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Natural Resource Wealth and Crime: The Role of International Price Shocks and Public Policy *

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Abstract

An extensive literature highlights the potential detrimental effects of natural resource wealth on social, economic and political outcomes. We study a largely unexplored relationship – the impact of natural resource wealth on criminal activity. Our empirical strategy exploits price fluctuations in 15 internationally traded minerals to study the impact of mineral wealth on local crime levels in South Africa – leveraging detailed data from 1,084 police precincts over 10 years. In contrast to prior work, we find that increased mineral wealth leads to less crime. An exploration of mechanisms suggest that the effect is due to changes in employment opportunities created by the mining industry. Our results suggest that low international mineral prices can cause surges in crime. To investigate how resilience against such surges can be achieved, we study a government employment guarantee program and show that it was effective in reducing the crime response to international price fluctuations.

Keywords: Extractive Industries, Mining, Crime, Employment Guarantee Program
JEL: K4, Q3, H5

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1 Introduction

Natural resources are key drivers of economic activity in many developing countries and the role of these resources for economic, political and social outcomes is widely debated (van der Ploeg, 2011). A growing body of evidence links natural resource abundance to increased rent-seeking, adverse political selection, conflict and civil war.[1] On the other hand, there is plenty of evidence of local wealth and welfare effects of natural resources (Cust and Poelhekke, 2015), and of mining in particular (Aragón and Rud, 2013; Aragón and Rud, 2016; Benshaul-Tolonen, 2018; Von der Goltz and Barnwal, 2019; Kotsadam and Tolonen, 2016; Mamo, Bhattacharyya, and Moradi, 2019). However, not all welfare effects are unequivocally positive. In particular, bust periods may result is larger reductions in welfare than the booms initially generated (Cust and Poelhekke, 2015).

In this paper, we add to the existing literature by exploring the impact of natural resource wealth on another outcome of great importance for welfare in developing countries: criminal activity. This relationship has been widely discussed in the media, but has received less scholarly attention.[2] This is despite the fact that crime is widely considered as a major obstacle to development (United Nations Office On Drugs And Crime, 2005; The World Bank, 2011). Surveys of citizens further highlight the concerns with criminality in many parts of the world — a study of 34 developing and emerging economies in 2014 showed that a median of 83% of respondents considered crime to be a "very big problem" (Pew Research Center, 2014). The effect of natural resource wealth on crime is theoretically ambiguous and will depend on how the returns from both legal and illegal activity is affected.[3]

We investigate the relationship between natural resources and crime in the context of the mining industry in South Africa. We argue that this setting is particularly well suited to study the broader question. Minerals are important natural resources globally and play a dominant role in 81 countries that collectively account for nearly 70 percent of those in extreme poverty (The World Bank, 2014). South Africa is no exception and has the fifth largest mining industry in the world, contributing to around 8 percent of GDP (Chamber of Mines, 2014). In addition, crime is a serious threat to development in the country, similar to many other natural resource dependent countries such as Venezuela, Peru, Nigeria, Angola and Papua New Guinea[4]. The size of the mining industry in South Africa and the wide range of minerals produced together with the high crime levels gives us plenty of variation to explore the causal effect of mining wealth on crime.

To estimate the effect of mining wealth on local crime, we exploit fluctuations in international mineral prices that we argue are exogenous to local production decisions. The idea is that production decisions are instead influenced by the exogenously determined possibility of profitably selling the minerals on the international market. This exogeneity assumption is supported by work arguing that international mineral prices

[1] Collier and Hoeffler (1998, 2004, 2005) were pioneers of the literature examining links between natural resources and civil war. Recent works include Berman et al. (2017); Buonanno et al. (2015); Maystadt et al. (2014). Brollo et al. (2013) studies the impact of resource wealth on political selection in Brazil.

[2] See e.g. a *New York Times* report on the relationship between crime and mining in South Africa (NYT, 2013).

[3] Previous theoretical work has argued that the capital intensity of natural resource extraction is important for understanding impacts on crime (Dal Bó and Dal Bó, 2011). According to this argument a positive shock to a capital-intensive industry will cause it to expand and labor-intensive industries to contract, making labor relatively more abundant and therefore reducing wages. Since wages decrease relative to the value of appropriable resources, crime will increase. With a similar reasoning a positive shock to a labour intensive sector would increase wages and increase the opportunity cost of engaging in illegal activities. Dube and Vargas (2013) study these two effects empirically in the context of conflict in Colombia. However, in the presences of linkages and positive spillovers to the local labor market (see Aragón and Rud 2013; Kotsadam and Tolonen 2016; Cust and Poelhekke 2015) this argument may not hold. If this is the case, expansion of natural resource extraction could shift the opportunity costs of engaging in illegal activities and thereby cause a reduction in criminal activity in line with the seminal works by Becker (1968) and Ehrlich (1973). In addition, natural resources wealth could also affect state capacity and policing resources, which could affect crime through deterrence and incapacitation effects.

[4] See table B1 in the Appendix.

are driven by demand rather than by supply factors (Slade, 1982; Álvarez and Skudelny, 2017; Stuermer, 2018). We carry out a number of different validity checks to ensure that this assumption indeed holds. In particular, we show that results are driven by minerals for which South Africa supplies a minor share (on average less than 1%) of total global exports. The benefit of this empirical strategy is that it allows us to address potential reverse causality (that criminal activity affect natural resource extraction) and omitted variable concerns (that other factors jointly determine local crime and resource extraction). Our data allows us to match 10 years of detailed crime data from 1,084 police precincts with the geographical location of 210 mines collectively producing 15 different minerals.

We find that the total number of local crimes fall by approximately .7% when the value of mining production increase by 10%. These results are driven by reductions in property crime and we find no significant reduction in violent crime in our baseline specification. To better understand these results, we first study how mining activity change in response to price fluctuations. We document that the variation in international prices that we exploit are associated with a significant reduction in the probability that the mine will stop operating, but that mine openings are not affected. These findings are consistent with higher prices making mining more profitable – preventing some mines from closing down. Mine openings on the other hand typically require longer start-up processes and therefore do not respond to short term price fluctuations.

To explore the mechanism explaining the negative effect on criminality, we link local employment data to police precincts. We show that increases in mining value generates local employment opportunities (possibly both directly in the mining sectors and through industry linkages).[5] These findings suggest that increased mining wealth affect the opportunity cost of engaging in crime (in line with Becker, 1968). Under the assumption that mining only affects crime through the employment margin, we can calculate employment-crime elasticities.[6] These are 1.2 for the total number of crimes and 1.8 for property crimes. Hence, our finding speak to a large literature studying the relationship between labour market opportunities and crime.[7] While a number of studies have documented this relationship for developed countries (Raphael and Winter-Ebmer, 2001; Gould, Weinberg, and Mustard, 2002; Fougère, Pouget, and Kramarz, 2009; Lin, 2008), there is much less evidence from developing countries – where crime levels are typically much higher (a recent exception is the work by Dix-Carneiro, Soares, and Ulyssea, 2018, on Brazil). We contribute to this literature by providing causal evidence in one of the most crime-ridden countries globally. Our estimates suggest crime-employment elasticities in this setting that are comparable to those in developed countries. The other key mechanism that could explain why an increase in natural resource wealth may reduce crime is that resource wealth improves the government's crime prevention capacity. Governments in many countries around the world have put in place revenue sharing schemes that ensure the state benefits from natural resource booms. However, whether such resources are actually improving state capacity has been questioned (see e.g. Brollo et al., 2013). We test for this mechanism by studying whether interventions by the South Africa Police Service and policing expenditure are affected by local mining wealth. Both of these tests suggest that the observed reduction in crime is not driven by increased crime prevention activities.

Our results imply that downward fluctuations in international mineral prices can cause surges in criminal

[5] Previous studies show that mine openings are associated with increased local economic activity, measured by nightlights (Benshaul-Tolonen 2018; Mamo, Bhattacharyya, and Moradi 2019). Mine closures, on the other hand, lead to decreased local economic activity and employment (Rhee et al., 2018). We confirm a positive statistically significant association between mining value and night lights of 0.048 in t+1. We caveat this analysis given the issues with blurring, top-coding, lack of calibration, and poor predictions in rural areas in the early years of nightlight data (Gibson et al., 2021)

[6] Note that the intensive margin is likely to be affected by price fluctuations as well.

[7] See Draca and Machin (2015) for a review of the literature.

activity in mineral producing countries, in line with previous findings that busts reduce local welfare (Cust and Poelhekke, 2015). To investigate how policy could prevent such surges, we explore the role of public employment insurance. Public insurance has the potential to protect individuals from income shocks experienced in response to price fluctuations and therefore prevent increases in criminal activity. As outlined in the 2014 World Development Report on "Risk and Opportunity", developing countries are highly exposed to a range of risk factors, including both employment and price shocks. At the same time, government spending on public insurance tend to be limited. To study this issue, we exploit the roll-out of South Africa's Community Work Programme (CWP). The CWP provides access to a minimum of two days of work per week to the unemployed. Hence, the program works as an insurance for those that may have lost their jobs due to contraction of the mining industry induced by price shocks. We document that the program reduces the sensitivity of crime (in particular property crime) to international mineral price shocks by between 3.5 - 10%. In addition to providing insights into how crime can be decoupled from international price shocks, this analysis also provides further support that our main results are driven by changes in employment opportunities.

This paper relates to a large literature studying the impact of natural resource wealth on conflict (see, e.g., Caselli, Morelli, and Rohner, 2015; Lei and Michaels, 2014; Maystadt et al., 2014; Rohner, 2006; Berman et al., 2017). The main argument in this literature is that an increased value of natural resources generates conflict by increasing the fight over these resources (the appropriation channel discussed above). Recent papers have also explored the links between extractive industries and violence at a sub-national level (see, e.g., Caselli, Morelli, and Rohner, 2015; Lei and Michaels, 2014; Maystadt et al., 2014; Rohner, 2006). With respect to crime, Couttenier, Grosjean, and Sangnier (2017) find that minerals play a role both historically and presently for U.S. homicide rates, James and Smith (2017) find that both property and violent crimes increased in counties affected by the shale gas boom in the US and Buonanno et al. (2015) document a relationship between natural resource endowments and the emergence of the Sicilian mafia. With respect to mining, Bellows and Miguel (2009) show that diamond mining increased armed clashes during the civil war in Sierra Leone. The paper in this literature most similar in spirit to ours is Berman et al. (2017), who investigate the impact of mining on conflict in Africa from 1997 to 2010.[8] The authors exploit within-mining area panel variation in violence due to changes in the world price of the relevant mineral and find that mining activity increases local area conflict, as measured by the The Armed Conflict Location Event Data (ACLED) dataset. There are many potential reasons why the impact of natural resource wealth might be different for crime and conflict. One such potential explanation is that the appropriation mechanism emphasized in the conflict literature is weaker for crime. The resources of mining companies are typically well protected by private security forces, making it hard for individual criminals to appropriate them while larger groups might be able to coordinate successful attacks. To ensure that the difference in results is indeed driven by our focus on crime, we also collect data on conflict-related events in South Africa as recorded by ACLED. Using this outcome we find imprecisely estimated positive point estimates that are smaller but of a broadly similar magnitude to those reported by Berman et al. (2017) for all of Africa. This suggests that our results are indeed driven by our focus on individual criminal activity. Hence, we conclude that the effects of natural resources wealth is more complex than the previous literature suggests. When considering the overall welfare effects of natural resources, the impact on crime also needs to be taken into consideration.

The organization of the paper is as follows. Section 2 provides a background on the mining industry and crime in South Africa. Section 3 describes the data and the construction of the samples used in estimation.

[8] In a similar paper, Berman and Couttenier (2015) find that local income opportunities are negatively correlated with conflict measures in sub-Saharan Africa.

Section 4 describes the empirical strategies employed. The results from our main specifications, investigation of the underlying mechanisms and robustness checks are reported in Section 5. Thereafter the analysis of the South Africa community work program is discussed in Section 6. Section 7 presents the results on conflict outcomes and Section 8 offers some concluding remarks.

2 Background

2.1 The Mining Industry

Large-scale mining plays an important role in South Africa's history. It first started in 1867 when alluvial diamonds were found along the Orange River. This was soon followed by the Kimberley diamond discovery and the Witwatersrand Gold Rush in the 1880s. The gold rush led to the onset of the Mineral Revolution, the rapid mineral-driven economic growth that laid the foundations for South Africa's economic capital Johannesburg. Today the South African mining industry is the fifth largest in the world (Chamber of Mines 2012), and the country has among the largest mineral endowments remaining, despite a long history of extraction. South Africa is a producer of many different metals and minerals. From a South African perspective, the economically most important mineral groups are platinum (platinum group metals, PGMs), gold, coal and iron ore.[9]

More than half a million people were employed in mining in 2012, an increase from 436,000 in 2003 (Chamber of Mines 2013). The employment opportunities are concentrated in certain regions; at the top of the list are the North West (141,000 miners in 2012), Mpumalanga (79,000), Limpopo (73,000), and Gauteng (32,000), but significant mining employment can also be found in Free State, KwaZulu-Natal, and Northern Cape (Statistics South Africa, 2013). The mining sector's economic importance relative to GDP exceeds its importance in terms of providing employment opportunities. In 2011, the sector employed 0.7 percent of the workforce, but made up 8.8 percent of national GDP. If upstream and downstream industries are included it constitutes as much as 18 percent of all economic activity (Statistics South Africa, 2013). Despite the small share of employment to value created, labor constitutes a significant share of the production costs, roughly 40 percent. The wage burden has increased over time. From 2007 to 2012, negotiated wage increases have exceeded inflation, putting more pressure on the industry and leading to staff reductions (Antin, 2013).

