legally export minerals from the member state (ICGLR, 2023).[15] Without certified status, mines are forced to illegally sell minerals at a lower price (Alusala, 2017; Childs, 2014).

Since armed groups attain income from taxing mine proceeds, the increase in audit probability after the initial visit and the risk of lower mineral prices from the loss of certified status make it less profitable to occupy the mine. In response, armed groups may find alternative sources of income (e.g., legal activities), move taxation efforts further away from the mine (e.g., to roadblocks), or relocate to mines that are not yet certified. We formalize this intuition using a stylized model presented in (Internet Appendix) Section IA1.

2.3 Certification Selection

In terms of certification selection, inspectors were initially provided with a list of mines for inspection, determined by the Comité Provincial de Suivi des Activités Minières (i.e., Provincial Committee for the Monitoring of Mining

[14] The certification also checks that the mine meets minimum social standards, including ensuring that the mine has no child labor or forced labor, transparency of payments made to illegal or political organizations, and the various environmental or community criteria each member state may impose.

[15] In addition to the DRC's duty to carry out the certification visits, they must disclose the contents and results of all initial and subsequent annual visits to the ICGLR Secretariat, who must develop and maintain an updated regional mine site database for all states. While the requirements of the visits are set out clearly and publicly by ICGLR, the regional mine site database is not available online. The ICGLR Secretariat has maintained for several years that the database will be available shortly, but we have not observed a change in the publicly available information.

Activities) in each province.[16] Purportedly, the selection criteria consist of security, accessibility, legality, and traceability.[17] Among these, the main concern is selection on security, which is associated with our main outcome variable. Though not explicitly included in the selection criteria, additional economic variables could also play a role in determining which mines are certified. Institutionally, we expect that economic activity, local economic importance of mining, and the relative inspection cost each impact the likelihood of certification.

In (Internet Appendix) Section IA3.2, we discuss and examine selection factors and find that pre-certification conflict intensity (security), average luminosity and distance to a population center (economic activity), and location within a protected area (legality) have little to no association with the selection of mines for certification.[18] On the contrary, lower vegetation (higher local reliance on mining) and shorter distance to a major road (accessibility) are both indicative of increased selection probability, but these effects are not present with territory-year fixed effects which we include in our main analyses. However, we do find spatial clustering in initial inspections even within territory, which indicates inspectors' cost considerations. This clustering may impact economic magnitudes, which we consider when interpreting results. Overall, of the eight alleged selection criteria mentioned above, only proximity to other certification visits seems to play a salient role in determining selection, which does not pose severe concerns to our research design.

Nevertheless, we have not been able to confirm selection criteria with the DRC Ministry of Mines. We are also unsure as to whether the DRC maintains compliance with the provisions set out in the ICGLR Certification Manual. The

[16] For details on the distribution of certifications, see (Internet Appendix) Section IA3.1.
[17] This information is based on private communication with a knowledgeable party.
[18] We also perform a robustness test controlling for these local economic factors, which is presented in (Internet Appendix) Section IA5.6.

manual states that requirements within each state may exceed but not fall below the requirements set within the manual, but full compliance may be hindered by corrupt practices, practical limitations, and/or negligence in fieldwork. Given the host of concerns one may have about the potential effectiveness of a certification scheme in the DRC institutional environment, providing evidence on the system's effectiveness in reducing conflict intensity is important.

3. Data and Sample

3.1 Artisanal Mine and Conflict Data

We obtain location and certification information on artisanal mines from IPIS Open Data, which combines information collected from various missions in the DRC. These include ICGLR certification visits as well as ground visits by other organizations. However, the IPIS documentation notes that only mines visited within these programs are documented, so the database is not an exhaustive list of artisanal mine sites. Given the extensive resources expended for these missions, we believe the sample includes most economically significant artisanal mines.

We obtain geolocated conflict data from the Armed Conflict Location & Event Database (ACLED, see Raleigh et al., 2010). The database includes information about the date, location, type, and fatality count of conflict events. They collect this information from local and regional news, humanitarian agencies, and research publications. While there may be potential biases in coverage, such as differences in regional media environments (Berman et al., 2017), we attempt to control for this using regional fixed effects throughout our analysis. We also include corresponding analyses using a less comprehensive but more accurate alternative data source (Eck, 2012) in (Internet Appendix) Section IA7.

To gauge variation in data coverage over time, we plot the number of conflict incidents and fatalities by year in Figure 2. There is an upward trend in conflict observations, likely (at least partly) a result of increased database coverage.

To address this issue, we control for time trends at the territory level using territory-year fixed effects, but this would still bias our estimates if within-territory trends line up with certification selection. However, for fatalities, there are multiple spikes coinciding with various historical events that affected conflict intensity, such as the end of the Second Congo War. Hence, fatalities are likely recorded more comprehensively throughout the sample period. To alleviate concerns over changes in coverage, we also use the number of fatalities as an alternative measure for conflict intensity.

3.2 Sample Selection and Descriptive Statistics

As in most prior studies (e.g., Stoop et al., 2018), we limit our analyses to the eleven provinces in or adjacent to the Eastern DRC—where the certification scheme is centered, most of the artisanal mine sites are located, and conflict intensity is the highest.[19] Utilizing a control group outside of this region cannot provide us with a comparable sample because mining activity is very sparse in the remainder of the country. Because of the clustering of conflicts within provinces of the DRC, we further limit our primary analysis to areas with at least one conflict incident over the entire sample period. We limit our primary analysis to 3TG mines as they are the focus of the certification scheme, mines for other minerals are not subject to any similar due-diligence requirements, and other minerals, namely cobalt and copper, are less valuable than 3TG minerals.[20]

The sample period begins in 2004 to avoid the Second Congo War and its immediate aftermath (Parker & Vadheim, 2017) and because this timing provides us with a sufficient pre-period for the certification scheme that started in 2011. This arrangement is necessary because we wish to observe the impact of certification

[19] These provinces are, in alphabetical order, Bas-Uele, Haut-Katanga, Haut-Lomami, Haut-Uele, Ituri, Lualaba, Maniema, Nord-Kivu, Sud-Kivu, Tanganyika, and Tshopo. For the distribution of mines by province and commodity, see (Internet Appendix) Table IA4.2.

[20] We perform a robustness test including non-3TG mines in the control sample, which is presented in (Internet Appendix) Section IA5.5.

visits on conflict during "peacetimes" when there is meaningful geographical variation in conflict intensity. We also exclude certification visits occurring in 2021, as the post-period to observe future conflict changes is inadequate. We exclude certified mines not awarded "green" status because we want to avoid the conflict effect of discontinued mine operations, which has additional economic and demographic implications for the surrounding area.[21] We restrict conflicts to those at least geolocated to a small part of a region, though most are geolocated to a precise village, town, or city. This criterion affords us more confidence in the spatial precision of conflict incidents (Berman et al., 2017). Finally, we limit conflict types to battles, civilian violence, riots, and looting (defined according to Stoop et al., 2018) because other conflict-event groups such as "peaceful surrender" do not reflect conventional violent conflict.

Section IA4.1 in the Internet Appendix reports the number of observations excluded by each of the sample selection criteria. Due to the data structure, the table is presented in several panels, each showing the sample selection for one raw dataset, and strictly follows the data coding and merging process. Overall, our mine-level primary sample contains a balanced panel between 2004 and 2022 of 3TG mines in conflict areas which are either uncertified or certified green. Our village-level primary sample contains a balanced panel between 2004 and 2022 of villages in conflict areas which have at least one proximal mine.

Table 2 reports descriptive statistics for all 3TG observations at the mine- and village-level and (Internet Appendix) Section IA4.3 provides more detail. We see that a much lower proportion of gold mines than 3T mines in our sample are certified, and this is due to a higher total count of gold mines but far fewer

[21] We perform a set of robustness tests including non-green certified mines in the treated sample, which are presented in (Internet Appendix) Section IA6.

certifications of gold mines (see also Table 1).[22] Specifically, 1.8% (2.9%) of gold mine-years (village-years) are post-certification in contrast to 16.7% (8.5%) of 3T mine-years (village-years). Further, there is no substantial difference for any type of conflict incidence or fatalities between gold and 3T mines nor is there a difference in the nearest distance to any type of conflict in a year. This alleviates concerns that gold and 3T mines are differentially located in high- or low-conflict areas. On average, 26.7% (11.0%) of mine-years (village-years) have at least one conflict documented within 10 kilometers (assigned to the village), so conflicts are reasonably prevalent in mining areas. These statistics are consistent with our expectations and do not present foreseeable issues for our analyses.

4. Effect of Mine Certifications on Conflicts

4.1 Average Effect of Certifications by Mineral Type

To provide evidence of certifications' effect on conflict intensity in mining areas, we first examine changes in the probability of conflict around the first certification visit for certified mines and villages. Villages with at least one certified mine within a 10-kilometer radius will hereafter be referred to as "certified villages," and the certification year is assigned to be the first year that a mine within the radius is certified. We use a difference-in-differences design that compares probability of conflict in geographic cells (with radii ranging from 10 to 50 kilometers) around certified mines or villages to cells around mines or villages that are not certified. To capture the dynamics of conflict probability over time, we plot yearly coefficient estimates and tabulate average coefficient estimates of the treatment effect from the following OLS regression:

$$\mathbb{1}(\textbf{\textit{All Conflicts}}_{c,t}) = \beta_1 \, \textbf{\textit{CFC}}_c \times \textbf{\textit{Year Relative to Cert}}_{c,t} + \textbf{\textit{Fixed Effects}} + \varepsilon_{c,t} \quad (1)$$

[22] Two potential explanations are possible for this observation. First, 3T mines are better documented by prior responsible sourcing initiatives (Matthysen & Gobbers, 2022), so it could be easier to locate and visit 3T mines. Second, 3T mines may be more established and exist longer than gold mines because the barrier to entry for 3T mining is higher (3T minerals are harder to sell), so locals may be better able to direct inspectors to 3T mines.

$\mathbb{1}$(*All Conflicts*) is an indicator variable for whether any conflict occurs in cell *c* during year *t*. *CFC* is an indicator equal to one if a mine or village is certified as conflict free. *Year Relative to Cert* is a set of indicators for each year defined relative to the year of the first certification visit. We omit the indicator for the year before certification, which serves as the benchmark period. To control for differences in conflict intensity arising from time-invariant (or slow-moving) factors specific to each mine or village (e.g., geographic location, property size), we include *Mine* or *Village* fixed effects. We also include *Territory*×*Year* fixed effects to control for time-varying institutional and political factors correlated with each territory in the Eastern DRC (shown in Figure 1 Panel A). We estimate Conley (1999) standard errors that account for spatial correlation within a 100-kilometer radius and infinite serial correlation.[23]

In Figure 4, we graph the yearly *CFC*×*Year Relative to Cert* coefficient estimates and their corresponding 95% confidence intervals for gold mines and 3T mines. In support of the parallel-trends assumption, treated and control cells have similar trends in conflict in years t-2 to t. Years t-3 and t-4 see a slight increase in conflict intensity that is most pronounced for villages. Consistent with certifications decreasing the local conflict probability for gold mines, beginning the year after certification, treated cells exhibit a gradually decreasing level of conflict intensity relative to control cells. From about 3 years after the certification, the treatment effect stabilizes at an approximately 20% lower level for mines and 10% lower level for villages. This economic magnitude is relatively large given that the unconditional probability of conflict is 25.5% for a gold mine and 11% for a village. Only a small effect is observed for 3T mines, and the coefficient estimates for 3T mines are generally close to zero in both the pre- and post-periods.

[23] All results remain robust with Conley (1999) standard errors that account for spatial correlation within a 200- and 500-kilometer radius as well as clustering by territory (see Section 4.3).

To estimate the average treatment effect and to simplify the reporting of sensitivity tests, we also present results where we replace the individual *Year Relative to Cert* indicators with a single *PostCert* indicator, which equals one for all years during or after the certification year. Table 3 reports the results. In Column (2), the *CFC×PostCert* coefficient estimate is negative and statistically significant, indicating that the probability of conflict decreases by approximately 9.4% around certified mines or villages relative to control cells.

If the observed decrease in conflict is indeed attributable to the certification itself, we expect the treatment effect's magnitude to diminish as we increase the cell radius, and the mine/village becomes a less central consideration in violent activity within the cell. In Figure 5, we graph the *CFC×PostCert* coefficient estimates and their corresponding 95% confidence intervals for cells with radii from 10 to 50 kilometers in intervals of 10 kilometers for gold mines. The coefficient estimate increases monotonically toward 0 with the cell's radius length, and the point estimates are only statistically significant for radii up to 20 kilometers, at which point the *CFC×PostCert* coefficient estimate implies a decrease in conflict probability of approximately 5%.

Because it is likely that conflicts are displaced from certified (treated) to uncertified (control) mines, the stable unit treatment values assumption (SUTVA) could be violated, which may inflate our estimated effect magnitude. Additionally, at the mine level, there is significant overlap in the 10-kilometer cells for conflicts, which may cause a spillover from treated mines to nearby treated mines, which would inflate the estimated effect magnitude, or to nearby control mines, which would moderate the magnitude.[24] The village level sees a similar overlap in the 10-kilometer cells for mines. Using both specifications alleviates these concerns, as the mine-level analysis ensures no duplicate mines and the village-level analysis

[24] Overall, we anticipate a net moderation because fewer than 6% of the observations in the main sample are treated (see Table 2).

ensures no duplicate conflicts. However, in interpreting the estimated magnitudes, potential spillover effects must be kept in mind.

4.2 Average Effect of Certifications by Conflict Type

The economic mechanism explaining the reduction in conflict intensity stems from the reduced ability of armed groups to extract illegal rents and taxes from certified mines. Because these mines are continuously inspected for armed group presence and are precluded from selling minerals for export if they do not pass inspection, armed groups likely recognize a lower potential to profit from controlling the mine. Theoretically, the armed group has incentives aligned with those of the miners—the more revenue the miners obtain from selling minerals, the more rents can be extracted (for instance, at roadblocks farther from the mine). If the armed group's presence will cause a restriction on selling to smelters for export or even the ultimate shutdown of the mine, there is an economic motivation for armed groups to cease or reduce operations within a mining area and shift to another more profitable area. Accordingly, we expect to observe a reduction in only armed-group-initiated conflict (i.e., battles and violence against civilians), not civilian-initiated conflict (i.e., riots).[25]

To test this prediction, we estimate Eq. (1) separately for battles, violence against civilians, and riots based on ACLED classifications (see Section 3.1). Figure 6 Panel A shows that the effect is significant for battles only and not for riots. Additionally, the effect for battles commences in the year after the certification visit, which is consistent with the certification causing the reduction in conflicts. Corroborating this finding, Table 4 shows a statistically significant treatment effect only for armed-group-initiated conflict and the estimated treatment effect is about 11 times larger for battles than for riots at the mine level. At the village level, the average treatment effect is statistically insignificant, but the point estimate is

[25] We develop a simple theoretical framework in (Internet Appendix) Section IA1 to explain the economic mechanism more concretely.

negative only for battles, consistent with the weaker but still observable difference in Figure 6 Panel B.

We also test for a reduction in fatality count by conflict type because we expect fatalities to be more comprehensively recorded throughout the sample period than conflict incidence (see Section 3.1). Replacing the indicator for conflicts with the inverse hyperbolic sine of fatalities as the dependent variable, we find a 14.2% decrease in battle fatalities and a 10.6% decrease in civilian violence fatalities at the mine level but a very small and statistically insignificant effect for riots. We observe a 3% decrease in battles at the village level (though statistically insignificant), but very small effects for civilian violence and riots. The effect observed around mines is economically significant, indicating a reduction of 1.22 deaths per certified-mine-year from battles.

4.3 Sensitivity Tests

To estimate the average treatment effect and to simplify the reporting of sensitivity tests, we also present results where we replace the individual *CFC×Year Relative to Cert* indicators with a single *CFC×PostCert* indicator, which equals one for all years after certification for certified mines. Because we only find a strong effect of certification for gold mines, we limit the sensitivity tests to gold mines. Figure 7 Panel A reports sensitivity test results at the mine level. For ease of comparison, we report the baseline specification from Table 3 Column 2.

Our first set of tests change sample restrictions to alleviate concerns that sample selection choices drive our main results. First, we use only the provinces of Nord- and Sud-Kivu, where most conflicts and artisanal mining are concentrated and where the certification program began.[26] Second, we include non-green certifications, which may cause discontinued mine operations and resultant

[26] We perform a robustness test to ensure the treatment effect is not driven by any one province or certification year, which is presented in (Internet Appendix) Sections IA5.1 and IA5.2. We also observe an effect for both early and late certifications in (Internet Appendix) Section IA5.3.

spillovers. Third, we include zero-conflict mines so that our results can generalize to all mining areas rather than simply apply to conflict-prone areas. Fourth, we exclude mines within 2 kilometers of another mine to attempt to partially alleviate the concern of spillovers from nearby mines while maintaining enough statistical power.[27] Our second set of tests shift to broader fixed-effect structures by replacing *Territory*×*Year* with either *Year* or *Province*×*Year*. Our third set of tests uses alternative model specifications. First, we use the inverse hyperbolic sine of the count of conflicts as the dependent variable; the coefficient indicates a nearly 20% reduction in the number of conflicts occurring within 10 kilometers of certified mines. Second, we perform a Stacked DiD, splitting into cohorts by certification year, to alleviate concerns over control group biases. Third, we perform a Poisson pseudo-maximum-likelihood (PPML) regression using a raw count dependent variable, which is not shown due to different units. Our fourth set of tests varies standard error clustering. First, we cluster by territory rather than spatially. Second, we cluster spatially within 200 and 500 kilometers rather than 100 kilometers. A statistically significant and negative coefficient at the mine level is maintained for each of these twelve sensitivity tests.

Figure 7 Panel B reports corresponding sensitivity test results at the village level. Except for the Stacked DiD, each specification yields similar negative (statistically insignificant) coefficient estimates.[28] Overall, we discern that our main results are not sensitive to various sample restrictions, fixed-effect structures, alternative specifications, or standard error clusters.

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[27] If we were to exclude overlapping mines within a 10-kilometer radius, the remaining sample would be too small to obtain reliable estimates. We perform a robustness test using smaller radii and excluding all overlapping mines, which is presented in (Internet Appendix) Section IA5.4.

[28] We do not perform a sensitivity test including zero-conflict villages because we determine the existence of villages based on the ACLED conflict dataset.

5. Geographic Displacement of Conflicts

Although the taxation of mineral extraction at mining sites is a source of financing for some militant factions, it is not their only source of income. Anecdotal evidence suggests that taxation at roadblocks, which has existed in the DRC since colonial times, has become an important source of income for some armed groups. Sierra (2020) also finds that, after a positive demand shock for gold, bandits often introduce illicit mining visas and taxes within the villages where mining income is spent. It is likely that the incentives created to avoid conflict in the vicinity of mines instead displaces conflicts geographically, given armed groups' proven ability to adapt to changing circumstances.[29] In fact, increased regulation could plausibly increase the need for "protection," a major source of revenue for many armed groups including the armed forces of the DRC. Because mine inspectors cannot observe these displacements, which nonetheless have severe adverse impacts on civilians, understanding whether and how they are occurring is important. For policy evaluation purposes, a displacement of conflicts from mining areas is much different from a broader reduction in conflicts, and they have very distinct political and economic implications.

5.1 Aggregate Effect of Certifications on Conflicts by Territory

To assess the aggregate effect of certifications on conflict intensity, we move from the mine and village levels to the territory level. That is, we now utilize the variation previously excluded by *Territory×Year* fixed effects to evaluate the overall success of certifications at improving territory-level conditions. Specifically,

[29] Supporting our displacement hypothesis, a recent IPIS report (Matthysen & Gobbers, 2022, p. 30) states the following: "Armed actors have adapted their strategies to circumvent increasing levels of scrutiny, for example taxation of mine managers at a distance from the mining site or exerting a monopoly on consumer goods in and around the mine. There have even been examples of armed groups that re-invest profits, illegally realized in agriculture, in the mineral trade: they become traders in the mineral business in urban trading centers (centres de négoce)."

to capture the aggregate effect of certifications on conflict by territory, we estimate the average treatment effect from the following OLS regression:

$$\textbf{asinh}(\textbf{\textit{All Conflicts}}_{r,t}) = \beta_1\ \textbf{asinh}\textbf{\textit{(Count)}}\ \text{OR}\ \textbf{\textit{Fraction}}_{r,t} + \textbf{\textit{Fixed Effects}} + \varepsilon_{r,t} \quad (2)$$

asinh(*All Conflicts*) is the inverse hyperbolic sine of the count of all conflicts in territory *r* and year *t*. asinh(*Count*) is the inverse hyperbolic sine of the count of certified gold mines in territory *r* and year *t*. *Fraction* is the count of certified gold mines divided by the count of total gold mines in territory *r* and year *t*. To control for differences in conflict arising from time-invariant (or slow-moving) factors specific to each territory (e.g., geographic location, population demographics), we include *Territory* fixed effects. We also include *Province*×*Year* fixed effects to control for time-varying institutional and political factors that are correlated with the eleven provinces in the Eastern DRC (shown in Figure 1). We estimate standard errors clustered at the territory level to account for serial correlation within a given territory across observation years.

Because the independent variable is no longer a *Treat*×*Post* indicator, we are unable to map out yearly coefficient estimates. We present the average treatment effect results in Table 6 for each conflict type. If anything, we find a statistically insignificant increase in conflicts across types for both the certification count and fraction measures, which indicates that mine certifications are not associated with a decrease in conflict at the broader territory level. In contrast to the reduced conflict intensity we find in certified mining areas, the static result at the territory level indicates that the reduction in conflict is limited to the immediate proximity around the mine and that conflicts are displaced to non-certified areas.

5.2 Effect of Certifications on Distance to Nearest Conflict

Because we observe a decrease in conflict proximal to certified mines and villages but no broader decrease at the territory level, it follows that we should observe an increase in the distance between certified mines and the nearest conflict after certification. To directly test this supposition, similar to Section 4, we plot yearly coefficient estimates of the treatment effect (*CFC×Year Relative to Cert*) from the following OLS regression:

$$\text{asinh}(\boldsymbol{Dist}_{m,t}) = \beta_1\ \boldsymbol{CFC}_m \times \boldsymbol{Year\ Relative\ to\ Cert}_{m,t} + \boldsymbol{Fixed\ Effects} + \varepsilon_{m,t} \quad (3)$$

asinh(*Dist*) is the inverse hyperbolic sine of the distance from mine *m* to the nearest conflict occurring in year *t*. The remainder of the variables are defined in the same way as those in Section 4, and the fixed-effect structure and standard error clustering are also identical. Again, we omit the indicator for the year before certification, which serves as the benchmark period.

In Figure 8 Panel A, we graph the yearly *CFC×Year Relative to Cert* coefficient estimates and their corresponding 95% confidence intervals for gold mines and 3T mines. In support of the parallel-trends assumption, treated and control cells have similar trends in conflict distance in years t-1 and t-2. Years t-3 and t-4 see a slight decrease in the distance to conflict for mines that are later certified. Consistent with certification increasing the distance from a gold mine to the nearest conflict, treated gold mines exhibit a gradually increasing distance to the nearest conflict in the three years following certification. In the third year, the effect translates to an approximately 50% longer distance to the nearest conflict even though there continues to be noise in subsequent periods. However, similar to our main result, there is only a weak effect observed for 3T mine certifications.

To estimate the average treatment effect, we also present results where we replace the individual *Year Relative to Cert* indicators with a single *PostCert* indicator, which equals one for all years during and after the certification year. Table 7 reports results. In Column (2), the *CFC×PostCert* coefficient estimate is positive and statistically significant, indicating that distance to the nearest conflict increases by approximately 18.3% for certified mines relative to uncertified mines.

This finding is economically significant, given that the magnitude of the change translates to an increase of approximately 9.03 kilometers to the nearest conflict.

As in Section 4.2, we anticipate that this effect is only present for armed group–initiated conflict (i.e., battles and violence against civilians) and not for civilian-initiated conflict (i.e., riots). To test this prediction, we estimate Eq. (3) separately for battles, violence against civilians, and riots based on classifications within the ACLED database (Raleigh et al., 2010). Figure 8 Panel B shows that the effect is only observed for battles and not for riots. Additionally, the effect for battles begins the year after the first certification visit, an outcome that is consistent with certification causing the increase in distance. The regression results in Table 7 corroborate this finding—the treatment effect is limited to battles (12.1% increase) and violence against civilians (6.9% increase, though statistically insignificant) while the point estimate for riots is close to zero.

5.3 Displacement of Conflict to Uncertified Villages

To accurately identify a displacement of conflicts from mining areas, we test for an increase in conflict around uncertified villages. Specifically, we use the sample of only uncertified villages (i.e., those with no certified mines within 10 kilometers) and assign the treatment group to be uncertified villages between 50 and 100 kilometers from a certified village. We use a similar OLS regression specification as in Eq. (1) except with updated treatment and control groups. Rather than *Territory×Year* fixed effects, we shift to *Province×Year* fixed effects to capture across-territory variation because treated villages may not be within the same territory as their corresponding certified villages.[30]

In Figure 9 Panel A, we graph the yearly *CFC×Year Relative to Cert* coefficient estimates for all conflicts separated into mining and non-mining areas

[30] We run this analysis with *Territory×Year* fixed effects in (Internet Appendix) Section IA5.7. As expected, the results become statistically insignificant and much smaller in magnitude, but the signs remain in the expected direction. This is consistent with our prediction that within-territory variation

and their corresponding 95% confidence intervals. In support of the parallel-trends assumption, treated and control cells have similar trends in conflict distance in all years before certification for mining villages (i.e., those with any mine within 10 kilometers). Consistent with the displacement of conflict to uncertified areas, beginning the year after certification, treated cells exhibit a gradually increasing level of conflict intensity relative to control cells. From about 3 years after the certification, the treatment effect stabilizes at an approximately 5% higher level for mining villages. However, there is no corresponding increase in conflict for non-mining villages, which indicates that conflict is displaced from certified areas to other mining areas but not to non-mining areas. Because artisanal mining forms a large part of the economy in the Eastern DRC, it is intuitive that armed groups would continue to cluster around mines to extract economic rents.

