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Intensive and Extensive Margins of Mining and Development: Evidence from Sub-Saharan Africa*

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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.

Night-lights increase in mining districts when mineral production expands (intensive margin), but large effects approximately equivalent to 16% increase in GDP 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 giant and major mineral discoveries as exogenous news shocks. In spite of the within district large effects, there is little evidence of significant spillovers to other districts reinforcing the enclave nature of mines in Africa.

Furthermore, the local effects disappear after mining activities come to an end which is consistent with the 'resource curse' view.

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Key words: mineral discovery; mineral production; night-time lights

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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 in cross-national data.[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 volatilty 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). While significant intellectual energy went into documenting the adverse consequences of natural resources in developing countries, establishing causality has remained somewhat elusive in this largely cross-country literature.[3]

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

[1] See van der Ploeg (2011) for a survey of this literature.

[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 in Africa (Bigsten and Söderbom, 2006).

[3] Acknowledging the adverse consequences of natural resources, a large body of literature engage with the question of harnessing natural wealth for economic development. See Venables (2016) for a survey.

been actively discussed by many scholars, thorough empirical analyses of the extent of spillovers are non-existent. 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. This is combined with mine level geo-referenced data on discovery and production.

According to the existing literature resource wealth adversely affects development. Ill-managed oil wealth in Nigeria and mineral wealth in the Democratic Republic of Congo are prime examples that attract attention and shape public perception. This narrative ignores nuances which we are able to explore using our district level geocoded dataset. For example, Figure 1 panels 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, the mean pixel value of night-time lights in Zabre is 0.00577. But in 2008 the mean pixel value increased by 19 percent to 0.03056. The following year 2009, Zabre again experienced an increase in night-time lights. 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. Again 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. In particular, night-lights expand by 55 percent on average due to mining expansion at the extensive margin as opposed to 2-4 percent at the intensive margin. 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.

Mining of exhaustible resources is often viewed as transitory. Therefore, an important task in a scientific endeavor such as ours is to ascertain what happens in mining districts after mine closure. We find that night-time lights after mine closure decline precipitously undoing most of the gains. This further reinforces the view that mining is transitory which is consistent with the 'resource curse' result in the macro literature.

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).[4] Furthermore, using GIS we are able to exclude all lights around 2 kilometer radius of a mine from our sample and our results remain qualitatively 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 select more prosperous districts for mining rather than mining driving development. 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

[4]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 1870s onwards 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.

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 subnational 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.

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 fractionalisation (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 Africa and the causal interpretation of intensive and extensive margin of mining.[5] 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 night-time lights. Note that the satellite data on night-time lights have been used by others recently as a credible measure of economic development at the local and regional levels (Henderson et al., 2012).

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

[5]More recent cross-country studies relating mainly oil and conflict 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. 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.

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). The former study the effect of natural resources on female employment in Africa and whereas the latter study the local effect of mining in Zambia. In contrast, we study the entire continent of sub-Saharan 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 satellite data on night-time lights and city growth to measure development at the regional and subnational levels. Michalopoulos and Papaioannou (2013, 2014) and Hodler and Raschky (2014) are examples of studies that use night-time lights. The factors identified as key determinants of African sub-national development by this literature are pre-colonial ethnic institutions (Michalopoulos and Papaioannou, 2013, 2014), birth region of leaders (Hodler and Raschky, 2014), and colonial railroads (Jedwab et al., 2016; 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 discusses general equilibrium and spillover effects of production and discovery. Section 5 investigates the effect of mine closure. 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.[6] Districts are the main units of observation in our study. They correspond to the second level subnational administrative classification of sub-Saharan Africa in 2000 obtained from (FAO GeoNetwork, 2013) (see Figure 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 night-time lights ("luminosity") provided by National Oceanic and Atmospheric Administration (2013). The

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

data is cleaned luminosity, after filtering for cloud coverage, other ephemeral lights, and background noise. The measure comes on a scale of 0 to 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. Figures 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.

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.[7]

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 90m 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 Meteorology using Satellite data (TAMSAT), and the district's land area classifed 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 and ethnic fractionalization constructed from the Ethnographic Atlas by Murdock (1959). 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.

