Journal of Development Economics 139 (2019) 28–49

Contents lists available at ScienceDirect

Journal of Development Economics

journal homepage: www.elsevier.com/locate/devec

Intensive and extensive margins of mining and development: Evidence from Sub-Saharan Africa☆

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ARTICLE INFO

JEL classification:
O11
O13
Q32

Keywords:
Mineral discovery
Mineral production
Night-time lights

ABSTRACT

What are the economic consequences of mining in Sub-Saharan Africa? Using a panel of 3,635 districts from 42 Sub-Saharan African countries for the period 1992 to 2012 we investigate the effects of mining on living standards (measured by night-lights and household/cohort characteristics from Demographic and Health Surveys) and public service provisions (from Afrobarometer). Night-lights increase in mining districts when mineral production expands (intensive margin), but large effects are mainly associated with new discoveries and new production (extensive margin). We identify the effect by carefully choosing feasible but not yet mined districts as a control group. In addition, we exploit first, single-first, giant and major discoveries as exogenous news shocks. Mines in Africa exhibit enclave characteristics as we find little evidence of significant spillovers to other districts.

1. Introduction

The industrial age of eighteenth and nineteenth century witnessed a coming together of coal, iron and steel, and steam power which propelled living standards to a level unprecedented in human history. Britain and other continental European countries were able to successfully utilize natural resources to industrialize and improve living standards. The post-independence development experience of resource rich developing nations especially in sub-Saharan Africa however have been dismal giving rise to the view that natural resources adversely affect economic development.

Indeed, a large body of predominantly macro literature document a negative correlation between growth rates of GDP per capita and resource reliance by exploiting variation across countries.[1] This literature broadly identifies three potential channels through which natural resources could hinder development. First, natural resource exports could appreciate the real exchange rate thereby disadvantaging the tradable non-resource sector (or the modern sector) of an economy (Corden and Neary, 1982). Adverse development outcomes could be permanent, if competitiveness cannot be regained.[2] Second, over-reliance on natural resources for government revenue could give rise to corruption and weak institutions as the state would no longer require relying on the non-resource sector as a major source of revenue (Robinson et al., 2006). Third, the high volatility of global commodity prices could disadvantage resource rich developing countries as they become more exposed to global shocks and macroeconomic instability (Deaton, 1999; Ramey and Ramey, 1995). Acknowledging the adverse consequences of natural resources, a large body of literature also engage with the question of harnessing natural wealth for economic development. See Venables (2016) for a survey.

Another literature that largely follows from the influential works of Rosenstein-Rodan (1943), Singer (1950) and Murphy et al. (1989)

☆ We are grateful to the Editor Nathan Nunn, two anonymous referees, Rabah Arezki, Richard Blundell, Richard Dickens, James Fenske, Paul Novosad, Steven Poelhekke and seminar and conference participants at the 2018 ICID-IFAD Conference (Rome), 2017 RES Conference (Bristol), 2016 Nordic Conference in Development Economics, 2016 LSE Spatial Economics Research Centre Annual Conference, 2015 CSAE Conference, 2015 RES Symposium for Junior Researchers for their comments. We also acknowledge comments from the seminar participants at ANU, HSE (Moscow), Monash, Oxford, Sussex and numerous other places. We gratefully acknowledge financial support from the Department of Economics, University of Sussex. All remaining errors are our own.

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1 See van der Ploeg (2011) for a survey of this literature. More recently Alexeev and Conrad (2009) report positive effects of oil and mineral wealth on growth.

2 This argument may not be relevant in the Sub-Saharan African context as the manufacturing sector is small and the exchange rate is not viewed as a key constraint for the same (Bigsten and Söderbom, 2006).

https://doi.org/10.1016/j.jdeveco.2019.02.001
Received 10 April 2018; Received in revised form 16 October 2018; Accepted 9 February 2019
Available online 13 February 2019

argue that mining in a developing country is typically an 'enclave'. It operates with very high productivity and capital intensity (McMillan et al., 2014), but exhibits very little demand and supply spillovers to institute large scale industrialization. As a result resource rich developing countries remain poor and underdeveloped. Even though the enclave nature of mining in Africa have been actively discussed by many scholars, empirical analyses of the extent of spillovers are rare. Aragón and Rud (2013) study the spillover effect of a Peruvian gold mine on the local population, but very little literature exist on Africa. The potential heterogeneous effects of a new mine as opposed to production expansion in an existing mine also remains largely unknown. In this paper we aim to fill the void by systematically exploring the causal effect of mineral resource discovery and extraction on development in Sub-Saharan Africa at district and regional levels. In particular, we distinguish between the effects of production volume expansion in existing mines (intensive margin), new production (extensive margin), and new discoveries. Using spatial econometrics and GIS we analyze the extent of spillovers from a mine. We construct a uniform measure of economic activity at different levels of spatial stratification using satellite data on night-time lights. In addition, we also estimate the effect of mineral discoveries on direct measures of living standards from the Demographic and Health Surveys (DHS) and public service provisions from Afrobarometer.

Fig. 1 illustrates our approach. Panel A and B reveal that mineral extraction and mineral discovery lead to significant improvements in economic activity measured by night-time lights. Panel A zooms into Zabre District in the Boulgou Region of Burkina Faso. Zabre has produced her first mineral commodity, gold, in 2008. The change in the economic fortunes of Zabre is visually apparent here via the satellite images of night-time lights before and after gold production. In 2007 before gold production, we do not observe any night-time lights. However, lights appear in 2008 and 2009. So much for night-time lights, what about population? In 2007, the Socioeconomic Data and Applications Centre estimates Zabre's population to be 135,582 and the population five years later in 2012 is estimated to be 160,150, an 18 percent increase. Panel B reveals a similar story before and after the discovery of a Sapphire mine in 1998 in the town of Ilakaka in the Ihosy district of Madagascar. The town Ilakaka did not exist before 1998.

Using regression analysis, we find that mineral production and mineral discovery significantly improves economic development at the district level in 42 sub-Saharan African countries over the period 1992 to 2012. Night-lights increase due to mining expansion at the intensive margin. However, large effects are observed at the extensive margin following new production and new discoveries. We observe that the positive influence of mineral production takes effect approximately two years prior to the actual start of mineral production. This is consistent with the view that installation of mining infrastructure and worker arrival typically predates production.

In order to precisely identify the effect of mining on development we exploit the exogenous variation in the discovery dates of giant and major deposits of 21 minerals. We find that the positive effect of discovery on night-time lights enter approximately six years after the first discovery. The magnitude of the effect of first discovery is 19 percent on the sixth year and continues to rise to 44 percent on the tenth year. Our empirical model also successfully negotiates placebo discovery treatments.

Our data covers 42 sub-Saharan African countries at the district level. Approximately 93 percent of the countries in our sample seem to have at least one district with a producing mine and 76 percent of the countries seem to have at least one discovery district. Therefore, the cross-country distribution of mineral production and discovery appears to be fairly representative giving credence to the internal validity of our results. Furthermore, the large sample size across 42 countries also adds credibility to the external validity of our results.

Our estimates using direct measures of living standards from the DHS and public service provisions from the Afrobarometer allow us to draw meaningful conclusions on the economic significance of these results. We find positive influence of discovery on household wealth index and urbanization. The effects on education of DHS birth cohorts, and piped water infrastructure appear to be negative. We notice some evidence of infrastructure building in terms of new schools and sewerage systems immediately after discovery which tends to disappear over time. We find no effect on electricity connection, infant mortality, and health clinics.

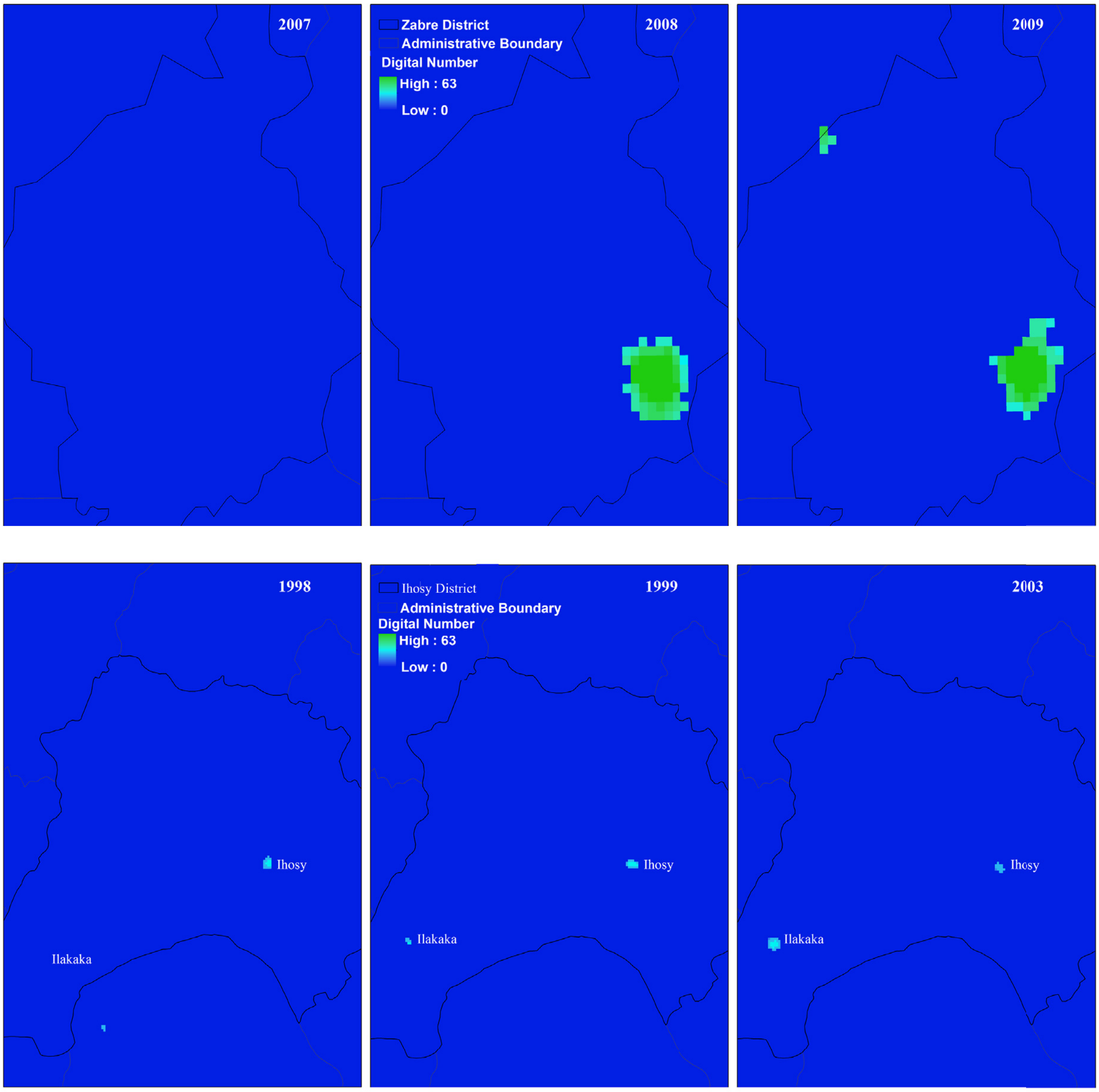
A skeptic's view of the positive effect of mining on night-lights is that it is entirely driven by lights emanating from the mines, particularly if the location of lights coincide with the same for the mine. Even though plausible, this view is not supported by mining industry facts on the ground in Africa (Banerjee et al., 2015).[3] Furthermore, using GIS we are able to exclude all lights around 2, 5 and 10 km radius of a mine from our sample and our results remain largely unchanged. This is suggestive of a strong within district effect from an active mine.

A major source of reverse causation in a study of this nature could be selection. Investors could pre-select more prosperous districts for mining. Exploiting cross-sectional information on the six stages of mining investment (grassroots, exploration, advanced exploration, pre-feasibility, feasibility, construction) in 2012 and regressing them on development indicators (night-lights density, population density, paved road density, railway density and electric grid density) in 2000 we are able to investigate whether this is indeed the case. With the exception of population density at the construction stage none of the variables register positive and significant effects on the very early stages of mining investment suggesting that causality runs from mining to development and not in the other direction. In fact railway density at the advanced exploration stage and electricity grid density at the exploration stage register weak negative effects reinforcing the observation that new mines typically open far from developed areas.

Economic development is a general equilibrium phenomenon. Therefore, analyzing the extent of spillovers from mines is crucial. Furthermore, focusing on the sub-national district level data might mask the fact that mining districts gain at the expense of non-mining districts. In order to unmask such patterns we estimate spatial spillover effects using spatial econometric techniques. We also test our model at a larger sized units of observation: regions instead of districts. We do not find evidence of spillover beyond the host district which attests to the enclave nature of mines in Africa.

In summary, the key contributions of our paper are as follows. First, we provide the first estimates of the local economic effects of mining at the intensive and extensive margins in Sub-Saharan Africa. Local economic effects are measured by nightlights, living standard variables from DHS, and indicators of public goods from Afrobarometer. Second, by using data on different stages of mining we are able to precisely estimate the effects of pre-existing local economic activity on mining investment. To the best of our knowledge, no other study provides such estimates. Third, we provide estimates of spillover effects of mines to surrounding areas using spatial econometric models.