To estimate the average treatment effect, we also present results where we replace the individual *Year Relative to Cert* indicators with a single *PostCert* indicator, which equals one for all years during and after the certification year. Table 8 reports results. In Column (2), the *CFC×PostCert* coefficient estimate is positive and statistically significant, indicating that the probability of conflict increases by approximately 2.6% around treated cells relative to control cells.

As in Section 4.2, we anticipate that this effect is only present for armed group–initiated conflict (i.e., battles and violence against civilians) and not for civilian-initiated conflict (i.e., riots). To test this prediction, we estimate the model separately for battles, violence against civilians, and riots based on classifications within the ACLED database (Raleigh et al., 2010). Figure 9 Panel B shows that the effect is only observed for battles and not for riots. Additionally, the effect for battles begins the year after the certification, but the coefficient for riots remains close to zero throughout. The regression results in Table 8 corroborate this

is unable to fully capture armed group movement because armed groups are highly mobile and most territories are less than 200 kilometers in length and width.

finding—the treatment effect is limited to battles (2.7% increase) and violence against civilians (1.8% increase) while the point estimate for riots is close to zero. These results capture the movement of conflict from certified to uncertified mining areas, providing direct evidence of conflict displacement.

Taken together, the insignificant increase in aggregate conflict intensity, the increase in mine-level distance to the nearest conflict, and the increase in conflict for nearby mining villages indicate that, rather than permanently reducing the level of conflict in Eastern DRC territories, mine certifications displace armed group–initiated conflict farther from certified mines. While this outcome may be beneficial for miners and mining villages, it does not accomplish the stated purpose of resolving the issue of armed violence along the eastern border. This finding is, however, consistent with anecdotal evidence that violence in the Eastern DRC has, in fact, not been improving in recent years despite various due-diligence initiatives and government programs. An IPIS study by Jaillon et al. (2019) also documents a strong difference in armed-group presence between certified mines (10%) and uncertified mines (40%), which aligns with our findings.

6. Conclusion

Recognizing the violence and humanitarian tragedies caused by armed groups in the Eastern DRC, governments in many developed countries have enacted regulations to curb the purchase of conflict minerals that may financially benefit armed-group operations. These conflict-mineral regulations, such as the US Dodd-Frank Act Provision 1502, require corporations to conduct and disclose due-diligence on mineral sourcing. In response to the need for supply-chain tracing, the ICGLR developed and implemented an artisanal mine certification scheme in 2011, shortly after the passage of Dodd-Frank. We provide evidence of conflict dynamics in the Eastern DRC subsequent to artisanal mine certifications.

We find that, after the certification visit, the probability of conflict (count of fatalities) around mines decreases by 9.4% (16.3%) within a 10-kilometer radius of certified gold mines, an effect that only exists for armed group–initiated conflict, not for civilian-initiated conflict. However, no significant reduction in the probability of conflict for tin, tantalum, and tungsten mining areas takes place. Consistent with anecdotal evidence on the lack of overall improvement, aggregate conflict intensity in Eastern DRC territories does not decline but is displaced farther from certified mines toward nearby uncertified mining villages.

These findings suggest that, even in nations characterized by weak institutions and rampant corruption, supply-chain certifications can enact meaningful change. However, we also provide a cautionary tale that local benefits may be accompanied by the displacement of conflict to non-certified areas, illustrating that supply-chain certification systems must be implemented in concert with a broader set of policies to work toward resolving complex geopolitical challenges, such as the humanitarian crisis in the DRC.

References

Alusala, N. (2017). The DRC's natural resources still awash with blood. *Institute for Security Studies.* https://issafrica.org/iss-today/the-drcs-natural-resources-still-awash-with-blood

Auty, R. M. (1993). *Sustaining development in mineral economies.* London: Routledge.

Baik, B., Even-Tov, O., Han, R., & Park, D. (2023). The real effects of supply chain transparency regulation – Evidence from Section 1502 of the Dodd-Frank Act. *SSRN Working Paper*. https://doi.org/10.2139/ssrn.3908233

Berman, N., Couttenier, M., Rohner, D., & Thoenig, M. (2017). This mine is mine! How minerals fuel conflicts in Africa. *American Economic Review*, *107*(6), 1564–1610. https://doi.org/10.1257/aer.20150774

Binzel, C., Fehr, D., & Link, A. (2023). Can international initiatives promote peace? Diamond certification and armed conflicts in Africa. *Working Paper*. https://cepr.org/publications/dp18450

Bocci, C., & Fortmann, L. (2023). Community and industrial forest concessions: Are they effective at reducing forest loss and does FSC certification play a role? *World Development*, *170*, 106315. https://doi.org/10.1016/j.worlddev.2023.106315

Childs, J. (2014). A new means of governing artisanal and small-scale mining? Fairtrade gold and development in Tanzania. *Resources Policy*, *40*, 128–136. https://doi.org/10.1016/j.resourpol.2014.01.007

Choy, S., Jiang, S., Liao, S., & Wang, E. (2023). Public environmental enforcement and private lender monitoring: Evidence from environmental covenants. *Journal of Accounting and Economics*, forthcoming, 101621. https://doi.org/10.1016/j.jacceco.2023.101621

Christensen, D. (2019). Concession stands: How mining investments incite protest in Africa. *International Organization*, *73*(1), 65–101. https://doi.org/10.1017/S0020818318000413

Christensen, H. B. (2022). Is corporate transparency the solution to political failure on our greatest problems? A discussion of Darendeli, Fiechter, Hitz, and Lehmann (2022). *Journal of Accounting and Economics*, *74*(2-3), 101542. https://doi.org/10.1016/j.jacceco.2022.101542

Christensen, H. B., Maffett, M., & Rauter, T. (2023). Reversing the resource curse: Foreign corruption regulation and the local economic benefits of resource extraction. *American Economic Journal: Applied Economics*, forthcoming. https://doi.org/10.2139/ssrn.3714027

Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics*, *92*(1), 1–45. https://doi.org/10.1016/S0304-4076(98)00084-0

Cuvelier, J., Bockstael, S.V., Vlassenroot, K., & Iguma, C. (2014). Analyzing the impact of the Dodd-Frank Act on Congolese livelihoods. *DRC Affinity Group*. https://www.ssrc.org/publications/analyzing-the-impact-of-the-dodd-frank-act-on-congolese-livelihoods/

DeFond, M., & Zhang, J. (2014). A review of archival auditing research. *Journal of Accounting and Economics*, *58*(2-3), 275–326. https://doi.org/10.1016/j.jacceco.2014.09.002

Dodd-Frank Wall Street Reform and Consumer Protection Act, 12 U.S.C. § 1502 (2010). https://www.congress.gov/bill/111th-congress/house-bill/4173

Eck, K. (2012). In data we trust? A comparison of UCDP GED and ACLED conflict events datasets. *Cooperation and Conflict*, *47*(1), 124–141. https://doi.org/10.1177/0010836711434463

EU Conflict Minerals Regulation, 2017/821 (2017). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A32017R0821

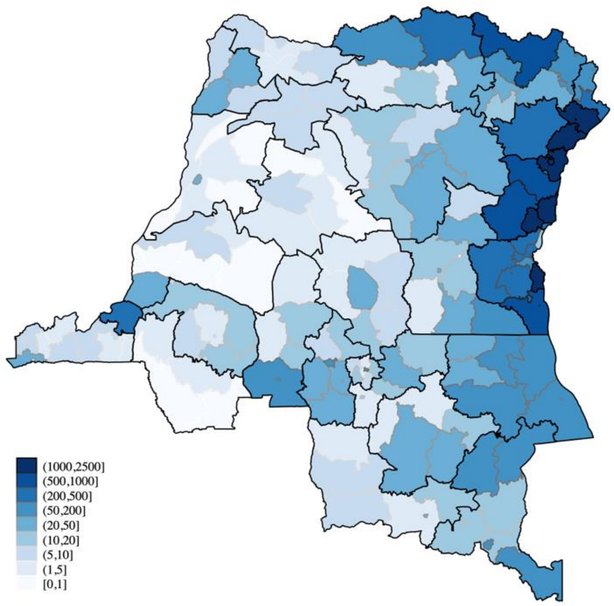
Fritz, M., McQuilken, J., Collins, N., & Weldegiorgis, F. (2017). Global trends in artisanal and small-scale mining (ASM): A review of key numbers and issues. *International Institute for Sustainable Development*. https://www.iisd.org/system/files/publications/igf-asm-global-trends.pdf

Hanai, K. (2021). Conflict minerals regulation and mechanism changes in the DR Congo. *Resources Policy, 74*, 102394. https://doi.org/10.1016/j.resourpol.2021.102394
Humphreys, M., Sachs, J., & Stiglitz, J. E. (2007). *Escaping the resource curse*. Columbia University Press.
ICGLR (2011). ICGLR regional certification mechanism (RCM) – Certification manual. https://www.oecd.org/investment/mne/49111368.pdf
ICGLR (2011). ICGLR regional certification mechanism (RCM) – Certification manual appendix. https://www.bgr.bund.de/EN/Themen/Min_rohstoffe/CTC/Downloads/ICGLR_criteria_app.pdf?__blob=publicationFile&v=4
ICGLR (2023). ICGLR model law RINR. https://icglr.org/wp-content/uploads/2023/06/Overview-of-the-SIx-Tools-of-the-RINR_Final.doc
IPIS (2021). Artisanal mining in DR Congo - IPIS open data. Available from https://ipisresearch.be/home/maps-data/open-data/
Jaillon, A., Gobbers, E., Bouuaert, M. C., Makori, T., & Heuty, A. (2019). Assessing the impact of due diligence programmes in Eastern DRC: A baseline study, IPIS report. *IPIS/Ulula*. https://ipisresearch.be/wp-content/uploads/2019/04/1904-Rapport-Due-Diligence-DRC.pdf
Jiang, X., Xin, B., & Xiong, Y. (2023). The value of mandatory certification: A real effects perspective. *Journal of Accounting Research*, *61*(1), 377–413. https://doi.org/10.1111/1475-679X.12460
Jin, G. Z., & Leslie, P. (2003). The effect of information on product quality: Evidence from restaurant hygiene grade cards. *Quarterly Journal of Economics, 118*(2), 409–451. https://doi.org/10.1162/003355303321675428
Laudati, A. (2013). Beyond minerals: Broadening 'economies of violence' in eastern Democratic Republic of Congo. *Review of African Political Economy, 40*(135), 32–50. https://doi.org/10.1080/03056244.2012.760446
Lawson, M. F. (2021, September 1). The DRC mining industry: Child labor and formalization of small-scale mining. *Wilson Center*. https://www.wilsoncenter.org/blog-post/drc-mining-industry-child-labor-and-formalization-small-scale-mining
Lezhnev, S., & Prendergast, J. (2009, November 10). From mine to mobile phone: The conflict minerals supply chain. *Enough Project*. https://enoughproject.org/reports/mine-mobile-phone
Martinez, G., Smith, N. M., & Veiga, M. M. (2022). Voluntary gold certification programs: A viable mechanism for improving artisanal and small-scale mining in Peru? *Journal of Rural Studies*, *94*, 54–62. https://doi.org/10.1016/j.jrurstud.2022.05.019
Matthysen, K., & Gobbers, E. (2022). Armed conflict, insecurity, and mining in Eastern DRC: Reflections on the nexus between natural resources and armed conflict. *IPIS/USAID*. https://ipisresearch.be/wp-content/uploads/2022/12/20221208_ILRG_IPIS_Armed-conflict-insecurity-and-mining-in-eastern-DRC.pdf
Mehlum, H., Moene, K., & Torvik, R. (2006). Institutions and the resource curse. *Economic Journal*, *116*(508), 1–20. https://doi.org/10.1111/j.1468-0297.2006.01045.x
OCHA (2023). Democratic Republic of the Congo – Subnational administrative boundaries. Available from https://data.humdata.org/dataset/cod-ab-cod.
Parker, D. P., & Vadheim, B. (2017). Resource cursed or policy cursed? US regulation of conflict minerals and violence in the Congo. *Journal of the Association of Environmental and Resource Economists*, *4*(1), 1–49. https://doi.org/10.1086/689865
Raleigh, C., Linke, A., Hegre, H., & Karlsen, J. (2010). Introducing ACLED: An armed conflict location and event dataset: Special data feature. *Journal of Peace Research, 47*(5), 651–660. https://doi.org/10.1177/0022343310378914
Robinson, J. A., Torvik, R., & Verdier, T. (2006). Political foundations of the resource curse. *Journal of Development Economics, 79*(2), 447–468. https://doi.org/10.1016/j.jdeveco.2006.01.008

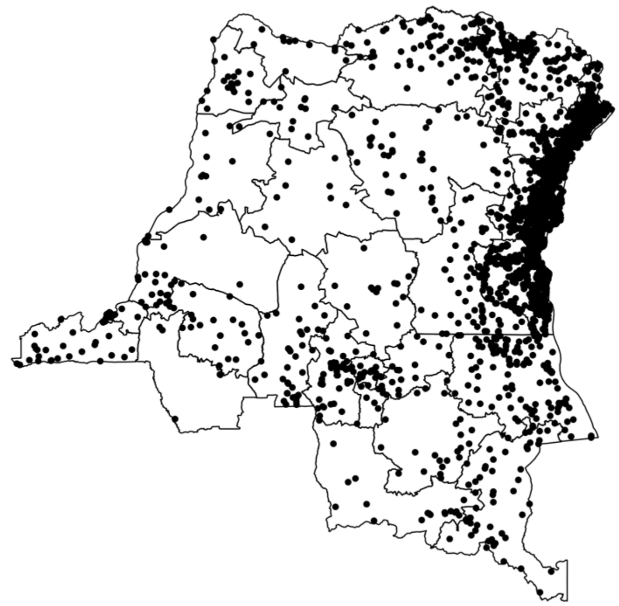
Sachs, J. D., & Warner, A. M. (1995). Natural resource abundance and economic growth. *NBER Working Paper*, 5398. https://doi.org/10.3386/w5398
Sarr, M., Bulte, E., Meissner, C., & Swanson, T. (2011). On the looting of nations. *Public Choice, 148*, 353–380. https://doi.org/10.1007/s11127-010-9659-9
Schütte, P. (2018). International mineral trade on the background of due diligence regulation: A case study of tantalum and tin supply chains from East and Central Africa. *Resources Policy, 62*, 674–689. https://doi.org/10.1016/j.resourpol.2018.11.017
Sierra, R. S. D. (2020). On the origins of the state: Stationary bandits and taxation in Eastern Congo. *Journal of Political Economy*, *128*(1), 32–74. https://doi.org/10.1086/703989
Stoop, N., Verpoorten, M., & Van der Windt, P. (2018). More legislation, more violence? The impact of Dodd-Frank in the DRC. *PLOS One, 13*(8), e0201783. https://doi.org/10.1371/journal.pone.0201783
Van Bockstael, S. (2018). The emergence of conflict-free, ethical, and Fair Trade mineral supply chain certification systems: A brief introduction. *The Extractive Industries and Society*, *5*(1), 52–55. https://doi.org/10.1016/j.exis.2017.12.014
Verweijen, J., & Brabant, J. (2017). Cows and guns. Cattle-related conflict and armed violence in Fizi and Itombwe, Eastern DR Congo. *Journal of Modern African Studies*, *55*(1), 1–27. https://doi.org/10.1017/S0022278X16000823
Vlassenroot, K., & Raeymaekers, T. (2004). *Conflict and social transformation in the Eastern DR Congo.* Academia Press Scientific Publishers.
Vogel, C., & Musamba, J. (2017). Brokers of crisis: The everyday uncertainty of Eastern Congo's mineral négociants. *Journal of Modern African Studies*, *55*(4), 567–592. https://doi.org/10.1017/S0022278X1700043X
Yu, J., & Xiao, S. (2023). Project certification and screening in the reward-based crowdfunding market. *Journal of Business Research*, *165*, 114004. https://doi.org/10.1016/j.jbusres.2023.114004

Figure 1. Artisanal Mines and Conflicts

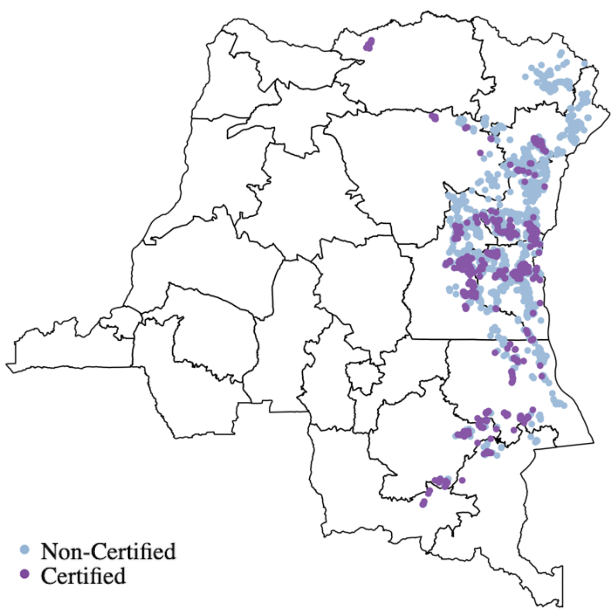
Panel A: Conflicts by Territory



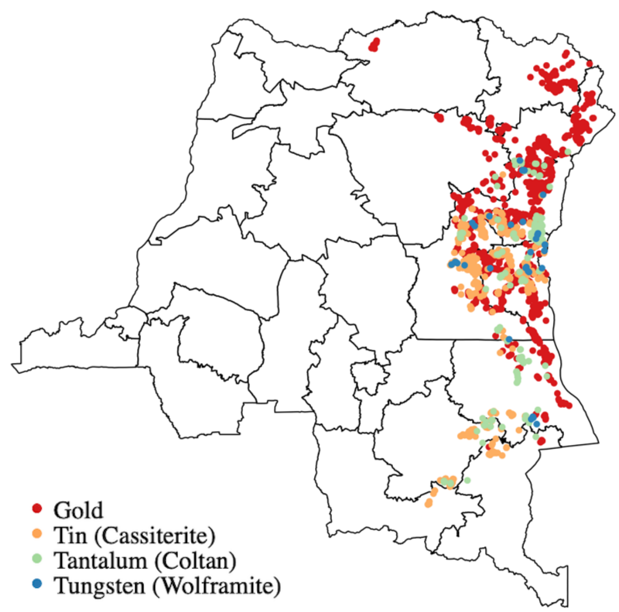
Panel B: Conflict Villages



Panel C: Mines by Certification Status

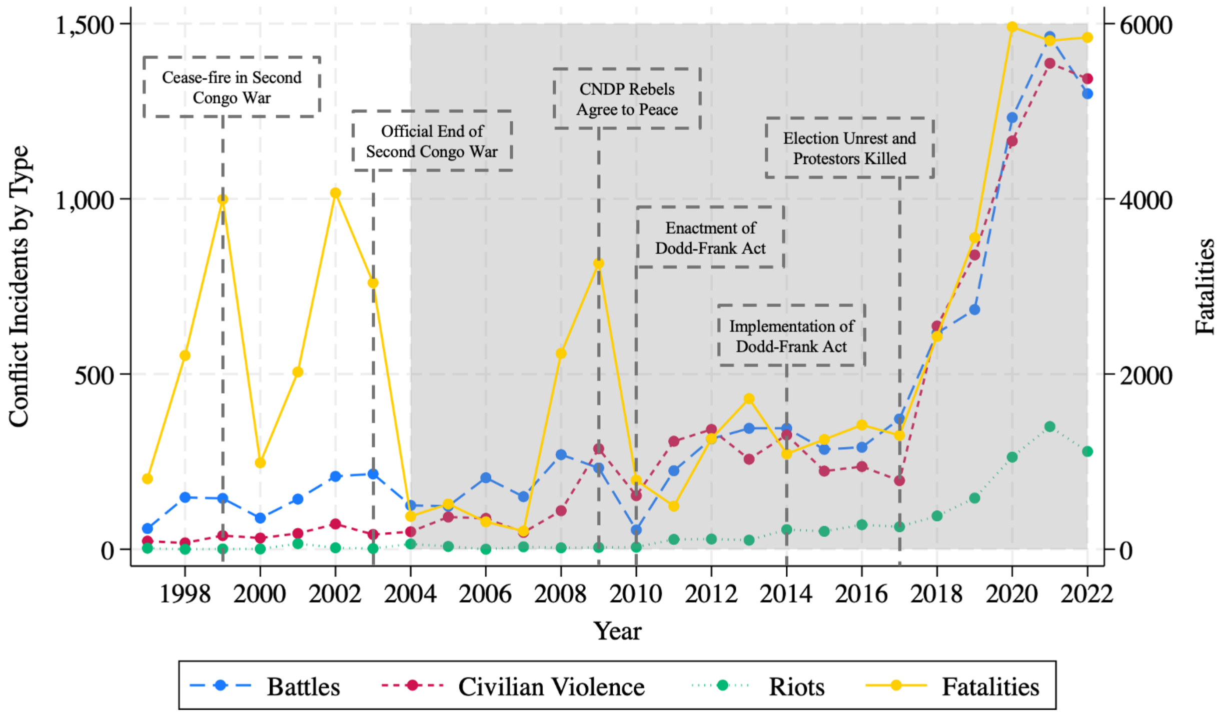


Panel D: Mines by Mineral



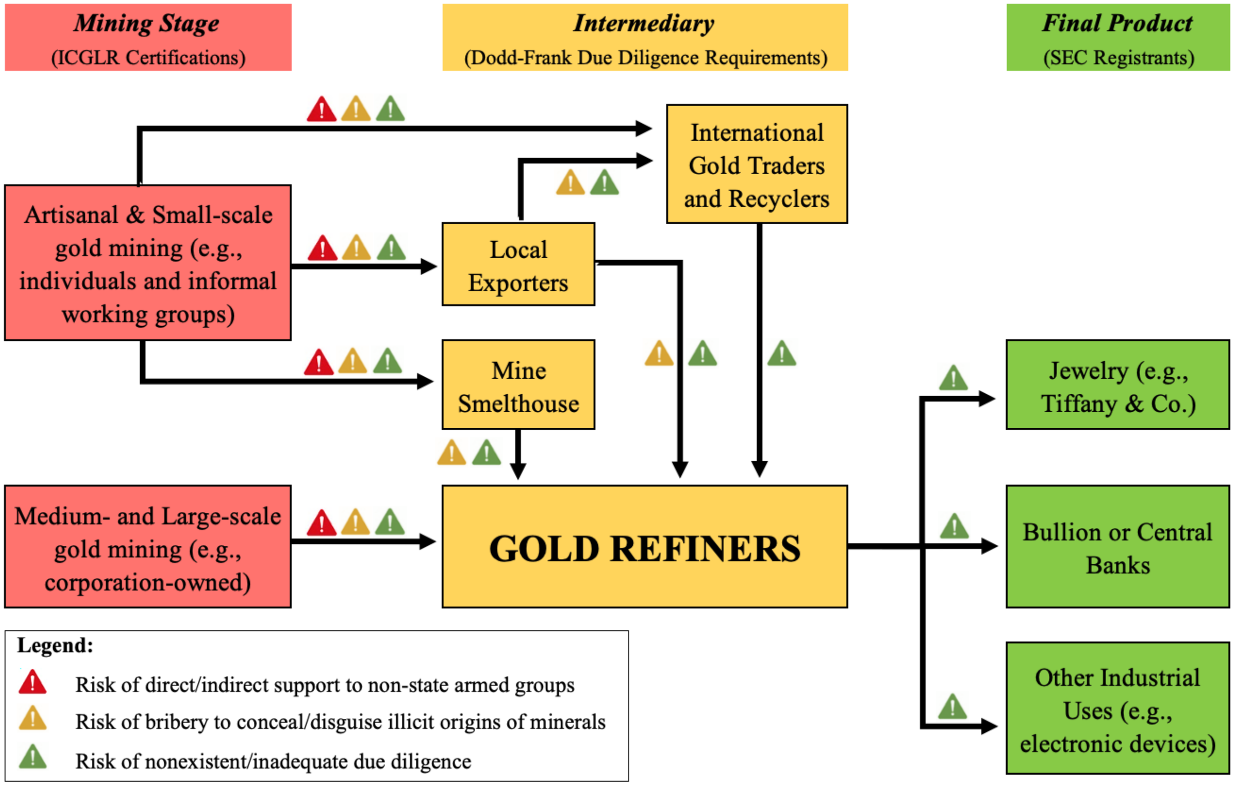
Notes: This figure shows the geographical locations of artisanal mines and conflict incidents in our sample. Panel A is a heat map showing the distribution of conflict incidents across territory in our sample period (2004–2022). Panel B locates all villages in the DRC that have at least one conflict incident documented across our entire sample period (2004–2022). Panel C separates mines by certification (treatment) status. Panel D separates mines by primary mineral (we only keep gold and 3T mines in our sample).

Figure 2. Conflict Incidents and Fatalities



Notes: This figure illustrates the evolution of conflict across time in the DRC by documenting conflict incidents and fatalities from the ACLED data. Periodic conflict-related events are superimposed onto the graph for ease of interpretation, but these events are aligned only to the year of occurrence. Our sample period (2004–2022) is shaded in gray.