2.2 Crime in South Africa

Although South Africa has seen a huge increase in the number of private security guards as well as a tripling of government spending on crime prevention since the mid-1990s, the country is one of the most crime-stricken in the world. Hopes that the levels would decrease after 1994 were not met; rather, in the period from 1994 to 2000, crime increased. For example, the annual increase in the number of crimes was higher in 1999 than in any single year from 1994-1998. These changes were mainly driven by huge rises in common robbery (121%), residential burglary (25%), assault (22%), rape (21%), and carjackings (20%). During the sample period of this study, from 2003 to 2012, crime numbers have been on the decline again as depicted in Figure A2 showing the total number of crimes for the three main crime categories considered in this study. However, from an international perspective the crime rates in South Africa are still exceptionally high. One proposed explanation for the high crime rates is widespread unemployment. In 2004, the beginning of our study period, unemployment was 30 to 41%, using narrow and broad definitions (Kingdon and Knight, 2004).

[9] These are the largest mineral groups in terms of employment and sales (Antin, 2013).

Recently, the link between mining and crime has received both media and government attention. A *New York Times* report (NYT 2013) suggests that crime has risen as townships have "fallen on hard times as gold mines have closed". In addition, previous historical studies have claimed that conditions in the mining industry have spurred criminality in South Africa (Kynoch, 1999, 2005). Previous arguments suggest that several factors inherent to the industry, such as a predominantly male workforce and poor living conditions in the mining areas, cause criminal behavior.

2.3 South Africa's Community Work Program

The Community Work Program (CWP) is an employment safety net program in South Africa. It aims to improve the quality of life for people in marginalised economic areas by providing work experience and promoting social and economic inclusion. The program targets unemployed and underemployed people and provides access to a minimum of two days of work a week (corresponding to 100 days of work a year), with a stipend guaranteed to be above the minimum wage, in localities where CWP sites have been established.[10] Each site is designed to support approximately 1,000 participants, who are allowed to remain in the program for as long as their economic status is not changed.

Tasks carried out by participants are based on priorities identified by local communities. These tasks have included, e.g., looking after orphans or vulnerable children, helping sick people, assisting teachers in schools, road maintenance, developing recreational spaces and sporting facilities, looking after children of working parents and working with the local police to improve safety and reduce crime. Hence, the program may improve local crime levels both by providing insurance against income loss as well as by improving crime prevention.

The program is funded by the central government but implemented by agents who engage with local stakeholders such as ward councilors, traditional authority figures, non-governmental and community organizations. Together these actors jointly identify what type of "useful work" that program participants could do in order to benefit the community. The central government initially appointed two non-governmental organisations as implementing agencies (with the total number of sites split roughly equally between them) to be responsible for project management, logistics, technical, support and financial management: Teba Development and The Seriti Institute. The focus of the first of these two organisations is particularly relevant for our analysis. Teba Development was formed in 2001 at the request of the Chamber of Mines and specifically target mining areas and ex-mineworkers (DoCG, 2009).

The first CWP pilot sites were established in 2008 and have been rolled out across South Africa since then with the target to involve at least two wards per municipality in South Africa by 2013/2014. The initial roll-out of the program faced a number of supply side constraints. This included the late contracting of funding in December 2009 following the move of the program to the Department of Cooperative Governance, which left little time left for expanded implementation (DoCG, 2009). The 2009/2010 Annual Report state that "funding uncertainty and the short timeframe within which ambitious targets had to be met constrained the CWP's ability to expand implementing capacity during 2009/2010" (DoCG, 2009). The report further states that "demand to participate [in the program] is a great deal higher than the opportunities available" and that while "all communities qualified in terms of poverty indicators and the quality of business plans presented" site selection was based on localities already having some infrastructure in place to implement the program rather than the local need. In 2012, the end of the sample period considered in this study, the

[10] In 2016, the majority of participants work two days a week and receive R81/day in stipends. See `www.gov.za/CommunityWorkProgramme`.

program had been rolled out to 154 sites and had 176,690 active participants (DoCG, 2013). These sites are located mainly in rural areas with high unemployment and where "alternatives seem likely to remain limited for the foreseeable future".

The roll-out of new sites described above is important for identification in this paper since it implies that sites are not set up in response to adverse economic shocks caused by international mineral price fluctuations. We discuss this assumption more in detail and test for its validity in Section 6.

3 Data and Sample Construction

3.1 Main Data Sources

3.1.1 Crime

We use data on local crime for the years 2003 to 2012 provided by the South African Police Service. The data set includes recorded crimes from all 1,084 police stations in South Africa. The geographic locations of these police stations are illustrated in Figure A1. Crimes are reported for each financial year (April to March) and divided into 29 different categories. Crime trends from 2003 and 2012 are mixed; for example, reported murders and carjackings decreased, while kidnappings and sex crimes increased. However, the overall crime rates went down. Theft, residential burglary and assault show the greatest number of reported incidents.

We create three main outcome variables: property, violent, and total crime.[11] **Property crime** consists of theft, burglary at non-residential premises, burglary at residential premises, common robbery, robbery at non-residential premises, robbery at residential premises, shoplifting, stock theft, theft of motor vehicle and motorcycle, and theft out of or from motor vehicle. **Violent crime** consists of arson, assault with the intent to inflict grievous bodily harm, attempted murder, common assault, culpable homicide, malicious damage to property, murder, public violence, robbery with aggravating circumstances, and sex crimes. **Total crime**, in addition to property and violent crime, also includes carjacking, crimen injuria, driving under the influence of alcohol or drugs, drug-related crime, illegal possession of firearms and ammunition, kidnapping, neglect and ill-treatment of children and truck hijacking. Previous validations comparing the police data with information from the *Victims of Crime Survey* conducted by Statistics South Africa have shown that recorded crime levels by the South African Police correspond well with actual crime rates (validations have been carried out by Demombynes and Özler (2005) and the Institute for Security Studies).

While our main outcome variable of interest is the number of crimes recorded for these three categories, we also construct per capita outcome variables for each precinct and year for validation purposes. Unfortunately, precinct level population data is only available from the 2011 census. Therefore, we need to rely on extrapolated population data to construct per capita outcomes. We do this by exploiting municipality level population data, which is also available from the 2001 census. Using municipality data from the 2001 and 2011 census, we calculate municipal level yearly growth rates and apply these to the 2011 precinct level census data to get extrapolated yearly population estimates.

[11] These categories have been defined ex-ante to avoid the multiple testing concerns of investigating a large group of similar outcomes.

3.1.2 Mining Activity

We use data on all large-scale mining operations across South Africa from 2003 to 2012. The data is licensed and provided by IntierraRMG.[12] For each mine we know the minerals extracted during the sample period (reported as main and non-main minerals) as well as the exact geographic location and ownership structure.[13] Our analysis sample consists of the 210 mines that were active in 2002 – the year before the first year for which we have crime data. We focus on the main mineral produced in each mine, which leaves us with 15 different minerals produced during the sample period.[14] The majority of mines produce gold, coal, platinum or chromite (Table B3), and there are 99 mine openings and 78 mine closures between 2002 and 2012 (Table B4). The geographic locations of all mines separated by mineral types are illustrated in Figure A1. Unfortunately, production data is not reported for many mines. We are therefore unable to construct yearly production figures for each mine. Instead we focus on constructing aggregate figures for a typical mine at the mineral-level. Figure A3 depicts this data and shows substantial fluctuations in production during our sample period. The industry is both expanding and contracting at the same time. Production per mine of gold and copper decreased during the sample period, whereas production of iron ore, lead and manganese ore increased.

3.1.3 International Mineral Prices

To construct an exogenously determined measure of the value of mining production in each precinct we match production data with international mineral prices. The main source of prices is the World Bank commodity price data, which has international price series for coal, copper, gold, iron ore, lead, nickel, phosphate rock, platinum and zinc. For minerals that are not available in the World Bank data, we collect prices from two additional sources: the U.S. Geological Survey (USGS) and the International Monetary Fund (IMF). USGS is the source for for antimony, chromite, manganese ore, titanium and vanadium, while uranium oxide is from the IMF. Nominal prices are converted to real prices using the MUV index deflator with 2010 as the base year. The price data covers the same years as those for which we have crime data (2003-2012), and is measured in real U.S. dollars per volume unit. Figure 1 shows the variation in international mineral prices during our sample period.

3.1.4 Local Labour Markets

To get a measure of the performance of the local labour market, data on the employment-to-population ratio (EPR) has been obtained from the Quarterly Labour Force Survey (QLFS) conducted by Statistics South Africa. The survey is a nationally representative repeated cross-section and collects data on the labour market activities of individuals aged 15 years and above. We use the question: *"In the last week, did you work for a wage, salary, commission or any payment in kind (including paid domestic work), even if it was only one hour?"* to construct the employment-to-population ratio. The data is available for the years 2008-2010 at the enumeration area level.[15] We match the enumeration areas to the geographic boundaries of police precincts to calculate the local EPR.

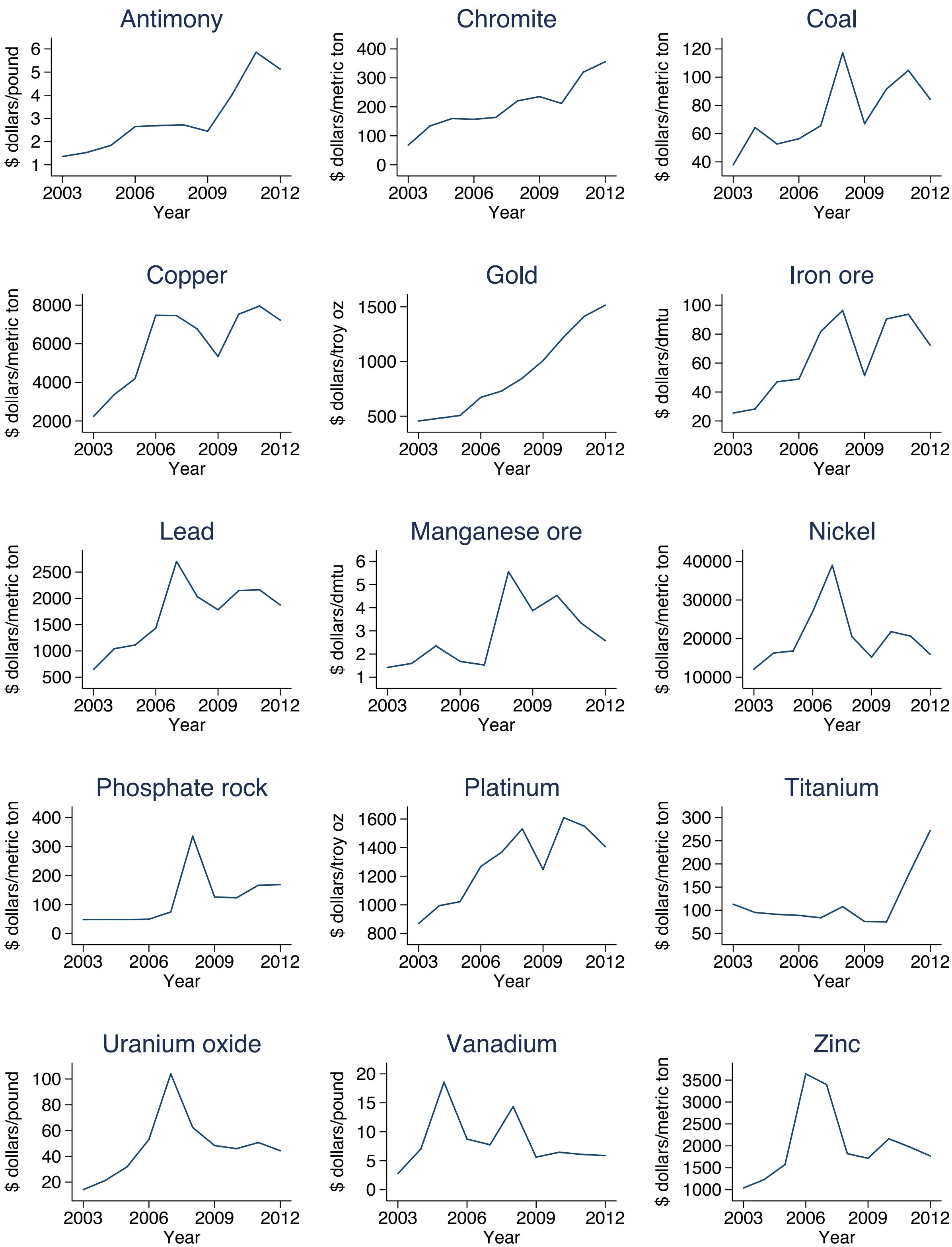
[12] `http://www.intierrarmg.com/Products/SNL_MnM_Databases.aspx`

[13] The geographic location provided is double-checked against information available from `mining-atlas.com`.