With the exception of rainfall and population, our control variables are time-invariant at the district level. Table 1 reports summary statistics on all variables used in the study. A detailed discussion of data and sources can be found in Appendix A2.

[7] Despite the consistency and spatially explicit population distribution of the world the gridded 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.

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.

We distinguish between value and quantity by expressing mineral production in 1992 constant US Dollars and 1992 constant commodity prices respectively. We expect quantity to be more important. 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.

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 2 shows effects at the intensive margin. Column 1 points to a positive association between mineral production values and night-lights. The association, however, is stronger when using production volumes instead (column 2), and in a horse race it is the latter that wins (column 3). 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. This is approximately more than 13 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.[8]

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 which we utilize here. They are grassroots, exploration, advanced exploration, pre-feasibility,

[8]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.

feasibility, and construction. 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 3 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 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 define two control groups. Firstly, we take districts that never had any mining activity as of 2012 (control 1). While we would not expect this to be a valid control group, the comparison is interesting in its own right. Secondly, we take districts, where the potential was examined in a feasibility study as of 2012, but where no mining has taken place yet (control 2). Feasibility studies are the final stage before construction.[9] 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 3, Panel A, column 1 presents the mean values for each observable characteristic and columns 2 and 3 present the normalized mean difference between treatment and the two control groups.[10] All observables are time-invariant or referring to the year 2000. Column 2 indicates that treated districts are

[9]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.

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

at a relatively higher altitude and are more rugged than never mined districts. They also have a larger land surface area, less rainfall, a more temperate climate, an ethnically more fractionalized population, and a higher railway density. In contrast, Column 3 suggests that the treated districts are fairly similar to feasible districts save their higher electric grid density. We rate the latter as a better underlying characteristic, which would bias estimate upwards.

In Table 3, 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. Figure 5, showing the development in night-lights of treated and control groups on an annual basis, confirms this result. While level differences are apparent, pre-treatment trends run parallel up to the point when districts start to begin mineral production (in 2002) at which then they start to outgrow their counterparts. Figure 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 accelarate 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.

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

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

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% (Figure 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:

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

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 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 $MD_{dt-j} = 1$ for *first discoveries* is the cleanest treatment group. In fact, the coefficient $\tilde{\gamma}_0$ 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 $\tilde{\gamma}_j$ measure the difference in night-lights j years after a discovery.

Table 4 displays the results. In Column 1, the coefficients reflect the change in night-

[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.

lights j ={0, 1, ..., 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 $\tilde{\gamma}_0$ 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 3). 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 (Figure 7). We test this idea using the same specification as in equation 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 nightlights corresponds to 54 percentage points for giant deposits compared to a 37 percentage points for major deposits. These are indeed large effects.

Finally, we follow a placebo strategy and test whether there are any effects for the pre-discovery period, in other words, whether the discovery districts follow the same trend as the virgin districts. We use model 2 replacing $\sum_{j=0}^{10} \tilde{\gamma}_j MD_{dt-j}$ with $\sum_{j=-10}^{-1} \tilde{\gamma}_j MD_{dt-j}$.

[13] Using the same model as in equation (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.

Because we do not have information on night-lights 1982-1992 we study only districts with mineral discoveries 2002-2012. This ensures that we have a full pre-discovery window of 10 years following the same 34 districts through to discovery.[15] Web Appendix Table A2 reports the placebo test. There is no trend in the pre-discovery coefficients, they are small and jointly insignificant (p-val: 0.23). As an alternative, we constructed a symmetric 5-year pre- and post-discovery window using $\sum_{j=-5}^{5} \tilde{\gamma}_j MD_{dt-j}$ and the 42 districts with discoveries 1997-2007. Neither the pre- nor post-discovery coefficients are significant (p-val: 0.37) which is in line with results in Table 4.

4 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 even in developing countries, forward and backward linkages are limited. This notwithstanding, existing studies of local development point to certain spill-overs. 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: 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 a 2 kilometer radius of a mine and mineral disocvery. Then, we re-estimate the regression models in Tables 2 and 4.[17]

[15] If we used the full data with discoveries 1992-2012, we would observe a smaller pre-discovery window for districts with discoveries in 1992-2001. By construction, this introduces an artificial correlation between MD_{dt-j} and $\tilde{\eta}_t$. Note that the number of discoveries averages 3 per year and does not follow a trend even though the years 1996, 1997, 2005 and 2006 had an unusually large number of 6 discoveries.

