UNIVERSITY OF COPENHAGEN
FACULTY OF ECONOMICS

Master's Thesis

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All That Glitters Is Not Gold

Conflicts & Mineral Extraction In South Africa

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Submitted on: 31. May, 2020

Number of characters: 120,595

Abstract

This thesis examines the causal relationship between mineral extraction and conflicts using sub-national data from South Africa. Using data from The Southern Africa - Towards Inclusive Economic Development (SA-TIED) project of 1,352 mine locations proxied by 12 different types of mineral and conflict data from Armed Conflicts and Events Database (ACLED) a significant and positive correlation between mineral extraction and conflict is found. This effect is relatively higher for valuable minerals and minerals that are important for the United States economy and defence. Further, exploring exogenous variation in mineral prices a mineral price-shock is found to be further increasing the probability of conflict. This effect is mainly driven by price-shocks to gold. Finally, the thesis takes on a novel approach and identifies expansion of mining areas as a source of conflict. This is done by carrying out a remote sensing change detection analysis which, to the knowledge of the author, this thesis is the first to do. Consistent with the rationalist explanations for war, it is here suggested that conflicts in South Africa occur as a consequence of information asymmetries between mining companies and communities.

Contents

1 Introduction

The mining sector is one of the keys contributors to the South African economy. Not only does the sector directly and indirectly provides income to millions of South Africans, the mining-centred holding companies invest in a number of economic activities which are creating growth in the country. But, alas, all that glitters is not gold as a non-negligible number of conflicts are also happening in the mining sector.

This thesis seeks to establish a causal relationship between mineral extraction and conflicts in South Africa through shocks to global mineral prices and by detecting expansions to mining sites. It thereby contributes to existing literature, where the majority explore cross-country data, by considering a single country case and thereby analyse the causes of conflict on the sub-national scale. This thesis is further one of the first of its kind that use remote sensing change detection analysis to address causality between mineral extraction and conflicts.

The explanations to what cause conflicts in mineral extraction are many. For one, rebels may extract revenues from the mines (Berman et al. , 2017) which makes rebellions more financially feasible in resource rich countries where they thus happen more frequently (Ross, 2006). However, conflicts involving rebels and militia are not that common in South Africa and the explanation must be found elsewhere. As argued in the influential paper by Fearon (1995) no part should ever want to engage in conflict if there are any costs related with it. Billions of Rand (the South African currency) are at stake in the extractive industry of South Africa, why the companies should be highly risk-averse and in general seek to avoid conflicts entirely. Likewise, mine workers and communities are depending on income and community investments from the mining companies. Instead conflicts happen due to issues of asymmetric information and commitment problems. Asymmetric information holds rational actors from reaching mutually preferable settlements while commitments problems arise as one or both actors for some reason cannot trust each other in abide an agreement which therefore gives incentive to renege.

These explanations for conflict have found support in the literature looking into what cause conflicts in the South African mining sectors and how these are further reinforced by changing mineral prices. Bond & Kirsch (2015) and Christensen (2019) thus argue that information asymmetries between mining companies and communities arise as their beliefs of how increasing mineral prices affects the well-being of the community and the profitability of the companies deviates. Looking further into what structural factors that make the company-community relationship more sensitive to issues of information asymmetries and commitments problems Farrell et al. (2012) and Hamann et al. (2005) find that cultural differences, local governance complexities and historical resentment may cause mistrust and keep mining companies and communities from negotiating agreements. However, information asymmetric may also happen if mining companies choose to withhold information for personal gains and in South Africa the disclosure of information in the mining sector is still widely voluntary.

This thesis seeks to establish the causal relationship between mineral extraction and conflicts in South Africa by first using exogenous variation in global mineral prices. To further investigate what factors are actually driving conflicts a remote sensing change detection analysis inspired by Connette et al. (2016) is also carried out. The analysis finds a significant and positive correlation between mines and the probability of conflict. Further, this effect is relatively higher for minerals with high rents (diamond, gold and platinum) and for minerals for which their supply is critical to the United States economy and defence (Downey et al., 2010). A price-shock is found to be significantly increasing the probability of conflict and by disaggregating the effect by mineral type a robust and significantly positive effect is found for gold. The same is found for a price-shock to platinum, but this effect is expected to be suffering from reverse causality as South Africa is the main producer of platinum and conflicts in the platinum mines could very well affect global platinum prices. Finally, the analysis finds that protests and riots are the conflict types most related to mineral extraction. This result suggests that conflicts are mainly driven by companies-communities disputes and not rebel activities.
The identifying assumption in the remote sensing change detection analysis is that expansions of mine areas cause conflict by creating information asymmetries and by intensifying social- and environmental stressors like environmental damages, distortion of traditional lifestyle, force resettlements, increased inequality in the communities etc. The analysis implies that expansion of the mining areas in Bojanala Platinum District is followed conflicts related to employment discrepancies between mining companies and communities

mainly caused by information asymmetries.

This thesis contributes to existing literature in three important ways. First, as already mentioned a causal relationship between mineral extraction and conflicts on a sub-national level is established. Secondly, using data from the SA-TIED (The Southern Africa - Towards Inclusive Economic Development) project for locations on small to large scale mining companies in South Africa, which are proxied by their nearest mineral deposit recorded by the South African Council for Geoscience, an extensive dataset of 1,352 mine location with 12 different mineral proxies is compiled. This is significantly more observations as compared to the Raw Mineral Data (RMD) used in papers alike (Berman et al. (2017), Mamo et al. (2019), von der Goltz & Barnwal (2019)) which only has locations on 277 large and medium South African mining companies. This not only adds variation to the data but also overcomes a potential upwards bias from only including large mines. Third, carrying out a remote sensing change detection analysis the papers offers an alternative to establish causality between mineral extraction and conflicts. Not having to rely on any other data other than freely available satellite imagery, such analysis overcomes the data limitations which is currently complicating causal interpretation of the relationship between natural resource extraction and conflicts. This thesis is, to the knowledge of the author, the first in the conflict literature to use this kind of analytical framework.

The rest of the thesis is organized as follows: Sections 2 motivates the theoretical background of the paper. First, explanations to what causes conflict and how conflicts are related to the extractive industry specifically are presented. This is done in relation to existing literature investigating this link in Africa and South Africa. Secondly, to better understand the country context a brief review of the South African mining sector followed the South African demographics and political landscape is also included. Section 3 presents the analysis which seeks to establish causality between mineral extraction and conflict through mineral price-shocks. In section 4 the remote sensing change detection analysis is carried out using Bojanala Platinum District as study area. Finally, the results are discussed in section 5 and section 6 concludes.

2 Motivation and Related Literature

This section will motive the subject on mineral extraction and conflict in South Africa and the related literature on the subject. First the theoretical framework of conflicts is presented followed by a review of the literature investigating how conflicts relate the natural resource extraction. As the causes of conflict may be relatively context specific, mostly papers considering South Africa or at least African countries as study cases are presented. Finally, characteristics of South Africa and the South African mining sector are presented. Specifically the political and demographic factors will be considered which in combination with the valuable and volatile mining industry makes South Africa prone to conflict.

2.1 Natural Resources and Conflicts

Literature has long linked natural resources and conflict. This is no exception for South Africa which is both rich in mineral resources but is also suffering from a high number of internal conflicts. There are several possible explanations to why this correlation exists. The contest model is a well established model in the civil war literature which originates from Haavelmo (1954). The model considers two competing actors and analyse their allocation of resources to either production or appropriation. An important prediction from this model is that the probability of winning increase with relative effectiveness of fighting technology. This model has thus supported evidence in a number of empirical papers on especially the success of rebel movements. The contest model predicts that rebellions are more feasible in resource rich countries and therefore happens more frequently (Ross, 2006). This mechanism is further reinforced as commodity prices increase, and especially commodities with higher rents have been found to the particularly conflict prone (Berman et al. , 2017). However, as argued by Fearon (1995) no actor should ever want to engage in war, or in a more broad sense conflict, if there are any costs associated with it. Where rebels cause conflicts as they seek to extract rent in the mines, conflicts between mining companies, mine workers and communities will never be optimal as they will loose profit, wages, community investments etc. This makes the typical contest model incomplete as war/conflict always occur in equilibrium. Instead, Fearon proposes two compelling reasons why conflict happens in cases where the actors

would be better off without: (i) *asymmetric information*, which cause rational actors to be unable to reach mutually preferable agreements and (ii) *commitment problems*, which arise if for some structural reason the actors cannot trust each other in to abide the agreement which gives incentive to renege.
The causes of conflict are not easy to establish. In relation to natural resources and conflict, exogenous variation in mineral prices is often used to establish causality, and will therefore also be applied here. Papers using this framework on cross-country data are inconclusive (Blattman & Miguel, 2010), which may be explained by conflicts being relatively country or even regional specific. Considering instead a single case like South Africa offers a more credible research design as within-country heterogeneity in conflict can be accounted for. In general rebel movements and militia are not as common in South Africa as in other African countries like the Democratic Republic of Congo and Sierra Leone (De La Sierra et al. , 2014; Rigterink, 2020). Therefore it is not expected that rebels movements drive conflicts in South Africa, but that instead conflicts between mining companies and communities caused by information asymmetries are. Literature investigating conflicts in the mining industry and the underlying factors driving them using both cross-country data on African countries and data on South Africa specifically will now be presented.

Mines frequently exacerbate social- and environmental stressors as local inequalities, disruption of traditional lifestyle and damages to the environment around the mine. Thus, conflict may occur if the mining companies do not properly account for the consequences their activities may have on the surrounding communities. Bond & Kirsch (2015) argue that an increase in mineral prices is a kind of structural violence, e.g. violence build into the structure of the way a system works. As the price of a mineral increases, the social- and environmental stressors presented above may be intensified and thereby cause further distress in the surrounding communities. They further argue that the mining companies, their shareholders and even the state may not consider increasing commodity prices as structural violence, whereas the community does make this connection, causing asymmetric information between the parties. The communities in distress responds to such structural violence with the only valid tool at their disposal; conflict. Using cross-country data on conflicts they find that for most conflicts in their sample, the related mineral had indeed spiked, up to the point of the conflict. The minerals most often associated with conflict were found to be amongst the most valuable; gold, diamond, platinum and copper.

Christensen (2019) instead argues that increasing commodity prices lead to conflict as mine workers and communities overestimate the profitability of the mines. In general the community members and mine workers have limited knowledge of the mine company's profitability. However, as the price of the extracted resource increase they may assume that this in turn increase the profit of the mine and therefore expects higher wages, community contributions etc. But, as will also be shown below, increasing mineral prices have in recent years not increased profits due to relatively higher increase in input costs. An obvious solution to this problem would be for the mine companies to simply disclose their inability to pay. However, if the community should accept the mine company's explanation this would also give profitable mine companies incentive to plead themselves unprofitably and thus keep a larger share of the surplus. As communities for this reason cannot trust the mining companies, they use protest as means of disclosing the company type. The 'honest' companies will rather shut down than meeting the demand of the protesters whereas the 'dishonest' companies in turn will quickly capitulate in order to keep production running. Based on this theory, the author finds that increasing mineral prices significantly increase the probability of protests and riots but not battles or rebel events. The latter finding supports the expectation that rebel movements are not driving conflicts in South Africa.

These are two examples of how asymmetric information between the companies and communities can lead to conflict. However, it is still not clear what keeps the mining companies and communities from properly communicate and disclose information if this in turn could reduce the risk of conflict. Further, the latter example also argued for a general distrust between the parties. Following here are some examples offering explanations to this puzzle.

The culture of an international mining company may be very different from that of a South African local community. Hence, it may be difficult for the mining company to properly communicate with the community, and thus decide on what considerations should be taken to ensure that the community is not negatively affected by the mining

operation. In this respect, Farrell et al. (2012) use a conflict incident in Angelo Platinum Mine in South Africa as a case study to determine what factors contributed to the escalation of conflict between the mining company and the community. They find that issues concerning low community representation and participation in decision making about the mining companies production plays a role in exacerbating or even mitigating company-community conflict. The authors argue that too much emphasis is placed on technical aspects of project management in the mines, and too little on need for social expertise to respond to the local community dynamics and complexities that the companies is operating in. This view is also shared by Hamann et al. (2005) that in several case studies find the local governance complexities combined with historical resentments and distrust of mining companies are fuelling company-community conflicts in many African countries, including cases in the South African platinum- and chrome mines. This implies that not only asymmetric information but also commitment problems are recurring issues.
The findings above suggest that companies should increase transparency to overcome issues of distrust and hence commitment problems, and that mining companies if they are not themselves able to, should be given more assistance when seeking to negotiate with the local communities.

Finally, Downey et al. (2010) takes on another view and argues that armed violence is used as means to ensure that minerals, which are critical to global industrial production and state power, continue to be extracted in sufficient quantities. The authors find examples where this has happened in South African mines as communities have been forced to resettles to allow for mine expansion and where protesting mine workers have been violently assaulted by the South African Police (SAP). The state may engage or escalate conflict when production of minerals that are important to the economy is at stake. The authors further identify ten minerals that are critical to the United States economy and defence and are therefore argued to be especially conflict prone as they are valuable, but also because the states supplying the minerals will be pressured by international forces to keep up the supply of these. Among these critical minerals is platinum for which South Africa is the biggest global producer. In 2012 mine workers in Lonmin Platinum Mine were striking demanding higher wages, but the mine was refusing arguing that they were financially unable to meet the demands. This essentially started out as a case of asymmetric information in line with the Christensen (2019) paper, but escalated into violent conflicts as South African Police (SAP) shot and killed 34 mine workers and seriously injured 78. This incident is known as the Marikana Massacre. Thus, the governance-authorized attack on civilians may very well be motivated by the state wanting to put a quick end to the strike which was costing the Lonmin Mine and hence the South African state billions of Rand [1].

As suggested above internal factors may contribute to information asymmetries in the mining company-community relationship. In the next section the South African mining industry and the demographics and political framework of the country are presented, to better understand the specific context in which conflicts in the South African mining sector occur.

2.2 The South African Context

South Africa is one of the most resource rich countries in the world. Some of the world's most valuable minerals such as diamonds, gold and platinum are found here along with other minerals such as coal, iron, manganese, chromium and copper. South Africa is holding the world's largest deposit of platinum group metals (PGMs) (94 percent), chromite (40 percent) and manganese (28.9 percent) along with the world's largest gold deposit, the Witwatersrand Basin. Though the manufacturing sector has far surpassed the mineral sector in number of employees and contribution to the GDP, the mining sector is still at the core of the South African economy as mining-centred holding companies invest in other economic activities [2]. By 2019 the mining sector employed 454,861 people and contributed 360.9 billion Rand to the South African GDP (8.1%). Furthermore, each person employed in the mining sector has up to nine indirect dependants (Mineral Council South Africa, 2020). The role of the mining sector at the provincial level varies substantially. Where it for the north-west provinces contributes to the provincial economies in GDP added value by 22-33 percent it plays a minor role in south-east provinces (Mineral Council South Africa, 2019).

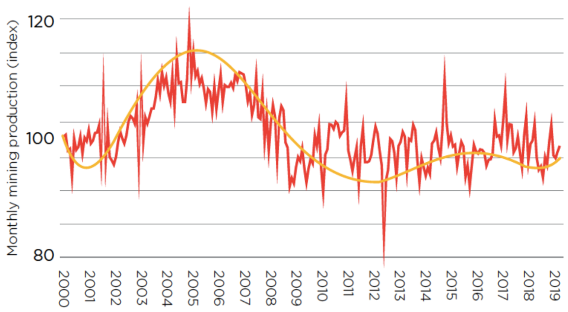
Figure 1 below depicts statistics of the South African mining sector, developed by Mineral

[1] https://www.sahistory.org.za/article/marikana-massacre-16-august-2012

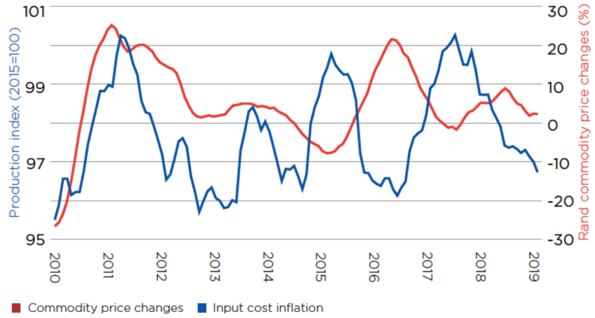
[2] https://www.britannica.com/place/South-Africa/Resources-and-power

Council South Africa (2020) for their annual sector review.

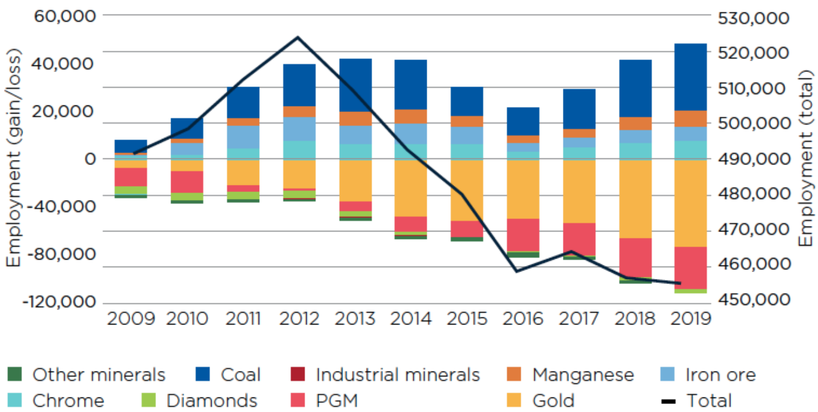
Figure 1: Key Figures: South African Mining Industry



(a) Productivity Index (2000=100)



(b) Commodity vs. Input Price



(c) Employment Index (2008=100)

Figure 1a shows the productivity index of the mining sector from 2000-2019. There has been a decrease in productivity since the financial crises hit the global economy in 2008. In recent years the productivity has stabilized at a level lower than that of 2000. The Mineral Council explains this by logical restraints such as rail capacity but also by community unrest, especially in the rural areas. Note also the sharp drop in productivity at the beginning of 2012. This may likely be explained by production loss at the Lonmin Mine, a major platinum producer, due to striking mine workers. In Figure 1b the development in input- and commodity costs are depicted. As the South African currency, Rand, during the recent decade has weakened relative to the US dollar the imported input costs to mineral production is putting pressure on the industry. This has in recent years resulted in input costs rising faster than commodity prices. The Mineral Council estimates that the input price inflation in 2019 alone was 7.6 percent, which is 2.9 percentage points higher than the national average production inflation rate. Finally, Figure 1c shows the development in total employment and by commodity. Since 2012 the overall employment in the mineral industry has decreased and by 2019 approximately 100,000 fewer were employed as compared to 2008. Considering that every employee in the sector provides for up to 9 other people, this lay-off has affected many already vulnerable South African households. Especially the gold industry has contributed to this trend. Gold was in many years the most important mineral in the South African economy. However, since the 2000s the mines have been forced to dig deeper to find rich reef patches increasing the cost of production, while at the same time the gold price continued to decrease [3]. Though the price of gold is once again increasing the rapid growth in input costs proceed to put pressure on the gold industry as well.