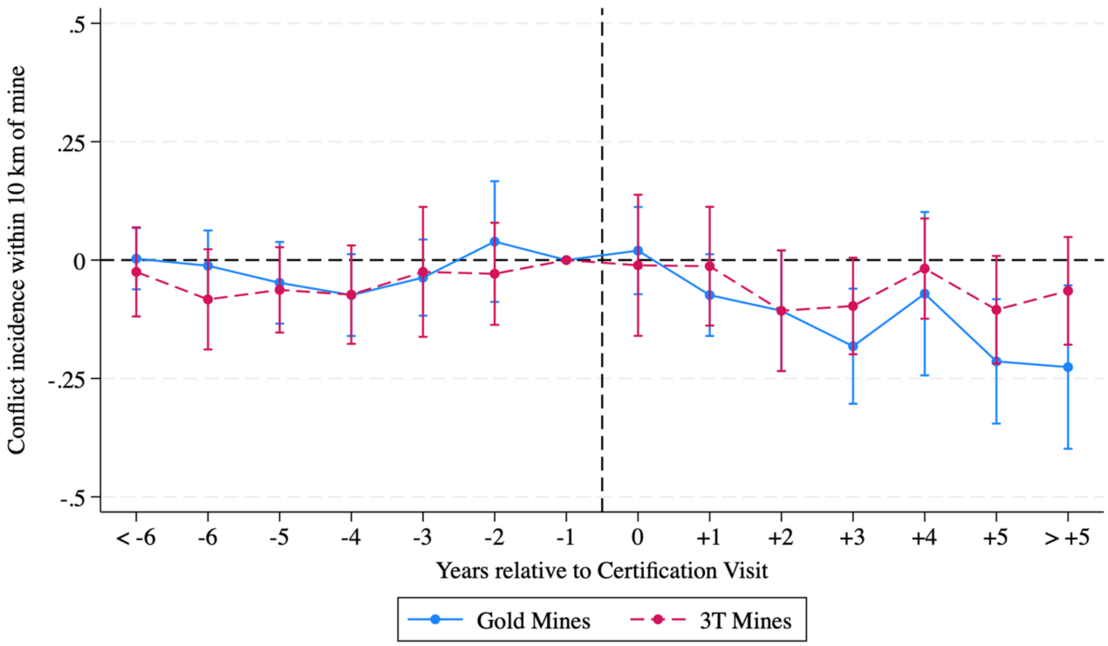
Figure 3. Supply Chain and Due Diligence



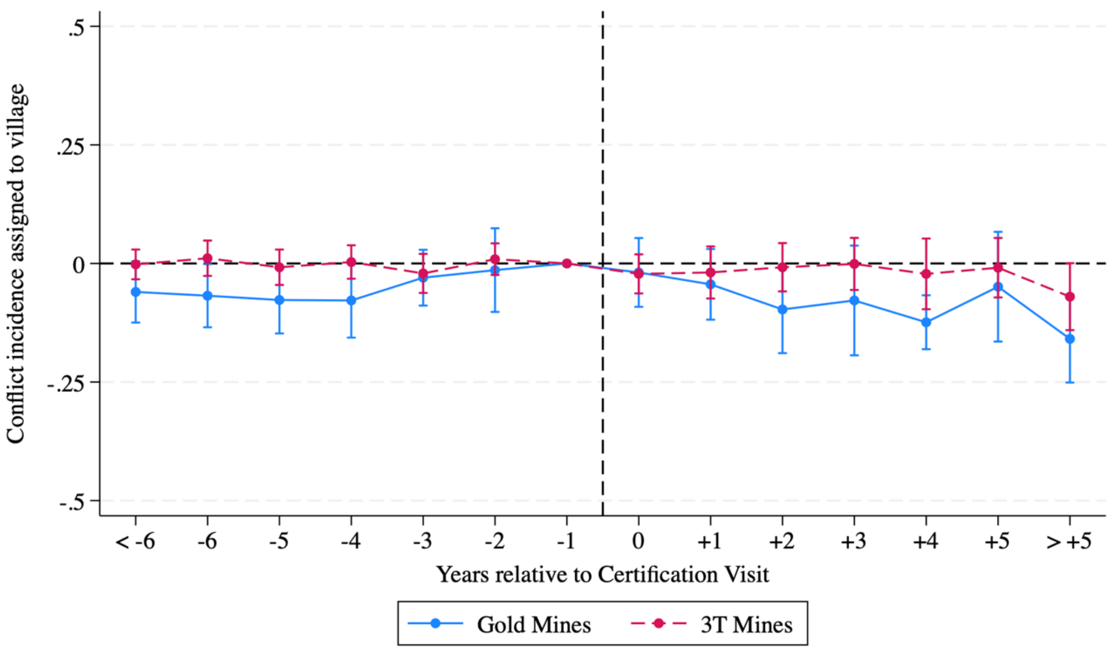
Notes: This figure illustrates the supply chain process for minerals extracted from artisanal mine sites as well as the risks involved for between-step transfers. Dodd-Frank requires registrants to audit smelters/refiners to make sure they: (1) only buy minerals from certified mines and (2) trace the country of origin. This figure is a modified version of a diagram found in the OECD Due Diligence Guidance (3rd Edition).

Figure 4. Change in Conflict After Certifications

Panel A: Mine Level



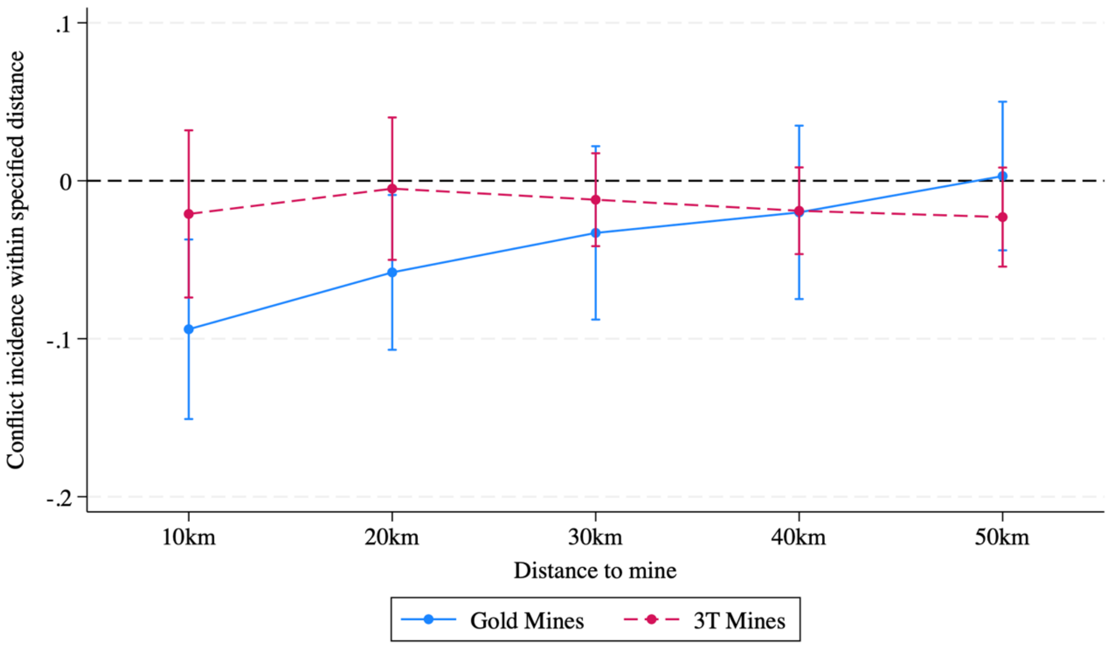
Panel B: Village Level



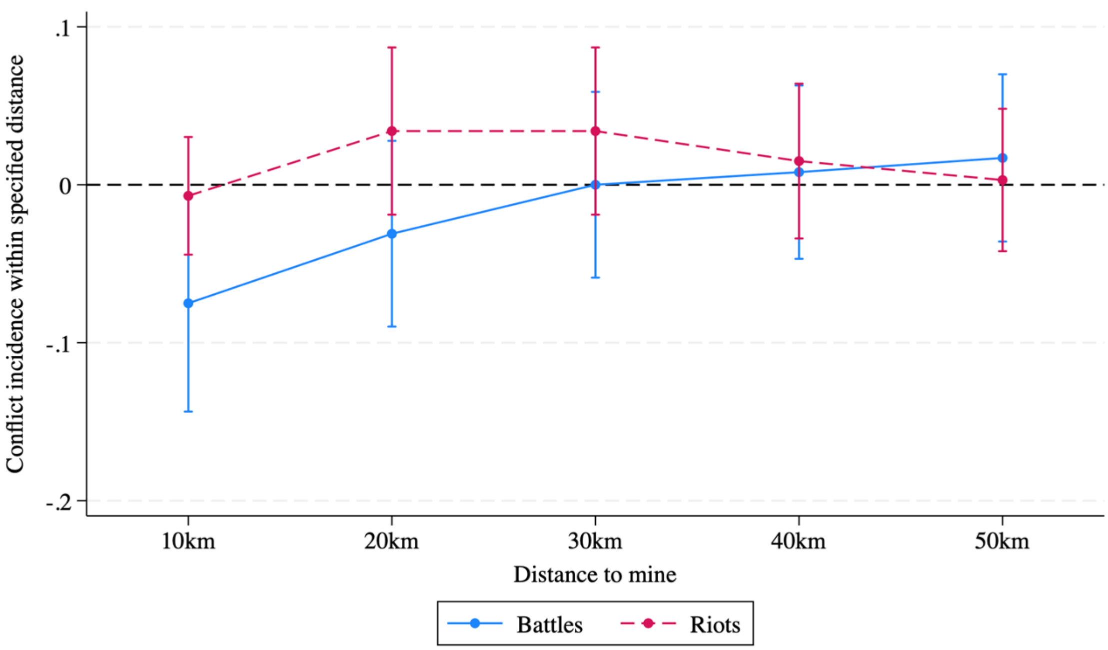
Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of 3TG mine certification on the probability of conflict incidence. We estimate the model from Table 3 but replace the *PostCert* indicator with separate interactions for each of the lead- and lag-years (except for the year before treatment, which serves as the benchmark). Panel A corresponds to Columns (2) and (3) of Table 3 (mine-level analysis), and Panel B corresponds to Columns (5) and (6) of Table 3 (village-level analysis).

Figure 5. Spatial Diffusion of Conflict Effect (Mine Level)

Panel A: Type of Mineral



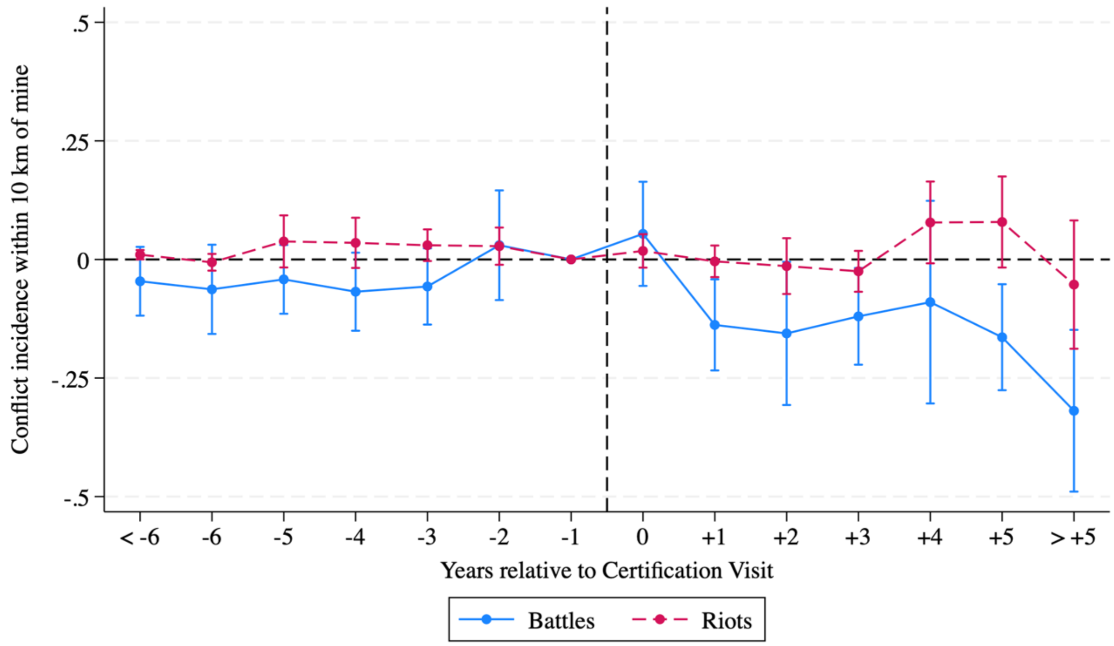
Panel B: Type of Conflict (Gold Only)



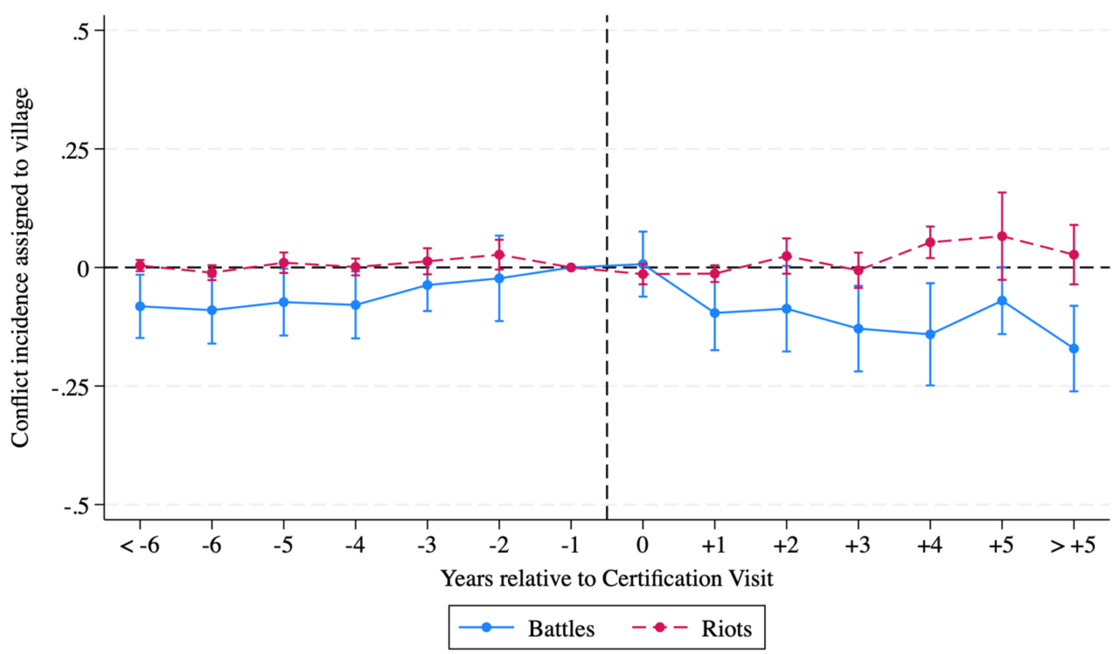
Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of 3TG mine certification on the probability of conflict incidence within 10km, 20km, 30km, 40km, and 50km of the mine, respectively. We estimate the model from Table 3 Columns (2) and (3) and Table 4 Columns (1) and (3) but use different radii for our dependent variable. Panel A splits the sample into gold and 3T mines, and Panel B further splits the gold-mine sample into battles and riots.

Figure 6. Gold Mines and Conflict Types

Panel A: Mine Level



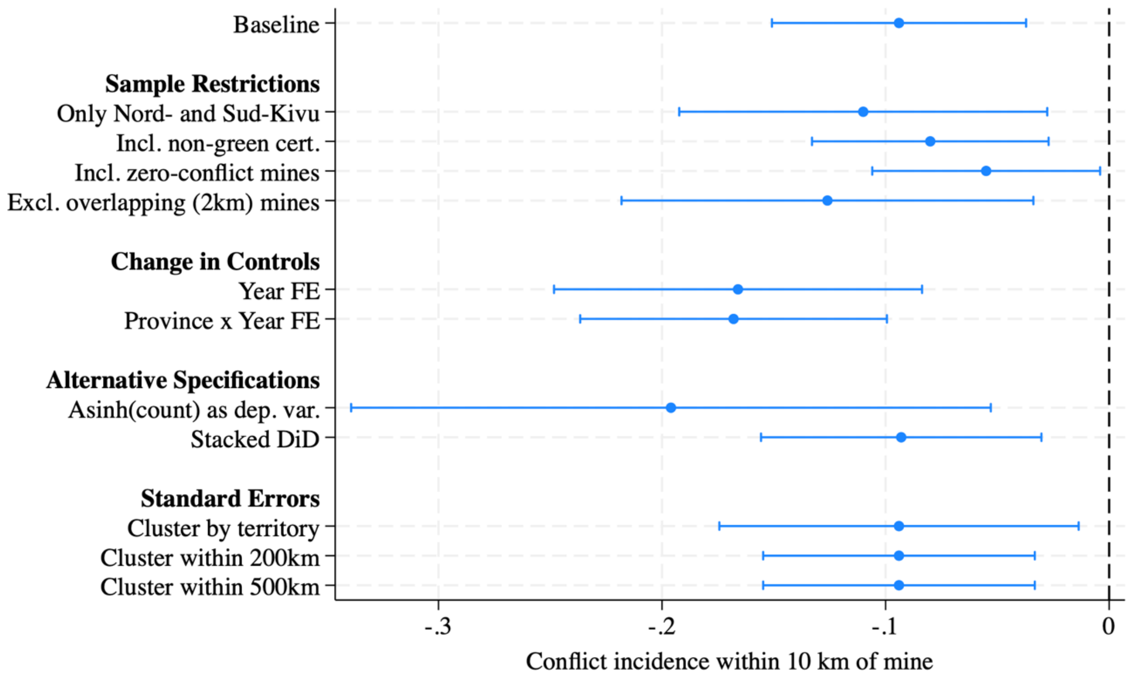
Panel B: Village Level



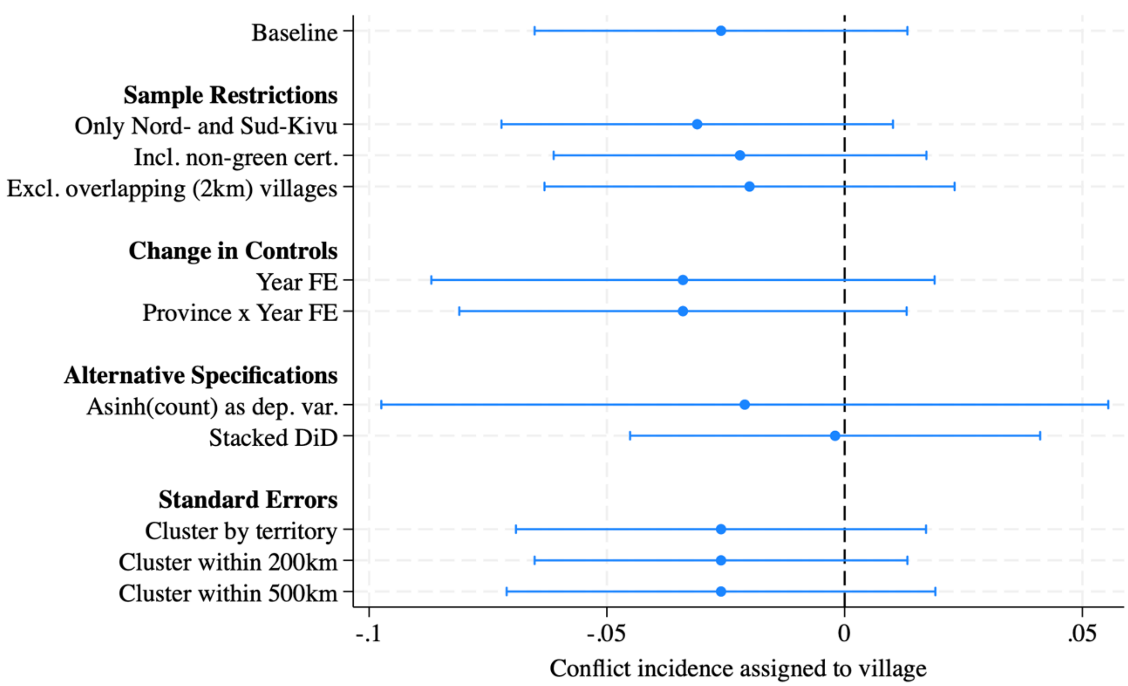
Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of gold mine certification on the probability of battle and riot incidence. We estimate the model from Table 4 but replace the *PostCert* indicator with separate interactions for each of the lead- and lag-years (except for the year before treatment, which serves as the benchmark). Panel A corresponds to Columns (1) and (3) of Table 3 (mine-level analysis), and Panel B corresponds to Columns (4) and (6) of Table 3 (village-level analysis).

Figure 7. Robustness to Different Specifications (Gold)

Panel A: Mine Level



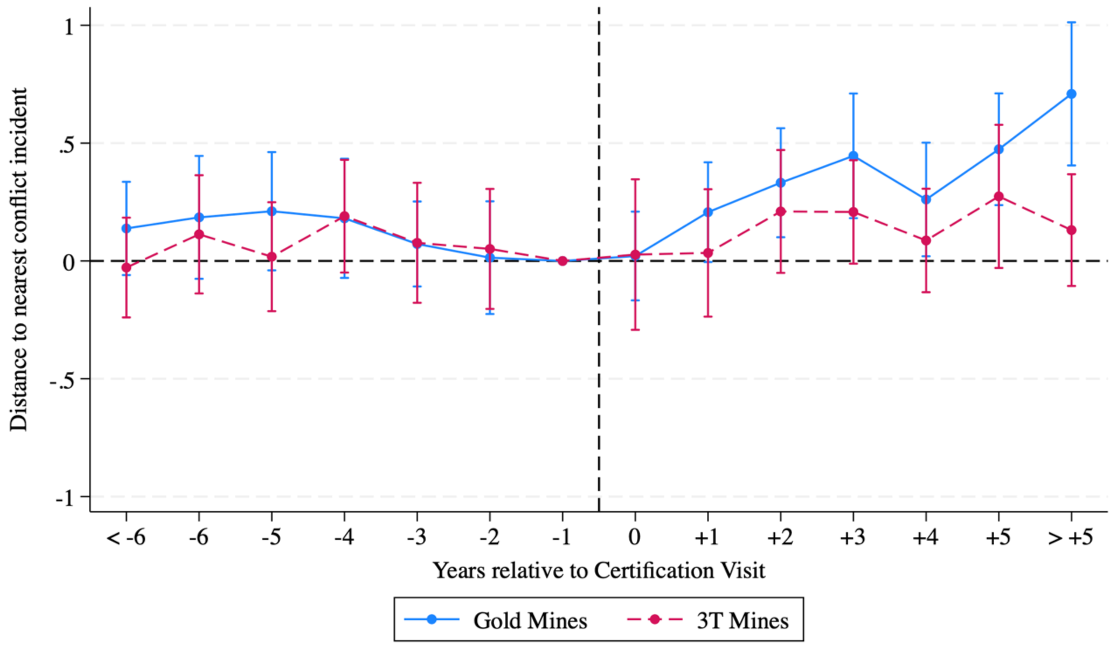
Panel B: Village Level



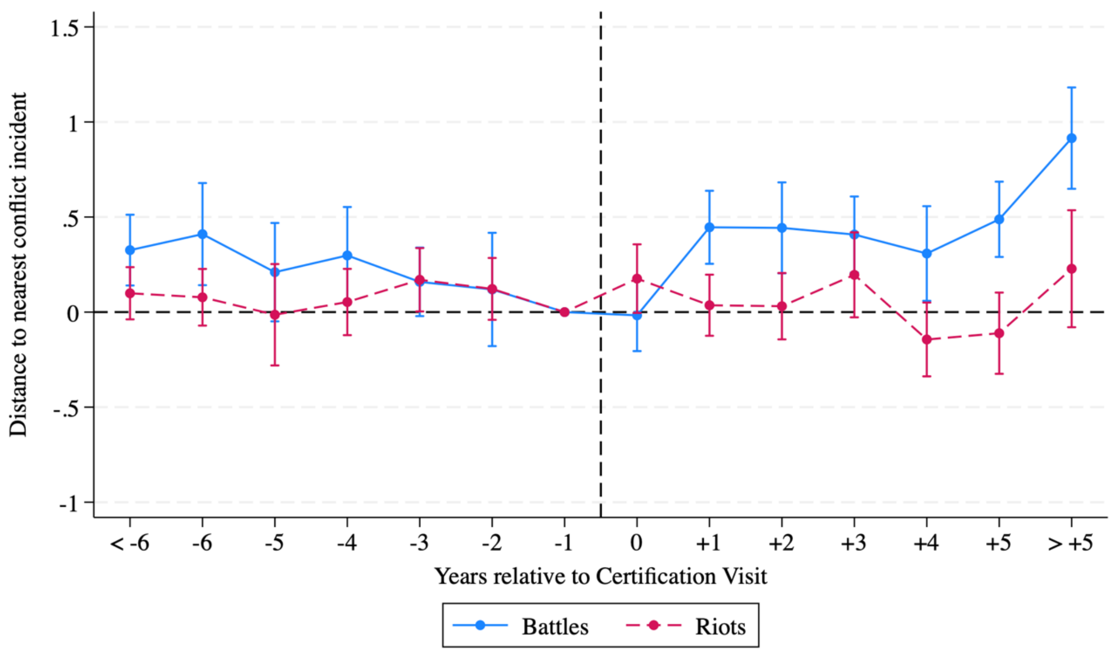
Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of gold mine certification on the probability of conflict incidence. We estimate the model from Table 3 Columns (2) and (5) but change various sample restrictions, fixed effects, and alternative specifications as identified in the figure.