[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 Figure 2).

[17] The choice of 2 kilometer is somewhat arbitrary. Note, however, 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 error,

Results, shown in Web Appendix Table A3 and A4, remain qualitatively unchanged with the size of coefficients decreasing only marginally. We therefore conclude that effects are not driven by.

We continue our investigation with modeling spatial spillover effects using techniques from spatial econometrics. In particular, we estimate a Spatial Durbin Model (SDM):

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

where our standard model with measures of mining activities MA, controls X, district and year fixed effects is augmented with a spatially lagged dependent variable WLD and spatially lagged explanatory variables WX and WMA. W denotes the spatial weights matrix that defines the potential for interaction between each pair of districts. We define neighbors as districts that share a common border (0/1 weights).[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 δ=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.

Among the class of models in spatial econometrics LeSage and Pace (2009) proposed

which is difficult to solve.

[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.

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 6 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 6 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.

[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 favor of the Spatial Autoregressive Model and/or the Spatial Error Model. We calculated Moran's I for the residuals in estimations in Table 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).

An alternative way to explore general equilibrium effects is to redefine the unit of interest, ideally so that any spill-over effects are confined to within those redefined units. As Imbens and Wooldridge (2009) wrote "aggregation is likely to make the no-interaction assumption more plausible, albeit at the expense of reduced precision." 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 kilometres (the median size is 17,878 square kilometres). Besides, when using regions the average Euclidian distance from an active mine to any point on the respective administrative border increases from 62 km (sd: 57) to 206 km (sd: 105) respectively.[21] Thus, unsuprisingly, using regions as unit of observation mines are more centrally located and spill-overs to neigbouring regions should be indeed less of a concern.

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 at district level. Second, we test how night-lights in non-mining districts respond to mining activities within the same region. For this, we exclude mining districts when aggregating. In other words, regions only consist of districts that never had any recorded mining activity. The effect will be smaller than in the first step, because we exclude the mining districts for which we so far found positive effects. Then, a positive/negative coefficient would point to positive/negative spill-overs within region. We also distinguish between intensive and extensive margins, because our results so far indicated that large effects are mainly associated with the latter.

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 at district level. Second, we aggregate non-mining districts to regions but exclude the mining districts from the aggregation (except for calculating the aggregate mining activity MA in the region). Re-estimating specification (1), we regress mining activities in a region on outcomes of non-mining districts within that region. The effect will necessarily be smaller than in the first step, because we exclude the mining districts for which we found positive effects so far. Then, a positive/negative coefficient would point to positive/negative spill-overs to non-mining districts within the mining regions. We now distinguish between intensive and extensive margin as we did in Table 2.

[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 7 shows 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 coefficients indicating positive but limited spill-overs to non-mining districts of the same region. Overall, analysing 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.

Spatial regression techniques and aggregation may be unable to model more complex, non-spatial patterns of spillovers. Gollin et al. (2016), for example, hypothesized that rents from minerals may be consumed in cities causing urbanization without industrialization. Note that with night-lights data we are unable to distinguish between consumption and investment. However, we could definitely examine the link between mining and night-lights in capital cities. We consider specification (1) and replace mineral production with an interaction term between a capital city dummy variable and mineral exports value (as well as an alternative mineral rents as a percentage).[22] If the estimated coefficient on this variable is positive and statistically significant then we can conclude that indeed the capital cities in mining countries are growing faster with mining windfalls. However, we find them to be statistically insignificant indicating very little non-spatial spillover. We obtain the same result when we study the two brightest lit cities as of 1992 instead of the capital city. These results are reported in Web Appendix Table A5.

[22] At this point, we avoid distinguishing between intensive and extensive margin. In 1992 all sub-Saharan African countries export some (even if tiny) quantity of mineral resources, hence we lack variation.