Meanwhile the legacy of apartheid and British colonization still affect the political landscape of South Africa. Not until 1997 was a new constitution adapted which put a formal end to apartheid policies favouring the white minority in the country. One of the principles in the new constitution was that of "cooperative government", thus the healthy corporation between the three tiers of elected government; the national, provincial and the local. There are nine provinces in South Africa (Limpopo, Gauteng, North West, Mpumalanga, Free State, Northern Cape, Kwazulu-Natal, Eastern Cape and Western Cape) each of which has a number of local governments as well as legally recognized traditional authorities. This makes governance in South Africa rather complex as elected governance and traditional authorities are often in dispute about property rights and because the traditional authorities, especially in the rural areas, are considered a higher authority than the government.

The population of South Africa is still racially segregated both within and outside the urban areas. During apartheid all non-whites were forced to resettle to the north-east part of the country, where a large share of the black population still live today, and many of these in informal settlements. It is the local governance who is responsible for these settlements, but due to inadequate maintenance and low community investments, many still have insufficient access to services such a running water, health and education [4].

[3] https://www.mineralscouncil.org.za/sa-mining/gold

[4] https://wp.wpi.edu/capetown/projects/p2014/wash-up-business/background-research/informal-settlements-in-south-africa/

Furthermore, in the beginning of the 2000s South Africa saw a rise in the number of immigrants from other African countries. The stream of immigrants to the northern part of South Africa increased the formation of information settlements amongst other places around the mines in which they were hired. These settlements are likewise experiencing poor living standards and high crime rates. Immigration also sparked political unrest as immigrants were accused of taking jobs from ethnic South Africans. The country still suffers xenophobic attacks and protests today [5].
The South African population, disproportionately towards black members of society, is poor and relatively uneducated and suffers high unemployment rates. In 1996 the government implemented the Black Economic Empowerment (BEE) focusing on increasing the employment opportunities of black members of society, improving their working skills and enhancing their income-earning potential. This concept was further defined and implemented in the Broad-Based Black Economic Empowerment (BBBEE) Act of 2004 which promotes racial-, gender- and social equality [6]. However, according to the Quarterly Labor Survey of the fourth quarter of 2019 the overall national unemployment rate is 38.5 percent and has been increasing since 2008. Whereas 46 percent of black South Africans are unemployed, only 9.8 percent of the white are. Likewise the north-east part of the country, where apartheid forced non-white South Africans to resettle, suffers from very high unemployment rates of approximately 47 percent [7].

Thus, South Africa rich in natural resources and their economy is therefore also highly depended on the extractive industry. However, their population suffers from racial segregation, poverty, unemployment and immigrations streams which along with complex local governance could make the company-community relationship more prone to conflicts caused by information asymmetries. Further, the relative importance of the mineral sector at the provincial level and arguably even the district level emphasise the importance of considering the conflict-mineral relationship at the sub-national level. The subsequent analysis will seek to establish a causal link between mineral extraction and conflicts through variation in global mineral prices.

[5] https://www.bbc.com/news/world-africa-47800718
[6] https://www.bbbeecommission.co.za/about-the-commission/
[7] http://www.statssa.gov.za/publications/P0211/P02114thQuarter2019.pdf

3 Conflict and Mineral Price-Shocks

Using exogenous variation in global mineral prices the following regression analysis will seek to establish a causal relationship between mineral extraction and conflicts in South Africa. First the data used in the analysis is presented followed by the a presentation of the methodological framework. The analysis will consider both the aggregated effect of a shock in mineral prices on the probability of conflict, and the disaggregated effect of the different types of minerals. A number of robustness checks will likewise be made.

3.1 Data

This section presents the four data components of the regression analysis; (i) Conflict data from the Armed Conflict and Event Data (ACLED) project is used to determine when and where conflicts have occurred in South Africa, (ii) data from the Southern African - Towards Inclusive Economic Development (SA-TIED) project is used to get locations on mining companies, (iii) a map from the South African Council for Geoscience showing mineral deposits is used to proxy the types of minerals extracted at the mine locations and (iv) global mineral prices from various data sources are used to measure mineral price-shocks. Data on conflicts and mineral prices are observed monthly from Jan. 2012 to Dec. 2019.

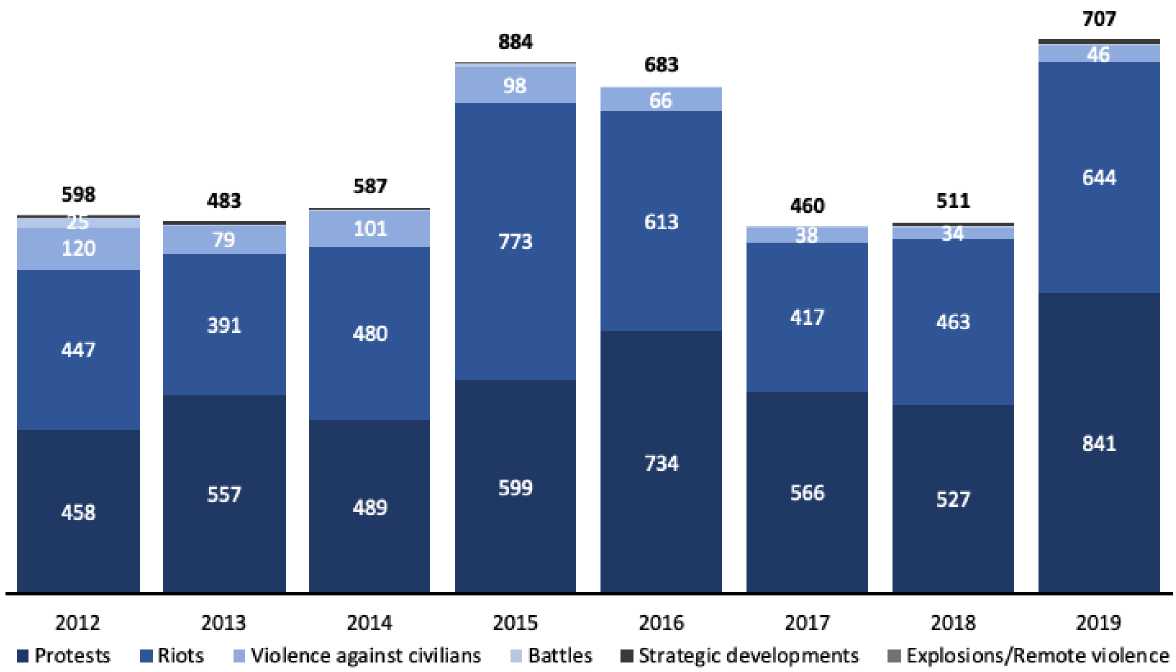
3.1.1 Conflict Data

Conflict data is obtained from ACLED; The Armed Conflict and Event Data Project (Raleigh et al. , 2010). The data consists of all 9,693 registered conflicts from the beginning of ACLED's coverage of South Africa in January 2012 to December 2019. ACLED's event data is collected from three secondary information sources: "...primary press accounts from local and regional news sources, Integrated Regional Information Network (IRIN), Relief Web, Factiva, and humanitarian agencies." (Raleigh et al. , 2010). The data is, however, subject to the pitfalls of relying on media as a data source. Thus, if media coverage is insufficient or in any way biased, so will ACLED's data be. ACLED is seeking to verify data by, when available, local accounts and discussions with regional experts prior to publication. All of the conflicts registered in ACLED have been divided into six event types. This gives the opportunity of also investigating the types of events that mineral extraction may be related to. ACLED (2019) defines the six types of conflict as follows:

- **Protests**: Non-violent demonstrations, involving typically unorganized action by members of society.
- **Riot**: Violent demonstrations, often involving a spontaneous action by unorganized, unaffiliated members of society.
- **Violence against civilians**: Violent attacks on unarmed civilians.
- **Battles**: Violent clashes between at least two armed groups.
- **Strategic Developments**: Activity that can broadly be described as 'non-violent' but differs in its role within contexts of disorder. Includes incidences of looting, peace-talks, high profile arrests, non-violent transfers of territory, recruitment into non-state groups etc.
- **Explosions/Remote Violence**: Event where an explosion, bomb or other explosive device was used to engage in conflict.

The yearly distribution of conflict types are depicted in Figure 2.

Figure 2: Conflicts in South Africa, Jan. 2012 - Dec. 2019

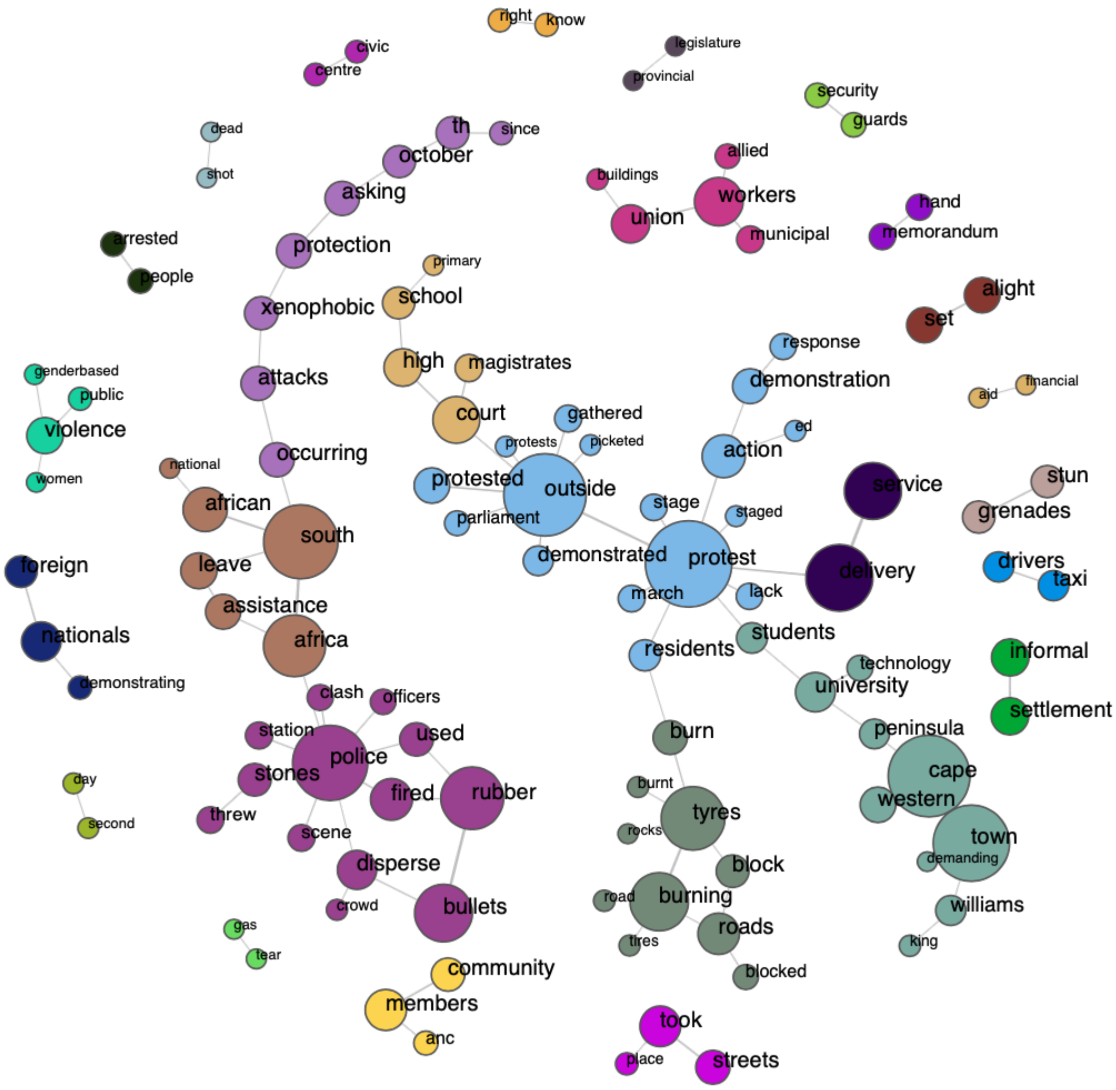


Source: ACLED

As seen in Figure 2 most of the registered conflicts are protests and riots. However, a non-negligible number of violent attacks on civilians also happen each year. Looking more into these conflict types it appears that many of them involves the South African Police (SAP). Police brutally in South Africa is a recurring problem also in relation to conflicts in the mines, the most famous incident being the Marikana Massacre. It could thus be expected that mineral extraction is also correlated with this type of conflict. Literature suggest that rent-seeking by armed groups (militia) is a source of conflict in many developing countries (Berman et al. , 2017; Rigterink, 2020; De La Sierra et al. , 2014). However, searching through the conflict events registered by ACLED only an average of ten events per year involves militia and rebels why such conflicts are not expected to be driving conflicts in South Africa. Instead, as discussed above, conflicts in the form of protest and riots between companies and communities are expected to be the driving force.

To get more insight into which types of conflict may occur in relation to mining, this thesis constructs a network of bigrams to describe conflicts located within 1 km from the nearest mine. A bigram is a sequence of two adjacent words in a string, which here is a conflict description. The 100 most common word-pairs which are also interconnected thus form a network of words. Words are divided into clusters given how likely they are to occur together and coloured accordingly. A larger bubble indicates a more common word. The network is depicted in Figure 3.

Figure 3: Bigrams: Common Descriptions of Conflicts near Mines



Not all conflicts within 1 km from a mine are necessarily mine-related. A lot of the mines in South Africa are located close to cities where conflicts occur due to a number of unrelated reasons. This is also visible in the bi-gram network where clusters describing conflicts related to student protests, gender based violence and taxi drivers are also included.

However, some of the words are likely related to mining. First, given the light-blue cluster of words, conflicts near mines are often protests and demonstrations. It is also clear from this cluster that a lot of the protests have been in relation to delivery services, i.e. housing, access to water, health services, infrastructure etc. A requirement of the Mineral and Petroleum Resource Development Act is that mining companies must ensure a decent standard of housing for the mine workers. These housing decisions must be made in collaboration with the community affected (Department of Minerals and Energy, 2009). Hence, if the communities feel that the companies do not fulfil this requirement, it could lead to conflicts. The light-purple cluster includes words like "xenophobic", "attacks" and "Pretoria". South Africa has been experiencing a high degree of violence against foreign citizens, especially in Johannesburg and Pretoria, where migrants are, amongst other things, accused of taking jobs from nationals (Dahir, 2019). These words are part of the network either because xenophobic attacks occur near the mines but are unrelated to them, or because some of the jobs that the immigrants are taking are in the mines. In relation to this, a small cluster including the words "informal" and "settlements" are also depicted. Informal settlements are common in the north-east part of the country and the number of these has further increased as a consequence of higher immigration from other African countries. The settlements mostly form around the mines where immigrants are seeking jobs, especially in the platinum mines in the Rustenburg area. The mining companies are responsible for the informal settlements that are formed by mine workers as they are, like argued above, required to ensure appropriate housing for their employees. The local government are on the other hand responsible for the informal settlements that were formed during apartheid and thus not directly as a consequence of mining activity. Conflicts related to informal settlements may therefore be related to inadequate care of both parties. Lastly it is clear from the words included in the network that conflicts near the South African mines are often relatively violent as road blocks and tyre burning are not uncommon. Furthermore the South African Police (SAP) is also often involved and takes violent measures in that several conflicts describe police firing rubber bullets, supporting the finding that SAP is involved in violent attacks against civilians (Figure 2). As previously argued the state may exert violence against protesters if there is risk of loosing profit from valuable minerals, as was the case in the Marikana Massacre in 2012.

3.1.2 Mine Data

The dataset on mine locations originates from the Southern African - Towards Inclusive Economic Development (SA-TIED) project [8]. The purpose of the SA-TIED project is to make high-level administrative tax data available to research and therefore includes information of South African firms from all sectors. After cleaning the data to only include mining companies for which geographical coordinates are available the dataset consists of 1,532 locations. Each location indicates a mining-firm. If a mining firm owns more than one mining-plot within a one kilometre radius, the firm is located in the point with the shortest distance to both plots.

The dataset does not contain information on the minerals extracted by the mining companies, for which a proxy is therefore needed. Data on mining activities, including localities of mines and mineral extraction in each mine, is notoriously difficult to obtain for developing countries. However, the Council for Geoscience in South Africa has in 2001 compiled a map which includes the simplified geology and selected mineral deposits in South Africa. This data stems from SAMINDABA (South Africa Mineral Deposits Database) database. The map is depicted in Appendix A, Figure A1. The map is made into an actual GIS[9] map using QGIS [10], and the geographical location and mineral of the mineral deposits marked on the map are collected. Only minerals for which it was possible to find price data are considered. These are; aluminium, coal, copper, diamond, gold, iron, lad, nickel, platinum, titanium, uranium and zinc. For the purpose of this thesis, a dataset of 795 deposits with 12 different types of minerals is thereby constructed and used to proxy the types of minerals extracted in the SA-TIED dataset. An overview of the proxy-dataset is provided in Appendix, Table A1. The mining firms are given a proxy corresponding to the deposit located closest to them. Thus, even if the mineral proxy may not necessarily be the exact mineral extracted by the firm, it is at least an indication of the type of mineral which is being extracted close by.

