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Regional Redistribution of Mineral Resource Wealth in Africa

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Abstract

We study the economic implications of mineral resource activity for non-mining regions at the grid-level across the African continent. We find that capital cities benefit from mineral resource activity anywhere in the country. Leaders' birth regions also benefit, but only in autocratic regimes. Generic non-mining regions, on the other hand, are worse off. These results suggest that regional redistribution of resource rents in Africa is primarily undertaken to the benefit of capital cities and leaders' birth regions. In contrast, non-mining regions do not appear to be sufficiently compensated for the negative spillovers they may face due to mining activity elsewhere in the country.

Keywords: Mineral resources, spillovers, spatiality, luminosity, favoritism, democracy, Africa.

JEL codes: H77, O13, R12.

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1 Introduction

Mineral resources are an important source of income in many countries. As of 2017, the share of mineral resource rents in GDP was as high as 28% in Mongolia or 14% in the Democratic Republic of Congo. On average, mineral resource rents constituted 0.5% of World GDP.[1] Besides pure rents, the mineral resource sector additionally contributes to national GDP by providing employment for millions of formal and informal workers across many countries (Ericsson and Löf, 2019).

A recent literature has attempted to understand the local implications of mineral resources using geolocalized data (Cust and Poelhekke, 2015), following a long strand of research using cross-country data to study their macroeconomic effects (Sachs and Warner, 1995; van der Ploeg, 2011). The main question explored in this literature is whether and how the exploitation of mineral resources affects mining regions. Overall, there appears to be a consensus that mineral resources have positive effects on local economic development and household wealth (Michaels, 2011; Mamo et al., 2019; Loayza et al., 2013), even if these may come at the cost of environmental and social damages (James and Aadland, 2011; Aragon and Rud, 2013; Kotsadam and Tolonen, 2016).[2]

While the implications of mineral resources on mining regions have thus been explored by what is now a relatively large literature, a related and equally important question has been largely neglected hitherto: how mineral resources affect economic outcomes in regions other than mining regions. This is an important gap as mineral resources have economic implications not only in the resource regions, but potentially across many different parts of a given country.

[1]Mineral resource rents are the difference between the value of production for a stock of minerals at world prices and their total costs of production. Data taken from the World Bank's World Development Indicators.

[2]For example, the resource sector may crowd out other sectors that may be more viable in the long-run (Cust and Viale, 2016). A related literature also identifies a trade-off between short-run and long-run effects of mines on development. For examples, mineral resource wealth can lead to a lower regional income in the long-run if children and young adults drop out of education to work in the mineral resource sector (Ahlerup et al., 2019).

In particular, mineral resource rents are typically shared across different layers of government, i. e., while resource rents often accrue to the national government, it then redistributes mining revenues across various regions of the country. In other words, the wealth that is generated through the exploitation of mineral resources is redistributed across space, from the mineral resource regions to other regions. Evidence suggests that such regional redistribution of resource wealth is economically important (Bauer et al., 2016). However, there is almost no systematic empirical evidence about how widespread of a phenomenon regional redistribution of resource wealth is, which regions benefit, and why governments pursue this policy.

In addition, mineral resources can have macroeconomic effects that affect individual regions differently. For example, the Dutch Disease literature suggests that while resource regions can experience booms, non-resource regions can be negatively affected by adverse terms of trade effects (Corden, 1984). Another possible macroeconomic consequence of mineral resource wealth is general political instability or declining quality of government (Humphreys et al., 2007; Berman et al., 2017). Especially in non-resource regions, such effects might outweigh any potentially positive effects of higher resource revenues.

In this paper, we shed light on how mineral resources affect various non-mining regions of a country using micro-level data from the African continent. Combining geo-referenced data on the operation of mines for different minerals with luminosity data over the period 1992-2013, we explore how the operation of mines affect luminosity in various non-mining regions of a country, notably in capital cities, the birth regions of national leaders, and generic non-mining regions.

We show that the opening of one additional mine anywhere in the country increases luminosity in the capital city. This ostensibly indicates that resources are shifted from mining regions to capital cities. We also observe that additional mines anywhere in the country increase luminosity in the current national leader's birth region in autocracies, but not in democracies. This suggest that the distribution of mineral resource wealth is subject to regional favoritism in non-democratic settings. Third, we observe that additional mines in a given country decrease luminosity in non-mining regions, compared to similar regions in adjacent countries. This finding suggest that mineral resources can have negative implications for non-mining regions due to e. g. negative terms of trade effects.

This paper is primarily related to a recent literature that studies the relationship between mineral resources and intergovernmental transfers. Existing studies, however, tend to focus on the implications of intergovernmental transfers funded by resource revenues allocated to the mining regions. For example, Cust and Ridwan (2014) present evidence from Indonesia that fiscal transfers related to oil production boost local GDP in oil-producing regions. The direct effect from project investments, on the other hand, appears to be more attenuated. Caselli and Michaels (2013) study the effect of oil revenue windfalls in Brazil on municipalities that benefit from fiscal sharing rules. However, they focus only on municipalities that are close to the offshore production facilities. While oil is not directly produced within the boundaries of the municipalities, this study is similar to the previous literature on local effects as these are municipalities that have a claim to the resource revenues.

This paper is also related to the literature on mineral resource wealth on political conflicts and instability. Berman et al. (2017) find that a rise in mineral prices can explain about one-fourth of violence across African countries during the observation period (1997-2010). Similarly, Lessmann and Steinkraus (2017) find that an unequal regional distribution of natural resources within countries exacerbate political tensions and cause conflicts. However, while these papers take into account that mineral resources can have global effects, they do not spatially disaggregate how individual non-mining regions are affected by aggregate mineral resource activity.

2 Background

2.1 Mineral resources and their exploitation in Africa

Minerals are materials with economic value in or on the Earth's crust. The list of minerals is long, prominent examples include gold, copper, or gemstones. In general, minerals can be extracted and applied as inputs in for various productive uses, including industrial applications.

Mineral resources of significant value typically belong to the state and can be an important source of public revenue. They are exploited either by state-owned corporations or private firms that have acquired a license from the government and thus pay royalties or are taxed according to production (Land, 2009). In Africa, most countries tend to rely on private investors due to limited domestic mining capacity (Laporte and Quatrebarbes, 2015).

Government taxation of mineral resources and the cost of licenses are thus the main means by which African governments tap into the resource rent. The rules by which revenues are shared between governments and private corporations vary between countries. Due to the idiosyncrasies of the mineral resource sector, corporations and investors often receive unique tax treatments. The share of the resource rent that accrues to the public sector thus varies depending on such factors as global market conditions or the bargaining power of governments. It is estimated that the rent captured by governments can range from 25% to 65% (Land, 2009).[3]

2.2 Regional distribution of mineral resource revenues

Governments are complex organizations where power is shared vertically and horizontally. Power is shared vertically between the national and subnational governments and horizontally among various subnational governments. This raises the issue of how resource rents to which the "government" is entitled are shared across the governmental units.