5 Mine Closure and Development

So far we found that mining triggers an increase in economic activity. However, a defining property of mineral resources is that they are exhaustible. The development trajectory of a mining district after mining comes to an end is therefore an important question. There are good reasons to expect hysteresis.[23] In our context this means that mining caused a new equilibrium, but removing mining will not restore the old equilibrium. The form is highly debated. On the one hand, mining could trigger economies of agglomeration via a large positive shock to infrastructure, migration flows and urbanization. It is possible that the remnants of agglomeration would remain after mine closure (Jedwab et al., 2016; Jedwab and Moradi, 2016; Aragón and Rud, 2016; Fafchamps et al., 2015). On the other hand, it is entirely possible that mining creates little if any economic activity beyond its lifetime, rather leaving behind environmental damage making the area worse off than before mining (Aragón and Rud, 2016).

We are able to shed light on the form of hysteresis. For this purpose we rely on the MinEx database, which reports production start and closure dates of the mines that worked the discoveries post-1950. In line with basic microeconomic theory we note that shutdowns can be temporary. Curiously, this distinction has not been made in the literature. According to MinEx, 28 mines of the 122 mines closed, 8 re-opened, mostly in the 2000s (when commodity prices increased).[24]

Our analysis is at district level and we focus on the extensive margin. We construct three variables that we add to specification (1). First, a dummy variable equal to 1, once a district had at least one producing mine. Second, a dummy variable equal to 1, if all mines in a district shut down. Third, a dummy variable equal to 1 if all mines in a district shut down and none reopens by 2012.

Identification comes from districts that change status during the 1992-2012 period. Unfortunately, the number of such districts is limited. Only 12 districts in the sample experienced an end to all mining activities in at least one year; in only 4 districts mining activities did not resume by 2012. Moreover, there may be endogeneity concerns. We therefore researched the backgrounds of the four districts more closely. Most of the closures seem to be driven by exogenous factors. Firstly, Poura district in Burkina Faso, 1999: "The mine closed due to low gold price" and the Burkinabe government is aiming

[23]Hysteresis is a property of ferromagnetic materials. After a material is magnetized and subsequently the magnetizing field is removed, the magnetized material will not revert back to its original state. It remembers its history which is known as hysteresis.

[24]There is a strong agreement between IntierraRMG and MinEx in the location of producing mines, see Figure 3 and 4. However, since MinEx does not go back before 1950, it reports less mines.

to bring production back (Africa Mining Intelligence, 2011). Secondly, Maféré district in Côte d'Ivoire, 1998 the mining company (SOMIAF) terminated its operation on the property. There was a feasibility study in 2013, which suggests that mining may recur (Taurus Gold Limited, 2012). Thirdly, Groblersdal, South Africa, 2011 where "at the existing low rand PGM (platinum group metals) prices and the rate of mine cost inflation in the country, the mine cannot operate economically." (MiningTechnology). Finally, Bonthe district in Sierre Leone 1995 stopped rutile production because the mine suffered damage and destruction when it was attacked by rebels during the civil war. The last case is indeed problematic.

Table 8 reports the results. In column (1), we note the large positive effect for districts that change status to mining. Night-lights increase by about 72 percentage points. Shutdowns have a large negative effect of 49 percentage points. In column (2) we distinguish between temporary shutdowns and what may be considered permanent in that mining activities have not resumed by 2012. Temporary shutdowns are associated with a decrease in night-lights of 22 percentage points, whereas districts that failed to recover mining by 2012 experienced an additional drop of 84 percentage points. In column (3), we exclude Bonthe district from the regression which indeed influences the estimates of the permanent effect. Interestingly, size of the effect of a permanent shutdowns is almost identical to the effect of a district entering mining. Hence, the results are suggestive that the activity created by the mine is largely lost once mining disappears.

6 Robustness

We subject our results to a battery of robustness checks. We focus on Table 2 and 4.

First, our 'intensive margin' results may be sensitive to how we treated 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.[25]

Second, recent studies raised concerns regarding night-lights data.[26] Min (2008) and Cogneau and Dupraz (2014) argue that in sparsely populated areas light intensity is dominated by noise. Min (2008) point to a minimum population threshold above which

[25] 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 managament of a company or governing of a country.

[26] Robustness results are shown in Web Appendix B1-B6 for Table 2 and B7-B11 for Table 4.

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 4 remain unchanged.

Third, by using districts as unit of observations we assign each district the same weight.[27] One may argue that more consideration should be given to population. Alternatively, one may argue that the same weight should be assigned to each country (as cross-country studies do). We therefore weight districts by their population size. We also weighted 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 4 and the results in fact become stronger.