This paper distinguish itself from papers like Berman et al. (2017), Mamo et al. (2019) and von der Goltz & Barnwal (2019) that all use data from Raw Material Data (RMD, IntierraRMG) which includes mine locations from all over the world and the mineral extracted at each location. However, a drawback of this data is that it only includes

[8] https://sa-tied.wider.unu.edu/data

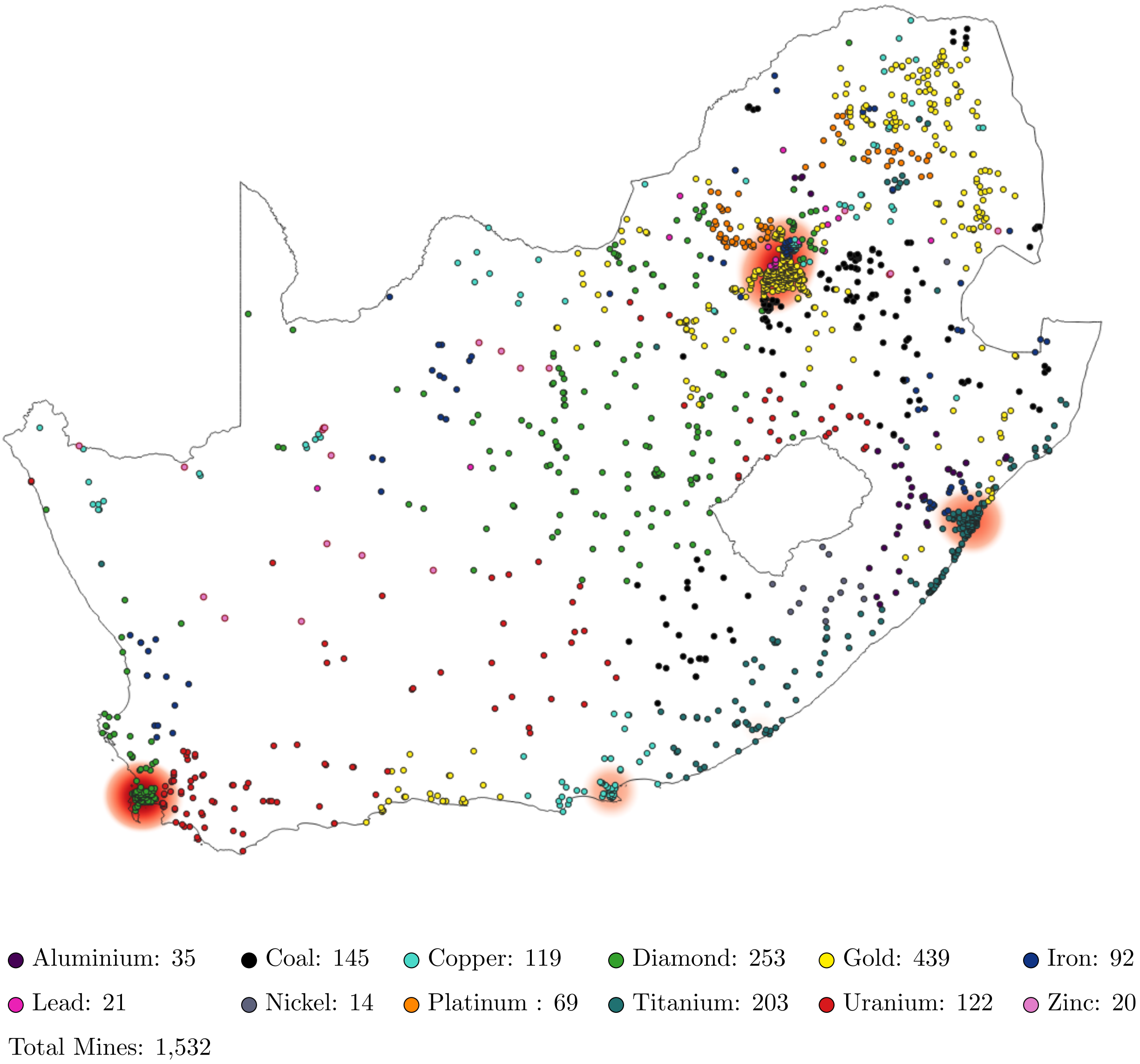
[9] GIS: Geographical Information System

[10] QGIS is an open-source geographical information system program for visualization, editing and analysis of such data

information on 277 large-scale South African mines. The dataset compiled for this thesis benefits from being significantly more extensive both because it includes almost five times as many mine locations but also because it includes mines all sizes. This should add more nuance to the regression results.

The mines coloured by their mineral proxies and a heat map of conflicts during the period Jan. 2012 - Dec. 2019 are shown together in Figure 4. The distance between a conflict and the nearest mine ranges from 0 to 65.7 km with mean 2.4 km. This implies that most conflicts are located fairly close to a mine. However, this may merely be because a lot of mines are located close to cities which makes natural epicentres of conflicts.

Figure 4: South Africa: Conflict Heatmap and Mine Locations

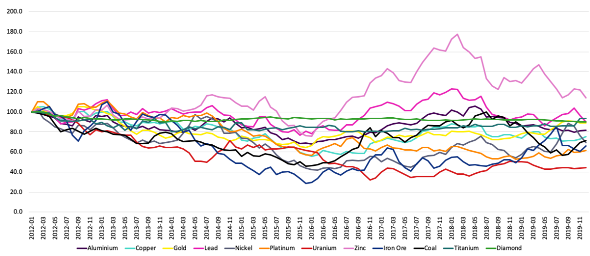


From Figure 4 above, it is clear that mines and conflicts cluster in the metropolitan cities such as Cape Town, Port Elizabeth, Pretoria and Durban. This potential bias will be accounted for in the analysis. Here it should also be noted that only few mines are proxied by nickel, zinc and lead. This could either cause the mineral types to be insignificant as there is too little variation or if the few proxies are spatially clustered they could easily be affected by other mineral types or by underlying fixed effects. This will also be accounted for in the analysis.

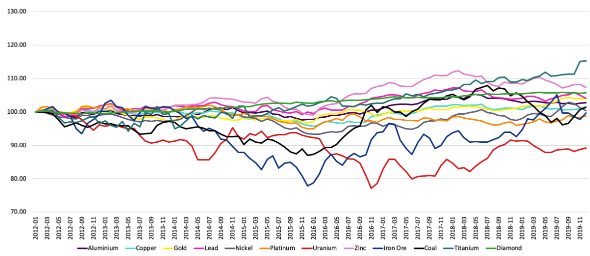
Mineral Prices

Monthly price data on each of the minerals have been collected from several different sources (see Appendix A Table A2). Three different price indices for the period Jan. 2012 - Dec. 2019 are shown in Figure 5.

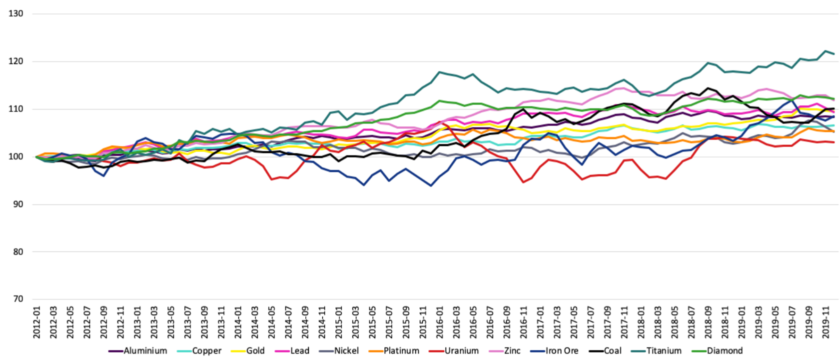
Figure 5: Mineral Price Indices (Jan. 2012 = 100)



(a) Log-transformed



(b) Deflated and log-transformed



(c) Currency converted (US dollars to SA Rand), deflated and log-transformed

Figure 5a depicts current log-transformed prices of minerals. To measure the actual change in prices and thus account for inflation, the prices are deflated using the South

African consumer-price index and the resulting indices depicted in Figure 5b. The variation in the price indices decrease significantly after this transformation. As a final step, in Figure 5c mineral prices are furthermore converted from US dollars to SA Rand before being deflated and log-transformed. These are the price that are realised by the South African mining companies and communities making this final transformation the most appropriate for the purpose of the analysis.

Mineral prices are driven by a variety of factors. These include supply disruption (for instance due to conflicts or natural disasters), increase in the United States interest rate, appreciation of the US dollar along with global economic factors such as trade tensions and growth rates. In general the commodity prices have been decreasing during the period 2012-2015, which is often attributed slow growth in China which is a major consumer [11]. As mineral producers were cutting their production the prices thus started to increase again from 2016 until 2019 where prices once again decreased. This can be explained by increased risk in the investment market for minerals in recent years, caused by the trade-war between China and the United States [12]. However, some minerals have despite this been performing well. The trade-war has made central banks increase investments in gold which is now amongst the best-performing commodities in terms of value. Also prices on nickel and iron continued to increase during 2019 which can mainly be attributed to Indonesia restricting export of nickel and a natural disaster causing major iron mines in Brazil to be flooded and thus decreasing supply [12].

The price of platinum is strongly determined by the supply in South Africa where about 80 percent of global reserves are found. Thus, conflicts in the South African platinum mines may affect global platinum prices. In 2012 a miners' strike started at the Lonmin mine and later in 2014 strikes also occurred in Angelo Platinum and Impala Platinum mines. These are among the world's biggest producers of platinum and the strikes thus hit 40 percent of the global production and ended up costing the three companies a revenue loss of 24 billion Rand ($2.25 billion)[13]. This potential reverse causality between conflict and global platinum prices will be discussed further during the analysis.

[11] https://www.ft.com/content/459ef70a-4a43-11e5-b558-8a9722977189

[12] https://insights.abnamro.nl/en/2019/10/economic-turmoil-affects-metals-prices

[13] https://www.gov.uk/government/publications/south-africa-platinum-strike-ends-june-2014/south-africa-platinum-strike-ends-june-2014

3.2 Methodology

This section will go through the methodology of the empirical analysis seeking to establish the relationship between mineral extraction and conflict in South Africa. First the identification strategy is presented along with the potential source of endogeniety that could prevent causal interpretation. The analysis will also carry out a number of robustness check that are likewise presented.

Identification Strategy

The units of observation are grids of size 10×10 km[14]. Using grids instead of administrative boundaries ensures that unit of observation is not endogenous to conflict. A similar approach is used by Berman et al. (2017) who apply a 55×55 kilometre grid on the African continent. Thus, the grid size used in their analysis is significantly larger than the ones applied here, even after doubling the grid size. However, as noted above, Berman et al. (2017) cover a larger area with fewer mines as compared to this analysis. Thus, in this analysis it is sensible to consider smaller grids in order to get enough variation in the data.

In order to establish causality between mineral extraction and conflicts the analysis will explore exogenous variation in monthly global mineral prices which are assumed to be unaffected by the South African mineral production. However, as noted above, since South Africa is a major producer of platinum it is likely that conflicts in the platinum mines could disrupt global platinum prices. This potential reverse causality will be discussed further. Specifically this analysis will seek to estimate the effect of a price-shock to a mineral on the probability of conflict. The mineral prices are converted from US dollars to SA Rand, deflated by the South African consumer price index and lastly log-transformed. Z-scores are measured and a shock defined as:

$$\text{Price-shock}_t = \left| \frac{\text{Price}_t - \overline{\text{Price}}}{\text{SD(Price)}} \right| > 2$$

Where Price_t is the price of the mineral at time t, $\overline{\text{Price}}$ is the period price average and SD(Price) is the price standard deviation. If a z-score in absolute value is more than two standard deviations from the mean, the price at the given time is considered a

[14]Too little variation were found using 5×5 grids, are is therefore not used in the analysis

shock. Using this specification price-shocks to coal, gold, iron, lead, nickel, platinum and uranium are detected during the period Jan. 2012 - Dec. 2019.

The model of choice is a binary response model where the outcome variable indicates if conflict is detected within the grid, i, during the month, t. Three baseline equations are defined:

$$\text{Conflict}_i = \beta_0 + \beta_1 \text{M}_i \tag{1}$$

$$\text{Conflict}_i = \beta_0 + \beta_1 \text{M}_i + \beta_2(\text{M}_i \times \text{MI}_i) \tag{2}$$

$$\text{Conflict}_{i,t} = \beta_0 + \beta_1 \text{M}_i + \beta_2(\text{M}_i \times \text{MI}_i) + \beta_3(\text{M}_i \times \text{MI}_i \times \text{PS}_t) + \text{FE}_{lm} + \text{FE}_{year} \tag{3}$$

The M_i and MI_i variables are interpreted as proxies for the extraction area of a given mineral(s) and the intensity of this, rather than effect of the actual mines. Equation (1) is a pooled OLS model which estimates the effect that an extraction area with a given mineral proxy has on the probability of conflict. It could be expected that large mines are involved in more conflicts than small mines as their operation both directly and indirectly affects a larger area and involves more people. In order to account for this effect Equation (2) includes the mineral intensity, which is the number of mines that has been proxied be a given mineral within a grid. The higher the mineral intensity the smaller the corresponding mines must be. If the expectation is true the mineral intensity variables are smaller than the mineral dummies.

Equation (1) and (2) merely estimates the *correlation* between the mineral extraction and conflict. In order to establish causality the price-shock variable PS_t is thus introduced in Equation (3). A number of fixed effects are also included in this estimation. First, FE_{lm} control for local municipality fixed effect which are included as conflicts and mines seem to cluster in urban cities (see Figure 4). Secondly, FE_{year} are year fixed effects which are included as conflicts and mineral price could both be endogenous to changes in the global economy. For instance, if there were to be worldwide expansion this could increase mineral prices while at the same time affecting conflict through income, remittances or aid. This would bias the results and obscure causal interpretation.

Note that all mine variables are time-invariant and do not account for the possibility that some mines may not have been producing or existing during the entire period. However, it is assumed that this would only be the case for relatively few mines in the dataset, and is thus not expected to have an effect on the estimation results. All regression models are clustered at cell level.

Robustness Checks

A number of robustness checks will be made during the analysis. First, due to the inclusion of several fixed effects, the baseline specifications are estimated using a Linear Probability Model (LMP), as the non-linear estimators are computational costly in such specifications. A logistic model will though be included as a robustness check. Secondly, inclusion of the different types of minerals may lead to multicollinearity caused by specific minerals always being extracted close to one another or due to few mineral observations. Therefore the baseline equations are also estimated including one mineral type at a time. Third, in the baseline equations a price-shock is assumed to have an effect on the probability of conflict within the same month. It may though take more time for a price-shock to manifest itself in conflict why price-shocks lagged two periods are also included [15]. As a further price check, a model including only the log-prices of minerals is estimated using fixed effects. The model thus estimates the effect of an increase in the log price of a mineral on the probability of conflict across all grids. These two specification are given below:

$$\text{Conflict}_{i,t} = \beta_0 + \beta_1 \text{M}_i + \beta_2(\text{M}_i \times \text{MI}_i \times \text{PS}_{t-1}) + \beta_3(\text{M}_i \times \text{MI}_i \times \text{PS}_{t-2}) \tag{4}$$

$$\text{Conflict}_{i,t} = \beta_0 + \beta_1(\text{M}_i \times \ln \text{P}_t) \tag{5}$$

Fourth, instead of only estimating the probability of conflict in general, the effect on each of the conflict types will also be considered. Due to few observations the conflict types "battles", "explosions/remote violence" and "strategic development" are aggregated in type "Other". Fifth, for some of the mines in the dataset the nearest mineral proxy may be relatively far away. The nearest and furthest mineral proxy to a mine is 0.5 km and 270 km away respectively with mean 45 km. The baseline models will therefore also be estimated using a restricted sample, where mines for which their proxy mineral is more than 45 away are excluded. Finally, some of the mines in South Africa are very big and the effect they have on the probability of conflict in the surrounding areas may be

[15] Including more lags does not lead to any significant results.

underestimated when using grids of 10×10 km. The baseline results are therefore also estimated using larger grids of 20×20 kilometres[16]. Descriptive statistics of the two grid sizes are shown in Table 1.

Table 1: Probable Outcomes Within the Grids

	10×10 **Grids**		20×20 **Grids**	
	Number	Share	Number	Share
Mine = 0, Conflict = 0	13,133	91.5	3,736	80
Mine = 1, Conflict = 0	446	3	312	6.5
Mine = 0, Conflict = 1	433	3	299	6.5
Mine = 1, Conflict = 1	351	2.5	321	7
Total	14,363		4,668	

Note: The table shows the distribution of the four possible scenarios within the grids and the shares of these for each of the two grid sizes.

For both grid sizes by far most of the cells do not contain any mines nor conflict. Increasing the grid size naturally increase the share of grids in which mines and conflict occur both separately and together. This could reflect that, as argued above, mines are large and therefore impact an area larger than what can be estimated using the 10×10 grids. However, increasing grid size also increase variability within the grids and unrelated conflicts and mines are also more likely to be captured within the same grids. Thus, using the smaller grids conflicts can more confidently be attributed to the mines.

3.3 Results

This section will go through the results of the empirical analysis. The baseline results using exogenous variation in mineral price-shock to establish causality between mineral extraction and conflict are presented, followed by the robustness checks of: (i) non-linearity of the model, (ii) multicollinearity of the mineral coefficients, (iii) changing price specification, (iv) disaggregating conflict type, (v) excluding mines with far-away mineral proxies and finally (vi) increasing grid size.

[16]All robustness checks are likewise estimated using 20×20 grids. These are found in Appendix B

Baseline Results

As a first step in the analysis the aggregated effect of a mineral proxy and a mineral price-shock on the probability of conflict is considered. To do this, the price-shock variable is defined as a price-shock to the main mineral within the given grid, i.e. the mineral with the highest sales value [17]. As there is only detected price-shocks to coal, gold, iron, lead, nickel, platinum and uranium the analysis is restricted to only include mines with these proxies. The mine dummy indicates if either of these minerals are proxied within the given grid, which also means that mine intensity is not considered here and can be disregarded in the model specification of Eq. (3). Using this specification the baseline Eq. (1) and (3) are estimated and the results presented in Table 2.

The result of Model 1 implies that there is a significant and positive correlation between mines and the probability of conflict. In Model 2 a price-shock to the main mineral within a grid further significantly increase the probability of conflict. This implies, if prices are exogenous, that dramatic changes to mineral prices can cause conflicts in the areas surrounding the mines. Accounting for local municipality fixed effect in Model 3 decreases the mine coefficient, which supports the expectation that an upwards bias occurs as mines and conflicts cluster near urban areas. Also controlling for the global business cycle by including year fixed effects in Model 4 does not change the results. This may be because currency exchanging and deflating prices already capture such potential effects.

[17] 2019 total sales numbers provided by Mineral Council South Africa (2020)

Table 2: Conflicts and Mineral Price-Shocks: Aggregated Effects

Estimator: LPM	**Model 1**		**Model 2**		**Model 3**		**Model 4**	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.
Mine	0.040***	(8.327)	0.040***	(8.250)	0.027***	(8.825)	0.027***	(8.830)
Mineral Price-Shock			0.017**	(3.138)	0.017**	(3.140)	0.017**	(3.023)
Constant	0.002***	(10.323)	0.002***	(10.323)	0.000	(1.008)	0.000	(1.101)
Local Municipality Fixed Effects	No		No		Yes		Yes	
Year Fixed Effects	No		No		No		Yes	
Observations	1,378,848		1,378,848		1,378,848		1,378,848	

Note: Outcome is a dummy variable indicating conflict. Model 1 reports estimates of Eq. (1) and Model 2-4 of Eq. (3), where the mine-intensity variable is disregarded. Model 3 accounts for local municipality fixed effects, and model 4 for local municipality and year fixed effects. All models are clustered at grid level. T-statistics are in parenthesis and level of significance is marked: *0.05 **0.01 ***0.001

Next the effects of the different mineral types and their related price-shocks on the probability of conflict are considered. The regression results of Eq. (1)-(3) are presented in Table 3. Model 5 estimates the effect of a mineral dummy on the probability of conflict. The presence of all mineral types, with exception of zinc, significantly increase the probability of conflict. Further considering the mineral intensities in Model 6 the coefficient are, with a few exceptions (diamond, iron, platinum), lower than their dummy counterparts. This implies, as expected, that larger mines have larger effect on the probability of conflict. Note that the results of Model 5 and 6 merely imply a significant correlation between areas in which minerals are extracted and conflicts. Thus, in Model 7 the price-shocks are included in order to establish causality. Significant positive effects on the probability of conflict are found in relation to price-shocks to gold and platinum. These two mineral are amongst the most valuable and the most important for the South African economy which supports the findings of Berman et al. (2017), Bond & Kirsch (2015) and Downey et al. (2010). However, as argued above, it could be expected that conflicts in platinum mines affect global platinum prices, violating the assumption of exogenous prices, which would then imply that the price-shock to platinum is actually caused by conflict. The issue of this reverse causality is returned to in the discussion.
Model 8 accounts for local municipality fixed effect which decrease the mine intensity coefficients, especially those that are mined close to Pretoria (gold and lead), Port Eliza-

beth (copper) and Cape Town (diamond and uranium). The effects of iron and nickel even becomes insignificant. Finally, Model 9 also includes year fixed effect and thereby controls for the global business cycle. This however does not change the regression results which could, as argued above, be due the price-shocks already accounting for such effect. Year fixed effects will for the remainder of the analysis not be included.