[14] The main mineral is the mineral that is listed by the mining company as the main focus of extraction at each mining site, and is often reflected in the name of the mine. Most mines have a primary mineral that they produce, although upon extraction, other minerals and metals may also be identified and isolated. In the robustness section we also report results including non-main minerals in the analysis.

[15] For the following years Statistics South Africa changed the way observations are linked to enumeration areas in the QLFS. We therefore focus on the 2008-2010 period.

Figure 1: International Mineral Prices 2003-2012



Notes: This figure shows the development of the international prices of all the minerals used in the analysis in this paper.

3.1.5 Policing

To investigate whether natural resources affect policing activity, two measures have been collected. First, we collect data on crime-prevention expenditure. This data is from the National Treasury's yearly budget reports and is available at the provincial level (National Treasury, 2015). Second, to get a local measure of policing activity we use information on actors from the ACLED dataset. More specifically, we collect data on whether an event recorded in the database involved the South African Police Service or not, and construct a yearly precinct level dataset on police interventions for our sample period.

3.1.6 CWP Sites

In order to study the role of the community work program, data has been collected from official reports produced by the Department of Cooperative Governance at the Ministry of Cooperative Governance and Traditional Affairs in South Africa. From these reports all CWP sites implemented from the beginning of the program in 2008 until the end of our sample period in 2012 have been identified and geographically linked to the relevant wards to which the job guarantee program was offered. This provides very precise information on the location of CWP sites (in 2011 South Africa consisted of 4,277 wards). However, a key challenge with linking this information to police precincts is that the borders of these two administrative units do not overlap. In addition, some wards are substantially larger than precincts while others are substantially smaller. We take two approaches when linking CWP sites to precincts. The first more conservative approach, which will be our baseline measure, considers a precinct to have access to the community work program if the police station is located within a municipality that has any CWP established (this approach likely overstates access to the CWP program). The second approach defines access to a CWP site if at least 50% of the area of the precinct is covered by a ward that has a CWP site (likely understates the access to the CWP program). We present results using both of these two matching strategies.

3.2 Baseline Sample and Construction of Key Variables

Using the data described above we construct a precinct-level panel covering 1,084 precincts over 10 years (2003-2012). Our main variable of interest is a measure of the value of mineral production ($value_{it}$) in a given precinct-year. We take the following steps to construct this measure. First, we consider all mines j that are actively producing in 2002, the year before our sample starts.[16] Then, we classify each mine by the main mineral k it produces according to IntierraRMG.[17] For each mineral type we calculate the average yearly production of a mine producing that type of mineral (vol_k) in South Africa during our sample period.[18] Importantly, to avoid capturing any endogenous response in production, this measure is constant across all mines in South Africa producing the same mineral and does not change between years. The purpose of this measure is to weight the relative importance of price changes across mines that produce different types of minerals. Thereafter, we interact this average production with the international price of the mineral ($price_{kt}$) produced in a mine and then sum across all the mines (J_i) in the precinct i using the exact geographical

[16]Note that this includes also those mines that we do not have yearly production data for.

[17]This follows a similar approach to Berman et al. (2017). The intuition behind this approach is that the main mineral will be the key determinant of production decisions at the mine (while other minerals are extracted as byproducts). In addition, we believe that we likely introduce additional measurement error considering these minerals since the total production of non-main minerals vary considerably more across mines. In the robustness section we present results including all minerals produced in a mine.

[18]Naturally, we are only using data from mines for which we have production data to do this calculation.

location of each mine.[19,20] Hence, our precinct-time level measure of the value of mining production is defined by:

$$value_{it} = \sum_{j=1}^{J_i} vol_k \times price_{kt} \tag{1}$$

The variations in this measure comes from price fluctuations of all main minerals produced in the precinct.[21] We follow Berman et al. (2017) and exclude diamonds from the main analysis given the lack of information on diamond quality and production quantity in the IntierraRMG dataset. Diamond quality varies considerably between mines and price series for different qualities can move in opposite directions. We therefore exclude it to limit measurement error in our mining value variable.

Summary statistics are presented in Table B2. The table reports summary statistics for the full sample as well as for areas with and without active mines in 2002. Overall, we see that crime rates are high, with an average of 2,100 crimes – corresponding to 72 crimes per 1,000 inhabitants, with a majority of these crimes being classified as property crime. The total number of crimes is higher in mining areas than in non-mining areas, but after accounting for higher average population this reflect lower crime rates. Figure A2 also shows that crime levels follow somewhat different trends in these two areas, where criminal activity increased more in mining districts than in non-mining districts in the 2007-2010 period. Table B2 further shows substantial variation in the value of mining activity, with an average of value of production of 654 million real US dollars in precincts with mining production at baseline. Mining activity also adjusts at the extensive margin and a number of mines both start and stop operating during the sample period. In areas that had mining activity at baseline, 6% of precinct-year observations experience at least one mine opening, while 5% experience a mine closing.[22]

Employment data from the quarterly labour force survey shows an average employment-to-population share of 70% in the full sample. This is slightly higher in mining areas than in non-mining areas. Finally, we see that Community Work Programme sites were implemented to similar degree in both mining and non-mining areas. Figure A4 shows how the share of precincts with a CWP site increase over time. In 2012, 50% of precincts had at least one site in their respective municipalities.

4 Identification and Empirical Strategy

To estimate the causal effect of mining wealth on local crime levels, we need to overcome two key identification challenges. First, that there are no other underlying factors that jointly determine local crime and mining activity, such as local economic development. Second, that mine production is not affected by changes in crime in the proximity of the mine - i.e. reverse causality. To address these issues our main identification strategy exploits changes in resource value driven by fluctuations in international mineral prices. Our focus on South Africa makes this strategy particularly credible, since we can exploit fluctuations in a large number

[19]We also consider geographical spillovers in mining activity by studying mines within a number of distances from the police precinct as discussed in the robustness section.

[20]Note that we will weight precincts with a larger number of mines of a particular type more. For example a precinct with two gold mines will have twice the average production of gold vol_k compared to a precinct with only one gold mine. However, we are not exploiting this cross-sectional variation for identification since we are controlling for precinct fixed effects in all specifications.

[21]We also construct alternative measures of the value of mining production in a precinct, e.g. following Berman et al. (2017), who focuses only on the most expensive mineral produced in a geograhical unit.

[22]Note that there are also some mine openings/closings in areas that did not have any mining activity at baseline, as indicated in Panel C.

of different minerals for which prices move in different directions (see Figure 1). The idea is that production decisions are largely influenced by the exogenously determined possibility of profitably selling the minerals on the international market. We substantiate this claim by providing empirical evidence of international mineral prices being an important determinant of both intensive (local employment) and extensive margin (opening/closing of mines) production decisions.

Our baseline estimation equation is given by:

$$y_{it} = \beta value_{it} + \gamma_i + \lambda_{mt} + \epsilon_{it}, \tag{2}$$

where y_{it} is the outcome of interest in police precinct i in year t, $value_{it}$ is our exogenously determined value of mining production defined above, γ_i are police precinct fixed effects and λ_{mt} are mining precinct by year fixed effects.[23] The identifying variation arises from changes in the international prices of the minerals produced in mining precincts at baseline to deal with potential endogenous production changes and exploration for new resources. Inclusion of mining precinct by year fixed effects further allows for economic and crime trends to be different in mining and non-mining districts. Most of our variables are heavily skewed and we therefore transform these using the inverse hyperbolic sine (asinh).[24] The key parameter of interest is β, which given the asinh transformation can be interpreted as the elasticity of the outcome with respect to the value of mining production. Standard errors are clustered on the police precinct to allow for serial correlation of the errors over time.[25]

Our key identification assumption is that international mineral prices are exogenously determined. This claim is supported by the fact that international mineral prices tend to be driven by demand rather than by supply factors (Slade, 1982; Álvarez and Skudelny, 2017; Stuermer, 2018). In particular, minerals are a key inputs in industrial production and price fluctuations therefore tend to be strongly affected by the economic performance of large Asian manufacturers. The identification assumption would be violated if crime levels affect local mineral production, which in turn affect the international mineral price. Such an effect would likely bias our results downward due to a potential positive association between crime and mineral prices. If an increase in local crime levels disrupt production this would in turn lower supply on the international market, which would drive up global prices. We perform a number of robustness checks in the following sections, where we exclude minerals where South Africa is a major exporter and precincts that are main producers, to mitigate this concern. Importantly, the analysis carried out in Section 5.3 suggests that our main results are driven by minerals for which South Africa is a minor exporter on the global market.

5 Results

5.1 Main Findings

Table 1 reports the main results from estimating Equation 2 for the key outcome variables. Results show that a 10% increase in the value of mineral production reduces the total number of crimes by about 0.7% (significant at the 5%-level). This reduction is driven by a reduction of property crime by 1.1% (significant at the 1%-level). Point estimates for violent crime are also negative but not significantly different from

[23]A precinct is defined as a mining precinct if it has an active mine in 2002 – the year before our sample starts.

[24]The asinh function is given by $asinh(z) = ln(z + \sqrt{1 + z^2})$. It closely parallels the natural logarithm function, but is well defined at 0.

[25]As a robustness we also report standard errors calculated using the spatial HAC technique suggested by Conley (1999), using a uniform kernel and distance cutoff of 50 kilometers, and standard errors clustered at the municipality.

zero at conventional levels.[26]. During the sample period the value of mineral production in South Africa increased by 154%, suggesting that it contributed to an overall reduction of crime by approximately 11% and a reduction of property crime of 17%.

To get a better understanding for which crime categories that are driving these results, Figure A5 reports the results for each of the 29 different crime categories (outcome variables are again the inverse hyperbolic sine transformation of the number of crimes in each of these categories). These show that results tend to be mostly driven by petty crime. In particular, we find large negative estimates for shoplifting, theft, drug-related crime and common robbery[27]

Table 1: Resource Value and Crime

	(1)	(2)	(3)
	asinh(Total)	asinh(Property)	asinh(Violent)
asinh(Mining Value)	-0.072**	-0.11***	-0.043
	(0.031)	(0.037)	(0.039)
	[0.032]	[0.039]	[0.039]
	{0.034}	{0.041}	{0.044}
Mean Outcome	7.51	6.74	6.54
Observations	10840	10840	10840
Precinct FE	Yes	Yes	Yes
Mining Precinct-Year FE	Yes	Yes	Yes

Notes: This table reports the results of estimating Equation 2 for the main crime outcomes. we report three sets of standard errors: 1) clustered at the police precincts in parenthesis, 2) following the spatial HAC technique suggested by Conley (1999) in hard brackets (using a uniform kernel and distance cutoff of 50 kilometers) and 3) clustered at the municipality in curly brackets. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

5.2 Mechanisms

The negative effect of mining value on crime is consistent with two key mechanisms: that mining activity contributes to local employment generation and thereby increases the opportunity cost of engaging in criminal activity (in line with the argument in Becker, 1968); and/or that revenues from mining operations strengthen government capacity to combat crime. The first of these two potential explanations seems particularly likely given the type of crime categories that are mostly affected. We report results from analyses exploring these mechanisms in Table 2.

To investigate the first of these two potential mechanisms, Panel A reports results on how international price fluctuations affect mining activity and local employment. Column (1) reports the effect on the probability that a mine starts operating in the police precinct. The point estimate is positive but not statistically different from zero. In other words, there is no evidence suggesting that short term price changes affect the opening up of new mines (at least not in areas where these minerals are currently extracted). This is perhaps not surprising given the long time horizon typically required to start mining operations – involving everything from acquiring operating licenses, purchasing equipment, hiring workers, etc. Column (2) reports the impact on the probability that the mine stops operating - a margin on which it is much easier for mining

[26]The results are robust to both using the spatial HAC technique suggested by Conley (1999) and to clustering standard errors at the municipality level

[27]We find no significant effect of resource value on sexual crimes, in line with results by Fourati et al. (2021) who find an association between artisanal mining resource value and sexual violence, but no association between industrial or capital intensive mining forms and sexual violence.

companies to respond.[28] This estimate is highly statistically significant and suggest that a 10% increase in mineral value reduces the probability that the mine will stop operating by 1.2 percentage points. Given that the mean value of this variable in precincts with an active mine at baseline is 0.05, this is a sizeable effect. To investigate whether these changes in production activity affect local labour market opportunities, Column (3) reports the impact of changes in the value of mining production on the local employment-to-population ratio (EPR). These show that a 10% increase in the mining value increases the local EPR by 0.63%. Hence, these estimates suggest employment-crime elasticities of 1.2 for the total number of crimes and of 1.8 for the number of property crimes.