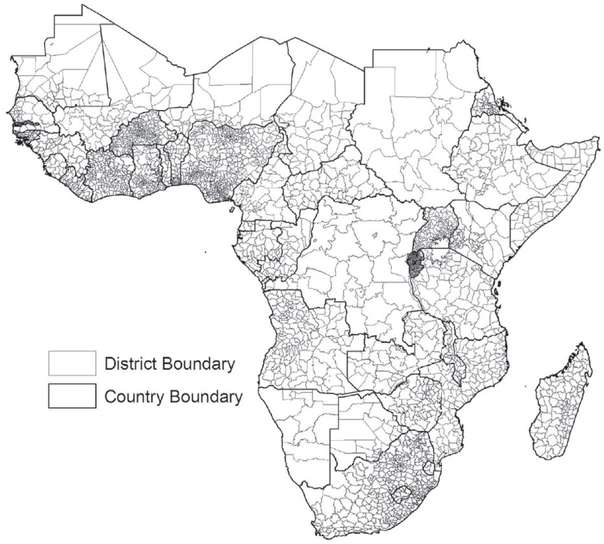
[3] Governments and mining corporations often try to keep workers near the mining site for lengthy periods of time by offering fixed contracts and prearranged wages. This creates mass migration and hence growth of mining towns and cities nearby that offer services. The mineral revolution in South Africa from the 1870 onward is a good example, which had an impact on urbanization, agriculture, infrastructure and local politics. The migration prompted changes in rural areas, as farms lost workers to the mines and demand for food increased.



Notes: The upper panel shows Zabre District in Burkina Faso starting gold production in 2008. The lower panel shows Ihosy District in Madagascar. After the discovery of Sapphire deposits at Ilakaka - a village with about 40 households - in 1998, the place saw an influx of migrants and turned into a major trading centre for sapphires and a town with an estimated population of now larger than 30,000. Until 1998 there were no nightlights visible in Ilakaka. After the discovery, the number of pixels with visible lights increased. Ihosy town, in contrast, has not experienced such growth; lights got smaller and weaker. Overall, however, the aggregate lit pixels have increased in Ihosy District. The lower panel is a replication of Figure 5 in Henderson et al. (2012).

Fig. 1. Mining discovery, mining production and nightlights.

Our paper is related to the predominantly cross-country macro literature on natural resources and economic development. Auty (2001), Gylfason (2001) and Sachs and Warner (2001, 2005) note that resource rich countries on average grow much slower than resource poor countries. Subsequent studies have argued that natural resources may lower the economic performance because they strengthen powerful groups, weaken legal frameworks, and foster rent-seeking activities (Tornell and Lane, 1999; Collier, 2000; Torvik, 2002; Besley, 2007). Others have argued whether natural resources are a curse or a blessing depends on country-specific circumstances especially institutional quality (Mehlum et al., 2006; Robinson et al., 2006; Collier and Hoeffler, 2009; Bhattacharyya and Hodler, 2010, 2014; Bhattacharyya and Collier, 2014), natural resource type (Isham et al., 2005) and ethnic fractionalization (Hodler, 2006). While these studies do not imply that resource rents inevitably reduce living standards, they show that it is entirely possible. The key innovations here are our focus on Sub-Saharan



Notes: This map shows the second level administrative units ('districts') for the year 2000 that we use in our analysis. The boundaries in GIS were obtained from FAO GeoNetwork (2013). We exclude small island countries (Saint Helena, Seychelles, Sao Tome and Principe, Reunion, Mayotte, Mauritius, Cape Verde and Comoros) and Djibouti. Our sample consists of 3,635 districts from 42 Sub-Saharan African countries.

Fig. 2. District level boundary map of sub-Saharan Africa.

Africa and the causal interpretation of intensive and extensive margin of mining.[4] We deliver on the causal interpretation by utilizing a new mine level dataset on mineral production and discovery in sub-Saharan Africa and relate it to nightlights and other measures of living standards.

Theory suggests that natural resources affect economic development through a general equilibrium channel. Therefore, the cross-national focus of the early empirical literature is understandable. However, there has been a shift in the focus more recently with several studies focusing on the local effects of resource extraction. For example, Aragón and Rud (2013) analyze the effect of a Peruvian gold mine on real incomes of households using a decade long household survey data and find positive effects. Caselli and Michaels (2013) and Allcott and Keniston (2014) focus on the local effects of oil boom in Brazil and shale oil and gas boom in the United States respectively. In spite of the growing interest on the local effects of resource boom, most of the studies remain country or mine specific calling into question the external validity of their findings. Furthermore, studies on Sub-Saharan Africa remain rare. Two notable exceptions are Kotsadam and Tolonen (2016) and Lippert (2014). Kotsadam and Tolonen (2016) merge mineral production data from IntierraRMG with the DHS data for Africa. Employing a difference-in-difference estimation strategy, they find that opening of new mines trigger a shift of female workers from agricultural self-employment to services. Male workers shift to skilled manual labor and mining. The participation rate of women decreases with mine openings, but it increases for men. The overall effect of a mine survives only within a 50 km buffer zone from the mine. After a mine closure, men typically return to agriculture whereas women exit the workforce. Lippert (2014) study the local effect of mining in Zambia. WorldBank (2017) presents a survey of the emerging literature on the local effects of mining in Africa.

Our paper is also related to a more recent literature on the determinants of development at the sub-national level. This literature makes use of nightlights and city growth data to measure development at the regional and sub-national levels (Michalopoulos and Papaioannou, 2013, 2014; Hodler and Raschky, 2014). The factors identified as key determinants of African sub-national development are pre-colonial ethnic institutions (Michalopoulos and Papaioannou, 2013, 2014), birth region of leaders (Hodler and Raschky, 2014), and colonial railroads (Jedwab et al., 2017; Jedwab and Moradi, 2016). Michalopoulos and Papaioannou (2014) also show that national institutions do not explain sub-national variation in development in Africa.

The remainder of the paper is structured as follows: Section 2 presents the data. Section 3 sheds light on where mining investments go before studying the local effects of mineral production, at the intensive and extensive margins, and mineral discovery. Section 4 analyses the economic significance of these effects by introducing direct measures of living standards and public goods as dependent variables. Section 5 discusses the general equilibrium and spillover effects. Section 6 deals with robustness and section 7 concludes.

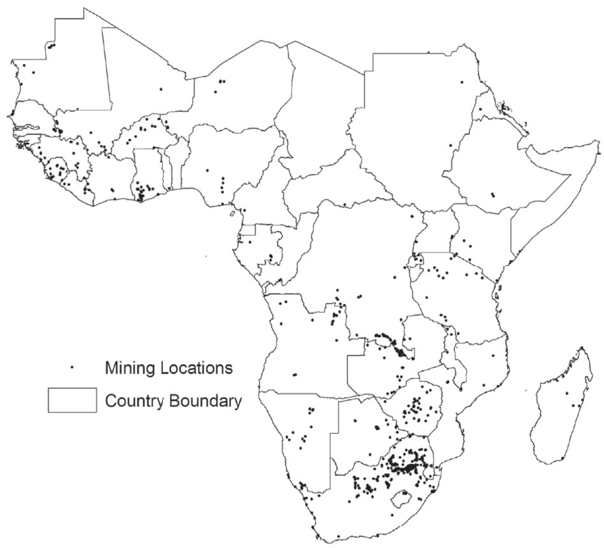
2. Data

We construct a panel of 3,635 districts from 42 Sub-Saharan African countries over the period 1992 to 2012.[5] Districts are the main units of observation here. They correspond to the second level subnational administrative classification of sub-Saharan Africa in 2000 obtained from FAO GeoNetwork (2013) (see Fig. 2). The average size of a district in our sample is 6,585 square kilometers.

As our main measure of development we use satellite data on nighttime lights ("luminosity") provided by National Oceanic and Atmospheric Administration (2013). The data is cleaned luminosity, after

[4] More recent studies relating oil, conflict and political institutions have used information on giant oil discovery to mitigate the causality challenge. Cotet and Tsui (2013) and Lei and Michaels (2014) study the effect of oil on conflict. Tsui (2011) study the effect of oil on democracy. Arezki et al. (2017) analyze the impact of oil discovery on macro variables. Bhattacharyya et al. (2017) study the effect of oil and mineral discoveries on fiscal decentralization.

[5] Appendix A1 presents a list of countries included in the sample.



Notes: The map shows the location of active, industrial size mines in sub-Saharan Africa. These mines are owned or operated by either large multinationals or state owned companies. We exclude small-scale mines and informal or illegal mines. Data is from IntierraRMG.

Fig. 3. Mining industry locations.

filtering for cloud coverage, other ephemeral lights, and background noise. The measure comes on a scale of 0–63, where higher values imply greater luminosity. The data are available at pixels of 30 arc-second dimension (equivalent to one square kilometer) which is very high resolution. We calculate light density by dividing the sum of all night-time lights pixel values within a district by the district's area. As an alternative measure, we also construct luminosity per capita.

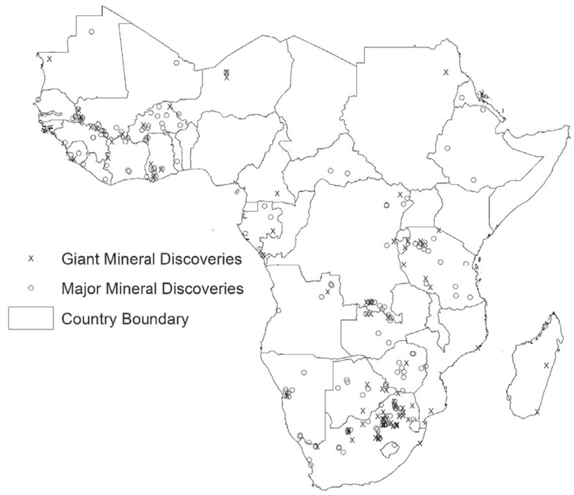
The distribution of night-time lights across districts is skewed. A substantial number of observations (about 31.5 percent of the sample) take the value zero. There are also a few extreme observations on the right tail of the distribution. To account for this, we follow Michalopoulos and Papaioannou (2013) and Hodler and Raschky (2014) and define the dependent variable as the natural log of night-time lights density plus 0.01. Such transformation ensures that all available observations are used and the leverage of outliers reduced. Note that the absence of reported night-time lights typically does not imply darkness, and certainly not absence of economic activity (Hodler and Raschky, 2014). There are also issues with the difference between true lights emanating into space and what is recorded by a satellite (Henderson et al., 2012). In particular, there is variation in recorded lights data across satellites. Measurement error of this nature is unlikely to be a concern here as it is orthogonal to our estimation models. Furthermore, because all districts in a particular year are covered by the same satellite, any cross-satellite variation in night-time lights is already accounted for in the model by the year fixed effects.

Information on mining at the local level comes from two sources. The first source is IntierraRMG. It provides data on production quantities and values, start-up year and mining status for 548 industrial size mines of 21 minerals for the period 1992–2012. All the mines are matched to the district administrative units. Where IntierraRMG do not provide a start-up date, we consult other sources (including the website of each mining company) and add the information. The second data source is MinEx Consulting. Their database reports discovery and production start-up dates of 259 giant and major mineral deposits for 11 minerals (gold, silver, platinum group elements (PGE), copper, nickel, zinc, lead, cobalt, molybdenum, tungsten and uranium oxide) from 1950 to 2012. MinEx codes a mineral deposit as giant if it has the capacity to generate at least USD 500 million of annual revenue for 20 years or more accounting for fluctuations in commodity price. A major mineral deposit is defined as one that could generate an annual revenue stream of at least USD 50 million but may not last as long as a giant deposit. Figs. 3 and 4 show the locations of industrial mines and mineral deposit discoveries respectively. In addition, we obtain annual price data for the 21 commodities from the U.S. Geological Survey (USGS) and extract the country level total production data of these commodities from Minerals UK of the British Geological Survey. Overall, 5.4 (2.1) percent of the 3,635 districts in our sample report at least one producing (discovery) mine.

Population density is an important control variable, as it exhibits a strong positive correlation with light density (Cogneau and Dupraz, 2014). Population data is obtained from the Socioeconomic Data and Applications Centre - Centre for International Earth Science Information Network (SEDAC - CIESIN). Population estimates are available for 1990, 1995, and 2000, and projections for 2005, 2010, and 2015. We follow Hodler and Raschky (2014) and aggregate the gridded population dataset to second level administrative units. We then construct annual district population 1992–2012 replacing missing years by linear interpolation.[6]

We use a set of geography, climate, political economy and infrastructure variables as controls. The geography variables are altitude, ruggedness, soil fertility, distance to the coast, and land surface area. From the 90 m Digital Elevation Database of the NASA Shuttle Radar Topographic Mission (SRTM), we construct mean and standard deviation of elevation. Soil fertility is expressed as the percentage of a district's land area with fertile soils for agricultural crops and is constructed from the index in FAO/UNESCO Digital Soil Map of the World. The climate variables are annual rainfall from Tropical Applications of

[6] Despite the consistency and spatially explicit population distribution of the world the grid level population estimates may not match the actual population at the district level. This could be seen as a standard measurement error because population projections are not based on night-time lights.



Notes: The map shows the location of giant and major mineral deposit discoveries in Sub-Saharan Africa over the period 1950-2012. Data from MinEx Consulting.

Fig. 4. Locations of mineral deposit discoveries.

