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The impact of mining on spatial inequality

Recent evidence from Africa

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Abstract: This paper investigates the relationship between mining and spatial inequality in Africa during 2001–12. The identification strategy is based on a unilateral causation between mining and district inequality. The findings show that when minerals are aggregated, mining increases district inequality. But an analysis of individual minerals shows that mining affects district inequality both positively and negatively, suggesting that mineral wealth can be both a curse and a blessing. Further analysis suggests that these results largely depend on whether mining is active or closed, the scale of mining operations, the value of minerals extracted, and the nature of mining activities—important dimensions for shaping mining policies aimed at bolstering socio-economic development in Africa.

Keywords: mineral resources, mining, spatial inequality, Africa
JEL classification: D63, L71, L72

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1 Introduction

Mineral wealth extraction and its impacts on development outcomes, especially in the developing world, have received considerable attention in the economic development literature. Recent studies have shown the impacts of mineral wealth extraction on economic growth and development (Beny and Cook 2009; Papyrakis and Gerlagh 2004; Van der Ploeg 2011; Venables 2016), conflict and civil unrest (Collier and Hoeffler 1998, 2002, 2005; Lujala 2009; Van der Ploeg 2011), agricultural growth (Andersson et al, 2015; Chuhan-Pole et al. 2015), women's employment (Kotsadam and Tolonen 2015), income and prices of goods (Aragón and Rud 2013), and revenues, public spending, and living standards (Caselli and Michaels 2013). Yet little is known about the relationship between mineral wealth and spatial inequality in resource-rich countries in general, or in producing regions in particular (see e.g., Ross 2007),[1] despite a widely held view that mineral-rich countries often exhibit large inequalities, both vertical and horizontal (see e.g., Auty 2001; Ross 2007).[2]

This paper fills this gap in the literature by examining whether the presence of mineral deposits and mining activities affects spatial inequality. Our main focus is on Africa, a continent endowed with minerals and with recently growing mining activities (Beny and Cook 2009), and where the lack of empirical evidence is persistent and somewhat rooted in the legacy of unreliable and inconsistent data, especially at the local scale (Kim 2008). The analysis builds on two important tenets: first, the theoretical explanations of the causes of spatial inequalities that identify natural geographical advantages (including the presence of mineral wealth) as one key candidate among others (see Kim 2008; Venables 2005); second, a unilateral causation between mining and spatial inequality—the presence of mining deposits and activities influences spatial inequality, and not vice versa—as an identification strategy. With the aid of night-time lights data to measure inequality across space and time, and geocoded mine-level data, we confine our analysis at the district level, effectively allowing us to investigate the within-district inequality effects of mining activities across countries over time.

There were several reasons for our choice of districts as units of analysis. First, by focusing on districts we systematically examined the nexus between mining and spatial inequality in proximity to mines and over time. This is useful for untying the effects of mining on spatial inequality at the subnational level: understanding how mining affects economic activities at local scales, and identifying the drivers of spatial differences between mineral-rich and mineral-poor countries—a needed ingredient for eliciting appropriate policy responses. Second, the use of lower-level geographical administrative units allowed us to control for unobserved country and regional differences, which naturally cannot be handled in a setting where analysis is focused at the country level. In the context of our data, controlling for country and regional fixed effects is important if we are to understand the dynamic effects of mining activities on spatial inequality net of other

[1] Producing regions can typically face forced displacement, population pressure due to in-migration, or environmental pollution and degradation (Akabzaa et al. 2007; Salami 2001), with little or no positive return in terms of higher incomes or better living standards.

[2] Vertical inequality refers to inequality amongst individuals within countries or regions, while horizontal inequality refers to inequality between countries or regions. These inequalities can create frustrations and grievances in producing regions, leading to the so-called resource curse. In a worst-case scenario, attempts to gain more control over natural resource wealth can degenerate into violent regional conflicts or secessionist movements, as in the Democratic Republic of Congo, Indonesia, Myanmar, Nigeria, Sudan, or Yemen. For more detail, see e.g., Bannon and Collier (2003), or Ross et al. (2012).

confounding and unobserved country- and region-specific characteristics, such as institutional structures and the quality of governance across countries.

The empirical analysis is divided into two main parts. In the first part, we estimate the effects of mining across the different minerals available in districts across countries over time. The main goal here is to understand the overall impact of mining activities—regardless of the individual minerals—on district inequality. The second part takes into account the individual minerals available across districts. This approach allows us to disentangle the effects of individual mineral commodities on district inequality. We argue that by separating the effects of individual minerals, our study is able to precisely identify what types of minerals affect spatial inequality, and by extension how they do so. To strengthen our empirical analysis, in both cases we identified and exploited the different sources of exogenous variation (i.e. mining status, mining scale, mining value, and the nature of mining activities) in mining activities at the district level.

We document two key findings. First, when we aggregate the different minerals, mining increased district inequality during 2001–2012. In fact, when we control for constant mineral prices, the regression estimates show that district inequality (measured using lights-based Gini) on average increases by 0.180 and 0.090 Gini points in districts with mineral deposits and mining sites respectively, relative to those with none. The results remain robust even when we use minerals' annual average prices, with an average increase of 0.166 and 0.083 Gini points for districts with mineral deposits and mining sites respectively.

Second, when we analyse individual minerals, the findings show that mining affected district inequality both positively and negatively. On the one hand, the findings show significant positive effects of mining on inequality for districts producing helium, garnet, diatomite, and gold. Since gold is a high-value metal and its prices were steadily on the rise during 2001–12 (see Figure 1), the positive effect can be explained along the lines of Boschini et al. (2007). However, the positive result for helium, garnet, and diatomite can be explained by the effect of steady declines in the prices of these commodities during 2011–12 (see Figure 1), with the underlying assumption that, *ceteris paribus*, price declines potentially led to an overall reduction in income of mineral-rich districts (relative to districts with none), resulting in increased inequality. On the other hand, the findings also show significant negative effects on inequality for districts producing iron ore and nickel, whose prices were on a steady rise during 2001–12 (see Figure 2), suggesting that increases in district incomes potentially led to a negative effect on overall district inequalities.

The findings are even more nuanced when we analyse the previously mentioned sources of exogenous variations. This analysis revealed that in addition to the price effect described above, the effects of mining on district inequality largely depended on whether mines were active or closed, the scale of mining operations, the value of the minerals extracted, and the nature of mining activities. For example, on the one hand, the results show statistically significant increases in inequality in districts with active mines and engaged in the production of low-value, large-scale, and transformational mining activities. On the other hand, the findings depict a negative and statistically significant effect in districts with closed mines or engaged in mineral extraction.

The findings on individual minerals are equally revealing in terms of the effects of the interaction between individual minerals' prices and the mentioned sources of exogenous variation. For example, our findings suggest that inequality increased significantly in districts with active mines producing helium, garnet, tin, and gold, and decreased in districts with active mines producing iron ore. For districts with closed mines, the results show that inequality declined where, amongst others, diamond, cement, platinum, nickel, and tin were produced. Also, the results indicate that inequality increased significantly in districts with low-value minerals (i.e. helium and garnet) and high-value minerals (i.e. gold), and declined in districts producing iron ore and nickel. Further, the positive effect remained for districts producing, among others, helium, garnet, gold, lithium, and manganese at a large scale, while districts engaged in the small-scale production of, for example, barite, bentonite, salt, and graphite experienced declines in the levels of inequality. Finally, results based on the nature of mining activities show closely similar findings.

In general, all the above results are robust both to different model specifications and to the inclusion of various controls such as district, regional, and country fixed effects (which also account for the differences in institutional structures, policies, and quality of governance), rainfall, proxies for agricultural productivity, and districts' spatial locations. Obviously, these nuanced findings are uniquely interesting and can elicit different policy prescriptions. In particular, for example, our finding that precious metals such as gold had statistically positive effects on district inequality resonate with the predictions and findings of Boschini et al. (2007) on the impacts of types of minerals and their appropriability for economic development outcomes. Overall, the main conclusion we draw from these results, also echoing Van der Ploeg (2011), is that mineral wealth and thus mining can indeed be both a curse and a blessing. But whether it is a curse or a blessing largely depends on the types and values of the minerals, and on a number of such important and interrelated factors as status of the mines, scale of operations, nature of mining activities, and values of minerals extracted.

Our paper makes several contributions to the existing literature. We first respond to Ross's (2007: 238) call for additional research on the relationship between natural resources and income inequality, an issue about which 'surprisingly little is known'. As far as the mining-spatial inequality nexus is concerned, our study is the first to our knowledge to offer an extensive empirical investigation across a panel of countries and at lower-level geographical administrative units in Africa. Further, our study contributes to a broader and controversial literature on the causes of spatial inequality, particularly in developing countries. As Kim (2008) and Venables (2005) assert, understanding how natural advantages (e.g., mineral wealth) affect spatial inequality is important for explaining the spatial differences that emerge as countries experience positive economic growth and development, as is the case in Africa. In the same vein, our study resonates with ongoing policy discussions on understanding the link between subnational regional development, spatial inclusion, and structural transformation in Africa (AfDB et al. 2015). Finally, our analysis encompasses a wider geographical coverage—2,182 districts across 653 regions in 38 African countries—thus providing evidence that is more representative and useful for policy than studies with more restricted coverage.

The remainder of this paper proceeds as follows. Section 2 briefly reviews the existing literature on the link between natural resources and socio-economic outcomes. Section 3 presents the data, a brief description of inequality estimation, and the summary statistics. Section 4 presents our empirical model. Section 5 discusses the main results. Section 6 concludes.

2 Related literature

The resource curse relates to the observation that natural-resource-rich countries tend to grow less rapidly than natural-resource-poor countries; or more broadly, that resource-rich countries tend to have worse development outcomes compared with resource-poor countries. This finding is documented in Sachs and Warner's (1995) seminal paper, as well as in a number of subsequent studies (e.g., Arezki and Van der Ploeg 2011; Gylfason et al. 1999; Mehlum et al. 2006; Sachs and Warner 1997, 2001). Sachs and Warner (1995) use growth in per-capita GDP as the dependent variable, and measure natural resource abundance using the share of primary-product exports in

GDP. They find that economies with a high ratio of natural resource exports to GDP (in the base year, 1970) tended to grow slowly during the subsequent 20 years.

Ding and Field (2005) suggest a distinction between resource dependence and resource abundance.[3] Exports of primary resources as a share of GDP or of total exports—used in Sachs and Warner (1995) and other studies—is viewed as measuring resource dependence rather than resource abundance. Using the World Bank's estimates of natural resource capital, Ding and Field measure resource dependence as the share of natural resource capital in total capital, and resource abundance as natural resource capital per capita. Their results indicate that resource endowment has a positive impact on economic growth, whereas resource dependence has a negative impact. Similarly, Brunnschweiler and Bulte (2008) find that resource dependence does not affect growth, while resource abundance positively affects growth.

The previous two studies suggest that the direct impact of resource wealth on growth is not a robust and generalizable phenomenon. However, there exist various 'indirect' channels through which natural resource wealth can affect development outcomes. A first negative impact of natural resource wealth relates to the so-called Dutch disease.[4] While earlier studies found no evidence of the Dutch disease in the manufacturing sector (see e.g., Gelb 1988; Spatafora and Warner 1999), more recent empirical evidence has become available. Harding and Venables (2016), using data on 41 resource exporters for 1970–2006, show that a dollar of resource revenue leads to a decrease in non-resource exports by approximately 75 cents and an increase in imports by 25 cents, with the manufacturing sector experiencing the largest crowding-out effect. Similarly, Ismail (2010) finds results indicating that, in oil exporting countries, a 10 per cent oil windfall is on average associated with a 3.4 per cent fall in value added across manufacturing. Evidence of the Dutch disease is also found in Brazil, where oil discoveries and exploitation led to service expansion and industry shrinkage (Caselli and Michaels 2013).

A concentrated distribution of natural resource rents can increase inequality (between rich and poor, or across regions of a country). For example, resource dependence is found to be correlated with a larger Gini index of inequality (Gylfason and Zoega 2003), while Fum and Hodler (2010) suggest that natural resources increase income inequality in ethnically divided societies but not in ethnically homogenous societies. Increased inequality can lead to frustration and social unrest, due for example to differences between actual and expected benefits (Ross 2007), particularly in producing regions. In this regard, Collier and Hoeffler (1998, 2002, 2005) show that natural resources significantly increase the chances of civil conflict in a country. Diamonds (Lujala 2009), oil (Fearon 2005; Fearon and Laitin 2003; Humphreys 2005; Ross 2004), and narcotics (Angrist and Kugler 2008) also pose the highest risks of war.

Mehlum et al. (2006) find that the resource curse applies typically in countries with rent-seeker-friendly institutions, but not in countries with producer-friendly institutions. Likewise, Boschini et al. (2007) find evidence suggesting that resource-rich countries experience a curse only when institutions are poor; in contrast, sufficiently good institutions can turn resource abundance into a blessing. Papyrakis and Gerlagh (2004) also show that natural resource wealth has a negative

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[3] They point out that a resource-abundant country such as the United States is not resource-dependent (i.e. has a small primary sector), while a resource-scarce country such as Burundi can be heavily dependent on primary resources.

[4] Natural resource exports generate significant foreign reserves, resulting in exchange rate appreciation. Such currency appreciation affects the international competitiveness of the traditional export sectors (agriculture or manufacturing), potentially leading to their shrinking in favour of the natural resource sector and non-tradable sector. This phenomenon is called the 'Dutch disease', as the discovery of natural gas in the North Sea caused the manufacturing sector in the Netherlands to decline (see e.g., Ellman 1981).

impact on growth, but does so through transmission channels such as investment, corruption, openness, terms of trade, and schooling.

Finally, the literature suggests that the impact of resources differs according to their type. Boschini et al. (2007) find results indicating that when countries are rich in diamonds and precious metals, both the positive and negative effects of natural resources are larger. This result can be explained by 'appropriability' characteristics (i.e. high value, easy storage, easy transportation or smuggling, and quick sale), which make these types of natural resources more prone to rent-seeking behaviour, corruption, and conflict. Easily appropriable point-source resources, such as oil, diamonds, and minerals, are more likely to be harmful to institutional quality and growth than diffuse resources such as agriculture (rice, wheat, and animals), whose rents are spread throughout the economy (Auty 1997; Isham et al. 2005; Mavrotas et al. 2011; Woolcook et al. 2001).

Most of the previous studies are cross-country analyses. A distinctive feature of our paper is that we use panel data on mineral deposits to estimate inequality at district level during 2001–2012, a period also characterized by relatively high growth in Africa. Gennaioli et al. (2014) argue that there are large regional differences within countries that need to be understood; the use of subnational panel data therefore accounts for intra- and inter-regional differences that can confound estimates. From an estimation standpoint, our study is also free from omitted variable bias emanating from the large unobservable differences that are usually present in cross-country studies.[5]

3 Data and district inequality estimation

3.1 Data

We combine an array of data sources to construct a data set with the relevant important variables for estimating the effects of mining activities on district inequality: the National Oceanic and Atmospheric Administration, National Geophysical Data Center (NOAA-NGDC)[6] for data on night-time lights intensity; the United States Geological Survey (USGS)[7] for data on the spatial location of mineral deposits and mining activities in Africa and historical US mineral prices; the United States Global Land Cover Facility (GLCF)[8] for the Normalized Difference Vegetation Index (NDVI)—a proxy for agricultural productivity. We also use Tropical Applications of Meteorology using Satellite Data (TAMSAT)[9] to extract data on rainfall—a proxy for climatic shocks. Finally, we extract population data from the Gridded Population of the World (GPW v4).[10] Since our units of analysis are districts, the combined data set constitutes three clustered levels—districts, regions, and countries.