Table 3: Conflicts and Mineral Price-Shocks: Mineral Type Effects

Estimator: LPM	**Model 5**		**Model 6**		**Model 7**		**Model 8**		**Model 9**	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.
Mineral Dummy										
Aluminium	0.019***	(3.516)								
Coal	0.022***	(5.395)								
Copper	0.059**	(3.191)								
Diamond	0.050***	(4.532)								
Gold	0.052***	(6.974)								
Iron	0.037*	(2.194)								
Lead	0.062**	(2.682)								
Nickel	0.010*	(2.180)								
Platinum	0.036**	(2.737)								
Titanium	0.077***	(4.800)								
Uranium	0.021***	(3.671)								
Zinc	0.002	(0.947)								
Mineral Intensity										
Aluminium			0.019***	(4.388)	0.019***	(4.388)	0.019***	(4.433)	0.019***	(4.433)
Coal			0.020***	(7.413)	0.020***	(7.440)	0.020***	(7.622)	0.020***	(7.621)
Copper			0.040**	(2.605)	0.040**	(2.605)	0.033**	(2.683)	0.033**	(2.683)
Diamond			0.058***	(6.656)	0.058***	(6.656)	0.052***	(6.608)	0.052***	(6.608)
Gold			0.038***	(6.729)	0.037***	(6.581)	0.031***	(6.597)	0.031***	(6.599)
Iron			0.049*	(2.051)	0.049*	(2.020)	0.046	(1.901)	0.046	(1.902)
Lead			0.047***	(3.320)	0.046**	(3.227)	0.039*	(2.556)	0.039*	(2.556)
Nickel			0.011*	(2.422)	0.010*	(2.094)	0.008	(1.668)	0.008	(1.677)
Platinum			0.044**	(2.728)	0.042**	(2.711)	0.043**	(2.680)	0.043**	(2.680)
Titanium			0.052***	(5.008)	0.052***	(5.008)	0.052***	(4.615)	0.052***	(4.615)
Uranium			0.022***	(3.661)	0.022***	(3.683)	0.018***	(3.681)	0.018***	(3.682)
Zinc			0.003	(1.412)	0.003	(1.412)	0.003	(1.460)	0.003	(1.460)
Mineral Price-Shock										
Aluminium					-	-	-	-	-	-
Coal					-0.006	(-0.569)	-0.006	(-0.569)	-0.006	(-0.553)
Copper					-	-	-	-	-	-
Diamond					-	-	-	-	-	-
Gold					0.018**	(2.913)	0.018**	(2.913)	0.018**	(2.863)
Iron					0.013	(1.312)	0.013	(1.312)	0.012	(1.262)
Lead					0.009	(0.346)	0.009	(0.346)	0.009	(0.343)
Nickel					0.026	(0.746)	0.026	(0.745)	0.025	(0.717)
Platinum					0.017*	(1.982)	0.017*	(1.982)	0.017*	(1.974)
Titanium					-	-	-	-	-	-
Uranium					0.007	(0.504)	0.007	(0.504)	0.007	(0.489)
Zinc					-	-	-	-	-	-
Constant	0.001***	(6.863)	-0.000	(-1.762)	-0.000	(-1.762)	-0.005*	(-2.244)	-0.005*	(-2.201)
Local Municipality Fixed Effects	No		No		No		Yes		Yes	
Year Fixed Effects	No		No		No		No		Yes	
Observations	1,378,848		1,378,848		1,378,848		1,378,848		1,378,848	

Note: Outcome is a dummy variable indicating conflict. Model 5 reports estimates of Eq. (1), Model 6 of Eq. (2) and Model 7-9 of Eq. (3). Model 8 accounts for local municipality fixed effects and Model 9 for both local municipality and year fixed effects. All models are clustered at grid level. T statistics are in parenthesis and level of significance is marked: *0.05 **0.01 ***0.001

None-linearity

Considering the relative effect of the different types of minerals on the probability of conflict found in Table 3 it could be expected that there is non-linearities that should be accounted for. For instance, the coefficients related to lead are relatively high, which could be caused by most of the already few lead-proxies being located in Pretoria (see Figure 4) where a lot of conflicts along with gold and platinum mines are also located. To account for possible non-linearities the baseline Eq. (1)-(3) are therefore also estimated using the logistic estimator. The results are depicted in Table 4.

Note that the coefficients return the marginal effects. Model 10 shows that, in line with the findings of the linear model in Table 3, all mineral dummies except zinc have a positive effect on the probability of conflict. Here the relative effects between the different types of minerals are also more in line with what could be expected. Thus, top five most important minerals in terms of effect on the probability of conflict are; titanium, gold, copper, platinum and diamond. These are all characterized as being amongst the most valuable (diamond, platinum and gold), supporting the finding of Berman et al. (2017) and Bond & Kirsch (2015), and among the ten most critical minerals to the US economy (titanium, platinum and copper), which is further supported by Downey et al. (2010). In Model 11 the mineral intensity coefficient are all smaller than their dummy counterparts, again indicating that larger mines have a larger effect on the probability of conflict. Lastly, Model 12 includes mineral price-shocks for which gold and platinum price shocks, as in the linear models, have significant positive effects on the probability of conflict. However, here a price-shock to iron is also found to significantly increase the probability of conflict. In 2019 a natural disaster flooded iron mines in Brazil and thus caused a large deficit of iron that increased the global price of iron. Supported by Bond & Kirsch (2015) this results suggests that a dramatic increase in the price of a mineral, even a bulky mineral such a iron, has to ability to significantly increase the probability of conflict.

Table 4: Conflicts and Mineral Price-Shocks: Non-linear Effects

Estimator: Logit	Model 10		Model 11		Model 12	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.
Mineral Dummy						
Aluminium	0.0169***	(10.590)				
Coal	0.0172***	(15.650)				
Copper	0.0182***	(13.860)				
Diamond	0.0174***	(14.990)				
Gold	0.0183***	(16.730)				
Iron	0.0150***	(11.560)				
Lead	0.0161***	(10.020)				
Nickel	0.0154***	(7.700)				
Platinum	0.0175***	(12.070)				
Titanium	0.0209***	(16.090)				
Uranium	0.0162***	(14.860)				
Zinc	0.0071	(1.180)				
Mineral Intensity						
Aluminium			0.0087***	(9.780)	0.0087***	(9.780)
Coal			0.0063***	(6.870)	0.0063***	(6.870)
Copper			0.0055***	(5.130)	0.0055***	(5.130)
Diamond			0.0051***	(4.490)	0.0051***	(4.490)
Gold			0.0042***	(11.460)	0.0042***	(11.450)
Iron			0.0055***	(5.820)	0.0054***	(5.780)
Lead			0.0079***	(6.330)	0.0079***	(6.290)
Nickel			0.0100***	(6.820)	0.0097***	(6.720)
Platinum			0.0084***	(11.300)	0.0083***	(11.230)
Titanium			0.0052***	(13.610)	0.0052***	(13.610)
Uranium			0.0076***	(14.100)	0.0076***	(14.180)
Zinc			0.0035	(1.090)	0.0035	(1.090)
Mineral Price-Shock						
Aluminium					-	-
Coal					-0.0003	(-0.470)
Copper					-	-
Diamond					-	-
Gold					0.0003**	(2.920)
Iron					0.0006**	(2.830)
Lead					0.0002	(0.380)
Nickel					0.0030	(1.130)
Platinum					0.0005*	(2.540)
Titanium					-	-
Uranium					0.0004	(0.550)
Zinc					-	-
Constant	0.005***	(20.240)	0.005***	(17.900)	0.005***	(17.900)
$\ln(\sigma_u^2)$	2.440***	(33.180)	2.337***	(36.590)	2.337***	(36.600)
Observations	1,378,848		1,378,848		1,378,848	

Note: Outcome is a dummy variable indicating conflict. The coefficients return the marginal effects. Model 10 reports estimates of Eq. (1), Model 11 of Eq. (2) and Model 12 of Eq. (3). All models are clustered at grid level. Panel-level variance is parameterized as $\ln(\sigma_u^2)$. T statistics are in parenthesis and level of significance are marked: *0.05 **0.01 ***0.001

Mineral Multicollinearity

Including the different types of minerals as covariates elicit the possibility of multicollinearity. Multicollinearity may occur if certain types of minerals are likely to be extracted close to one another, or if the mineral type only has few observations. To account for such possible multicollinearity Table 5 returns the baseline Eq. (1)-(3) only including one mineral at a time.

In Model 13 and 14 most of the mineral coefficient are similar to those in Table 3 as do thus not seem to suffer from multicollinearity. However, there are a few important exceptions related to lead and nickel. The lead mineral dummy and intensity coefficients in Model 13 and 14 have increased whereas they for nickel have become insignificant. These two minerals have, along with zinc, very few observations (21 and 14 respectively) and are therefore both prone to multicollinearity. As argued above, most of the lead proxies are located in Pretoria where a lot of conflicts are registered, which could create an upwards bias in the lead coefficients. Including local municipality fixed effect does indeed suggest that this may be the case as the lead mineral intensity coefficient becomes insignificant in Model 16.

Thus the results imply that, with exception of lead and nickel, the mineral coefficients do not suffer from multicollinearity.

Table 5: Conflicts and Mineral Price-Shocks: Mineral Multicollinearity

Estimator: LPM	**Model 13**		**Model 14**		**Model 15**		**Model 16**	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.
Mineral Dummy								
Aluminium	0.016**	(2.941)						
Coal	0.020***	(4.748)						
Copper	0.058**	(3.066)						
Diamond	0.048***	(4.413)						
Gold	0.052***	(6.885)						
Iron	0.038*	(2.132)						
Lead	0.075**	(2.649)						
Nickel	0.007	(1.462)						
Platinum	0.036**	(2.769)						
Titanium	0.074***	(4.635)						
Uranium	0.018**	(3.121)						
Zinc	-0.001	(-0.520)						
Mineral Intensity								
Aluminium			0.016***	(3.566)	0.016***	(3.566)	0.017***	(3.814
Coal			0.019***	(6.435)	0.019***	(6.449)	0.019***	(7.118)
Copper			0.041**	(2.624)	0.041**	(2.624)	0.031*	(2.354)
Diamond			0.058***	(6.539)	0.058***	(6.539)	0.052**	(6.521)
Gold			0.038***	(6.811)	0.037***	(6.660)	0.029***	(6.010)
Iron			0.053*	(2.209)	0.053*	(2.176)	0.041	(1.781)
Lead			0.065***	(4.120)	0.064***	(4.031)	0.027	(1.469)
Nickel			0.007	(1.462)	0.005	(1.171)	0.007	(1.476)
Platinum			0.042**	(2.633)	0.041**	(2.614)	0.042**	(2.598)
Titanium			0.051***	(4.852)	0.051***	(4.852)	0.051***	(4.539)
Uranium			0.019**	(3.154)	0.019**	(3.169)	0.015**	(3.210)
Zinc			-0.001	(-0.613)	-0.001	(-0.613)	0.001	(0.465)
Mineral Price-Shock								
Aluminium					-	-	-	-
Coal					-0.006	(-0.570)	-0.006	(-0.570)
Copper					-	-	-	-
Diamond					-	-	-	-
Gold					0.018**	(2.918)	0.018**	(2.918)
Iron					0.013	(1.326)	0.013	(1.326)
Lead					0.008	(0.337)	0.008	(0.337)
Nickel					0.026	(0.746)	0.026	(0.746)
Platinum					0.017*	(1.980)	0.017*	(1.980)
Titanium					-	-	-	-
Uranium					0.007	(0.504)	0.007	(0.504)
Zinc					-	-	-	-
Local Municipality Fixed Effects	No		No		No		Yes	
Observations	1,378,848		1,378,848		1,378,848		1,378,848	

Note: Outcome is a dummy variable indicating conflict. Model 13 reports estimates of Eq. (1), Model 14 of Eq. (2), Model 15 and 16 of Eq. (3) where Model 16 further includes local municipality fixed effects. All equations are run only including one mineral-type at a time. Thus, each equation is estimated 12 times. All models are clustered at grid level. T-statistics are in parenthesis and level of significance is marked: *0.05 **0.01 ***0.001

Price Robustness

Next models with different prices specifications are estimated. The estimates of Eq. (5) and (4) are depicted in Table 6 below. Model 17 estimates the specification of Eq. (4) including the mineral price-shock lagged two periods, as it may take some time for a price-shock to manifest a reaction in the form of conflict. The analysis suggests that in the few months following a price-shock to lead and nickel the probability of conflict may significantly decrease. This implies that a price-shock to some types of mineral can in the longer run actually decrease the probability of conflict. However, from the robustness checks above it was found that the lead- and nickel coefficients suffers from multicollinearity and are sensitive to non-linearities. The price-shocks coefficients of these two minerals could thus also be driven by this, and are therefore not considered valid. Another important implication though follows from this result; since the lagged price-shocks to gold and platinum are insignificant, the reaction to a price-shock is relatively immediate as they only increase probability of conflict within the same month.

Model 18 estimates the pure price-effect of Eq. (5). The results of this model show that an increase in the log-price of gold, titanium and uranium significantly increase the probability of conflict across all grids and hence across all of South Africa. On the contrary an increase in the log-price of platinum decrease the probability. An increase in the log-price of a mineral can have both negative and positive effects on the probability of conflict across all of South Africa. If the externalities, positive as negative, of mineral extractions are very strong, this could explain why the effects are significant. However, as has already been argued, there is potential heterogeneity as the importance of mining in the South African provinces varies substantially along with the demographic factors and the quality of governance. The results could thus be driven by factors not explained by the model.

Table 6: Conflicts and Mineral Price-Shocks: Lagged Prices and Log-Prices

Estimator: LPM	Model 17		Model 18	
	Coef.	T Stat.	Coef.	T Stat.
Mineral Intensity				
Aluminium	0.019***	(4.513)		
Coal	0.021***	(7.594)		
Copper	0.040**	(2.617)		
Diamond	0.058***	(6.638)		
Gold	0.037***	(6.603)		
Iron	0.049*	(2.010)		
Lead	0.049***	(3.324)		
Nickel	0.011*	(2.285)		
Platinum	0.041**	(2.678)		
Titanium	0.052***	(5.039)		
Uranium	0.022***	(3.748)		
Zinc	0.003	(1.411)		
Mineral Price-Shock t-1				
Aluminium	-	-		
Coal	0.016	(0.969)		
Copper	-	-		
Diamond	-	-		
Gold	0.008	(0.862)		
Iron	0.008	(0.769)		
Lead	-0.036*	(-2.204)		
Nickel	-0.010*	(-2.200)		
Platinum	-0.008	(-0.374)		
Titanium	-	-		
Uranium	0.01	(0.889)		
Zinc	-	-		
Mineral Price-Shock t-2				
Alumina	-	-		
Coal	-0.014	(-1.889)		
Copper	-	-		
Diamond	-	-		
Gold	0.008	(1.170)		
Iron	0.012	(1.318)		
Lead	-0.036*	(-2.135)		
Nickel	0.024	(1.038)		
Platinum	0.026	(1.024)		
Titanium	-	-		
Uranium	-0.001	(-0.194)		
Zinc	-	-		
Mineral Price (log)				
Aluminium			0.017	(0.486)
Coal			0.027	(1.451)
Copper			-0.011	(-0.380)
Diamond			0.013	(1.045)
Gold			0.052***	(3.384)
Iron			0.006	(0.482)
Lead			0.029	(0.693)
Nickel			0.021	(0.475)
Platinum			-0.154**	(-3.006)
Titanium			0.066**	(2.667)
Uranium			0.056*	(1.981)
Zinc			0.010	(1.053)
Constant	0.000	(-0.047)	-0.001	(-0.438)
Panel Fixed Effects	No		Yes	
Observations	1,350,122		1,378,848	

Note: Outcome is a dummy variable indicating conflict. Model 16 reports estimates of Eq. (4) and Model 17 of Eq. (5) estimated with fixed effects. All models are clustered at grid level. T statistics are in parenthesis and level of significance are marked: *0.05 **0.01 ***0.001

Conflict Types

Next, the effect of mineral extraction on the probability of the different types of conflicts are considered. The estimation results of the baseline Eq. (3) for each conflict type are depicted in Table 7. The conflict types "Explosions/Remote Violence", "Battles" and "Strategic Development" are aggregated in type "Other" as there are too few observations in the individual categories.

The top section of the Table 7 uses the specification previously described, and hence estimates the effect of a price-shock to the most valuable mineral within a grid on the probability of conflict. The mineral dummy is significant and positive for all conflict types but is highest for "Protests" and "Riots". Considering next the effect of a price-shock to the main-mineral within the grids, the probability of "Protest" and "Riots" are further increased.

In the bottom section of the Table 7 the effects of the different types of minerals are once again considered. In general most of the mineral dummies have significant positive effect on the probability of the different conflict types. Again, as was also seen in the aggregated models above these effects are highest for the conflict types "Protest" and "Riots". It is also evident here that the minerals which have the relative largest effects on the probability of conflict are those that are either amongst the world's most valuable (diamond, platinum and gold) or amongst the ten most critical to the US economy (platinum, titanium and copper). Furthermore, several of the mineral types also significantly increase the probability of "Violence Against Civilians". This could be expected as it from Figure 3 was found that several of the conflicts in data, that are located close the mines, were involving the South African Police (SAP) who during several of these incidents fired rubber bullets. Further, it was found that approximately 70 violent attacks on civilians happen every year and a lot of them involves the (SAP)(see Figure 2). If, as argued by Downey et al. (2010), the state and hence SAP are willing to exert violence in order to keep up the production of mineral that are critical for United States economy and defence, this would also explain why the effect is likewise highest in relation to titanium and platinum.