Figure 8. Distance to Nearest Conflict (Mine Level)

Panel A: Type of Mineral



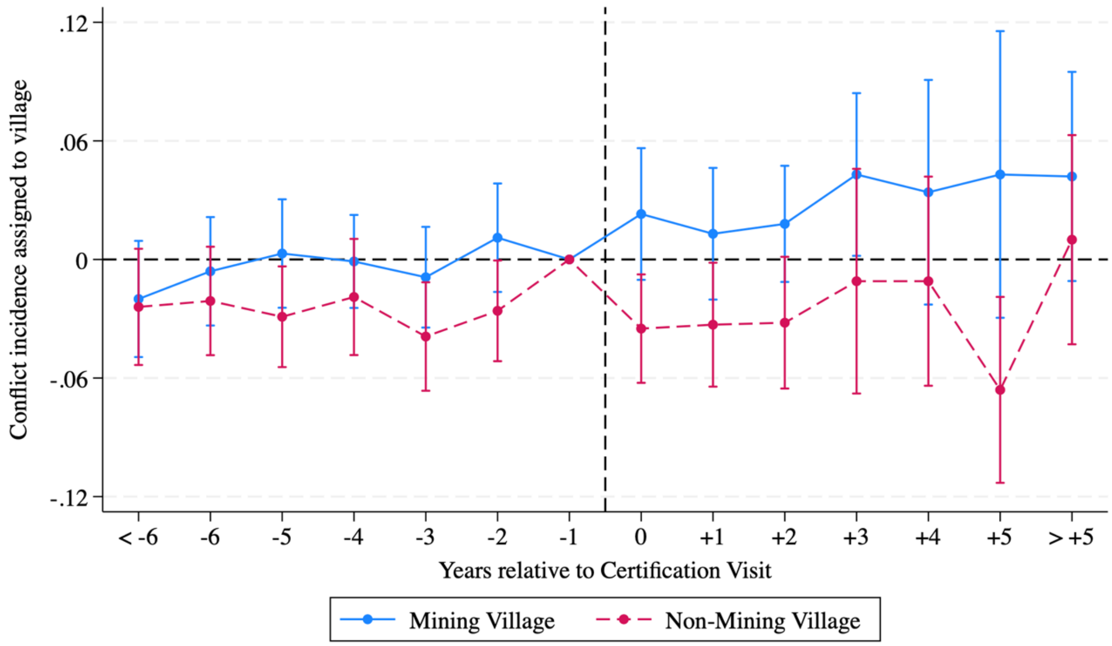
Panel B: Type of Conflict (Gold Only)



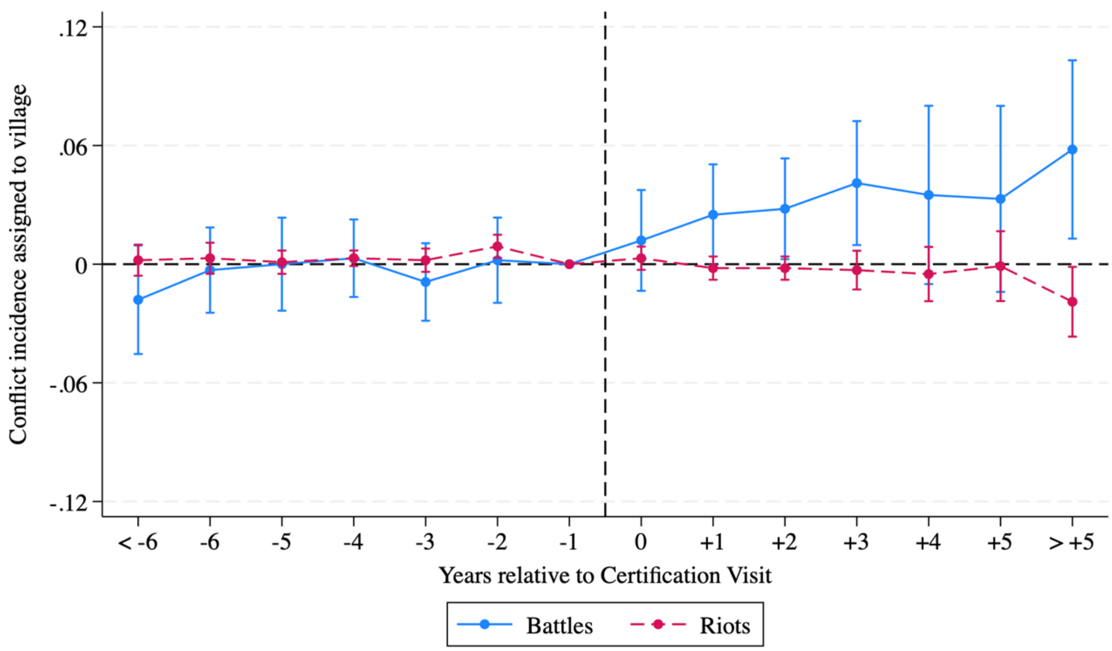
Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of gold mine certification on the distance from a mine to the nearest conflict in a year. We estimate the model from Table 7 but replace the *PostCert* indicator with separate interactions for each of the lead- and lag-years (except for the year before treatment, which serves as the benchmark). Panel A corresponds to Columns (1) and (2) of Table 7 (all conflicts), and Panel B corresponds to Columns (3) and (5) of Table 7 (battles and riots).

Figure 9. Displacement of Conflict (Village Level)

Panel A: Mining vs. Non-Mining Villages



Panel B: Type of Conflict (Mining Only)



Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of gold mine certification on the probability of battle and riot incidence in uncertified villages 50 to 100 kilometers away. We estimate the model from Table 8 but replace the *PostCert* indicator with separate interactions for each of the lead- and lag-years (except for the year before treatment, which serves as the benchmark). Panel A corresponds to Columns (1) and (2) of Table 8 (all conflicts), and Panel B corresponds to Columns (3) and (5) of Table 8 (battles and riots).

Table 1. Certifications by Year

Panel A: By Certification Status

First Cert. Year	Green		Yellow		Red		Blue (No Status)	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2011	19	3.99	17	48.57	5	55.56	0	0.00
2012	29	6.09	2	5.71	0	0.00	0	0.00
2013	70	14.71	3	8.57	1	11.11	0	0.00
2014	52	10.92	2	5.71	2	22.22	1	8.33
2015	74	15.55	0	0.00	0	0.00	1	8.33
2016	42	8.82	1	2.86	0	0.00	0	0.00
2017	88	18.49	7	20.00	0	0.00	0	0.00
2018	76	15.97	2	5.71	1	11.11	9	75.00
2019	26	5.46	1	2.86	0	0.00	1	8.33
Total	476	100.00	35	100.00	9	100.00	12	100.00

Panel B: By Mineral (Green Only)

First Cert. Year	All 3TG		Gold		3T	
	Freq.	%	Freq.	%	Freq.	%
	(1)	(2)	(3)	(4)	(5)	(6)
2011	19	3.99	2	1.89	17	4.59
2012	29	6.09	0	0.00	29	7.84
2013	70	14.71	4	3.77	66	17.84
2014	52	10.92	2	1.89	50	13.51
2015	74	15.55	19	17.92	55	14.86
2016	42	8.82	20	18.87	22	5.95
2017	88	18.49	10	9.43	78	21.08
2018	76	15.97	47	44.34	29	7.84
2019	26	5.46	2	1.89	24	6.49
Total	476	100.00	106	100.00	370	100.00

Notes: This table shows the annual number of initial ICGLR artisanal mine certification visits in the Eastern DRC from 2011 to 2019. Panel A separates the certifications by status, and Panel B separates the certifications by mineral. We observe a total of 532 initial certification visits from the IPIS database.

Table 2. Descriptive Statistics

Mean	Mine-Year All 3TG	Mine-Year Gold	Mine-Year 3T	Village-Year All 3TG	Village-Year Gold	Village-Year 3T
	(1)	(2)	(3)	(4)	(5)	(6)
CFC x *PostCert*	0.059	0.018	0.167	0.107	0.029	0.085
𝟙(*All Conflicts*)	0.267	0.255	0.300	0.110	–	–
𝟙(*Battles*)	0.184	0.177	0.202	0.067	–	–
𝟙(*Civilian Violence*)	0.184	0.178	0.201	0.062	–	–
𝟙(*Riots*)	0.045	0.041	0.055	0.009	–	–
Count(*Fatalities*)	2.929	3.067	2.565	0.570	–	–
Count(*Battle Fatalities*)	1.693	1.756	1.527	0.322	–	–
Count(*Civ. Viol. Fatalities*)	1.176	1.260	0.953	0.237	–	–
Count(*Riot Fatalities*)	0.058	0.051	0.077	0.012	–	–
Distance to Nearest Conflict	34.972	33.133	39.834	–	–	–
Distance to Nearest Battle	47.401	44.284	55.640	–	–	–
Distance to Nearest Civ. Viol.	46.017	43.666	52.231	–	–	–
Distance to Nearest Riot	151.554§	154.015§	145.050§	–	–	–
Observations (count)	38,076	27,626	10,450	26,505	26,505	26,505

Notes: This table presents descriptive statistics for our main sample, which is a balanced panel of mine- and village-year observations. We use this sample in Figures 4–7 and Tables 3–7. The sample is from 2004 to 2022. *CFC* x *PostCert* (presented as an interaction because control mines are not assigned treatment years) is a binary indicator equal to one for certified (green) mines or villages during and after the year of certification. 𝟙(*All Conflicts*), 𝟙(*Battles*), 𝟙(*Civilian Violence*), and 𝟙(*Riots*) are binary indicators equal to one if one or more conflict, battle, civilian violence, or riot incidence, respectively, is documented within 10km of a mine or assigned to a village. Count(*Fatalities*), Count(*Battle Fatalities*), Count(*Civ. Viol. Fatalities*), and Count(*Riot Fatalities*) are count variables for the number of fatalities from all conflicts, battles, civilian violence, or riots, respectively, documented within 10km of a mine or assigned to a village. *Distance to Nearest Conflict*, *Battle*, *Civ. Viol.*, and *Riot* are continuous variables for the distance in kilometers between a mine and the nearest instance of conflict, battle, civilian violence, or riot, respectively, in a given year. Only *PostCert* is separated across category for villages because the sample remains the same. (§Fewer observations are available for this estimate as there are no riot observations in 2006.)

Table 3. Certifications and Conflict

Dep. Var.: 𝟙(*All Conflicts*)	Mine Level			Village Level		
	All 3TG	Gold	3T	All 3TG	Gold	3T
	(1)	(2)	(3)	(4)	(5)	(6)
CFC x *PostCert*	-0.056**	-0.094***	-0.021	-0.027*	-0.026	-0.024
	(0.026)	(0.029)	(0.027)	(0.014)	(0.020)	(0.016)
Mine FE	Yes	Yes	Yes			
Village FE				Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.575	0.588	0.604	0.377	0.377	0.377
Observations (Mine-Year)	38,000	27,550	10,374			
Observations (Village-Year)				26,391	26,391	26,391

Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal mine certification visits with "green" status on mine- and village-level conflict incidence by mineral type. We describe the sample selection in Section IA4 of the Internet Appendix, and we further drop singletons corresponding to the fixed-effect structure. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. 𝟙(*All Conflicts*) is a binary indicator for whether one or more incidents of conflict, defined according to Stoop et al. (2018), is observed within 10km of a mine or assigned to a village. *CFC* is a binary indicator for whether a mine has been treated or whether any mine within 10km of a village has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine or village.

Table 4. Certifications and Conflict by Type

Dep. Var.: 𝟙(*Conflict Type*)	Mine-Level			Village-Level		
	Battles	Civ. Viol.	Riots	Battles	Civ. Viol.	Riots
	(1)	(2)	(3)	(4)	(5)	(6)
CFC x *PostCert*	-0.075**	-0.073***	-0.007	-0.030	0.007	0.006
	(0.035)	(0.029)	(0.019)	(0.021)	(0.021)	(0.009)
Mine FE	Yes	Yes	Yes			
Village FE				Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.513	0.577	0.426	0.306	0.299	0.232
Observations (Mine-Year)	27,550	27,550	27,550			
Observations (Village-Year)				26,391	26,391	26,391

Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal gold mine certification visits with "green" status on mine- and village-level conflict incidence by conflict type. We describe the sample selection in Section IA4 of the Internet Appendix, and we further drop singletons corresponding to the fixed-effect structure. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. 𝟙(*Conflict Type*) is a binary indicator for whether one or more incidents of the specified type of conflict, defined according to Stoop et al. (2018), is observed within 10km of a mine or assigned to a village. *CFC* is a binary indicator for whether a mine has been treated or whether any mine within 10km of a village has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine or village.

Table 5. Certifications and Fatalities

	Mine Level				Village Level			
Dep. Var.: asinh(*Fatality Count*)	All Conflicts	Battles	Civ. Viol.	Riots	All Conflicts	Battles	Civ. Viol.	Riots
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CFC x *PostCert*	-0.164*	-0.142**	-0.106*	0.009	-0.032	-0.030	0.002	-0.006
	(0.086)	(0.075)	(0.060)	(0.021)	(0.049)	(0.041)	(0.030)	(0.009)
Mine FE	Yes	Yes	Yes	Yes				
Village FE					Yes	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.605	0.529	0.578	0.343	0.343	0.274	0.281	0.160
Observations (Mine-Year)	27,550	27,550	27,550	27,550				
Observations (Village-Year)					26,391	26,391	26,391	26,391

Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal gold mine certification visits with "green" status on mine- and village-level fatalities by conflict type. We describe the sample selection in Section IA4 of the Internet Appendix, and we further drop singletons corresponding to the fixed-effect structure. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. asinh(*Fatality Count*) is the inverse hyperbolic sine of the count of fatalities from the specified type of conflict within 10km of a mine or associated with a village. *CFC* is a binary indicator for whether a mine has been treated or whether any mine within 10km of a village has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine or village.

Table 6. Certifications and Aggregate Conflict (Territory Level)

	Certification Count					Certification Fraction				
Dep. Var.: asinh(*Conflict Count*)	All Conflicts	Battles	Civ. Viol.	Riots	Fatalities	All Conflicts	Battles	Civ. Viol.	Riots	Fatalities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
asinh(*Gold Cert. Count*)	0.029	0.021	0.033*	-0.003	0.005					
	(0.019)	(0.020)	(0.018)	(0.016)	(0.017)					
Gold Cert. Fraction						0.439	-0.034	0.497*	0.247*	0.155
						(0.340)	(0.177)	(0.254)	(0.148)	(0.274)
Territory FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.734	0.692	0.707	0.587	0.642	0.734	0.692	0.706	0.588	0.642
Observations (Territory-Year)	1,615	1,615	1,615	1,615	1,615	1,615	1,615	1,615	1,615	1,615

Notes: This table reports coefficient estimates of OLS regressions estimating the aggregate effect of artisanal gold mine certification visits with "green" status on territory-level conflict incidence by type and fatalities. We describe the sample selection in Section IA4 of the Internet Appendix, and we further drop singletons corresponding to the fixed-effect structure. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. asinh(*Conflict Count*) is the inverse hyperbolic sine of the count of conflicts of the specified type within a territory. asinh(*Gold Cert. Count*) is the inverse hyperbolic sine of the count of certified gold mines within a territory. *Gold Cert. Fraction* is the count of certified gold mines divided by the total number of gold mines within a territory.

Table 7. Certifications and Distance to Nearest Conflict (Mine Level)

Dep. Var.: asinh(*Distance to Nearest Conflict*)	3T Mines	Gold Mines			
	All Conflicts	All Conflicts	Battles	Civ. Viol.	Riots
	(1)	(2)	(3)	(4)	(5)
CFC x *PostCert*	0.092*	0.184***	0.121*	0.069	-0.017
	(0.058)	(0.062)	(0.064)	(0.065)	(0.047)
Mine FE	Yes	Yes	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.806	0.766	0.773	0.789	0.904
Observations (Mine-Year)	10,374	27,550	27,550	27,550	26,100

Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal mine certification visits with "green" status on distance between a mine and the nearest conflict incident. We describe the sample selection in Section IA4 of the Internet Appendix, and we further drop singletons corresponding to the fixed-effect structure. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. asinh(*Distance to Nearest Conflict*) is the inverse hyperbolic sine of the distance, in kilometers, between a mine and the nearest conflict incident of the specified type. *CFC* is a binary indicator for whether a mine has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine. ([§]Only 26,172 observations are available for this specification since there are no riot observations in 2006.)

Table 8. Certifications and Conflict Displacement (Village Level)

	Non-Mining	Mining			
Dep. Var.: 𝟙(*Conflict Type*)	All Conflicts	All Conflicts	Battles	Civ. Viol.	Riots
	(1)	(2)	(3)	(4)	(5)
CFC x *PostCert*	-0.005	0.027**	0.028***	0.019**	-0.004
	(0.012)	(0.011)	(0.010)	(0.009)	(0.003)
Village FE	Yes	Yes	Yes	Yes	Yes
Province x Year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.323	0.337	0.268	0.252	0.180
Observations (Village-Year)	33,953	24,149	24,149	24,149	24,149

Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal gold mine certification visits with "green" status on village-level conflict incidence by conflict type in uncertified villages 50 to 100 kilometers away. The sample is a balanced panel of all uncertified villages from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. 𝟙(*Conflict Type*) is a binary indicator for whether one or more incident of the specified type of conflict, defined according to Stoop et al. (2018), is assigned to a village. *CFC* is a binary indicator for whether any mine within 10km of a village has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified village.

Online Appendix to

Nothing Gold Can Stay: Artisanal Mine Certifications and Conflict Dynamics in the Congo

By SAMUEL CHANG and HANS B. CHRISTENSEN

November 2023

Contents

Section IA1. Theoretical Framework for Conflict Displacement 1

Section IA2. Institutional Details on Artisanal Mining 6

Section IA3. Certification Selection 7
IA3.1 Geographic Distribution of Certifications 7
IA3.2 Criteria for Certification Selection 10
IA3.3 Criteria for Certification Selection (Gold Only) 15

Section IA4. Sample Selection and Composition 18

Section IA5. Supplementary Tests 22
IA5.1 Jackknife Excluding Certification Years 22
IA5.2 Jackknife Excluding Provinces 24
IA5.3 Separating Early and Late Certifications 26
IA5.4 Smaller Radii and Excluding Overlapping Areas 27
IA5.5 Including Non-3TG Control Mines 29
IA5.6 Controlling for Local Economic Factors 30
IA5.7 Displacement of Conflict Using Territory-Year FE 31

Section IA6. Tests including Non-Green Certifications 33
IA6.1 Effect of Mine Certifications on Conflict 33
IA6.2 Geographic Displacement of Conflict 36

Section IA7. Tests using Alternative UCDP Conflict Data 39
IA7.1 Sample Selection and Descriptive Statistics 39
IA7.2 Effect of Mine Certifications on Conflict 43
IA7.3 Geographic Displacement of Conflict 47

Section IA8. References 51

Section IA1. Theoretical Framework for Conflict Displacement

IA1.1 General Framework

In this section, we develop a simple model to explain artisanal mine and armed group economic incentives as a framework to interpret our main results. Consider one representative artisanal mine and one armed group. We ignore any agency problems that may occur within either unit and assume both units have uniform economic considerations. Further assume that global mineral prices are exogenous and the amount artisanal mines receive for their output is fixed.

A mine can sell their minerals in two ways: (1) officially to a refiner/smelter and (2) unofficially to a smuggler. However, a mine failing certification may only sell to the smuggler while a mine passing or not considered for certification may sell to either.[31] For simplicity, we assume the latter mines will only sell officially to obtain higher income. Thus, not considering armed group involvement, the mine's utility equals:

$$U(q) = \begin{cases} u(q), & \text{if passed certification or not considered} \\ (1-\alpha)u(q), & \text{if failed certification} \end{cases} \tag{1}$$

where $u(q)$ is the amount of money received by a mine selling mineral output q and $\alpha \in (0,1)$ is the discount from selling illegally. $u(\cdot)$ is a linear function because the market is assumed to be perfectly competitive and each mine can sell as much of the mineral as they produce at the fixed price.

An armed group controlling a mine has economic considerations partially aligned with those of the mine because they achieve economic rents from illegally taxing the mine's income. Specifically, they extract a fraction $\beta \in (0,1)$ of whatever the mine earns from mineral sales $u(q)$. In the event of a certification, the armed group must consider whether it is optimal to move away from the mine to avoid certification failure and the subsequent reduction in mineral sales price (and extracted rents). The armed group has three choices: (1) staying at the same distance from the mine, (2) moving to a distance further away from the mine, and (3) relocating to a distinct uncertified mine. We explore the latter two possibilities in the next two sections.

[31] Because of due diligence requirements imposed on smelters, they may only purchase from conflict-free mines.

IA1.2 Case 1: Movement Away from Mine

The first action that an armed group could take is moving a distance away from a mine but continuing to control and tax it. This would reduce the probability of detection at some cost of controlling a larger area. This strategy is consistent with institutional evidence that roadblock taxation is one of the biggest sources of income for armed groups in the DRC (Matthysen & Gobbers, 2022).

Imagine that an uncertified mine has a nonzero probability p of being certified (i.e., visited for the first time by a certification inspector) at any given moment. On the other hand, a certified mine (regardless of the initial outcome) will be visited with certainty ($p = 1$) at some point within one year.[32] Given that there is an armed group present within distance d from a mine, it will fail the certification visit with probability $r(d)$ where r is decreasing in d. An armed group occupying a mine with output q incurs some nonzero cost $c(q,d)$ from moving to a distance d away, where c is increasing in both q and d.

We assume that, when an unanticipated initial certification visit occurs, the armed group cannot move operations immediately. Therefore, the armed group may only evaluate its optimal action subsequent to the visit. Regardless of the outcome of the initial visit, mines are guaranteed at least one subsequent visit during which they are reconsidered or recertified. Thus, the utility of the armed group can be expressed as:

$$V(\beta, q, d) = (1-p)\beta u(q) + p\big(1 - r(d)\big)\beta u(q) + pr(d)\beta(1-\alpha)u(q) - c(q,d) \quad (2)$$

The utility for uncertified mines is composed of three cases: (1) there is no certification visit and the mine continues to sell minerals at the official price, (2) there is a certification visit and the mine passes and continues to sell minerals at the official price, and (3) there is a certification visit but the mine fails and must sell minerals to smugglers at a discounted price. For certified mines, the armed group knows with certainty that a future inspection visit will occur, so its utility is composed of only the latter two cases. Since we are interested in certified mines, we set $p = 1$ and drop the first term in the following analyses.

[32] This is consistent with the provisions in the ICGLR manual, which we assume are accurately implemented within the program. If a mine passed certification on a previous visit (green rating), it will be revisited annually to ensure continued adherence to conflict-free standards. On the contrary, if a mine failed certification on a previous visit (red or yellow rating), it will be given a new chance at certification in the subsequent year.

We can maximize the utility function in Eq. (2) with respect to d to determine the optimal distance that an armed group stays away from a mine. The first-order condition gives:

$$-\alpha\beta r'(d)u(q) - c_d(q, d) = 0 \tag{3}$$

In order to solve this and draw inferences, it is easier to assume functional forms for $r(d)$, $u(q)$, and $c(q,d)$. We intuit reasonable functions from our institutional setting. Since the probability of detection of an armed group likely decreases quickly within a short distance of a mine (inspectors have time constraints), we assume that $r(d) = e^{-d}$, which is a decreasing and convex function in d. We know that mineral prices are constant with quantity, so $u(q) = kq$ where k is the price per unit of the mineral output. Since moving away from the mine means that the armed group must control a larger area to continue collecting taxes, we say that $c(q,d) = cqd^2$, which increases linearly in the size of the mine q, linearly in some cost multiplier c, and quadratically in the distance from the mine d. Using these forms, the second-order condition is also satisfied, as both $c_{dd}(q,d)$ and $r''(d)$ are positive, making the expression negative. Inserting these into Eq. (3) and solving, we get:

$$de^d = \frac{\alpha\beta k}{2c} \tag{4}$$

From this, we derive the following proposition:

Proposition 1. *The optimal distance d for the armed group to move away from the mine is decreasing in c and increasing in α, β, and k.*

First and most straightforward, we can see that armed groups move further away from mines if the per-unit cost of moving c is lower. Second, armed groups move further away if the discount from selling illegally α is higher, which means that they would lose more if the mine fails certification. Finally, for similar reasons, armed groups move further away if the proportion of taxation β or the unit price of minerals k are higher. These theoretical predictions are consistent with our empirical design and findings.

IA1.3 Case 2: Relocation to Another Mine

The second action that an armed group could take is entirely relocating to a different uncertified mine. This would reduce the probability of detection at some cost of relocation. While no institutional evidence directly supports this strategy, it is highly likely given armed groups are very mobile and can easily establish control over mines.

Similar to the previous situation, say that an uncertified mine has a nonzero probability p of being certified (i.e., visited for the first time by a certification inspector) at any given moment. A certified mine (regardless of the initial outcome) will be visited with certainty ($p = 1$) at some point within one year. Given that there is an armed group present at the mine, it will fail the certification visit with probability r. An armed group occupying a mine with output q incurs some nonzero cost $c(q)$ from relocating to another mine. In this case, we do not consider distance d and simply assume that the armed group is occupying the mine.