The traditional fiscal federalism literature appears to suggest that resource rents should accrue to the national government (Oates, 1999). National governments are better equipped to deal with the inherent volatility of resource revenues, which are for example subject to global demand shocks. Subnational governments may also lack sufficiently competent staff and the

[3]According to Laporte and Quatrebarbes (2015), whether governments (and other domestic stakeholders) receive their "fair" share of resource rents is up for debate. How resource rents should be shared between governments and private investors is a question that is separate from how rents should be shared across the various regions within the country. Basic economic theory suggests that pure rents can be fully captured by the government (e.g. by a lump-sum tax), but in practice this is not feasible due to e. g. international production capacity constraints.

absorptive capacity to make adequate use of resource rents. Consequently, they might make inefficient investments or waste resources on vanity projects (Broiso and Singh, 2014).

African countries seem to follow the recommendations given in the traditional fiscal federalism literature.[4] While the national constitutions tend to only make vague statements regarding ownership, proclaiming that resources belong to the "people" or the "state", both legislation that concretizes the constitution and administrative reality indicate that it is the national governments that is the first claimant of any resource revenues.[5]

Therefore, it is the national government that typically negotiates with the private corporations and decides on their tax treatment. There are various taxes that national governments levy on mineral resources, ranging from income and profit taxes, to royalties and licensing fees, sales and excise taxes, VATs on goods and services, and stamp duties etc. (Otto, 2001).[6] The share of the rent that accrues to the national government is then distributed across governmental units, and thus either explicitly or implicitly across different regions of the country. Whether this regional distribution takes place according to pre-determined rules or in a discretionary fashion depends on the institutional arrangements in a given country.

Many African countries have a formal revenue sharing scheme by which regional governments participate in national government revenues (both from resource rents and other revenue sources).[7] A general feature of revenue sharing in Africa is that the resource producing regions

[4]Of course, the true reason why revenues are assigned in this way may not be the normative prescriptions of this literature but political expediency.

[5] Natural resource rents are typically only allocated to local governments if their economic importance is small (Broiso and Singh, 2014). With the recent wave of decentralization, ownership of resource rents has also been partially transferred to subnational governments, but national governments generally continue to be the main claimants (Broiso and Singh, 2014).

[6]Depending on the country in question, regional and local governments may also be allowed to tax resource rents to some degree using such taxes.

[7]Indeed, Fjeldstad et al. (2014) point out that local governments in Africa, with the possible exception of South Africa, rely heavily on central government transfers to fund their expenses. One notable example is Botswana, where rural councils receive 92% and urban areas receive 62% of their revenues from the central government.

receive a relatively large share of the rents (Broiso and Singh, 2014). This is often justified as a compensation for the environmental or social damages due to the mining activities.

Non-producing regions also often receive a share of the resource rents through formal revenue sharing mechanisms. One normative reason for why non-mining regions should benefit from resource rents is a standard insurance argument. Ex-ante, it is unclear which regions will have valuable mineral resources. Under a veil of ignorance, it is thus welfare increasing to share resource revenues. However, national governments also allocate resource revenues discretionarily to non-resource regions. Such discretionary transfers may be normatively justifiable if they are granted to achieve desirable economic or social and environmental goals. On the other hand, discretionary transfers might be granted to pursue a narrow political or electoral agenda or due to clientelism and favoritism. In general, there is a lack of evidence about the motives that would lead national governments to redistribute resource rents to non-mining regions.

Besides explicit transfers that affect subnational revenues, national governments can also use a share of the resource rents to fund national expenses. National government spending generally has distributional consequence across space, with some regions benefiting more than others (Berry et al., 2010). In general, it is opaque and dependent on idiosyncratic country-specific political and institutional circumstances which regions will benefit from any higher national spending, either due to new found mineral resource wealth or other reasons (Reingewertz and Baskaran, 2019).

Given such complexities of intergovernmental equalization, it is difficult to identify the economic effects of mineral resources beyond the mining regions using only fiscal data. Without knowledge of the entirety of transfers that flow from the national to subnational governments (vertical transfers) and between subnational governments (horizontal transfers) and a spatial disaggregation of national government spending, it is nearly impossible to arrive at an accurate assessment. In addition, intergovernmental transfer schemes in Africa are generally not sufficiently developed to adequately transfer resource rents across regions (Broiso and Singh, 2014). A significant part of the spatial redistribution in Africa thus takes place discretionarily and on an ad-hoc fashion. For these reasons, we rely in the following on night time luminosity as a catch-all measure of the economic implications of the redistribution of mineral resource rents beyond the mining regions.

2.3 Spatially heterogeneous effects of mineral resource exploitation

3 Data

3.1 Grid-level data

To study the spatial effects of mineral resources, we overlay a grid of 0.5×0.5 degree pixels (0.5 degrees correspond to about 55km at the equator) over the African continent. We then intersect this grid with a map of country borders to identify within which country a particular pixel is located. We then drop from this grid all pixels that are located in more than two countries. The final sample consists of 9068 pixels over the period 1992-2013. We plot all remaining data discussed below on this grid (See e. g. Figure 5).[8]

3.2 Mineral resource data

This mineral resource data is from MinEx Consulting, which is a private mining consulting company. The database contains a comprehensive list of *significant and unique* deposits in Africa. Overall, Minex Consulting estimates that its data covers 99% of all giant-sized deposits, 95% of all major deposits, 70% of moderate deposits and 50% of minor deposits.[9]

[8]In the regressions, nine small pixels are dropped due to a missing value for luminosity. The reason is that the these pixels are at country borders and hence smaller than the size of the pixels in the luminosity raster datasets. For such pixels, no luminosity value can be calculated.

[9]The thresholds for precious metals are: Minor $\geq$ 0.03 Moz Au (millions of ounces gold) equivalents, Moderate $\geq$ 0.32 Moz Au equivalents, Major $\geq$ 2.24 Moz Au equivalents, Giant $\geq$ 11.18 Moz Au equivalents, Supergiant $\geq$ 80.00 Moz Au equivalents. For other minerals, the thresholds are: Minor $\geq$ 0.03 Mt Cu (millions of megatonnes of copper) equivalents, Moderate $\geq$ 0.32 Mt Cu equivalents, Major $\geq$ 2.45 Mt Cu equivalents, Giant $\geq$ 18.97 Mt Cu equivalents, Supergiant $\geq$ 35.00 Mt Cu equivalents.

The database lists 519 deposits that were in operation at least for one year during the 1992-2013 period. Of these 519 mines, we lack information on the exact startup or shutdown date for 228 mines. We omit these mines from the analysis, which leaves us with a final sample of 291 mines of any size (coverage 56%).

Second, among the 519 deposits, 246 were classified as major, giant or supergiant. Among these 246 deposits that were of at least major size, we lack information on startup or shutdown dates for only 47 mines, leaving us with a sample of 199 at least major mines (coverage 81%). Given the better coverage of larger mines in the sample, we estimate wherever appropriate separate specifications for mines of at least major size in addition to specifications with all mines.[10]

We project the latitude and longitude coordinates of the 291 mines in our sample onto a map of the countries included in our sample; see Figure 1. Figure 2 shows the number of operational mines across Africa included in each year of our sample period. Figure 3 and 4 show the number of mine openings and closings per year in our sample. There is ostensibly significant variation in mining activity during the sample period. It is apparent that openings generally outnumber closures, particularly in the second half of the sample period.