Meteorology using Satellite data (TAMSAT), and the district's land area classified as tropical climate, arid climate and temperate climate (Kottek et al., 2006). The infrastructure variables are paved road density (i.e. paved road length per square kilometer), railway density (i.e. railway length per square kilometer) and electric grid density (i.e. electric transmission cable length per square kilometer). They are derived from the African Development Bank and DIVA-GIS for the year 2000. Finally, the political economy variables are a 'capital' dummy variable equal to one if the district contains, or itself is the capital city, distance to the capital city. We constructed a measure of ethnic fractionalization following the famous ELF measure but using land shares constructed from the Ethnographic Atlas by Murdock (1959) instead of population shares

Table 1
Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Main Variables					
Log(0.01 + nighttime lights per sq. km)	76,335	−2.365	2.385	−4.605	4.507
Log(Mineral production)	1802	16.859	3.466	−0.235	27.61
Log(Min. prod. 1992 commodity prices)	1802	16.962	3.056	1.658	27.571
Mineral production (1 = yes)	76,335	0.039	0.195	0	1
Mineral discovery	76,335	0.001	0.031	0	1
Mineral discovery (permanent switch)	76,335	0.011	0.105	0	1
Controls: Population and Geography Variables					
Log(Population per sq. km)	76,335	3.985	1.609	0.025	10.037
Log(Altitude in m)	3635	5.885	1.382	0.617	7.914
Log(Ruggedness)	3635	4.051	1.139	0	6.931
Share of district with fertile soil	3635	18.600	29.453	0	100
Log(Distance to the coast in km)	3635	5.559	1.373	0	7.453
Log(Land surface area in sq. km)	3635	7.413	1.728	−0.707	12.788
Controls: Climate Variables					
Log(Annual average rainfall in mm)	76,335	5.127	0.766	0.029	6.789
Share of district with tropical climate	3635	60.199	47.120	0	100
Share of district with temperate climate	3635	14.320	32.639	0	100
Share of district with dry/arid climate	3635	25.283	42.137	0	100
Controls: Urbanization and Political Economy Variables					
Capital city (1 = yes)	3635	0.012	0.107	0	1
Log(Distance to the capital city in km)	3635	5.472	0.973	0.664	7.543
Ethnic Fractionalization	3635	0.207	0.237	0	0.932
Controls: Infrastructure Variables					
Log(Paved road per sq. km (2000))	3635	0.023	0.042	0	0.519
Log(Railway per sq. km (2000))	3635	1.005	1.729	0	6.790
Log(Electric-grid per sq. km (2000)	3635	0.072	0.175	0	2.256

Notes: This table reports descriptive statistics. All variables are measured at the district level. Discovery is a dummy variable which takes the value 1 for a district-year if there is a giant or major discovery for that year and 0 otherwise. The variable mineral discovery (permanent switch) is a dummy variable taking the value 1 for the discovery year and every year thereafter. Summary statistics for mineral production is limited to districts with mineral production, hence the smaller number of observations. Log transformation for variable x is conducted using the formula Log($1 + x$) if x could potentially be equal to 0.

Table 2
Descriptive statistics of mineral discovery and production.

Country	Number of Districts		Share of Districts	
	Mine Production(1)	Mine Discovery(2)	Mine Production(3)	Mine Discoveries(4)
Angola	3	1	1.54	1.37
Botswana	5	–	2.56	–
Burkina Faso	6	13	3.08	17.81
Cameroon	1	1	0.51	1.37
CAR	–	1	–	1.37
Congo	–	1	–	1.37
Cote d'Ivoire	5	3	2.56	4.11
DRC	6	2	3.08	2.74
Eritrea	1	1	0.51	1.37
Ethiopia	1	2	0.51	2.74
Gabon	3	2	1.54	2.74
Ghana	12	7	6.15	9.59
Guinea	7	1	3.59	1.37
Kenya	1	–	0.51	–
Lesotho	2	–	1.03	–
Liberia	1	2	0.51	2.74
Madagascar	1	1	0.51	1.37
Malawi	1	–	0.51	–
Mali	6	2	3.08	2.74
Mauritania	2	2	1.03	2.74
Mozambique	5	3	2.56	4.11
Namibia	5	1	2.56	1.37
Niger	2	–	1.03	–
Nigeria	1	–	0.51	–
Rwanda	1	–	0.51	–
Senegal	1	–	0.51	–
Sierra Leone	6	2	3.08	2.74
South Africa	76	9	38.97	12.33
Sudan	1	–	0.51	–
Swaziland	1	–	0.51	–
Tanzania	8	12	4.1	16.44
Togo	–	1	–	1.37
Uganda	2	1	1.03	1.37
Zambia	11	2	5.64	2.74
Zimbabwe	11	2	5.64	2.74

Notes: This table provides descriptive statistics of the number and share of districts with mineral production (1 = yes) and discovery (1 = yes) in each country over the sample period (1992–2012). Columns (1) and (2) presents the number of districts with mineral production and discovery in each sample country. Columns (2) and (3) presents the share.

(Alesina et al., 2003). The typical assumption here is that proximity to the capital city is associated with better quality institutions whereas high levels of ethnic fractionalization are associated with poor institutional quality.

We also use living standards data from the DHS and public goods data from the Afrobarometer. More on this follows in section 4.

With the exception of rainfall and population, our control variables are time-invariant at the district level. Table 1 reports summary statistics and Table 2 reports the number and share of districts with at least one mineral production and discovery. A detailed discussion of the data and sources can be found in Appendix A2.

3. Mining and development in Sub-Saharan Africa

3.1. Intensive and extensive margins of mining

We start with exploring the effect of mineral production at the intensive margin. Our main specification uses annual data for the period 1992–2012:

$$LD_{dt} = \alpha_d + \eta_t + X_{dt}\beta + \gamma MP_{dt} + \epsilon_{dt} \tag{1}$$

where LD_{dt} is the natural log of night-lights density plus 0.01 in district d in year t, MP_{dt} is the natural log of mineral production value, α_d are district fixed effects, η_t are year fixed effects, and X_{dt} is a vector of time-variant control variables including the natural log of population density and rainfall. Districts without mineral production are dropped from the regression. The coefficient of interest is γ, the elasticity of mineral production at the intensive margin.

Mineral production is measured using two distinct approaches. The first approach measures production in US dollars using 1992 (=100) as the base year thereby allowing both the price and the quantity to change. We call this the *production value approach*. In contrast, the second approach measures the value of mineral production for a particular year by multiplying production quantity in that year with the mineral price in 1992. This approach only captures the movement in production quantity while keeping price unchanged. We call this the *production volume approach*.

The second approach is relatively advantageous as it mutes the effect of short term price fluctuations on night lights. Note that Commodity prices are determined at the world market and can fluctuate widely (Deaton, 1999). However, mining companies may have little scope or incentive to adjust production to price fluctuations in the short-term. Therefore, prices and demand for local inputs (wages, food, services) may be less affected. Windfall gains and losses may then largely accrue to capital owners and/or the state.

Table 3
Mineral production and night-lights at the district level.

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Log(Mineral production)	0.024*		−0.061	
	(0.014)		(0.047)	
Log(Mineral production in 1992 commodity prices)		0.038**	0.102*	
		(0.018)	(0.057)	
Mineral production (1 = yes)				0.554***
				(0.117)
Population density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
N	1,802	1,802	1,802	76,335
N(Districts/Regions/Countries)	137/80/28	137/80/28	137/80/28	3,635/519/42
R-squared adj.	0.979	0.979	0.979	0.945

Notes: This table shows the association between night-lights and various measures of mining activity in a panel of district-year observations for the period 1992–2012. Dependent variable is log(0.01 + nighttime lights density) at the district-year level. Column 1 expresses mineral production in US dollars using 1992 (=100) as the base year and thereby allowing both the price and the quantity to change. Column 2 expresses the mineral production in a particular year as the product of production quantity in that year and the mineral price in 1992. Column 3 includes both of these indicators. Column 4 uses a dummy variable equal to one if the district had a producing mine thereby using the full sample. For a detailed variable description, see Data Appendix. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

To study the extensive margin, we replace MP_{dt} with a dummy variable equal to one if the district has - or ever had - a producing mine. Under this specification the sample includes all districts. The estimated coefficient identifies the change in night-lights associated with a change in a district's status from non-mining to mining. Note that district fixed effects absorb variation in night-lights in districts that do not change status.

Identification comes from the temporal variation within mineral producing districts. The validity of this strategy rests on the assumption that fluctuations in mineral production are driven by factors external to the district. This may not be true. For example, shocks - such as power cuts or violent conflicts - may affect both mining and economic activity during a certain district-year and are not absorbed by the district fixed effect. The same reasoning applies to the extensive margin. The opening of a mine can be delayed or coincide with conditions such as opening of a new road. Keeping these caveats in mind, the results nevertheless help to establish the stylized facts that we probe more thoroughly later.

Columns 1–3 of Table 3 shows effects at the intensive margin. Column 1 points to a positive association between mineral *production value* and night-lights. The association, however, is stronger when we use *production volumes* (column 2), and in a horse race it is the latter that wins (column 3). The effects of one standard deviation change in the mineral production (at the intensive margin) variables on night-lights in columns 1 and 2 are 0.08 percent and 0.12 percent respectively. In column 4 we examine the effect of mining at the extensive margin on night-lights and find that a switch from a non-mining district to a mining district is associated with an increase in night-lights by 55.4 percent. In other words, one standard deviation increase in the mineral production dummy variable increases night-lights by 11.1 percent. This is approximately more than 92 times the effect of mining expansion at the intensive margin and hence a large effect.

3.2. Mineral production onset and development

Mines will open when and where the expected net present value of mineral extraction (NPVME) is positive. One could conjecture that this is more likely in economically more developed districts. For example, existing infrastructure (railroads, roads, ports, electricity) may reduce the need to build one. An existing labor pool may reduce the need to attract one. Such advantages create cost savings, rendering the NPVME more likely to be positive. However, one can easily come up with other stories that are less clear-cut. For example, the geology of mineral resources may be correlated with soil quality and water availability (riverbeds); certain underlying factors might trigger local opposition to mining.[7]

For our analysis, this is an important issue because it may violate the unconfoundedness assumption thereby threatening the identification of causal estimates: Districts that enter mineral production may do so because of certain unobservable characteristics that are associated both with the start of mineral production (the 'assignment') and with the potential outcomes.

To the best of our knowledge, there has been no systematic study that looks into what, on average, attracts a mining industry to one particular site while ignoring others. We can shed some light on this issue. Mining companies assess profitability of a site going through a sequence of stages (grassroots, exploration, advanced exploration, pre-feasibility, feasibility, construction) of filtering, which is usually referred to as "mining sequence". It covers all aspects of mining activity, but precise boundaries between the stages may vary. The IntierraRMG dataset records six stages of mining investment as mentioned above which we utilize here. The first three stages are predominantly exploratory whereas the last three stages determine commercial viability of a project. After each stage, selection intensifies. So where do mining investments go?

In Table 4 we relate the stages of investment recorded in 2012 to district level indicators of development observed in the year 2000. Note that all estimates in this table are based on cross-section information. At no point are night-lights at the district level significantly correlated with mining investments. Contrary to the original conjecture, we observe in columns 2 and 3 that exploration and advanced exploration in mining are less likely in districts with higher electricity grid

[7] Opposition may be more likely with the presence of small-scale extraction and negative externalities. There may also be disagreement about the distribution of rents. For example, a consultant explained to the authors how local chiefs in Sierra Leone were extracting rents from iron ore mining (for the construction of schools) by threatening to obstruct railroad transportation.

density and railway density respectively. This is suggestive that mining investments and especially exploration tend to take place in remote and unexplored locations. We find in column 6 that at the construction stage a higher population density is attracting investments. This is unsurprising given that mining construction requires a steady supply of labor.

Keeping these results in mind, we now identify the effect of mining at the extensive margin by dividing the data into a control and treatment group. The challenge is to identify a suitable control group that matches the treatment group in every respect except the treatment. We choose districts with mining potential identified in a feasibility study as of 2012, but not yet mined as a control group. Feasibility studies are the final stage before construction therefore feasible districts are fairly similar to the treatment districts.[8] Still, only a subset of districts may pass from the feasibility stage to construction and finally production. We therefore rely on the same pre-treatment trends to lend confidence to the parallel trend assumption. In order to facilitate pre-treatment comparison, we define the treatment group as those districts that started mineral production for the first time between 2003 and 2012, hence we have a symmetric pre- and post-treatment period of 1992–2002 and 2003–2012 respectively.

We first examine whether there is any systematic difference in observable characteristics between treated and control districts. Table 5, Panel A, column 1 presents the mean values for each observable characteristic for the treated and column 2 presents the normalized mean difference between treatment and the control group.[9] All observables are time-invariant or referring to the year 2000. Column 2 suggests that the treated districts are fairly similar to the feasible districts save their higher electric grid density. We rate this as a better underlying characteristic, which would bias estimate upwards. Note that we do not use the never mined districts as of 2012 as controls. Cust and Harding (2014) show that institutions strongly influence oil and gas exploration which renders never mined districts as an unconvincing control group.

In Table 5, Panel B we report decadal growth rates in the outcome variables for the 1992–2002 and 2003–2012 period by treatment status. We do not find any pre-existing divergent trend in night-lights across treated and control districts prior to the production treatment (before 2003). In contrast, during the treatment period trends significantly diverge. After a decade night-lights in the treated districts have grown by about 50 percentage points more. Fig. 5, showing the development in night-lights of treated and control groups on an annual basis, confirms this result.[10] While level differences are apparent, their magnitudes remain the same for the years before 2002 (pre-treatment) until districts start to begin mineral production (in 2003) at which point they start to outgrow their counterparts. Fig. 6 shows the evolution of night-lights in districts 10 years before and after the start of mineral production. Here, mining districts serve as their own control. The log-transformation allows us to interpret the slope as growth rates in night-lights. We observe that districts have a steady growth rate until two years before the start of production. Then, growth rates strongly accelerate for a period of about 4 years. This is consistent with an interpretation that infrastructure moves closer to the site one or two years prior to the actual start of production. While growth rates slow down afterwards, they are nevertheless steeper than compared to the pre-mining period.