Finally, we address concerns that second level subnational administrative boundaries may be endogenous by construction. Administrative boundary demarcations in a country are typically determined by geographic and demographic characteristics of the area, which could be determinants of local economic development. To mitigate this concern, we use 0.5 x 0.5 degree grid cells as units of observation (i.e. around 55 x 55 kilometers 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 4 remain unaffected by this change in the unit of analysis.

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 mining at the extensive margin. The effect of mining appears to be transitory as it typically disappears when mining comes to an end. This is consistent with the macro resource curse result. Furthermore, the enclave nature of mining is demonstrated by our data as we hardly observe any spillover of the positive effects of mining beyond the host district.

How big are the economic significance of these effects? A simple test would be to

[27] 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 (see Figure 2).

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 the Demographic and Health Survey (DHS) data at the subnational level and estimate the elasticity between luminosity and composite wealth index to be 0.7. Based on such estimates we could speculate that a switch from non-mining to mining would increase a district's GDP by 55 x 0.3=16.5 percent.

Our findings imply that resource depletion in sub-Saharan African countries offer a temporary opportunity to improve local living standards. Furthermore, the absence of significant positive spillovers represent additional challenges. These challenges could potentially be tackled in an environment of relatively high global commodity prices and new resource discoveries in Africa through pro-active policy on infrastructure improvement, market linkage promotion, and business friendly regulatory and institutional reforms. Such policies may potentially trigger agglomeration effects via new cities and new infrastructure especially at the extensive margin. This is an opportunity 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 the mine's 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-second 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) 90m 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 kilometer) 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 gauge 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 centroids and the capital city (in kilometers). Furthermore, we measure ethnic fractionalization calculating the Herfindahl-Hirschman index from the ethnic groups mapped by Murdock (1959).