Table 2: Mechanisms: Employment and Policing

	(1)	(2)	(3)
Panel A: Mining Operation and Employment			
	Open (0/1)	Close (0/1)	asinh(EPR)
asinh(Mining Value)	0.042	-0.12***	0.063***
	(0.040)	(0.033)	(0.024)
Mean Outcome	0.0085	0.0066	0.64
Observations	10840	9756	2375
Panel B: Policing			
	SAPS (0/1)	SAPS (0/1)	asinh(SAPS Budget, million)
asinh(Mining Value)	-0.018	-0.16	-0.038
	(0.031)	(0.34)	(0.16)
Mean Outcome	0.036	0.44	17.4
Observations	10840	680	10840
Panel C: Controlling for Police Expenditure			
	asinh(Total)	asinh(Property)	asinh(Violent)
asinh(Mining Value)	-0.072**	-0.11***	-0.043
	(0.030)	(0.036)	(0.038)
asinh(SAPS Budget, million)	-0.013***	-0.017***	-0.0065
	(0.0045)	(0.0054)	(0.0048)
Mean Outcome	7.51	6.74	6.54
Observations	10840	10840	10840
Precinct FE	Yes	Yes	Yes
Mining Precinct-Year FE	Yes	Yes	Yes

Notes: This table reports the results of estimating Equation 2 for the main mechanism outcomes. Panel A show results on whether a mine opens/closes in a given year and on the employment to population rate. Note that we have fewer observations in the closing specification than in our baseline sample since we cannot calculate whether a mine closes down in the last year of our sample period. That would require information about activity in the subsequent production period, which we do not have access to. Column (1) in Panel B reports results on the probability that the South African Police Service was involved in an ACLED incident in the precinct and Column (2) reports the results for the same outcome for a sample limited to ACLED incidents. Column (3) in Panel B reports the impact on the province crime prevention budget, which is used as a control in Panel C. Robust standard errors clustered at the police precinct level in parentheses. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

Taken together these results show that spikes in international mineral prices reduce the probability that mines close down, but do not affect the likelihood of new mine openings in current mining areas. This suggests that the main impact on crime reported above is likely driven by mine closings rather than by

[28]We have fewer observations for this specification since we cannot calculate whether a mine closes down in the last year of our sample period. That would require information about activity in the subsequent production period, which we do not have access to.

mine openings. Since we only have one exogenous variable, we cannot instrument both mine openings and closings.[29] Instead, in Table B5 in the Appendix we run a fixed effect specification where we include both the opening and closing of mines variables. This shows that mine closings are associated with higher property crime and lower EPR (significant at the 10%-level), but that no such association exist for mine openings. While these associations can not be ascribed a causal interpretation, they do provide additional support for our suggested interpretation of our main findings.

The impact on employment that we document could be due to changes in both mining employment and non-mining employment through backward and forward linkages (Rhee et al., 2018). To shed some further light on this, we explore heterogeneous effects by labour versus capital-intensive mines. If results are primarily driven by direct employment effects, we would expect larger impacts on employment and crime for labour intensive mines (following the earlier work by Dal Bó and Dal Bó, 2011; Dube and Vargas, 2013). However, if results are primarily driven by indirect linkages that is not necessarily the case (since linkages could be equally strong or stronger for capital intensive mines). To investigate this we follow the approach suggested by Berman et al. (2017) who separately estimate the impact of underground and open pit mining. Large-scale open pit (OP) mining is generally categorized as capital intensive, since the production sites allow for easy access to heavy machinery. Large-scale underground (UG) mining, in contrast, involves more space restrictions and deep, possibly, narrow shafts, that may hinder the use of large heavy machinery. Therefore, OP mining is relatively capital intensive and UG mining is relatively labour intensive (Amponsah-Tawiah and Dartey-Baah, 2011). We create a variable capturing the share of mines within a precinct that are UG and interact it with our baseline treatment variable. Our results are presented in Table B6 in the Appendix and show that coefficients are larger for all outcomes, except for violent crime, in precincts with a greater share of UG mining. These differences are however small and not statistically significant. Hence, we find no evidence showing that our results are driven by labour intensive mining and could thus be due to linkages to other industries affected by the production changes in the mining industry. However, as noted by Berman et al. (2017), the differences in labour and capital intensiveness across mines is relatively small (cf. Dube and Vargas, 2013) and we therefore do not wish to draw too strong conclusions from this analysis.

The second potential mechanism, that resource revenues strengthen the government's crime prevention capacity, is tested in Panel B using two types of outcomes. We first measure the effect of changes in mineral prices on the probability of the South African Police Services (SAPS) being recorded as an actor in the ACLED event database. SAPS interventions are frequently recorded in the ACLED database with 42% of the ACLED events recorded during our sample period involving SAPS as one of the actors. Column (1) shows that changes in mining value did not affect police operation – the point estimate is small, negative and not significantly different from zero. One potential issue with this specification is that the police may only intervene when there is an incident that they can respond to. Column (2) therefore reports the results for the same specification on the sample of observation for which there was an incident reported in ACLED.[30] Using this specification, we again find a negative and insignificant coefficient. Finally, since ACLED cover a wide range of different events to which the police response might be different, we conduct an investigation of the impact on the ACLED sub-categories in Table B11 in the Appendix. The table shows that we do not find any evidence of mining activity affecting either the occurrence of any of the ACLED sub-categories

[29] Under the assumption that mine opening are not affected we can get the implied effect of a mine closing by interpreting the coefficients in Table 1 as the reduced form and those in Panel A of Table 2 as the first stage. However, the exclusion restriction is not likely to hold for such an interpretation of our findings since international price fluctuations also likely affect mining operation at the intensive margin (and through that affect employment).

[30] Note that this specification needs to be interpreted with caution because it conditions on a potential outcome. However, as shown in Panel A of Table B11 mining value does not have a significant impact on the likelihood of an ACLED event.

(battle, remote violence, riots, strategic development and violence against civilians) nor police intervention for any of these event types. Together this suggests that an increase in mining value does not lead to an increased response by the police. However, given the limited overlap of the crime covered in ACLED with the reported crime statistics we use in the main analysis we interpret these results with caution. To complement this analysis, column (3) in Table 2 report results from an alternative strategy that estimates the effect of mining value on crime-prevention expenditure. Unfortunately, to our knowledge, this data is only available at the province level, which leaves us with limited variation to exploit. However, when using this specification, we again find negative and insignificant estimates. As a final check we control for crime-prevention expenditures in the baseline specification in Panel C. The main estimate remains the same in terms of both size and significance, while the coefficient on police expenditure is negative and significant. Bearing in mind the limitations of these tests, we do not find any evidence that the value of mining activity improves the government's crime prevention capacity.

Even if the government's crime prevention capacity is not affected, an alternative possibility is that the mining industry makes use of private security companies. If increased mining value results in more private security forces this could potentially lead to lower crime levels.[31] Unfortunately, we do not have any data on private security forces to directly test this. However, given the operation of security firms in South Africa we do not expect this to be driving our results. As outlined by the director of the global security company G4S when discussing South Africa, "the priority is to control access in order to counter external criminal threats against the company's equipment and infrastructure, while maintaining order among the large workforce" (Mining Technology, 2014). Since we focus on crime in a larger area around a mine and our results are driven by crime categories that would likely not be a priority by private security firms to stifle (such as shoplifting), we believe that it is unlikely that results are driven by increased hiring of private security.

5.3 Robustness

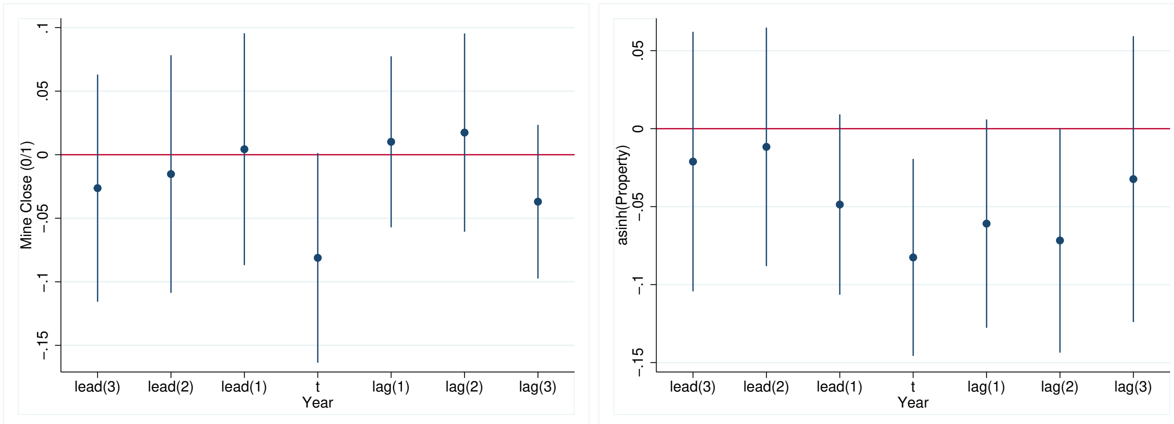
This section presents a number of robustness checks for the main results. First, the analysis in the paper assumes that current value spikes in mining have a direct impact on mining activity and crime and that international price fluctuations are not anticipated. To test this we include leads and lags of our mining value variable in the baseline specification. Figure 2 presents these estimates for our two key outcomes – mine closings and property crime. Panel A in the figure shows that both leads (reported to the left of year t) and lags (reported to the right of year t) are unrelated to mine closings in year t. Estimates tend to be close to zero and are not statistically significant. This lends credibility to the assumption that it is indeed the international price at time t that matters. Results for property crime are reported in Panel B. These show that property crime in year t is not statistically significantly related to leads in mining value (although there seems to be a drop in the coefficient for the one year lead). Importantly, there is a large and highly statistically significant drop in property crime for the mining value in year t. Property crime also tend to be lower for the two year lags suggesting that there is some persistence in the impact on crime.

To further ensure that results are not driven by underlying trends in criminal activity we present results from a number of additional specifications in Table 3 that flexibly control for trends. Column (1) reports the baseline specification for comparison, column (2) reports results when adding province linear trends, column (3) adds precinct linear trends, column (4) flexibly controls for province non-linear trends by including province by year fixed effects, while column (5) controls for year fixed effects interacted with quartile of

[31] However, note that the argument could also be made that the presence of private security firms would improve detection of crime and that it could therefore lead to an increase in recorded crime rates.

Figure 2: Lags and Leads

Panel A: Mine Closings *Panel B: Property Crime*



Notes: This figure reports the results from adding three lags and leads of the mining value variable to Equation 2. Each panel reports point estimates and 95% confidence intervals. Panel A reports these estimates for the outcome dummy indicating any mine closing and Panel B for the property crimes outcome.

population size of the precinct. While point estimates vary somewhat, the results are consistent across all five specifications which suggests that local trends are not driving the main results.

The key identification assumption is that international mineral prices are exogenously determined, i.e. that international prices are not affected by production decisions in South African mines. Since South Africa is a major producer of several minerals this is a potential concern. First it is important to note that to the extent that South Africa affect international prices that would likely bias our results downward. For example, if higher local crime levels disrupt production this would lower the quantity supplied by South Africa on the international market which in turn would drive up global prices – creating a for our intentions spurious positive association between mineral prices and local crime.

To test the validity of our assumption and the above reasoning we conduct two robustness checks. First, we sequentially exclude precincts that have the most valuable production during the sample period. The idea behind this exercise is that large producers are those that would be able to affect the international mineral price and by excluding them we limit this concern. The results are reported in Table 4, which shows estimates from Equation 2 excluding the precincts with the 10%, 20%, 30%, 40% and 50% largest total production value during the sample period. Hence, the most restrictive of these specifications exclude half of all the precincts that have any mineral production during the sample period. The results are stable across all these sample restrictions and remain statistically significant at conventional levels. In fact, point estimates for total crime are slightly larger in the most restrictive specification. A potential limitation with this test is that precincts that are not major producers within South Africa might still be important producers globally for specific minerals. This could be the case, for example, if the size and concentration of production differs substantially across mineral types.