3.3 Luminosity data

We use nighttime luminosity as a proxy for economic developments at the local level (Alesina et al., 2016; Hodler and Raschky, 2014; Michalopoulos and Papaioannou, 2016; Bruederle and Hodler, 2018). This data is based on images of the earth at night obtained by satellites of the US Air Force (USAF) Defense Meteorological Satellite Program Operational Linesman System (DBMS-OLD). The original imagery is processed by the National Oceanic and Atmospheric Agency (NOAA) and released to the public as raster datasets.

The raster datasets consist of annual average stable night lights between 8.30pm to 10pm and are available at a resolution of 30 arc-seconds (about 0.86 square kilometer at the equator)

[10] Another advantage of larger mineral deposits is that they are likely to have a stronger and thus more easily detectable economic effect.

for all years after 1992. Each pixel of the dataset stores a digital value ranging from 0 to 63 indicating the amount of average light of an area covering 30 arc-seconds. Higher values imply that a pixel emanates more light (Henderson et al., 2012).

To obtain pixel-level measure of economic development, we overlay the grid of pixels over the raster datasets and calculate the area mean of the digital values of each cell with size 30 arc-seconds that falls within the boundaries of each of the 0.5×0.5 degree pixels.

3.4 Further data sources

We use information on the birth cities of national leaders from the Archigos database (Goemans, 2016); in cases where information on birth regions was missing, we add this information ourselves. We then geocode the birth cities using ArcGIS. We retrieve information on the location of national capitals from the CEPII's GeoDist database (Mayer and Zignago, 2011). To capture the extent of democracy and civil rights in a country, we use data from Freedom House (House, 2019). To measure the relative power of various ethnicities across Africa, we use geospatial data from Vogt et al. (2015).

4 Results

4.1 Mineral resources and luminosity in capital regions

Our aim is to study how mineral resource exploitation anywhere in a given country affects economic outcomes in non-mining regions of the country. We begin by studying the effect of mines on luminosity in the nation's capital. Capitals are a natural candidates that might particularly benefit from mineral resources anywhere in the country as it is the national government that typically has the primary ownership rights to them (see the discussion in Section 2.2).

To identify pixels that belong to capital regions, we draw a buffer of 10km size across the longitude and latitude coordinates for capital cities given in the CEPII's GeoDist database. All pixels that fall within each buffer are indicated as capital regions; see Figure 5.[11] Using this categorization of pixels as capital regions and non-capital regions, we estimate difference-in-differences specifications of the following form.

$$y_{i,t} = \alpha_i + \sum_c \gamma_t \times c + \beta \text{Mines}_{i,t} \times \text{Capital}_i + \varepsilon_{i,t}, \quad (1)$$

with y_{it} the log of the mean of luminosity in pixel i in year t, α_i pixel fixed effects, γ_t year fixed effects and c country dummies (i. e. we include country-specific year fixed effects).

The variable of interest is the interaction between $\text{Mines}_{i,t}$ and Capital_i. $\text{Mines}_{i,t}$ is a count variable capturing the total number of mines in the country. $\text{Capital}_{i,t}$ is a dummy variable that is 1 if a pixel is a capital region.

No capital was moved during the sample period in Africa, and hence there is no within-pixel variation in capital regions.[12] Second, the sum of mines is perfectly collinear with the country-year fixed effects. For these reasons, this specification only include the interaction between the sum of mines and the capital dummy. β hence measures the disproportionate effect of an additional mine anywhere in the country on luminosity in the pixels covering the capital regions, compared to pixels in other (non-mining) regions.

The key identifying assumption for this specification is that the variation in the number of mines in a given year throughout the country is orthogonal to unobserved variables in capital regions. This appears to be a reasonable assumption as the startup or closures of mines across the country is plausibly unrelated to specific developments in capital regions (recall that we account for country-wide developments with the country-year fixed effects).

The results are collected in column (1)-(2) of Table 1. We find that capitals benefit disproportionately more from additional mines anywhere in the country than other regions. Luminosity

[11] We draw a buffer around the geographic coordinates to capture capitals that are close to the sea. Due to projection inaccuracies, the longitude and latitude coordinates may be projected slightly outside of the range of the African land pixels. We also drop capitals that are so close to their country's border that they falls only within pixels that cover both countries.

[12] We omit the capital of South Sudan, Juba, as this country came to existence only in 2011.

increases on average by about 5.7% more in capital regions than in other regions if an additional mine of any type is in operation (column 1). The effect is slightly larger, about 6.6%, for large mines (column 3).

Overall, the results imply that a significant share of mineral resource rents are shifted to the national capital. This may, on the one hand, appear due to spending on public goods by the national government using the additional revenues. Alternatively, since the national elite resides in the capital, it may also be that the increase in luminosity is due to higher private incomes. In this case, this increase in luminosity in the nation's capital may indicate that at least part of the resource rents is siphoned off and mostly benefits well-connected individuals.

4.2 Mineral resources and luminosity in leaders' birthregions

Another region where we might expect to see an increase in luminosity when overall mineral activity in the country expands is the birth region of the national leader. Evidence suggests that national leaders engage in regional favoritism and try to allocate additional resources to their homelands (Hodler and Raschky, 2014; Asatryan et al., 2021a,b). Whether they increase the extent of regional favoritism if additional revenues are available due to expanding mineral activity or cut back favoritism if revenues decline due to the closure of mines is, however, an open question.

To study this question, we estimate the following specification:

$$y_{i,t} = \alpha_i + \sum_c \gamma_t \times c + \delta \text{Leader}_{i,t} + \beta \text{Mines}_{i,t} \times \text{Leader}_i + \varepsilon_{i,t}, \quad (2)$$

where $\text{Leader}_{i,t}$ is a dummy that is one when a pixel covers the birth region of the contemporaneous national leader and 0 else. All other variables are defined as above.

To identify pixels covering a leader's birth region, we draw, as for capital cities, a buffer of 10km around each leader's birth city's longitude and latitude coordinates and classify all pixels that fall within this buffer as treated. Note that unlike for capital regions, we can estimate the effect of the leader's birth region since leader's birth regions change whenever there is a transition of power.

The results are collected in column (3)-(4) of Table 1. In contrast to capital cities, we find that neither generic mines nor large mines result in a disproportionately large increase in luminosity. That is, there does not appear to be a disproportionate transfer of resources to leader's birth regions after a new mine starts to operate.

4.3 Mineral resources and luminosity in generic regions

We next explore the effect of mineral resources in generic non-mining regions. For this, we cannot rely on within-country variation. Unlike for such well-defined geographical units as capital cities or leader's birth regions, it is not possible to explore whether generic regions are disproportionately affected by mineral resources as there is, by definition, no appropriate comparison within a given country. In methodological terms, this means we cannot include country-specific year fixed effects in our specifications. However, omitting country-specific year fixed effects would give rise to what is essentially a cross-country empirical design with the corresponding identification issues (Maddala, 1999).

We therefore adopt a strategy centered around border regions to identify the effect of mines on generic non-mining regions. Specifically, we compare luminosity in (non-mining) border regions of a country where an additional mine begins operation with luminosity in border regions in neighboring countries. The identifying assumption is that year-specific effects in border regions of different countries will be similar. If this assumption holds, a disproportionate increase in luminosity in the border regions of a country where a new mine starts operation, compared to the border regions of neighboring countries can be ascribed to mineral resource rents.