[8] We do not use the construction stage as control group, because construction by itself already constitutes economic activity caused by mining. We aim to present an even cleaner strategy when investigating mineral discoveries, see section 3.3.

[9] The normalized difference between treatment t and control group c is defined as $\Delta_X = (\overline{X}_t - \overline{X}_c)/\sqrt{(S_t^2 + S_c^2)/2}$ where $\overline{X}$ and S^2 refer to sample means and variances respectively.

[10] Because of differences in the calibration of satellites, Fig. 5 is not suited to inform about absolute trends.

Table 4
Where do mining investments go?.

	Grassroots in 2012 (1)	Exploration in 2012 (2)	Adv. Expl. in 2012 (3)	Pre-Feasibility in 2012 (4)	Feasibility in 2012 (5)	Construction in 2012 (6)
Number of districts at each stage	353	290	203	86	82	19
Log(Nightlights density in 2000)	0.003	−0.001	−0.002	−0.001	0.002	0.001
	(0.005)	(0.004)	(0.004)	(0.002)	(0.003)	(0.001)
Ln (Population density in 2000)	−0.007	−0.001	0.007	−0.002	0.007	0.003*
	(0.008)	(0.006)	(0.006)	(0.003)	(0.004)	(0.002)
Log(Paved road density in 2000)	0.083	0.093	−0.054	−0.061	0.077	−0.023
	(0.096)	(0.082)	(0.084)	(0.053)	(0.055)	(0.041)
Log(Railway density in 2000)	−0.005	0.002	−0.007*	−0.001	−0.002	0.001
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.001)
Log(Electric grid density in 2000)	0.012	−0.048*	0.025	−0.011	−0.026	0.001
	(0.024)	(0.026)	(0.033)	(0.016)	(0.016)	(0.005)
Geographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Climatic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Political Economy Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	3,635	3,635	3,635	3,635	3,635	3,635
N(Districts/Regions/Countries)	3,635/519/42	3,635/519/42	3,635/519/42	3,635/519/42	3,635/519/42	3,635/519/42
R-squared adj.	0.291	0.294	0.233	0.251	0.205	0.171

Notes: This table reports the correlation between district characteristics in 2000 and different stages of mining exploration in 2012 in a cross-section of district observations. The stages of mining exploration data is derived from IntierraRMG. We test for six stages that mining projects typically undergo, from grassroots explorations to construction. With the passing of each stage mineral production becomes more likely. In columns (1)–(6), the dependent variable is a dummy equal to one if a district experiences grassroots exploration, exploration, advanced exploration, pre-feasibility study, feasibility study and actual construction of a mine, respectively. Linear Probability Model is used for the estimation. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5
Comparison of treated and control districts (mineral production treatment).

	Treated (1)	Normalized Difference (Treated-Control) (2)
Number of Districts	53	156
Panel A: Time-Invariant Cross-Sectional Variables		
Log(Altitude in m)	6.18	−0.00
Log(Ruggedness)	4.31	−0.04
Share of district with fertile soil	16.09	−0.09
Log(Distance to the Coast in km)	5.76	0.05
Log(Land surface area in sq. km)	8.40	−0.03
Log(Average annual rainfall in mm)	4.73	0.03
Share of district with tropical climate	50.88	−0.09
Share of district with dry/arid climate	27.17	0.00
Share of district with temperate climate	21.94	0.11
Capital city (1 = yes)	0	−0.08
Log(Distance to the capital city in km)	5.56	−0.03
Ethnic Fractionalization	0.31	0.02
Log(Paved road per sq. km in 2000)	0.02	0.10
Log(Railway per sq. km in 2000)	1.66	0.03
Log(Electric-grid per sq. km in 2000)	0.06	0.16**
Panel B: Trend Comparison		
Log(0.01 + Nighttime Lights Density)		
Pre-treatment growth 1992–2002	0.60	0.00
Post-treatment growth 2003–2012	1.33	0.53***
Log(0.01 + Nighttime Lights Per Capita)		
Pre-treatment growth 1992–2002	0.40	0.02
Post-treatment growth 2003–2012	1.17	0.55***
District Level Conflict Intensity		
Pre-treatment growth 1992–2002	−0.79	−0.02
Post-treatment growth 2003–2010	−0.06	0.05
District Level Conflict Fatality		
Pre-treatment growth 1992–2002	−1.28	−0.08
Post-treatment growth 2003–2010	−0.25	0.08

Notes: This table shows the difference in observables and outcomes between treated and control districts. Treated districts started mineral production for the first time between 2003 and 2012 (cf. mining districts in Fig. 5). The control group is defined as districts yet without mining but with mineral deposits, which potential is examined in a feasibility study (cf. prospective mining districts in Fig. 5). In column (1), coefficients represent the mean value of each variable for the treatment group. In column (2), we present the normalized mean difference relative to the control group as recommended in Imbens and Wooldridge (2009). Panel A presents the comparison of time invariant variables. Panel B presents decadal growth rates before treatment (1992–2002) and after treatment (2003–2012) except for the conflict variable (2003–2010), as the conflict data is reported until 2010. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

In sum, we observe large positive effects of mineral production at the extensive margin in sub-Saharan Africa. The effects of mining at the intensive margin is also positive and significant even though smaller in magnitude.

3.3. Mineral discovery and development

In this section we relate the news shock of mineral discoveries to development. Analysing *mineral discoveries* enables us to explore and mitigate potential endogeneity challenges associated with *mineral production.* First, one potential concern is that districts with better unobservable fundamentals may be more likely to enter production. Discoveries are likely to follow a different, less selective model, because they require less capital, and returns are largely driven by the size of the deposit which is unknown exante.[11] Certain discoveries may not enter production at all. Discoveries can be interpreted as intention-to-treat. Second, the timing of the discovery can be considered exogenous, if discovery represents 'news' to economic agents. We believe that this element of surprise is particularly likely in districts without any mining history prior to the discovery. Third, there may be a significant delay between discovery and start of production. Our data indicates that 10 years after a discovery, only 27.2% of the sites entered production. After 20 years, the figure rises to 48.3% (Fig. 7). Setting up mining infrastructure and attracting the labor force to work in the mines constitute economic activity *caused by mining* but it typically predates production. This effect could be wrongly attributed to the pre-mining era comparison group. In contrast, mining discovery constitutes a clean start of the experiment. Overall, we can treat the discovery date as an exogenous news shock, much more in line with the start of the experiment, enabling us to mitigate potential reverse causality challenges associated with mineral production.

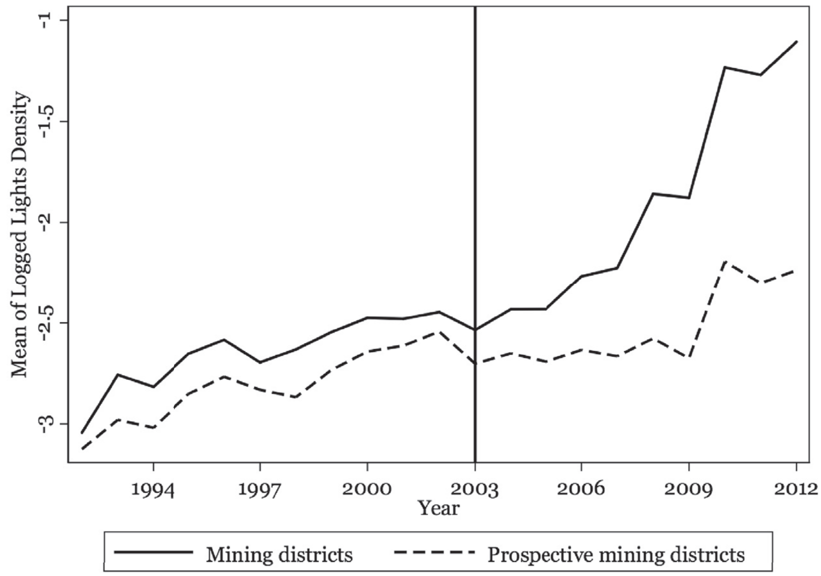
We focus on discoveries between 1992 and 2012. To identify the effect of discovery shocks on local development, we estimate the following model:

$$LD_{dt} = \widetilde{\alpha}_d + \widetilde{\eta}_t + X_{dt}\widetilde{\beta} + \sum_{j=0}^{10} \widetilde{\gamma}_j MD_{dt-j} + \widetilde{\epsilon}_{dt} \tag{2}$$

where MD_{dt-j} is a dummy variable equal to 1 if a mineral discovery has been made in year $t-j$, 0 if no discovery has been made and missing for every year post-discovery other than $t-10$.

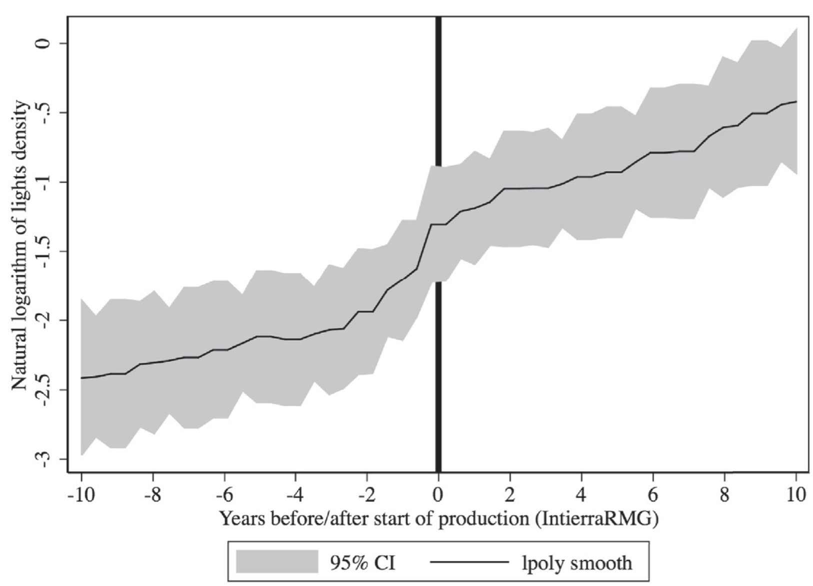
We restrict MD_{dt-j} to *first discoveries*, that is to discoveries in districts that never had any mining activity before, and the comparison group to non-mining districts without any discoveries. This restriction serves two

[11] In Section 4 we shed more light on the district characteristics that are associated with exploration and mining investments.



Notes: The graph shows the evolution of nightlights for two categories of districts: i) districts that started mineral production after 2002 (treatment) and ii) districts that are yet to be mined but with substantial mineral deposits identified in feasibility studies (control group). Data is from IntierraRMG.

Fig. 5. Trends in lights density before and after mineral production treatment.

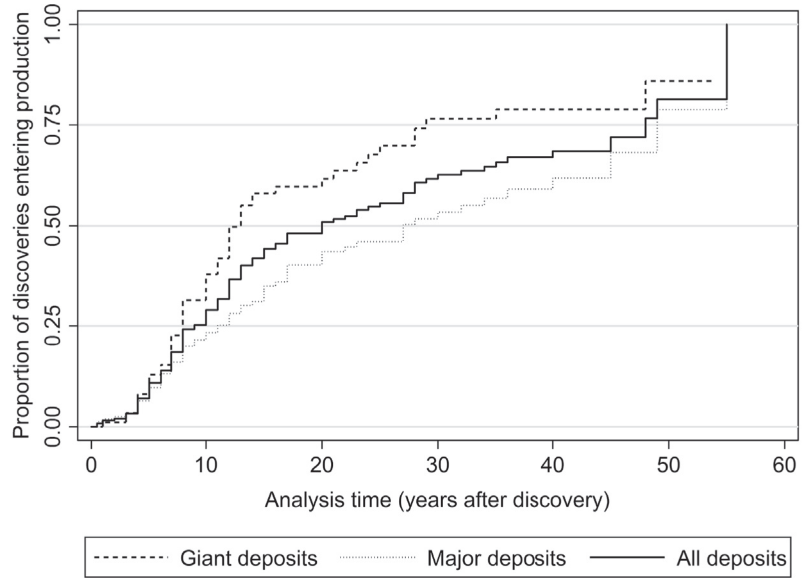


Notes: The graph shows the evolution of nightlights in mining districts in the run-up to production and the years thereafter. Production starts at time t=0. Data is from IntierraRMG.

Fig. 6. Effect of mineral production on lights density.

purposes. First, existing mining activities may affect local development and it is difficult to disentangle this effect from the effect of a new discovery. Second, economic agents may arguably anticipate repeated discoveries due to the knowledge of past discoveries and geology (Lei and Michaels, 2014). In contrast, a discovery and its exact timing is much harder to predict for 'virgin' non-mining districts.[12] Thus, setting

[12] Mineral discoveries in virgin districts are not heavily clustered in administrative regions with pre-existing mining activities either. For the 1992–2012 period, 36 out of the 73 first discoveries occurred in districts, where the corresponding region had no recorded mining activity as well.



Notes: The graph shows Kaplan-Meier failure estimates for mineral discoveries 1950-2013, whereby mineral deposits become "at risk" when discovered and "fail" when entering production. Discoveries with a reported status of "Undeveloped" or "Feasibility" were coded as not having started production. We excluded mineral discoveries (N=12), for which the start-up year was missing but current status was reported as "unknown", "operating" and "closed". N(major discoveries/giant discoveries at risk)=(156/88). Data from MinEx Consulting.