To test for this concern we calculate the South African market share of global mineral exports for all the minerals included in our main analysis. Using the world mineral statistics data from the British Geological Survey we construct South Africa's share of total exports in 2002 (the year before our analysis starts) for each mineral.[32] The South African market share is reported in Table B12. As can be seen from this table

[32]When doing this we sum across all sub-commodities (such as metal, oxide and ore). We are able to construct export shares for all minerals in our data except for uranium, for which no export information is reported for 2002. For uranium we therefore

Table 3: Robustness I: Additional Specifications

	(1)	(2)	(3)	(4)	(5)
	Baseline	Local Time Trends		Local Time FE	
	asinh(Total)	asinh(Total)	asinh(Total)	asinh(Total)	asinh(Total)
asinh(Mining Value)	-0.072**	-0.059**	-0.054**	-0.046	-0.066**
	(0.031)	(0.030)	(0.022)	(0.031)	(0.031)
	asinh(Property)	asinh(Property)	asinh(Property)	asinh(Property)	asinh(Property)
asinh(Mining Value)	-0.11***	-0.094**	-0.051	-0.084**	-0.11***
	(0.037)	(0.037)	(0.032)	(0.038)	(0.036)
	asinh(Violent)	asinh(Violent)	asinh(Violent)	asinh(Violent)	asinh(Violent)
asinh(Mining Value)	-0.043	-0.043	-0.090***	-0.018	-0.034
	(0.039)	(0.036)	(0.032)	(0.037)	(0.040)
Precinct FE	Yes	Yes	Yes	Yes	Yes
Mining Precinct-Year FE	Yes	Yes	Yes	Yes	Yes
Province Linear Trends	No	Yes	No	No	No
Precinct Linear Trends	No	No	Yes	No	No
Province-Year FE	No	No	No	Yes	No
Population Quartile-Year FE	No	No	No	No	Yes
Mean Outcome	6.54	6.54	6.54	6.54	6.54
Observations	10840	10840	10840	10840	10840

Notes: This table reports the results of estimating Equation 2 for the main outcomes with each column adding controls for different types of local time effects. Robust standard errors clustered at the police precinct level in parentheses. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

Table 4: Robustness II: Resource Value and Crime, excluding large producers

	(1)	(2)	(3)	(4)	(5)	(6)
	Full	10%	20%	30%	40%	50%
	asinh(Total)	asinh(Total)	asinh(Total)	asinh(Total)	asinh(Total)	asinh(Total)
asinh(Mining Value)	-0.072**	-0.076**	-0.076**	-0.076**	-0.077**	-0.077**
	(0.031)	(0.031)	(0.032)	(0.033)	(0.034)	(0.038)
	asinh(Property)	asinh(Property)	asinh(Property)	asinh(Property)	asinh(Property)	asinh(Property)
asinh(Mining Value)	-0.11***	-0.12***	-0.11***	-0.11***	-0.11**	-0.11**
	(0.037)	(0.038)	(0.039)	(0.041)	(0.042)	(0.045)
	asinh(Violent)	asinh(Violent)	asinh(Violent)	asinh(Violent)	asinh(Violent)	asinh(Violent)
asinh(Mining Value)	-0.043	-0.049	-0.050	-0.058	-0.069	-0.071
	(0.039)	(0.039)	(0.040)	(0.042)	(0.042)	(0.047)
Precinct FE	Yes	Yes	Yes	Yes	Yes	Yes
Mining Precinct-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10840	10740	10670	10540	10440	10350

Notes: This table reports the results of estimating Equation 2 for the main outcomes for different sample restrictions. Column (1) reports the results for the full sample, while subsequent columns exclude precincts with the 10%, 20%, 30%, 40% and 50% highest value of mining production. Robust standard errors clustered at the police precinct level in parentheses. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

South Africa's share of total exports varies considerably across minerals – ranging from 40% for vanadium to less than 0.1% for Zinc.

We start by excluding minerals for which South African exports were more than 10% of total global exports in 2002 (Vanadium, Chromite and Manganese Ore). Results are presented in Panel A of Table 5 and show estimates that are larger and slightly less precisely estimated than in the baseline sample (-0.087 rather than -0.072 for total crime). The estimate for the total number of crimes is significant at the 10%-level, while the property crime estimate is significant at the 5%-level. This is a first indication that our main results are not driven by minerals for which South African production levels are likely to affect international mineral prices. To further investigate what is driving our main results, we construct two separate mining value variables: one that corresponds to the value for all minerals for which South Africa has a major share of total exports (above 2.5%) and one for which South Africa has a minor share of total exports (less than 2.5%) in 2002. Panel B in Table 5 shows that all results are driven by the minerals where South Africa arguably has no market power and where South African production would therefore not affect the international price. The point estimates for these minerals are of a similar magnitude to those in the baseline specification and are statistically significant at the 5-% level for total and property crime. Notably, effects for violent crime are negative of a similar magnitude and statistically significant. Point estimates for the minerals where South Africa has potential market power are substantially smaller and not significantly different from zero. The latter two facts might suggest that the downward bias discussed above affects some of the minerals in our baseline analysis. In particular, the lack of a significant negative estimate for violent crime in the baseline specification could potentially be driven by violent crime disrupting production of some major minerals. However, importantly, taking market power into account does not alter the main takeaway from our analysis and estimates for total and property crime remain stable[33].

Table B8 in the Appendix reports seven additional sensitivity tests. Panel A reports results when we include non-main minerals in the construction of our mining value variable.[34] The results show that our findings are similar when considering these additional set of minerals, but with point estimates slightly smaller.[35] Panel B reports estimates of an alternative specification following the main specification used by Berman et al. (2017).[36] The key difference with our baseline specification is that their strategy only exploits price variation for the most expensive mineral within each geographical unit (while we exploit variation for all main minerals produced within a precinct). We follow their approach and identify the most valuable mineral using the total production volume during the sample period and evaluate at the price of the mineral at baseline (in our case 2003 prices). Table B8 show that results are very similar to our baseline specification; estimates for property crime are identical in terms of point estimates as well as significance level. For total crime the point estimate is -0.070 with the Berman et al. (2017) specification, while our baseline estimate is

rely on total production data in 2002 provided by the United Nations Energy Statistics Database.

[33] As an additional robustness check, we run the main specification but separating the value generated from gold mining from other minerals. The main treatment coefficient is -0.055, statistically significant at the 10% level. The coefficient for gold value is negative but not statistically significant, suggesting that upward trend in gold prices during our sample period is not driving our main results. Further robustness checks show that the main treatment coefficients are not driven by underlying trends in certain minerals. While the price of most minerals increase during our sample period, several peak around 2008. If we separately estimate the effect for minerals that increase and decrease after 2008, we find similar point estimates for the two groups (although imprecisely estimated). These additional results are reported in Table B7.

[34] This increases the number of minerals included in our analysis to 20, since we have production data for five additional minerals that are not main-minerals during our sample period. These are cobalt, palladium, rhodium, silver and zirconium.

[35] We believe that we likely introduce additional measurement error in this specification since the total production of non-main minerals vary considerably more across mines.

[36] We estimate a specification mimicking equation 2 in their paper. In our case this corresponds to: $y_{it} = \beta M_i \times log(price)_{it} + \gamma_i + \lambda_{mt} + \epsilon_{it}$, where M_i is an indicator for any mining activity during the sample period and price is the international price of the most valuable mineral in the precinct.

Table 5: Robustness III: Resource Value and Crime, excluding major export minerals

	(1)	(2)	(3)
Panel A: Excluding top minerals			
	asinh(Total)	asinh(Property)	asinh(Violent)
asinh(Mining Value, excl. >10%)	-0.087*	-0.13**	-0.032
	(0.048)	(0.054)	(0.062)
Panel B: Splitting by export market share			
	asinh(Total)	asinh(Property)	asinh(Violent)
asinh(Mining Value, Major Exporter)	-0.0072	-0.029	0.0078
	(0.039)	(0.045)	(0.045)
asinh(Mining Value, Minor Exporter)	-0.075**	-0.089**	-0.083**
	(0.037)	(0.044)	(0.041)
Precinct FE	Yes	Yes	Yes
Mining Precinct-Year FE	Yes	Yes	Yes
Observations	10840	10840	10840

Notes: This table presents results excluding minerals for which South Africa is major exporter on the global market. Panel A reports results when excluding minerals where South Africa had more than 10% of total exports in 2002 (Vanadium, Chromite and Manganese Ore). Panel B reports results for two separate variables split by whether South Africa is a major (Vanadium, Chromite, Manganese Ore, Coal, Antimony, Iron Ore, Titanium, Gold, Platinum) or minor (Phosphate rock, Lead, Copper, Uranium, Nickel, Zinc) exporter. Robust standard errors clustered at the police precinct level in parentheses. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

-0.072.

The sensitivity tests in Panel C-E investigate how our estimates change when we modify the definition of our outcome variable. As discussed above, our main outcome is the inverse hyperbolic sine transformation of the number of crimes in the precinct. We prefer this specification because we do not have population statistics at the precinct level. However, to test whether our results are robust to defining our outcome variable as a crime rate we create per capita outcome variables for each year by using the precinct population data that we have from 2011 and the population growth rates that we can estimate at the municipality level (a procedure that will most likely introduce measurement error in our outcome variable). Panel C presents the results and show that estimates are slightly smaller and somewhat less precisely estimated, but still of a similar magnitude to the baseline estimates (0.056 vs. 0.072 for total crime and 0.097 vs. 0.11 for property crime). For completeness we also report results for crime rates without taking the inverse hyperbolic sine transformation of the outcome variable (note that the per capita outcome variables are substantially less skewed). As can be seen in Panel D, our main results remain robust to this specification as well. For completeness, Panel E reports the results using count variable for the three crime categories and shows that results remain robust.

Lastly, we consider migration. Mining activities in sub-Saharan African countries have been linked to influx of people and urbanization pressure (Fafchamps, Koelle, and Shilpi, 2017). The history of mining and migration is longstanding in South Africa: prior to democratization, the labor in South African mines was supplied by domestic and international migrants, made sure by apartheid policy (Cox, Hemson, and Todes, 2004) and migration remains important in supplying labor to the mining sector in South Africa. The failure to correct for migration changes would likely lead to an underestimate of the effects since inward migration would increases during mining booms, while at times of mining busts, outward migration increases. Our main effects are the opposite: during mining booms, crime rates decrease, while crime rates increase during mining busts.

To test to what extent migration patterns affect our main results, we perform an additional robustness check in which we flexibly control for differential trends in areas depending on their baseline migration share. To perform this analysis we rely on municipality-level migration data from the South African census. We divide all municipalities into 20 groups depending on their international migrant share in 2003 and interact these 20 groups with year fixed effects.[37] The results are presented in Table B8 panels F and G. Panel F considers total international migrants, while panel G considers male migrants from Southern African Development Community (SADC) countries (the most likely mining workers in the migrant population). Both estimates are close to our main results, with results in Panel G being even slightly larger than our baseline estimate – consistent with our baseline estimates being lower bounds.

Another potential concern with our baseline specification is that mining activity may affect crime in neighbouring areas. If this is the case, our estimates may be biased. To test for such a spillover effect we create two additional treatment variables that capture the value of mining production within 0-10km and within 10-20km from the border of the precinct, respectively. These variables are constructed using the same strategy outlined in Section 3.2 and their summary statistics are reported in Table B2. Table B9 reports the results from estimating Equation 2 adding these two variables. The baseline estimates are largely unaffected by including these additional variables and the estimates of the spillover variables (0-10 km or 10-20 km) are small and statistically insignificant, but with the same sign as our baseline estimate.

6 The Role of the Community Work Program

To investigate whether employment insurance can decouple the relationship between international mineral prices and crime, we exploit the roll-out of the South Africa community work program between 2008 and 2012. We estimate the following specification:

$$y_{it} = \beta_0 value_{it} + \beta_1 cwp_{it} + \beta_2 cwp_{it} \times value_{it} + \gamma_i + \lambda_{mt} + \epsilon_{it}, \tag{3}$$

where cwp_{it} is an indicator variable which takes on the value one if there is a community work program in precinct i in year t. All other variables are the same as in Equation 2. The key parameter of interest is β_2, which shows the difference in the response to a change in the value of mining activity when a community work program is available.

Table 6 reports the results from estimating Equation 3 for the two matching strategies (municipality and ward) used to define the community work program indicator discussed in Section 3. For both of these definitions, the response to a change in the value of mining activity is smaller when the community work program has been implemented. Note that there are two potential explanations for this: (1) that the program provided legal employment opportunities that affect the opportunity cost of engaging in criminal activity and/or (2) that the anti-crime and security interventions implemented under the program directly prevented crime. While part of this program directly targeted formerly employed miners (as discussed in Section 2.3) the effects could also work through supporting people that were indirectly affected by the down-scaling of mining through backward and forward linkages (Rhee et al., 2018).

[37] In the census data for 2011, respondents answer the following question: "In which year did [you] move to South Africa?". This allow us to identify international migrant shares with the caveat that we are only able to capture inflows.

Table 6: Resource Value, Crime and the Community Work Program

	(1)	(2)	(3)
Panel A: Municipality Matching			
	asinh(Total)	asinh(Property)	asinh(Violent)
asinh(Mining Value)	-0.074**	-0.12***	-0.046
	(0.030)	(0.037)	(0.038)
CWP	-0.0080	-0.028**	-0.014
	(0.012)	(0.014)	(0.013)
asinh(Mining Value) × CWP	0.0026*	0.0043**	0.0034*
	(0.0014)	(0.0017)	(0.0019)
Panel B: Ward Matching			
	asinh(Total)	asinh(Property)	asinh(Violent)
asinh(Mining Value)	-0.075**	-0.12***	-0.045
	(0.030)	(0.037)	(0.039)
CWP (Ward)	-0.066***	-0.079**	-0.027
	(0.025)	(0.034)	(0.026)
asinh(Mining Value) × CWP (Ward)	0.0077***	0.010***	0.0037
	(0.0029)	(0.0038)	(0.0032)
Precinct FE	Yes	Yes	Yes
Mining Precinct-Year FE	Yes	Yes	Yes
Mean Outcome	7.51	6.74	6.54
Observations	10840	10840	10840

Notes: This table reports the results of estimating Equation 3 for the three crime outcomes. Panel A reports the results for assigning CWP sites to a precinct if the parent municipality has at least one site, while Panel B reports the results for assigning a CWP site to a precinct if at least 50% of the area of the precinct is covered by a ward that has a CWP site. Robust standard errors clustered at the police precinct level in parentheses. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

While results are potentially consistent with both of these explanations the fact that estimates are larger and more precisely estimated for property crime tend to suggest that the program is reducing crime by providing job safety. Estimates are larger and more precise with the ward matching strategy than with municipality matching and range from a 3.5% - 10% reduction in the total number of crimes to mining value elasticity. These findings suggests that the CWP enables workers to insure themselves against the negative income/employment shock caused by reductions in mining activity and therefore engage less in crime.