This identifying assumption appears plausible in the African context. First, national borders are generally porous in Africa (Ikome, 2012). Second, the grip of the national government tends to weaker in the hinterlands (Jackson and Rosberg, 1982). Thus, national level trends (that would be captured by country-specific year fixed effects) should be less relevant for border pixels. As such, long-run local conditions and economic trajectories should be similar in "treated" and "control" units.

To implement this identification strategy, we first classify each pixel on whether it is adjacent to it's country's border. We use a distance of 250km as the threshold. These pixels constitute our basic sample; see Figure 7 for a map that indicates these pixels. Next, we calculate for each border pixel in a given country the average luminosity of all pixels within a 250km distance that are located in a different country. This average luminosity across neighboring foreign pixels constitutes the counterfactual for our domestic index pixel. Figure A.1 in the Appendix shows how mean luminosity in index pixels and their neighbors evolve during the sample period. The trends are remarkably similar, suggesting that pixels in neighboring countries can provide a reasonable counterfactual for the border pixels in a given country.

Using this data, we estimate the following specification:

$$y_{i,t} - \bar{y}_{i,t} = \alpha_i + \gamma_t + \beta \text{Mines}_{i,t} + \varepsilon_{i,t}, \tag{3}$$

with y_{it} the log of the mean of luminosity in pixel i in year t and $\bar{y}_{it}$ the log of the mean luminosity in average across pixels located in neighboring countries within 250km distance. As above, α_i are pixel fixed effects, γ_t are year fixed effects (that are not differentiated by country), and $\text{Mines}_{i,t}$ is the number of mines in the country where pixel i is located in year t.

The results are collected in column (5)-(6) of Table 1. We find that an additional mine decreases luminosity in generic (border) regions located in the respective country relative to luminosity in pixels located closeby but in neighboring countries. Specifically, the difference declines by one to three percentage points.[13] These results suggest that non-mining regions are disadvantaged by additional mining operations. It appears that negative effects such as the Dutch Disease outweigh the benefits of any spatial redistribution that non-mining regions might benefit from.

[13] For the specification with all mines, we observe a non-linear effect, indicating that the negative effects of mines in generic regions becomes more pronounced with the existing number of mines (Column 2). When we focus on large mines, on the other hand, we observe no non-linearities.

4.4 Extensions

4.4.1 Democracy and the spatial effects of mineral resources

While we do not find that leaders' birthregions benefit from additional mining activity on average, there may be heterogeneity depending to the level of democracy. In particular, previous research suggests that (regional or ethnic) favoritism is more prevalent in non-democracies (Burgess et al., 2015). Similarly, capital regions may appear to benefit more in non-democratic settings if a lack of accountability and oversight enables national elites to capture more of the resource rent (Libman, 2013).[14] To explore this, we estimate models where we interact the number of mines variable with dummy variables for the level of democracy in a country.

The results for capital regions are collected in column (1)-(2) of Table 2. We find no difference in the effect of additional mining activity on capital regions between democracies and autocracies. In both political regimes, capital regions appear to benefit similarly. For all mines, we estimate an effect of about 5.5%, for large mines, we estimate an effect of 6.1%. That the disproportionate increase in capital cities' luminosity is similar in autocracies and democracies might suggest that the reason why capital regions benefit from mineral activity is relatively benign. Both democracies and autocracies might increase spending on (national) public goods that are located in capital cities.

For leaders' birth regions, on the other hand, we observe heterogeneous effects for larger mines (column (3)-(4) of Table 2). Specifically, we find that in autocracies, additional mines increase luminosity in leaders' birth regions by about 0.7%. The effect is slightly stronger at about 0.9% for large mines. No similar effects exists for democracies. As discussed above, this result is consistent with previous findings on the importance of democracy for the prevalence of regional or ethnic favoritism.

[14] Libman (2013), for example, shows that the effect natural resources on regional economic performance depends on the level of *subnational* democracy using variation in the level of subnational democracy across the Russian Federation.

For generic regions, we again observe that the effect of mineral activity depends on the extent of democracy. According to column (5)-(6), we find that while generic regions are disadvantaged by additional mineral activity in autocracies, luminosity increases in democracies. As before, this result again points to significant differences across political regimes in how resource rents are redistributed. While autocracies seem to use rents to benefit the governments' supporters, democracies appear to aim for a more equitable spatial distribution of resources. On average, however, the effect of mineral resources appears to be negative as shown in columns (5)-(6) of Table 1, likely because most African countries were autocratic or semi-autocratic during the sample period (see the summary statistics in Table A.5).

4.4.2 Ethnicity and luminosity in mining regions

In this section, we explore how the economic effects of mineral resources affect mining regions. While previous research has documented that mineral resources on average improve economic outcomes in mining regions, less is known how the effect of minerals depends on the political status of the mining regions. Specifically, we are interested in whether luminosity grows less in those resource regions that are inhabited by ethnicities that have a politically weak or strong position at the national level.[15]

As discussed, we rely on data form Vogt et al. (2015) on ethnic power to measure the concurrent political status of an ethnicity. We classify ethnicities that are considered as having a "monopoly" on power or as "dominant" in the ethnic power dataset as politically strong. We consider ethnicities classified as "discriminated" as politically weak. We classify all other ethnicities as political neutral. See Figure 8 for a map of Africa in which regions are indicated according to the political status of the inhabiting ethnicities. Note that ethnicities can change their status over time due to power shifts at the national level.

Using this data, we estimate specifications of the following form:

[15] We report results for the local effect of mineral resources in Appendix Table A.1 and for its spatial diffusion in Appendix Table A.2. In line with most previous findings, we find that mineral resources have a strong positive effect on luminosity.

$$y_{it} = \alpha_i + \sum_c \gamma_t \times c + \sum_p \beta_p \text{Mine}_{i,t} \times Power_{i,t} + \varepsilon_{i,t}, \quad (4)$$

with $y_{i,t}$ and $\gamma_t \times c$ defined as above, $\text{Mine}_{i,t}$ a dummy that is 1 if a pixel had at least one operating mine in year t, and *Power* a dummy variable that is 1 if region i was inhabited by a politically strong or weak ethnicity, respectively.

The results show that luminosity increases noticeably less in mining regions that are inhabited by ethnicities considered as politically weak. While luminosity in regions with politically strong or neutral ethnicities increases by about 80-90% when a mine starts up it's operation, the increases is about 63 percentage points lower in regions with politically weak ethnicities. This result suggests that mineral resources have smaller benefits for politically weak, arguably due to interregional redistribution to regions that the national government deems as more important.

5 Conclusion

We study how mineral resources are redistributed across space and how they affect economic conditions in non-mining regions in Africa. Focusing on countries across the African mainland, we show that mineral resources have noticeable economic implications in non-mining regions. In particular, we find (i) that capital cities benefit from mineral resource activity anywhere in the country, (ii) that leaders' birth regions benefit in autocratic regimes, and (iii) that generic non-mining regions are disadvantaged in autocracies but not in democracies. We also observe that among mining regions, those located in the homelands of politically weak ethnicities display a smaller increase in luminosity than those located in politically strong regions.