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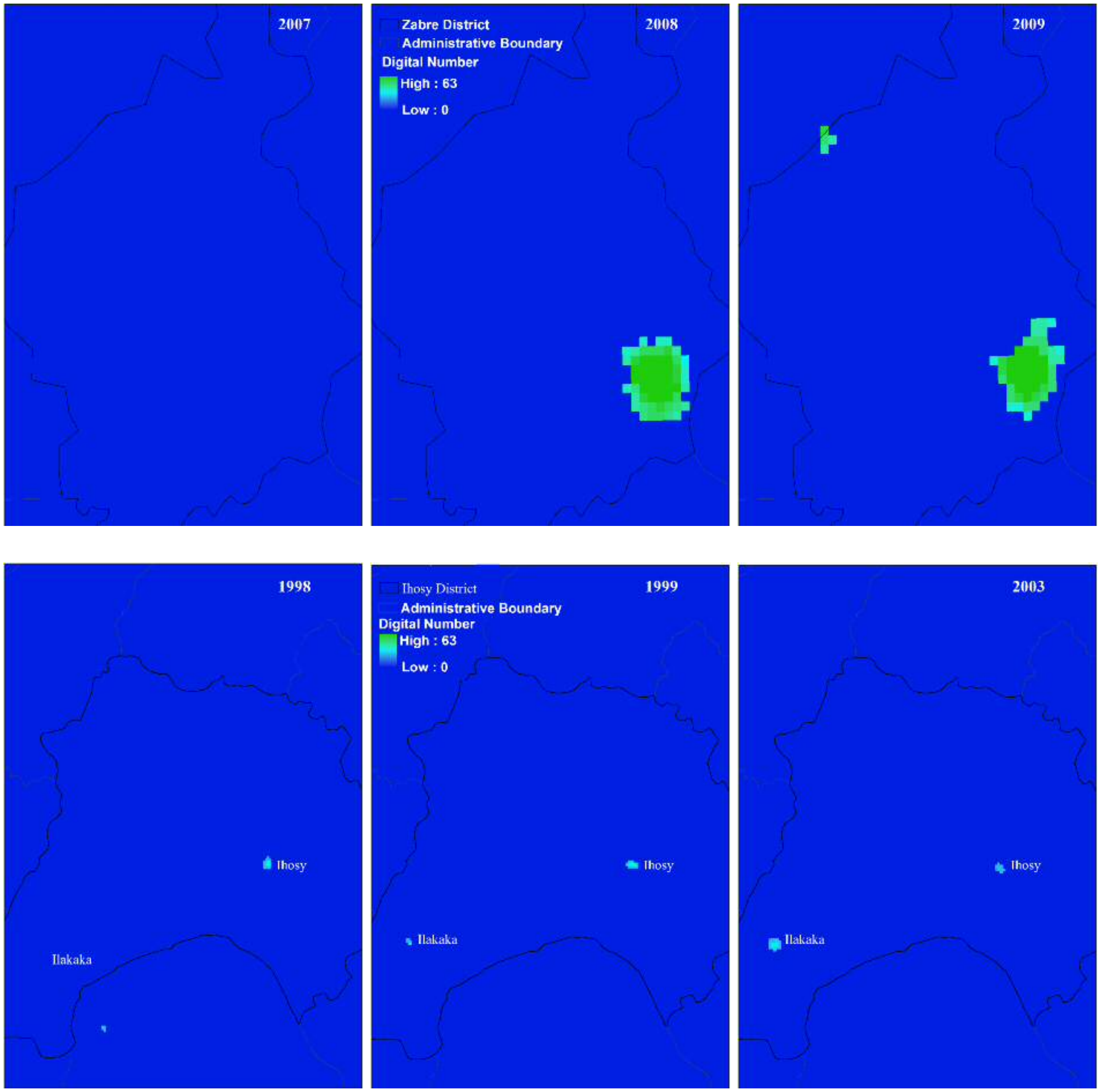
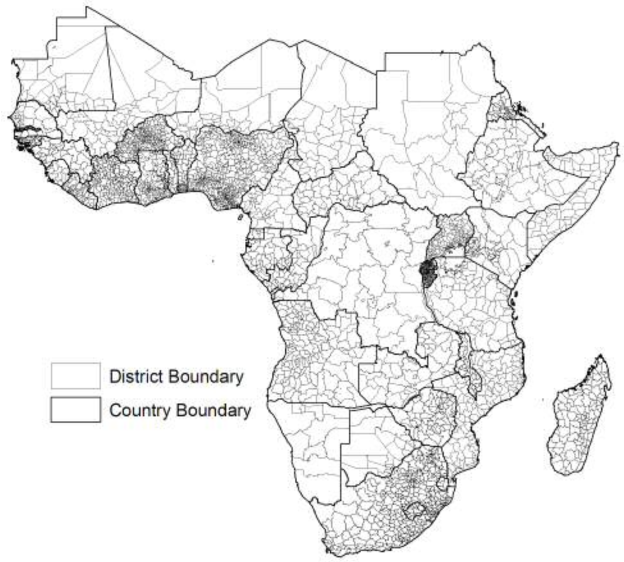
Figure 1: Mining Discovery, Mining Production and Nightlights



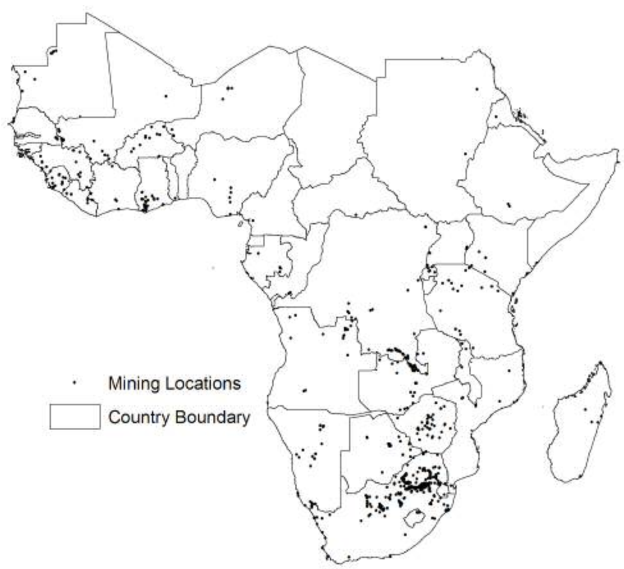
Notes: The upper panel shows Zabre District in Burkina Faso starting gold production in 2008. The lower panel shows Ihosy District in Madagascar. After the discovery of Sapphire deposits at Ilakaka - a village with about 40 households - in 1998, the place saw an influx of migrants and turned into a major 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).