Again, we assume that, when an unanticipated initial certification visit occurs, the armed group cannot move operations immediately. Thus, the utility of the armed group controlling a certified mine can be expressed as:

$$\begin{cases} (1-p)\beta u(q) + p(1-r)\beta u(q) + pr\beta(1-\alpha)u(q), & \text{if not certified} \\ (1-r)\beta u(q) + r\beta(1-\alpha)u(q), & \text{if certified (no move)} \\ (1-p)\beta u(q) + p(1-r)\beta u(q) + pr\beta(1-\alpha)u(q) - c(q), & \text{if relocated} \end{cases} \tag{5}$$

We are again interested in the latter two cases, which are the options for an armed group after the mine is certified. Comparing the two utility functions shows that the armed group should:

$$\begin{cases} \text{move}, & \text{if } 1 > p + \dfrac{c(q)}{\alpha\beta r u(q)} \\ \text{stay}, & \text{if } 1 < p + \dfrac{c(q)}{\alpha\beta r u(q)} \end{cases} \tag{6}$$

In this case, functional forms are unnecessary to draw conclusions. From Eq. (6), we derive the following proposition:

Proposition 2. *Holding all else equal, there exists some c(q) and p below which and some r, α, and β above which it is optimal for an armed group to relocate to an uncertified mine.*

First and most straightforward, we can see that a higher movement cost $c(q)$ deters movement. Second, a higher probability of certification p for uncertified mines deters movement because the chance that the destination mine also becomes certified in the future increases. Third, a higher detection probability r encourages movement due to an increased chance of failure if the armed group stays. Finally, for economic considerations as before, an increased discount from selling illegally α and an increased proportion of taxation β encourage movement. These theoretical predictions are similar to those from Proposition 1 and consistent with our empirical design and findings.

Section IA2. Institutional Details on Artisanal Mining

Artisanal and small-scale mining is a large sector of the DRC economy, employing an estimated two million people (Glencore, 2023). Such labor is often "pursued as a route out of poverty or as an activity to complement insufficient income" (Fritz et al., 2018, p. 4) for struggling communities in African countries. Artisanal mining also, to a large extent, operates as part of the informal economy, making it an ideal financing source for militant factions including the Congolese Army, who oftentimes act as an intermediary between the mines and global markets. In the process of selling the minerals up the supply chain, illegal rents and taxes are extracted, which then fund violent operations in and around the mining areas.

Stoop et al. (2019) show that rising mineral prices increase battles around artisanal mines, but the expansion of industrial mines crowds out artisanal mines and triggers riots, violence against civilians, and looting. These results indicate that, while artisanal mines do play a role in financing violent operations, an abrupt halt turns desperate miners to illegal activities such as looting or joining an armed group in order to support themselves and their families (Stoop & Verpoorten, 2020). One example of such a ban occurred in the Democratic Republic of the Congo (DRC) in 2009 (Schütte, 2018). Rather than targeting real conflict actors to reduce conflict in the region, it hurt artisanal miners and small-scale traders in the area by depressing prices and eliminating their only source of livelihood. In addition to this, such a ban even damaged recent progress made in certifying and regulating the mineral trade (de Koning, 2009).

Most NGOs agree that such a halt of artisanal mining operations is neither a feasible nor effective way to address the issue because there are typically few other opportunities for employment. Instead, NGOs have suggested that initiatives to encourage more jobs along the mineral supply chain, provide initial funding for family farming, and certify mines to reduce illegal taxation are more effective ways of resolving the issues associated with artisanal mining (Fritz et al., 2018). Artisanal and small-scale mines in the DRC are almost exclusively located in the eastern provinces, and the certification scheme focuses on mines located in the provinces with the highest conflict intensity (see Figure 1 Panels A, C, and D in the paper).

Section IA3. Certification Selection

IA3.1 Geographic Distribution of Certifications

In this section, to supplement information from Figure 1 Panel C, we tabulate the geographic and time-series distribution of certified mines to provide more insight on certification selection. These are based on the same IPIS artisanal mine data as our main analyses.

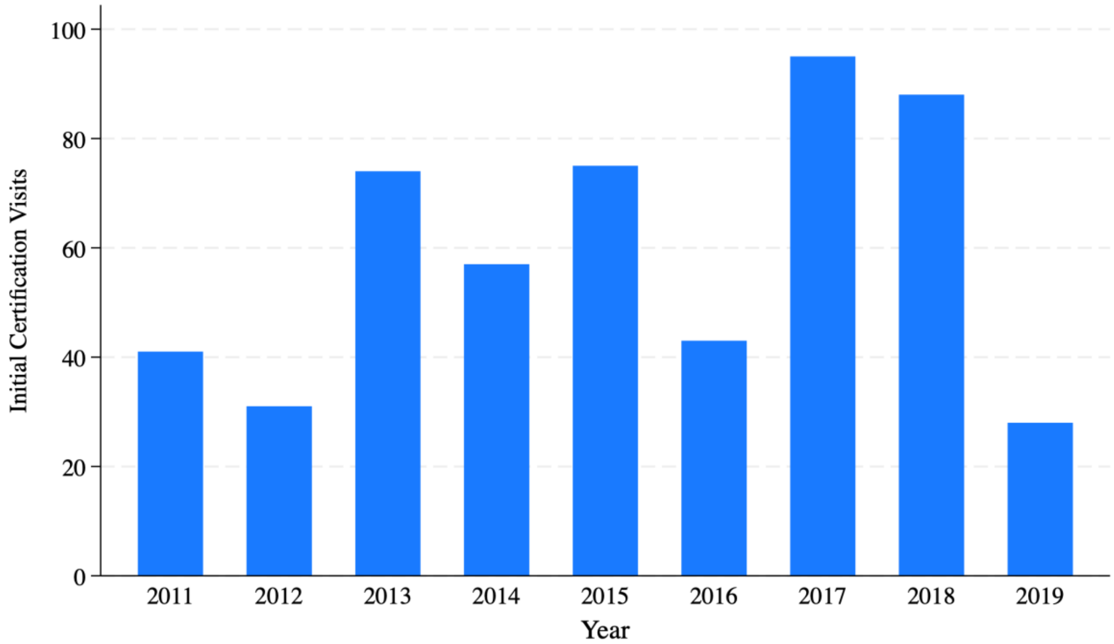
In Panel A of Figure IA3.1, we observe that ICGLR certification visits started in 2011 and our sample only includes visits as recent as 2019. While more initial certification visits occur in 2021, we do not include these in our sample because we do not have an adequate post-period for analysis. Within the sample of initial visits, the distribution is relatively even across years with a smaller number of visits in the former years of the program (2011–2012) and larger number of visits in the latter years (2013–2018). This is consistent with inspections becoming more efficient and widespread as experience is gained.

In Panel B of Figure IA3.1, we observe that there are the most tin mine certifications followed by gold, tantalum, and tungsten in that order. Tin certifications peak in 2017 and gold certifications peak in 2018. This is consistent with tin and gold being the more common 3TG minerals mined in the DRC and, specifically, in artisanal mines.

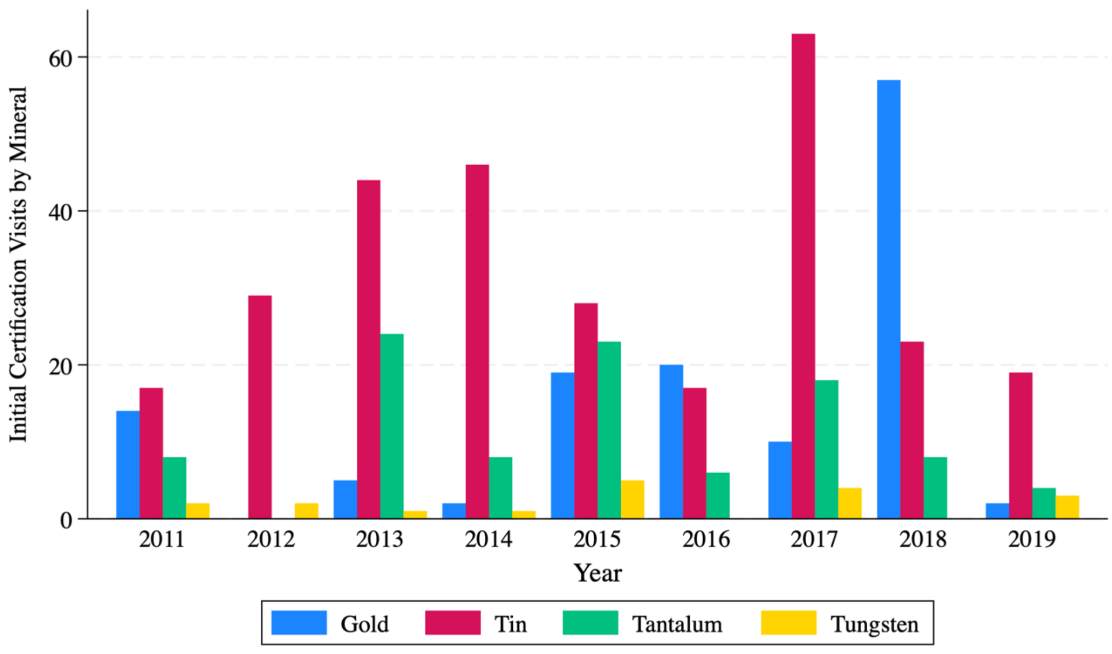
In Table IA3.1, we observe evidence that supports the geographic clustering of certification visits within year. As stated in Section 2.2 of the paper, this reflects inspectors' cost considerations. Because sending an inspection mission into conflict areas (such as the eastern DRC) requires significant logistical planning and incurs nontrivial costs, we anticipate that missions will target specific areas within a territory to save the hassle of transportation. We do see such clustering of visits, examples being the certification of mines in Lualaba in 2014, Bas-Uele in 2015, and Ituri and Tshopo in 2018. As mentioned in Section 2.2 in the paper, we take potential spillover effects into account when interpreting economic magnitudes.

Figure IA3.1. Certifications by Year

Panel A: All Minerals



Panel B: By Mineral Type



Notes: This figure shows the distribution of all initial certification visits by year, including mines not part of our main sample. Panel A shows all visits. Panel B splits the sample by commodity.

Table IA3.1. Certifications by Province and Year

Year	*Bas-Uele*	*Haut-Katanga*	*Haut-Lomami*	*Haut-Uele*	*Ituri*	*Lualaba*	*Maniema*	*Nord-Kivu*	*Sud-Kivu*	*Tanganyika*	*Tshopo*	**TOTAL**
2011	0	0	0	0	0	0	0	14	27	0	0	**41**
2012	0	0	0	0	0	0	26	0	5	0	0	**31**
2013	0	2	16	0	0	0	17	0	2	37	0	**74**
2014	0	7	11	0	0	8	0	17	9	5	0	**57**
2015	12	6	2	0	6	0	17	21	7	3	1	**75**
2016	0	0	0	0	0	0	15	15	13	0	0	**43**
2017	0	0	1	0	0	0	19	10	30	35	0	**95**
2018	0	0	0	0	22	0	0	18	38	0	10	**88**
2019	0	0	7	0	0	0	1	4	14	2	0	**28**
TOTAL	**12**	**15**	**37**	**0**	**28**	**8**	**95**	**99**	**145**	**82**	**11**	**532**

Notes: This table describes the distribution of initial certification visits by year and province, including mines not part of our main sample.

IA3.2 Criteria for Certification Selection

Purportedly, criteria for selection of certifications consist of security, accessibility, legality, and traceability.[33] Among these, the main concern is selection on security, which is associated with our main outcome variable. Accessibility and legality are also observable and likely to be a key factor in selection. Though not explicitly included in the selection criteria, additional economic variables could also play a role in determining which mines are certified. Institutionally, we expect that economic activity, local economic importance of mining, and the relative cost of certification each impact the likelihood of initial inspection. To gauge whether these factors affect selection, we empirically estimate the following OLS regression:

$$\begin{gathered}\mathbb{1}(Initial\ Cert) = \beta_0 + \beta_1\ \textbf{asinh}(Conflict\ 10km)_{m,t-1} + \beta_2\ \textbf{asinh}(Avg\ Lum\ 1km)_{m,t-1} \\ +\beta_3\ EVI\ 1km_{m,t-1} + \beta_4\ \textbf{asinh}(Dist\ to\ Road)_m + \beta_5\ \textbf{asinh}(Dist\ to\ Maj\ Road)_m \\ +\beta_6\ \textbf{asinh}(Dist\ to\ Pop)_m + \beta_7\ \textbf{asinh}(Dist\ to\ Cert)_{m,t} + \beta_8\ \mathbb{1}(Protected\ Area)_m + \varepsilon_m\end{gathered} \tag{1}$$

$\mathbb{1}$(*Initial Cert*) is an indicator variable for whether a mine *m* is first certified in year *t*. asinh(*Conflict 10km*) is the inverse hyperbolic sine of the count of all conflicts within 10 kilometers of mine *m* in year *t-1*, which represents the pre-certification security around the mine. asinh(*Avg Lum 1km*) is the inverse hyperbolic sine of the average luminosity within 1 kilometer of the nearest population center to mine *m* in year *t-1*, which represents local economic activity.[34] *EVI 1km* is the enhanced vegetation index within 1 kilometer of mine *m* in year *t-1*, which represents centrality of agriculture–the main alternative to mining.[35] asinh(*Dist to Road*) and asinh(*Dist to Maj Road*) are the inverse hyperbolic sines of the time-invariant distances from mine *m* to the nearest road and major road, respectively, which represent the accessibility to the mine.[36] asinh(*Dist to Pop*) is the inverse hyperbolic sine of the time-invariant distance from mine *m* to the nearest population center (i.e., city, town, village, or hamlet), which is also a determinant of mine accessibility.[37] asinh(*Dist to Cert*) is the inverse hyperbolic sine of the distance from mine *m* to the nearest mine certified in

[33] This information is based on private communication with a knowledgeable party.
[34] Average luminosity is obtained from DMSP nighttime stable light data (2011–2013) and DMSP-like VNL light data (2014–2019) organized by the Colorado School of Mines (Baugh et al., 2010; Ghosh et al., 2021). This data can be found at https://eogdata.mines.edu/products/dmsp/.
[35] Enhanced vegetation index is obtained from NASA MODIS data exported from the AppEEARS software. This software can be found at https://appeears.earthdatacloud.nasa.gov. This measure is for a 1-kilometer radius around mines because that was the maximum radius that could be exported.
[36] Road locations are obtained from Humanitarian Data Exchange. The major and local road data can be found at https://data.humdata.org/dataset/democratic-republic-of-congo-drc-major-roads-network-openstreetmap-export and https://data.humdata.org/dataset/democratic-republic-of-congo-drc-local-roads-openstreetmap-export, respectively.
[37] Population center locations are obtained from Humanitarian Data Exchange. This data can be found at https://data.humdata.org/dataset/democratic-republic-of-congo-drc-localities-openstreetmap-export.

year t (other than mine m itself), which represents the incremental cost of certification assuming spatial clustering saves resources. $\mathbb{1}$(*Protected Area*) is a time-invariant indicator variable for whether a mine m is located within a federally protected area (e.g., national park), which represents the legality of the mine.[38] We use lagged variables for *Conflict 10km*, *Avg Lum 1km*, and *EVI 1km* because we assume prior characteristics enter into the selection choice. Though mines are selected before the initial inspection, we do not lag *Dist to Cert* because spatial clustering is only economically efficient when nearby mines are consecutively certified. When we include *Territory×Year* fixed effects, we remove the β_0 coefficient. We estimate Conley (1999) standard errors that account for spatial correlation within a 100-kilometer radius.

For the selection model, we use all mines that could potentially have been selected for certification each year (i.e., those not already certified) as our sample. We construct an (unbalanced) panel that represents the province mining committee's selection choice each year and identify those chosen to be certified. We present descriptive statistics for our selection variables in Table IA3.2 Panel A. These are aggregated across all years of certification, so they do not provide decision-specific information for each year.

We present the results for the selection model in Table IA3.2 Panel B. Across years, we find a coefficient close to 0 for lagged conflict and luminosity, indicating that mines are not selected based on security or economic activity. This alleviates concerns that our results are due to selection biases that impact the variables of interest. However, we do find a significant negative result for lagged Enhanced Vegetation Index in some years as well as in the aggregate (without fixed effects), indicating that areas in which mining is more central to the local economy are more likely to be selected for certification. This is intuitive, as we expect the province mining committee to certify mines in areas where certification is most likely to be effective. Next, we do find a significant negative result for distance to the nearest major road (but not any road) in some years as well as in the aggregate, providing evidence that mines more accessible by major roads are more likely to be certified. On the other hand, we do not find that mines closer to population centers (i.e., cities, towns, villages, or hamlets) are more likely to be certified, which alleviates concerns that inspectors take a convenience sample around populated areas. Perhaps least interesting and most mechanical, we find a significant negative result across all columns for distance to nearest

[38] Protected area locations are obtained from the World Bank (UNEP-WCMC, 2016). This data can be found at https://datacatalog.worldbank.org/search/dataset/0040279.

certification, reinforcing our descriptive evidence that contemporaneous certifications are geographically clustered. Finally, we also do not find any evidence that mines in protected areas (e.g., national parks) are more likely to be certified, which indicates that legality is not considered for the selection decision. In the aggregate, the coefficients for *EVI 1km* and asinh(*Dist to Maj Road*) are drastically reduced in magnitude and no longer statistically significant after including territory-year fixed effects, consistent with a lack of within-territory effects, while the coefficient for distance to nearest certification becomes larger in magnitude and remains statistically significant, consistent with inspector cost savings from visiting proximal mines. Implications of these results are discussed in Section 2.2 in the paper.

Table IA3.2. Certification Selection Criteria

Panel A: Descriptive Statistics for Selection Variables

Variable	Obs	Mean	SD	P1	P25	P50	P75	P99
𝟙(*Certified*)	25784	0.021	0.142	0.000	0.000	0.000	0.000	1.000
asinh(*Conflict 10km*)$_{t-1}$	25784	0.642	3.153	0.000	0.000	0.000	0.000	14.000
asinh(*Avg Lum 1km*)$_{t-1}$	25784	0.138	1.100	0.000	0.000	0.000	0.000	5.000
EVI 1km$_{t-1}$	25784	0.466	0.061	0.299	0.427	0.471	0.509	0.582
asinh(*Dist to Road*)	25784	3.516	5.412	0.003	0.155	1.060	4.985	26.579
asinh(*Dist to Maj Road*)	25784	5.265	7.619	0.004	0.267	1.778	7.211	33.324
asinh(*Dist to Pop*)	25784	10.715	14.621	0.073	1.944	5.227	13.941	75.012
asinh(*Dist to Cert*)$_t$	25784	163.897	151.803	0.781	51.483	117.199	234.587	614.125
𝟙(*Protected Area*)	25784	0.044	0.205	0.000	0.000	0.000	0.000	1.000

Notes: This table presents a selection model to descriptively compare characteristics of mines selected and not selected for certification. This mine-year sample is composed of all untreated mines as of the beginning of each year, so the sample size decreases as more mines are treated over time. The sample is an unbalanced panel from 2011 to 2019, which are the possible treatment years. Panel A presents descriptive statistics for the selection model sample. Panel B reports coefficient estimates of OLS regressions estimating the impact of various determinants on certification selection. Conley (1999) standard errors allowing for spatial correlation within a 100km radius are reported in parentheses. 𝟙(*Certified*) is a binary indicator for whether the mine is chosen for certification in that year. asinh(*Conflict 10km*)$_{t-1}$ is the inverse hyperbolic sine of the count of conflict incidents within 10km of the mine in the year before. asinh(*Avg Lum 1km*)$_{t-1}$ is the inverse hyperbolic sine of the average luminosity (measured between 0 and 63) within 1km of the population center (i.e., city, town, village, or hamlet) nearest to the mine in the year before. *EVI 1km*$_{t-1}$ is the enhanced vegetation index within 1km of a mine in the year before. asinh(*Dist to Road*) and asinh(*Dist to Maj Road*) are the inverse hyperbolic sines of the time-invariant distances to the nearest road and major road, respectively. asinh(*Dist to Pop*) is the inverse hyperbolic sine of the time-invariant distance to the nearest city, town, village, or hamlet. asinh(*Dist to Cert*)$_t$ is the distance to the nearest mine certified in the same year. 𝟙(*Protected Area*) is a time-invariant binary indicator for whether the mine is located within a protected area (e.g., national park).

Panel B: Selection Model Estimation

Dep. Var.: 𝟙(*Certified*)	Individual Years									All Years	
	2011	2012	2013	2014	2015	2016	2017	2018	2019	No FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
asinh(*Conflict 10km*)$_{t-1}$	-0.012*	-0.006**	-0.003	-0.009	-0.002	0.009	0.001	0.000	0.003	-0.003	0.001
	(0.007)	(0.003)	(0.006)	(0.008)	(0.007)	(0.006)	(0.008)	(0.007)	(0.005)	(0.002)	(0.002)
asinh(*Avg Lum 1km*)$_{t-1}$	-0.001	-0.004	-0.002	-0.001	0.000	0.001	0.020*	0.002	0.007	0.000	-0.001
	(0.005)	(0.007)	(0.007)	(0.004)	(0.006)	(0.004)	(0.010)	(0.005)	(0.009)	(0.003)	(0.003)
EVI 1km$_{t-1}$	-0.298***	-0.139**	-0.179*	-0.239***	-0.060	-0.111	0.056	-0.060	-0.121***	-0.156***	-0.035
	(0.115)	(0.062)	(0.107)	(0.084)	(0.084)	(0.070)	(0.132)	(0.079)	(0.033)	(0.054)	(0.027)
asinh(*Dist to Road*)	0.004	-0.001	-0.000	-0.007	-0.005	0.006***	0.012*	-0.007	-0.011**	-0.001	0.000
	(0.006)	(0.003)	(0.007)	(0.005)	(0.007)	(0.002)	(0.007)	(0.014)	(0.005)	(0.003)	(0.001)
asinh(*Dist to Maj Road*)	-0.012***	-0.003**	-0.005	-0.006**	-0.003	-0.014***	-0.019***	0.002	0.004	-0.006**	-0.002
	(0.004)	(0.001)	(0.004)	(0.003)	(0.005)	(0.004)	(0.007)	(0.017)	(0.004)	(0.003)	(0.002)
asinh(*Dist to Pop*)	0.007***	0.003	0.007	0.010	-0.005	0.006	0.012*	0.015**	0.004	0.005**	0.002
	(0.002)	(0.002)	(0.005)	(0.007)	(0.005)	(0.004)	(0.006)	(0.006)	(0.002)	(0.002)	(0.001)
asinh(*Dist to Cert*)$_t$	-0.038***	-0.030**	-0.045***	-0.030***	-0.042***	-0.032***	-0.073***	-0.042***	-0.018***	-0.037***	-0.056***
	(0.001)	(0.012)	(0.012)	(0.006)	(0.010)	(0.006)	(0.015)	(0.007)	(0.002)	(0.005)	(0.008)
𝟙(*Protected Area*)	-0.014	0.000	0.013	-0.009	0.089	0.003	-0.005	-0.013	-0.003	0.005	-0.004*
	(0.021)	(0.007)	(0.015)	(0.009)	(0.079)	(0.008)	(0.025)	(0.013)	(0.010)	(0.017)	(0.002)
Constant	0.369***	0.250**	0.336***	0.284***	0.271***	0.232***	0.375***	0.215***	0.154***	0.285***	
	(0.063)	(0.103)	(0.088)	(0.066)	(0.066)	(0.061)	(0.121)	(0.053)	(0.018)	(0.043)	
Territory x Year FE	No	No	No	No	No	No	No	No	No	No	Yes
R-squared	0.197	0.112	0.168	0.110	0.122	0.108	0.265	0.114	0.044	0.126	0.242
Observations (Mine)	3,085	3,044	3,013	2,939	2,882	2,807	2,764	2,669	2,581	25,784	25,748

Notes for both panels of the table are presented on the previous page.

IA3.3 Criteria for Certification Selection (Gold Only)

We rerun the selection test for gold mines only in Table IA3.3 because our main result in the paper focuses on gold mines. The results remain qualitatively similar with the exception of the coefficient on *EVI 1km* becoming statistically insignificant in most columns. In addition, certification year 2012 is excluded because no gold certifications occur in that year. Overall, magnitudes and directions remain similar, and equivalent conclusions can be made as in Section IA3.2.

Table IA3.3. Certification Selection Criteria (Gold Only)

Panel A: Descriptive Statistics for Selection Variables

	Obs	Mean	SD	P1	P25	P50	P75	P99
𝟙(*Certified*)	18661	0.007	0.083	0.000	0.000	0.000	0.000	0.000
asinh(*Conflict 10km*)	18661	0.558	2.599	0.000	0.000	0.000	0.000	12.000
asinh(*Avg Lum 1km*)	18661	0.146	1.173	0.000	0.000	0.000	0.000	4.667
EVI 1km	18661	0.467	0.055	0.331	0.432	0.470	0.506	0.580
asinh(*Dist to Road*)	18661	3.870	5.844	0.003	0.153	1.158	5.643	29.449
asinh(*Dist to Maj Road*)	18661	5.609	7.887	0.003	0.250	1.892	7.813	32.561
asinh(*Dist to Pop*)	18661	10.751	14.660	0.063	1.965	5.423	14.123	82.713
asinh(*Dist to Cert*)	18661	179.914	146.535	1.630	64.185	135.909	268.018	575.289
𝟙(*Protected Area*)	18661	0.044	0.206	0.000	0.000	0.000	0.000	1.000

Notes: This table presents a selection model to descriptively compare characteristics of gold mines selected and not selected for certification. This mine-year sample is composed of all untreated gold mines as of the beginning of each year, so the sample size decreases as more gold mines are treated over time. The sample is an unbalanced panel from 2011 to 2019, which are the possible treatment years. Panel A presents descriptive statistics for the selection model sample. Panel B reports coefficient estimates of OLS regressions estimating the impact of various determinants on certification selection. Conley (1999) standard errors allowing for spatial correlation within a 100km radius are reported in parentheses. 𝟙(*Certified*) is a binary indicator for whether the mine is chosen for certification in that year. asinh(*Conflict 10km*)$_{t-1}$ is the inverse hyperbolic sine of the count of conflict incidents within 10km of the mine in the year before. asinh(*Avg Lum 1km*)$_{t-1}$ is the inverse hyperbolic sine of the average luminosity (measured between 0 and 63) within 1km of the population center (i.e., city, town, village, or hamlet) nearest to the mine in the year before. *EVI 1km*$_{t-1}$ is the enhanced vegetation index within 1km of a mine in the year before. asinh(*Dist to Road*) and asinh(*Dist to Maj Road*) are the inverse hyperbolic sines of the time-invariant distances to the nearest road and major road, respectively. asinh(*Dist to Pop*) is the inverse hyperbolic sine of the time-invariant distance to the nearest city, town, village, or hamlet. asinh(*Dist to Cert*)$_t$ is the distance to the nearest mine certified in the same year. 𝟙(*Protected Area*) is a time-invariant binary indicator for whether the mine is located within a protected area (e.g., national park).