These results can advance our understanding of how mineral resources affect local economies. In particular, they help us to understand how governments concurrently balance the interests of the local mineral resource communities with those of other regions. For example, the fact that in autocracies, leaders' birth regions appear to benefit from mineral resources suggests that that favoritism toward elites residing in the national leader's home region is one important motivation for regional redistribution of mineral resources.

Consistent with this conclusion, the finding that generic non-mining regions seem to be disadvantaged by mineral resource activity in autocracies indicates that autocratic governments do not redistribute sufficient resources from mining regions to generic non-mining regions to counter the potentially adverse macroeconomic effects faced by them. This apparent lack of regional redistribution to generic regions might be due to a general disinterest in good governance in autocracies. In addition, such redistribution may be difficult given that reallocating substantial resources away from mining regions may be perceived as unjust. Indeed, perceived injustices of explicit or implicit redistribution of mineral resource wealth across regions are frequently a source of political conflicts, particularly if politically connected regions like capital cities or leaders' birth towns benefit disproportionately from regional redistribution.

There are various avenues for future research. One important avenue is to investigate the mechanisms through which mineral resources affect luminosity in non-mining regions. While luminosity may decline due to macroeconomic effects, another reason may be migration out of non-mining to mining regions. Relatedly, further research should also study on a country-by-country basis whether resources are redistributed through formalized intergovernmental transfer schemes or informally by ad-hoc government allocations. Finally, it would be interesting to explore in more detail who specifically benefits from the transfer of resources to capital and leader's birth regions using individual-level data.

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Figure 1: Mines across Africa. This figure shows the location of all mines included in our sample across Africa.

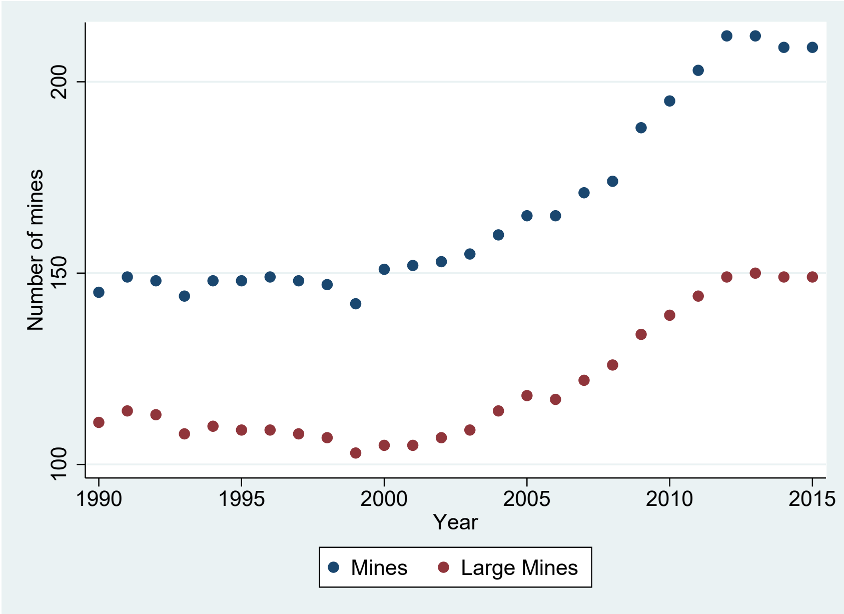
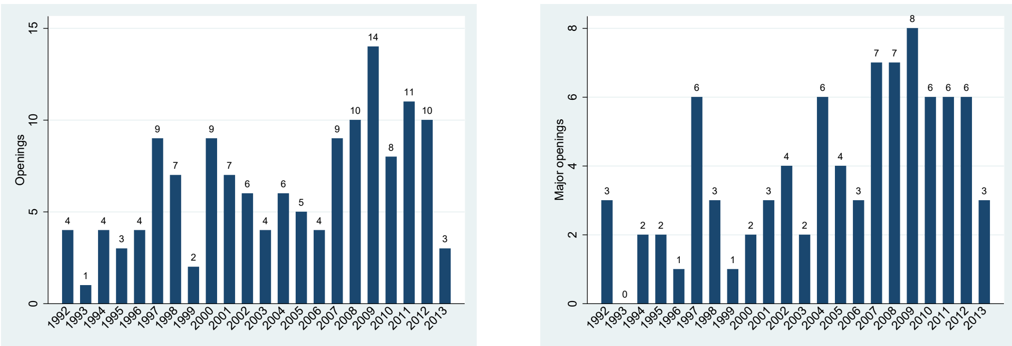


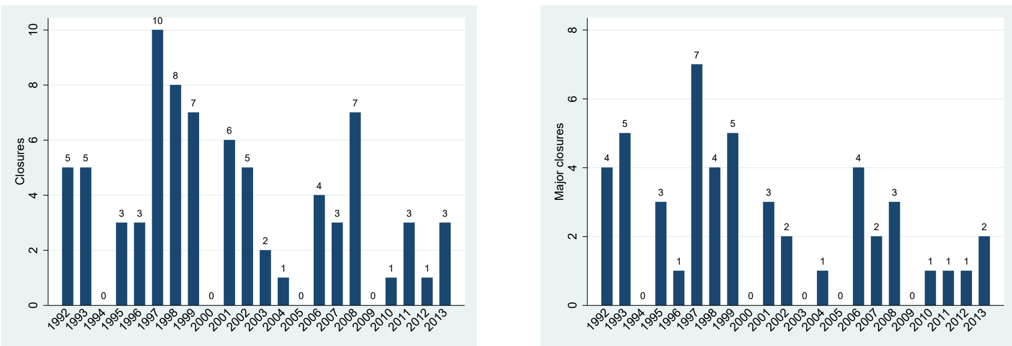
Figure 2: Number of active mines in Africa over time. This figure shows the number of active mines across Africa included in our sample for each year in the sample period.



(a) Openings, any mine

(b) Openings, major mines

Figure 3: This figure shows the total number of mine openings in each year during the sample period.



(a) Closures, any mine

(b) Closures, major mines

Figure 4: This figure shows the total number of mine openings in each year during the sample period.

Figure 5: Grid of Africa with included and capital city pixels. This figure displays a grid over Africa. It indicates all pixels that cross two or more countries and are therefore dropped in the analysis (orange) and all pixels that are within a 10km buffer around the capital city of each country (red). Note that capital cities that are close to a country border are dropped from the sample and therefore not included (e.g. Kinshasa (DR Congo) or Bangui (Central African Republic)).

Figure 6: Grid of Africa with included and leader region pixels. This figure displays a grid over Africa. It indicates all pixels that cross two or more countries and are therefore dropped in the analysis (orange) and all pixels that are within a 10km buffer around the coordinates for the birthplace of a country's leader (red). Note that birthplaces that are close to a country border are dropped from the sample and therefore not included.

Figure 7: Grid of Africa with pixels included in the border regressions. This figure displays a grid over Africa. It indicates all pixels that are within 250km of any given country's border. These pixels are included in the border pixel regressions.