[5] Lederman and Maloney (2008) consider cross-country heterogeneity a key reason for the elusiveness of empirical evidence on the resource curse.

[6] The data are available at: www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html (accessed 16 June 2014).

[7] The data are available at: minerals.usgs.gov/minerals/pubs/country/africa.html (accessed 5 July 2015).

[8] Sponsored by the University of Maryland, NASA, and Global Observation Forest and Land Cover Dynamics. Available at: glcf.umd.edu/data/lc/ (accessed 30 December 2016).

[9] The data are available at: www.met.reading.ac.uk/~tamsat/cgi-bin/data/rfe.cgi (accessed 5 July 2015).

[10] Available at: beta.sedac.ciesin.columbia.edu/data/collection/gpw-v4 (accessed 23 August 2015).

NOAA-NGDC data include annual time-series night-time lights intensity data, which are globally recorded across countries daily from 20:30 to 22:00 local time by a satellite orbiting the earth. The use of this data set follows recent literature that attempts to circumvent the absence of reliable and consistent subnational data (for a detailed discussion, see Chen and Nordhaus 2011; Henderson et al. 2012), particularly in Africa.[11] These data come in three main formats: cloud-free, average visible, and stable light composites. We use the stable light composites, which are clear of ephemeral events, background noise, summer light, and auroral activities. Moreover, we remove gas flares to eliminate potential bias in our estimates.

USGS data provide spatial locations of mineral deposits, and details of the types of mineral activities taking place across Africa (see Table 2 in Appendix 1 for the list of countries). These include the status (active or closed) of the mines; the type of mining activity (extraction or transformation); whether minerals of high or low value are extracted; whether the mining operations are large or small scale. These characteristics present unique exogenous variation that we exploit, as discussed in the empirical strategy. In general, we match USGS spatial mineral[12] data to 2,182 districts in 653 regions across 38 African countries. We measure mineral wealth using a binary indicator for districts with mineral production. However, one limitation of our study, as detailed in Section 5, is the lack of mine's actual production, which would have been useful in accounting for total mineral production and revenues for an unbiased estimates of mining activities on district inequality in Africa.

To partially address this limitation, we take advantage of the available time-series minerals prices data and use them as numeraires for minerals at the district level across countries over time. We thus use mineral prices data for the United States since 1900 available from USGS.[13] These price data are recorded in constant prices and annual average prices. As detailed in the empirical strategy, we use the constant prices to examine the main impacts of minerals' constant unit dollar values on district inequality in Africa. We then use annual average prices for robustness checks on our main results. Our analysis is strengthened by the inclusion of mineral price data, since we are better able to account for the effects of mineral prices' volatility on spatial inequality in Africa.

GLCF data on NDVI[14] were used to construct a measure of district-level vegetation, which has been shown to be a good proxy for agricultural output (see e.g., Labus et al. 2002 Ren et al. 2008).[15]

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[11] For example, Elvidge et al. (2009) use night light data to construct a global poverty map, while Elvidge et al. (2012) develop a 'night light development index' to measure human development and track the distribution of wealth and income across countries. Other studies have used light data to measure economic growth (Henderson et al. 2012), income per capita (Alesina et al. 2015; Chen and Nordhaus 2011; Gennaioli et al. 2014; Hodler and Raschky 2014; Michalopoulos and Papaioannou 2013), and more recently regional income inequality (Mveyange 2015).

[12] Our constructed data set contains over 40 mineral types. Using the standard international trade classification (SITC), we group these mineral types into 25 major types, as shown in Table 1 in Appendix 1.

[13] We refrained from using mineral prices data from the Global Economic Monitor (GEM) of the World Bank because these do not cover all commodity categories in our sample, making the analysis less comparable. However, when we compare a similar set of minerals prices from the GEM and USGS, the overall correlation is 0.93 (unreported), suggesting that the use of US mineral prices is not unreasonable.

[14] It is calculated as NDVI = (NIR - Red) / (NIR + Red), with NIR being near infrared (technical detail available at: earthobservatory.nasa.gov/Features/MeasuringVegetation/measuring_vegetation_2.php, accessed 18 November 2014). Similarly to Andersson et al. (2015), we also use the MODIS Land Cover Type product (MCD12Q1) to extract the NDVI. These data are available for the period 2001–2012, and are provided at a 16-day temporal resolution and a 250 m spatial resolution, making it possible to pair with other data at the district level.

[15] For example, NDVI has been shown to be a good measure of vegetation greenness, primary productivity of vegetation, and leaf area index. NDVI is also useful for evaluating the evolution of vegetation cover over time (see Andersson et al. 2015 for details and more sources on technical studies in this area.)

High NDVI suggests a favourable vegetation landscape relative to low NDVI. NDVI is handy as a proxy, because consistent data on agriculture productivity across all districts in Africa are difficult to find. Obviously, district inequality is likely to be correlated with agriculture—a dominant sector in Africa. Andres and Ramlogan-Dobson (2011) and Chong (2004) assert that income distribution is relatively equally distributed across agriculture-dependent economies. We therefore control for the district NDVI standard deviation to account for this fact.

Using TAMSAT data, we constructed annual district rainfall averages and standard deviations aggregated from monthly rainfall averages data. We use rainfall data in two ways: first, as a control for climate variability, and second, as a proxy for agricultural productivity variations, similar in spirit to Miguel, Satyanath, and Sergenti (2004).

Finally, we used Gridded Population of the World (GPW v4) data to construct data on district population counts. At a grid cell resolution of 30 arc-minutes (approximately 1 km at the equator), the GPW provides estimates of population count between 1990 and 2020 at a 5-year interval. We extracted these data at the district level and followed Hodler and Raschky (2014) to linearly interpolate the data to estimate population counts for the missing years, in turn allowing us to have population counts for the period 2000–2015.

3.2 District inequality estimation and trends

To estimate district inequality using night-time lights data, we followed Mveyange (2015) to calculate inequality indices for 2,182 districts in 653 regions across 38 countries in Africa. We computed several measures of district inequality as outcome variables: Gini and the entropy measures (mean logarithmic deviation (MLD) and Theil)). These measures have several desirable properties, e.g., symmetry, mean independence, Pigou-Dalton transfer sensitivity, and population size independence (Haughton and Khandker 2009). However, our main results are based on Gini—a commonly and widely used measure of inequality.

To calculate Gini at the district level, we identified (based on geographical administrative units' data from the Global Administrative Areas database[16]) and cut countries' districts into 0.01 square decimal degree grid cells (about 1.1 km^2 at the equator—an equivalent to the size of a town or village). We then exploited the spatial and temporal variation of light intensity across these grid cells to estimate average inequality at the district level across countries for all the years between 2001 and 2012. We calculate Gini[17] as follows:

$$Gini = \frac{n}{n-1} * \left(\frac{\sum_{i=1}^{n}(2i-n-1)*y_i}{n^2 P}\right) \qquad [1]$$

[16] Available at: www.gadm.org/ (accessed 16 July 2014).

[17] Similar to Damgaard and Weiner (2000).

where i is grid cell rank order, n is total number of grid cells, y_i is grid cell value light intensity per capita, and P is grid cell population count. For the robustness checks we use the entropy[18] measures of inequality and a measure of spatial inequality proposed by Bonet (2006).[19]

3.3 District inequality trends and summary statistics

Figure 3 plots the average trends of district light intensity Gini between 2001 and 2012. The figure shows the variation across districts with no mining activities, with active mines, and with closed mines. The figure suggests that overall there was a modest decline in spatial inequality in Africa between 2001 and 2012. The figure also reveals a clear difference in spatial inequality between districts with mining activities and those with none, inequality in the former being higher by a considerable margin. When districts with mining activities are divided into active mines and closed mines, the figure suggests that districts with closed mines experienced relative higher inequality than districts with active mines.

Turning to the summary statistics, Table 3 describes the composition of the mining sites based on the previously mentioned exogenous variations: status, scale, values, and types of mining activities. Overall, the table shows that mining sites constitute 17.2 per cent of all 2,182 districts in our sample during 2001–2012. Moreover, for the status of mining activities, the table shows that out of the 17 per cent, active mines constitute about 15.3 per cent, and closed mines about two per cent. Classifying the districts' mining sites by scale of mining operations, the table further shows that mining operations in Africa are predominantly large scale (about 16.2 per cent), with small-scale operations constituting only one per cent. This is not surprising in a sector that is capital intensive and on a continent where the mining sector has attracted significant direct foreign investment in recent years. Whereas most of the operations are large scale, the table shows that most of these districts' operations are extractive industries (12.4 per cent) and of low value (13.4 per cent). High-value minerals and transformation industries constitute a small share—3.8 and 4.8 per cent respectively—of districts where mineral deposits and mining activities are present or closed.

Table 4 reports the summary statistics for all variables of interest in our analysis. These descriptive statistics cover the period 2001–2012. Overall, the table indicates that except for Gini, rainfall, NDVI, and population sizes, the dispersion of average district MLD, Theil, and mineral prices (in logarithms) varies quite considerably around their respective means. In the next section we present our empirical strategy.

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[18] MLD is calculated using the following formula: $MLD = \frac{1}{N}\sum_{i=1}^{N} ln\left(\frac{y_i}{\bar{y}}\right)$ and $Theil = \frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\bar{y}} ln\left(\frac{y_i}{\bar{y}}\right)$, where y_i is grid cell value (i.e. light intensity per capita), $\bar{y}$ is the average grid cell lights, and $N$is the population size within the grid cells.

[19] Defined as $\left|\frac{LPC_{d,t}}{LPC_{c,t}} - 1\right|$ where, c is country, d is district, t is year, $LPC_{d,t}$ is an average lights per capita at the district level, and $LPC_{n,t}$ is average lights per capita at the country level. Bonet (2006: 668) asserts that this measure of spatial inequality is based on the concept of relative lights per capita, with perfect equality achieved with the equality of district and national average lights per capita.

4 Empirical strategy

This section describes the empirical strategy we use to estimate the effects of mineral resources on district inequality. The analysis relies on panel data across districts during 2001–2012. Since the main covariates of interest are dummies, the first difference models of panel data analysis are inappropriate. Thus the empirical framework uses linear fixed effect estimators (i.e. least square dummy variable—LSDV) to model and estimate the effects of mining activities on district inequality. One natural advantage of LSDV is its ability to address endogeneity concerns. Given the hierarchical nature of our data, the use of LSDV is handy for capturing confounding and unobserved country and regional fixed effects in addition to district fixed effects, thus purging our estimates of any time-invariant unobservable biases. Our baseline model thus takes the following forms:

$$DI_{c,r,d,t} = \alpha Mine_{c,r,d,t} + X'_{c,r,d,t}\beta + Price_{m,t} + \mathrm{T}_t + \Psi_i + \Gamma_{c,t} + \epsilon_{c,r,d,t} \quad [2]$$

$$DI_{c,r,d,t} = \vartheta Intensity_{c,r,d,t} + X'_{c,r,d,t}\varphi + Price_{m,t} + \mathrm{T}_t + \Psi_i + \Gamma_{c,t} + \varepsilon_{c,r,d,t} \quad [3]$$

where DI stands for district inequality (measured using spatial lights Gini index), c, r, d, t and m stand for country, region, district and time respectively, and $i \in (c, r, d)$. Mine is a binary indicator—1 if a district has mineral deposits, 0 otherwise. Intensity denotes the number of mining sites available in a district in a given year. This model specification tests whether the presence of mineral deposits and mining sites has any measurable effects on district inequality in Africa. The coefficients of interest are α and ϑ, capturing the effects on district inequality of mineral deposits' and mining sites' presence respectively. Following the propositions of the resource curse literature, the underlying hypothesis of this specification is $(\alpha, \vartheta) > 0$: that is, districts with mineral deposits and mining sites are likely to be more unequal relative to those with none.

The vector $X_{c,r,d,t}$ captures time-varying observables. As noted in the data section, our specification takes into account several factors that would otherwise potentially bias our coefficient estimates. These factors include a proxy for agricultural productivity (NDVI), population size, a climatic variable (i.e. rainfall), and districts' geographical locations measured using absolute latitude. As noted previously, all these have a bearing on how mining activities impact on spatial inequality at the district level. Moreover, it is also possible for the estimates to be driven by lights emission in districts with active mining activities relative to districts with fewer or no activities. To control for this potential upward bias, we also control for total number of lit grid cell pixels in a district.

To explain whether mining has an impact on spatial inequality we also need to take into account the effects of mineral prices. To account for mineral prices' specific effects at the district level we include $Price_{m,t}$, which proxies the district-level average minerals prices. As detailed later, we note that a more robust way is to account for individual minerals' specific prices in order to understand the precise mechanisms underpinning the effects of mining on spatial inequality. We also control for time fixed effects denoted by T_t, and district, regional, and country fixed effects captured by Ψ. Finally, we control for country-year fixed effects ($\Gamma_{c,t}$) to capture year-specific shocks to the countries in our sample.

District, regional, and country fixed effects capture unobserved differences such as decisions to open mining sites, levels of economic activity, technology employed in the mining sector, and other factors such as ethnicity, which as Fum and Hodler (2010) assert is also likely to affect inequality. Country-year fixed effects account for observed and unobserved shocks, such as privatization of the minerals sector, which has been rampant in Africa; the differences in the types of investment incentive (e.g., royalties, taxes) offered to attract foreign investors and boost mining activities; turbulent international market conditions such as volatile world commodity prices; and countrywide institutional and policy changes that affect individual countries over time. $\epsilon_{c,r,d,t}$ and $\varepsilon_{c,r,d,t}$ are stochastic random error terms. To control for potential intra-region and intra-district correlations, we cluster the standard errors at the country level in all our model specifications, unless otherwise specified. Note also that we use similar notations for model specifications unless stated otherwise.

The above specifications, however, only tell us what the effects are of mineral deposits' and mining sites' presence on district inequality. They exclude such potential exogenous variations as the status of mining (i.e. active and closed mines); the scale of mining (i.e. small and large scale); values of minerals extracted (i.e. mines producing high- or low-value minerals); and the nature of mining activities (i.e. whether the mines are involved in the extraction or transformation of minerals). All these variations have the potential to explain how mining can affect district inequality in Africa and thus elicit relevant policy responses. To account for all these sources of exogenous variation, we re-specify equation [2] as:

$$DI_{c,r,d,t} = \boldsymbol{\Phi}^{j\,\prime}_{c,r,d,t}\boldsymbol{\theta^j} + \boldsymbol{X}'_{\boldsymbol{c,r,d,t}}\varphi + Price_{m,t} + \mathrm{T}_t + \Psi_i + \Gamma_{c,t} + \nu_{c,r,d,t} \qquad [4]$$

where j refers to the four different sources of exogenous variation defined above. Φ is a vector of categorical variables coded as 0, 1, and 2, all meant to capture the above-mentioned exogenous variations in mining activities. Thus 0 denotes the base (no mining). 1 and 2 separately but respectively denote either active or closed mines; small- or large-scale mines; high- or low-value mining activities; and mining extraction or transformation. This extended baseline specification allows us to evaluate whether, for example, the districts with active or closed mines experience higher or lower inequality compared with districts with no mines. The same logic also applies to the other sources of exogenous variation mentioned. The coefficient of interest, which disentangles α in equation [2], is θ^j, with the underlying hypothesis, still following the resource curse literature, being $\theta j > 0$. ν is an error term.