Panel B: Certification Selection Model Estimation

	Individual Years									All Years	
Dep. Var.: 𝟙(*Certified*)	2011	2012	2013	2014	2015	2016	2017	2018	2019	No FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
asinh(*Conflict 10km*)$_{t-1}$	-0.002		0.003	0.003	-0.004	0.002	0.000	0.009	-0.001	-0.001	0.002**
	(0.004)		(0.004)	(0.003)	(0.005)	(0.002)	(0.002)	(0.007)	(0.001)	(0.001)	(0.001)
asinh(*Avg Lum 1km*)$_{t-1}$	-0.004		-0.005**	-0.001	0.007	0.002	0.006	0.000	-0.001	-0.002	-0.003
	(0.006)		(0.002)	(0.001)	(0.006)	(0.002)	(0.004)	(0.005)	(0.001)	(0.002)	(0.002)
EVI 1km$_{t-1}$	-0.216*		-0.068	-0.031*	0.011	-0.016	0.076	-0.032	-0.016	-0.041	-0.031
	(0.131)		(0.053)	(0.018)	(0.055)	(0.027)	(0.057)	(0.096)	(0.010)	(0.028)	(0.030)
asinh(*Dist to Road*)	0.003		-0.001	-0.002	0.000	0.003	0.001	0.013**	0.000	0.001	0.001
	(0.005)		(0.003)	(0.001)	(0.005)	(0.002)	(0.002)	(0.007)	(0.001)	(0.002)	(0.001)
asinh(*Dist to Maj Road*)	-0.009*		-0.002	-0.000	-0.005	-0.010***	-0.005**	-0.018**	-0.001	-0.005***	-0.001
	(0.005)		(0.003)	(0.001)	(0.005)	(0.004)	(0.002)	(0.007)	(0.001)	(0.002)	(0.001)
asinh(*Dist to Pop*)	0.005*		0.002	0.001*	-0.009	0.003	0.006	0.015***	0.001*	0.002	0.001
	(0.003)		(0.002)	(0.001)	(0.007)	(0.002)	(0.005)	(0.006)	(0.000)	(0.001)	(0.001)
asinh(*Dist to Cert*)$_t$	-0.030***		-0.013**	-0.002*	-0.023	-0.023***	-0.022*	-0.036***	-0.003*	-0.019***	-0.029***
	(0.005)		(0.006)	(0.001)	(0.015)	(0.008)	(0.013)	(0.006)	(0.002)	(0.003)	(0.004)
𝟙(*Protected Area*)	-0.001		0.029	-0.001	0.126	0.006	0.005	0.003	-0.001	0.019	0.000
	(0.010)		(0.025)	(0.001)	(0.108)	(0.007)	(0.008)	(0.012)	(0.001)	(0.017)	(0.003)
Constant	0.284***		0.104**	0.028**	0.142*	0.146***	0.085	0.172***	0.026*	0.127***	
	(0.092)		(0.049)	(0.013)	(0.081)	(0.052)	(0.054)	(0.047)	(0.014)	(0.018)	
Territory x Year FE	No	No	No	No	No	No	No	No	No	No	Yes
R-squared	0.163		0.080	0.013	0.152	0.088	0.100	0.090	0.008	0.069	0.258
Observations (Mine)	2,114	2,100	2,100	2,095	2,093	2,074	2,054	2,044	2,581	18,661	18,640

Notes for both panels of the table are presented on the previous page.

Section IA4. Sample Selection and Composition

This section provides additional details on sample selection and composition, which may help with interpretation of results. As mentioned throughout the paper and main tables, Table IA4.1 delineates the overall sample selection process for each portion of data cleaning. This can be referred to for replication.

Additionally, Table IA4.2 provides a detailed listing of the count of certified and uncertified mines by province and mineral which make up our final sample. Table IA4.3 provides additional descriptive statistics to complement Table 2 in the paper. These should be helpful for detailed data concerns.

Table IA4.1. Sample Selection Criteria

Panel A: Conflict Incidents

Selection Criterion		Obs. Count
ACLED DRC Conflict Database		28,977
Less:	Geographically imprecise	(602)
Less:	Non-conflict events	(5,016)
Less:	Non-eastern provinces	(1,953)
Less:	Before 2004 or after 2022	(2,233)
Final conflict sample		19,173

Panel B: Mines and Certifications

Selection Criterion		Obs. Count
IPIS DRC Mine Database		6,375
Less:	Duplicate visits (cert. or not)	(2,847)
Less:	Mines certified in 2021	(238)
Less:	Non-3TG mines	(204)
Less:	Ambiguous territory	(1)
Final mine sample		3,085

Panel C: Final Panel (Mine Level)

Selection Criterion		Obs. Count
Conflicts and Mines Merged (x 19 years)		58,615
Less:	Non-3TG mines	(7,999)
Less:	Non-conflict areas	(12,141)
Less:	Non-green certified mines	(399)
Final mine sample		38,076

Panel D: Final Panel (Village Level)

Selection Criterion		Obs. Count
Conflicts and Mines Merged		60,458
Less:	Non-mining villages	(33,953)
Final village sample		26,505

Notes: This table describes the sample selection process for our main analyses by step. The sample is from 2004 to 2022. The observation counts in the analyses do not exactly match the numbers in this table because we drop singleton observations for various fixed effect structures. Panel A describes selection for the ACLED conflict database. Panel B describes selection for the IPIS mines database. Panels C and D describe additional changes made after the conflict and mine databases were merged and collapsed to the mine- and village-levels, respectively. Panels C and D end with the final mine- and village-level samples used in our analyses.

Table IA4.2. Mine Level Distribution

Panel A: Mines by Province

Province	# Certified Mines	# Uncertified Mines	Total Mines	% Certified
Bas-Uele	0	0	0	0.00%
Haut-Katanga	6	8	14	42.86%
Haut-Lomami	5	2	7	71.43%
Haut-Uele	0	43	43	0.00%
Ituri	21	395	416	5.05%
Lualaba	0	0	0	0.00%
Maniema	40	108	148	27.03%
Nord-Kivu	69	445	514	13.42%
Sud-Kivu	106	609	715	14.83%
Tanganyika	53	70	123	43.09%
Tshopo	1	23	24	4.17%
TOTAL	301	1703	2004	100.00%

Panel B: Mines by Commodity

Commodity	# Certified Mines	# Uncertified Mines	Total Mines	% Certified
Gold	162	239	401	40.40%
Tantalum	57	69	126	45.24%
Tin	78	1376	1454	5.36%
Tungsten	4	19	23	17.39%
TOTAL	301	1703	2004	100.00%

Notes: This table describes the distribution of mines included in our main sample split between certified and uncertified without making a distinction as to the year of certification. Panel A splits the sample by province. Panel B splits the sample by commodity.

Table IA4.3. Additional Descriptive Statistics

Panel A: Mine-Year Level

	Obs	Mean	SD	P1	P25	P50	P75	P99
CFC x *PostCert*	38,076	0.059	0.235	0	0	0	0	1
𝟙(*All Conflicts*)	38,076	0.267	0.443	0	0	0	1	1
𝟙(*Battles*)	38,076	0.184	0.387	0	0	0	0	1
𝟙(*Civilian Violence*)	38,076	0.184	0.388	0	0	0	0	1
𝟙(*Riots*)	38,076	0.045	0.208	0	0	0	0	1
Count(*Fatalities*)	38,076	2.929	13.942	0	0	0	0	69
Count(*Battle Fatalities*)	38,076	1.693	8.566	0	0	0	0	42
Count(*Civ. Viol. Fatalities*)	38,076	1.176	7.510	0	0	0	0	26
Count(*Riot Fatalities*)	38,076	0.058	0.662	0	0	0	0	2

Panel B: Village-Year Level

	Obs	Mean	SD	P1	P25	P50	P75	P99
CFC x *PostCert*	26,505	0.107	0.309	0	0	0	0	1
𝟙(*All Conflicts*)	26,505	0.110	0.313	0	0	0	0	1
𝟙(*Battles*)	26,505	0.067	0.249	0	0	0	0	1
𝟙(*Civilian Violence*)	26,505	0.062	0.241	0	0	0	0	1
𝟙(*Riots*)	26,505	0.009	0.096	0	0	0	0	0
Count(*Fatalities*)	26,505	10.834	41.042	0	0	2	7	154
Count(*Battle Fatalities*)	26,505	0.322	3.121	0	0	0	0	8
Count(*Civ. Viol. Fatalities*)	26,505	0.237	3.150	0	0	0	0	5
Count(*Riot Fatalities*)	26,505	0.012	0.321	0	0	0	0	0

Notes: This table presents more detailed descriptive statistics for our main sample, which is a balanced panel of mine- and village-year observations. This is an extension of Table 2 but uses all 3TG mines rather than splitting the sample by mineral. The sample is from 2004 to 2022. *CFC* x *PostCert* (presented as an interaction because control mines are not assigned treatment years) is a binary indicator equal to one for certified (green) mines or villages during and after the year of certification. (*All Conflicts*), 𝟙(*Battles*), 𝟙(*Civilian Violence*), and 𝟙(*Riots*) are binary indicators equal to one if one or more conflict, battle, civilian violence, or riot incidence, respectively, is documented within 10km of a mine or assigned to a village. Count(*Fatalities*), Count(*Battle Fatalities*), Count(*Civ. Viol. Fatalities*), and Count(*Riot Fatalities*) are count variables for the number of fatalities from all conflicts, battles, civilian violence, or riots, respectively, documented within 10km of a mine or assigned to a village. *Distance to Nearest Conflict*, *Battle*, *Civ. Viol.*, and *Riot* are continuous variables for the distance in kilometers between a mine and the nearest instance of conflict, battle, civilian violence, or riot, respectively, in a given year.

Section IA5. Supplementary Tests

IA5.1 Jackknife Excluding Certification Years

In Table IA5.1 below, we present results dropping each year of certified mines from the sample in turn. We use the specification with only gold mines, from which we drew our main inferences. Our results remain robust and similar in magnitude across all columns, which indicates that the treatment effect is not driven by certifications in any given year.

Table IA5.1. Jackknife Excluding Certification Years

Dep. Var.: 𝟙(*All Conflicts*)	Baseline	Year of Certifications Excluded								
		2011	2012	2013	2014	2015	2016	2017	2018	2019
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CFC x *PostCert*	-0.094***	-0.086***	-0.094***	-0.076***	-0.094***	-0.110***	-0.090***	-0.094***	-0.123**	-0.097***
	(0.029)	(0.029)	(0.029)	(0.028)	(0.030)	(0.031)	(0.033)	(0.030)	(0.049)	(0.030)
Mine FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.588	0.588	0.588	0.588	0.588	0.588	0.587	0.587	0.587	0.588
Observations (Mine-Year)	27,550	27,512	27,550	27,512	27,512	27,436	27,227	27,360	26,866	27,531

Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal gold mine certification visits with "green" status on mine-level conflict incidence. We estimate the model from Column (2) of Table 3 in the paper as the baseline but separately exclude gold mines certified in individual years. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. 𝟙(*All Conflicts*) is a binary indicator for whether one or more incidents of conflict, defined according to Stoop et al. (2018), is observed within 10km of a mine. *CFC* is a binary indicator for whether a mine has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine.

IA5.2 Jackknife Excluding Provinces

In Table IA5.2 below, we present results dropping each province from the sample in turn. We again use the specification with only gold mines, from which we drew our main inferences. We provide a specification excluding each province though some do not have any mines, yielding identical coefficients. Our results remain robust and similar in magnitude across all columns, which indicates that the treatment effect is not driven by any one province.

Table IA5.2. Jackknife Excluding Provinces

Dep. Var.: 𝟙(*All Conflicts*)	Baseline	Province Excluded										
		Bas-Uele	*Haut-Katanga*	*Haut-Lomami*	*Haut-Uele*	*Ituri*	*Lualaba*	*Maniema*	*Nord-Kivu*	*Sud-Kivu*	*Tangan-yika*	*Tshopo*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CFC x *PostCert*	-0.094***	-0.094***	-0.094***	-0.094***	-0.094***	-0.122***	-0.094***	-0.081***	-0.097***	-0.075**	-0.094***	-0.094***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.037)	(0.029)	(0.031)	(0.032)	(0.034)	(0.029)	(0.029)
Mine FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.588	0.588	0.588	0.588	0.587	0.567	0.588	0.580	0.608	0.603	0.585	0.588
Observations (M-Y)	27,550	27,550	27,550	27,550	26,752	19,665	27,550	26,087	21,014	18,031	26,619	27,132

Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal gold mine certification visits with "green" status on mine-level conflict incidence. We estimate the model from Column (2) of Table 3 in the paper as the baseline but separately exclude gold mines in individual provinces. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. 𝟙(*All Conflicts*) is a binary indicator for whether one or more incidents of conflict, defined according to Stoop et al. (2018), is observed within 10km of a mine. *CFC* is a binary indicator for whether a mine has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine.

IA5.3 Separating Early and Late Certifications

In Table IA5.3 below, we present results keeping only mines certified in certain years. The control sample (uncertified mines) remains the same in each specification. We use the specification with only gold mines, from which we drew our main inferences. The earlier certifications seem to have a larger effect magnitude though both periods remain statistically significant, which indicates that the treatment effect is not driven by certifications in either period.

Table IA5.3. Separating Early and Late Certifications

		Certification Years	
Dep. Var.: 𝟙(*All Conflicts*)	Baseline	2011-2015	2016-2019
	(1)	(2)	(3)
CFC x *PostCert*	-0.094***	-0.158*	-0.078***
	(0.029)	(0.093)	(0.030)
Mine FE	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes
R-squared	0.588	0.585	0.589
Observations (Mine-Year)	27,550	26,334	27,322

Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal gold mine certification visits with "green" status on mine-level conflict incidence. We estimate the model from Column (2) of Table 3 in the paper as the baseline but separately exclude gold mines certified in either half of the certification period. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. 𝟙(*All Conflicts*) is a binary indicator for whether one or more incidents of conflict, defined according to Stoop et al. (2018), is observed within 10km of a mine. *CFC* is a binary indicator for whether a mine has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine.

IA5.4 Smaller Radii and Excluding Overlapping Areas

In Table IA5.4 below, we present results using smaller radii and completely excluding overlapping mines. Because excluding all mines within 10 kilometers of another mine would critically reduce the sample size, we were not able to do this in the main robustness figure. However, using smaller radii (2km and 1km), we are able to exclude all overlapping cells and still keep an adequate, albeit much smaller, sample. The baseline results for smaller radii (not excluding any observations) are presented in Panel A, and we exclude overlapping cells in Panel B. Our results for gold mines remain robust but are much smaller in magnitude, likely due to elimination of double-counted conflicts and reduction of the number of conflicts observed within the small radii. This indicates that gold mines experience a 4.9% (1.7%) decrease in conflict within 2 kilometers (1 kilometer) after an initial certification visit, and we are confident that this magnitude is a lower-bound. Similar to the main results in the paper, we find a coefficient close to 0 for 3T mines within either radius.

Table IA5.4. Smaller Radii and Excluding Overlapping Areas

Panel A: Smaller Radii

	Radius = 2km			Radius = 1km		
Dep. Var.: 𝟙(All Conflicts)	All 3TG	Gold	3T	All 3TG	Gold	3T
	(1)	(2)	(3)	(4)	(5)	(6)
CFC x *PostCert*	-0.023**	-0.015	-0.035***	-0.013**	-0.019***	-0.016*
	(0.009)	(0.015)	(0.013)	(0.006)	(0.005)	(0.009)
Mine FE	Yes	Yes	Yes	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.385	0.370	0.454	0.339	0.299	0.436
Observations (Mine-Year)	38,000	27,550	10,374	38,000	27,550	10,374

Panel B: Excluding Overlapping Areas

	Radius = 2km			Radius = 1km		
Dep. Var.: 𝟙(All Conflicts)	All 3TG	Gold	3T	All 3TG	Gold	3T
	(1)	(2)	(3)	(4)	(5)	(6)
CFC x *PostCert*	-0.019	-0.049***	-0.014	-0.007	-0.017***	-0.001
	(0.013)	(0.015)	(0.021)	(0.007)	(0.006)	(0.010)
Mine FE	Yes	Yes	Yes	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.427	0.329	0.560	0.351	0.270	0.505
Observations (Mine-Year)	8,968	6,251	2,660	18,525	13,300	5,111

Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal mine certification visits with "green" status on mine-level conflict incidence by mineral type. In Panel A, we estimate the model from Columns (1)–(3) Table 3 but use radii of 2km or 1km instead of 10km. In Panel B, we replicate Panel A except excluding mines with overlapping radii (i.e., within 2km or 1km of another mine). The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. 𝟙(*All Conflicts*) is a binary indicator for whether one or more incidents of conflict, defined according to Stoop et al. (2018), is observed within 2km or 1km of a mine. *CFC* is a binary indicator for whether a mine has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine.

IA5.5 Including Non-3TG Control Mines

In Table IA5.5 below, we present results including non-3TG mines in the control sample. These mainly consist of copper and cobalt mines, as mentioned in Section 2.4 of the paper. Because gold and 3T minerals are valuable and require relatively little infrastructure to extract, most artisanal mines specialize in 3TG minerals. Therefore, only 80 additional mines (1520 mine-year observations) are included in this sample as compared to our main sample. Compared to the baseline, our result remains nearly identical.

Table IA5.5. Including Non-3TG Control Mines

Dep. Var.: 𝟙(*All Conflicts*)	Baseline (1)	Incl. Non-3TG (2)
CFC x *PostCert*	-0.056**	-0.055**
	(0.026)	(-0.026)
Mine FE	Yes	Yes
Territory x Year FE	Yes	Yes
R-squared	0.575	0.579
Observations (Mine-Year)	38,000	39,444

Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal mine certification visits with "green" status on mine-level conflict incidence. We estimate the model from Column (1) of Table 3 in the paper as the baseline but then include non-3TG mines in the control sample. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. 𝟙(*All Conflicts*) is a binary indicator for whether one or more incidents of conflict, defined according to Stoop et al. (2018), is observed within 10km of a mine. *CFC* is a binary indicator for whether a mine has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine.

IA5.6 Controlling for Economic Factors

In Table IA5.6 below, we present results including time-variant economic controls in the model. Specifically, we include luminosity as a measure of local economic activity and vegetation as a proxy for the centrality of mining to the local economy. These are also variables utilized in our selection model in Section IA3.2, so see that section for luminosity and vegetation data details. The result for gold mines remains nearly identical, indicating that our main findings are robust to economic controls. None of the controls show statistically significant coefficients for gold mines, though the signs make intuitive sense. Higher luminosity (more economic activity) and higher vegetation (lower economic reliance on mining) predict lower conflict incidence around mines.

Table IA5.6. Controlling for Economic Factors

	Without Controls			With Controls		
Dep. Var.: 𝟙(*All Conflicts*)	All 3TG	Gold	3T	All 3TG	Gold	3T
	(1)	(2)	(3)	(4)	(5)	(6)
CFC x *PostCert*	-0.041	-0.082**	-0.002	-0.042	-0.081*	-0.003
	(0.033)	(0.042)	(0.031)	(0.032)	(0.042)	(0.031)
asinh(*Avg Lum 1km*)				-0.039*	-0.026	-0.086***
				(0.020)	(0.023)	(0.027)
EVI 1km				-0.021	-0.154	0.158
				(0.202)	(0.216)	(0.326)
Mine FE	Yes	Yes	Yes	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.542	0.549	0.577	0.543	0.549	0.577
Observations (Mine-Year)	32,000	23,200	8,736	32,000	23,200	8,736

Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal mine certification visits with "green" status on mine-level conflict incidence by mineral type. We estimate the model from Columns (1)–(3) of Table 3 in the paper as the baseline but then include economic factors as control variables. The sample is a balanced panel from 2004 to 2019 because the luminosity data is only available until 2019. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. 𝟙(*All Conflicts*) is a binary indicator for whether one or more incidents of conflict, defined according to Stoop et al. (2018), is observed within 10km of a mine. *CFC* is a binary indicator for whether a mine has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine. asinh(*Avg Lum 1km*) is the inverse hyperbolic sine of the average luminosity (measured between 0 and 63) within 1km of the population center (i.e., city, town, village, or hamlet) nearest to the mine. *EVI 1km* is the enhanced vegetation index within 1km of a mine.

IA5.7 Displacement of Conflict with Territory-Year FE

In Table IA5.7 and Figure IA5.7 below, we present results for the village-level displacement analysis (corresponding to Section 4.3 in the paper) using *Territory×Year* fixed effects rather than *Province×Year* fixed effects. We illustrate that within-territory variation is too geographically specific to fully capture armed group movement because armed groups are highly mobile and most territories are less than 200 kilometers in length and width. Specifically, the coefficient estimates become statistically insignificant and smaller in magnitude, but the signs remain in the expected directions. Further, separating the effect into individual years in Figure IA5.7 before and after treatment, we no longer see an apparent effect around the treatment period though the parallel-trends assumption seems to remain valid.

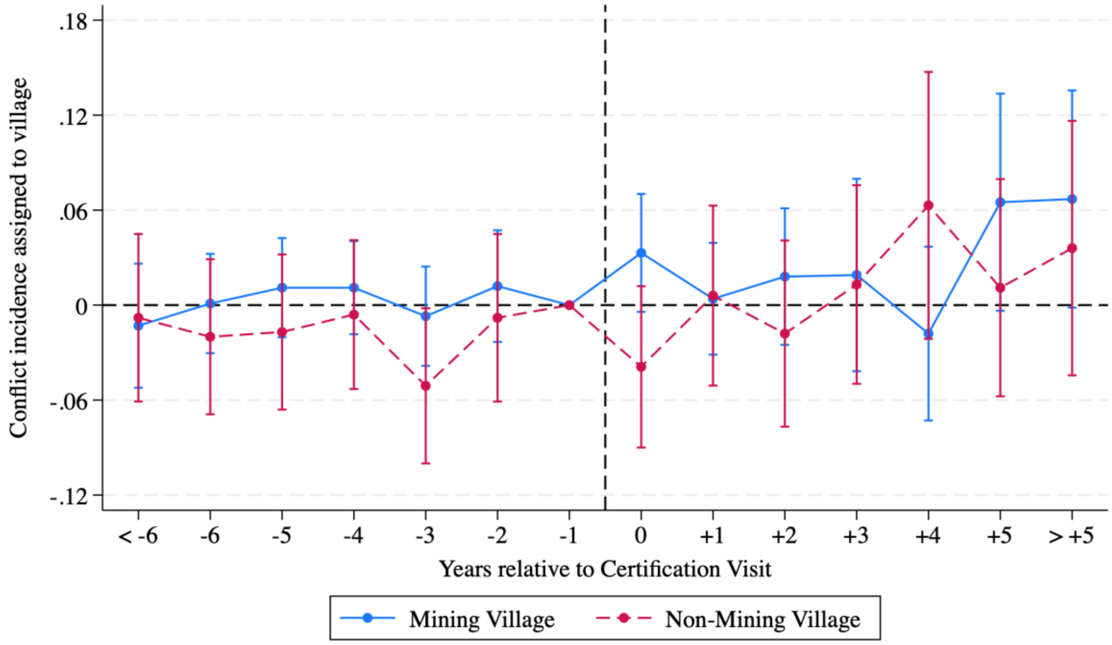
Table IA5.7. Displacement of Conflict with Territory-Year FE

	Non-Mining	Mining			
Dep. Var.: 𝟙(Conflict Type)	All Conflicts	All Conflicts	Battles	Civ. Viol.	Riots
	(1)	(2)	(3)	(4)	(5)
CFC x *PostCert*	0.018	0.010	0.007	0.013	-0.007
	(0.017)	(0.015)	(0.012)	(0.012)	(0.005)
Village FE	Yes	Yes	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.370	0.379	0.308	0.291	0.241
Observations (Village-Year)	33,801	24,054	24,054	24,054	24,054

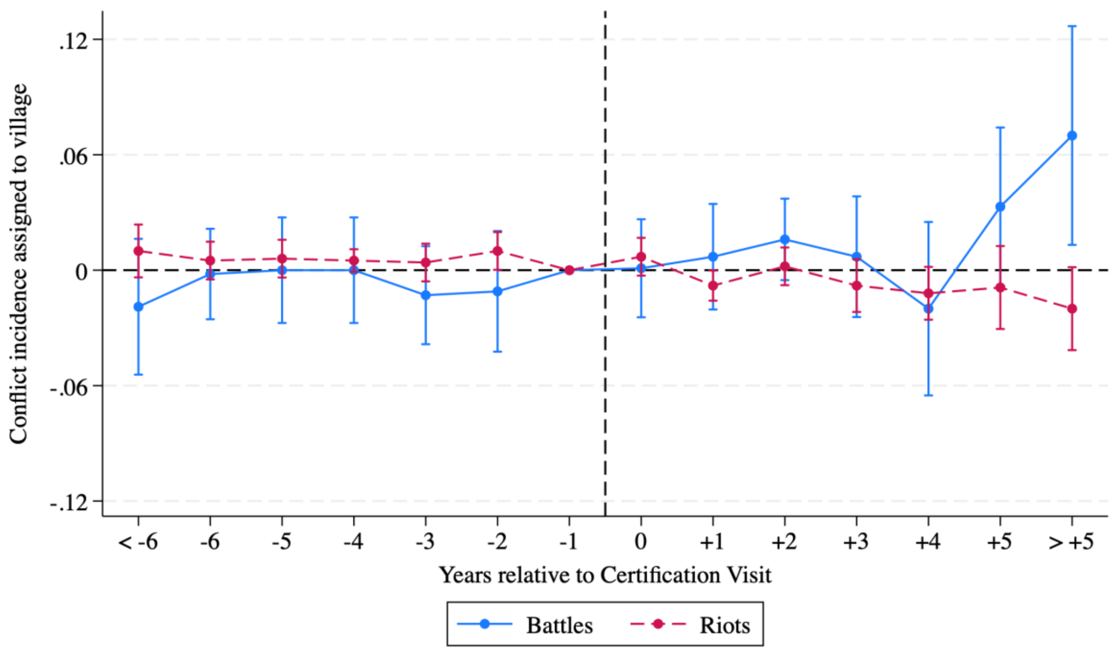
Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal gold mine certification visits with “green” status on village-level conflict incidence by conflict type in uncertified villages 50 to 100 kilometers away. The sample is a balanced panel of all uncertified villages from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. 𝟙(*Conflict Type*) is a binary indicator for whether one or more incident of the specified type of conflict, defined according to Stoop et al. (2018), is assigned to a village. *CFC* is a binary indicator for whether any mine within 10km of a village has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified village.