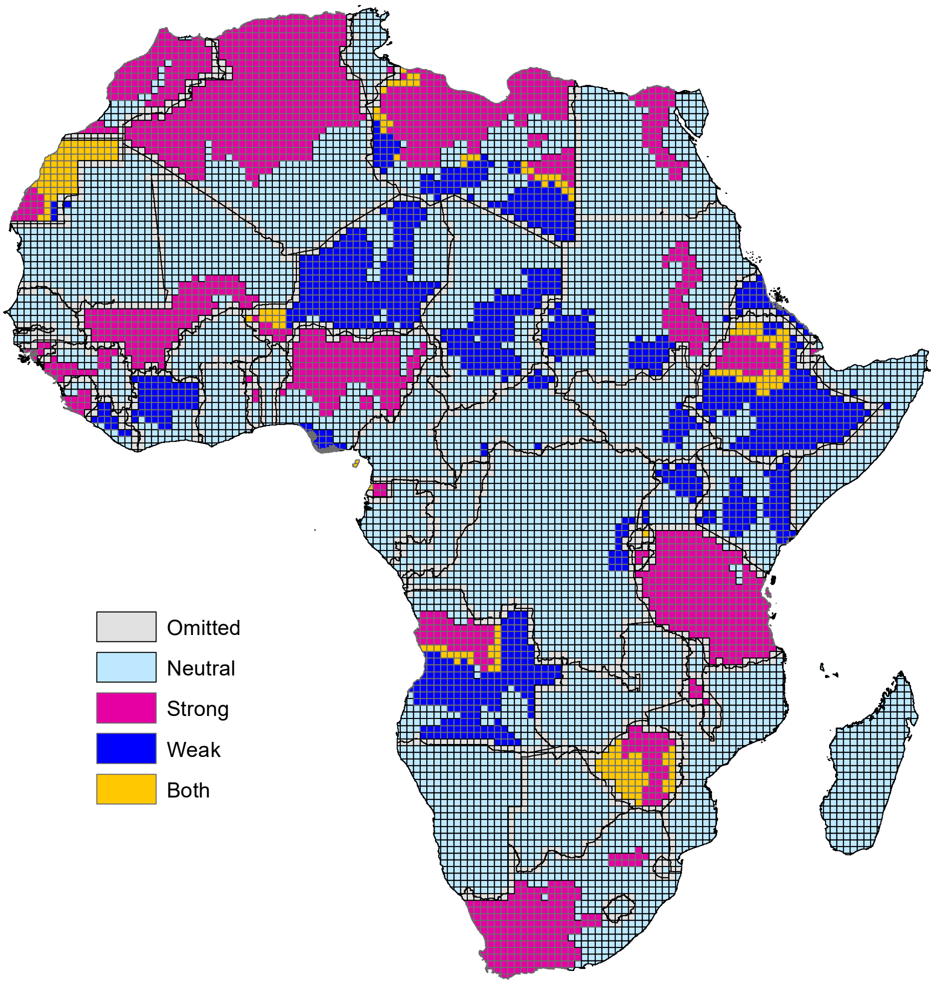


Figure 8: Grid of Africa with included and ethnic power. This figure displays a grid over Africa. It indicates all pixels that cross two or more countries and are therefore dropped in the analysis (orange). It also indicates pixels according to the degree of power the ethnicities that inhabit a pixel have held at the national level during the sample period. To identify ethnic homelands as well as their degree of power at the national level, (geospatial) data from Vogt et al. (2015) was used. We define a ethnicity as having a strong position if Vogt et al. (2015) code its power status as "Monopoly" or "Dominant" and as having a weak position if they code its status as "Discriminated". Pixels that are inhabited by two or more ethnicities are coded as strong / discriminated if at least one of the ethnicities has the corresponding status (i. e. pixels can be simultaneously coded as strong and weak). In the figure, pixels that were inhabited by an ethnicity with a strong position for at least one year during the sample period are marked red. Pixels that were inhabited by an ethnicity that was discriminated for at least one year are marked blue. Pixels with ethnicities that were discriminated and strong at different points during the sample period and pixels with two or more ethnicities with different status are marked in light orange.

Table 1: MINERAL RESOURCES AND LUMINOSITY ACROSS NON-MINING REGIONS

	(1)	(2)	(3)	(4)	(5)	(6)
A: Capital regions						
Capital × Mines	0.057***					
	(0.015)					
Capital × Large Mines		0.066***				
		(0.021)				
B: Leader regions						
Leader			0.055	0.054		
			(0.041)	(0.041)		
Leader × Mines			-0.001			
			(0.003)			
Leader × Large Mines				-0.001		
				(0.003)		
C: Generic regions						
Mines					-0.023***	
					(0.007)	
Large Mines						-0.033***
						(0.007)
Pixel FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	No	No
Year FE	NA	NA	NA	NA	Yes	Yes
Pixels	9059	9059	9059	9059	1374	1374
N	199298	199298	199298	199298	30228	30228

[a] This table reports results on whether mines lead to a disproportinate increase in luminosity in capital cities. The dependent variable is the log of mean light output in each pixel. We study whether mines lead to an increase in luminosity in capital cities (column (1)-(2), in leader's birth regions (column (2)-(3), and in generic regions (column (5)-(6)). We report separate regressions for all mines and large mines. Only operating mines with available information on startup and shutdown dates in the MinEx data are included. Stars indicate significance levels at 10%(*), 5%(**) and 1%(***). Heteroscedasticity robust standard errors in parentheses.

Table 2: MINERAL RESOURCES AND LUMINOSITY: DEMOCRACIES VS. AUTOCRACIES

	(1)	(2)	(3)	(4)	(5)	(6)
A: Capital regions						
Capital × Mines × Democracy	0.055***					
	(0.016)					
Capital × Mines × Autocracy	0.055***					
	(0.015)					
Capital × Large Mines × Democracy		0.066***				
		(0.024)				
Capital × Large Mines × Autocracy		0.063***				
		(0.021)				
B: Leader regions						
Leader × Democracy			-0.046	-0.046		
			(0.090)	(0.091)		
Leader × Autocracy			0.023	0.026		
			(0.042)	(0.041)		
Leader × Mines × Democracy			-0.000			
			(0.003)			
Leader × Mines × Autocracy			0.007***			
			(0.002)			
Leader × Large Mines × Democracy				-0.000		
				(0.004)		
Leader × Large Mines × Autocracy				0.009***		
				(0.003)		
C: Generic regions						
Democracy					-0.548***	-0.647***
					(0.134)	(0.192)
Mines × Democracy					0.069***	
					(0.024)	
Mines × Autocracy					-0.026***	
					(0.007)	
Large Mines × Democracy						0.085**
						(0.034)
Large Mines × Autocracy						-0.035***
						(0.007)
Pixel FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	No	No
Year FE	NA	NA	NA	NA	Yes	Yes
Pixels	8961	8961	8961	8961	1374	1374
N	182506	182506	182506	182506	29092	29092

[a] This table collects difference-in-difference regressions that relate mineral resource activity (operating mines) to luminosity at the grid-level for all of Africa (0.5 × 0.5 decimal degree pixels). We study whether mines lead to an increase in luminosity in capital cities (column (1)-(2), in leader's birth regions (column (2)-(3), and in generic regions (column (5)-(6)). We distinguish between autocracies and democracies by estmating each of the models with appropriately defined subsamples. For further notes, see Table 1.