One advantage of equation [4] is that it brings into the analysis the mentioned exogenous variation in mining activities, which is useful for explaining the mechanisms through which mining activities can affect district inequality in Africa. However, the impact of mining activities on district inequality is likely to be driven by the specific minerals commodities available (Boschini et al. 2007). This latent effect cannot be captured by $\mathrm{Price}_{m,t}$ in equations [2] and [4].

Obviously, controlling for minerals' values is important to obtain unbiased estimates and explain the mining-spatial inequality nexus. As noted in Section 3, our analysis, which relies on USGS mineral data, suffers from the lack of data on mineral production at mining sites in Africa. However, the available mineral prices data offer a possibility to circumvent this limitation: the use of minerals unit prices as numeraires for minerals across districts where mineral deposits and mining activities are available. For districts where mineral deposits and mining activities are absent, we assign zero values in unit mineral prices. We therefore update equation [4] slightly differently to take into account the idea of using mineral prices as numeraires. The updated specification takes the following form:

$$\begin{aligned} DI_{c,r,d,t} = \psi\big(Mineral_{c,r,d,t} \times Price_{m,t}\big) + \boldsymbol{X}'_{\boldsymbol{c,r,d,t}}\tau \\ + \mathrm{T}_t + \Psi_i + \Gamma_{c,t} + \omega_{c,r,d,t} \end{aligned} \qquad [5]$$

where $Mineral_{c,r,d,t}$ denotes the dummies for the major mineral commodities types (see Table 2) available in our sample, and $\omega_{c,r,d,t}$ is an error term. A unique feature of equation [5] is the interaction term $Mineral_{c,r,d,t} \times Price_{m,t}$, which underlies the use of minerals' unit prices as numeraires. In principle, equation [5] mimics the underlying structure of equation [2]: the interaction term $Mineral_{c,r,d,t} \times Price_{m,t}$ captures coefficient estimates for all districts with mineral numeraires relative to the base (non-numeraire) districts, effectively measuring the effect of individual minerals' unit values on district inequality in Africa. As an added value, this specification makes it possible to attribute changes in district inequality to changes in specific mineral numeraires, which is useful for identifying the specific types of mineral that influence the dynamics of district inequality during the period 2001–2012. As above, the underlying testable hypothesis is $\psi > 0$, suggesting that district inequality increases with increasing mineral numeraires.

Understanding how specific mineral commodities affect district inequality in Africa is undoubtedly necessary but not sufficient, especially if we are to understand the precise sources of the effects. We thus extend equation [5] one step further to pin down the precise mechanisms at work in the mining-spatial inequality nexus. The extended specification is of the following form:

$$DI_{c,r,d,t} = \kappa\left(Mineral_{c,r,d,t} \times Price_{m,t} \times \mathbf{\Phi}^{j}_{c,r,d,t}\right) + \boldsymbol{X}'_{\boldsymbol{c,r,d,t}}\delta$$
$$+\mathrm{T}_t + \Psi_i + \Gamma_{c,t} + \zeta_{c,r,d,t} \qquad [6]$$

where $\Phi^{j}_{c,r,d,t}$ is the same as in equation [3], and $\zeta_{c,r,d,t}$ is a residual term. A key term of interest is $Mineral_{c,r,d,t} \times Price_{m,t} \times \Phi^{j}_{c,r,d,t}$, which shows the distribution of mineral numeraires by the status, scale, value, and nature of district mining activities. The main advantage of equation [6] is that it helps to untie the effects of mineral numeraires on district inequality by attempting to identify where these effects originate. For example, we are bound to know if the effects on district inequality are driven by active or closed mines, high- or low-value minerals, the scale of mining activities, or the nature of mining activities (i.e. extraction or transformation). As above, the underlying testable hypothesis is $\kappa > 0$.

5 Results

Table 5 reports our main results. Columns 1 and 2 show the estimates when regressions exclude the mineral prices. Columns 3 and 4 show the estimates in which constant mineral prices are included as price controls. Finally, in columns 5 and 6 we report the estimates when using average annual mineral prices as price controls. Columns 5 and 6 are intuitively direct sensitivity checks of the results in columns 3 and 4. Note that columns 1, 3, and 5 present the results without the relevant controls (i.e. NDVI as a proxy for agricultural productivity variations, rainfall, population sizes, and district geographical locations). Similarly, columns 2, 4, and 6 (which are also our main results) report the estimates with these controls.

Column 1 shows that the presence of mineral deposits [equation 2] and mining sites [equation 3] has positive impacts on the district lights Gini index when the analysis excludes the relevant controls, with statistically significant coefficient sizes being 0.087 and 0.011 Gini point increments. Even with the inclusion of the relevant controls, in column 2, the coefficient sizes, although they drop slightly, remain positive and robust. Except for doubled coefficient sizes—mainly explained by the inclusion of price controls—the estimates in columns 3 and 4, as well as in columns 5 and 6, are not qualitatively different from those in columns 1 and 2. When comparing the estimates based on constant prices (columns 3 and 4) with those based on average annual prices (columns 5 and 6), Table 5 reports slightly lower coefficient estimates for the latter than the former.

Note also that the R-squared drops moderately from 0.763 to 0.762 when price controls are included. Columns 1 and 2 have more observations, because we capture the entire sample of districts with mining activities. However, this is not the case when we include price controls, because of the lack of mineral price data for some of the mineral commodities (see Table 2). Taken together, the positive effects are unsurprising: *ceteris paribus*, the districts with natural advantages in mineral deposits and mining sites are likely to create more jobs, generate more income, and enjoy more gains from mining activities than districts with no minerals, eventually widening the inequality gap across districts with and without mineral endowments. This finding is consistent with the standard wisdom of the resource curse literature.

The positive effects of mineral deposits and mining intensity reported in Table 5 mask a myriad of explanations as to the precise mechanisms through which mineral endowment and mining intensity can increase inequality at the district level in Africa. To understand the mechanisms, we estimate the baseline model using different sources of exogenous variation in mining activities. That is, we use dummy variables to identify and exploit the status of mining activities (i.e. active or closed); whether mining sites produce high- or low-value minerals; the scale (small or large) of mining operations; and the types of mining activities (i.e. extraction or transformation) (see equation [4]).

Table 6 reports the regressions showing the estimates for all the different sources of exogenous variations in mining activities. The columns in Table 6 are organized similarly to those in Table 5. Columns 1 and 2 (which report the estimates without price controls) document statistically significant positive effects of mining activities across all four sources of exogenous variation, with slight declines in the coefficient sizes when relevant controls are included.

Worth noting are both the similarities and the stark differences in the coefficient sizes. For example, whereas districts with active mines, large-scale mining operations, and low-value mineral production tend to have similar coefficient sizes, this is not the case when we compare the coefficient sizes for districts with closed mines or high-value minerals and districts engaged in mineral transformation activities, which altogether are higher in magnitude—suggesting that the effects of mining activities are indeed pronounced in these specific sources of variation.

The results change quite considerably when we include price controls in columns 3–6. First, districts with closed mines and those engaged in mining extraction experience statistically significant and large declines in their levels of inequality, while districts with small-scale operations and those producing high-value minerals experience insignificant effects in their levels of inequality. However, the estimates remain unchanged (i.e. positive and statistically significant) for districts with active mines, districts with large-scale mining operations, and districts producing low-value minerals. Evidently, these estimates suggest that the impact of mining activities on district inequality largely depends on whether mines are active or closed, mining operations are small or large scale, the minerals produced are of low or high value, and the mining activities are extractive or transformational.

As mentioned previously, to further understand the mechanisms at work between mining activities and district inequality, it is imperative that we identify and isolate the effects of individual minerals. To do so, we investigate the effects of mineral numeraires on district inequality (see equation [5]). Table 7 reports the regression estimates. Models 1 and 3 report estimates without the relevant controls, while models 2 and 4 report the estimates with the relevant controls.

As the table demonstrates, on the one hand, district inequality increases with the increase in helium (produced in Kenya), garnet (produced in Algeria), and diatomite (produced in Kenya and Mozambique) numeraires. The positive effect of helium and garnet is statistically significant with both constant and average mineral prices, while that of diatomite is insignificant with the former and borderline with the latter. On the other hand, the table also shows that iron-ore-producing districts in Sierra Leone, South Africa, Tunisia, Zambia, and Zimbabwe, as well as nickel-producing districts in Zimbabwe, overall experience declining inequality relative to other districts producing other types of minerals. The coefficient estimates for the other types of mineral numeraires are both negative (e.g., diamond, barite, bentonite, clay, dolomite, fluorspar, salt, vermiculite, fluorine, graphite, cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, tungsten, arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, wollastonite, phosphate rock, phosphoric acid, and zinc) and positive (e.g., stones—crushed and dimension, limestone, gypsum, marble, silicon, cement, platinum, and tin), but statistically insignificant.

Again, these results reinforce the notion that the effect of mining on district inequality is largely dependent on the different types and prices of minerals produced. One interesting aspect of the results in Table 7 is that high-value minerals such as diamond appear not to play a major role in explaining district inequality in Africa. We investigate whether this is indeed the case in subsequent analysis detailed below. Overall, in all the specifications, the R-squared remains unchanged, while the coefficient sizes decline moderately with the inclusion of the relevant controls.

Table 8 shows the estimates when the source of variation is the status (i.e. active or closed) of mining activities. The results are, in general, quite revealing. On the one hand, the lights Gini index increases in districts with active helium, garnet, and gold mining. If constant mineral prices are used, the coefficient estimates for helium (0.126) and garnet (0.141) are statistically significant, while those for gold (0.047) are marginally significant. On the other hand, the table also reveals two results. First, when mines are closed down, district inequality declines quite significantly. This is the case for minerals such as diamond (0.346), phosphate and phosphoric acid (0.127), cement (0.008), platinum (0.056), nickel (0.158), and tin (0.029). Obviously, the results suggest greater inequality declines in districts with closed-down diamond, nickel, and phosphate and phosphoric acid mines. Second, active mining of iron ore (0.046) and tin (0.042) significantly reduces districts' inequality. Note that when we use the average mineral prices, the coefficient estimates change slightly but remain robust, and the interpretation remains qualitatively the same.

Tables 9–11 reveal more nuanced estimates capturing the effects of mineral numeraires based on different sources of exogenous variation in mining activities). All the tables are organized in the same way as Table 7.

Table 9 reports the estimates when the source of variation in equation [6] is the value (i.e. low or high) of the minerals extracted. The results show that, on the one hand, the lights Gini index increases in districts where both low-value minerals (i.e. helium and garnet) and high-value minerals (i.e. gold) are mined. The statistically significant coefficients show that a point increase in the value of mined helium, garnet, and gold increases district inequality by 0.126, 0.138, and 0.040 Gini points respectively if constant mineral prices are used, and by 0.137, 0.198, and 0.035 Gini points respectively if average mineral prices are used. On the other hand, the mining of low-value minerals such as tin and nickel significantly depresses district inequality. That is, if we use the constant mineral prices, district inequality declines by 0.045 and 0.037 Gini points for a point increase in the value (in logarithms) of mined tin and nickel respectively. However, when we use the average mineral prices for the analysis, district inequality declines by 0.155 and 0.139 for a point increase in the value (in logarithms) of mined tin and nickel, respectively.

Table 10 reports the estimates when the source of variation is the scale (i.e. small or large) of mining operations. On the one hand, the results show that the lights Gini index increases in districts with both small-scale mining operations (i.e. for arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, wollastonite, and gold) and large-scale mining operations (i.e. for helium, garnet, and gold). The statistically significant coefficients show that the increase in district inequality lies between 0.083 and 0.20 Gini points if constant prices are used in the analysis, and between 0.071 and 0.193 Gini points if average prices are used instead, for a point increase in the value of minerals in districts with both small- and large-scale mining operations. Note also that despite its presence in both small- and large-scale operations, gold mining has a consistent positive effect on district inequality. On the other hand, the results also show two contrasting results. First, the lights Gini index significantly declines in districts endowed with barite, bentonite, clay, dolomite, fluorspar, salt, vermiculite, fluorine, graphite, cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, tungsten, and tin and whose operations are small scale. Second, inequality also declines in districts with large-scale operations engaged in the extraction of iron ore and nickel. In both cases, the estimated inequality declines are in the range of 0.045–0.536 Gini points when constant prices are used for analysis. A qualitatively similar result holds when we used the average mineral prices instead.

Table 11 shows the estimates when the source of variation is the nature of the mining activities (i.e. extractive or transformational). As above, we have two sets of contrasting results. In the first set, the results show that districts engaged in extractive activities experience increases in levels of inequality in the magnitude of 0.124, 0.141, 0.042, and 0.044 for helium, garnet, tin, and gold respectively. Moreover, the results indicate that inequality increases in districts engaged in transformational activities for minerals such as cement, diatomite, and platinum. The magnitude of the increments in Gini points is 0.024, 0.204, and 0.069 respectively. The second set of results report negative effects on district inequality. Similarly, there are two subsets of these results. First, for the districts engaged in extractive mining activities, inequality declines by 0.059, 0.170, and 0.154 Gini points for a point increase in the value of iron ore, diatomite, and nickel respectively. Second, for districts engaged in transformational activities, inequality declines are between 0.028 and 0.108 Gini points for minerals such as cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, tungsten, arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, wollastonite, diatomite, tin, and gold. A noteworthy point is that the value of gold appears to have a differential impact on district inequality: if extracted, it increases inequality, while when passed on for transformation to final product it reduces inequality. All the discussed estimates are conditioned by using constant mineral prices in the analysis. When we use the average mineral prices, the coefficient estimates change slightly but remain robust, and the interpretation remains qualitatively the same.

We also demonstrate the robustness of our main results by carrying out several sensitivity checks. We first employ other different measures of district inequality to re-estimate all our baseline models. Tables 12–20 report the results of our sensitivity checks. Second, we test our results using a different modelling approach—the multilevel[20] analysis suggested by Rabe-Hesketh and Skrondal (2012). This check is ideal given the hierarchical nature of our data.

[20] With this approach, we modelled the hierarchical structure of the data to understand the differences in the main coefficient estimates across countries, regions, and districts. Taking into account the time dimension of our hierarchical data, our modelling goal was to fit a random slope model, which, using maximum likelihood, specifically estimated the standard deviations in their respective random residuals (commonly known as unstructured variance covariance) within and between countries, regions, and districts. Allowing for different slopes over time across districts, Rabe-Hesketh and Skrondal (2012) also assert that this modelling strategy is useful to pin down the precise

The results of our sensitivity tests are quite revealing, and show that our estimates are indeed robust to other measures of spatial inequality. In our first test, the results are also robust to using both constant and average mineral prices in the analysis. Of course, the magnitudes of coefficients do change considerably across MLD, Theil, and relative lights per capita (RLP), but the qualitative interpretations remain the same when compared with the baseline Gini. Worth noting, however, is a change in the R-squared across these different specifications: from 0.763 on the baseline Gini to 0.627, 0.677, and 0.464 on MLD, Theil, and RLP respectively. In our second test, when we model the data using multilevel analysis, although the magnitude varies across the different specifications, the qualitative interpretation of the results (unreported)[21] remains the same and robust.

Overall, although the aggregated analysis suggests that mining activities increase spatial inequality in favour of districts with natural advantages in mineral endowment, disaggregating the analysis to accommodate individual minerals shows that changes in inequality within districts and across countries are sensitive to the types of minerals and to whether mining activities are active or closed, small or large scale, of low or high value, and extractive or transformational. Based on these findings, we argue that mining activities can be both a curse and a blessing.