Figure IA5.7. Displacement of Conflict with Territory-Year FE

Panel A: Mining vs. Non-Mining Villages



Panel B: Type of Conflict (Mining Only)



Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of gold mine certification on the probability of battle and riot incidence in uncertified villages 50 to 100 kilometers away. We estimate the model from Table IA5.7 but replace the *PostCert* indicator with separate interactions for each of the lead- and lag-years (except for the year before treatment, which serves as the benchmark). Panel A corresponds to Columns (1) and (2) of Table IA5.7 (all conflicts), and Panel B corresponds to Columns (3) and (5) of Table IA5.7 (battles and riots).

Section IA6. Tests Including Non-Green Certifications

We exclude non-green certified mines throughout the analyses because they do not fit within the economic mechanism of conflict reduction. Because red-rated mines are typically required to cease operations, we do not expect them to play a continuing role in the economic considerations of armed groups. Similarly yellow-rated mines, while allowed to continue operations, are given a very negative signal from the inspector. Since these are typically small mines that can easily shut down, it is likely that at least a portion of mines receiving yellow ratings also cease operations.

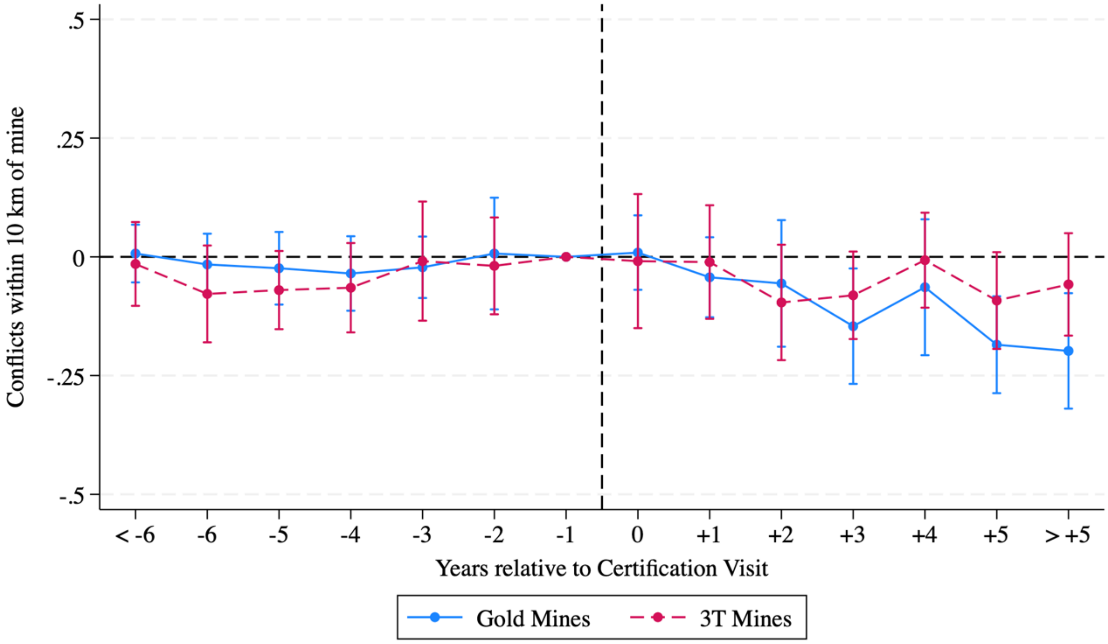
However, this introduces concern of a bias in the treatment effect. By excluding non-green certified mines, we are not capturing the intent-to-treat effect and may instead be biasing the effect toward lower-conflict mines. Therefore, we conduct corresponding analyses including non-green certifications to support our main findings and discern whether the results are strengthened or attenuated.

IA6.1 Effect of Mine Certifications on Conflict

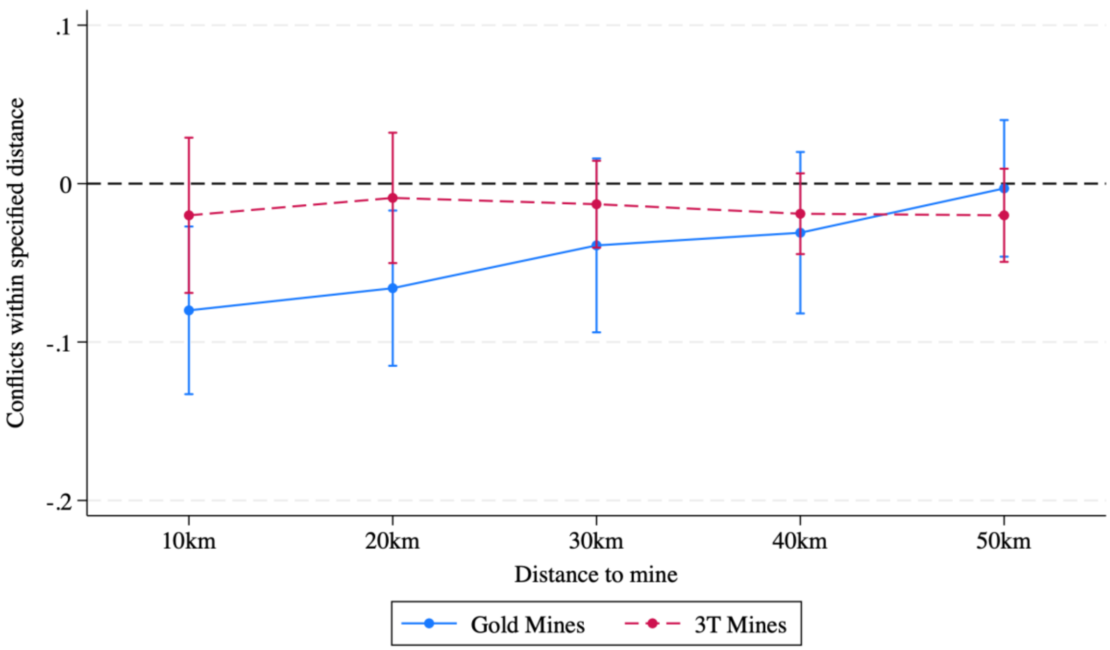
Corresponding to Section 3 in the paper, we examine changes in the probability of conflict around the first certification visit for certified mines. In Figure IA6.1 Panel A, we find a similar effect for the gradual reduction in conflict after certification for gold mines. We also see a monotonic spatial diffusion effect for gold mines in Figure IA6.1 Panel B as we move from a 10- to 50-kilometer radius. However, we observe that the average treatment effect is slightly attenuated for both conflict incidence and fatality count in Table IA6.1. This indicates that, consistent with our economic mechanism, including yellow- and red-rated mines attenuates the estimated reduction in proximal conflict subsequent to the initial certification visit.

Figure IA6.1. Change in Conflict After Certifications (Mine Level)

Panel A: Gradual Effect



Panel B: Spatial Diffusion



Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of 3TG mine certification on the probability of conflict incidence. Panel A estimates the model from Table IA6.1 Columns (2) and (3) but replaces the *PostCert* indicator with separate interactions for each of the lead- and lag-years (except for the year before treatment, which serves as the benchmark). Panel B also estimates the model from Table 3 Column (2) but uses different radii for the dependent variable.

Table IA6.1. Certifications and Conflict

	Conflict Incidents			Fatalities		
	All 3TG	Gold	3T	All 3TG	Gold	3T
	(1)	(2)	(3)	(4)	(5)	(6)
CFC x *PostCert*	-0.052**	-0.080***	-0.020	-0.056	-0.153**	0.029
	(0.023)	(0.027)	(0.025)	(0.049)	(0.075)	(0.059)
Mine FE	Yes	Yes	Yes	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.574	0.589	0.601	0.609	0.604	0.673
Observations (Mine-Year)	38,912	27,968	10,868	38,912	27,968	10,868

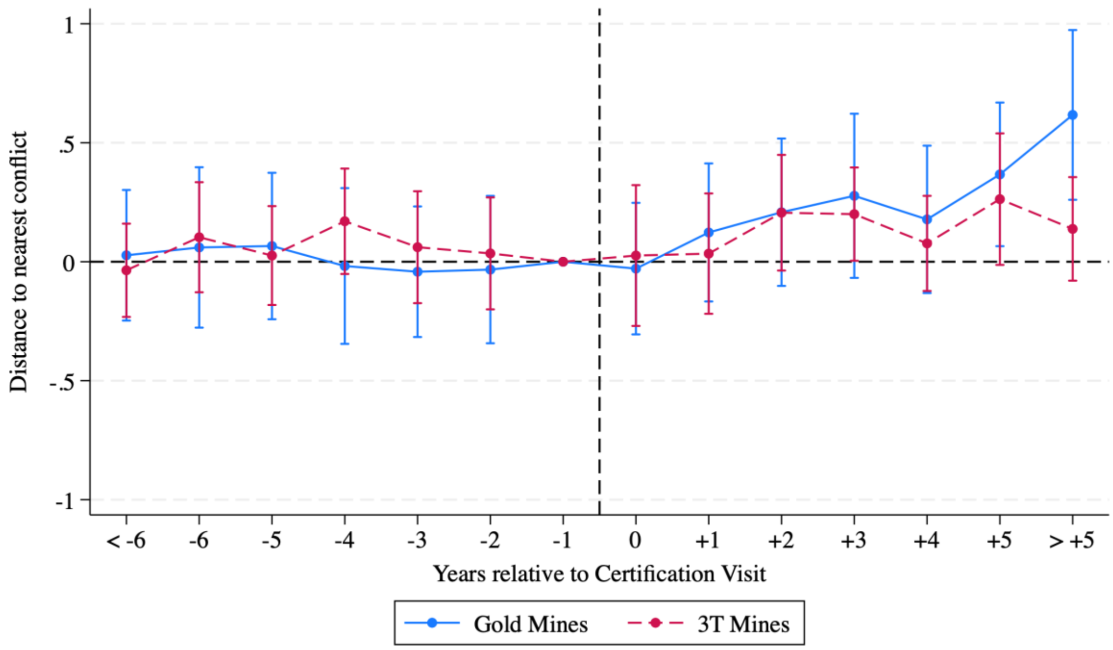
Notes: This table reports coefficient estimates of OLS regressions estimating the effect of all artisanal mine certification visits on mine-level conflict incidence and fatalities by mineral type. We describe the sample selection in Section IA4, and we further drop singletons corresponding to the fixed-effect structure. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. $\mathbb{1}$(*Conflicts*) is a binary indicator for whether one or more incidents of conflict is observed within 10km of a mine or assigned to a village. asinh(*Fatalities*) is the inverse hyperbolic sine of the number of fatalities documented within 10km of a mine or assigned to a village. *CFC* is a binary indicator for whether a mine has been treated or whether any mine within 10km of a village has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine or village.

IA6.2 Geographic Displacement of Conflict

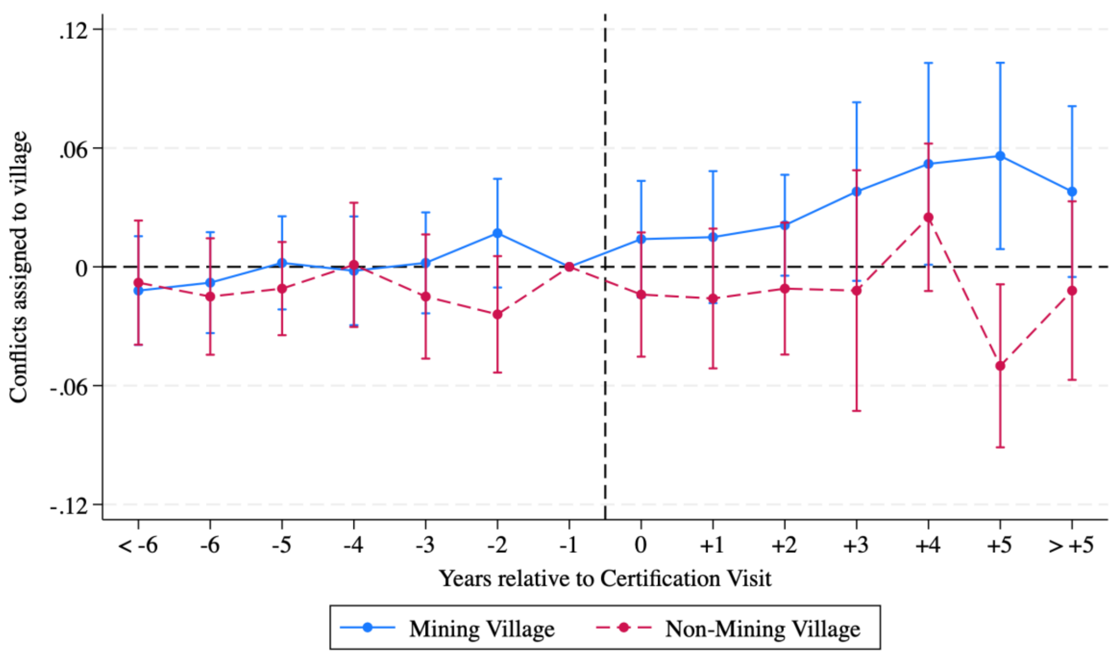
Corresponding to Section 4 in the paper, we examine evidence on the displacement of conflict to uncertified areas. In Figure IA6.2 Panel A, we similarly find a gradual increase in distance between a certified mine and the nearest conflict incident after certification for gold mines. In Figure IA6.2 Panel B, we also see a gradual increase in conflict for uncertified villages between 50 and 100 kilometers away from certified villages. Interestingly, we observe a slight strengthening of the distance effect, which could be capturing the local movement (within the 10 kilometer radius) of the armed group slightly away from the mine after it ceases operations. Intuitively, if an armed group was controlling the mine, it would stop occupying the mine itself after closure. However, we do still observe a slight attenuation of the displacement effect, which is consistent with our economic mechanism.

Figure IA6.2. Distance and Displacement

Panel A: Distance to Nearest Conflict (Mine Level)



Panel B: Displacement of Conflict (Village Level)



Notes: Panel A shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of gold mine certification on the distance from a mine to the nearest conflict in a year and the displacement of conflict to uncertified villages 50 to 100 kilometers away. We estimate the model from Table IA6.2 but replace the *PostCert* indicator with separate interactions for each of the lead- and lag-years (except for the year before treatment, which serves as the benchmark). Panel A corresponds to Columns (1) and (2) of Table 7 (distance), and Panel B corresponds to Columns (3) and (4) of Table 7 (displacement).

Table IA6.2. Distance and Displacement

	Distance (Mine Level)		Displacement (Village Level)	
	Gold Mines	3T Mines	Mining	Non-Mining
	(1)	(2)	(3)	(4)
CFC x *PostCert*	0.208***	0.096*	0.025***	-0.001
	(0.060)	(0.054)	(0.009)	(0.010)
Mine FE	Yes	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes
R-squared	0.766	0.807	0.337	0.323
Observations (Mine-Year)	27,968	10,868	24,149	33,953

Notes: This table reports results for mine-level distance to the nearest conflict and village-level conflict displacement. Columns (1) and (2) report coefficient estimates of OLS regressions estimating the effect of all artisanal mine certification visits on distance between a mine and the nearest conflict incident. Columns (3) and (4) report coefficient estimates of OLS regressions estimating the effect of all artisanal gold mine certification visits on village-level conflict incidence by conflict type in uncertified villages 50 to 100 kilometers away. We describe the sample selection in Section IA4, and we further drop singletons corresponding to the fixed-effect structure. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. asinh(*Distance*) is the inverse hyperbolic sine of the distance, in kilometers, between a mine and the nearest conflict incident. $\mathbb{1}$(*Conflicts*) is a binary indicator for whether one or more incidents of conflict is assigned to a village. *CFC* is a binary indicator for whether a mine has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine.

Section IA7. Tests using Alternative UCDP Conflict Data

IA7.1 Sample Selection and Descriptive Statistics

As stated in Section 2.3 of the paper, we utilize geolocated conflict data from the Armed Conflict Location & Event Database (ACLED, see Raleigh et al., 2010) throughout the paper. This follows Berman et al. (2017) and other influential papers in the literature to maintain comparability between studies. However, Eck (2012) points out various issues with ACLED including coverage inconsistencies and event coding errors which may interfere with the inference of results. Another dataset that has been used in the more recent conflict literature (e.g., Ayana et al., 2016; Pettersson et al., 2021) is the Uppsala Conflict Data Program Georeferenced Events Dataset (UCDP GED; hereafter, UCDP). Eck (2012) compares the two datasets and finds various tradeoffs with both. For example, only ACLED documents non-armed-group-initiated conflicts (i.e., riots), which is one reason why we utilize it in the main analyses. Additionally, the ACLED includes "far more conflict events because of its lack of restrictions on inclusion," (p. 127) which is beneficial for observing a more time-variant measure of conflicts proximal to mines and villages but raises concerns about the validity of documented events. On the contrary, UCDP only includes about a quarter of the number of conflicts as ACLED during our sample period (2004–2022), but Eck (2012) shows a case study in Table 2 of her paper that demonstrates a markedly lower proportion of events with detected problems in the UDCP dataset. These issues include incorrect provinces/territories, double-coded events, and/or missing events (compared to the other dataset). Given these issues that have been emphasized, we conduct corresponding analyses using the UCDP dataset to support our main findings.

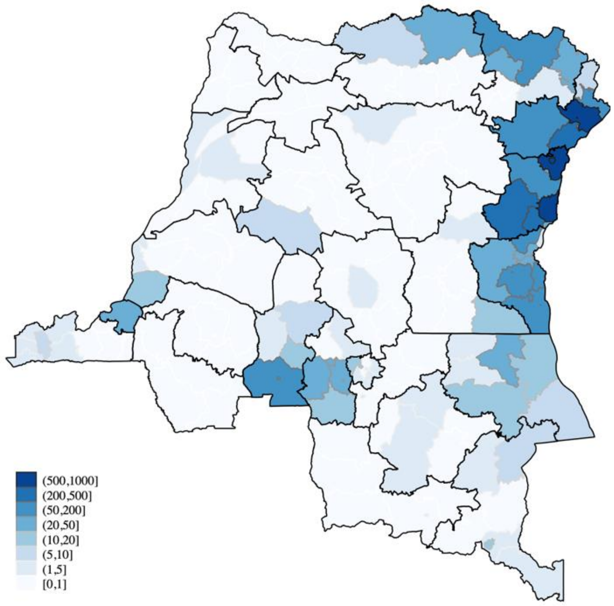
Other than the change in the dataset, we do not change any other parts of the methodology or data cleaning unless necessary. The mine data we use is also the same, though there are still differences in the descriptive statistics because we continue to drop observations that have no conflict within 10 kilometers. We are unable to split by armed-group-initiated vs. non-armed-group-initiated conflict because UCDP does not provide such a distinction, so we only perform analyses with all conflicts and fatalities. Further, we do not report village-level analyses (except for direct displacement) because villages were defined by conflict incidents, so given the low number of UCDP conflict incidents, we are unlikely to observe meaningful time-series variation in conflicts assigned to villages. Panel A of Table IA7.1 reports the number of observations excluded by each of the sample selection criteria for the conflict data while the mine selection criteria remain identical to what is shown in Panel B of Table IA4.1.

Figure IA7.1 Panels A and B show geographic intensity and locations of conflict across DRC provinces measured as the total number of conflict incidences from 2004 through 2022. This figure again illustrates that the conflict is most intense in the eleven provinces in the eastern DRC and, even within these provinces, is clustered in the easternmost territories. However, there are notably fewer observations than we observe in the ACLED dataset. Similarly, when we plot the number of conflict incidents and fatalities by year in Figure IA7.1 Panel C, we see notably fewer observations, especially before 2016. However, we do still observe an upward trend in conflict observations.

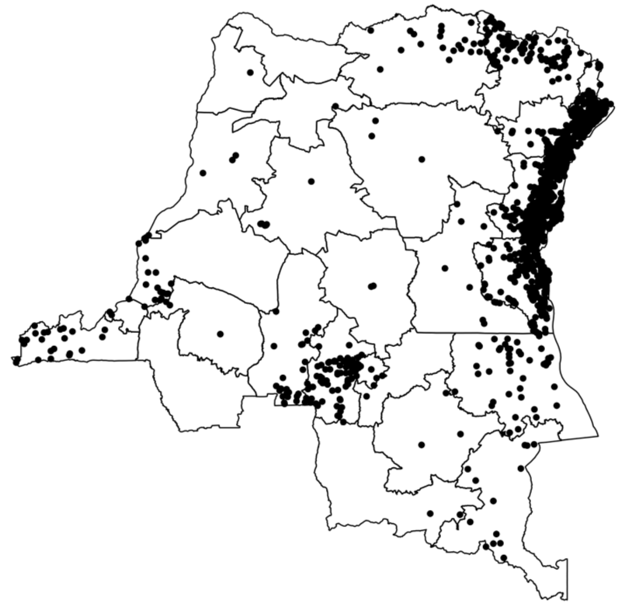
Descriptively, we can see in Table IA7.1 Panel B that approximately 1.7% (15.9%) of gold (3T) mine-years are post-certification because there is a higher total count of gold mines but far fewer certifications of gold mines. Further, there is no substantial difference for conflict incidence or fatalities between the 10-kilometer radius around gold and 3T mines. This alleviates concerns that gold and 3T mines are differentially located in high- or low-conflict areas. In Sections IA7.2 and IA7.3, we conduct corresponding analyses using the UCDP dataset.

Figure IA7.1. Conflict Incidents and Fatalities (UCDP)

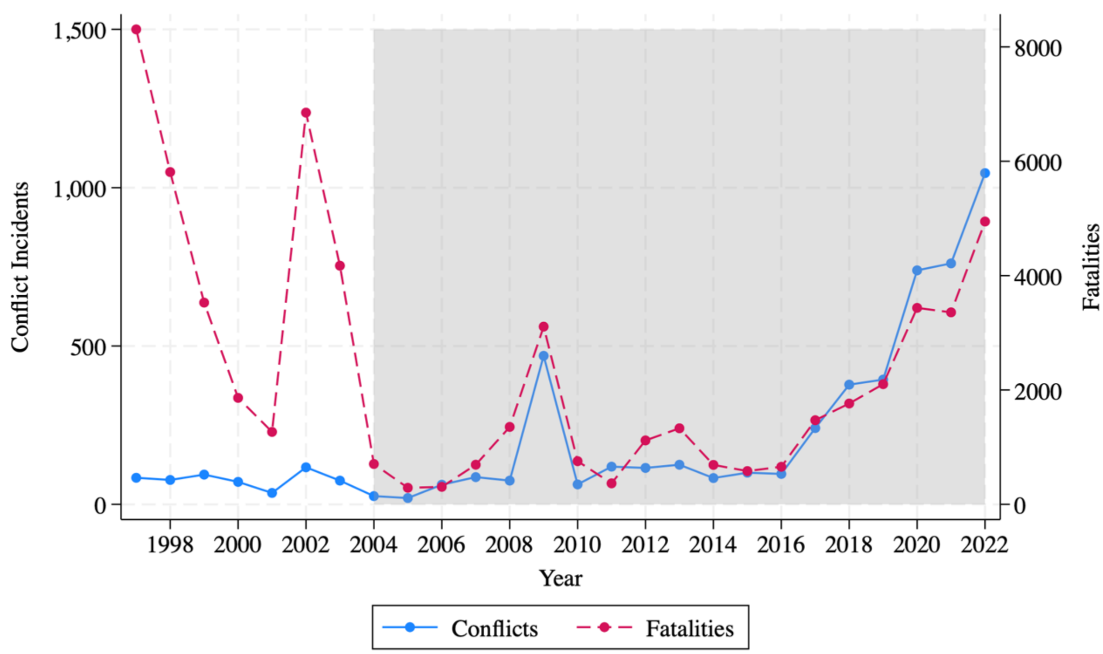
Panel A: Conflicts by Territory



Panel B: Conflict Locations



Panel C: Conflicts by Type Over Time



Notes: This figure shows the geographical and longitudinal distribution of UCDP conflict incidents in our sample. Panel A is a heat map showing the distribution of conflict incidents across territory in our sample period (2004–2022). Panel B locates all locations in the DRC that have at least one conflict incident documented across our entire sample period (2004–2022). Panel C illustrates the evolution of conflict across time in the DRC by documenting conflict incidents and fatalities from the UCDP data. Our sample period (2004–2022) is shaded in gray.