Fig. 7. Kaplan-Meier estimates of mineral discoveries entering production.

$MD_{dt-j} = 1$ for *first discoveries* is the cleanest treatment group. In fact, the coefficient $\widetilde{\gamma}_0$ tests whether there is a significant level difference between non-mining districts and districts in which a discovery has just been made. Overall, the coefficients $\widetilde{\gamma}_j$ measure the difference in night-lights j years after a discovery.

Table 6 displays the results. In Column 1, the coefficients reflect the change in night-lights $j = \{0, 1, \ldots, 10\}$ years after a discovery relative to the pre-discovery era and trends in night-lights of non-mining districts in the same year.[13] The coefficient $\widetilde{\gamma}_0$ is indeed very close to zero and remains small and insignificant up to four years after a mineral discovery. After year 6, at $j = 6$, however, point estimates become positive and significant and they increase with j. At $j = 10$, nightlights are 43.8 percentage points higher. This coefficient is below the estimate that we obtained when using the start of mineral production as explanatory variable (column 4 in Table 2 and column 3 in Table 4). It is important to stress that this is an average treatment effect. The increase in nightlights may be attributed to two effects. First, an increasing number of districts entering production after the discovery has been made and second, night-lights still expanding in districts where production has already started.

The coefficients in Column 1 do not necessarily measure the effect of a single discovery, as more discoveries may follow after the first discovery. In our data there are seven districts that had more than one discovery. In Column 2, we limit the sample to the time when there was no subsequent discovery. Coefficients remain virtually unchanged. Having an additional discovery after the first discovery does not seem to matter much. This again supports the view that the extensive margin of mining has a much larger effect on development than the intensive margin.

We would expect heterogeneous effects with respect to the size of mineral deposits. In particular, giant deposits should have a larger effect because of their higher economic value and because they tend to enter production more quickly than major deposits (Fig. 7). We test this idea using the same specification as in Eq. (2), but with dummy variables MD_{dt-j} indicating the first discovery of giant (major) deposits exclusively. Column 3 and 4 shows the estimates for giant deposits and major deposits respectively. While standard errors are large indicating that there are no statistically significant differences between giant and major deposits, point estimates indeed confirm a pattern by which night-lights take off slightly earlier (at about year 5) and at a steeper rate after a discovery of a giant mineral deposit.[14] At year 10 after the discovery, the increase in night-lights corresponds to 54 percentage points for giant deposits compared to a 37 percentage points for major deposits. These are indeed large effects.

4. Nightlights, living standards and public service provision

How big is the economic significance of the estimated effects on nightlights? A simple test would be to tally them with the district level real GDP data. Henderson et al. (2012, Table 3) find that for low and middle income countries with poor quality national accounts data the elasticity of growth of lights emanating into space with respect to GDP growth at the national level is close to 0.3. Michalopoulos and Papaioannou (2013) use DHS data at the sub-national level for four selective countries (Tanzania, Zimbabwe, Congo DRC, and Nigeria) and

[13] Using the same model as in Eq. (2) but region instead of district fixed effects, we obtain very similar coefficients indicating that virgin districts that just experienced a discovery are, on average, hardly different from other districts in the same administrative region that had not had a mineral discovery.

[14] There are an average of 25 giant and 48 major deposits in our 10 year time horizon.

Table 6
Mineral discoveries and night-lights in virgin districts.

MD_{dt-j}: Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j = 0$	−0.029	−0.028	−0.032	−0.024
	(0.061)	(0.063)	(0.098)	(0.081)
$j = 1$	0.023	0.024	0.100	−0.005
	(0.073)	(0.075)	(0.111)	(0.091)
$j = 2$	−0.011	−0.008	0.075	−0.043
	(0.079)	(0.081)	(0.106)	(0.098)
$j = 3$	0.019	0.006	−0.015	0.039
	(0.086)	(0.087)	(0.131)	(0.094)
$j = 4$	0.071	0.068	0.085	0.070
	(0.100)	(0.104)	(0.167)	(0.111)
$j = 5$	0.126	0.114	0.146	0.122
	(0.104)	(0.109)	(0.174)	(0.114)
$j = 6$	0.194*	0.190*	0.314	0.134
	(0.112)	(0.118)	(0.220)	(0.118)
$j = 7$	0.242**	0.218*	0.342	0.190
	(0.121)	(0.126)	(0.235)	(0.123)
$j = 8$	0.387***	0.391***	0.484**	0.331**
	(0.137)	(0.147)	(0.235)	(0.161)
$j = 9$	0.401***	0.402***	0.477**	0.355**
	(0.149)	(0.155)	(0.247)	(0.171)
$j = 10$	0.438***	0.431***	0.538**	0.373**
	(0.149)	(0.156)	(0.253)	(0.166)
Pop. density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
N	74,234	74,178	73,150	73,828
N(Discoveries)	[66, 79]	[57, 77]	[21, 28]	[38, 55]
N(Districts/Regions/Countries)	3,560/516/42	3,557/516/42	3,493/515/42	3,530/515/42
R-squared adj.	0.944	0.944	0.944	0.944

Notes: This table reports the effect of mineral resource discoveries on night-lights in a panel of district-year observations. Districts with pre-existing mining activities were dropped from the regression. In column (1), the variable of interest MD_{dt-j} is a dummy variable equal to 1 if a giant or major mineral deposit was discovered *j* years ago, 0 if no discovery has been made and missing for every post-discovery year $j > 10$. In column (2), the dummies are set to missing the year a second discovery was made in the same district. In column (3) and (4), the dummy refers to giant and major deposit discoveries respectively. Because of the 10-year lag, the discoveries and numbers referred to by each dummy variable may vary. All regressions include year and district fixed effects. We also control for population density and annual average rainfall. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

estimate the elasticity between luminosity and composite wealth index to be 0.7. Hodler and Raschky (2014) also report very similar relationship at the level of sub-national regions. Based on such estimates we could speculate that a switch from non-mining to mining would increase a district's GDP by $55 \times 0.3 = 16.5$ percent.

Moreover, we also present estimates of our own using the micro-level DHS and Afrobarometer datasets. In Table 7 we estimate the effect of mineral discoveries on five direct measures of living standards - has electricity (1 = yes), wealth index, urbanization (1 = urban), infant mortality, and education.[15] The first three variables are from the DHS Household recode (household as the unit of analysis) and the last two variables are from the DHS birth recode (birth or children as the unit of analysis). Both DHS survey recodes are geocoded at the DHS cluster level by survey rounds. Fig. 8 reports the centroid of these clusters. We match the latitude and longitude of these clusters with our 3,635 districts from 42 Sub-Saharan African countries. The household recode surveys are not annual and therefore we have repeated cross-sections for columns 1–3. In contrast the birth recodes in columns 4 and 5 allow us to analyze changes on an annual basis among people belonging to the same birth cohort.

The wealth index is constructed using composite information on the household's ownership of selected assets (radio, telephones, car etc.), dwelling characteristics such as flooring material, types of drinking water access, sanitation facilities and other characteristics that are related to wealth status. The index is an ordered variable, ranging from 0 (poorest) to 5 (richest). The infant mortality variable is coded as 1 if a child has died at less than 12 months of age, and 0 if a child is still alive or died at 12 or more months of age. The educational attainment variable ranges from 0 for no formal education to 1 for higher education.

We find discoveries have no effects on electricity and mortality (columns 1 and 4) and moderately positive effects on wealth index and urbanization (columns 2 and 3). The effect on education appears to be negative (column 5).

Next in Table 8 we estimate the effects of discoveries on public service provision using the Afrobarometer surveys. Fig. 9 reports the centroids of the Afrobarometer survey areas which we match with our districts. The dataset here is repeated cross-section with individual respondents or citizens as the unit of analysis. We use the dummy variables coding citizens' access to basic services such as schooling, piped water system, sewerage system, and health clinics. Respondents were asked whether these public goods and services were present in the primary sampling unit or enumeration area. We find some early positive effects on schools and sewerage systems which subsequently gets nullified over time (columns 1 and 3). This fits the narrative of some non-durable initial concessions made by the mining companies or the state to the locals. Investments in local public services appear to increase momentarily only to wither away over time. The effect on piped water supply appears to be negative (column 2). Mining is often water intensive and therefore affects the domestic water supply of the district negatively. Discoveries appear to have no effect on health clinics (column 4).

[15] Given the less-than-annual frequency of DHS, this exercise is more suitable for relatively persistent explanatory variables such as mineral discoveries as opposed to strongly fluctuating explanatory variables such as mineral production. Hence the focus on discovery here.

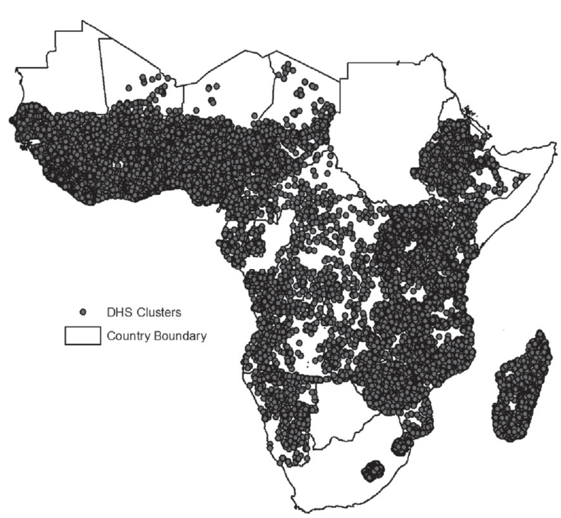
Table 7
Mineral Discovery and Living Standards using DHS Data.

MD_{dt-j}: Mine discovery made in year $t - j$	DHS Repeated Surveys			DHS Birth Cohorts	
	Electricity (1)	Wealth Index (2)	Urbanization (3)	Mortality (4)	Education (5)
$j = 0$	0.027	−0.192	−0.029	0.006	−0.039
	(0.035)	(0.160)	(0.056)	(0.008)	(0.024)
$j = 1$	−0.002	0.408	0.096	−0.001	−0.023
	(0.047)	(0.339)	(0.072)	(0.010)	(0.020)
$j = 2$	−0.005	0.033	0.041	0.000	−0.041
	(0.036)	(0.149)	(0.052)	(0.009)	(0.028)
$j = 3$	0.065	0.116	0.021	0.002	−0.030
	(0.047)	(0.183)	(0.061)	(0.012)	(0.025)
$j = 4$	−0.024	0.023	−0.006	0.011	−0.040
	(0.021)	(0.090)	(0.043)	(0.009)	(0.032)
$j = 5$	−0.023	−0.188	0.033	−0.003	−0.052**
	(0.036)	(0.248)	(0.072)	(0.010)	(0.027)
$j = 6$	−0.022	−0.039	−0.003	0.001	−0.063**
	(0.026)	(0.146)	(0.055)	(0.011)	(0.027)
$j = 7$	−0.018	0.226	0.100	0.003	−0.033
	(0.035)	(0.190)	(0.091)	(0.016)	(0.030)
$j = 8$	0.037	0.306**	−0.001	−0.014	−0.068*
	(0.061)	(0.147)	(0.055)	(0.011)	(0.036)
$j = 9$	0.032	0.246***	0.098***	0.002	−0.089***
	(0.029)	(0.079)	(0.037)	(0.012)	(0.026)
$j = 10$	0.047	0.247**	0.055	−0.011	0.003
	(0.058)	(0.122)	(0.056)	(0.011)	(0.036)
Population Density	Yes	Yes	Yes	Yes	Yes
Rainfall	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1,078,491	924,789	1,089,838	2,025,409	2,025,354
N(Districts)	2,787	2,675	2,792	2,780	2,780
R-squared adj.	0.389	0.359	0.401	0.0342	0.382

Notes: This table is a re-estimation of Table 6. It reports the effect of mineral resource discoveries on household's access to electricity (1 = yes), household's main residence (1 = urban), household's wealth index indicating cumulative living standard, infant mortality and children educational attainment using data from Demographic and Health Surveys (DHS) between 1992 and 2012. In Columns (1)–(5), the variable of interest MD_{dt-j} is a dummy variable equal to 1 if a giant or major mineral deposit was discovered j years ago, 0 if no discovery has been made and missing for every post-discovery year $j > 10$. All regressions include year and district fixed effects. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

5. Spillovers and general equilibrium effects

So far, we implicitly assumed that mining leads to some relatively broad development within the district where the mine is located, but that effects are mostly limited to that district. Theories of enclave development question the existence of meaningful spillover effects. While mining industries are highly productive, forward and backward linkages are limited. This notwithstanding, existing studies of



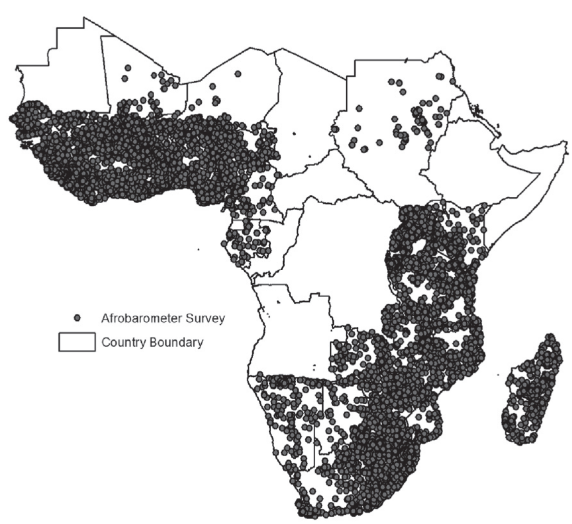
Notes: This map shows the geographical distribution of DHS clusters (centroid of the sampling area). DHS clusters are coded by survey rounds or phases for each countries.