Figure 2: District Level Boundary Map of Sub-Saharan Africa



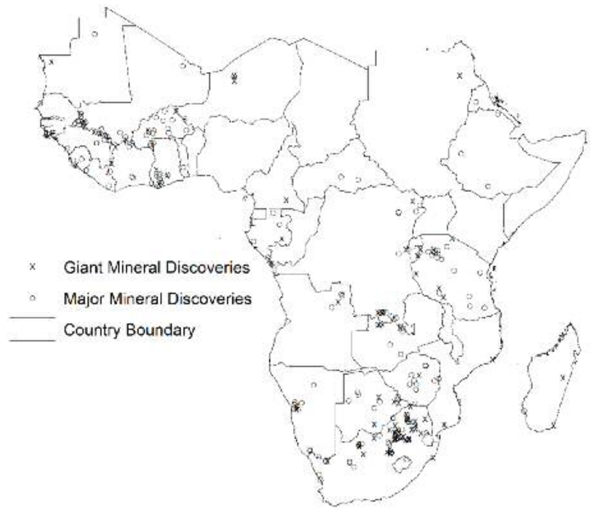
Notes: This map shows the second level administrative units ('districts') for the year 2000 that we use in our analysis. The boundaries in GIS were obtained from FAO GeoNetwork (2013). We exclude small island countries (Saint Helena, Seychelles, Sao Tome and Principe, Reunion, Mayotte, Mauritius, Cape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

Figure 3: Mining Industry Locations



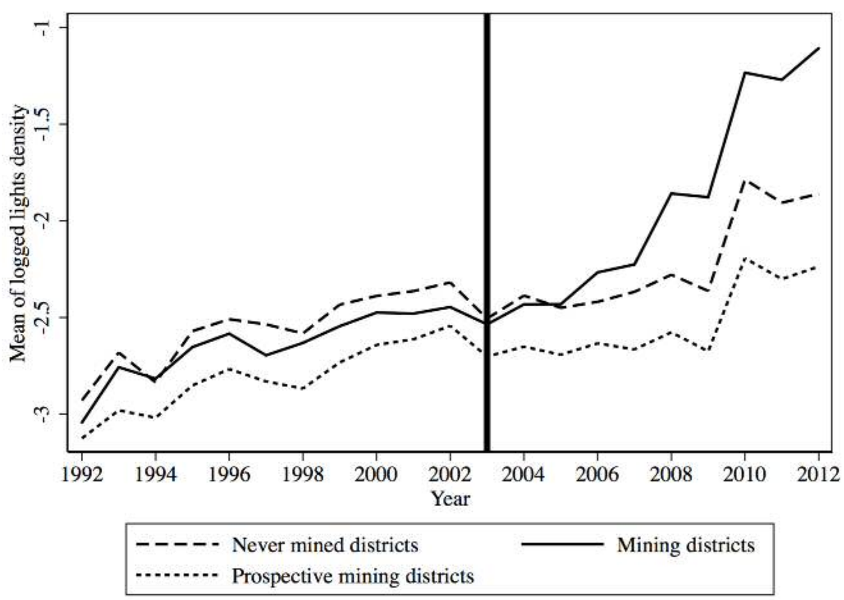
Notes: The map shows the location of active, industrial size mines in sub-Saharan Africa. These mines are owned or operated by either large multinationals or state owned companies. We exclude small-scale mines and informal or illegal mines. Data is from IntierraRMG.