Table 3: MINERAL RESOURCES AND LUMINOSITY ACCORDING TO ETHNIC POWER

	(1: Strong)	(2: Weak)	(3: Both)
Mine	0.838***	0.861***	0.860***
	(0.125)	(0.124)	(0.125)
Strong	-0.049		-0.051
	(0.036)		(0.035)
Strong × Mine	-0.091		0.017
	(0.119)		(0.126)
Weak		0.133***	0.133***
		(0.028)	(0.028)
Weak × Mine		-0.619***	-0.628***
		(0.208)	(0.219)
Pixel FE	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes
Pixels	7285	7285	7285
N	158636	158636	158636

This table collects difference-in-difference regressions that relate mineral resource activity (operating mines) to luminosity at the grid-level for all of Africa (0.5 × 0.5 decimal degree pixels). In these specifications, we study whether mines lead to an increase in luminosity in regions inhabited by ethnicities that have a strong or weak position at the national level. The dependent variable is the log of average light output in each pixel. The main independent variables are (a) a dummy variable that is 1 if a pixel had an operating mine and (b) interaction variables between the mineral resource dummy and dummies for whether a pixel is inhabited by at least one ethnicity that has a strong or weak position at the national level. To identify ethnic homelands as well as their degree of power at the national level, (geospatial) data from Vogt et al. (2015) was used. We define a ethnicity as having a strong position if Vogt et al. (2015) code its power status as "Monopoly" or "Dominant" and as having a weak position if they code its status as "Discriminated". Pixels that are inhabited by two or more ethnicities are coded as strong / discriminated if at least one of the ethnicities has the corresponding status (i. e. pixels can be simultaneously coded as strong and weak). Only mines with available data on startup and shutdown dates are included. Stars indicate significance levels at 10%(*), 5%(**) and 1%(***). Heteroscedasticity robust standard errors in parentheses.

Appendix

A.1 Mineral activity and luminosity in mining regions

In this appendix, we study the effect of mineral resources on the local economy in mining regions by estimating a standard difference-in-differences specification at the pixel-level. The model is as follows:

$$y_{it} = \alpha_i + \sum_c \gamma_t \times c + \text{Mine}_{i,t} + \varepsilon_{i,t}, \tag{A.1}$$

with y_{it} the log of the mean of luminosity in pixel i in year t, α_i pixel fixed effects, γ_t year fixed effects and c country dummies (i. e. we include country-specific year fixed effects), and $Mine_{i,t}$ a dummy that is 1 when there is at least one operating mine in pixel i in year t and 0 else.

The identifying assumption is that the operation of mines is exogenous. Naturally, the setup and operation of a mine in a given locality is not a random event and it is accordingly difficult to fully validate the identifying assumption. However, pixel fixed effects can account for time-constant geographical or environmental characteristics of pixels. Similarly, country-specific year fixed effects account for country-level developments that might be correlated with startups or closures of mines. In any case, note that the local effects of mineral resources is not our main focus in this paper. The main purpose of these estimations is to confirm for Africa the findings in previous research that document strong local economic effects of mineral resources.

In Table A.1, we study the effect of mines of different sizes in the mining pixels themselves. We observe large positive effects. A generic mine increases luminosity by about 87% in the mining pixel. We also find that larger mines have stronger effects on luminosity. In Table A.2, we study geographic spillovers of mines. We find that luminosity increases the most in the mining pixels and declines successively in pixels that are further away. Mines cease to have a noticeable effect on luminosity in pixels that are about 30km away from a mine.

A.2 Robustness tests

In this section, we collect the results of two robustness tests. First, we include all available pixels in the baseline regressions and do not specifically account for pixels covering mining regions. As such, the mining regions might confound our estimate for "non-mining" regions (capital cities, leaders' birth regions, generic non-mining regions). To address this issue, we estimate the specifications in Table 1 after dropping all pixel-year pairs where mining activity was ongoing. The results are collected in Table A.3. The estimates are virtually identical to the baseline estimates.

Second, we explore whether the baseline results are dependent on our choices regarding how we identify the relevant non-mining regions. Specifically, for the results in Table 1, we use a buffer of 10km around the latitude and longitude coordinates to identify capital regions or leaders' birth regions. We also use a distance threshold of 250km to identify border pixels. The spatial expanse of capital or leaders' birth regions might, however, be larger. On the other hand, border pixels and their neighboring pixels in other countries might be more similar if the distance threshold were smaller than 250km. We thus re-estimate the baseline specifications after using a buffer of 30km and a distance threshold of 125km. The results are collected in Table A.4 and are resemble the baseline results.

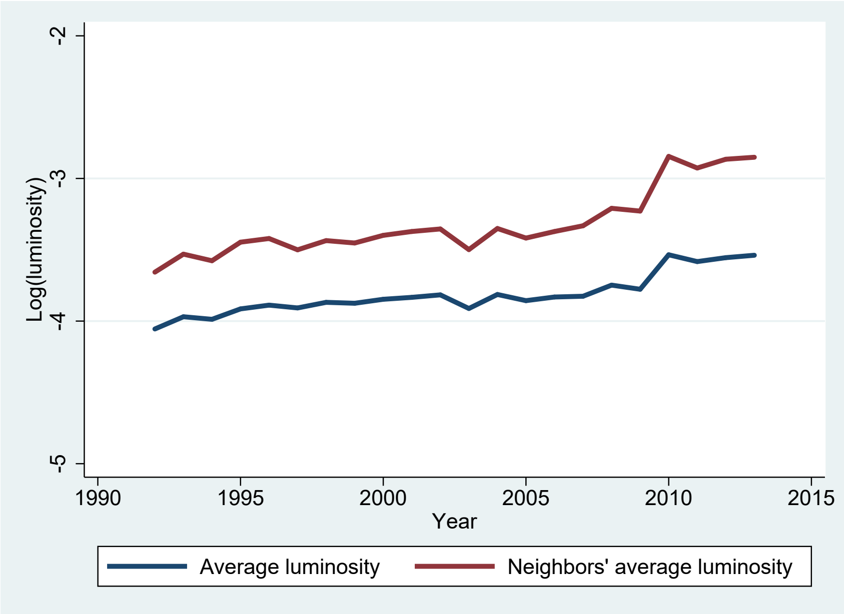


Figure A.1: Evolution of mean luminosity in index pixels and their neighboring pixels during the sample period. This figure shows the evolution of the average mean luminosity of all pixels close to their country's border and the average mean luminosity of their neighbors. Specifically, for the blue line, we take the average of the luminosity values of each border pixel. For the red line, we calculate for each index pixel the average value of luminosity across all pixels in neighboring countries within a distance of 250km and then calculate the average value of neighboring pixels' luminosity for all index pixels. The pixels included in these calculations are colored yellow in Figure 7.