6 Conclusions

This paper analysed the effects of mining activities on spatial inequality in 2,182 districts over 653 regions across 38 African countries. Our study employed novel spatial data enabling analysis at the local scale. District inequality was measured using night light data from the National Oceanic and Atmospheric Association's National Geophysical Data Centre, while mineral production data came from the United States Geological Survey.

Our study offers three main conclusions. First, when the analysis is aggregated, mining activities significantly increase spatial inequality in Africa, a finding that is consistent with the standard resource curse literature. Second, when the analysis is disaggregated to include individual minerals, our findings suggest that mining activities impact on spatial inequality both positively and negatively, with the effects varying quite considerably across different minerals. This finding suggests that mineral wealth can be both a blessing and a curse. More importantly, this finding—a unique contribution of this study—reinforces the idea that disentangling the effects of individual minerals is more revealing of the effects of mining activities on development outcomes, and thus is important for eliciting the relevant policy responses.

Finally, our study shows that the effects of mining activities are leveraged by other important forces that underpin mining operations. For example, our analysis suggests that the coefficients of interest largely depend on whether mining activities are active or closed, small or large scale, of low or high value, and extractive or transformational. We argue that these are also relevant variables for informing appropriate policy responses aimed at addressing the nexus between mining activities and spatial inequality in Africa.

source of coefficient estimate differences, i.e. either from the random slopes or from the variability in the variance components.

[21] We have not reported these results here due to space constraints, but they are available from the authors upon request.

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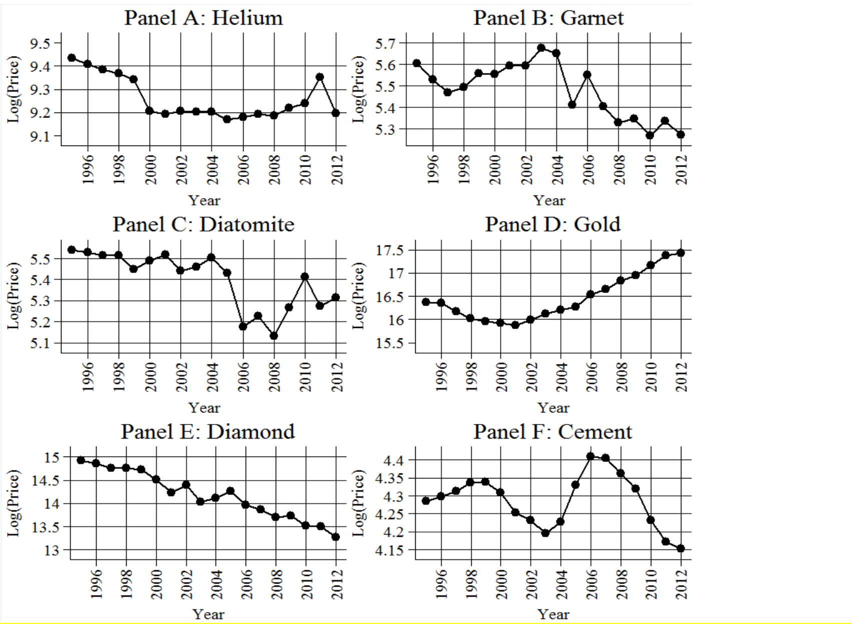
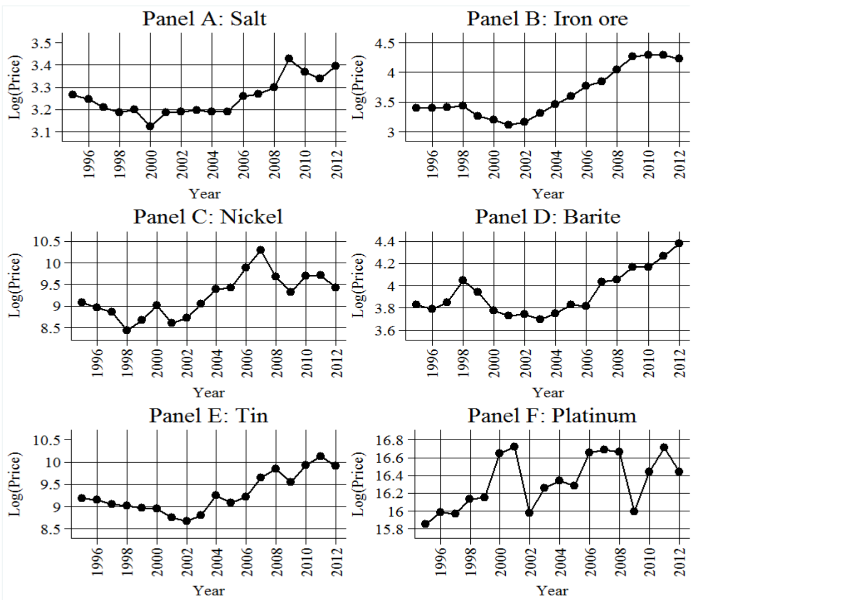
Figure 1: Minerals price trends



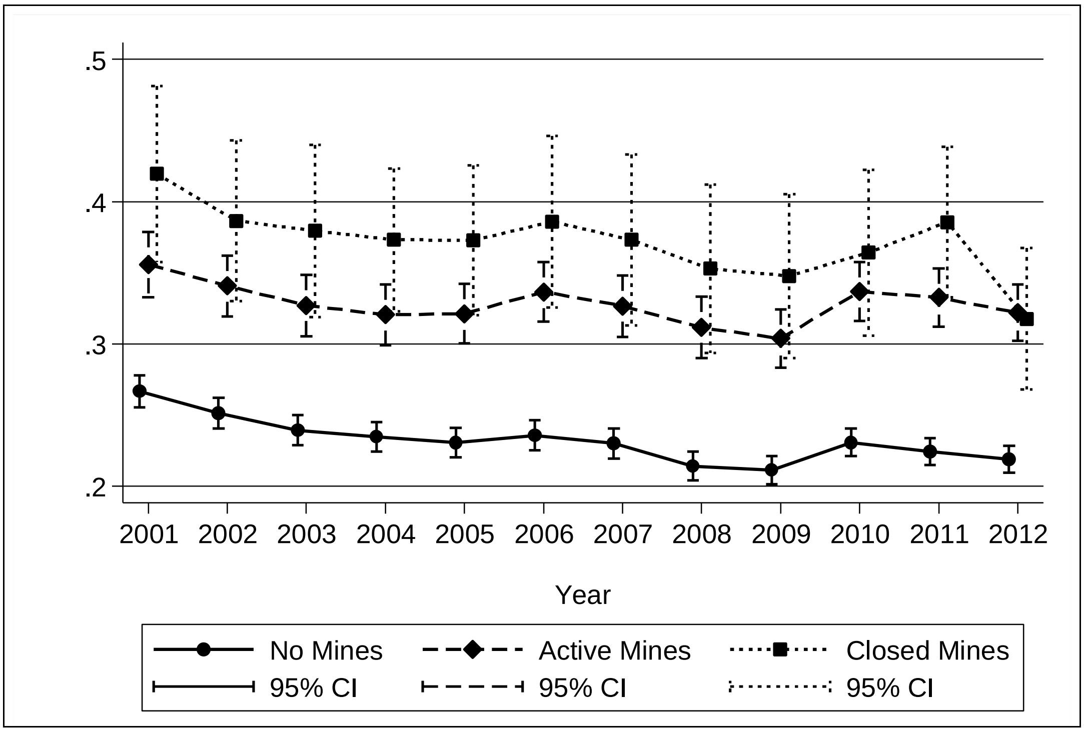
Source: authors' construction (based on United States Geological Survey (USGS) data).

Figure 2: Minerals prices trends



Source: authors' construction (based on USGS data).

Figure 3: Average lights Gini trends in Africa, 2001–2012



Source: author's construction.

Table 1: List of countries

Algeria	Djibouti	Mauritania	South Africa
Angola	Ethiopia	Morocco	Sudan
Benin	Gabon	Mozambique	Tanzania
Botswana	Gambia	Namibia	Togo
Burundi	Guinea-Bissau	Niger	Tunisia
Cameroon	Kenya	Nigeria	Uganda
Chad	Liberia	Rwanda	Zambia
Côte d'Ivoire	Madagascar	Senegal	Zimbabwe
Congo	Malawi	Sierra Leone	
Democratic Republic of Congo	Mali	Somalia	

Source: USGS data.

Table 2: Names of mineral commodities and their SITC codes by district, region, and country of production

Name*	SITC code	Commodity names	Price data	Districts	Regions	Countries of production
SITC_1	120	Helium	Yes	1	1	Algeria
SITC_2	264	Garnet (industrial)	Yes	1	1	Kenya
SITC_3	273	Stones (crushed, dimension), limestone, gypsum, marble, and silicon	Yes	23	22	Algeria, Angola, Ethiopia, Madagascar, Malawi, Mauritania, Mozambique, Rwanda, South Africa, Sudan, Tunisia, Uganda, and Zambia
SITC_4	274	Sulphur	Yes	13	12	Ethiopia, Kenya, Malawi, Namibia, South Africa, Zambia, and Zimbabwe
SITC_5	277	Diamond	Yes	27	17	Angola, Botswana, Cameroon, Liberia, Namibia, Sierra Leone, South Africa, Tanzania, and Zimbabwe
SITC_6	278	Barite, bentonite, clay, dolomite, fluorspar, graphite, salt, vermiculite, fluorine, and graphite	Yes	42	35	Algeria, Botswana, Chad, Djibouti, Ethiopia, Kenya, Madagascar, Morocco, Mozambique, Namibia, South Africa, Tanzania, Tunisia, Uganda, and Zimbabwe
SITC_7	281	Iron ore	Yes	12	10	Sierra Leone, South Africa, Tunisia, Zambia, and Zimbabwe
SITC_8	283	Copper	Yes	27	18	Algeria, Democratic Republic of Congo, Mauritania, Morocco, Namibia, Nigeria, Republic of Congo, South Africa, Zambia, and Zimbabwe
SITC_9	287	Cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, and tungsten	Yes	18	17	Botswana, Burundi, Ethiopia, Gambia, Madagascar, Mozambique, Nigeria, Rwanda, Sierra Leone, South Africa, Uganda, and Zimbabwe
SITC_10	522	Arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, and wollastonite	Yes	13	11	Chad, Cote d'Ivoire, Kenya, Morocco, Namibia, South Africa, Zambia, and Zimbabwe
SITC_11	523	Phosphate rock, and phosphoric acid	Yes	8	6	Malawi, South Africa, Tanzania, Togo, and Tunisia

SITC_12	661	Cement	Yes	52	48	Algeria, Angola, Benin, Burundi, Cameroon, Chad, Democratic Republic of Congo, Ethiopia, Gabon, Kenya, Liberia, Malawi, Mauritania, Morocco, Mozambique, Niger, Nigeria, Republic of Congo, Senegal, Sierra Leone, Somalia, South Africa, Sudan, Tanzania, Togo, Tunisia, and Zimbabwe
SITC_13	662	Diatomite	Yes	2	2	Kenya and Mozambique
SITC_14	681	Platinum	Yes	8	7	Botswana, Ethiopia, South Africa, and Zimbabwe
SITC_15	683	Nickel	Yes	1	1	Zimbabwe
SITC_16	686	Zinc	Yes	2	2	Algeria and South Africa
SITC_17	687	Tin	Yes	6	6	Nigeria, Rwanda, and Uganda
SITC_18	971	Gold	Yes	35	26	Algeria, Burundi, Cote d'Ivoire, Ethiopia, Kenya, Liberia, Mali, Republic of Congo, South Africa, Tanzania, Uganda, Zambia, and Zimbabwe
SITC_19	282**	Steel	No	16	14	Kenya, Mozambique, Nigeria, South Africa, Sudan, and Uganda
SITC_20	289**	Gemstones	No	13	10	Botswana, Ethiopia, Madagascar, Mozambique, and Rwanda
SITC_21	321**	Coal	No	37	22	Botswana, Burundi, Ethiopia, Malawi, Morocco, Mozambique, Niger, Nigeria, South Africa, Tanzania, Zambia, and Zimbabwe
SITC_22	525**	Uranium	No	2	2	Namibia and Niger
SITC_23	663**	Chromite	No	8	6	South Africa, Sudan, and Zimbabwe
SITC_24	684**	Aluminium, ammonia, and bauxite	No	5	5	Cameroon, Mozambique, Nigeria, and South Africa
SITC_25	728**	Asbestos	No	4	3	South Africa
Subtotal				376	304	
Base	999	No commodities	n.a.	1806	349	
Total				2182	653	

* Names assigned by authors for purposes of analysis and ease of understanding of results. ** These commodities were dropped from the regressions that included mineral prices; this explains the differences in the numbers of countries in the regression tables.

Source: authors' construction (based on USGS data).

Table 3: Mining sites by districts in Africa, 2001–2012

Status of mining activities						
	Status	No mine	Active mines	Closed mines	Total	
Mineral deposits	No	1806	0	0	1806	82.8%
	Yes	0	333	43	376	17.2%
	Total	1806	333	43	2182	100%
		82.8%	15.3%	2.0%	100%	
Scale of mining operations						
	Status	No mine	Large-scale	Small-scale	Total	
Mineral deposits	No	1806	0	0	1806	82.8%
	Yes	0	354	22	376	17.2%
	Total	1806	354	22	2182	100%
		82.8%	16.2%	1.0%	100%	
Extracted minerals' value						
	Status	No mine	High value	Low value	Total	
Mineral deposits	No	1806	0	0	1806	82.8%
	Yes	0	83	293	376	17.2%
	Total	1806	83	293	2182	100%
		82.8%	3.8%	13.4%	100%	
Types of mining activities						
	Status	No mine	Extraction	Transformation	Total	
Mineral deposits	No	1806	0	0	1806	82.8%
	Yes	0	271	105	376	17.2%
	Total	1806	271	105	2182	100%
		82.8%	12.4%	4.8%	100%	

Source: authors' calculation (based on USGS data).

Table 4: Summary statistics

	Obs.	Mean	Std dev.	Min.	Max.
Gini index	21433	0.256	0.200	0.0	0.940
Mean logarithmic deviation	21433	0.271	0.334	0.0	4.353
Theil index	21433	0.247	0.331	0.0	7.289
Sen index	21433	0.072	0.778	0.0	43.545
Std dev. rainfall (mm)	26014	4.538	4.617	0.0	88.428
Std dev. NDVI	26014	0.826	1.532	0.0	7.838
Log(Population)	26014	11.173	1.425	3.651	15.931
Log(Constant prices)	23745	1.051	3.239	0.0	17.424
Log(Average prices)	23745	1.078	3.301	0.0	17.767

Notes: (1) The table shows descriptive statistics across a sample of 2,247 districts across 39 countries in Africa during 2001–2012. (2) Inequality indicators are at the district level and measured using night-time light intensity. (3) The number of observations varies because some districts have observations with zero light intensity. (4) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (5) NDVI stands for Normalized Difference Vegetation Index, a proxy for agricultural productivity.

Source: authors' calculations.