The key identification assumption for this exercise is that the timing of the roll-out of the CWP program is not related to a precinct's exposure to mineral price shocks.[38] As discussed in Section 2.3, such a response is unlikely since the establishment of a new CWP site requires an extensive consultation and verification process. This makes it hard to quickly establish new sites in response to changes in local conditions. In addition, evidence in Section 2.3 suggests that the roll-out of new sites is largely depending on supply-side constraints on the financing provided by the central government (as opposed to local needs). To formally investigate the empirical support for this assumption, we perform a set of additional test reported in Table B10 in the Appendix. First, we explore how the value of mining activity in a locality is related to the establishment of CWP sites in the cross-section (using our two definitions of the CWP roll-out). These results, reported in Columns (1) and (3) show that the likelihood of getting a CWP site is not significantly different across areas with higher and lower levels of mining value. While this is reassuring, we might still be concerned that changes in mining intensity (booms or busts) would be driving the likelihood of

[38]Note that this identification assumption is less demanding than that for identifying the overall impact of the program on crime, which requires the standard parallel-trends assumption.

establishment of a CWP program. We test this by estimating Equation 2 with the CWP site identifiers as outcome variables. Also this specification shows that changes in mining value has no statistically significant impact on the likelihood of having an active CWP site - the two different CWP site identifiers show point estimates in different directions. Taken together the results suggest that CWP sites are not established in response to changes in mining activity.

To further empirically evaluate the validity of the identification assumption, we estimate an event-study version of Equation 3. More specifically, we estimate:

$$y_{it} = \alpha_0 value_{it} + \sum_{j=-m, j\neq -1}^{q} \beta_j cwp_{it}(t=k+j) + \sum_{j=-m, j\neq -1}^{q} \theta_j cwp_{it}(t=k+j) \times value_{it} + \gamma_i + \lambda_{mt} + \epsilon_{it}, \quad (4)$$

where k is the time of CWP adoption in precinct i. Our primary interest is to estimate the θ_j parameters. We follow standard practice and set the year before the adoption of CWP as baseline. Results are estimated from at least 3 years prior to at most 1 year after the installment of a CWP site. We are not able estimate additional post-program lags since the CWP program was only initiated at the end of our sample period.

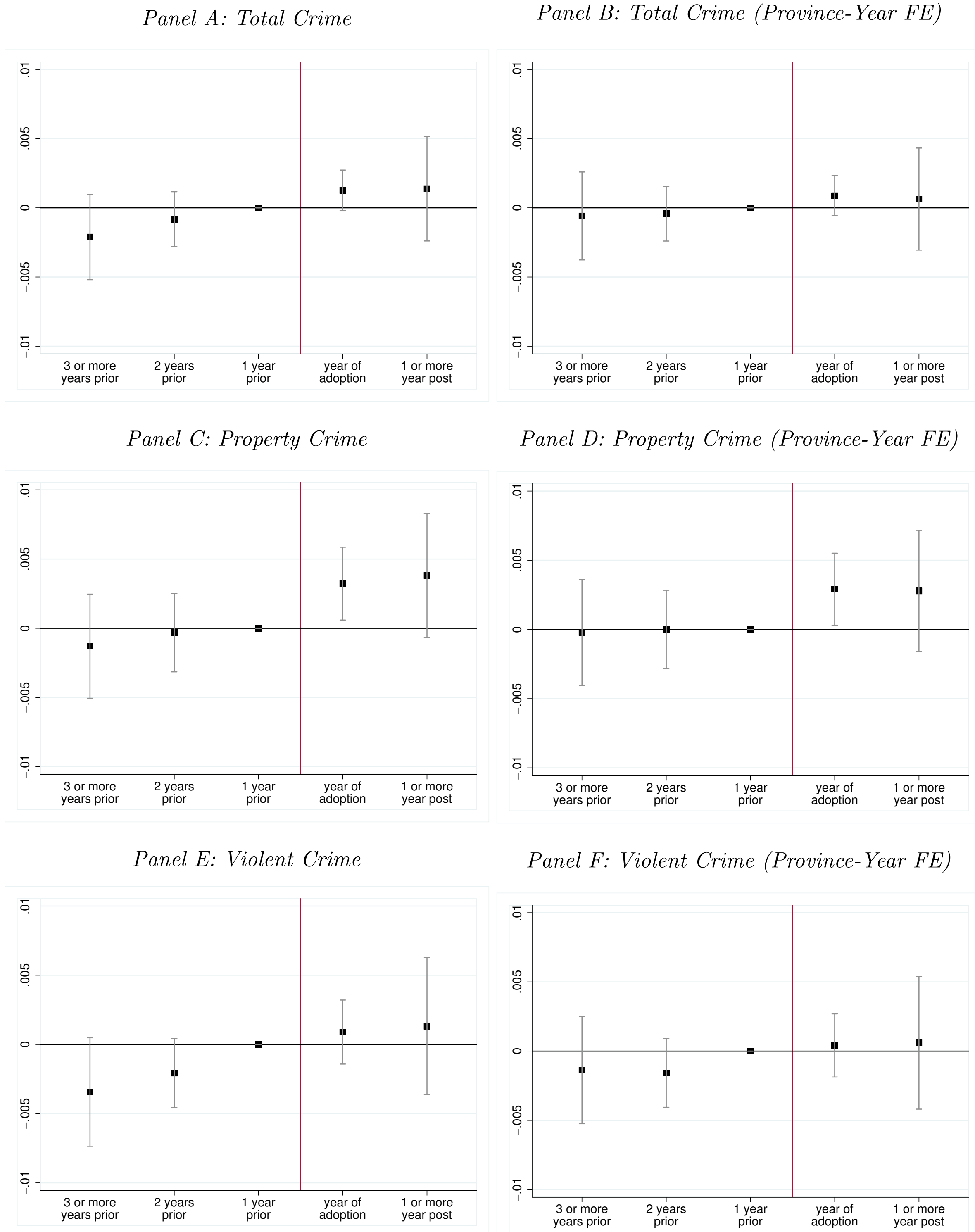
Figure 3 plots the coefficients for the interaction terms (the θ_j) around the introduction of the community work program. Panels A, C and E report results for the total number of crimes, property as well as violent crimes respectively. As can be seen from these figures results are only statistically significant at conventional levels for property crime at the time of CWP adoption. Estimates for subsequent years are of a similar magnitude, but less precisely estimated. One concern with these graphs is that there is some indication for an underlying positive trend for total and violent crime. To deal with this and ensure that this is not affecting our results, we estimate a second specification in which we introduce province by year fixed effects to deal with differential underlying trends (reported in panels B, D and F). For these specifications there is no longer any indication of a pre-trend in any of the specifications (estimates before the adoption of the program are very close to zero) and the estimate for the year of adoption is still significant and of a similar magnitude. This suggests that the reduced response to price shocks observed for property crime is indeed driven by the community work program and not by differential trends in the areas where the CWP program was implemented.

7 Relationship to Conflict Literature

As discussed above, earlier studies have found that natural resources can lead to increased violent grabbing, appropriation and conflict. To investigate whether this relationship holds true also in our setting, we collect geographical data on conflict events from ACLED and match these to the precincts. Table B11 reports results from estimating our baseline specification for this outcome. Columns (1)-(3) in Panel A show estimates for the total number of ACLED events, the inverse hyperbolic sine transformation of the number of events and a dichotomous variable indicating any event. All these point estimates are positive, but not statistically significant at conventional levels. The point estimates are smaller, but of a broadly similar magnitude to those reported by Berman et al. (2017).[39] This finding suggests that the causal effect of resource value on crime is different from the effect on conflict. However, it should be noted that given the relatively stable political situation in South Africa during our sample period this outcome is recording different types of events than in many other African countries. Most of the ACLED events in South Africa during our sample

[39]Note that the baseline specification reported by Berman et al. (2017) is slightly different. The corresponding coefficients estimates are 0.25, 0.09, 0.045 (reported in Table 2 and 11 in Berman et al. (2017)).

Figure 3: CWP Timing



Notes: This figure reports the estimates and 95% confidence intervals from the event study version of Equation 3 presented in footnote 28. Each panel reports estimates from a separate regression and reports the coefficients on the interaction term between a variables indicating pre and post CWP adoption and the value of mining production (the θ_j coefficients). Panels A, C and E including the baseline set of fixed effects, while Panels B, D and F also control for province-year fixed effects to deal with potential differential province trends.

period are either riots, protests or violence against civilians. Panel B of the same table shows that these results also hold for the different ACLED sub-categories.

8 Concluding Remarks

It is widely documented that natural resource wealth can have detrimental effects on social, economic and political outcomes. We contribute to this line of research by investigating how mineral wealth shapes criminality.

Overall, we paint a somewhat more positive picture than previous studies. By exploiting changes in the value of mineral resources stemming from fluctuations in international mineral prices, we show that higher mining wealth leads to a reduction in the total number of crimes committed. We document that this effect is driven by changes in property crime. An analysis of the mechanism suggests that increased mining wealth can support local job creation and thereby increases the opportunity cost of engaging in crime (in line with Becker, 1968). We find no evidence that increased mining wealth improves the government's crime prevention capacity.

On the flip side, our results suggest that mineral production is sensitive to fluctuations in demand of internationally traded minerals. We document that exogenous price shocks have a significant impact on the probability that industrial mines close down, which can create surges in local crime levels. Providing resilience against such price shocks is thus important from a policy perspective.

Finally, we study one potential policy solution to decouple crime from fluctuations in international mineral prices – providing guaranteed employment. To investigate this we exploit the roll-out of the community work program implemented in South Africa between 2008-2012. We show that this program reduces the sensitivity of crime to changes in international mineral prices. Thus, our findings suggest that social programs can help societies deal with some of the negative consequences caused by volatile extractive industries.

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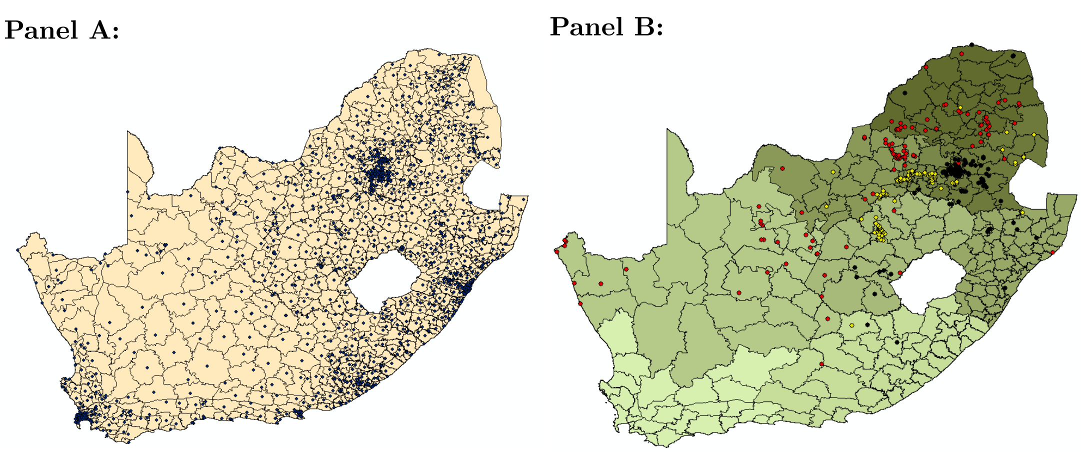
Appendix