Turning next to the effects of the mineral price-shocks, a gold price-shock significantly increase the probability of 'Protest' in a magnitude equal to that of Model 7 in Table 3. This supports the argument by Christensen (2019) that increasing mineral prices cause protests as communities are forcing the mining companies to disclose whether they can increase wages, job opportunities etc. or not. It is also found that a price-shock to lead significantly decrease the probability of "Protest" and "Violence Against Civilians". Again, the lead coefficient have been found the be very sensitive in a number of robustness checks why this effect could very well be invalid. Lastly, note that the platinum price-shock does not have a significant effect on any of the conflict types. Disaggregating the conflict types impose the risk of blurring the results found when estimating the overall probability of conflict. This could very well be the case here.

Table 7: Conflicts and Mineral Price-Shocks: Conflict Types

Estimator: LPM	**Protests**		**Riots**		**Violence Against Civil.**		**Other**	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.
Mine	0.020***	(5.611)	0.022***	(7.777)	0.004***	(5.654)	0.001***	(4.561)
Mineral Price-Shock	0.010**	(2.940)	0.009*	(2.164)	0.001	(0.729)	0.002	(1.310)
Constant	0.001***	(7.345)	0.001***	(9.579)	0.000***	(6.589)	0.000***	(5.213)
Mineral Intensity								
Aluminium	0.004***	(3.703)	0.012***	(4.395)	0.004	(1.933)	0.001	(1.328)
Coal	0.010***	(7.117)	0.011***	(5.248)	0.001**	(2.882)	0.001*	(2.348)
Copper	0.026*	(2.181)	0.023*	(2.531)	0.002*	(2.313)	0.001	(1.393)
Diamond	0.042***	(4.644)	0.032***	(4.817)	0.005**	(2.722)	0.001**	(2.932)
Gold	0.022***	(4.082)	0.020***	(5.749)	0.004***	(3.417)	0.001*	(2.284)
Iron	0.042	(1.672)	0.030*	(2.070)	0.008	(1.688)	0.001	(1.330)
Lead	0.020*	(1.989)	0.022*	(2.337)	0.004*	(2.369)	0.000	(0.337)
Nickel	0.004	(1.872)	0.006*	(2.357)	0.001	(1.157)	0.000	(1.634)
Platinum	0.018*	(2.023)	0.025**	(2.929)	0.008*	(2.056)	0.001**	(2.644)
Titanium	0.032**	(3.091)	0.031***	(3.660)	0.009**	(2.860)	0.001*	(2.192)
Uranium	0.012**	(3.196)	0.011***	(3.933)	0.001**	(2.982)	0.000	(1.604)
Zinc	0.003	(1.700)	0.001	(1.360)	0.001	(1.179)	0.000	(1.619)
Mineral Price-Shock								
Aluminium	-	-	-	-	-	-	-	-
Coal	-0.003	(-0.382)	-0.003	(-0.454)	-0.001**	(-2.947)	-0.001*	(-2.318)
Copper	-	-	-	-	-	-	-	-
Diamond	-	-	-	-	-	-	-	-
Gold	0.018**	(3.228)	0.004	(1.115)	-0.000	(-0.013)	0.001	(0.677)
Iron	0.019	(1.736)	0.002	(0.295)	0.010	(1.819)	0.004	(0.693)
Lead	-0.032**	(-2.965)	0.042	(1.641)	-0.006**	(-3.133)	-0.001	(-0.948)
Nickel	-0.003	(-1.527)	0.030	(0.868)	-0.001	(-1.038)	0.000	(-0.852)
Platinum	0.001	(0.291)	0.009	(1.378)	0.009	(1.021)	0.001	(0.702)
Titanium	-	-	-	-	-	-	-	-
Uranium	0.008	(0.818)	-0.002	(-0.295)	-0.001**	(-2.805)	0.000	(-1.552)
Zinc	-	-	-	-	-	-	-	-
Constant	-0.001**	(-3.230)	-0.000	(-1.374)	-0.000	(-1.958)	0.000	(-1.634)
Observations	1,378,848		1,378,848		1,378,848		1,378,848	

Note: The models estimate the probability of the different types of conflict. "Other" includes the conflict types "Battles", "Explosions/Remote Violence" and "Strategic Development". All models estimate Eq. (3) and are clustered at grid level. T-statistics are in parenthesis and level of significance are marked: *0.05 **0.01 ***0.001

Proxy Robustness

Here the robustness of the mineral proxies are tested by excluding mines for which their proxy is more than 45 km away. This leads to a decrease from 1,352 to 1,126 mines in the dataset. The estimation results of the baseline Eq. (1)-(3) using this data are presented in Table 8.

As compared to the model using the full dataset presented in Table 3, excluding some of the mines from the analysis changes the coefficients and the relative effect of the different mineral types. First the nickel- and uranium coefficients becomes insignificant. Further, the magnitudes of some of the minerals have changed quite a lot; where copper- and titanium mineral dummies have increased by approximately 2 percentage points, the diamond mineral dummy on the other hand has decreased by almost 3 percentage points. Finally, in model 21 and 22 the effect of a platinum-price shock is no longer significant, but the coal price-shock has in turn become significant and decreases the probability of conflict. The gold price-shock is robust and has even increased. These results implies that the results are not robust to excluding mines for which their proxy is more than 45 km away. The finding of Table 3 should though not be disregarded as the 45 km cut-off is relatively arbitrary and thus a slightly higher cut-off could yield additional different results. Further, 45 km is not very far especially considering how large some of the mines and the mineral deposits in South Africa are. And most importantly, causality between mineral extraction and conflicts holds as a price-shock to gold is still significantly increasing the probability of conflicts.

Table 8: Conflicts and Mineral Price-Shocks: Subset of Mine Data

Estimator: LPM	Model 19		Model 20		Model 21		Model 22	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.
Mineral Dummy								
Aluminium	0.024***	(3.604)						
Coal	0.023***	(4.431)						
Copper	0.083**	(2.965)						
Diamond	0.021**	(3.247)						
Gold	0.059***	(6.558)						
Iron	0.049*	(2.077)						
Lead	0.071**	(2.742)						
Nickel	0.007	(0.896)						
Platinum	0.039**	(2.609)						
Titanium	0.091***	(3.680)						
Uranium	0.005	(1.567)						
Zinc	0.004	(0.895)						
Mineral Intensity								
Aluminium			0.021***	(4.107)	0.021***	(4.107)	0.023***	(4.547)
Coal			0.022***	(5.650)	0.022***	(5.652)	0.023***	(5.777)
Copper			0.043*	(2.189)	0.043*	(2.189)	0.036*	(2.169)
Diamond			0.027**	(3.198)	0.027**	(3.197)	0.028***	(3.329)
Gold			0.041***	(5.782)	0.040***	(5.652)	0.032***	(5.237)
Iron			0.059*	(2.092)	0.058*	(2.051)	0.057*	(2.003)
Lead			0.058***	(3.327)	0.058**	(3.231)	0.048*	(2.454)
Nickel			0.007	(0.953)	0.007	(0.960)	0.005	(0.651)
Platinum			0.047**	(2.723)	0.045**	(2.715)	0.047**	(2.773)
Titanium			0.055***	(4.043)	0.055***	(4.043)	0.048***	(3.644)
Uranium			0.006	(1.555)	0.006	(1.561)	0.007	(1.850)
Zinc			0.003	(0.915)	0.003	(0.915)	0.004	(1.212)
Mineral Price-Shock								
Aluminium					-	-	-	-
Coal					-0.024***	(-5.749)	-0.024***	(-5.748)
Copper					-	-	-	-
Diamond					-	-	-	-
Gold					0.021**	(2.772)	0.021**	(2.772)
Iron					0.019	(1.470)	0.019	(1.470)
Lead					0.007	(0.219)	0.007	(0.219)
Nickel					-0.009	(-1.118)	-0.009	(-1.118)
Platinum					0.017	(1.841)	0.017	(1.840)
Titanium					-	-	-	-
Uranium					-0.007	(-1.852)	-0.007	(-1.852)
Zinc					-	-	0.000	-
Constant	0.002***	(8.810)	0.001***	(5.071)	0.001***	(5.071)	-0.004	(-1.865)
Local Municipality Fixed Effects	No		No		No		Yes	
Observations	1,378,848		1,378,848		1,378,848		1,378,848	

Note: Mines for which the proxy is more than 45 km away are excluded from this analysis leading to a decrease from 1,352 to 1,126 mines in the dataset. Outcome is a dummy variable indicating conflict. Model 19 reports estimates of Eq. (1), Model 20 of Eq. (2) and Model 21 and 22 of Eq. (3) where Model 22 further includes local municipality fixed effects. All models are clustered at grid level. T-statistics are in parenthesis and level of significance are marked: *0.05 **0.01 ***0.001

Increasing Grid Size

Finally the grid size is increased from 10×10 km to 20×20 km. As argued, some mines may be very large and the effect between mine and conflict captured using 10×10 grids could therefore be underestimated. Thus, the baseline Eq. (1)-(3) are replicated using a larger grid size of 20 × 20. Table 9 presents the aggregated effects specified above, and thus estimate the effect of a price-shock to the most valuable mineral within a grid on the probability of conflict. All coefficient are strongly significant and increase the probability of conflict. In line with expectations the coefficient increase with grid size. This result is further supported by Berman et al. (2017). However, the relative difference between these estimates and those of Table 2 decrease when accounting for local municipality fixed effects. This suggest that increasing grid size also captures more unrelated mines and conflicts within the same grids. It is also noted that including year fixed effects in Model 26 decreases the price-shock coefficient. This in turn implies that increasing grid size also makes the price-effect more sensitive to the effect of the global business cycle.

Table 9: Conflicts and Mineral Price-Shocks: 20 × 20 km Grids

Estimator: LPM	**Model 23**		**Model 24**		**Model 25**		**Model 26**	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.
Mine	0.049***	(7.566)	0.048***	(7.484)	0.031***	(7.346)	0.031***	(7.360)
Mineral Price-Shock			0.017*	(2.546)	0.017*	(2.544)	0.015*	(2.260)
Constant	0.006***	(8.776)	0.006***	(8.776)	0.001	(1.037)	0.001	(1.220)
Local Municipality Fixed Effects	No		No		Yes		Yes	
Year Fixed Effects	No		No		No		Yes	
Observations	448,128		448,128		448,128		448,128	

Note: Outcome is a dummy variable indicating conflict. Model 23 reports estimates of Eq. (1) and Model 24-26 of Eq. (3). Model 25 accounts for local municipality fixed effects and Model 26 for both local municipality and year fixed effects. All models are clustered at grid level. T-statistics are in parenthesis and level of significance are marked: *0.05 **0.01 ***0.001

Table 10 reports the estimation results of the baseline Eq. (1)-(3) considering the different types of minerals. In Model 27 and 28 all mineral coefficients, except copper which is unchanged, have increased with the larger grid size. This results is supported by the evidence of Berman et al. (2017). Increasing the grid size has though also resulted in the gold price-shock becoming insignificant. On the contrary, the platinum price-shock has increased and becomes even more significant on the probability of conflict. This thus implies that some of the platinum mines are so large that the 10 × 10 grids underestimated the effect they have on the surrounding community. As South Africa, as discussed, holds major deposits of platinum and major platinum mines are therefore located here, this could be expected. However, increasing the grid size also increase variation within the grids along with the probability that unrelated conflicts and mines are captured within the same grids. If gold mines are in general relatively small, increasing the grid size may therefore blur the effect of a price shock to this minerals. Thus, in general using the smaller grid size of 10×10 km more confidently links conflicts to mines.

Table 10: Conflicts and Mineral Price-Shocks: 20×20 km Grids

Estimator: LPM	**Model 27**		**Model 28**		**Model 29**		**Model 30**		**Model 31**	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.		
Mineral Dummy										
Aluminium	0.032**	(3.264)								
Coal	0.025***	(5.066)								
Copper	0.059**	(2.700)								
Diamond	0.047***	(3.890)								
Gold	0.061***	(5.929)								
Iron	0.040*	(2.066)								
Lead	0.087*	(2.455)								
Nickel	0.018**	(2.982)								
Platinum	0.055**	(2.805)								
Titanium	0.095***	(4.730)								
Uranium	0.024***	(3.341)								
Zinc	-0.002	(-0.409)								
Mineral Intensity										
Aluminium			0.026***	(4.376)	0.026***	(4.376)	0.023***	(3.487)	0.023***	(3.487)
Coal			0.019***	(7.349)	0.019***	(7.392)	0.017***	(7.066)	0.017***	(7.065)
Copper			0.058***	(4.017)	0.058***	(4.017)	0.053***	(4.329)	0.053***	(4.329)
Diamond			0.047***	(10.275)	0.047***	(10.275)	0.042***	(9.609)	0.042***	(9.608)
Gold			0.030***	(9.015)	0.030***	(8.990)	0.027***	(8.812)	0.027***	(8.815)
Iron			0.021	(1.263)	0.020	(1.212)	0.026*	(1.972)	0.026*	(1.976)
Lead			0.042***	(5.692)	0.042***	(5.667)	0.065***	(5.303)	0.065***	(5.305)
Nickel			0.021***	(3.422)	0.018**	(3.124)	0.012	(1.951)	0.012	(1.971)
Platinum			0.048***	(4.587)	0.046***	(4.458)	0.043***	(4.289)	0.043***	(4.292)
Titanium			0.044***	(9.430)	0.044***	(9.430)	0.050***	(9.379)	0.050***	(9.378)
Uranium			0.029***	(4.070)	0.028***	(4.088)	0.026***	(4.150)	0.026***	(4.152)
Zinc			0.000	(0.037)	0.000	(0.037)	0.003	(0.580)	0.003	(0.580)
Mineral Price-Shock										
Aluminium					-	-	-	-	-	-
Coal					-0.007	(-0.824)	-0.007	(-0.824)	-0.008	(-0.824)
Copper					-	-	-	-	-	-
Diamond					-	-	-	-	-	-
Gold					0.003	(0.769)	0.003	(0.769)	0.003	(0.633)
Iron					0.015	(1.438)	0.015	(1.437)	0.014	(1.284)
Lead					-0.025	(-1.735)	-0.025	(-1.735)	-0.026	(-1.794)
Nickel					0.054	(1.387)	0.054	(1.386)	0.051	(1.307)
Platinum					0.019**	(3.058)	0.019**	(3.057)	0.019**	(3.018)
Titanium					-	-	-	-	-	-
Uranium					0.035	(1.874)	0.035	(1.873)	0.035	(1.854)
Zinc					-	-	-	-	-	-
Constant	0.001***	(4.444)	-0.001**	(-2.769)	-0.001**	(-2.769)	-0.028*	(-2.054)	-0.026	(-1.905)
Local Municipality Fixed Effects	No		No		No		Yes		Yes	
Year Fixed Effects	No		No		No		No		Yes	
Observations	448,128		448,128		448,128		448,128		448,128	

Note: Outcome is a dummy variable indicating conflict. Model 27 reports estimates of Equ. (1), Model 28 of Eq. (2) and Model 29-31 of Eq. (3). Model 30 accounts for local municipality fixed effects and model 31 for both local municipality and year fixed effects. All models are clustered at grid level. T-statistics are in parenthesis and level of significance are marked: *0.05 **0.01 ***0.001

In conclusion, from the empirical analysis presented above, a significant and positive correlated between mines and conflict in South Africa was found. Further the results suggested that this effect is largest for mines which have been proxied by minerals that are the most valuable (gold, diamond, platinum) and that are most important for the global economy, specifically the US economy and defence (platinum, copper and titanium). Using exogenous variation in global mineral prices to further establish a causal relationship, it was found that gold- and platinum price-shocks significantly increase the probability of conflict, though the latter is expected to be suffering from reverse causality. Furthermore the results implied that protests and riots are most commonly related to mines, but that attacks on civilians also occur. The results were tested in a variety of robustness checks, and though the results were not entirely robust to the different checks, the overall implications described still holds. Having establish the significant relationship between mines and conflict, the following part of the analysis will take a step further and consider the specific drivers of conflicts in relation to mining. This is done by carrying out a remote sensing change detection analysis.

4 Conflict and Mine Expansion

This second part of the analysis will take a closer look at the causes of conflict. For this purpose expansion of mining areas will explored as a potential cause of conflict. The identifying assumption is that expansion of a mining areas affect the probability of conflict by causing information asymmetries and by intensifying social- and economic stressor at the community level. Using short descriptions of the conflicts occurring close to a newly-expanded mine, the the analysis will seek to describe what motivates conflicts. Inspiration and methodological framework is attributed to Connette et al. (2016). First the study area, Bojanala Platinum District, is presented. Next the three data components used in the analysis are presented followed by the methodological framework of remote sensing change detecting analysis and lastly the results.

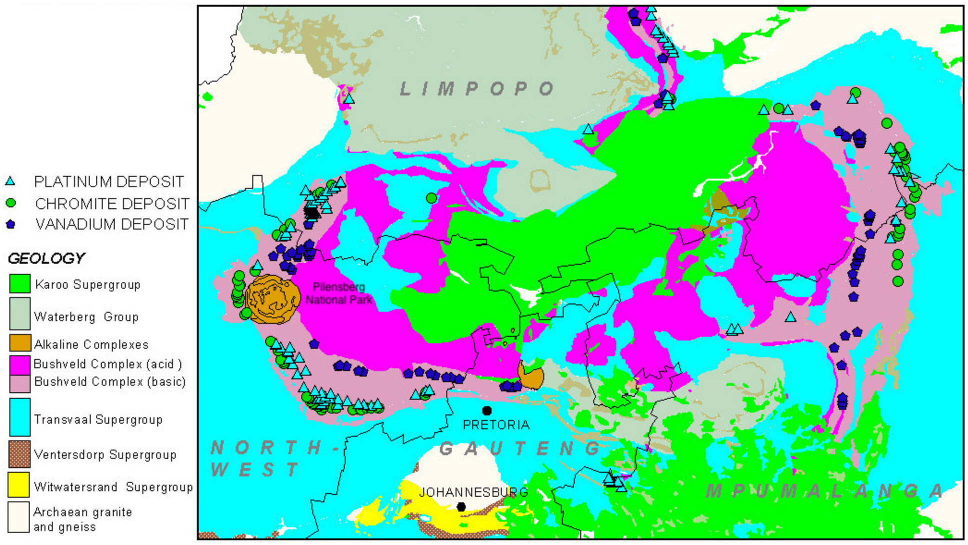
4.1 Study Area: Bojanala Platinum District

The remote sensing change detection analysis of mining areas is performed within known mining boundaries in the Bojanala Platinum District Municipality in the North West province of South Africa. A part of Bojanala is covered by the Bushveld Complex , which is the world's largest igneous intrusion. The complex is the most important global supplier of, amongst others, platinum-group metals (PGE) (80 percent of global resources) and chromite [18]. The Bushveld Complex of South Africa and the platinum-, chromite-

[18] https://en.wikipedia.org/wiki/Bushveld_Igneous_Complex

and vanadium deposits are shown in Figure 6.