Table IA7.1. Sample Selection and Descriptive Statistics (UCDP)

Panel A: Sample Selection for Conflict Incidents

Selection Criterion		Obs. Count
UCDP Conflict Database		7,220
Less:	Geographically imprecise	(928)
Less:	Non-eastern provinces	(524)
Less:	Before 2004 or after 2022	(768)
Final conflict sample		4,998

Panel B: Descriptive Statistics

	Mine-Year		
Mean	All 3TG	Gold	3T
	(1)	(2)	(3)
CFC x *PostCert*	0.055	0.017	0.159
𝟙(*Conflicts*)	0.183	0.179	0.194
Count(*Fatalities*)	3.321	3.443	2.993
Observations (count)	28,652	20,919	7,733

Notes: This table outlines sample selection for UCDP conflicts and presents descriptive statistics for our UCDP sample, which is a balanced panel of mine-year observations. We use this sample in Figures IA7.2a–IA7.3 and Tables IA7.2–IA7.3b. The sample is from 2004 to 2022. *CFC* x *PostCert* (presented as an interaction because control mines are not assigned treatment years) is a binary indicator equal to one for certified (green) mines or villages during and after the year of certification. 𝟙(*Conflicts*) is a binary indicator equal to one if one or more conflicts is documented within 10km of a mine. Count(*Fatalities*) is a count variable for the number of fatalities documented within 10km of a mine or assigned to a village.

IA7.2 Effect of Mine Certifications on Conflict

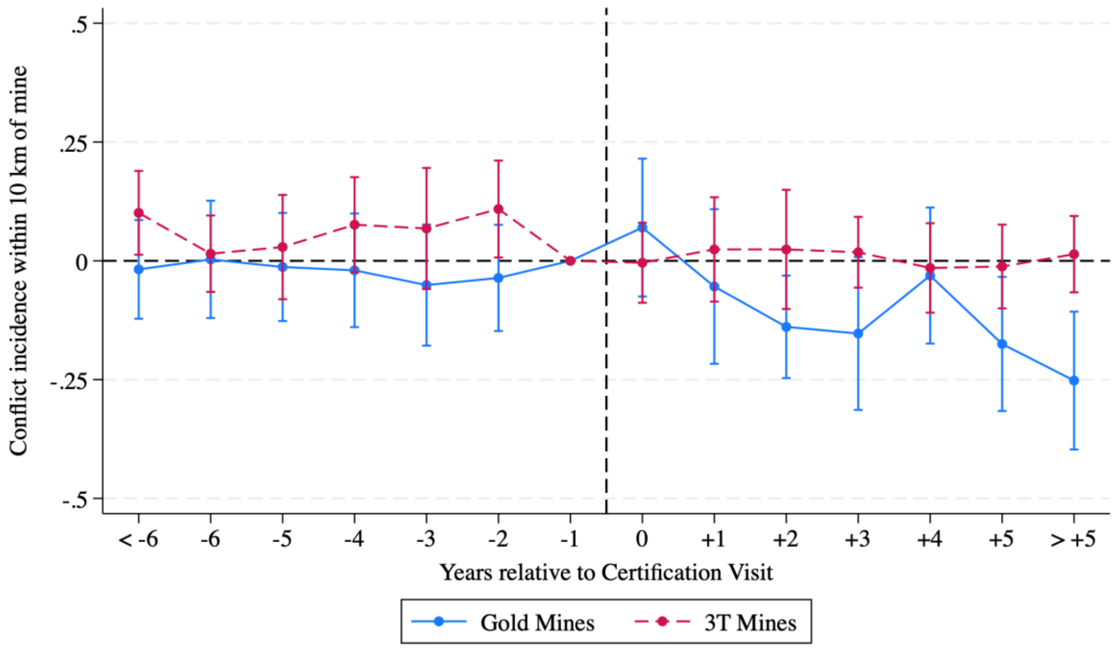
Corresponding to Section 3 in the paper, we examine changes in the probability of conflict around the first certification visit for certified mines. In Figure IA7.2a Panel A, we find a similar effect for the gradual reduction in conflict after certification for gold mines. In Figure IA7.2a Panel B, we also see a monotonic spatial diffusion effect for gold mines as we move from a 10- to 50-kilometer radius. Supporting this finding, we observe a negative and statistically significant coefficient for both conflict incidence and fatality count in Table IA7.2.

Interestingly, we also observe an average effect of similar magnitude and higher statistical significance for conflict incidence around 3T mines. However, Figure IA7.2a Panel A does not show a clear treatment effect at the certification year nor a gradual effect after certification. Similarly, the result in Table IA7.2 for fatality count is much weaker in both magnitude and statistical significance. Therefore, these results support our main findings that certifications have a notably weaker effect for 3T mines than for gold mines.

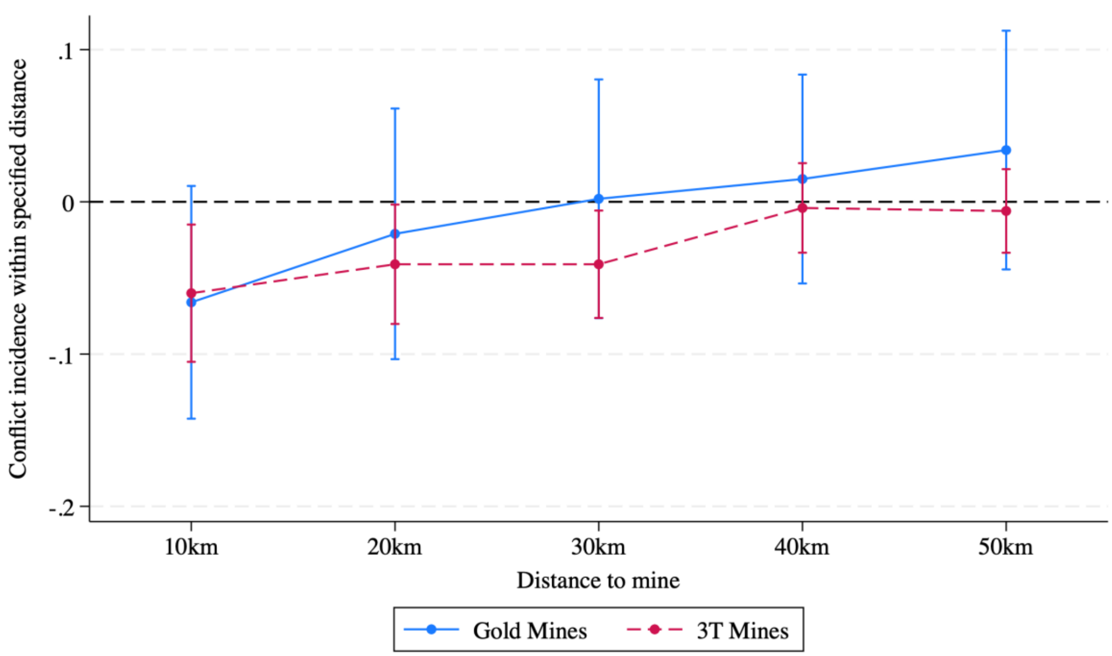
We also estimate our main set of sensitivity tests for the UCDP sample in Figure IA7.2b. With the exception of only Nord- and Sud-Kivu mines and including zero-conflict mines, the results remain qualitatively similar. The larger variation in coefficient magnitude is likely due to the much smaller conflict count that is available from UCDP data, causing reduced consistency in the dependent variable.

Figure IA7.2a. Change in Conflict After Certifications (Mine Level, UCDP)

Panel A: Gradual Effect



Panel B: Spatial Diffusion



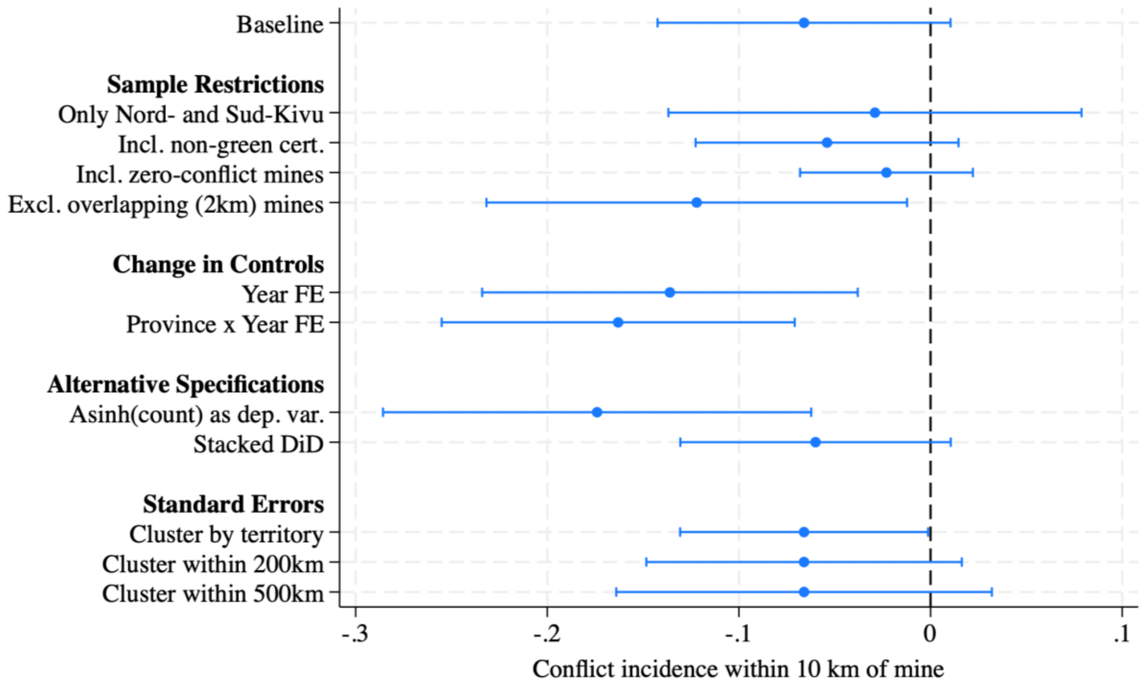
Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of 3TG mine certification on the probability of conflict incidence. Panel A estimates the model from Table IA7.2 Columns (2) and (3) but replaces the *PostCert* indicator with separate interactions for each of the lead- and lag-years (except for the year before treatment, which serves as the benchmark). Panel B also estimates the model from Table 3 Column (2) but uses different radii for the dependent variable.

Table IA7.2. Certifications and Conflict (UCDP)

	𝟙(*Conflicts*)			asinh(*Fatalities*)		
	All 3TG	Gold	3T	All 3TG	Gold	3T
	(1)	(2)	(3)	(4)	(5)	(6)
CFC x *PostCert*	-0.063***	-0.066*	-0.060***	-0.227***	-0.323***	-0.177*
	(0.023)	(0.039)	(0.023)	(0.083)	(0.103)	(0.104)
Mine FE	Yes	Yes	Yes	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.503	0.512	0.556	0.532	0.555	0.523
Observations (Mine-Year)	28,614	20,843	7,638	28,614	20,843	7,638

Notes: This table reports coefficient estimates of OLS regressions estimating the effect of artisanal mine certification visits with "green" status on mine-level conflict incidence and fatalities by mineral type. We describe the sample selection for UCDP conflicts in Table IA7.1 Panel A and for all other data in Section IA4, and we further drop singletons corresponding to the fixed-effect structure. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. 𝟙(*Conflicts*) is a binary indicator for whether one or more incidents of conflict is observed within 10km of a mine or assigned to a village. asinh(*Fatalities*) is the inverse hyperbolic sine of the number of fatalities documented within 10km of a mine or assigned to a village. *CFC* is a binary indicator for whether a mine has been treated or whether any mine within 10km of a village has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine or village.

Figure IA7.2b. Robustness to Different Specifications (Gold, UCDP)



Notes: This figure shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of gold mine certification on the probability of conflict incidence. We estimate the model from Table IA7.2 Column (2) but change various sample restrictions, fixed effects, and alternative specifications as identified in the figure.

IA7.3 Geographic Displacement of Conflict

Corresponding to Section 4 in the paper, we examine evidence on the displacement of conflict to uncertified areas. In Table IA7.3a, we again do not observe a decrease in aggregate conflict at the territory level; if anything, we see a statistically insignificant increase. In Figure IA7.3 Panel A, we similarly find a gradual increase in distance between a certified mine and the nearest conflict incident after certification for gold mines. In Figure IA7.3 Panel B, we also see a gradual increase in conflict for uncertified villages between 50 and 100 kilometers away from certified villages, but this effect is less apparent than in the main results. This is likely because we were forced to use village-level analysis, which is problematic (see Section IA7.1). Supporting these findings, we observe positive and statistically significant coefficients for both distance and displacement in Table IA7.3b.

Similar to the result for proximal conflict, we also observe an average effect of similar magnitude and higher statistical significance for distance to the nearest conflict for 3T mines. However, Figure IA7.3 Panel A does not show a clear treatment effect at the certification year nor a gradual effect after certification. Therefore, these results support our main findings that certifications have a notably weaker effect for 3T mines than for gold mines.

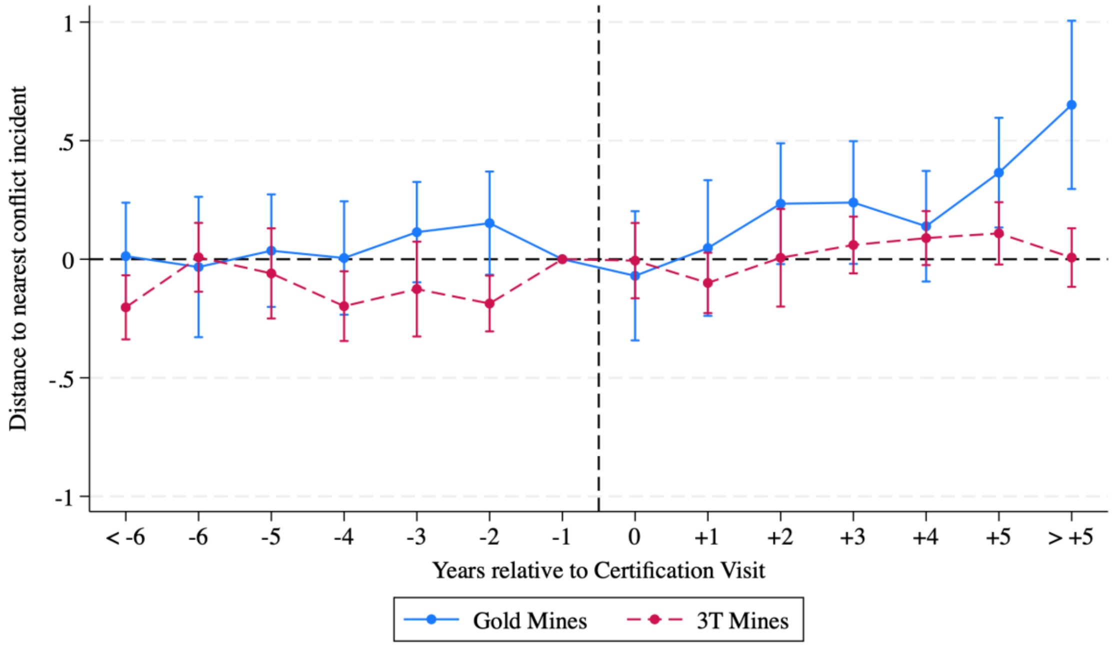
Table IA7.3a. Certifications and Aggregate Conflict (UCDP)

Dep. Var.: asinh(*Conflicts* OR *Fatalities*)	invhs(Gold Cert. Count)		Gold Cert. Fraction	
	Conflicts	Fatalities	Conflicts	Fatalities
	(1)	(2)	(3)	(4)
asinh(*Gold Cert. Count*)	0.014	0.029		
	(0.022)	(0.031)		
Gold Cert. Fraction			0.071	0.229
			(0.199)	(0.388)
Territory FE	Yes	Yes	Yes	Yes
Province x Year FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.640	0.566	0.639	0.565
Observations (Territory-Year)	1,330	1,330	1,330	1,330

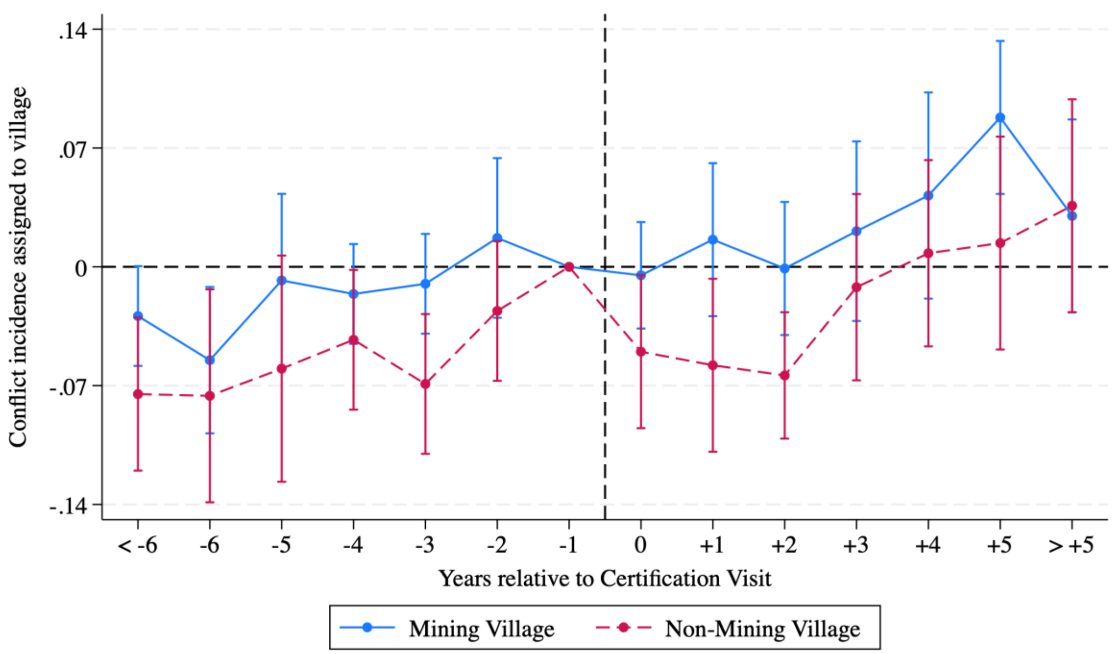
Notes: This table reports coefficient estimates of OLS regressions estimating the aggregate effect of artisanal gold mine certification visits with "green" status on territory-level conflict incidence and fatalities. We describe the sample selection for UCDP conflicts in Table IA7.1 Panel A and for all other data in Section IA4, and we further drop singletons corresponding to the fixed-effect structure. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. asinh(*Conflicts*) is the inverse hyperbolic sine of the count of conflicts within a territory. asinh(*Fatalities*) is the inverse hyperbolic sine of the number of fatalities documented within a territory. asinh(*Gold Cert. Count*) is the inverse hyperbolic sine of the count of certified gold mines within a territory. *Gold Cert. Fraction* is the count of certified gold mines divided by the total number of gold mines within a territory.

Figure IA7.3. Distance and Displacement (UCDP)

Panel A: Distance to Nearest UCDP Conflict (Mine Level)



Panel B: Displacement of Conflict (Village Level)



Notes: Panel A shows coefficient estimates and 95% confidence intervals for OLS regressions estimating the effect of gold mine certification on the distance from a mine to the nearest conflict in a year and the displacement of conflict to uncertified villages 50 to 100 kilometers away. We estimate the model from Table IA7.3b but replace the *PostCert* indicator with separate interactions for each of the lead- and lag-years (except for the year before treatment, which serves as the benchmark). Panel A corresponds to Columns (1) and (2) of Table 7 (distance), and Panel B corresponds to Columns (3) and (4) of Table 7 (displacement).

Table IA7.3b. Distance and Displacement (UCDP)

	Distance asinh(*Distance*)		Displacement $\mathbb{1}$(*Conflicts*)	
	Gold Mines	3T Mines	Mining	Non-Mining
	(1)	(2)	(3)	(4)
CFC x *PostCert*	0.152*	0.149***	0.032**	0.017
	(0.087)	(0.041)	(0.014)	(0.019)
Mine FE	Yes	Yes	Yes	Yes
Territory x Year FE	Yes	Yes	Yes	Yes
R-squared	0.790	0.855	0.230	0.201
Observations (Mine-Year)	20,843	7,638	18,050	22,287

Notes: This table reports results for mine-level distance to the nearest conflict and village-level conflict displacement. Columns (1) and (2) report coefficient estimates of OLS regressions estimating the effect of artisanal mine certification visits with "green" status on distance between a mine and the nearest conflict incident. Columns (3) and (4) report coefficient estimates of OLS regressions estimating the effect of artisanal gold mine certification visits with "green" status on village-level conflict incidence by conflict type in uncertified villages 50 to 100 kilometers away. We describe the sample selection for UCDP conflicts in Table IA7.1 Panel A and for all other data in Section IA4, and we further drop singletons corresponding to the fixed-effect structure. The sample is a balanced panel from 2004 to 2022. Conley (1999) standard errors allowing for spatial correlation within a 100km radius and for infinite serial correlation are reported in parentheses. asinh(*Distance*) is the inverse hyperbolic sine of the distance, in kilometers, between a mine and the nearest conflict incident. $\mathbb{1}$(*Conflicts*) is a binary indicator for whether one or more incidents of conflict is assigned to a village. *CFC* is a binary indicator for whether a mine has been treated. *PostCert* is a binary indicator for whether the observation year is during or after the certification year for a certified mine.

Section IA8. References

Ayana, E. K., Ceccato, P., Fisher, J. R. B., & DeFries, R. (2016). Examining the relationship between environmental factors and conflict in pastoralist areas of East Africa. *Science of The Total Environment, 557-558*, 601-611. https://doi.org/10.1016/j.scitotenv.2016.03.102

Baugh, K., Elvidge, C. D., Ghosh, T., & Ziskin, D. (2010). Development of a 2009 stable lights product using DMSP-OLS data. *Proceedings of the Asia-Pacific Advanced Network*, *30*, 114. https://doi.org/10.7125/APAN.30.17

Berman, N., Couttenier, M., Rohner, D., & Thoenig, M. (2017). This mine is mine! How minerals fuel conflicts in Africa. *American Economic Review*, *107*(6), 1564–1610. https://doi.org/10.1257/aer.20150774

Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics*, *92*(1), 1–45. https://doi.org/10.1016/S0304-4076(98)00084-0

Davies, S., Pettersson, T., & Öberg, M. (2023). Organized violence 1989-2022 and the return of conflicts between states? *Journal of Peace Research*, *60*(4), 691–708. https://doi.org/10.1177/00223433231185169

Eck, K. (2012). In data we trust? A comparison of UCDP GED and ACLED conflict events datasets. *Cooperation and Conflict*, *47*(1), 124–141. https://doi.org/10.1177/0010836711434463

Fritz, M., McQuilken, J., Collins, N., & Weldegiorgis, F. (2017). Global trends in artisanal and small-scale mining (ASM): A review of key numbers and issues. *International Institute for Sustainable Development*. https://www.iisd.org/system/files/publications/igf-asm-global-trends.pdf

Ghosh, T., Baugh, K. E., Elvidge, C. D., Zhizhin, M., Poyda, A., & Hsu, F-C. (2021). Extending the DMSP nighttime lights time series beyond 2013. *Remote Sensing, 13*(24), 5004. https://doi.org/10.3390/rs13245004

Glencore (2023). *Artisanal and small-scale mining (ASM)*. https://www.glencore.com/sustainability/esg-a-z/artisanal-and-small-scale-mining

de Koning, R. (2009, June 25). The mining ban in the Democratic Republic of the Congo: Will soldiers give up the habit? *Stockholm International Peace Research Institute*. https://www.sipri.org/commentary/essay/thu-06-25-2009-14-00/mining-ban-democratic-republic-of-congo-will-soldiers-give-up-habit

Matthysen, K., & Gobbers, E. (2022). Armed conflict, insecurity, and mining in Eastern DRC: Reflections on the nexus between natural resources and armed conflict. *IPIS/USAID.* https://ipisresearch.be/wp-content/uploads/2022/12/20221208_ILRG_IPIS_Armed-conflict-insecurity-and-mining-in-eastern-DRC.pdf

Pettersson, T., Davies, S., Deniz, A., Engström, G., Hawach, N., Högbladh, S., & Öberg, M. S. M. (2021). Organized violence 1989–2020, with special emphasis on Syria. *Journal of Peace Research*, *58*(4), 809–825. https://doi.org/10.1177/00223433211026126

Raleigh, C., Linke, A., Hegre, H., & Karlsen, J. (2010). Introducing ACLED: An armed conflict location and event dataset: Special data feature. *Journal of Peace Research*, *47*(5), 651–660. https://doi.org/10.1177/0022343310378914

Schütte, P. (2018). International mineral trade on the background of due diligence regulation: A case study of tantalum and tin supply chains from East and Central Africa. *Resources Policy, 62*, 674–689. https://doi.org/10.1016/j.resourpol.2018.11.017

Stoop, N., & Verpoorten, M. (2020). Would you fight? We asked aggrieved artisanal miners in Eastern Congo. *Journal of Conflict Resolution*, *65*(6), 1159–1186. https://doi.org/10.1177/0022002720983437

Stoop, N., Verpoorten, M., & Van der Windt, P. (2019). Artisanal or industrial conflict minerals? Evidence from Eastern Congo. *World Development, 122*, 660–674. https://doi.org/10.1016/j.worlddev.2019.06.025

Sundberg, R., & Melander, E. (2013). Introducing the UCDP georeferenced event dataset. *Journal of Peace Research, 50*(4), 523–532. https://doi.org/10.1177/0022343313484347

UNEP-WCMC (2016). World database on protected areas. *Protected Planet*. https://www.protectedplanet.net/

Uppsala Conflict Data Program (2021). Battle-related deaths (number of people) – Congo, Dem. Rep. Available from https://data.worldbank.org/indicator/VC.BTL.DETH?locations=CD.