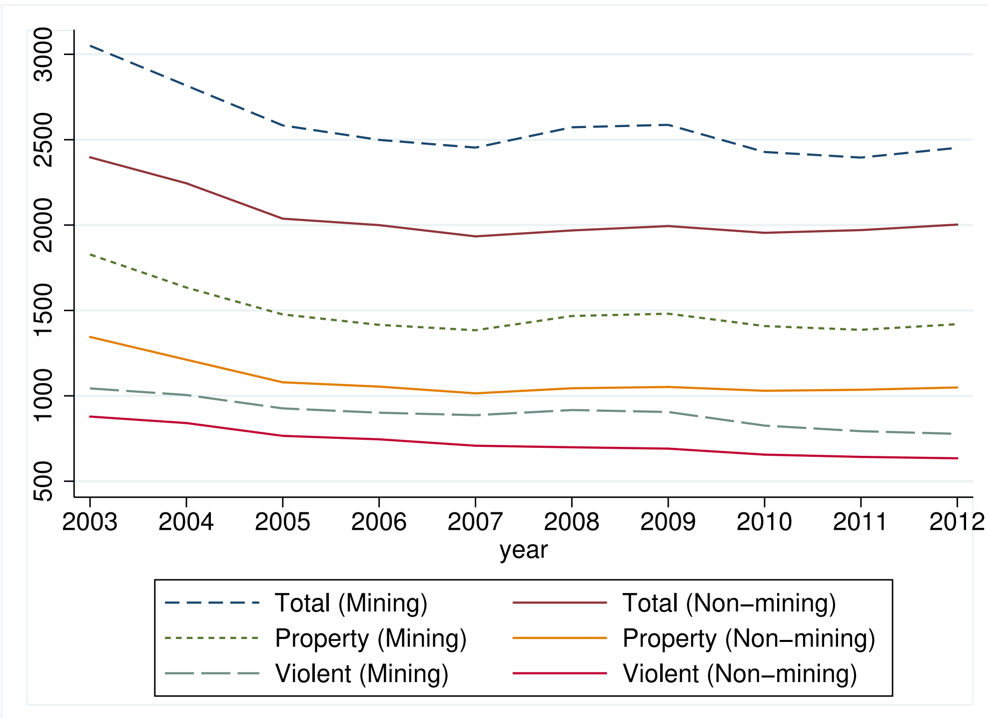
A Additional Figures

Figure A1: Police Stations and Mines in South Africa



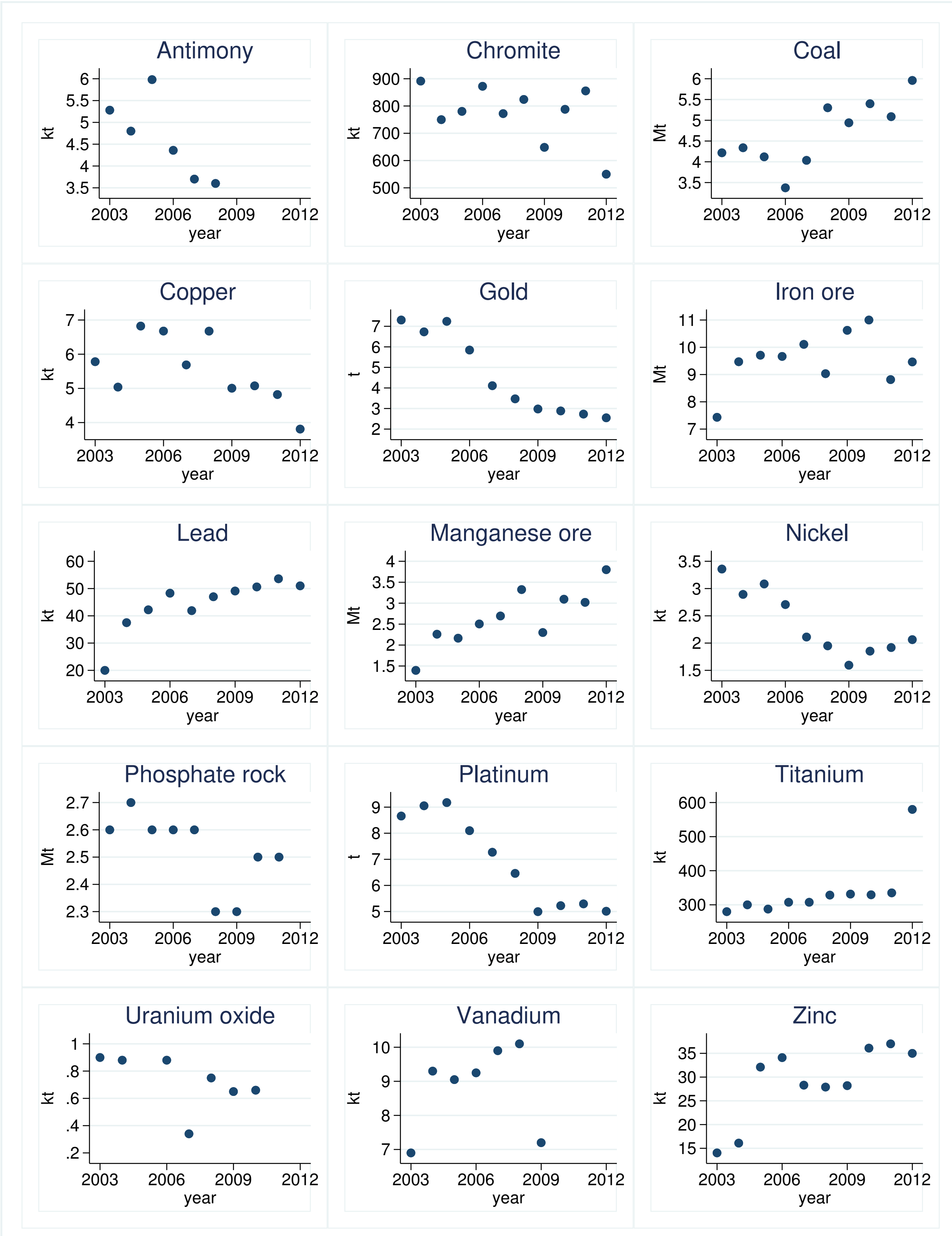
Notes: Panel A shows a map of all police station as well as the borders of all police precincts in 2003. Panel B shows a map of the locations of all mines in South Africa for which data is available. Gold mines are illustrated with yellow points and coal mines with black points, whereas all other mines are illustrated with red points. The map also shows municipality borders as defined in the 2011 census and provinces are color coded.

Figure A2: Crime Trends in Mining and Non-mining Precincts



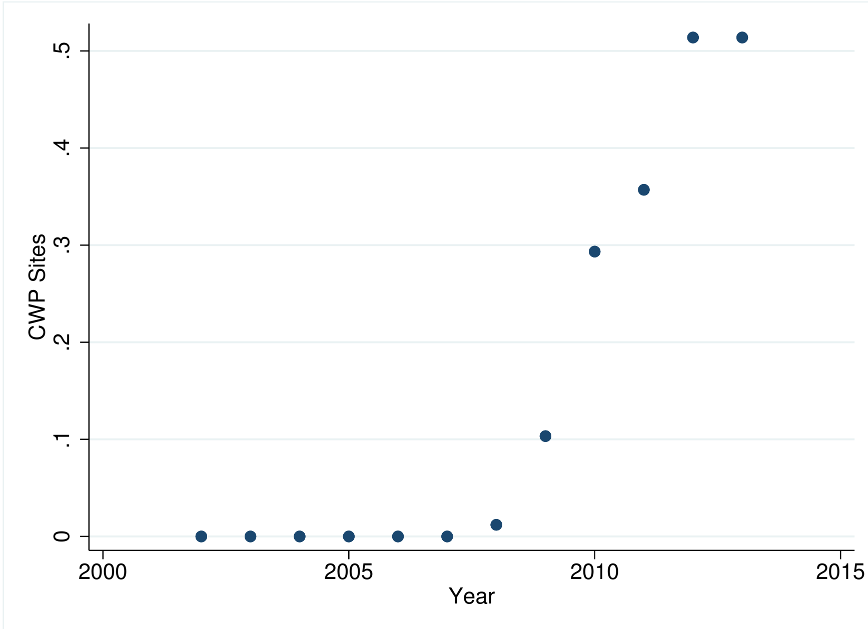
Notes: This figure shows how the total number of crimes, the number of violent crimes as well as the number of property crimes have developed during the sample period in precinct that had an active mine at baseline (dashed lines) as well as precincts that did not have an active mine at baseline (solid lines).

Figure A3: Aggregate mineral production in South Africa



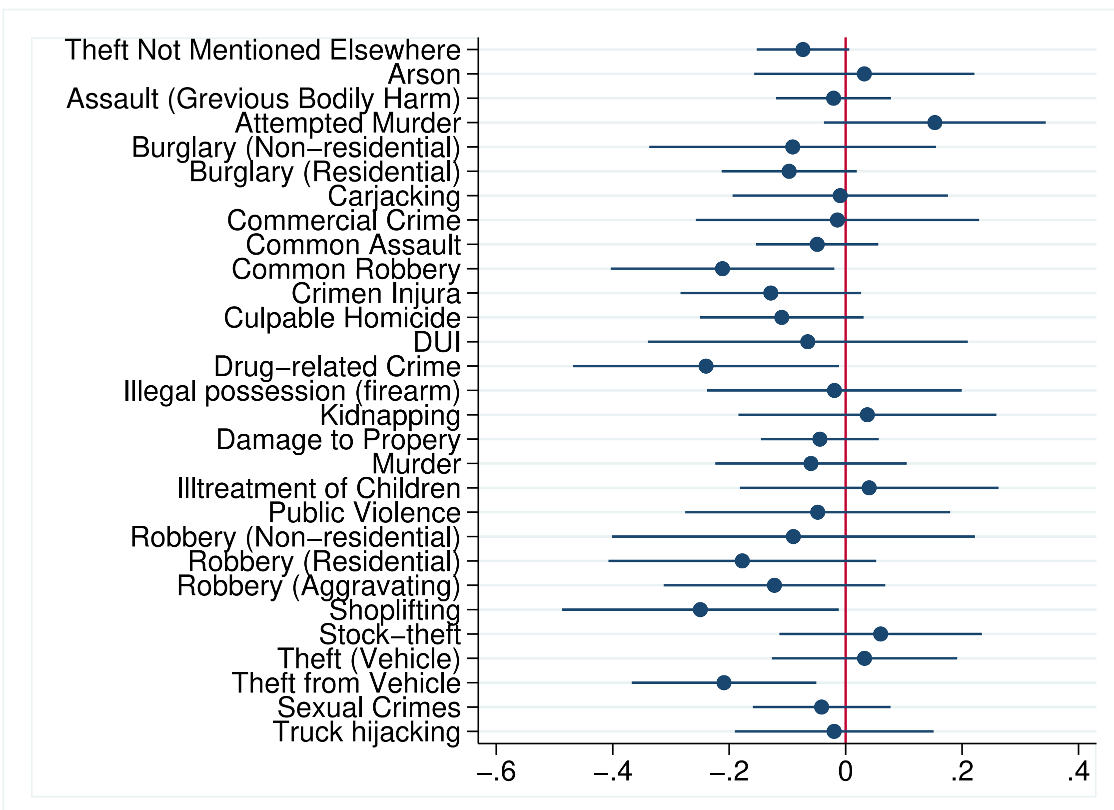
Notes: These graphs show the average annual mineral production per mine in South Africa for the main minerals used in the analysis. Note that this graph is for illustration purposes only, since this variation is not exploited for identification (see Section 3.2). As shown in the graph, production volumes are not always reported and information is therefore missing for some years for antimony, phosphate rock, uranium oxide and vanadium.

Figure A4: Share of Precincts with a CWP Site in the Municipality



Notes: This graph shows the roll-out of the CWP program over time by plotting the share of precincts with at least one CWP site in the municipality where the police station is located.

Figure A5: Resource Values and Crime, by crime category



Notes: This figure reports the estimates and 95% confidence intervals on the mining value variable from separately estimating Equation 2 for each crime category outcome.

B Additional Tables

Table B1: Crime Index and Natural Resource Dependence (% of GDP) by Quintiles

Country	**Crime Index**	**Natural resource dependence** (measured as % of GDP) by Quintiles
Venezuela	84.36	5
Papua New Guinea	80.04	4
South Africa	77.29	4
Afghanistan	76.97	2
Honduras	76.65	3
Trinidad and Tobago	72.43	4
Brazil	68.31	3
Guyana	68.15	5
El Salvador	67.84	2
Syria	67.42	5
Jamaica	67.2	3
Namibia	66.12	3
Angola	65.74	4
Peru	65.65	4
Bangladesh	63.82	2
Nigeria	63.27	4
Bahamas	62.74	1
Libya	62.27	5
Argentina	62.26	3
Kenya	61.73	3

Notes: The crime index data is per capita and comes from World Population Review. The natural resource dependence data is based on statistics by The World Bank, with the quintile level forthcoming in Baum and Benshaul-Tolonen (2021). The second quintile has a dependency of 0.18-1.03%, quintile 3 (1.19-3.48%), quintile 4 (3.57-11.63%), and quintile 5 (11.94-46.44%).