Table 5: The effects of mineral deposits' and mining sites' presence on lights Gini index

Dependent variable: district lights Gini index

	No prices		Constant mineral prices		Average mineral prices	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Equation [2]:						
Deposits [1=present]	0.087***	0.081***	0.190***	0.180***	0.176***	0.166***
	[0.000]	[0.004]	[0.048]	[0.048]	[0.043]	[0.043]
Equation [3]:						
Mining sites	0.011***	0.010***	0.095***	0.090***	0.088***	0.083***
	[0.000]	[0.001]	[0.024]	[0.024]	[0.021]	[0.022]
Log(Prices)			0.005	0.005	0.007	0.007
			[0.009]	[0.009]	[0.008]	[0.008]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
N	20703	20703	19298	19298	19298	19298
R-squared	0.763	0.763	0.762	0.762	0.762	0.762
Countries	38	38	38	38	38	38

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions use the presence of mineral deposits and mining sites to explain spatial-temporal variations in lights Gini. (3) Gini index is at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) Prices (measured at constant 1998 US dollars and as annual averages) come from USGS. (6) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (7) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 6: The effects of mining activities on lights Gini index

Dependent variable: district lights Gini index

	No Prices		Constant mineral prices		Average mineral prices	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Active mines	0.087***	0.081***	0.190***	0.180***	0.176***	0.166***
	[0.000]	[0.004]	[0.048]	[0.048]	[0.043]	[0.043]
Closed mines	0.314***	0.313***	-0.193**	-0.191**	-0.213***	-0.211***
	[0.000]	[0.005]	[0.071]	[0.072]	[0.063]	[0.064]
High-value minerals	0.144***	0.135***	0.063	0.054	0.022	0.014
	[0.000]	[0.006]	[0.158]	[0.157]	[0.135]	[0.135]
Low-value minerals	0.087***	0.081***	0.190***	0.180***	0.176***	0.166***
	[0.000]	[0.004]	[0.048]	[0.048]	[0.043]	[0.043]
Small-scale mines	0.144***	0.135***	0.063	0.054	0.022	0.014
	[0.000]	[0.006]	[0.158]	[0.157]	[0.135]	[0.135]
Large-scale mines	0.087***	0.081***	0.190***	0.180***	0.176***	0.166***
	[0.000]	[0.004]	[0.048]	[0.048]	[0.043]	[0.043]
Mineral extraction	0.087***	0.081***	-0.444***	-0.448***	-0.462***	-0.465***
	[0.000]	[0.004]	[0.061]	[0.061]	[0.054]	[0.055]
Mineral transformation	0.215***	0.203***	0.190***	0.180***	0.176***	0.166***
	[0.000]	[0.012]	[0.048]	[0.048]	[0.043]	[0.043]
Log(Prices)			0.005	0.005	0.007	0.007
			[0.009]	[0.009]	[0.008]	[0.008]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
N	20703	20703	19298	19298	19298	19298
R-squared	0.763	0.763	0.762	0.762	0.762	0.762
Countries	38	38	38	38	38	38

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions use the presence of active and closed mining activities to explain spatial-temporal variations in inequality measures. (3) Gini index is at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) Prices (measured at constant 1998 US dollars and as annual averages) come from USGS. (6) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (7) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). (8) High-value refers to mining sites where high-value minerals are extracted, whereas low-value refers to places where low-value minerals are extracted. (9) Small-scale refers to sites with artisanal mining activities, while large-scale refers to sites where large-scale mining activities are taking place. (10) Mineral extraction refers to mining sites where extractive mining activities are taking place, and mineral transformation refers to sites where the value addition of raw minerals is performed. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 7: The effects of mineral prices on lights Gini index

Dependent variable: district lights Gini Index

	Constant mineral prices				Average mineral prices			
	Model 1	S.E.	Model 2	S.E.	Model 3	S.E.	Model 4	S.E.
SITC_1 x log(Price)	0.131***	[0.001]	0.126***	[0.006]	0.149***	[0.001]	0.137***	[0.014]
SITC_2 x log(Price)	0.137***	[0.007]	0.138***	[0.008]	0.195***	[0.008]	0.198***	[0.011]
SITC_3 x log(Price)	0.013	[0.089]	0.014	[0.089]	0.022	[0.085]	0.023	[0.085]
SITC_5 x log(Price)	-0.006	[0.049]	-0.005	[0.049]	-0.007	[0.062]	-0.006	[0.062]
SITC_6 x log(Price)	-0.086	[0.080]	-0.085	[0.078]	0.026	[0.062]	0.025	[0.062]
SITC_7 x log(Price)	-0.045***	[0.010]	-0.045***	[0.010]	-0.037***	[0.008]	-0.037***	[0.008]
SITC_9 x log(Price)	-0.003	[0.020]	-0.003	[0.019]	-0.002	[0.019]	-0.002	[0.019]
SITC_10 x log(Price)	-0.047	[0.057]	-0.048	[0.056]	-0.039	[0.045]	-0.039	[0.044]
SITC_11 x log(Price)	-0.051	[0.031]	-0.051	[0.032]	-0.046	[0.028]	-0.046	[0.029]
SITC_12 x log(Price)	0.013	[0.009]	0.013	[0.009]	0.014	[0.009]	0.014	[0.009]
SITC_13 x log(Price)	0.017	[0.143]	0.016	[0.143]	0.750*	[0.416]	0.747*	[0.419]
SITC_14 x log(Price)	0.005	[0.019]	0.005	[0.018]	0.033	[0.032]	0.033	[0.031]
SITC_15 x log(Price)	-0.155***	[0.003]	-0.155***	[0.003]	-0.139***	[0.003]	-0.139***	[0.003]
SITC_16 x log(Price)	-0.110	[0.106]	-0.111	[0.104]	-0.098	[0.092]	-0.099	[0.091]
SITC_17 x log(Price)	0.001	[0.027]	0.001	[0.027]	0.004	[0.025]	0.004	[0.026]
Fixed effects	Yes		Yes		Yes		Yes	
Controls	No		Yes		No		Yes	
N	19298		19298		19298		19298	
R-squared	0.763		0.763		0.763		0.763	
Countries	38		38		38		38	

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions use the presence of mining activities to explain spatial-temporal variations in lights Gini. (3) Gini index is at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) Prices (measured at constant 1998 US dollars and as annual averages) come from USGS. (6) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (7) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). (8) SITC_1: helium. (9) SITC_2: garnet (industrial). (10) SITC_3: stones (crushed, dimension), limestone, gypsum, marble, and silicon. (11) SITC_5: diamond. (12) SITC_6: barite, bentonite, clay, dolomite, fluorspar, graphite, salt, vermiculite, fluorine, and graphite. (13) SITC_7: iron ore. (14) SITC_9: cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, and tungsten. (15) SITC_10: arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, and wollastonite. (16) SITC_11: phosphate rock and phosphoric acid. (17) SITC_12: cement. (18) SITC_13: diatomite. (19) SITC_14: platinum. (20) SITC_15: nickel. (21) SITC_16: zinc. (22) SITC_17: tin. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.
Source: authors' estimations.

Table 8: The effects of mining activities on lights Gini index

Dependent variable: district lights Gini index

	Constant mineral prices				Average mineral prices			
	Model 1	S.E.	Model 2	S.E.	Model 3	S.E.	Model 4	S.E.
SITC_1 x Active x log(Price)	0.132***	[0.001]	0.126***	[0.006]	0.149***	[0.001]	0.137***	[0.015]
SITC_2 x Active x log(Price)	0.140***	[0.005]	0.141***	[0.006]	0.197***	[0.006]	0.201***	[0.010]
SITC_3 x Active x log(Price)	0.013	[0.089]	0.014	[0.089]	0.022	[0.085]	0.023	[0.085]
SITC_5 x Active x log(Price)	0.026	[0.037]	0.027	[0.037]	0.031	[0.048]	0.032	[0.048]
SITC_5 x Closed x log(Price)	-0.346***	[0.002]	-0.346***	[0.002]	-0.407***	[0.002]	-0.407***	[0.002]
SITC_6 x Active x log(Price)	-0.063	[0.091]	-0.063	[0.089]	0.003	[0.065]	0.003	[0.065]
SITC_6 x Closed x log(Price)	-0.286	[0.176]	-0.282	[0.177]	0.195***	[0.050]	0.190***	[0.051]
SITC_7 x Active x log(Price)	-0.046***	[0.011]	-0.046***	[0.010]	-0.039***	[0.009]	-0.039***	[0.009]
SITC_9 x Active x log(Price)	-0.003	[0.019]	-0.003	[0.019]	-0.003	[0.019]	-0.003	[0.019]
SITC_10 x Active x log(Price)	-0.047	[0.057]	-0.048	[0.056]	-0.039	[0.044]	-0.039	[0.044]
SITC_11 x Active x log(Price)	-0.037	[0.026]	-0.037	[0.026]	-0.034	[0.023]	-0.034	[0.023]
SITC_11 x Closed x log(Price)	-0.127***	[0.001]	-0.127***	[0.002]	-0.115***	[0.001]	-0.115***	[0.001]
SITC_12 x Active x log(Price)	0.015	[0.010]	0.015	[0.010]	0.016	[0.010]	0.016	[0.010]
SITC_12 x Closed x log(Price)	-0.009***	[0.003]	-0.008***	[0.002]	-0.006***	[0.001]	-0.005***	[0.001]
SITC_13 x Active x log(Price)	0.017	[0.143]	0.016	[0.143]	0.751*	[0.415]	0.748*	[0.418]
SITC_14 x Active x log(Price)	0.009	[0.020]	0.010	[0.019]	0.038	[0.035]	0.038	[0.034]
SITC_14 x Closed x log(Price)	-0.056***	[0.002]	-0.056***	[0.002]	-0.035***	[0.003]	-0.035***	[0.003]
SITC_15 x Closed x log(Price)	-0.158***	[0.002]	-0.158***	[0.003]	-0.142***	[0.002]	-0.142***	[0.003]
SITC_16 x Closed x log(Price)	-0.110	[0.105]	-0.111	[0.104]	-0.098	[0.092]	-0.099	[0.091]
SITC_17 x Active x log(Price)	0.042***	[0.005]	0.042***	[0.005]	0.042***	[0.003]	0.042***	[0.003]
SITC_17 x Closed x log(Price)	-0.028***	[0.000]	-0.029***	[0.001]	-0.024***	[0.000]	-0.024***	[0.001]
SITC_18 x Active x log(Price)	0.047*	[0.025]	0.047*	[0.025]	0.040*	[0.021]	0.041*	[0.021]
SITC_18 x Closed x log(Price)	0.001	[0.015]	0.001	[0.014]	0.001	[0.013]	0.001	[0.013]
Fixed effects	Yes		Yes		Yes		Yes	
Controls	No		Yes		No		Yes	
N	19298		19298		19298		19298	
R-squared	0.763		0.763		0.763		0.763	
Countries	38		38		38		38	

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions use the presence of active and closed mining activities to explain spatial-temporal variations in inequality and welfare measures. (3) Gini index is at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (6) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (7) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). (8) SITC_1: helium. (9) SITC_2: garnet (industrial). (10) SITC_3: stones (crushed, dimension), limestone, gypsum, marble, and silicon. (11) SITC_5: diamond. (12) SITC_6: barite, bentonite, clay, dolomite, fluorspar, graphite, salt, vermiculite, fluorine, and graphite. (13) SITC_7: iron ore. (14) SITC_9: cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, and tungsten. (15) SITC_10: arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, and wollastonite. (16) SITC_11: phosphate rock and phosphoric acid. (17) SITC_12: cement. (18) SITC_13: diatomite. (19) SITC_14: platinum. (20) SITC_15: nickel. (21) SITC_16: zinc. (22) SITC_17: tin. (23) SITC_18: gold. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 9: The effects of minerals' value on lights Gini index

Dependent variable: district lights Gini index

	Constant mineral prices				Average mineral prices			
	Model 1	S.E.	Model 2	S.E.	Model 3	S.E.	Model 4	S.E.
SITC_1 x Low value x log(Price)	0.131***	[0.001]	0.126***	[0.006]	0.149***	[0.001]	0.137***	[0.014]
SITC_2 x Low value x log(Price)	0.137***	[0.007]	0.138***	[0.008]	0.195***	[0.008]	0.198***	[0.011]
SITC_3 x Low value x log(Price)	0.013	[0.089]	0.014	[0.089]	0.022	[0.085]	0.023	[0.085]
SITC_5 x High value x log(Price)	-0.006	[0.049]	-0.005	[0.049]	-0.007	[0.062]	-0.006	[0.062]
SITC_6 x Low value x log(Price)	-0.086	[0.080]	-0.085	[0.078]	0.026	[0.062]	0.025	[0.062]
SITC_7 x Low value x log(Price)	-0.045***	[0.010]	-0.045***	[0.010]	-0.037***	[0.008]	-0.037***	[0.008]
SITC_9 x Low value x log(Price)	-0.003	[0.020]	-0.003	[0.019]	-0.002	[0.019]	-0.002	[0.019]
SITC_10 x Low value x log(Price)	-0.047	[0.057]	-0.048	[0.056]	-0.039	[0.045]	-0.039	[0.044]
SITC_11 x Low value x log(Price)	-0.051	[0.031]	-0.051	[0.032]	-0.046	[0.028]	-0.046	[0.029]
SITC_12 x Low value x log(Price)	0.013	[0.009]	0.013	[0.009]	0.014	[0.009]	0.014	[0.009]
SITC_13 x Low value x log(Price)	0.017	[0.143]	0.016	[0.143]	0.750*	[0.416]	0.747*	[0.419]
SITC_14 x High value x log(Price)	0.005	[0.019]	0.005	[0.018]	0.033	[0.032]	0.033	[0.031]
SITC_15 x Low value x log(Price)	-0.155***	[0.003]	-0.155***	[0.003]	-0.139***	[0.003]	-0.139***	[0.003]
SITC_16 x Low value x log(Price)	-0.110	[0.106]	-0.111	[0.104]	-0.098	[0.092]	-0.099	[0.091]
SITC_17 x Low value x log(Price)	0.001	[0.027]	0.001	[0.027]	0.004	[0.025]	0.004	[0.026]
SITC_18 x High value x log(Price)	0.040**	[0.018]	0.040**	[0.018]	0.034**	[0.016]	0.035**	[0.016]
Fixed effects	Yes		Yes		Yes		Yes	
Controls	No		Yes		No		Yes	
N	19298		19298		19298		19298	

R-squared	0.763	0.763	0.763	0.763
Countries	38	38	38	38

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions use the classification of minerals' value to explain spatial-temporal variations in inequality. (3) Gini index is at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (6) High value refers to mining sites where high-value minerals are extracted, whereas low value refers to places where low-value minerals are extracted. (7) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (8) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). (9) SITC_1: helium. (10) SITC_2: garnet (industrial). (11) SITC_3: stones (crushed, dimension), limestone, gypsum, marble, and silicon. (12) SITC_5: diamond. (13) SITC_6: barite, bentonite, clay, dolomite, fluorspar, graphite, salt, vermiculite, fluorine, and graphite. (14) SITC_7: iron ore. (15) SITC_9: cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, and tungsten. (16) SITC_10: arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, and wollastonite. (17) SITC_11: phosphate rock and phosphoric acid. (18) SITC_12: cement. (19) SITC_13: diatomite. (20) SITC_14: platinum. (21) SITC_15: nickel. (22) SITC_16: zinc. (23) SITC_17: tin. (24) SITC_18: gold. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 10: The effects of the scale of mining activities on lights Gini index