Fig. 8. Geospatial distribution of DHS clusters.

Table 8
Mineral Discovery and Public Service Provision using Afrobarometer.

MD_{dt-j}: Mine discovery made in year $t-j$	School (1)	Piped Water (2)	Sewerage System (3)	Health Clinic (4)
$j = 0$	0.236***	0.115	0.060**	0.260
	(0.059)	(0.080)	(0.029)	(0.232)
$j = 1$	−0.176*	−0.107	−0.287**	−0.176
	(0.096)	(0.068)	(0.133)	(0.177)
$j = 2$	−0.199	0.114	0.026	−0.083
	(0.187)	(0.109)	(0.033)	(0.349)
$j = 3$	0.154*	−0.126	0.052	0.102
	(0.080)	(0.092)	(0.036)	(0.190)
$j = 4$	0.076	0.088	−0.027	0.019
	(0.170)	(0.167)	(0.064)	(0.244)
$j = 5$	−0.128	0.122	−0.175**	−0.291
	(0.103)	(0.088)	(0.080)	(0.189)
$j = 6$	0.179	−0.183**	−0.072	0.031
	(0.116)	(0.079)	(0.076)	(0.248)
$j = 7$	0.087	−0.006	0.093	−0.140
	(0.123)	(0.115)	(0.059)	(0.231)
$j = 8$	0.100	0.088	−0.124	0.134
	(0.149)	(0.099)	(0.128)	(0.251)
$j = 9$	0.233	0.024	−0.020	0.120
	(0.141)	(0.067)	(0.058)	(0.213)
$j = 10$	−0.213	−0.084	−0.117	−0.162
	(0.168)	(0.099)	(0.147)	(0.195)
Population Density	Yes	Yes	Yes	Yes
Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
N	97,056	96,911	95,579	95,561
N(Districts)	1,911	1,906	1,904	1,908
R-squared adj.	0.212	0.428	0.436	0.258

Notes: This table is a re-estimation of Table 6. It reports the effect of mineral resource discoveries on public service provision (school, piped water, sewerage system and health clinic). We use repeated surveys data from Afrobarometer between 1999 and 2012. In Columns (1)–(4), the variable of interest MD_{dt-j} is a dummy variable equal to 1 if a giant or major mineral deposit was discovered j years ago, 0 if no discovery has been made and missing for every post-discovery year $j > 10$. All regressions include year and district fixed effects. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.



Notes: This map shows the subnational geocoded Afrobarometer survey location. The locations of enumeration or sampling areas are coded by survey rounds.

Fig. 9. Geospatial distribution of Afrobarometer sampling locations.

local development point to certain spillovers. In their study of a large gold mine in Northern Peru, Aragón and Rud (2013) found income effects declining with distance and being insignificant beyond 100 km from the mine. Similarly Kotsadam and Tolonen (2016) found effects on female employment up to a distance of 75 km. Both studies relate these effects to local demand created by mining. In our data, distances between neighboring districts average 69.4 km (sd:

Table 9
Mineral Production and Night-Lights at the District Level (Dropping light pixels emanating from the industry).

	2 KM (1)	5 KM (2)	10 KM (3)
Panel A: Intensive Margin			
Log(Mineral production in 1992 commodity prices)	0.038**	0.028	0.024
	(0.017)	(0.020)	(0.027)
N	1,802	1,802	1,802
N(Districts/Regions/Countries)	137/80/28	137/80/28	137/80/28
R-squared adj.	0.979	0.971	0.957
Panel B: Extensive Margin			
Mineral production (1 = yes)	0.543***	0.543***	0.542***
	(0.115)	(0.115)	(0.116)
N	76,335	76,335	76,335
N(Districts/Regions/Countries)	3,635/519/42	3,635/519/42	3,635/519/42
R-squared adj.	0.947	0.946	0.945
Population density & Rainfall	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes

Notes: This table is a re-estimation of Table 3. It shows associations between mining activities and night-lights in a panel of district-year observations for the period 1992–2012. In this table, the dependent variable (i.e. log of nighttime lights density) excludes lights emanating from the mining industries (i.e deleting pixel values of the light data around 2–10 km radius of mining industries). In Panel A, the variable of interest in Columns (1)–(3) expresses the mineral production value in 1992 constant commodity prices. In Panel B, the variable of interest in Columns (1)–(3) uses a dummy variable equal to one if the district had a producing mine thereby using the full sample. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

59.5).[16] While spillover effects are of fundamental interest in themselves, they are also potential threat for our estimation strategy, as they give rise to endogeneity issues. Positive (negative) spillovers would lead to an under(over-)estimation of the true causal effect of mining activities.

We start with studying an extreme case of enclave development where the increase in nightlights is driven by lights emanating from the industry itself, e.g. by lighting up the immediate area of the construction site, the pit, or the workers' houses at night. We address this concern by dropping all light pixels around 2, 5, and 10 km radius of mines and mineral discoveries. Then, we re-estimate the regression models reported in Tables 3 and 6.[17] Results are shown in Table 9 (intensive and extensive margins) and 10 (discoveries). The intensive margin coefficient (Table 9 panel A) stays positive throughout but loses significance at the 5 km buffer. In contrast, the extensive margin coefficient (Table 9 panel B) is positive and significant throughout. The discovery coefficients in Table 10 also stays positive throughout but loses significance at the 10 km buffer. We therefore conclude that the overall effects are unlikely to be solely driven by lights emanating from the mines.

We continue our investigation by estimating a Spatial Durbin Model (SDM):

$$LD_{dt} = \alpha_d + \eta_t + \rho WLD_{dt} + X_{dt}\beta + WX_{dt}\theta + MA_{dt}\gamma + WMA_{dt}\delta + \epsilon_{dt} \tag{3}$$

which includes standard measures of mining activities *MA*, controls *X*, district and year fixed effects along with spatially lagged dependent variable *WLD* and spatially lagged explanatory variables *WX* and *WMA*. *W* denotes the spatial weight matrix that defines the potential for interaction between each pair of districts. We define neighbors as districts that share a common border (0/1 wt).[18] Hence, *WX* can be easily interpreted as *X* averaged over a district's neighbors.

The SDM has certain attractive features. The parameter ρ measures the spatial correlation of lights between neighboring districts. Mining activities *MA* may affect a district's night-lights *LD* and this change in lights may spill over to neighboring districts as ρWLD. However, if mining has indeed less forward and backward linkages than other sectors of the economy, then such spillover of mining induced lights would be smaller than what is typically the case. This effect is allowed for by $WMA\delta$. If $\delta < 0$ then spillover effects from mining are smaller than the average. Alternatively, if $\delta = 0$ then mining is like any other economic activity.

The model's autoregressive element ρWLD means that spillovers transmit through the whole system of spatially dependent districts, as neighboring districts have neighbors that in turn have neighbors that have neighbors and so on. Besides, there are also feedback effects in that impacts through neighboring districts pass back to the mining district (the mining district is the neighbor's neighbor). This makes it difficult to see the size of the effects from ρ, δ and γ (unless the former two are both zeros which imply that there are no spillover or feedback effects from mining). We therefore report the average effect to the mining districts (direct effect) and average spillover effect to the neighbors (indirect effect) separately. The direct and indirect effects are theoretically calculated as $[(I-\rho W)^{-1} \times (\gamma I + \delta W)]^{\overline{d}}$ and $[(I-\rho W)^{-1} \times (\gamma I + \delta W)]^{\overline{rsum}}$ respectively and are different from the point estimates. Note that I is the identity matrix, the superscript $\overline{d}$ is the operator that calculates the mean diagonal elements of a matrix, and the superscript $\overline{rsum}$ is the operator that calculates the mean row sum of the non-diagonal elements of a matrix. In practice we obtain the estimates using Stata's *xsmle* command written by Belotti et al. (2013).

[16] The minimum distance is 1.6 km and the maximum is 573.5 km. The differences in the distance are explained by the size of the country and the number of districts within that country (see Fig. 2).

[17] Note that increasing the radius increasingly excludes lights not directly produced by the mine. So there is a trade-off between type I and type II errors here.

[18] One perceived weakness of spatial econometric models is that results are sensitive to the somewhat arbitrary choice of the spatial weights matrix *W*. LeSage and Pace (2014) call this "the biggest myth in spatial econometrics" as W_aX are typically highly correlated with W_bX.

Table 10
Mineral Discoveries and Night-Lights in Virgin Districts (Deleting lights emanating from the industry).

MD_{dt-j}: Mineral discovery made in year $t-j$	2 KM (1)	5 KM (2)	10 KM (3)
$j=0$	−0.034	−0.029	−0.013
	(0.062)	(0.056)	(0.054)
$j=1$	0.025	0.011	0.009
	(0.072)	(0.066)	(0.065)
$j=2$	−0.008	−0.025	−0.022
	(0.078)	(0.072)	(0.072)
$j=3$	0.013	0.001	−0.018
	(0.088)	(0.079)	(0.071)
$j=4$	0.065	0.014	−0.029
	(0.096)	(0.081)	(0.069)
$j=5$	0.108	0.036	−0.022
	(0.102)	(0.084)	(0.067)
$j=6$	0.172*	0.085	0.044
	(0.102)	(0.089)	(0.075)
$j=7$	0.210*	0.094	0.043
	(0.111)	(0.096)	(0.082)
$j=8$	0.330***	0.164*	0.082
	(0.121)	(0.092)	(0.082)
$j=9$	0.335**	0.200*	0.118
	(0.131)	(0.121)	(0.114)
$j=10$	0.383***	0.248**	0.164
	(0.135)	(0.123)	(0.116)
Pop. density & Rainfall	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes
N	73,428	73,428	73,428
N(Districts/Regions/Countries)	3,560/516/42	3,557/516/42	3,493/515/42
R-squared adj.	0.947	0.947	0.947

Notes: This table is a re-estimation of Table 6. It reports the effect of mineral resource discoveries on night-lights in a panel of district-year observations. In this table, the dependent variable (i.e. log of nighttime lights density) excludes lights emanating from the mining industries (i.e deleting pixel values of the light data around 2–10 km radius of mine discoveries). In Columns (1)–(4), the variable of interest MD_{dt-j} is a dummy variable equal to 1 if a giant or major mineral deposit was discovered j years ago, 0 if no discovery has been made and missing for every post-discovery year $j > 10$. All regressions include year and district fixed effects. We also control for population density and annual average rainfall. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Among the class of models in spatial econometrics LeSage and Pace (2009) proposed the SDM as the model of departure.[19] It includes spatially lagged explanatory variables. Omitting them if relevant brings in the issue of endogeneity. In contrast, ignoring spatial dependence in the error term will result in a loss of efficiency but leave the coefficients unbiased. The SDM can then be simplified to a Spatial Autoregressive Model (SAR) if $\theta = \delta = 0$ and to a Spatial Error Model (SEM) if $\theta = -\rho\beta$ and $\delta = -\rho\gamma$.[20]

We focus on the extensive margin. We use two measures of mining based on i) mineral production and ii) mineral discovery. For the former we use a dummy variable if the district has a producing mine. Mineral discoveries are more complex as the effect unfolds over time. For the sake of simplicity, we use three dummies equal to 1 if the district had its first mineral discovery in the last 5, 6–9, and more than 10 years ago. Because we use district fixed effects, identification comes from districts that change their status from non-mining to mining within the 1992–2012 period.

Table 11 presents the results. Columns 1 and 3, Panel A present the OLS estimates that serve as a benchmark. Mineral production is associated with a significant increase in lights by 55%. The pattern for mineral discoveries confirms the one previously found, whereby lights do not change much during the first 5 years after a discovery, start to expand thereafter, and reach 59% after more than 10 years. Columns 2 and 4 show the SDM estimates. The autoregressive coefficient ρ is highly significant and indicating a strong positive correlation in lights across space. The spatial lags of mineral activities, in contrast, are negative indicating that lights in the mining district's neighbors do indeed expand by less than one would expect from spatial correlation patterns generally observed in lights. However, none of the spatial lagged explanatory variables are statistically significant. Likelihood ratio tests fail to unambiguously favour SAR over SEM, which indicates that the SDM is more appropriate here being the more general form of the two. Panel B of Table 11 shows the implied direct and indirect effects. Spatial spillover effects are negligible with respect to mineral production. Discovery of mineral resources, in contrast, reduce lights in neighboring districts rendering the total effect small and non-significant well until 10 years after a discovery, when direct and indirect effects increase and become positive. Overall, we conclude that there is little evidence of large and significant spatial spillovers from mining. Results from the OLS estimator are qualitatively the same.

An alternative way to explore general equilibrium effects is to redefine the unit of observation, ideally so that any spill-over effects are confined to within those redefined units. We therefore study regions (1st level administrative units), which are one aggregate higher than districts (2nd level administrative unit). The average region in our sample comprises seven districts and 46,120 square kilometers (the median size is 17,878 square kilometers). Furthermore, when using regions the average Euclidean distance from an active mine to any point on the respective administrative border increases from 62 km (sd: 57) to

[19] Elhorst (2010) instead proposed a slightly different approach. In his view, the Spatial Durbin Model should be estimated if the OLS model is rejected in favour of the Spatial Autoregressive Model and/or the Spatial Error Model. We calculated Moran's I for the residuals in estimations in Tables 2 and 4 and found a significant positive spatial autocorrelation of the residuals. In line with Elhorst (2010) this is sufficient to motivate the Spatial Durbin Model.