Table B2: Summary Statistics

	(MEAN)	(SD)	(MIN)	(MAX)	(OBS)
Panel A: Full Sample					
Total Crime	2101.633	3053.966	4	40813	10840
Property Crime	1129.854	1822.098	1	23075	10840
Violent Crime	742.612	1047.808	0	15245	10840
Total Crime/PC	72.234	641.776	2	24794	10830
Property Crime/PC	44.503	519.582	1	21532	10830
Violent Crime/PC	19.117	41.316	0	1545	10830
Mining Value (million US $)	62.805	297.827	0	5485	10840
Mining Value (million US $) $_{0-10km}$	109.913	398.317	0	7680	10840
Mining Value (million US $)$_{10-20km}$	129.670	384.408	0	4388	10840
Open (0/1)	0.008	0.092	0	1	10840
Close (0/1)	0.007	0.081	0	1	9756
ACLED	0.086	0.280	0	1	10840
SAPS (0/1)	0.036	0.187	0	1	10840
SAPS Budget (million)	34.286	36.006	0	145	10840
QLFS Local Employment Share	0.695	0.190	0	1	2398
CWP	0.128	0.334	0	1	10840
Panel B: Active Mining at Baseline					
Total Crime	2583.980	2935.249	46	17947	1040
Property Crime	1490.277	1889.088	11	11630	1040
Violent Crime	898.180	941.401	10	5502	1040
Total Crime/PC	51.682	31.902	7	212	1040
Property Crime/PC	29.939	22.754	2	151	1040
Violent Crime/PC	17.603	8.822	3	67	1040
Mining Value (million US)	654.618	733.182	0	5485	1040
Open (0/1)	0.061	0.239	0	1	1040
Close (0/1)	0.051	0.221	0	1	936
ACLED	0.106	0.308	0	1	1040
SAPS (0/1)	0.047	0.212	0	1	1040
SAPS Budget (million)	35.012	38.287	0	145	1040
QLFS Local Employment Share	0.723	0.164	0	1	262
CWP	0.117	0.322	0	1	1040
Panel C: No Active Mining at Baseline					
Total Crime	2050.445	3061.982	4	40813	9800
Property Crime	1091.604	1810.737	1	23075	9800
Violent Crime	726.103	1057.174	0	15245	9800
Total Crime/PC	74.417	674.890	2	24794	9790
Property Crime/PC	46.050	546.413	1	21532	9790
Violent Crime/PC	19.277	43.358	0	1545	9790
Mining Value (million US)	0.000	0.000	0	0	9800
Open (0/1)	0.003	0.054	0	1	9800
Close (0/1)	0.002	0.043	0	1	8820
ACLED	0.084	0.277	0	1	9800
SAPS (0/1)	0.035	0.184	0	1	9800
SAPS Budget (million)	34.209	35.756	0	145	9800
QLFS Local Employment Share	0.691	0.192	0	1	2136
CWP	0.129	0.335	0	1	9800

Notes: This tables reports the summary statistics for the main variables used in the analysis. Panel A report statistics for the full sample, while Panel B reports the same information for precinct with an active mine at baseline and Panel C for precincts without any active mine at baseline (i.e. for precincts without any variation in our measure of mining value).

Table B3: Main Metals in the Dataset and Share of Mines

Main Metal/Mineral	**Share of mines (%)**
Gold	36.09
Coal	28.13
Platinum	10.09
Chromite	7.95
Iron	1.53
Vanadium	1.53
Copper	1.22
Manganese	1.22
Phosphate	0.92
Titanium	0.92
Zinc	0.61
Nickel	0.31
Lead	0.31
Antimony	0.31
Uranium	0.31

Notes: Excludes diamond mines.

Table B4: Annual Openings and Closures 2002 – 2012

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Openings	6	11	10	6	7	19	5	13	5	11	6
Closures	7	13	6	14	4	6	5	11	5	4	3

Notes: Excludes diamond mines.

Table B5: Fixed Effects: Mine Openings and Closings

	(1)	(2)	(3)	(4)
	asinh(Total)	asinh(Property)	asinh(Violent)	asinh(EPR)
Open (0/1)	0.023	0.011	0.028	0.0086
	(0.018)	(0.024)	(0.021)	(0.018)
Close (0/1)	0.028	0.037*	-0.00095	-0.038*
	(0.023)	(0.020)	(0.040)	(0.021)
Precinct FE	Yes	Yes	Yes	Yes
Mining Precinct-Year FE	Yes	Yes	Yes	Yes
Mean Outcome	7.51	6.75	6.55	0.64
Observations	9756	9756	9756	2375

Notes: This table reports the associations between dummy variables indicating the opening and closing of any mine in a precinct. Note that we have fewer observations in the these specifications than in our baseline sample since we cannot calculate whether a mine closes down in the last year of our sample period. That would require information about activity in the subsequent production period, which we do not have access to. Robust standard errors clustered at the police precinct level in parentheses. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

Table B6: Heterogeneity Results By Mine Type

	(1)	(2)	(3)	(4)
	asinh(EPR)	asinh(Total)	asinh(Property)	asinh(Violent)
asinh(Mining Value)	0.058**	-0.069*	-0.11**	-0.053
	(0.029)	(0.041)	(0.050)	(0.057)
asinh(Mining Value) × Share UG	0.011	-0.0067	-0.0068	0.022
	(0.042)	(0.069)	(0.073)	(0.088)
Precinct FE	Yes	Yes	Yes	Yes
Mining Precinct-Year FE	Yes	Yes	Yes	Yes

Notes: This table reports the results of estimating our baseline specification for four different outcomes, including an interaction effect for the share of mines in a precinct that are underground. Robust standard errors clustered at the police precinct level in parentheses. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

Table B7: Sample Periods and Minerals with Different Time Trends

	(1)	(2)	(3)	(4)
	asinh(Total)	asinh(Total)	asinh(Total)	asinh(Total)
asinh(Value, excl. Gold)	-0.055*			
	(0.032)			
asinh(Gold Value)	-0.023			
	(0.046)			
asinh(Mining Value)		-0.052	-0.070**	
		(0.043)	(0.030)	
asinh(Value, Inc)				-0.042
				(0.055)
asinh(Value, Dec)				-0.068
				(0.057)
Observations	10840	5420	5420	5420
Sample	Full	Pre 2008	Post 2008	Post 2008
Precinct FE	Yes	Yes	Yes	Yes
Mining Precinct-Year FE	Yes	Yes	Yes	Yes

Notes: This table reports the results of estimating our baseline specification (1) separately for gold mining value, (2) pre-2008, (3) post-2008, (4) for minerals whose price increased or decreased during 2008-2013, with the sample limited to 2008-2013. 2008 is chosen as a cutoff point since mineral prices were affected by the financial crisis. Robust standard errors clustered at the police precinct level in parentheses. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

Table B8: Robustness IV: Resource Value and Crime, alternative specification and variables

	(1)	(2)	(3)
Panel A: Including non-main minerals			
	asinh(Total)	asinh(Property)	asinh(Violent)
asinh(Mining Value, incl. non-main)	-0.053*	-0.087**	-0.029
	(0.031)	(0.037)	(0.039)
Panel B: Berman et. al (2017)			
	asinh(Total)	asinh(Property)	asinh(Violent)
log(price)	-0.070**	-0.11***	-0.039
	(0.031)	(0.038)	(0.040)
Panel C: Crime per capita (asinh)			
	asinh(Total/PC)	asinh(Property/PC)	asinh(Violent/PC)
asinh(Mining Value)	-0.056*	-0.097**	-0.028
	(0.032)	(0.038)	(0.040)
Panel D: Crime per capita			
	Total Crime/PC	Property Crime/PC	Violent Crime/PC
asinh(Mining Value)	-5.55**	-4.03**	-1.47*
	(2.49)	(1.84)	(0.77)
Panel E: # Crimes (count)			
	Total Crime	Property Crime	Violent Crime
asinh(Mining Value)	-330.3***	-230.3***	-89.8**
	(109.7)	(74.9)	(41.7)
*Panel F: Migration*Year FE*			
	asinh(Total)	asinh(Property)	asinh(Violent)
asinh(Mining Value)	-0.067**	-0.11***	-0.033
	(0.032)	(0.038)	(0.038)
*Panel G: SADC Migration*Year FE*			
	asinh(Total)	asinh(Property)	asinh(Violent)
asinh(Mining Value)	-0.080***	-0.12***	-0.050
	(0.030)	(0.038)	(0.038)
Precinct FE	Yes	Yes	Yes
Mining Precinct-Year FE	Yes	Yes	Yes
Observations	10840	10840	10840

Notes: This table presents a set of additional robustness tests for the main crime outcomes. Panels A presents results with a modified mining value variable, which includes non-main minerals produced as well. Panel B presents the main results when using the empirical specification advocated by Berman et. al (2017). Panels C and D use crime per capita outcome variables. Panel E uses incidences of crime (count variable). Panel F and G include fixed effect for migration share in 2003 interacted with year, limited to male migrants from the Southern African Development Community (SADC) countries in Panel G. Robust standard errors clustered at the police precinct level in parentheses. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

Table B9: Resource Value and Crime: Spillovers

	(1)	(2)	(3)
	asinh(Total)	asinh(Property)	asinh(Violent)
asinh(Mining Value)	-0.065**	-0.11***	-0.037
	(0.032)	(0.038)	(0.040)
asinh(Mining Value)$_{0-10km}$	-0.018	-0.0067	-0.013
	(0.023)	(0.027)	(0.028)
asinh(Mining Value)$_{10-20km}$	-0.019	-0.0096	-0.018
	(0.020)	(0.024)	(0.023)
Precinct FE	Yes	Yes	Yes
Mining Precinct-Year FE	Yes	Yes	Yes
Mean Outcome	7.51	6.74	6.54
Observations	10840	10840	10840

Notes: This table reports the results of estimating Equation 2, adding controls for the value of mineral production for mines within 0-10km from the border of the precinct and for the value of mineral production 10-20km from the border of the precinct. Robust standard errors clustered at the police precinct level in parentheses. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

Table B10: CWP Roll-out and Mining Value

	(1)	(2)	(3)	(4)
	CWP	CWP	CWP (Ward)	CWP (Ward)
asinh(Mining Value)	-0.00051	-0.021	0.00049	0.026
	(0.00083)	(0.060)	(0.00047)	(0.036)
Mean Outcome	0.13	0.13	0.021	0.021
Observations	10840	10840	10840	10840
Precinct FE	No	Yes	No	Yes
Mining Precinct-Year FE	No	Yes	No	Yes

Notes: This table reports the results of regressing whether a precinct has an active CWP site or not (using the two different definitions in the main analysis) on the value of mining resources in the precinct. Columns (1) and (3) present the unadjusted correlation between the variables, while columns (2) and (4) mimic equation 2. Robust standard errors clustered at the police precinct level in parentheses. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

Table B11: Additional ACLED Results

	(1)	(2)	(3)	(4)	(5)
Panel A: Aggregate ACLED Outcomes					
	# ACLED	asinh(ACLED)	ACLED (0/1)		
asinh(Mining Value)	0.16	0.046	0.015		
	(0.15)	(0.069)	(0.043)		
Mean Outcome	0.27	0.12	0.086		
	Battle	**Remote Violence**	**Riots**	**Strategic Development**	**Violence Against Civilians**
Panel B: Sub-category ACLED Outcomes					
asinh(Mining Value)	0.0070	-0.0048	0.0089	-0.0030	0.013
	(0.013)	(0.0039)	(0.041)	(0.011)	(0.024)
Mean Outcome	0.0044	0.00074	0.073	0.0020	0.024
Panel C: Police Intervention by Sub-category ACLED Outcomes					
asinh(Mining Value)	0.00074	0	-0.021	-0.0011	0.0097
	(0.010)	(3.2e-18)	(0.029)	(0.011)	(0.011)
Mean Outcome	0.0027	0.000092	0.032	0.0011	0.0030
Precinct FE	Yes	Yes	Yes	Yes	Yes
Mining Precinct-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of estimating Equation 2 for ACLED outcomes. Panel A report estimates on aggregate outcomes. Column (1) report results for the number of ACLED events in a precinct, Column (2) reports the results for the inverse hyperbolic sine transformation of the number of events. Column (3) reports results for any ACLED event. Panel B report estimates for ACLED sub-categories and Panel C for police interventions for different ACLED sub-categories. Robust standard errors clustered at the police precinct level in parentheses. Statistical significance is indicated by *** at 1%, ** at 5%, and * at 10%.

Table B12: South Africa Export Share in 2002

Mineral	Share of total export (%)	Export Rank	Number of Exporters
Vanadium	40.2	1	15
Chromite	39.7	1	38
Manganese	19.8	3	29
Coal	9.7	4	32
Antimony	7.9	3	32
Iron	4.8	5	30
Titanium	4.7	7	43
Gold	4.6	7	68
Platinum Group Metals	3.7	8	35
Uranium*	2.3	10	21
Phosphate	1.1	13	32
Lead	1.0	18	65
Copper	0.5	33	85
Nickel	0.1	21	42
Zinc	0.1	42	60

Notes: This table reports South Africa's share of total export in 2002 by mineral. These statistics have been calculated by the authors using the world mineral statistics provided by the British Geological Survey. We calculate the share of total exports across all sub-commodities (such as metals, oxides and ore) for all minerals except uranium for which export data is not available by the British Geological Survey. * Figures for uranium are instead based on total production volume (rather than export volume) in 2002. This data is provided by the United Nations Energy Statistics Database. This is most likely an upper bound on the total export share. Data from 2019 suggest that South Africa contribute about 0.2% of uranium exports world wide.