Figure 6: The Bushveld Complex of South Africa



Source: South Africa Council for Geoscience. Map complied in April 2000

A large fraction of the deposits are placed within the boundaries of Bojanala Platinum District. Especially, a large band of platinum- and chromite deposits are located north-west from Pilensberg National Park. Naturally, the biggest economic sector in Bojanala is mining (30-35 percent of district GDP) [19]. The Rustenburg area in Bojanala is facing severe sustainable development challenges. The area which hosts some of the world's biggest platinum companies (Angelo, Impala, Lonmin) has attracted immigrants seeking employment in the mines. This has lead to large informal settlements around the mines with social- and infrastructural challenges. The local governance in the area is failing to deal with these informal settlements which can be attributed to irresponsibility and non-collaboration between the mining companies and the local government. The local government is struggling with limited capacity and legitimacy and the mining companies are failing to sufficiently invest in sustainable development of the affected local communities (Hamann et al. , 2005). As implied by the results from the regression analysis, platinum mineral is highly related to conflicts. And conflicts in the platinum mines (assuming reserve causality) have the ability to effect global platinum prices. Further, platinum is one of the most critical mineral to the US economy and defence, and the

[19] https://municipalities.co.za/overview/139/bojanala-platinum-district-municipality

South African state and hence the police have before been willing to use force in order to stop protests in platinum mines. Based on this the Bojanala Platinum District should therefore serve as a good study area. The findings of the analysis cannot be generalized to areas outside the specified study area, but should still serve as evidence of what cause conflict at the district level in South Africa.

4.2 Data

This section introduces the three data components used in the change detection analysis; (i) The SA-TIED project data (cf. Section 3.1.2) is used to find and create polygons of the mining areas in Bojanala Platinum District, (ii) Landat-8 satellite images collected one a each year from 2012-2019 are used to detect changes in the mining area polygons and (iii) conflict data from ACLED (cf. Section 3.1.1) is used to determine which conflicts happened during the year following an expansion of a mining area, and what caused the conflicts.

4.2.1 Satellite Images

Satellite images of Bojanala Platinum District is collected via United States Geological Surveys (USGS) EarthExplorer. EarthExplorer contains satellite image from a variety of data sources. For this analysis, Landsat 8 images are used. Landsat 8 was launched on February 11th. 2013 by NASA and has since acquired 740 scenes a day using nine spectral bands (band 1 through 9, specification in Appendix A Table A3) (Ihlen, 2019). EarthExplorer offers top of atmosphere (TOA) reflectance correction of the satellite images acquired by Landsat 8. Specifically, surface reflectance measures the fraction of incoming solar radiation reflected from earth's surface to the Landsat sensor. This in turn improves comparison between multiple images over the same region, as it accounts for atmospheric effects such as aerosol scattering and thin clouds (Department of the Interior USGS, 2019). Aerosols, which are airborne particles such as fog, mist and dust, may scatter or absorb sunlight depending on their size. For instance, aerosols that are smaller than the wavelength of light reflects radiation in different directions and back towards space (NASA Earth Observatory, 2010).

Images covering Bojanala Platinum District for as many years a possible from the Landsat 8 launch to present time are acquired. However, two important criteria must be met in choosing the proper satellite images. First, for comparability, images should as far as possible be acquired during the same time of year. This is to ensure that changes in land surface reflectance due to seasonal variation is vegetation is not mistaken for changes in mining sites. Secondly, only images with less than 10 percent cloud coverage are considered. Based on these criteria, TOA reflectance corrected satellite images from September/October 2014 to 2019 are used. These are spring months in Bojanala were vegetation is starting to become more dense which makes the difference in reflectance between mining sites and the surrounding ground more distinct.

4.3 Methodology

Polygons of known mining areas are manually created in Google Earth Engine based on recent satellite images. The mining areas was found using the mine locations from the SA-TIED data, which was also applied in the regression analysis. It should be noted that a polygon is not necessarily one mine, but an areas which is being mined. In total 60 mine-polygons, which do not include underground mines and other non-detectable mines along with processing plants, are created.

For each of the TOA reflectance corrected satellite images used in the analysis, the diffuse-visible albedo is calculated for each of the pixels within the image. Albedo measures the reflectivity of Earth's surface. Since bare ground brightly reflects light and thus will look more white, and vegetation in turn absorbs light and thus looks dark in satellite images, changes in albedo should serve as a good measure for detecting changes to mining areas. Hence, if the albedo of a pixel within a mining area significantly increase between two years, this should indicate an expansion of the mining area. The following equation proposed by Connette et al. (2016) is used for calculating the diffuse-visible albedo:

$$(0.556 \times \text{Band 2}) + (0.218 \times \text{Band 3}) + (0.163 \times \text{Band 4}) - 0.0014$$

Where Band 2 is visible blue, Band 3 is visible green and Band 4 is visible red. The calculation is done for each of the images between 2014-2019 in QGIS. The albedo values within each of the images are further normalized in R[20]. Images of a mine in true colours and in diffuse-visible albedo are depicted in Figure 7 below.

[20]R is an open-source programming and statistical language

Figure 7: 2019 Satellite Images, Pilanesberg Platinum Mine

(a) True color image (b) Diffuse-visible albedo image

In order to determine if the change in albedo of a pixel is significant and thus indicates new mining area, two thresholds should be met. These are likewise proposed by Connette et al. (2016):

1. The pixel albedo has become significantly more bright such that:
   $(\text{Albedo}_t - \text{Albedo}_{t-1}) > 300$

2. The new bare ground is very bright, indicating new mining area and not natural high reflectance:
   $\text{Albedo}_t > 1,150$

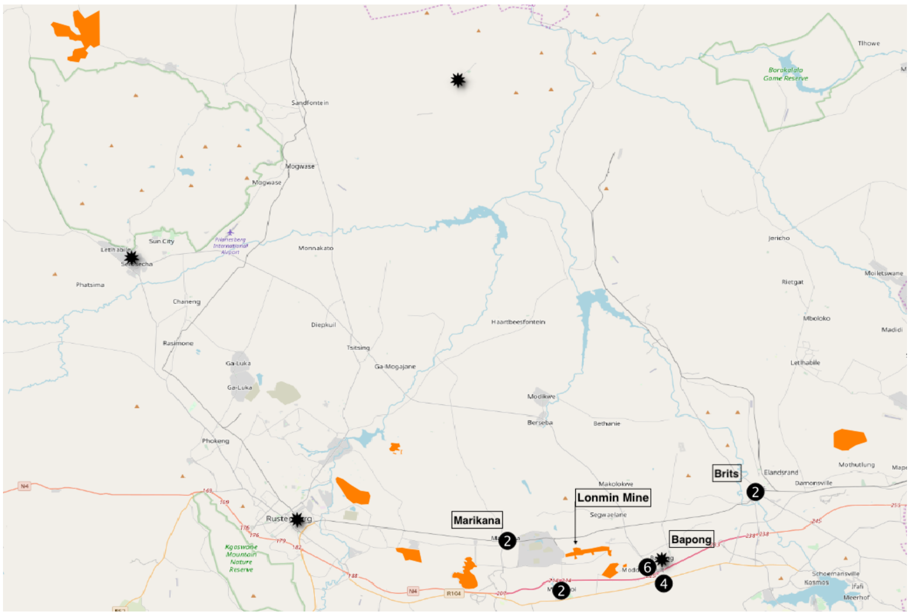
For each of the albedo calculated satellite images, pixel values within each of the mining areas are extracted and the thresholds evaluated with R .

The robustness of the detected changes to mining areas are subject to changes in reflectance of ground within the mining areas that may be caused by other things than expansion of the mine. For instance, if the climate in one year were relatively more dry as compared to the other, changes to the albedo could be caused by dry vegetation. The second threshold should account for most of such effects. Further, the albedo calculations are also subject to the quality of the satellite image which may be varying between years, for instance due to interference from haze and shadows in the terrain. Interpretation of changes to mining areas is likewise relative to the 30×30 meter resolution of the Landsat 8 satellite images. Thus there may be changes to mining areas which are not detected if they are relatively small compared to the pixel size. Finally, the change detection does not differ between new mining area, waste piles, roads etc. However, all of these should still indicate changes to the mining production and thus potential sources of conflict.

4.4 Results

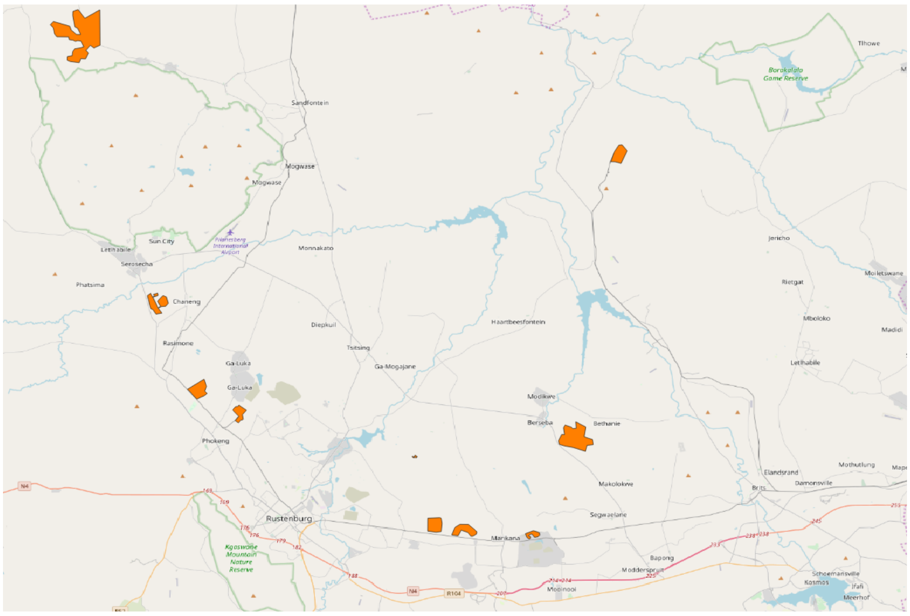
In this section, the results from the mine change detection analysis are presented. In the following map images, expanded mining areas in which at least one pixel (30×30 meters) has been found to be significantly changed and between two years are depicted. ACLED registered conflicts related to mining in a one year period after the detected mine expansions are likewise depicted.

Figure 8: Change Detection, Bojanala Platinum, 2014-2015



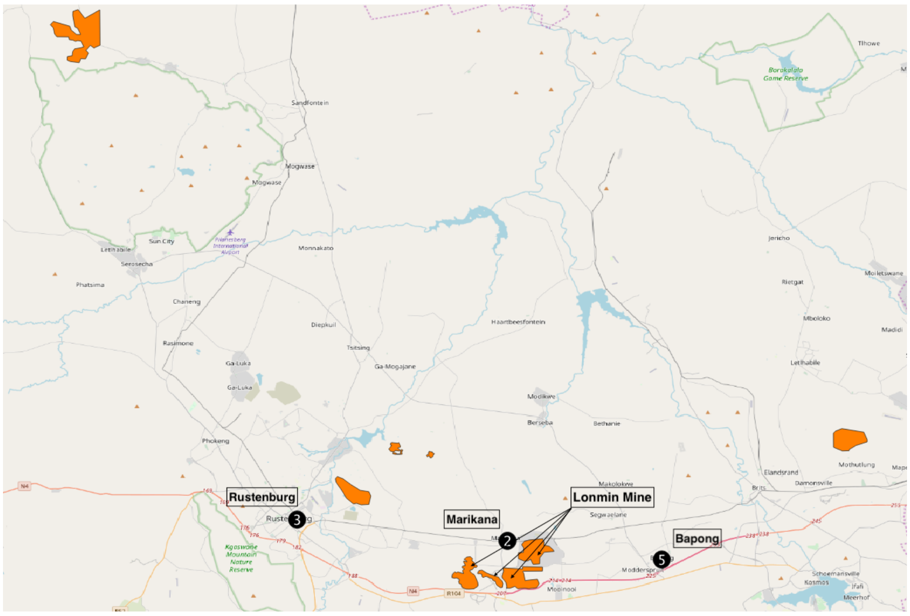
Between 2014-2015 expansions of eight mining areas have been detected and twenty mine-related conflicts. Most of the conflicts cluster around Marikana and Bapong. All of these are related to employment of mineworkers. Specifically workers in the Lonmin Mine were protesting an anticipated retrenchment of some of the workers, while demonstrators from Modderspruit, Majakaneng and Marikana accused nearby mines (including Lonmin) of failing to provide employment for locals as promised. The two conflict in Brits (far right) are likewise related to employment promises in the Lonmin mine.

Figure 9: Change Detection, Bojanala Platinum, 2015-2016



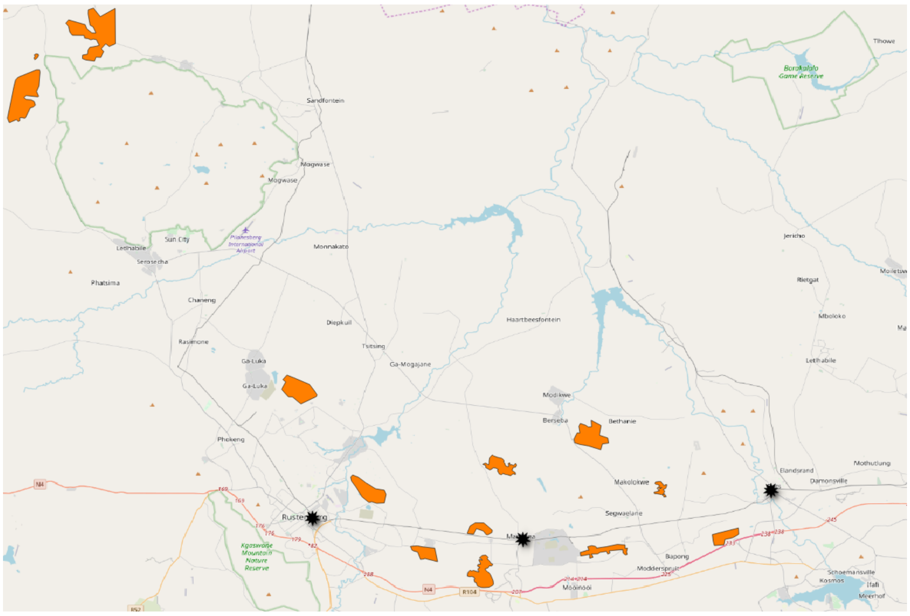
Between 2015 and 2016 expansions of nine mining areas have been detected, but no registered mine-related conflicts. However, 2016 was a municipality selection year in which a lot of political conflicts took place. The lack of mine-related conflicts can either be explained by there not being any, or by a lack of media coverage. The latter is one of the pitfalls of using ACLED data, as they rely mostly on media coverage of conflicts.

Figure 10: Change Detection, Bojanala Platinum, 2016-2017



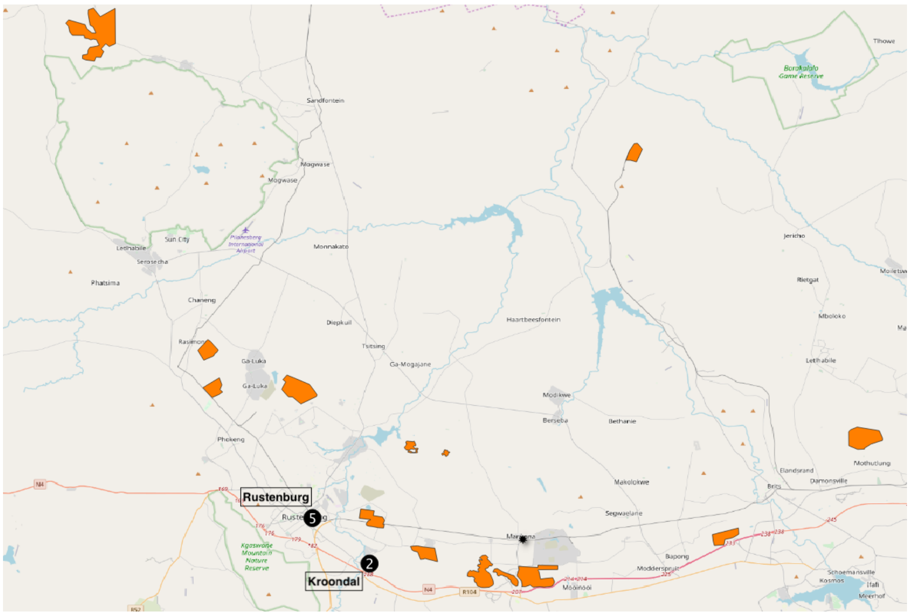
Between 2016 and 2017 expansions of nine mining areas have been detected and ten mine-related conflicts. The cluster of five conflicts located in Bapong and the two in Marikana were all violent and related to employment issues in the Lonmin mine, for which changes have been detected. As in 2015 the protester were demanding jobs in the mine. One of the conflicts in Marikana even lead to one fatality. The three conflicts in Rustenburg are related to the Impala mine located just outside of Rustenburg. However, no changes to the mining area of this mine has been detected.

Figure 11: Change Detection, Bojanala Platinum, 2017-2018



Between 2017 and 2018 expansions of twelve mining areas has been detected and three mine-related conflicts. However, none of the conflicts seem to be related to any of the mining area expansions.

Figure 12: Change Detection, Bojanala Platinum, 2018-2019



Lastly, between 2018 and 2019 expansion of fourteen mining areas has been detected and seven mine-related conflicts. One of the two conflicts in Kroondal was the youth demanding jobs in the nearby mines, several of these in which expansion is detected. The second conflict relates to mine workers who are being transferred from two mines just outside Kroondal to mines north of Rustenburg, were expansion has been detected. The five conflicts in Rustenburg are related to missing salary and a sexual harassment case in one of the nearby mines. These conflicts cannot be directly related to any of the detected mine expansions.

In conclusion, the conflicts near the detected mine-expansions were mainly between mining companies and communities. Specifically, it seems that companies and communities are failing to match expectations as a lot of conflict in general comes down employment discrepancies. Further, the Lonmin Mine was involved in more of these conflicts. The is also the mining company that in 2012 was involved in the Marikana Massacre where a strike escalated into violent conflict as the South African Police killed 34 mine workers and seriously injured 78.

Whether if the mines had actually promised employment but failed to provide them cannot be told here, but it is at least clear that the communities expected so which, all things equal, means that these conflicts arise from information asymmetries. In relation to mine expansions this issue may arise for the same reason as in the context of increasing mineral prices. Thus, as mines expand the surrounding communities may see this as a signal for more employment opportunities. However the mining companies may not be financially able to employ more people as, like discussed above, the input prices to production are increasing making it hard for the South African mining companies to accumulate profit. On the other hand, some mining companies might actually be able but unwilling to hire more workers and will for this reason have incentive to wrongfully declare themselves unable. The communities, that cannot trust the mining companies on their word, will therefore protest in order to force the mining companies to show their true colour. Further, this trust issues could also be a sign of commitment problems which could likewise explain why Lonmin Mine continuous to be involved in conflict. The communities may, for good reason, hold grudges against the mining company making it even more difficult for the two parties to settle agreements. The employment discrepancies should also bee seen in relation to the very high unemployment rate in this area. As argued above, the unemployment rate in the north-east part of the country, where Bojanala Platinum District is located, is 47 percent. The distress caused by this could therefore be expected to further reinforce information asymmetries.