[20] Hence, if the true model is an SEM, the SDM will produce correct standard errors (Elhorst, 2010).

Table 11
Spatial spillovers from mining.

	Start-up of Mineral Production		First Mineral Discovery	
	OLS	SDM	OLS	SDM
	(1)	(2)	(3)	(4)
Panel A: Estimated Coefficients				
District has a producing mine	0.554***	0.559***		
	(0.117)	(0.115)		
W(District has a producing mine)		−0.153		
		(0.182)		
Discovery in the past 5 years			0.009	0.011
			(0.072)	(0.067)
Discovery in the past 6–10 years			0.257**	0.247**
			(0.113)	(0.108)
Discovery more than 10 years ago			0.593***	0.572***
			(0.150)	(0.145)
W(Discovery in the past 5 years)				−0.121
				(0.176)
W(Discovery in the past 6–10 years)				−0.128
				(0.211)
W(Discovery more than 10 years ago)				0.056
				(0.286)
Population density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
ρ		0.232***		0.232***
		(0.016)		(0.016)
$\delta = 0$ (χ^2-Test, p-val)				0.66
$\theta = \delta = 0$ (χ^2-Test, p-val)		0.38		0.45
$\theta = -\rho\beta$ and $\delta = -\rho\gamma$ (χ^2-Test, p-val)		0.19		0.43
N	76,335	76,335	76,335	76,335
N(Districts/Regions/Countries)	3,635/519/42	3,635/519/42	3,635/519/42	3,635/519/42
R-squared	0.947	0.173	0.947	0.145
Panel B: Direct & Indirect Effects of Mining from SDM				
	Direct	Indirect	Direct	Indirect
District has a producing mine	0.573***	0.004		
	(0.115)	(0.264)		
Discovery in the past 5 years			0.013	−0.172
			(0.064)	(0.276)
Discovery in the past 6–10 years			0.230**	−0.139
			(0.104)	(0.242)
Discovery more than 10 years ago			0.518***	0.172
			(0.129)	(0.296)

Notes: This table reports spatial spillover effects from mining on neighboring districts in a panel of district-year observations. The dependent variable is the natural log of night-lights density plus 0.01. Column (1) and (3) show OLS baselines estimates, whereas (2) and (4) show estimates of a Spatial Durbin Model (SDM). The direct effect refers to the effect in the mining district, whereas the indirect effect refers to the average spillover effect into neighboring districts. The total effect of mining is the sum of the two effects. Estimates are based on a spatial weights matrix W that assigns a 1 to districts that share a common border. Robust standard errors in parentheses are clustered by region. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

206 km (sd: 105).[21] Since mines are more centrally located within a region, the spill-overs to neighboring regions should be less.

Our testing strategy is as follows. First, we aggregate districts to regions and re-estimate specification (1) using regions as units of observation. We expect the coefficient to be positive but smaller than estimates using districts as unit of observation. Second, we aggregate night-lights in non-mining districts to regions but exclude the mining districts from the aggregation. Note that while aggregating mining activity from districts to regions we include both mining as well as non-mining districts. We then re-estimate specification (1). Note that we are regressing mining activities in a region on night-lights of non-mining districts within that region. The effect will necessarily be smaller than in strategy one, because we are excluding the mining districts for which we found positive effects. A positive/negative coefficient in this specification would point to positive/negative spill-overs to non-mining districts within the mining regions. We also distinguish between intensive and extensive margins as we did in Table 3.

Table 12 presents the results. Column 1–4 study the intensive margin. Column 1 estimates the effect of mineral production values on night-lights within a region. The effect is positive but small. Column 3 focuses on mineral production quantity keeping the commodity prices at 1992 levels. We find a significant positive effect at the regional level. When we use the sample of regions that only aggregates from non-mining districts (column 2 and 4), the coefficients are smaller and non-significant, pointing to limited spill-over effects to non-mineral producing district of a mining region. Column 5–8 study the extensive margin. Column 5 shows the effect of a region starting mineral production. The effect is positive and significant. Column 7 shows the effect of discoveries. We obtain a similar pattern as at district level, whereas night-lights tend to increase after discovery, but reach significant levels only after more than 10 years. Column 6 and 8 exclude mining districts from the region. We obtain positive but relatively small and non-significant

[21] For this exercise, we created a node every 5 km and 50 km along the district and region border respectively. Then, after calculating the distance between every mine location and every node on the border we calculated the mean.

Table 12
Mineral production, discovery and night-lights at the region level.

	Intensive margin				Extensive margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Region excluding districts with mineral activities	No	Yes	No	Yes	No	Yes	No	Yes
Log(Mineral production)	0.018	−0.006						
	(0.018)	(0.019)						
Log(Mineral production in 1992 commodity prices)			0.032*	0.005				
			(0.018)	(0.019)				
Mineral production (1 = yes)					0.295***	0.101		
					(0.082)	(0.069)		
Discovery in the past 5 years							0.003	0.016
							(0.047)	(0.065)
Discovery in the past 6–10 years							0.052	0.032
							(0.056)	(0.085)
Discovery more than 10 years ago							0.166**	0.056
							(0.084)	(0.104)
Population density & Rainfall	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,057	948	1,057	948	10,899	10,710	10,805	10,710
N (Regions/Countries)	80/28	72/27	80/28	72/27	519/42	510/42	516/42	510/42
R-squared adj.	0.984	0.983	0.984	0.983	0.957	0.957	0.957	0.956

Notes: This table shows associations between mining activities and night-lights in a panel of region-year observations for the period 1992–2012. Dependent variable is log(0.01 + nighttime lights density) at the district-year level. Column (1) & (2) expresses the mineral production value in 1992 constant USD. Column (3) & (4) expresses the mineral production value in 1992 constant commodity prices. Column (5) & (6) uses a dummy variable equal to one if the region had a producing mine thereby using the full sample. Column (7) & (8) expresses mining activity as a dummy equal to one if the region had at leaset one discovery in the last 5, 6–10, and more than 10 years ago. In every odd column, the unit of observation is a region aggregated over all districts, whereas in every even column region aggregate excludes districts with any recorded mining activity. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

coefficients indicating positive but limited spill-overs to non-mining districts of the same region. Overall, analyzing regions confirms the results from the SDM model: Regions benefit from mineral production and discoveries, mostly at the extensive margin, but the effects are largely limited to within the districts in which in the mineral deposits are located.

6. Robustness

We subject our results to a battery of robustness checks. Tables A1-A3 report placebo test, mining and capital city linkages, and the effect of mine closure. Further robustness results are shown in Online Appendix Tables A4-A10 for Table 2 and Tables A11–A16 for Table 5.

First, our ‘intensive margin’ results may be sensitive to how we treat missing values in mineral production data (see data appendix for details). To check robustness we drop district-year observations from the estimation of Table 2 if production quantity of a single commodity produced by a (single) mine in the district is missing. Coefficients increase, but our results remain qualitatively unchanged.[22]

Second, recent studies raised concerns regarding night-lights data. Min (2008) and Cogneau and Dupraz (2014) argue that in sparsely populated areas light intensity is dominated by noise. Min (2008) points to a minimum population threshold above which one can reliably assume that the lack of visible night-lights indicate lack of electrification and outdoor lights. We follow Min (2008) and exclude sparsely populated districts with less than 4 people per square kilometer from the sample. Furthermore, we follow Cogneau and Dupraz (2014) and drop zero luminosity districts from the sample. Key estimates reported in Tables 2 and 5 remain unchanged.

Third, by using districts as the unit of observation we assign each district the same weight which might lead to over representation of districts with greater population density. The concern became self-evident when contrasting Mali with Burkina Faso. While the two countries have roughly the same population size, the number of districts is 46 and 301 respectively. One may argue that more consideration should be given to population size at the district level. We therefore weight districts by their population size. We also weight districts by the inverse of the total number of districts in that country, thereby assigning equal weights to countries. Again, we re-estimate Tables 2 and 5 and the results in fact become stronger.

Fourth, we address concerns that second level sub-national administrative boundaries may be endogenous by construction. Administrative boundary demarcations in a country are typically determined by geographic, demographic, and political characteristics of the area, which could be determinants of local economic development. To mitigate this concern, we use $0.5 \times 0.5°$ grid cells as units of observation (i.e. around 55×55 km at the equator). Several recent studies have implemented similar grid-cell level approach (see for example Dell et al. (2012); Alesina et al. (2016); Michalopoulos and Papaioannou (2013)). Our results in Tables 2 and 5 remain unaffected by this change in the unit of analysis.

Finally, the variation in the data could be driven by region level unobservables. Therefore, we control for region and year fixed effects in the regression instead of district and year fixed effects. Again our results in Tables 2 and 5 remain unaffected.

7. Concluding remarks

The paper investigates how mining affects living standards in Sub-Saharan Africa. In doing so it explores some nuanced question. Are the development effects of a new mine (extensive margin) any different from a pre-existing mine (intensive margin)? To what extent can we observe spillovers from mining? The study finds positive effects of mining at the intensive margin, however large effects are associated with

[22] On the one hand, the increase in coefficients may be attributed to measurement error and attenuation bias that we introduce by interpolating production data. On the other hand, relying on exceptionally well-documented cases may introduce selection bias. After all, detailed reporting may be associated with good management of a company or governing of a country.

mining at the extensive margin. The enclave nature of mining is demonstrated by our data as we hardly observe any spillover of the positive effects beyond the host district.

Regression analysis using data from the DHS and Afrobarometer show that the effects on nightlights are indeed economically significant even though not uniform across all indicators. Therefore we can conclude that the changes in luminosity density due to mining is indeed reflective of some changes in living standard.

Our findings imply that resource depletion in sub-Saharan African countries offer a temporary opportunity to improve local living standards. However, the absence of significant positive spillovers represent additional challenges for the durability of these effects. Nevertheless, this is perhaps a generational opportunity for economic transformation not to be missed by sub-Saharan Africa.

Appendices

A1. List of countries in the sample

Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Democratic Republic of Congo, Cote d'Ivoire, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Namibia, Niger, Nigeria, Republic of Congo, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Sudan, Swaziland, Tanzania, Togo, Uganda, Zambia, Zimbabwe.

A2. Data appendix

Administrative units of Sub-Saharan Africa

We use districts as the main units of observation. Districts are second level sub-national administrative units. We obtained the political boundaries from a shapefile entitled "Sub-National Administrative and Political Boundaries of Africa (2000)" deposited at FAO GeoNetwork (FAO GeoNetwork, 2013). The 3,635 districts belong to 521 regions and 42 Sub-Saharan African countries. The average area of a district is 6,585 square kilometers.

Mineral production, mineral discovery and mining status

The value of mineral production is calculated as production quantity in metric tons (t) multiplied by the international price (1992$/t) summed over 21 mineral commodities (diamond, iron, gold, silver, copper, nickel, aluminum, cobalt, zinc, lead, manganese, bauxite, tantalum, zircon, tin, chromite, antimony, platinum-group metals (PGE), vanadium, vermiculite and graphite). The prices of mineral commodities are sourced from Minerals UK (British Geological Survey, 2014). The production data for 548 industrial size mines are from IntierraRMG, now known as SNL (IntierraRMG, 2014). Mines are matched to the district using their location coordinates from IntierraRMG. Information for every mine, commodity (particularly for secondary minerals) and year is sometimes lacking. We dealt with missing production data as follows. We replaced missing values by linearly interpolating production quantities at the district-commodity level. Any negative values were set to zero and we entirely dropped commodities if only observed in a single year. This results in a balanced panel of district production data for the period 1992–2012. We complemented IntierraRMG's information on production start-up year with our own efforts consulting sources such as the website of the respective company. From IntierraRMG we also extracted information on the status of mining (grassroots, exploration, advanced exploration, pre-feasibility, feasibility, and construction). The first three stages of mining investment are predominantly exploratory whereas the last three stages determine commercial viability of a project. The data on discoveries of major or giant mineral deposits are from (MinEx Consulting, 2014). We have the date of discovery, location coordinates, and the date of production start-up for 263 mineral discoveries from 1950 to 2012. Finally, we make use of some macro data commonly used in the literature. Data on mineral exports value as a % of GDP and mineral rents as a % of GDP are drawn from the Bank (2015) and the Wealth of Nations Database (Hamilton and Clemens, 1999) respectively.

Night-time lights

The data on night-time lights 1992–2012 come from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) and are provided by National Oceanic and Atmospheric Administration (2013) at a high resolution of 30-s grids (equivalent to 1 square kilometer). Satellites captured images of the earth between 20:30 to 22:00 local time. The night-time lights data is the cleaned luminosity after the cloud coverage, other ephemeral lights, and background noise is excluded. The measure comes on a scale from 0 to 63 (digital number) where higher values imply higher night-time light intensities.

Population statistics

District population was constructed from the Gridded Population of the World, Version 3 (GPWv3) produced by the Centre for International Earth Science Information Network (CIESIN, 2005). GPWv3 provides population counts at 2.5 arc-minute resolution for 1990, 1995, and 2000 and population projections for 2005, 2010, and 2015. We obtained the district population for the years {1990, 1995, …, 2015} by areal weighting and imputed values for single years 1992–2012 by linear interpolation.

Public infrastructure

Shapefiles of the road network and electricity grids in 2000 come from the African Development Bank (2013), and the railway shapefiles are from DIVA-GIS (Hijmans et al., 2012). Using GIS we calculated the total length (km) of paved roads, railways and electric grid in each district, expressing it then as densities: i) road density (i.e. paved road length per square kilometer), ii) railway density (i.e. railway length per square kilometer) and iii) electric grid density (i.e. electric transmission cable length per square kilometer).