Dependent variable: district light Gini index

	Constant mineral prices				Average mineral prices			
	Model 1	S.E.	Model 2	S.E.	Model 3	S.E.	Model 4	S.E.
SITC_1 x Large scale x log(Price)	0.132***	[0.001]	0.126***	[0.006]	0.150***	[0.001]	0.137***	[0.014]
SITC_2 x Large scale x log(Price)	0.133***	[0.005]	0.134***	[0.007]	0.189***	[0.007]	0.193***	[0.010]
SITC_3 x Large scale x log(Price)	0.011	[0.089]	0.012	[0.089]	0.020	[0.086]	0.021	[0.085]
SITC_5 x Small scale x log(Price)	-0.105	[0.063]	-0.103	[0.065]	-0.116	[0.087]	-0.113	[0.090]
SITC_5 x Large scale x log(Price)	0.002	[0.054]	0.002	[0.054]	0.001	[0.068]	0.001	[0.068]
SITC_6 x Small scale x log(Price)	-0.536***	[0.005]	-0.536***	[0.005]	-1.177***	[0.004]	-1.173***	[0.004]
SITC_6 x Large scale x log(Price)	-0.076	[0.082]	-0.076	[0.080]	0.051	[0.059]	0.051	[0.059]
SITC_7 x Large scale x log(Price)	-0.045***	[0.010]	-0.045***	[0.010]	-0.037***	[0.008]	-0.037***	[0.008]
SITC_9 x Small scale x log(Price)	-0.065***	[0.001]	-0.066***	[0.002]	-0.067***	[0.000]	-0.067***	[0.002]
SITC_9 x Large scale x log(Price)	0.005	[0.020]	0.005	[0.020]	0.006	[0.019]	0.006	[0.019]
SITC_10 x Small scale x log(Price)	0.200***	[0.003]	0.200***	[0.003]	0.156***	[0.002]	0.157***	[0.002]
SITC_10 x Large scale x log(Price)	-0.063	[0.059]	-0.063	[0.059]	-0.052	[0.046]	-0.052	[0.045]
SITC_11 x Large scale x log(Price)	-0.051	[0.031]	-0.051	[0.032]	-0.046	[0.028]	-0.046	[0.029]
SITC_12 x Large scale x log(Price)	0.013	[0.009]	0.013	[0.009]	0.014	[0.009]	0.014	[0.009]
SITC_13 x Large scale x log(Price)	0.015	[0.143]	0.014	[0.143]	0.751*	[0.415]	0.748*	[0.418]
SITC_14 x Large scale x log(Price)	0.005	[0.019]	0.005	[0.018]	0.034	[0.032]	0.034	[0.031]
SITC_15 x Large scale x log(Price)	-0.156***	[0.003]	-0.156***	[0.003]	-0.140***	[0.003]	-0.140***	[0.003]
SITC_16 x Large scale x log(Price)	-0.110	[0.106]	-0.112	[0.105]	-0.098	[0.092]	-0.099	[0.091]
SITC_17 x Small scale x log(Price)	-0.231***	[0.001]	-0.230***	[0.002]	-0.242***	[0.001]	-0.241***	[0.002]
SITC_17 x Large scale x log(Price)	0.003	[0.027]	0.002	[0.028]	0.005	[0.025]	0.005	[0.026]

SITC_18 x Small scale x log(Price)	0.082***	[0.023]	0.083***	[0.023]	0.070***	[0.020]	0.071***	[0.020]
SITC_18 x Large scale x log(Price)	0.034*	[0.019]	0.034*	[0.019]	0.029*	[0.017]	0.030*	[0.017]
Fixed effects	Yes		Yes		Yes		Yes	
Controls	No		Yes		No		Yes	
N	19298		19298		19298		19298	
R-squared	0.763		0.763		0.763		0.763	
Countries	38		38		38		38	

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions use the scale of district mining operations to explain spatial-temporal variations in inequality. (3) Gini index is at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (6) Small scale refers to sites with artisanal mining activities, while large scale refers to sites where large-scale mining activities are taking place. (7) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (8) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). (9) SITC_1: helium. (10) SITC_2: garnet (industrial). (11) SITC_3: stones (crushed, dimension), limestone, gypsum, marble, and silicon. (12) SITC_5: diamond. (13) SITC_6: barite, bentonite, clay, dolomite, fluorspar, graphite, salt, vermiculite, fluorine, and graphite. (14) SITC_7: iron ore. (15) SITC_9: cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, and tungsten. (16) SITC_10: arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, and wollastonite. (17) SITC_11: phosphate rock and phosphoric acid. (18) SITC_12: cement. (19) SITC_13: diatomite. (20) SITC_14: platinum. (21) SITC_15: nickel. (22) SITC_16: zinc. (23) SITC_17: tin. (24) SITC_18: gold. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 11: The effects of the nature of mining activities on lights Gini index

Dependent variable: district lights Gini index

	Constant mineral prices				Average mineral prices			
	Model 1	S.E.	Model 2	S.E.	Model 3	S.E.	Model 4	S.E.
SITC_1 x Extraction x log(Price)	0.130***	[0.001]	0.124***	[0.006]	0.148***	[0.001]	0.135***	[0.014]
SITC_2 x Extraction x log(Price)	0.140***	[0.005]	0.141***	[0.007]	0.196***	[0.006]	0.200***	[0.011]
SITC_3 x Extraction x log(Price)	0.015	[0.120]	0.016	[0.119]	0.065	[0.099]	0.066	[0.098]
SITC_3 x Transform x log(Price)	0.003	[0.097]	0.004	[0.097]	-0.069	[0.106]	-0.068	[0.104]
SITC_5 x Extraction x log(Price)	-0.006	[0.049]	-0.006	[0.049]	-0.007	[0.062]	-0.007	[0.062]
SITC_6 x Extraction x log(Price)	-0.095	[0.080]	-0.093	[0.078]	0.034	[0.066]	0.033	[0.066]
SITC_6 x Transform x log(Price)	0.116*	[0.067]	0.091	[0.059]	-0.168***	[0.018]	-0.171***	[0.017]
SITC_7 x Extraction x log(Price)	-0.059***	[0.013]	-0.059***	[0.013]	-0.049***	[0.011]	-0.049***	[0.011]
SITC_7 x Transform x log(Price)	0.026	[0.033]	0.026	[0.033]	0.022	[0.029]	0.022	[0.028]
SITC_9 x Extraction x log(Price)	0.003	[0.019]	0.003	[0.019]	0.004	[0.019]	0.004	[0.018]
SITC_9 x Transform x log(Price)	-0.109***	[0.001]	-0.108***	[0.001]	-0.099***	[0.001]	-0.098***	[0.001]

SITC_10 x Extraction x log(Price)	-0.043	[0.068]	-0.043	[0.068]	-0.037	[0.055]	-0.038	[0.055]
SITC_10 x Transform x log(Price)	-0.068**	[0.030]	-0.069**	[0.030]	-0.041*	[0.024]	-0.041*	[0.024]
SITC_11 x Extraction x log(Price)	-0.070	[0.043]	-0.071	[0.043]	-0.064	[0.039]	-0.065	[0.039]
SITC_11 x Transform x log(Price)	-0.003	[0.103]	-0.002	[0.105]	-0.001	[0.095]	-0.000	[0.096]
SITC_12 x Extraction x log(Price)	-0.019	[0.023]	-0.019	[0.023]	-0.018	[0.021]	-0.018	[0.021]
SITC_12 x Transform x log(Price)	0.024**	[0.010]	0.024**	[0.010]	0.025**	[0.011]	0.025**	[0.011]
SITC_13 x Extraction x log(Price)	-0.170***	[0.007]	-0.170***	[0.008]	1.293***	[0.003]	1.294***	[0.003]
SITC_13 x Transform x log(Price)	0.205***	[0.006]	0.204***	[0.006]	0.203***	[0.004]	0.196***	[0.009]
SITC_14 x Extraction x log(Price)	-0.008	[0.011]	-0.007	[0.011]	0.016	[0.022]	0.016	[0.021]
SITC_14 x Transform x log(Price)	0.070***	[0.001]	0.069***	[0.001]	0.127***	[0.001]	0.124***	[0.002]
SITC_15 x Extraction x log(Price)	-0.154***	[0.003]	-0.154***	[0.003]	-0.138***	[0.003]	-0.138***	[0.003]
SITC_16 x Extraction x log(Price)	-0.110	[0.106]	-0.112	[0.104]	-0.098	[0.092]	-0.099	[0.091]
SITC_17 x Extraction x log(Price)	0.042***	[0.005]	0.042***	[0.005]	0.042***	[0.003]	0.043***	[0.003]
SITC_17 x Transform x log(Price)	-0.028***	[0.000]	-0.028***	[0.001]	-0.024***	[0.000]	-0.024***	[0.001]
SITC_18 x Extraction x log(Price)	0.044**	[0.019]	0.044**	[0.019]	0.038**	[0.016]	0.038**	[0.016]
SITC_18 x Transform x log(Price)	-0.054***	[0.001]	-0.053***	[0.001]	-0.047***	[0.000]	-0.047***	[0.000]
Fixed effects	Yes		Yes		Yes		Yes	
Controls	No		Yes		No		Yes	
N	19298		19298		19298		19298	
R-squared	0.763		0.763		0.763		0.763	
Countries	38		38		38		38	

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 countries across 38 countries in Africa during 2001–2012. (2) The regressions use the nature of mining activities to explain spatial-temporal variations in inequality. (3) Gini index is at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (6) Extraction refers to mining sites where extractive mining activities are taking place, and transform refers to sites where value addition to raw minerals is performed. (7) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (8) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). (9) SITC_1: helium. (10) SITC_2: garnet (industrial). (11) SITC_3: stones (crushed, dimension), limestone, gypsum, marble, and silicon. (12) SITC_5: diamond. (13) SITC_6: barite, bentonite, clay, dolomite, fluorspar, graphite, salt, vermiculite, fluorine, and graphite. (14) SITC_7: iron ore. (15) SITC_9: cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, and tungsten. (16) SITC_10: arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, and wollastonite. (17) SITC_11: phosphate rock and phosphoric acid. (18) SITC_12: cement. (19) SITC_13: diatomite. (20) SITC_14: platinum. (21) SITC_15: nickel. (22) SITC_16: zinc. (23) SITC_17: tin. (24) SITC_18: gold. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 12: The effects of mineral deposits' and mining sites' presence on district inequality

	Constant mineral prices				Average mineral prices			
	Gini	MLD	Theil	RLP	Gini	MLD	Theil	RLP
Equation [2]:								
Deposits [1=present]	0.180***	0.277***	0.206**	17.504***	0.166***	0.255***	0.178**	17.240***
	[0.048]	[0.095]	[0.091]	[2.040]	[0.043]	[0.085]	[0.082]	[1.914]
Equation [3]:								
Mining sites	0.090***	0.139***	0.103**	8.752***	0.083***	0.127***	0.089**	8.620***
	[0.024]	[0.047]	[0.046]	[1.020]	[0.022]	[0.043]	[0.041]	[0.957]
Log(Prices)	0.005	-0.003	0.003	-0.045	0.007	0.001	0.008	0.006
	[0.009]	[0.017]	[0.018]	[0.049]	[0.008]	[0.014]	[0.015]	[0.059]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19298	19298	19298	23745	19298	19298	19298	23745
R-squared	0.762	0.625	0.676	0.463	0.762	0.625	0.676	0.463
Countries	38	38	38	38	38	38	38	38

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions use the presence of mineral deposits and mining sites to explain spatial-temporal variations in lights Gini. (3) All inequality indicators are at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) MLD stands for mean logarithmic deviation, and RLP stands for relative lights per capita. (6) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (7) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (8) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 13: The effects of the status of mining activities on district inequality

	Constant mineral prices				Average mineral prices			
	Gini	MLD	Theil	RLP	Gini	MLD	Theil	RLP
Active mines [1=Active]	0.180***	0.277***	0.206**	17.504***	0.166***	0.255***	0.178**	17.240***
	[0.048]	[0.095]	[0.091]	[2.040]	[0.043]	[0.085]	[0.082]	[1.914]
Closed mines [2=Closed]	-0.191**	-0.463***	-0.407***	-4.435***	-0.211***	-0.496***	-0.447***	-4.822***
	[0.072]	[0.129]	[0.141]	[1.014]	[0.064]	[0.112]	[0.124]	[1.209]
Log(Prices)	0.005	-0.003	0.003	-0.045	0.007	0.001	0.008	0.006
	[0.009]	[0.017]	[0.018]	[0.049]	[0.008]	[0.014]	[0.015]	[0.059]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19298	19298	19298	23745	19298	19298	19298	23745
R-squared	0.762	0.625	0.676	0.463	0.762	0.625	0.676	0.463
Countries	38	38	38	38	38	38	38.	38

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions use the presence of active and closed mining activities to explain spatial-temporal variations in inequality and welfare measures. (3) All inequality indicators are at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) MLD stands for mean logarithmic deviation, and RLP stands for relative lights per capita. (6) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (7) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (8) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 14: The effects of the scale of mining activities on district inequality

	Constant mineral prices				Average mineral prices			
	Gini	MLD	Theil	RLP	Gini	MLD	Theil	RLP
Small-scale mines	0.054	0.184	0.072	3.851***	0.014	0.113	-0.011	3.001***
	[0.157]	[0.285]	[0.301]	[1.154]	[0.135]	[0.240]	[0.257]	[0.985]
Large-scale mines	0.180***	0.277***	0.206**	17.504***	0.166***	0.255***	0.178**	17.240***
	[0.048]	[0.095]	[0.091]	[2.040]	[0.043]	[0.085]	[0.082]	[1.914]
Log(Prices)	0.005	-0.003	0.003	-0.045	0.007	0.001	0.008	0.006
	[0.009]	[0.017]	[0.018]	[0.049]	[0.008]	[0.014]	[0.015]	[0.059]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19298	19298	19298	23745	19298	19298	19298	23745
R-squared	0.762	0.625	0.676	0.463	0.762	0.625	0.676	0.463
Countries	38	38	38	38	38	38	38	38

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions exploit the scale of mining operations to explain spatial-temporal variations in district inequality. (3) All inequality indicators are at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) MLD stands for mean logarithmic deviation, and RLP stands for relative lights per capita. (6) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (7) Small-scale refers to sites with artisanal mining activities, while large-scale refers to sites where large-scale mining activities are taking place. (8) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (9) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 15: The effects of minerals' value on district inequality

	Constant mineral prices				Average mineral prices			
	Gini	MLD	Theil	RLP	Gini	MLD	Theil	RLP
High-value minerals	0.054	0.184	0.072	3.851***	0.014	0.113	-0.011	3.001***
	[0.157]	[0.285]	[0.301]	[1.154]	[0.135]	[0.240]	[0.257]	[0.985]
Low-value minerals	0.180***	0.277***	0.206**	17.504***	0.166***	0.255***	0.178**	17.240***
	[0.048]	[0.095]	[0.091]	[2.040]	[0.043]	[0.085]	[0.082]	[1.914]
Log(Prices)	0.005	-0.003	0.003	-0.045	0.007	0.001	0.008	0.006
	[0.009]	[0.017]	[0.018]	[0.049]	[0.008]	[0.014]	[0.015]	[0.059]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19298	19298	19298	23745	19298	19298	19298	23745
R-squared	0.762	0.625	0.676	0.463	0.762	0.625	0.676	0.463
Countries	38	38	38	38	38	38	38	38

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions exploit the value of minerals to explain spatial-temporal variations in district inequality. (3) All inequality indicators are at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) MLD stands for mean logarithmic deviation, and RLP stands for relative lights per capita. (6) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (7) High-value refers to mining sites where high-value minerals are extracted, whereas low-value refers to places where low-value minerals are extracted. (8) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (9) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 16: The effects of the nature of mining activities on district inequality.