Even though the findings of this analysis cannot be generalized to outside of the Bojanala Platinum District they at least indicate, as expected, that issues of information asymmetries and commitments problems are possible explanations of why conflicts occur at the sub-national level in relation to mineral extraction in South Africa.

5 Discussion

In this thesis the relationship between mineral extraction and conflicts in South Africa was explored through exogenous variation in global mineral prices and by changes to mining areas. The data on mine location used here is an alternative to what has been applied in papers like Berman et al. (2017), Mamo et al. (2019) and von der Goltz & Barnwal (2019) who all use Raw Material Data (RMD, InterierraRMG). The RMD contains information on mines located across the globe including their geographic information, site name, opening and closing dates, and the type and amount of mineral extracted at the mines. Thus, Berman et al. (2017) analyse cross-country data on mines and use opening and closing date to create a difference-in-difference framework. The RMD further allows them to differentiate this effect between mineral types, for which they find that mineral with higher rents are more conflict prone. The mine data used in the present analysis thus distinguish itself from the RMD in three important ways: (i) The data includes locations on 1,352 mine companies of all sizes whereas the RMD only includes 277 large to medium companies. This not only means that the data used here has more variation but is also overcomes the potential upwards bias from only including large mines. (ii) The data is time-invariant as it does not, like RMD, include information on closing and opening dates of the mines. A concern is that some of the mines used in this analysis, which are assumed to be operating at all times, are actually not open which could create an upwards bias in the results. It is though assumed that even if this is the case, it would only be for few of the of 1,352 mines in the sample, and it is therefore not expected to affect the results. This assumption is further supported when considering the estimation results of Berman et al. (2017) which are similar in magnitude to those found here. Furthermore, more than half of the mines in the RMD are South African which also increase similarities. [21]. (iii) There is no information on the minerals extracted at the mines, and instead a dataset of mineral proxies created for the purpose of this thesis is used instead. Even though this is a clear limitation, the data still benefits from being significantly more extensive both in terms of number of mines included, but also the size variation of these. Accordingly the findings of the analysis, which will be discussed shortly, are supported by other similar papers which suggests that the mineral-proxy data used is on average accurate.

The goal of the thesis was to establish causality between mineral extraction and conflicts at a sub-national scale. First and foremost a significant and positive correlation between mines and conflicts is found. Specifically, the presence of a mine increases the probability of conflict by 2.7 percentage points after accounting for local municipality effects. Considering the effect related to the different kinds of minerals another pattern emerges; the minerals with the highest rents (gold, diamond and platinum) and those that are amongst the most critical to the Untied States economy and defence (platinum, copper and titanium) are those with the relative highest effects of the minerals included in the analysis. This is in line with the findings of Berman et al. (2017), Bond & Kirsch (2015) and Downey et al. (2010). Accounting for the mineral proxy intensity, further implies that relatively larger mines have larger effects on the probability of conflict. Larger mines will, all things equal, have more employees and affect a relatively larger community and may therefore subject to more conflicts. In extension to this result, the grid size was increased from 10×10 to 20×20 kilometres to allow for large mines to affect the probability of conflict in a larger area. The larger grid size did increase the coefficients implying, in line with Berman et al. (2017), that some mines in South Africa are very large and the effect they have on the surrounding community could be underestimated using a smaller grid size. It is noted that Berman et al. (2017) use significantly larger grids (55×55 and increased to 110×110 kilometres) than what are used in this analysis. However, the authors also gridded the entire African continent and has also fewer mine locations. It is therefore sensible to use smaller grids in this analysis to obtain enough variation in the data.

Further, by disaggregating conflict into the different types defined by ACLED, it was

[21] See Berman et al. (2017) Table 2 Column 6

in line with expectations found that protests and riots are most related to mineral extraction. This implies that conflicts are mostly related to discrepancies between mining companies and communities as found by Bond & Kirsch (2015), Christensen (2019), Farrell et al. (2012) and Hamann et al. (2005), and not to violent acts of rebels. However, violent attacks on civilians are also significantly more probable in areas with mineral extraction and this effect was further found to be mostly related to titanium and platinum. This finding could be explained by the argument by Downey et al. (2010) that the state is willing to exert violence in order to ensure supply of minerals that are important to the United States economy and defence and thus capital accumulation, political power and international relations. The South African Police (SAP), who are acting on behalf of the government, have been involved in several attacks on civilians also in relation to strikes at the South African mines. Even though these types of conflicts occurring in relation to mineral extraction are indeed very serious and violates human rights, they are in general not the drivers of conflicts which instead protests and riots are.

A similar result is found in the remote sensing change detection analysis, using Bojanala Platinum District as study area. The identifying assumption here is that mine expansion affect the probability of conflict by intensifying social- and economic stressors and creating information asymmetries. The conflicts that occurred near the newly-expanded mines were related to discrepancies between mining companies and communities. As the mines were expanding the surrounding communities expected more job opportunities. The mines refused to meet the communities' demands either because they were not financially able to, or because they would rather keep a larger share of the production value to themselves. This issue of information asymmetries relates to the paper by Christensen (2019). As the community does not know which "type" the mining company is and they can therefore not trust them by their word, they engage in conflict to force the companies to disclose their type. Though the finding of this part of the analysis cannot be generalized to outside the study area it still support expectations that information asymmetries between mining companies and communities drives conflicts. It could likewise be argued that the district is more prone to such information asymmetries as employment rates are very high, a general resentment of the mining companies exists and pressure from immigration streams cause further distress in the communities here.

When seeking to establish causality in the regression analysis an important assumption is that global prices are exogenous. However, South Africa is the main producer of platinum and assuming that conflicts in the platinum mines could not affect global platinum prices may therefore not be accurate. As has been mentioned several times already, conflicts in the Lonmin mine during a workers' strike in 2012 ended up not only costing lives but also production for the mining company which is among the world's biggest of its sort. The productivity index of the South Africa mining sector depicted in Figure 1a even shows a dramatic decrease in overall sector productivity around this time. This would then imply that the significant positive effect of a price-shock to platinum found in the analysis is indeed reverse. Instead the conflicts in the Lonmin mine in 2012 significantly increase the global platinum price through a decrease in South African supply. Excluding platinum mines from the estimations in Table 2 does however not change the results (see Appendix C)

Considering the other mineral price-shocks, that are still assumed to be exogenous, a price-shock to the main mineral detected in the grids is significantly increasing the probability of conflict by 1.7 percentage points. Further, the price-shock to gold was found to be robustly and significantly increasing the probability of conflict by 1.8 percentage points, which was found to be primarily related to protests. Gold has since 2019 been performing well as the trade-war between China and the United States has increased investments in this mineral. The spark in the gold price, measured here as a shock is thus translated into increased probability of conflict in South Africa. Putting the dramatic increase in gold price in relation to the massive lay-off of mine worker in the gold mines during recent years (see Figure 1c), it could be expected that communities that have been affected by this lay-off see the increasing gold prices are an opportunity for getting their jobs back. However as also argued before, the mining industry is suffering not only from increasing input prices but also production prices as they are forced to dig deeper to find gold. If the communities workers are not properly aware that the mines cannot afford the re-employ workers despite the increasing gold-prices this leads to information asymmetries eventually causing conflict. Similarly, an increase in the log price of gold was also found in Model 18 (Table 6) to increase the probability of conflict not only around the mines but across all of South Africa. This finding suggests that there are strong spill-over effects from the gold mines and that the negative externalities affect the entire country.

However the results of Model 18, including those of platinum, titanium and uranium, are subject to unexplained heterogeneity. There could be factors other than the increase in mineral prices that are driving the results. Another interesting result found in the logistic Model 12 (Table 4) is that the iron price-shock coefficient is also found to significantly increase the probability of conflict. A natural disaster caused major iron mines in Brazil to be flooded which in turn increased global iron prices, and as also found by Bond & Kirsch (2015) a dramatic increase in even a bulky mineral such a iron, has the potential to increase conflict.

Finally, in the second part of the analysis causality between mineral extraction and conflict was established through expansion of mining areas. The remote sensing change detection analysis used for this purpose serves to show how some of the data limitations discussed above can be overcome. Not having to rely on data which is continually proven to be insufficient and at times even inaccurate a more precise causal relationship between mineral extraction and conflicts can be established. Thus, remote sensing analysis has become widely popular in assessing mining extent and expansion in developing countries and war zones where such data is generally difficult to come by. The analysis by Connette et al. (2016), which was the main inspiration for the analysis applied in the present paper, use freely available satellite data to identify mines and expansion of these in Myanmar. Similar methods are applied by Schimmer (2008), Areendran et al. (2013), Akiwumi & Butler (2008) and Li et al. (2015) and has become particularly popular in detecting environmental damages of mining. However, to the knowledge of the author, remote sensing analysis has still not manifested in the conflict literature. This thesis is therefore among the first of its kind to apply such methodology.

The analysis suggests that living in area with mineral extraction is increasing the probability of experiencing conflict by 2.7 percentage points which is further increased by 1.7 percentage points by a price-shock to the main mineral extracted in the area. To put this effect into perspective, two other ways by which value are introduced in the society and how these may affect conflicts are also considered; foreign direct investments (FDI) and aid. For both FDI and aid the evidence of the effect on conflict are mixed. Most of the literature that find positive correlations (ie. more FDI and aid lead to more conflicts) argue that this is primarily due to FDI and aid giving incentives for rebels to seek rents. Specifically Pinto & Zhu (2018) find that probability of conflict at the country level increase by 21 percent from a one std. deviation increase in FDI. However, those that find that FDI and aid may actually decrease conflicts emphasise the importance of sustainable development that FDI projects and aid may also bring. Both FDI and aid have potential to increase growth, employment and infrastructure. Likewise the World Bank also gives aid to conflict-sensitive programs. Thus Gehring et al. (2019) using regional level data from a number of African countries find that a one standard deviation increase in FDI significantly decrease the probability of conflict by 1.59 percentage points. However, the authors find another curious result namely that aid from China increase the probability of repression by 0.77 percent in regions that have not before received Chinese aid. Even though these results cannot be directly compared to the results of this thesis, they still suggest that the probability of conflict in developing countries are affected by global interference both in the form of increasing global prices, international aid and foreign direct investments. Whether these interferences have positive or negative effects on conflicts seems to depend on country specific factors. However, comparing the positive effect of 1.59 percentage points from aid found by Gehring et al. (2019), it seem that the negative effect from mineral extraction of 2.7 to 4.3 percentage points found here are relatively large. Especially considering that the effect of aid is within a region whereas the effect found here is within an area of only 10×10 kilometres. This further emphasise the importance of dealing with the conflict inducing factors in the mining industry of South Africa.

Mining companies are loosing profit or worse the right to extract minerals all together and the government, which is also loosing tax income, may also loose political endorsement when conflicts occur in the mineral industry. However, as implied by the analysis carried out in this paper, conflicts are still significantly related to mineral extracting. The South African state is regulating the mining sector and is seeking to implement corporate social responsibility (CRS). In order to achieve a mining grant companies are required by The Minerals and Petroleum Resource Development Act to submit a Social and Labour Plan (SLP) to the Department of Mineral Resources and Energy [22]. SLPs are instruments for

[22] https://www.mineralscouncil.org.za/sa-mining/slps

achieving the transformation formulated by the Mining Charter, which essentially enforce corporate social responsibility (CSR). However, one major drawback still remains as disclosure of company information is still widely voluntary, and this especially in relation to social- and environmental information. It is thus not a requirement for companies to disclose approved SLPs nor their annual compliance report to the Department of Mineral Resources. Even though companies are encourage to disclose such information through the Mineral Council of South Africa [22] few are choosing to do so. If, as argued above, asymmetric information issues are driving conflicts then changing this could potentially help the problem. It is also worth noting that according to Stedman & Green (2018) South Africa ranks amongst the worst on "Socioeconomic Agreements/ Community Development Conditions" and "Labor Regulations/Employment Agreements and Labour Militancy/Work Disruptions".

Despite efforts to regulate the mining industry, South Africa still have not managed to manifest sustainable development in the mining sector. This could be due to regulations not being strong enough, as in the case of voluntary disclosure of SLPs, or due to corruption, which is not unheard of especially in a developing country context. But even more complex issues such as culture and historical resentment of both the government and the mining industry have deep roots in South Africa. If companies are not accounting for such complexities when carrying out their operation, information asymmetries between themselves and the surrounding communities will be a recurring problem that will continue to cause conflicts.

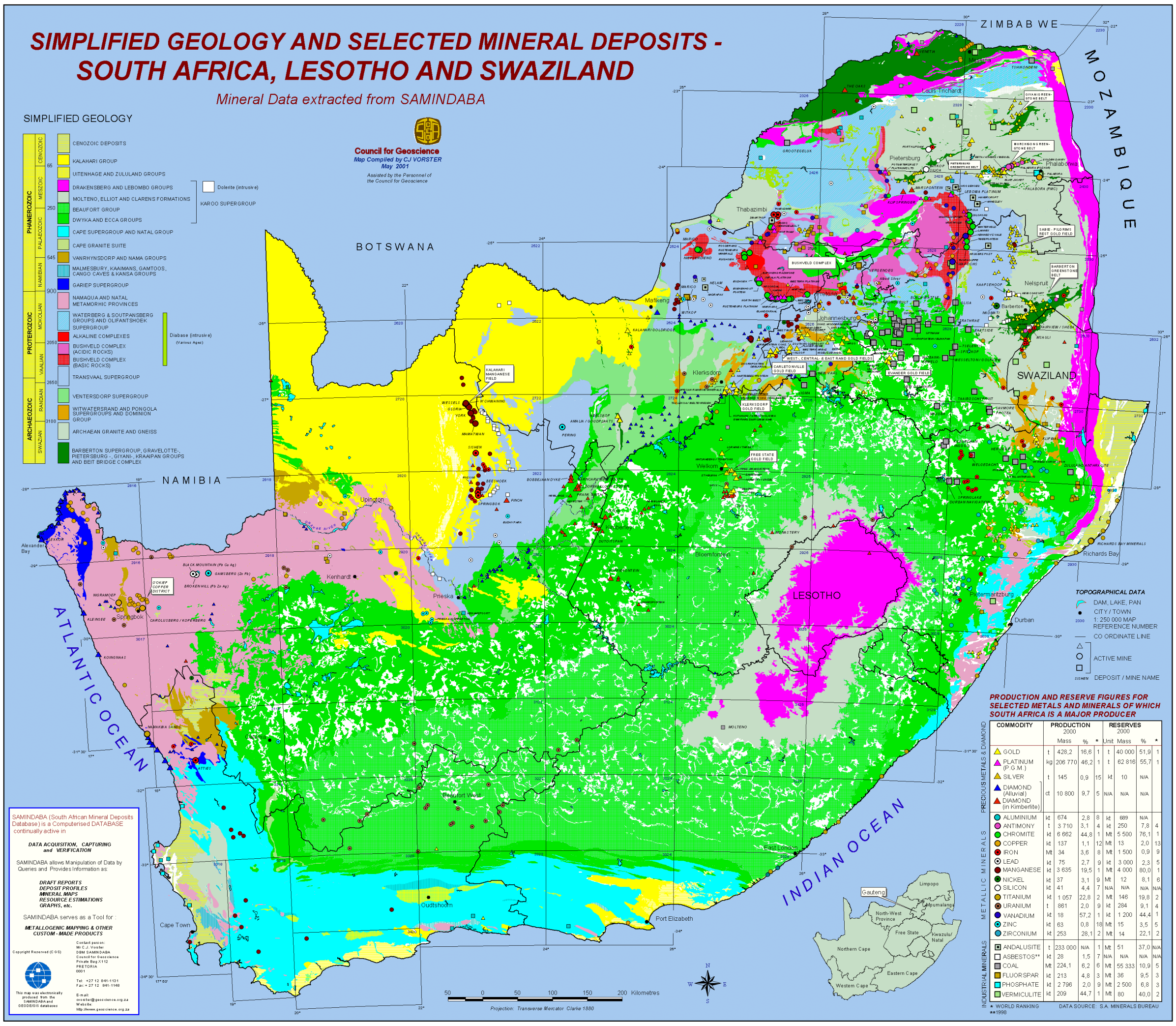
6 Conclusion

The aim of this thesis was to establish a causal relationship between mineral extraction and conflicts. This was first done using exogenous variation in global mineral prices. An extensive dataset of 1,352 mines with 12 different mineral proxies was used for this purpose, offering more variation in data than the Raw Mineral Dataset used in similar papers (Berman et al. , 2017; Mamo et al. , 2019; von der Goltz & Barnwal, 2019). The thesis contributes to the existing literature, which mostly considers cross-country data, by establishing causality on a sub-national scale. Such microeconomic analysis offers, according to Blattman & Miguel (2010), more credible research design as many conflicts are context-depended. Further, this thesis is one of the first of its kind to carry out a remote sensing change detection analysis to establish causality between mineral extraction and conflicts. Not relying on any other data than freely available satellite imagery the analysis thus overcomes data limitation which is currently affecting the conflict literature. In the regression analysis a significant and positive correlation between mines and conflicts was found. Disaggregating this effect to the different kinds of minerals in the data the relationship is relatively stronger for minerals with high rents (diamond, gold and platinum) and for mineral that are critical to the US economy and defence (platinum, copper and titanium). A mineral price-shock was found to additionally increase the probability of conflict, and by also disaggregating this effect by mineral type a robust and significantly position effect was found for gold. The same was also found for platinum price-shock, but since South Africa is the main global supplier of this mineral, the result is expected to be suffering from reverse causality. Further, the conflict types most related to mineral extraction are protests and riots, which supported the expectation that conflicts are not driven by violent acts of rebels but instead by conflicts between company-community (Bond & Kirsch, 2015; Christensen, 2019; Farrell et al. , 2012). This was also supported in the remote sensing change detection analysis in which the identifying assumption was that expansion of a mine affects the probability of conflict by causing information asymmetries and intensifying social- and economic stressors in the surrounding communities. The conflicts occurring at the newly-expanded mines were related to employment discrepancies between mining companies and communities caused by information asymmetries and arguably also commitment problems. It is argued that information asymmetries occur as communities interpret a mineral price-shock or expansion of a mine as potential for higher wages or job-opportunities. However, the South African mining companies are struggling to generate profit as despite increasing mineral prices, the input prices to production are increasing relatively more. The mining companies may therefore not be able to cater the communities expectations. Should the communities take the companies on their word, this will give incentive for profitable companies to also declare themselves unable to meet expectations to keep a higher profit-share. These information asymmetries cause the communities to protest or riot to force the mining companies to disclose their true type. Information asymmetries of this type should also be considered in relation to other factors that are putting the communities under distress such a high unemployment rates, a massive lay-off in the gold industry, poverty, immigration streams etc. Such factors may thus make the company-community relationship in the South African mining sector more eligible for issues of information asymmetries.