Altitude, ruggedness, fertility, coastal proximity and land area

Topographical data of the NASA Shuttle Radar Topographic Mission (SRTM) 90 m Digital Elevation Database was retrieved from the Consortium for Spatial Information (CGIAR-CSI) of the Consultative Group for International Agricultural Research (CGIAR) (Jarvis et al., 2014). We calculated the altitude as the mean elevation above sea level of a district (in 100s of meters). Ruggedness measures a district's average standard deviation of elevation (in 100s of meters). Using data from FAO/UNESCO Digital Soil Map of the World (FAO, 2014), we constructed soil fertility as the percentage of a district's land surface area with good fertile soil for agricultural crops. Using GIS we calculated the shortest distance from a district's centroids to the coast (in kilometers). We measure the area of the district as the land surface area (in square kilometers) using the shapefile of administrative boundaries.

Rainfall, tropical climate, arid climate and temperate climate

Average annual rainfall (in mm) in each district for the period 1992–2012 is constructed using rainfall data from the TAMSAT Research Group (TAMSAT, 2014). TAMSAT rainfall estimations are locally calibrated using historic rain gage records (ground-based observations) in real-time to provide an internally consistent rainfall dataset. Using data from Kottek et al. (2006) we calculated the percentage of the district's land surface area that are classified as tropical climate, arid climate and temperate climate.

Political economy

Using GIS we created a capital dummy variable equal to one if a district contains the capital city, or if the district itself is the capital city. We also use GIS to calculate the distance between a district's centroid and the capital city (in kilometers). Furthermore, we measure ethnic fractionalization as one minus the Herfindahl-Hirschman index of the area shares that ethnic groups occupy according to Murdock (1959):

$$FRACT_d = 1 - \sum_{i=1}^{N} s_{id}^2 \tag{4}$$

where s_{id} is the share of land of ethnic group i in district d. Analogous to the ethnolinguistic fractionalization measure ELF it indicates the probability that two randomly selected geographic units (e.g. grids of the same size) belong to the same ethnic group. If population densities are the same across ethnic groups, it is equivalent to ELF (the probability that two randomly selected individuals belong to the same ethnic group).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jdeveco.2019.02.001.

References

African Development Bank, 2013. Africa Development Bank: AICD - Road Netwrok in 2000. http://www.infrastructureafrica.org.

Alesina, Alberto, Arnaud, Devleeschauwer, Easterly, William, Kurlat, Sergio, Wacziarg, Romain, 2003. Fractionalization. J. Econ. Growth 8, 155–194.

Alesina, Alberto, Michalopoulos, Stelios, Elias, Papaioannou, 2016. Ethnic inequality. J. Polit. Econ. 124, 428–488.

Alexeev, Michael, Conrad, Robert, 2009. The elusive curse of oil. Rev. Econ. Stat. 91, 586–598.

Allcott, Hunt, Keniston, Daniel, 2014. Dutch disease or agglomeration? The local economic effects of natural resource booms in modern America. Rev. Econ. Stud. 20508.

Aragón, Fernando M., Rud, Juan Pablo, 2013. Natural resources and local communities: evidence from a Peruvian gold mine. Am. Econ. J. Econ. Pol. 5, 1–25.

Arezki, Rabah, Ramey, Valerie A., Sheng, Liugang, 2017. News shocks in open economies: evidence from giant oil discoveries. Q. J. Econ. 132, 103–155.

Auty, Richard, 2001. The political economy of resource-driven growth. Eur. Econ. Rev. 45, 839–846.

Banerjee, Sudeshna Ghosh, Romo, Zayra, McMahon, Gary, Toledano, Perrine, Robinson, Peter, Arroyo, Inés Pérez, 2015. The Power of the Mine: A Transformative Opportunity for Sub-saharan Africa. Technical report. The World Bank Group, Washington DC.

Bank, World, 2015. World Development Indicators. World Bank, Washington, D.C.

Belotti, Federico, Hughes, Gordon, Mortari, Andrea Piano, 2013. XSMLE: Stata Module for Spatial Panel Data Models Estimation. Statistical Software Components S457610.

Besley, Timothy, 2007. Principled Agents? the Political Economy of Good Government. Princeton University Press, Princeton NJ.

Bhattacharyya, Sambit, Collier, Paul, 2014. Public capital in resource rich economies: is there a curse? Oxf. Econ. Pap. 66, 1–24.

Bhattacharyya, Sambit, Conradie, Louis, Arezki, Rabah, 2017. Resource discovery and the politics of fiscal decentralization. J. Comp. Econ. 45, 366–382.

Bhattacharyya, Sambit, Hodler, Roland, 2010. Natural resources, democracy and corruption. Eur. Econ. Rev. 54, 608–621.

Bhattacharyya, Sambit, Hodler, Roland, 2014. Do natural resource revenues hinder financial development? The role of political institutions. World Dev. 57, 101–113.

Bigsten, Arne, Söderbom, Måns, 2006. What have we learned from a decade of manufacturing enterprise surveys in Africa? World Bank Res. Obs. 21, 241–265.

British Geological Survey, 2014. British Geological Survey: African Mineral Production. https://www.bgs.ac.uk/mineralsuk/.

Caselli, Francesco, Michaels, Guy, 2013. Do oil windfalls improve living standards? Evidence from Brazil. Am. Econ. J. Appl. Econ. 5, 208–238.

CIESIN, 2005. Center for International Earth Science Information Network - CIESIN - Columbia University, United Nations Food and Agriculture Programme - FAO, and Centro Internacional de Agricultura Tropical - CIAT (2005) - Gridded Population of the World, Version 3 (GPWv3): Population Count Grid. https://doi.org/10.7927/H4639MPP.

Cogneau, Denis, Dupraz, Yannick, 2014. Questionable Inference on the Power of Pre-colonial Institutions in Africa. Paris School of Economics Working Paper, p. 25.

Collier, Paul, 2000. Ethnicity, politics and economic performance. Econ. Pol. 12, 225–245.

Collier, Paul, Hoeffler, Anke, 2009. Testing the neocon agenda: democracy in resource-rich societies. Eur. Econ. Rev. 53, 293–308.

Corden, W. Max, Peter Neary, J., 1982. Booming sector and de-industrialisation in a small open economy. Econ. J. 92, 825–848.

Cotet, Anca, Tsui, Kevin, 2013. Oil and conflict: what does the cross country evidence really show? Am. Econ. J. Macroecon. 5, 49–80.

Cust, James, Harding, Torfinn, 2014. Institutions and the Location of Oil Exploration. OxCarre Research Paper, p. 127.

Deaton, Angus, 1999. Commodity prices and growth in Africa. J. Econ. Perspect. 13, 23–40.

Dell, Melissa, Jones, Benjamin F., Olken, Benjamin A., 2012. Temperature shocks and economic growth: evidence from the last half century. Am. Econ. J. Macroecon. 4, 66–95.

Elhorst, J. Paul, 2010. Applied spatial econometrics: raising the bar. Spatial Econ. Anal. 5, 9–28.

FAO, 2014. FAO/UNESCO Soil Map of the World. http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/faounesco-soil-map-of-the-world/en/.

FAO GeoNetwork, 2013. Sub-National Administrative and Political Boundaries of Africa (2000). www.fao.org/geonetwork/.

Gylfason, Thorvaldur, 2001. Natural resources, education and economic development. Eur. Econ. Rev. 45, 847–859.

Hamilton, Kirk, Clemens, Michael, 1999. Genuine savings rates in developing countries. World Bank Econ. Rev. 13, 333–356.

Henderson, Vernon, Adam, Storeygard, Weil, David N., 2012. Measuring economic growth from outer space. Am. Econ. Rev. 102, 994–1028.

Hijmans, Robert J., Guarino, Luigi, Mathur, Prem, 2012. DIVA-GIS. http://www.diva-gis.org/documentation.

Hodler, Roland, 2006. The curse of natural resources in fractionalized countries. Eur. Econ. Rev. 50, 1367–1386.

Hodler, Roland, Raschky, Paul A., 2014. Regional favoritism. Q. J. Econ. 129, 995–1033.

Imbens, Guido W., Wooldridge, Jeffrey, 2009. Recent developments in the econometrics of Program evaluation. J. Econ. Lit. 47, 5–86.

IntierraRMG, 2014. SNL Metal and Mining. http://www.snl.com/Sectors/metalsmining/Default.aspx.

Isham, Jonathan, Woolcock, Michael, Pritchett, Lant, Busby, Gwen, 2005. The varieties of resource experience: natural resource export structures and the political economy of economic growth. World Bank Econ. Rev. 19, 141–174.

Jarvis, Andy, Isaak Reuter, Hannes, Nelson, Andy, Guevara, E., 2014. Hole-filled NASA Shuttle Radar Topographic Mission (SRTM) for the Globe Version 4, Available from the CGIAR-CSI SRTM 90m Database. http://srtm.csi.cgiar.org.

Jedwab, Remi, Kerby, Edward, Moradi, Alexander, 2017. History, path dependence and development: evidence from colonial railroads, settlers and cities in Kenya. Econ. J. 127, 1467–1494.

Jedwab, Remi, Moradi, Alexander, 2016. The permanent effects of transportation revolutions in poor countries: evidence from Africa. Rev. Econ. Stat. 98, 268–284.

Kotsadam, Andreas, Tolonen, Anja, 2016. African mining, gender, and local employment. World Dev. 83, 325–339.

Kottek, Markus, Grieser, Jurgen, Beck, Christoph, Rudolf, Bruno, Rubel, Franz, 2006. World Map of the Köppen-Geiger climate classification updated. Meteorol. Z. 15, 259–263.

Lei, Yu-Hsiang, Michaels, Guy, 2014. Do giant oilfield discoveries fuel armed conflicts? J. Dev. Econ. 110, 139–157.

LeSage, James, Kelley Pace, Robert, 2009. Introduction to Spatial Econometrics. CRC Press, Boca, Raton.

LeSage, James P., Kelley Pace, R., 2014. The biggest myth in spatial econometrics. Econometrics 2, 217–249.

Lippert, Alexander, 2014. Spill-Overs of a Resource Boom: Evidence from Zambian Copper Mines. OxCarre Research Paper, p. 131.

McMillan, Margaret, Rodrik, Dani, Verduzco-Gallo, Íñigo, 2014. Globalization, structural change, and productivity growth, with an update on Africa. World Dev. 63, 11–32.

Mehlum, Halvor, Karl, Moene, Torvik, Ragnar, 2006. Institutions and the resource curse. Econ. J. 116, 1–20.

Michalopoulos, Stelios, Papaioannou, Elias, 2013. Pre-colonial ethnic institutions and contemporary african development. Econometrica 81, 113–152.

Michalopoulos, Stelios, Papaioannou, Elias, 2014. National institutions and subnational development in Africa. Q. J. Econ. 129, 151–213.

Min, Brian, 2008. Democracy and Light: Electoral Accountability and the Provision of Public Goods. UCLA Working paper, mimeo).

MinEx Consulting, 2014. MinEx Consulting - FERDI Study Major Discoveries since 1950.

Murdock, Rupert Peter, 1959. Africa: its Peoples and Their Culture History. McGraw-Hill Book Company, New York.

Murphy, Kevin M., Shleifer, Andrei, Vishny, Robert W., 1989. Industrialization and the big push. J. Polit. Econ. 97, 1003–1026.

National Oceanic, Atmospheric Administration, 2013. Global DMSP-OLS Nighttime Lights Time Series 1992 - 2012 (Version 4). http://ngdc.noaa.gov/eog/.

Ramey, Garey, Ramey, Valerie A., 1995. Cross-country evidence on the link between volatility and growth. Am. Econ. Rev. 85, 1138–1151.

Robinson, James, Torvik, Ragnar, Verdier, Thierry, 2006. Political foundations of the resource curse. J. Dev. Econ. 79, 447–468.

Rosenstein-Rodan, P.N., 1943. Problems of industrialisation of eastern and south-eastern europe. Econ. J. 53, 202–211.

Sachs, Jeffrey, Warner, Andrew, 2001. The curse of natural resources. Eur. Econ. Rev. 45, 827–838.

Sachs, Jeffrey, Warner, Andrew, 2005. Leading Issues in Economic Development, Chapter Natural Resource Abundance and Economic Growth. Oxford University Press, Inc., New York.

Singer, H.W., 1950. The distribution of gains between investing and borrowing countries. Am. Econ. Rev. 40, 473–485.

TAMSAT, 2014. Daily Rainfall Estimates - TAMSAT African Rainfall Climatology and Time-Series (TARCAT v2.0). http://www.met.reading.ac.uk/tamsat/data/rfe_anom.html.

Tornell, Aaron, Lane, Philip, 1999. The voracity effect. Am. Econ. Rev. 89, 22–46.

Torvik, Ragnar, 2002. Natural resources, rent seeking and welfare. J. Dev. Econ. 67, 455–470.

Tsui, Kevin K., 2011. More oil, less democracy: evidence from worldwide crude oil discoveries*. Econ. J. 121, 89–115.

van der Ploeg, Frederick, 2011. Natural resources: curse or blessing? J. Econ. Lit. 49, 366–420.

Venables, Anthony, 2016. Using natural resources for development: why has it proven so difficult? J. Econ. Perspect. 30, 161–184.

WorldBank, 2017. Mining in Africa: Are Local Communities Better off? World Bank, Washington, DC.