	Constant mineral prices				Average mineral prices			
	Gini	MLD	Theil	RLP	Gini	MLD	Theil	RLP
Mineral extraction	-0.448***	-0.603***	-0.530***	-3.395***	-0.465***	-0.630***	-0.564***	-3.726***
	[0.061]	[0.111]	[0.118]	[0.741]	[0.055]	[0.096]	[0.104]	[0.907]
Mineral transformation	0.180***	0.277***	0.206**	17.504***	0.166***	0.255***	0.178**	17.240***
	[0.048]	[0.095]	[0.091]	[2.040]	[0.043]	[0.085]	[0.082]	[1.914]
Log(Prices)	0.005	-0.003	0.003	-0.045	0.007	0.001	0.008	0.006
	[0.009]	[0.017]	[0.018]	[0.049]	[0.008]	[0.014]	[0.015]	[0.059]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19298	19298	19298	23745	19298	19298	19298	23745
R-squared	0.762	0.625	0.676	0.463	0.762	0.625	0.676	0.463
Countries	38	38	38	38	38	38	38	38

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 countries across 38 countries in Africa during 2001–2012. (2) The regressions exploit the nature of mining activities to explain spatial-temporal variations in district inequality. (3) All inequality indicators are at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) MLD stands for mean logarithmic deviation, and RLP stands for relative lights per capita. (6) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (7) Mineral extraction refers to mining sites where extractive mining activities are taking place, and mineral transformation refers to sites where value addition to raw minerals is performed. (8) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (9) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 17: The effects of the status of mining activities by mineral type on district inequality

	Constant mineral prices				Average mineral prices			
	Gini	MLD	Theil	RLP	Gini	MLD	Theil	RLP
SITC_1 x Active x log(Price)	0.126***	0.207***	0.105***	9.333***	0.137***	0.201***	0.109***	13.313***
	[0.006]	[0.020]	[0.014]	[1.080]	[0.015]	[0.047]	[0.035]	[2.704]
SITC_2 x Active x log(Price)	0.141***	0.296***	0.366***	0.404***	0.201***	0.560***	1.332***	0.025
	[0.006]	[0.016]	[0.016]	[0.131]	[0.010]	[0.017]	[0.024]	[0.188]
SITC_3 x Active x log(Price)	0.014	-0.178	0.020	-0.873	0.023	-0.160	-0.045	-0.261
	[0.089]	[0.223]	[0.129]	[0.808]	[0.085]	[0.194]	[0.161]	[0.882]
SITC_5 x Active x log(Price)	0.027	0.065	-0.002	0.611	0.032	0.081	0.008	0.619
	[0.037]	[0.067]	[0.081]	[1.044]	[0.048]	[0.087]	[0.106]	[1.153]
SITC_5 x Closed x log(Price)	-0.346***	-0.821***	-0.570***	-0.796***	-0.407***	-0.976***	-0.673***	-0.911***
	[0.002]	[0.003]	[0.004]	[0.068]	[0.002]	[0.004]	[0.005]	[0.080]
SITC_6 x Active x log(Price)	-0.063	-0.099	0.050	-7.762	0.003	-0.020	0.012	0.404
	[0.089]	[0.135]	[0.168]	[6.670]	[0.065]	[0.095]	[0.091]	[1.054]
SITC_6 x Closed x log(Price)	-0.282	-0.412**	-0.610**	-1.658	0.190***	0.331**	0.279***	2.558**
	[0.177]	[0.152]	[0.246]	[1.341]	[0.051]	[0.135]	[0.089]	[1.015]
SITC_7 x Active x log(Price)	-0.046***	-0.160***	-0.069***	-0.065	-0.039***	-0.135***	-0.058***	-0.049
	[0.010]	[0.032]	[0.023]	[0.138]	[0.009]	[0.028]	[0.019]	[0.118]
SITC_9 x Active x log(Price)	-0.003	-0.018	-0.012	0.182*	-0.003	-0.019	-0.009	0.176*
	[0.019]	[0.036]	[0.040]	[0.104]	[0.019]	[0.034]	[0.041]	[0.101]
SITC_10 x Active x log(Price)	-0.048	-0.090	-0.131	-0.562	-0.039	-0.076	-0.105	-0.481*
	[0.056]	[0.132]	[0.184]	[0.336]	[0.044]	[0.106]	[0.150]	[0.274]
SITC_11 x Active x log(Price)	-0.037	-0.087*	-0.022	-0.269**	-0.034	-0.079*	-0.019	-0.241*
	[0.026]	[0.044]	[0.042]	[0.132]	[0.023]	[0.040]	[0.038]	[0.121]
SITC_11 x Closed x log(Price)	-0.127***	-0.234***	-0.276***	0.801***	-0.115***	-0.207***	-0.255***	0.721***
	[0.002]	[0.004]	[0.004]	[0.159]	[0.001]	[0.003]	[0.003]	[0.147]
SITC_12 x Active x log(Price)	0.015	0.029	0.030	0.082	0.016	0.029	0.031	0.080
	[0.010]	[0.020]	[0.019]	[0.051]	[0.010]	[0.020]	[0.020]	[0.050]
SITC_12 x Closed x log(Price)	-0.008***	-0.038***	-0.006	-1.502**	-0.005***	-0.029***	0.006	-1.532**
	[0.002]	[0.013]	[0.040]	[0.698]	[0.001]	[0.010]	[0.041]	[0.689]
SITC_13 x Active x log(Price)	0.016	-0.316	-0.166	0.487	0.748*	1.097***	1.018**	0.334
	[0.143]	[0.667]	[0.418]	[0.426]	[0.418]	[0.323]	[0.390]	[0.290]
SITC_14 x Active x log(Price)	0.010	0.048***	0.005	0.394***	0.038	0.090**	0.062	0.655***
	[0.019]	[0.011]	[0.049]	[0.137]	[0.034]	[0.039]	[0.066]	[0.148]
SITC_14 x Closed x log(Price)	-0.056***	-0.251***	-0.094***	-0.344***	-0.035***	-0.208***	-0.066***	-0.249***
	[0.002]	[0.003]	[0.004]	[0.026]	[0.003]	[0.006]	[0.008]	[0.044]
SITC_15 x Closed x log(Price)	-0.158***	-0.379***	-0.225***	-0.091***	-0.142***	-0.346***	-0.202***	-0.086**
	[0.003]	[0.005]	[0.005]	[0.032]	[0.003]	[0.005]	[0.006]	[0.036]
SITC_16 x Closed x log(Price)	-0.111	-0.362	-0.229	0.581*	-0.099	-0.325	-0.206	0.675*
	[0.104]	[0.300]	[0.188]	[0.288]	[0.091]	[0.268]	[0.169]	[0.385]
SITC_17 x Active x log(Price)	0.042***	0.083***	0.037***	0.012	0.042***	0.083***	0.038***	0.002

	[0.005]	[0.009]	[0.005]	[0.452]	[0.003]	[0.006]	[0.004]	[0.390]
SITC_17 x Closed x log(Price)	-0.029***	-0.190***	-0.041***	0.035	-0.024***	-0.163***	-0.034***	0.033
	[0.001]	[0.003]	[0.003]	[0.532]	[0.001]	[0.003]	[0.003]	[0.460]
SITC_18 x Active x log(Price)	0.047*	0.087*	0.053	-0.134	0.041*	0.074*	0.045	-0.114
	[0.025]	[0.045]	[0.045]	[0.147]	[0.021]	[0.039]	[0.039]	[0.128]
SITC_18 x Closed x log(Price)	0.001	-0.049	0.033**	0.208	0.001	-0.045	0.026*	0.190
	[0.014]	[0.050]	[0.015]	[0.184]	[0.013]	[0.045]	[0.014]	[0.158]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19298	19298	19298	23745	19298	19298	19298	23745
R-squared	0.763	0.628	0.677	0.464	0.763	0.628	0.677	0.463
Countries	38	38	38	38	38	38	38	38

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions exploit the status of mining activities to explain spatial-temporal variations in inequality and welfare measures. (3) All inequality indicators are at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (6) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (7) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). (8) SITC_1: helium. (9) SITC_2: garnet (industrial). (10) SITC_3: stones (crushed, dimension), limestone, gypsum, marble, and silicon. (11) SITC_4: sulphur. (12) SITC_5: diamond. (13) SITC_6: barite, bentonite, clay, dolomite, fluorspar, graphite, salt, vermiculite, fluorine, and graphite. (14) SITC_7: iron ore. (15) SITC_8: copper. (16) SITC_9: cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, and tungsten. (17) SITC_10: arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, and wollastonite. (18) SITC_11: phosphate rock and phosphoric acid. (19) SITC_12: cement. (20) SITC_13: diatomite. (21) SITC_14: platinum. (22) SITC_15: nickel. (23) SITC_16: zinc. (24) SITC_17: tin. (25) SITC_18: gold. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 18: The effects of the scale of mining activities by mineral type on district inequality

	Gini	MLD	Theil	RLP	Gini	MLD	Theil	RLP
SITC_1 x Large scale x log(Price)	0.126***	0.206***	0.105***	9.326***	0.137***	0.202***	0.110***	13.289***
	[0.006]	[0.019]	[0.014]	[1.085]	[0.014]	[0.046]	[0.034]	[2.714]
SITC_2 x Large scale x log(Price)	0.134***	0.280***	0.359***	0.456***	0.193***	0.543***	1.324***	0.147
	[0.007]	[0.021]	[0.019]	[0.132]	[0.010]	[0.021]	[0.027]	[0.205]
SITC_3 x Large scale x log(Price)	0.012	-0.179	0.016	-0.844	0.021	-0.163	-0.046	-0.268
	[0.089]	[0.225]	[0.129]	[0.805]	[0.085]	[0.194]	[0.160]	[0.880]
SITC_5 x Small scale x log(Price)	-0.103	-0.150	-0.451	-0.122	-0.113	-0.141	-0.533	-0.141
	[0.065]	[0.224]	[0.398]	[0.141]	[0.090]	[0.312]	[0.502]	[0.156]
SITC_5 x Large scale x log(Price)	0.002	-0.002	-0.020	0.581	0.001	-0.002	-0.015	0.589
	[0.054]	[0.102]	[0.096]	[1.142]	[0.068]	[0.129]	[0.125]	[1.265]
SITC_6 x Small scale x log(Price)	-0.536***	-0.010	-0.159***	0.703	-1.173***	-1.565***	-1.135***	0.526
	[0.005]	[0.013]	[0.009]	[3.941]	[0.004]	[0.013]	[0.009]	[2.979]
SITC_6 x Large scale x log(Price)	-0.076	-0.132	-0.018	-7.390	0.051	0.058	0.068	0.621
	[0.080]	[0.120]	[0.158]	[6.261]	[0.059]	[0.097]	[0.088]	[1.064]
SITC_7 x Large scale x log(Price)	-0.045***	-0.156***	-0.069***	-0.074	-0.037***	-0.131***	-0.058***	-0.058
	[0.010]	[0.030]	[0.023]	[0.142]	[0.008]	[0.025]	[0.019]	[0.119]
SITC_9 x Small scale x log(Price)	-0.066***	-0.173***	-0.147***	0.467	-0.067***	-0.180***	-0.147***	0.453
	[0.002]	[0.003]	[0.003]	[0.401]	[0.002]	[0.003]	[0.003]	[0.390]
SITC_9 x Large scale x log(Price)	0.005	0.003	0.006	0.134	0.006	0.002	0.008	0.130
	[0.020]	[0.033]	[0.042]	[0.101]	[0.019]	[0.030]	[0.043]	[0.097]
SITC_10 x Small scale x log(Price)	0.200***	0.185***	0.168***	-1.229***	0.157***	0.157***	0.136***	-0.932***
	[0.003]	[0.006]	[0.007]	[0.272]	[0.002]	[0.004]	[0.005]	[0.205]
SITC_10 x Large scale x log(Price)	-0.063	-0.108	-0.151	-0.529	-0.052	-0.091	-0.122	-0.461
	[0.059]	[0.141]	[0.196]	[0.339]	[0.045]	[0.114]	[0.160]	[0.280]
SITC_11 x Large scale x log(Price)	-0.051	-0.110**	-0.060	-0.135**	-0.046	-0.099**	-0.054	-0.122**
	[0.032]	[0.051]	[0.069]	[0.060]	[0.029]	[0.046]	[0.064]	[0.052]
SITC_12 x Large scale x log(Price)	0.013	0.022	0.027	-0.079	0.014	0.023	0.030	-0.085
	[0.009]	[0.018]	[0.017]	[0.112]	[0.009]	[0.018]	[0.018]	[0.113]
SITC_13 x Large scale x log(Price)	0.014	-0.324	-0.169	0.466	0.748*	1.096***	1.016**	0.298
	[0.143]	[0.667]	[0.421]	[0.441]	[0.418]	[0.323]	[0.390]	[0.308]
SITC_14 x Large scale x log(Price)	0.005	0.027	-0.003	0.338**	0.034	0.071	0.053	0.580***

	[0.018]	[0.029]	[0.048]	[0.154]	[0.031]	[0.043]	[0.062]	[0.169]
SITC_15 x Large scale x log(Price)	-0.156***	-0.372***	-0.224***	-0.094***	-0.140***	-0.339***	-0.201***	-0.085**
	[0.003]	[0.006]	[0.007]	[0.032]	[0.003]	[0.006]	[0.007]	[0.038]
SITC_16 x Large scale x log(Price)	-0.112	-0.363	-0.230	0.582*	-0.099	-0.326	-0.207	0.671*
	[0.105]	[0.300]	[0.188]	[0.288]	[0.091]	[0.268]	[0.169]	[0.386]
SITC_17 x Small scale x log(Price)	-0.230***	-0.413***	-0.205***	-1.130***	-0.241***	-0.434***	-0.213***	-0.982***
	[0.002]	[0.003]	[0.003]	[0.238]	[0.002]	[0.003]	[0.004]	[0.207]
SITC_17 x Large scale x log(Price)	0.002	-0.073	-0.007	0.264	0.005	-0.058	-0.003	0.225
	[0.028]	[0.105]	[0.031]	[0.314]	[0.026]	[0.094]	[0.029]	[0.268]
SITC_18 x Small scale x log(Price)	0.083***	0.136*	0.138*	-0.389	0.071***	0.114*	0.116*	-0.351
	[0.023]	[0.080]	[0.079]	[0.393]	[0.020]	[0.067]	[0.068]	[0.352]
SITC_18 x Large scale x log(Price)	0.034*	0.056*	0.037	-0.032	0.030*	0.048*	0.031	-0.023
	[0.019]	[0.030]	[0.039]	[0.112]	[0.017]	[0.026]	[0.034]	[0.096]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19298	19298	19298	23745	19298	19298	19298	23745
R-squared	0.763	0.627	0.677	0.464	0.763	0.627	0.677	0.463
Countries	38	38	38	38	38	38	38	38