7 Appendix

Appendix A

Figure A1: Geology and Mineral Map, South Africa



Source: Council for Geoscience, South Africa

Table A1: Mineral proxy dataset

Precious Metals and Diamond		Metallic Minerals		Industrial Metals	
Gold	244	Aluminum	27	Coal	58
Platinum	22	Copper	85		
Diamond	197	Iron	52		
		Lead	26		
		Nickel	8		
		Titanium	24		
		Uranium	33		
		Zinc	19		
Total 795					

Source: Council of Geoscience, South Africa.

Note: This dataset is complied from the mineral deposits depicted in Figure A1 above. The dataset only includes the mineral deposits for which there is a significant number of deposits (thus excluding silver for which there is only one) and price data is available. The data does not distinguish between Alluvial and Kimberline diamond.

Table A2: Mineral Prices, Data Sources

Mineral	**Source**	**Price frequency**
Gold	markets.businessinsider.com/commodities/gold-price	Daily
Aluminium	markets.businessinsider.com/commodities/aluminium-price	Daily
Coal	indexmundi.com/commodities/?commodity=coal-south-african	Monthly
Platinum	markets.businessinsider.com	Daily
Diamond	diamondse.info/diamonds-price-index.asp	Monthly
Copper	markets.businessinsider.com/commodities/copper-price	Daily
Iron	indexmundi.com/commodities/?commodity=iron-ore	Monthly
Lead	markets.businessinsider.com/commodities/lead-price	Monthly
Nickel	markets.businessinsider.com/commodities/nickel-price	Daily
Titanium	fred.stlouisfed.org/series/WPU102505	Monthly
Uranium	markets.businessinsider.com/commodities/urnaium-price	Daily
Zink	markets.businessinsider.com/commodities/zinc-price	Daily

Note: All prices are in US dollars. The data source for titanium is actually a price index with baseline 1983=100. Prices are derived based on titanium price in 1983 which according to https://pubs.usgs.gov/sir/2012/5188/sir2012-5188.pdf#Titanium was $5.70.

Table A3: Landsat 8: Spectral Bands

Band 1 Visible (0.43 - 0.45 μm) 30 m
Band 2 Visible (Blue) (0.450 - 0.51 μm) 30 m
Band 3 Visible (Green) (0.53 - 0.59 μm) 30 m
Band 4 Red (0.64 - 0.67 μm) 30 m
Band 5 Near-Infrared (0.85 - 0.88 μm) 30 m
Band 6 SWIR 1(1.57 - 1.65 μm) 30 m
Band 7 SWIR 2 (2.11 - 2.29 μm) 30 m
Band 8 Panchromatic (PAN) (0.50 - 0.68 μm) 15 m
Band 9 Cirrus (1.36 - 1.38 μm) 30 m

Source: United States Geological Survey, Landsat 8: https://www.usgs.gov/land-resources/nli/landsat/landsat-8?qt-science_support_page_related_con=0#qt-science_support_page_related_con

Appendix B: Robustness checks using 20×20 km grids

Table A4: Conflicts and Mineral Price-Shocks: Non-linear Effects

Estimator: Logit	**Model 10a**		**Model 11a**		**Model 12a**	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.
Mineral Dummy						
Aluminium	0.033***	(8.340)				
Coal	0.029***	(11.730)				
Copper	0.027***	(7.410)				
Diamond	0.028***	(10.560)				
Gold	0.033***	(12.660)				
Iron	0.022***	(6.270)				
Lead	0.024***	(6.680)				
Nickel	0.031***	(6.820)				
Platinum	0.035***	(9.770)				
Titanium	0.040***	(11.970)				
Uranium	0.026***	(10.260)				
Zinc	0.005	(0.560)				
Mineral Intensity						
Aluminium			0.013***	(9.420)	0.013***	(9.420)
Coal			0.007***	(5.550)	0.007***	(5.550)
Copper			0.007***	(5.380)	0.007***	(5.380)
Diamond			0.007***	(6.770)	0.007***	(6.770)
Gold			0.004***	(7.390)	0.004***	(7.410)
Iron			0.005	(1.880)	0.005	(1.860)
Lead			0.006*	(2.190)	0.006*	(2.190)
Nickel			0.017***	(5.670)	0.017***	(5.280)
Platinum			0.009***	(6.480)	0.009***	(6.500)
Titanium			0.007***	(8.000)	0.007***	(8.000)
Uranium			0.009***	(9.610)	0.009***	(9.440)
Zinc			0.003	(0.650)	0.003	(0.650)
Mineral Price-Shock						
Aluminium					-	-
Coal					-0.001	(-0.620)
Copper					-	-
Diamond					-	-
Gold					0.000	(0.700)
Iron					0.001*	(2.470)
Lead					-0.001	(-1.600)
Nickel					0.008*	(2.170)
Platinum					0.001*	(2.470)
Titanium					-	-
Uranium					0.002**	(2.850)
Zinc					-	-
Constant	0.013	(15.070)	0.011	(19.890)	0.011	(19.880)
$\ln(\sigma_u^2)$	2.066***	(27.446)	1.852***	(32.180)	1.853	(32.172)
Observations	448,128		448,128		448,128	

Note: Outcome is a dummy variable indicating conflict. Model 10a reports estimates of Eq. (1), Model 11a of Eq. (2) and Model 12a of Eq. (3). All models are clustered at grid level. Panel-level variance is parameterized as $\ln(\sigma_u^2)$. T-statistics are in parenthesis and level of significance are marked: *0.05 **0.01 ***0.001

Table A5: Conflicts and Mineral Price-Shocks: Mineral Multicollinearity

Estimator: LPM	Model 13a		Model 14a		Model 15a		Model 16a	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.
Mineral Dummy								
Aluminium	0.027**	(2.854)						
Coal	0.021***	(3.674)						
Copper	0.061**	(2.696)						
Diamond	0.042***	(3.496)						
Gold	0.063***	(6.159)						
Iron	0.045*	(2.172)						
Lead	0.106*	(2.465)						
Nickel	0.009	(1.487)						
Platinum	0.053**	(2.717)						
Titanium	0.092***	(4.568)						
Uranium	0.016*	(2.096)						
Zinc	-0.007**	(-3.043)						
Mineral Intensity								
Aluminium			0.021***	(3.553)	0.021***	(3.553)	0.0021**	(2.937)
Coal			0.016***	(5.854)	0.016***	(5.875)	0.014***	(5.320)
Copper			0.064***	(4.417)	0.064***	(4.417)	0.058***	(4.029)
Diamond			0.045***	(9.374)	0.045***	(9.374)	0.041***	(8.491)
Gold			0.031***	(9.285)	0.031***	(9.265)	0.025***	(8.393)
Iron			0.051*	(2.446)	0.051*	(2.394)	0.039	(1.644)
Lead			0.082***	(7.144)	0.083***	(7.095)	0.051***	(4.705)
Nickel			0.009	(1.487)	0.007	(1.143)	0.011	(1.801)
Platinum			0.046***	(4.329)	0.044***	(4.202)	0.040***	(3.713)
Titanium			0.043***	(9.140)	0.043***	(9.140)	0.050***	(9.391)
Uranium			0.024**	(2.904)	0.023**	(2.895)	0.022***	(3.809)
Zinc			-0.005	(-1.306)	-0.005	(-1.306)	0.001	(0.233)
Mineral Price-Shock								
Aluminium					-	-	-	-
Coal					-0.007	(-0.825)	-0.007	(-0.825)
Copper					-	-	-	-
Diamond					-	-	-	-
Gold					0.003	(0.789)	0.003	(0.789)
Iron					0.015	(1.448)	0.015	(1.448)
Lead					-0.023	(-1.581)	-0.023	(-1.581)
Nickel					0.054	(1.387)	0.054	(1.386)
Platinum					0.019**	(3.019)	0.019**	(3.019)
Titanium					-	-	-	-
Uranium					0.035	(1.874)	0.035	(1.874)
Zinc					-	-	-	-
Local Municipality Fixed Effects	No		No		No		Yes	
Observations	448,128		448,128		448,128		448,128	

Note: Outcome is a dummy variable indicating conflict. Model 13a reports estimates of Eq. (1), Model 14a of Eq. (2) and Model 15a and 16a Eq. (3). Model 16a includes local municipality fixed effects. All equations are run only including one mineral-type at a time. Thus, each equation is estimated 12 times. All models are clustered at grid level. T-statistics are in parenthesis and level of significance are marked: *0.05 **0.01 ***0.001

Table A6: Conflicts and Mineral Price-Shocks: Lagged Prices and Log-Prices

Estimator: LPM	Model 17a		Model 18a	
	Coef.	T Stat.	Coef.	T Stat.
Mineral Intensity				
Aluminium	0.026***	(4.329)		
Coal	0.019***	(7.558)		
Copper	0.058***	(4.027)		
Diamond	0.047***	(10.432)		
Gold	0.030***	(8.942)		
Iron	0.02	(1.207)		
Lead	0.043***	(5.861)		
Nickel	0.021**	(3.273)		
Platinum	0.045***	(4.467)		
Titanium	0.044***	(9.411)		
Uranium	0.028***	(4.217)		
Zinc	0	(0.050)		
Mineral Price-Shock t-1				
Aluminium	0	(.)		
Coal	0.005	(0.405)		
Copper	0	(.)		
Diamond	0	(.)		
Gold	-0.001	(-0.128)		
Iron	0.005	(0.352)		
Lead	-0.041	(-1.457)		
Nickel	-0.020**	(-3.069)		
Platinum	0.003	(0.185)		
Titanium	0	(.)		
Uranium	0.031	(1.592)		
Zinc	0	(.)		
Mineral Price-Shock t-2				
Aluminium	0	(.)		
Coal	-0.013	(-1.772)		
Copper	0	(.)		
Diamond	0	(.)		
Gold	0.003	(0.598)		
Iron	0.016	(1.434)		
Lead	-0.041	(-1.842)		
Nickel	0.024	(1.038)		
Platinum	0.015	(0.740)		
Titanium	0	(.)		
Uranium	-0.005	(-0.546)		
Zinc	0	(.)		
Mineral Price (log)				
Aluminium			0.048	(1.515)
Coal			0.041**	(4.145)
Copper			-0.033	(-1.602)
Diamond			0.020	(1.432)
Gold			0.021**	(2.749)
Iron			0.016	(1.484)
Lead			0.042	(2.087)
Nickel			0.045	(0.894)
Platinum			-0.125**	(-2.680)
Titanium			0.022	(1.514)
Uranium			0.080**	(3.051)
Zinc			0.016	(1.282)
Constant	0.030*	(2.335)	-0.005	(-0.836)
Panel Fixed Effects	No		Yes	
Observations	448,128		438,792	

Note: Outcome is a dummy variable indicating conflict. Model 17a reports estimates of Eq. (4) and Model 18a of Eq. (5) estimated with fixed effects. All models are clustered at grid level. T-statistics are in parenthesis and level of significance are marked: *0.05 **0.01 ***0.001

Table A7: Conflicts and Mineral Price-Shocks: Conflicts Types

Estimator: LPM	**Protests**		**Riots**		**Violence Against Civil.**		**Other**	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.
Mine	0.023***	(4.966)	0.029***	(7.066)	0.006***	(4.933)	0.001***	(4.075)
Mineral Price-Shock	0.009*	(2.237)	0.012*	(2.095)	0.002	(0.893)	0.003	(1.333)
Constant	0.003***	(6.283)	0.004***	(7.532)	0.001***	(5.192)	0.000***	(4.883)
Mineral Intensity								
Aluminium	0.007***	(4.334)	0.015***	(6.189)	0.007	(1.706)	0.001	(1.291)
Coal	0.009***	(6.999)	0.010***	(5.257)	0.001***	(3.294)	0.001*	(2.376)
Copper	0.047***	(3.295)	0.037**	(3.104)	0.006**	(2.845)	0.002*	(1.996)
Diamond	0.038***	(6.803)	0.035***	(6.684)	0.009***	(3.838)	0.001***	(3.629)
Gold	0.018***	(4.174)	0.019***	(6.823)	0.004**	(3.173)	0.001**	(3.142)
Iron	0.018	(1.125)	0.011	(0.940)	0.005	(1.636)	0.000	(0.210)
Lead	0.026**	(2.913)	0.010	(1.245)	0.003	(1.673)	-0.001	(-1.476)
Nickel	0.008**	(3.254)	0.011**	(3.085)	0.003	(1.817)	0.000***	(3.472)
Platinum	0.020**	(3.162)	0.028***	(4.826)	0.009**	(2.976)	0.002**	(2.987)
Titanium	0.032***	(5.367)	0.031***	(6.266)	0.009***	(5.071)	0.002***	(3.391)
Uranium	0.016***	(3.764)	0.014***	(4.288)	0.002**	(2.594)	0.001*	(2.542)
Zinc	0.001	(0.264)	-0.001	(-0.464)	0.001	(0.966)	0.000	(-0.205)
Mineral Price-Shock								
Aluminium	-	-	-	-	-	-	-	-
Coal	-0.002	(-0.247)	-0.006	(-1.100)	-0.001**	(-2.938)	-0.001*	(-2.267)
Copper	-	-	-	-	-	-	-	-
Diamond	-	-	-	-	-	-	-	-
Gold	0.008*	(2.388)	-0.001	(-0.133)	-0.001	(-0.757)	0.001	(0.612)
Iron	0.020*	(1.984)	0.003	(0.435)	0.004	(1.304)	0.005	(0.755)
Lead	-0.053***	(-4.761)	0.024	(1.674)	-0.010***	(-3.875)	-0.001	(-0.976)
Nickel	0.012	(0.770)	0.044	(1.199)	-0.002	(-1.437)	0.000	(0.000)
Platinum	-0.001	(-0.388)	0.015***	(3.652)	0.013	(1.891)	0.003	(0.895)
Titanium	-	-	-	-	-	-	-	-
Uranium	0.02	(1.446)	0.013	(0.972)	-0.002*	(-2.304)	-0.001*	(-2.264)
Zinc	-	-	-	-	-	-	-	-
Constant	-0.003***	(-4.846)	-0.001***	(-3.477)	-0.001***	(-4.391)	-0.000***	(-3.472)
Observations	448,128		438,792		438,792		438,792	

Note: The models estimate the probability of the different types of conflict. "Other" includes "Battles", "Explosions/Remote Violence" and "Strategic Development". Models estimate Eq. (3) and are clustered at grid level. T-statistics are in parenthesis and level of significance are marked: *0.05 **0.01 ***0.001

Table A8: Conflicts and Mineral Price-Shocks: Limiting Mine Data

Estimator: LPM	Model 19a		Model 20a		Model 21a		Model 22a	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.
Mineral Dummy								
Aluminium	0.027*	(2.342)						
Coal	0.026***	(3.871)						
Copper	0.093**	(2.597)						
Diamond	0.021**	(2.588)						
Gold	0.067***	(5.396)						
Iron	0.055	(1.942)						
Lead	0.108*	(2.476)						
Nickel	0.025*	(2.233)						
Platinum	0.052*	(2.422)						
Titanium	0.109***	(3.589)						
Uranium	0.004	(1.253)						
Zinc	-0.009	(-0.738)						
Mineral Intensity								
Aluminium			0.025***	(3.606)	0.025***	(3.606)	0.023**	(2.806)
Coal			0.021***	(7.627)	0.021***	(7.628)	0.019***	(6.933)
Copper			0.067***	(4.222)	0.067***	(4.222)	0.060***	(4.663)
Diamond			0.025**	(2.887)	0.025**	(2.887)	0.025**	(3.226)
Gold			0.034***	(8.122)	0.034***	(8.083)	0.031***	(8.279)
Iron			0.012	(0.650)	0.011	(0.600)	0.021	(1.441)
Lead			0.052***	(3.947)	0.053***	(4.020)	0.082***	(5.332)
Nickel			0.026*	(2.332)	0.023*	(2.296)	0.017	(1.298)
Platinum			0.049***	(4.329)	0.047***	(4.212)	0.046***	(4.385)
Titanium			0.051***	(4.256)	0.051***	(4.255)	0.054***	(3.988)
Uranium			0.004	(1.536)	0.004	(1.556)	0.006*	(2.438)
Zinc			-0.005	(-0.441)	-0.005	(-0.441)	0.003	(0.334)
Mineral Price-Shock								
Aluminium					-	-	-	-
Coal					-0.023***	(-7.347)	-0.023***	(-7.345)
Copper					-	-	-	-
Diamond					-	-	-	-
Gold					0.004	(0.831)	0.004	(0.831)
Iron					0.019	(1.593)	0.019	(1.592)
Lead					-0.026	(-1.276)	-0.026	(-1.276)
Nickel					0.074	(1.507)	0.074	(1.507)
Platinum					0.020***	(3.342)	0.020***	(3.341)
Titanium					-	-	-	-
Uranium					-0.006*	(-2.473)	-0.006*	(-2.472)
Zinc					-	-	-	-
Constant	0.004***	(7.503)	0.003***	(4.654)	0.003***	-4.654	-0.029	(-1.959)
Local Municipality Fixed Effects	No		No		No		Yes	
Observations	448,128		438,792		438,792		438,792	

Note: Mines for which the proxy is more than 45 kilometres away are excluded from this analysis leading to a decrease from 1,352 to 1,126 mines in the dataset. Outcome is a dummy variable indicating conflict. Model 19a reports estimates of Eq. (1), Model 20a of Eq. (2) and Model 21a and 22a of Eq. (3). Model 22a further includes local municipality fixed effects. All models are clustered at grid level. T-statistics are in parenthesis and level of significance are marked: *0.05 **0.01 ***0.001

Appendix C

Table A9: Conflicts and Mineral Price-Shocks: Aggregated Effects Excluding Platinum

Estimator: LPM	Model 1b		Model 2b		Model 3b		Model 4b	
	Coef.	T Stat.	Coef.	T Stat.	Coef.	T Stat.		
Mine	0.041***	(7.803)	0.040***	(7.742)	0.026***	(8.223)	0.026***	(8.228)
Mineral Price-Shock			0.018**	(2.609)	0.017**	(2.602)	0.017*	(2.475)
Constant	0.003***	(10.700)	0.003***	(10.700)	0.000	(1.008)	0.000	(1.254)
Local Municipality Fixed Effects	No		No		Yes		Yes	
Year Fixed Effects	No		No		No		Yes	
Observations	1,378,848		1,378,848		1,378,848		1,378,848	

Note: Outcome is a dummy variable indicating conflict. Platinum mines are excluded from this analysis, as there is expected to be reverse causality between conflicts and platinum price-shocks. Model 1c reports estimates of Eq. (1) and Model 2c-4c of Eq. (3). Model 3c further accounts for local municipality fixed effects and model 4c for both local municipality and year fixed effects. All models are clustered at grid level. T-statistics are in parenthesis and level of significance are marked: *0.05 **0.01 ***0.001

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