Table A.1: MINERAL RESOURCES AND ECONOMIC ACTIVITY IN MINING REGIONS I

	(1: All mines)	(2: At least major)	(3: At least giant)	(4: Less than major)	(5: Less than moderate)
Mine	0.866***	1.077***	1.322***	0.394***	0.151*
	(0.115)	(0.154)	(0.272)	(0.118)	(0.091)
Pixel FE	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes
Pixels	9059	9059	9059	9059	9059
N	199298	199298	199298	199298	199298

[a] This table collects difference-in-difference regressions that relate mineral resource activity (operating mines) to luminosity at the grid-level for all of Africa (0.5 × 0.5 decimal degree pixels). In this specification, we study whether mines increase luminosity in mining regions. The dependent variable is the log of average light output in each pixel. The independent variable is a dummy variable that is 1 if a pixel had an operating mine. Only mines with available data on startup and shutdown dates are included. Stars indicate significance levels at 10%(*), 5%(**) and 1%(***). Heteroscedasticity robust standard errors in parentheses.

Table A.2: Mineral resources and economic activity in mining regions II

	(1: All mines)	(2: at least major)	(3: at least giant)	(4: less than major)	(5: less than moderate)
Mine	0.897***	0.903***	0.906***	0.910***	0.905***
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)
10 km	0.284***	0.292***	0.294***	0.299***	0.294***
	(0.084)	(0.084)	(0.084)	(0.085)	(0.085)
20-30 km		0.101**	0.104**	0.108**	0.103**
		(0.042)	(0.042)	(0.043)	(0.044)
30-50 km			0.021	0.026	0.021
			(0.036)	(0.037)	(0.038)
50-100 km				0.012	0.007
				(0.021)	(0.023)
100-200 km					-0.010
					(0.015)
Pixel FE	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes
Pixels	9059	9059	9059	9059	9059
N	199298	199298	199298	199298	199298

[a] This table collects difference-in-difference regressions that relate mineral resource activity (operating mines) to luminosity at the grid-level for all of Africa (0.5×0.5 decimal degree pixels). In this specification, we study whether mines increase luminosity in neighboring pixels. The dependent variable is the log of average light output in each pixel. The independent variable is a dummy variable that is 1 if a pixel had an operating mine. Only mines with available data on startup and shutdown dates are included. Stars indicate significance levels at 10%(*), 5%(**) and 1%(***). Heteroscedasticity robust standard errors in parentheses.

Table A.3: MINERAL RESOURCES AND LUMINOSITY ACROSS NON-MINING REGIONS: ROBUSTNESS TO OMITTING MINING PIXELS

	(1)	(2)	(3)	(4)	(5)	(6)
A: Capital regions						
Capital × Mines	0.059***					
	(0.014)					
Capital × Large Mines		0.068***				
		(0.021)				
B: Leader regions						
Leader			0.060	0.059		
			(0.042)	(0.041)		
Leader × Mines			-0.002			
			(0.003)			
Leader × Large Mines				-0.002		
				(0.004)		
C: Generic regions						
Mines					-0.027***	
					(0.007)	
Large Mines						-0.037***
						(0.007)
Pixel FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pixels	8999	8999	8999	8999	1364	1364
N	197181	197181	197181	197181	29864	29864

[a] This table reports a replication of the baseline results after dropping pixel-year pairs with ongoing mineral resource activity. The dependent variable is the log of mean light output in each pixel. We study whether mines lead to an increase in luminosity in capital cities (column (1)-(2), in leader's birth regions (column (2)-(3), and in generic regions (column (5)-(6)). We report separate regressions for all mines and large mines. Only operating mines with available information on startup and shutdown dates in the MinEx data are included. Stars indicate significance levels at 10%(*), 5%(**) and 1%(***). Heteroscedasticity robust standard errors in parentheses.

Table A.4: MINERAL RESOURCES AND LUMINOSITY ACROSS NON-MINING REGIONS: ROBUSTNESS TO DEFINITION OF NON-MINING REGIONS

	(1)	(2)	(3)	(4)	(5)	(6)
A: Capital regions						
Capital × Mines	0.053***					
	(0.013)					
Capital × Large Mines		0.057***				
		(0.019)				
B: Leader regions						
Leader			0.047	0.046		
			(0.029)	(0.029)		
Leader × Mines			0.001			
			(0.002)			
Leader × Large Mines				0.002		
				(0.002)		
C: Generic regions						
Mines					-0.014**	
					(0.007)	
Large Mines						-0.022***
						(0.007)
Pixel FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pixels	9059	9059	9059	9059	1661	1661
N	199298	199298	199298	199298	36542	36542

[a] This table reports a replication of the baseline results using different distances for the buffers around the geocodes for capital cities and leaders birth towns as well as a different threshold for the definition of border pixels. Specifically, we use a larger buffer of 30km and a narrower threshold of 125km. The dependent variable is the log of mean light output in each pixel. As in the baseline regressions, we study whether mines lead to an increase in luminosity in capital cities (column (1)-(2), in leader's birth regions (column (2)-(3), and in generic regions (column (5)-(6)). We report separate regressions for all mines and large mines. Only operating mines with available information on startup and shutdown dates in the MinEx data are included. Stars indicate significance levels at 10%(*), 5%(**) and 1%(***). Heteroscedasticity robust standard errors in parentheses.

Table A.5: SUMMARY STATISTICS

Variable		Mean	Std. Dev.	Min.	Max.	Obs.
Log(mean luminosity)	overall	-3.605	1.798	-4.605	4.119	199298.0
	between	.	1.748	-4.605	3.965	9059.0
	within	.	0.422	-8.728	1.457	22.0
Mines	overall	5.536	13.934	0.000	73.000	199496.0
	between	.	13.852	0.000	65.864	9068.0
	within	.	1.518	-1.373	13.809	22.0
Large Mines	overall	4.210	11.413	0.000	63.000	199496.0
	between	.	11.343	0.000	53.682	9068.0
	within	.	1.274	-0.472	13.528	22.0
Capital	overall	0.006	0.080	0.000	1.000	199496.0
	between	.	0.080	0.000	1.000	9068.0
	within	.	0.000	0.006	0.006	22.0
Capital × Mines	overall	0.022	0.759	0.000	73.000	199496.0
	between	.	0.751	0.000	65.864	9068.0
	within	.	0.107	-6.887	8.295	22.0
Capital × Large Mines	overall	0.016	0.611	0.000	63.000	199496.0
	between	.	0.606	0.000	53.682	9068.0
	within	.	0.073	-4.666	9.334	22.0
Leader	overall	0.008	0.088	0.000	1.000	199496.0
	between	.	0.067	0.000	1.000	9068.0
	within	.	0.057	-0.947	0.962	22.0
Leader × Mines	overall	0.035	1.131	0.000	73.000	199496.0
	between	.	0.623	0.000	29.500	9068.0
	within	.	0.944	-29.465	63.444	22.0
Leader × Large Mines	overall	0.026	0.920	0.000	63.000	199496.0
	between	.	0.504	0.000	23.682	9068.0
	within	.	0.769	-23.656	54.799	22.0
Democracy	overall	0.150	0.357	0.000	1.000	182683.0
	between	.	0.326	0.000	1.000	8970.0
	within	.	0.119	-0.759	1.104	20.4
Autocracy	overall	0.850	0.357	0.000	1.000	182683.0
	between	.	0.326	0.000	1.000	8970.0
	within	.	0.119	-0.104	1.759	20.4

The within number of observations is the average number of observations per pixel.

IMPRINT

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