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions use the scale of district mining operations to explain spatial-temporal variations in inequality. (3) All inequality indicators are at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (6) Small scale refers to sites with artisanal mining activities, while large scale refers to sites where large-scale mining activities are taking place. (7) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (8) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). (9) SITC_1: helium. (10) SITC_2: garnet (industrial). (11) SITC_3: stones (crushed, dimension), limestone, gypsum, marble, and silicon. (12) SITC_4: sulphur. (13) SITC_5: diamond. (14) SITC_6: barite, bentonite, clay, dolomite, fluorspar, graphite, salt, vermiculite, fluorine, and graphite. (15) SITC_7: iron ore. (16) SITC_8: copper. (17) SITC_9: cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, and tungsten. (18) SITC_10: arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, and wollastonite. (19) SITC_11: phosphate rock and phosphoric acid. (20) SITC_12: cement. (21) SITC_13: diatomite. (22) SITC_14: platinum. (23) SITC_15: nickel. (24) SITC_16: zinc. (25) SITC_17: tin. (26) SITC_18: gold. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 19: The effects of minerals' value by mineral type on district inequality

	Constant mineral prices				Average mineral prices			
	Gini	MLD	Theil	RLP	Gini	MLD	Theil	RLP
SITC_1 x Low value x log(Price)	0.126***	0.206***	0.105***	9.326***	0.137***	0.201***	0.109***	13.285***
	[0.006]	[0.019]	[0.014]	[1.086]	[0.014]	[0.046]	[0.034]	[2.715]
SITC_2 x Low value x log(Price)	0.138***	0.286***	0.367***	0.432***	0.198***	0.551***	1.334***	0.112
	[0.008]	[0.018]	[0.018]	[0.125]	[0.011]	[0.018]	[0.026]	[0.197]
SITC_3 x Low value x log(Price)	0.014	-0.177	0.019	-0.851	0.023	-0.160	-0.044	-0.269
	[0.089]	[0.223]	[0.128]	[0.805]	[0.085]	[0.193]	[0.160]	[0.878]
SITC_5 x High value x log(Price)	-0.005	-0.012	-0.050	0.504	-0.006	-0.011	-0.051	0.511
	[0.049]	[0.095]	[0.093]	[1.002]	[0.062]	[0.121]	[0.120]	[1.112]
SITC_6 x Low value x log(Price)	-0.085	-0.129	-0.020	-7.041	0.025	0.023	0.044	0.624
	[0.078]	[0.118]	[0.155]	[5.969]	[0.062]	[0.101]	[0.089]	[1.016]
SITC_7 x Low value x log(Price)	-0.045***	-0.156***	-0.067***	-0.074	-0.037***	-0.131***	-0.057***	-0.059
	[0.010]	[0.030]	[0.024]	[0.140]	[0.008]	[0.025]	[0.020]	[0.118]
SITC_9 x Low value x log(Price)	-0.003	-0.018	-0.012	0.182*	-0.002	-0.018	-0.009	0.175*
	[0.019]	[0.036]	[0.040]	[0.104]	[0.019]	[0.034]	[0.041]	[0.100]
SITC_10 x Low value x log(Price)	-0.048	-0.090	-0.131	-0.571	-0.039	-0.076	-0.105	-0.492*
	[0.056]	[0.132]	[0.184]	[0.339]	[0.044]	[0.106]	[0.150]	[0.277]
SITC_11 x Low value x log(Price)	-0.051	-0.109**	-0.060	-0.136**	-0.046	-0.099**	-0.054	-0.123**
	[0.032]	[0.051]	[0.069]	[0.060]	[0.029]	[0.046]	[0.063]	[0.052]
SITC_12 x Low value x log(Price)	0.013	0.022	0.027	-0.080	0.014	0.023	0.029	-0.085
	[0.009]	[0.018]	[0.018]	[0.113]	[0.009]	[0.018]	[0.018]	[0.114]
SITC_13 x Low value x log(Price)	0.016	-0.319	-0.164	0.459	0.747*	1.095***	1.015**	0.298
	[0.143]	[0.666]	[0.421]	[0.438]	[0.419]	[0.325]	[0.392]	[0.305]
SITC_14 x High value x log(Price)	0.005	0.026	-0.002	0.349**	0.033	0.069	0.054	0.584***
	[0.018]	[0.029]	[0.048]	[0.143]	[0.031]	[0.043]	[0.062]	[0.165]
SITC_15 x Low value x log(Price)	-0.155***	-0.371***	-0.222***	-0.099***	-0.139***	-0.338***	-0.199***	-0.090**
	[0.003]	[0.005]	[0.007]	[0.031]	[0.003]	[0.005]	[0.007]	[0.037]
SITC_16 x Low value x log(Price)	-0.111	-0.363	-0.230	0.581*	-0.099	-0.326	-0.207	0.670*
	[0.104]	[0.300]	[0.188]	[0.288]	[0.091]	[0.268]	[0.169]	[0.386]
SITC_17 x Low value x log(Price)	0.001	-0.076	-0.008	0.021	0.004	-0.060	-0.004	0.015
	[0.027]	[0.103]	[0.030]	[0.421]	[0.026]	[0.093]	[0.028]	[0.362]
SITC_18 x High value x log(Price)	0.040**	0.066**	0.050	-0.087	0.035**	0.056**	0.043	-0.073
	[0.018]	[0.030]	[0.037]	[0.131]	[0.016]	[0.026]	[0.032]	[0.113]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19298	19298	19298	23745	19298	19298	19298	23745

R-squared	0.763	0.627	0.676	0.464	0.763	0.627	0.676	0.463
Countries	38	38	38	38	38	38	38	38

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 regions across 38 countries in Africa during 2001–2012. (2) The regressions use the classification of minerals' value to explain spatial-temporal variations in inequality. (3) All inequality indicators are at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (6) High value refers to mining sites where high-value minerals are extracted, whereas low value refers to places where low-value minerals are extracted. (7) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (8) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). (9) SITC_1: helium. (10) SITC_2: garnet (industrial). (11) SITC_3: stones (crushed, dimension), limestone, gypsum, marble, and silicon. (12) SITC_4: sulphur. (13) SITC_5: diamond. (14) SITC_6: barite, bentonite, clay, dolomite, fluorspar, graphite, salt, vermiculite, fluorine, and graphite. (15) SITC_7: iron ore. (16) SITC_8: copper. (17) SITC_9: cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, and tungsten. (18) SITC_10: arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, and wollastonite. (19) SITC_11: phosphate rock and phosphoric acid. (20) SITC_12: cement. (21) SITC_13: diatomite. (22) SITC_14: platinum. (23) SITC_15: nickel. (24) SITC_16: zinc. (25) SITC_17: tin. (26) SITC_18: gold. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.

Table 20: The effects of the nature of mining activities by mineral type on district inequality

	Constant mineral prices				Average mineral prices			
	Gini	MLD	Theil	RLP	Gini	MLD	Theil	RLP
SITC_1 x Extraction x log(Price)	0.124***	0.205***	0.104***	9.266***	0.135***	0.199***	0.107***	13.299***
	[0.006]	[0.018]	[0.013]	[1.068]	[0.014]	[0.044]	[0.033]	[2.713]
SITC_2 x Extraction x log(Price)	0.141***	0.301***	0.366***	0.444***	0.200***	0.549***	1.321***	0.089
	[0.007]	[0.020]	[0.013]	[0.118]	[0.011]	[0.028]	[0.019]	[0.184]
SITC_3 x Extraction x log(Price)	0.016	-0.171	0.063	-0.351	0.066	-0.077	0.080	0.178
	[0.119]	[0.270]	[0.159]	[1.141]	[0.098]	[0.248]	[0.164]	[0.843]
SITC_3 x Transform x log(Price)	0.004	-0.201	-0.091	-1.250	-0.068	-0.338*	-0.310*	-0.871
	[0.097]	[0.222]	[0.129]	[0.974]	[0.104]	[0.176]	[0.179]	[1.774]
SITC_5 x Extraction x log(Price)	-0.006	-0.013	-0.050	0.482	-0.007	-0.012	-0.051	0.515
	[0.049]	[0.095]	[0.093]	[0.978]	[0.062]	[0.121]	[0.120]	[1.106]
SITC_6 x Extraction x log(Price)	-0.093	-0.137	-0.084	-1.495	0.033	0.036	0.057	0.022
	[0.078]	[0.117]	[0.118]	[1.512]	[0.066]	[0.107]	[0.095]	[0.729]
SITC_6 x Transform x log(Price)	0.091	0.083	1.458	-145.355	-0.171***	-0.273*	-0.270***	16.046
	[0.059]	[0.150]	[1.102]	[113.332]	[0.017]	[0.143]	[0.020]	[14.116]
SITC_7 x Extraction x log(Price)	-0.059***	-0.189***	-0.088***	-0.149	-0.049***	-0.159***	-0.074***	-0.123

	[0.013]	[0.035]	[0.031]	[0.112]	[0.011]	[0.029]	[0.026]	[0.097]
SITC_7 x Transform x log(Price)	0.026	0.003	0.035	0.249	0.022	0.003	0.029	0.228
	[0.033]	[0.092]	[0.024]	[0.547]	[0.028]	[0.078]	[0.021]	[0.474]
SITC_9 x Extraction x log(Price)	0.003	-0.008	-0.000	0.209*	0.004	-0.009	0.002	0.201*
	[0.019]	[0.036]	[0.041]	[0.113]	[0.018]	[0.035]	[0.042]	[0.108]
SITC_9 x Transform x log(Price)	-0.108***	-0.169***	-0.197***	-0.457***	-0.098***	-0.156***	-0.180***	-0.425***
	[0.001]	[0.003]	[0.002]	[0.098]	[0.001]	[0.003]	[0.002]	[0.094]
SITC_10 x Extraction x log(Price)	-0.043	-0.092	-0.164	-0.741*	-0.038	-0.080	-0.135	-0.660*
	[0.068]	[0.165]	[0.229]	[0.409]	[0.055]	[0.136]	[0.190]	[0.338]
SITC_10 x Transform x log(Price)	-0.069**	-0.083	0.024	0.273	-0.041*	-0.053	0.030	0.208
	[0.030]	[0.277]	[0.060]	[0.295]	[0.024]	[0.214]	[0.044]	[0.219]
SITC_11 x Extraction x log(Price)	-0.071	-0.150**	-0.107*	0.070	-0.065	-0.135**	-0.098*	0.080
	[0.043]	[0.070]	[0.054]	[0.161]	[0.039]	[0.064]	[0.050]	[0.151]
SITC_11 x Transform x log(Price)	-0.002	-0.010	0.055	-0.714*	-0.000	-0.009	0.053	-0.702*
	[0.105]	[0.164]	[0.191]	[0.356]	[0.096]	[0.150]	[0.174]	[0.350]
SITC_12 x Extraction x log(Price)	-0.019	-0.015	-0.009	0.116	-0.018	-0.015	-0.008	0.104
	[0.023]	[0.026]	[0.013]	[0.089]	[0.021]	[0.025]	[0.011]	[0.090]
SITC_12 x Transform x log(Price)	0.024**	0.035	0.039	-0.151	0.025**	0.036	0.042*	-0.157
	[0.010]	[0.024]	[0.024]	[0.145]	[0.011]	[0.024]	[0.025]	[0.152]
SITC_13 x Extraction x log(Price)	-0.170***	-1.185***	-0.717***	1.062***	1.294***	1.522***	1.526***	0.664***
	[0.008]	[0.012]	[0.012]	[0.147]	[0.003]	[0.006]	[0.007]	[0.188]
SITC_13 x Transform x log(Price)	0.204***	0.553***	0.382***	0.125*	0.196***	0.665***	0.499***	-0.140
	[0.006]	[0.019]	[0.012]	[0.072]	[0.009]	[0.014]	[0.014]	[0.095]
SITC_14 x Extraction x log(Price)	-0.007	0.016	-0.028	0.313*	0.016	0.053	0.021	0.357**
	[0.011]	[0.032]	[0.042]	[0.161]	[0.021]	[0.039]	[0.042]	[0.131]
SITC_14 x Transform x log(Price)	0.069***	0.077***	0.125***	0.958***	0.124***	0.157***	0.226***	1.671***
	[0.001]	[0.003]	[0.003]	[0.164]	[0.002]	[0.006]	[0.005]	[0.326]
SITC_15 x Extraction x log(Price)	-0.154***	-0.370***	-0.221***	-0.123***	-0.138***	-0.336***	-0.198***	-0.094**
	[0.003]	[0.005]	[0.007]	[0.043]	[0.003]	[0.005]	[0.007]	[0.039]
SITC_16 x Extraction x log(Price)	-0.112	-0.363	-0.229	0.549*	-0.099	-0.326	-0.207	0.671*
	[0.104]	[0.300]	[0.188]	[0.275]	[0.091]	[0.268]	[0.169]	[0.387]
SITC_17 x Extraction x log(Price)	0.042***	0.083***	0.037***	0.161	0.043***	0.083***	0.038***	0.137
	[0.005]	[0.009]	[0.005]	[0.408]	[0.003]	[0.006]	[0.004]	[0.361]

SITC_17 x Transform x log(Price)	-0.028***	-0.190***	-0.040***	-0.635***	-0.024***	-0.163***	-0.034***	-0.556***
	[0.001]	[0.003]	[0.003]	[0.156]	[0.001]	[0.003]	[0.002]	[0.138]
SITC_18 x Extraction x log(Price)	0.044**	0.068**	0.052	-0.083	0.038**	0.057**	0.044	-0.076
	[0.019]	[0.032]	[0.039]	[0.129]	[0.016]	[0.027]	[0.034]	[0.117]
SITC_18 x Transform x log(Price)	-0.053***	0.033***	-0.001	-0.080***	-0.047***	0.027***	-0.002**	-0.090***
	[0.001]	[0.002]	[0.001]	[0.021]	[0.000]	[0.001]	[0.001]	[0.021]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19298	19298	19298	23745	19298	19298	19298	23745
R-squared	0.763	0.627	0.677	0.471	0.763	0.627	0.677	0.463
Countries	38	38	38	38	38	38	38	38

Notes: (1) The table shows the regression results for a sample of 2,182 districts in 653 countries across 38 countries in Africa during 2001–2012. (2) The regressions use the nature of mining activities to explain spatial-temporal variations in inequality. (3) All inequality indicators are at the district level and measured using night-time light intensity. (4) The standard errors, clustered at the country level, are in the brackets. (5) Constant (measured at constant 1998 US dollars) and average (measured as annual averages) prices come from USGS. (6) Extraction refers to mining sites where extractive mining activities are taking place, and transform refers to sites where value addition to raw minerals is performed. (7) Fixed effects include time fixed effects, district fixed effects, regional fixed effects, country fixed effects, and country-year fixed effects. (8) Controls include a proxy for agricultural productivity, rainfall, population sizes, lights pixels lit, and district geographical locations (measured in absolute latitudes). (9) SITC_1: helium. (10) SITC_2: garnet (industrial). (11) SITC_3: stones (crushed, dimension), limestone, gypsum, marble, and silicon. (12) SITC_4: sulphur. (13) SITC_5: diamond. (14) SITC_6: barite, bentonite, clay, dolomite, fluorspar, graphite, salt, vermiculite, fluorine, and graphite. (15) SITC_7: iron ore. (16) SITC_8: copper. (17) SITC_9: cobalt, chromium, niobium (columbium), tantalum, titanium, zirconium, and tungsten. (18) SITC_10: arsenic trioxide, lithium, manganese, pyrophyllite, soda ash, sodium silicate, and wollastonite. (19) SITC_11: phosphate rock and phosphoric acid. (20) SITC_12: cement. (21) SITC_13: diatomite. (22) SITC_14: platinum. (23) SITC_15: nickel. (24) SITC_16 zinc. (25) SITC_17: tin. (26) SITC_18: gold.
* $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Source: authors' estimations.