Figure 4: Locations of Mineral Deposit Discoveries



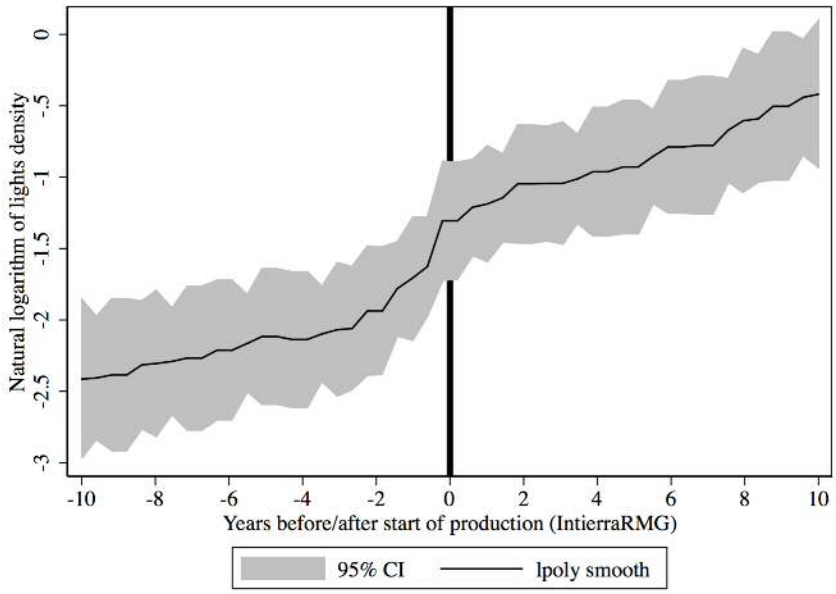
Notes: The map shows the location of giant and major mineral deposit discoveries in Sub-Saharan Africa over the period 1950-2012. Data from MinEx Consulting.

Figure 5: Trends in Lights Density before and after Mineral Production Treatment



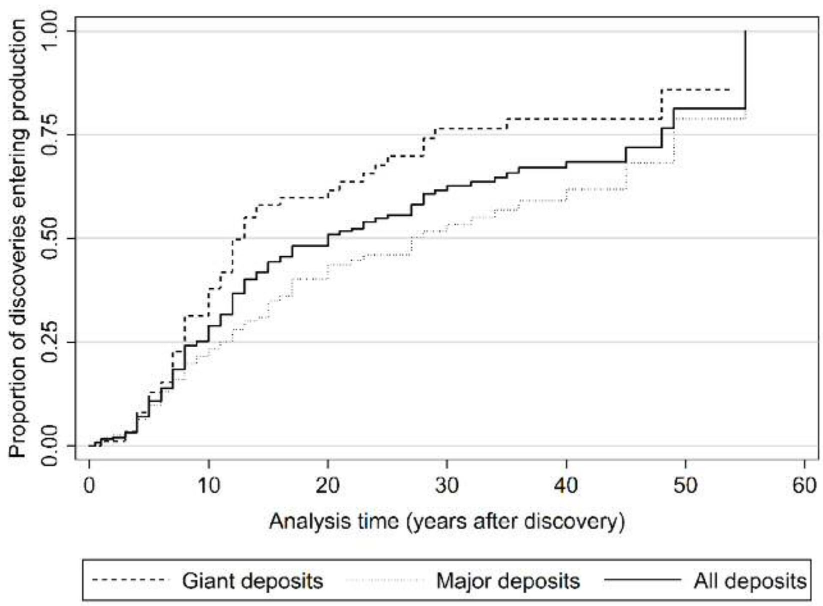
Notes: The graph shows the evolution of nightlights for three categories of districts: i) districts that started mineral production after 2002 (treatment), ii) districts that never had any mining activity (control group 1) and iii) districts that are yet to be mined but with substantial mineral deposits identified in feasibility studies (control group 2). Data is from IntierraRMG.

Figure 6: Effect of Mineral Production on Lights Density



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.

Figure 7: Kaplan-Meier Estimates of Mineral Discoveries Entering Production



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.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Main Variables					
Ln(0.01+Lights density per sq. km)	76335	-2.36	2.38	-4.61	4.51
Ln(Mineral production)	1802	16.86	3.47	-0.23	27.63
Ln(Min. prod. 1992 commodity prices)	1802	16.96	3.06	1.66	27.57
Mineral production (1=yes)	76335	0.04	0.20	0	1
Mineral discovery	76335	0.00	0.03	0	1
Mineral discovery (permanent switch)	76335	0.01	0.10	0	1
Controls: Population and Geography Variables					
Ln(Population density per sq. km)	76335	3.98	1.61	0.02	10.04
Ln(Altitude in m)	76335	5.88	1.38	0.62	7.91
Ln(Ruggedness)	76335	4.05	1.14	0	6.93
Share of district with fertile soil	76335	18.60	29.45	0	100
Ln(Distance to the coast in km)	76335	5.55	1.39	-4.23	7.45
Ln(Land surface area in sq. km)	76335	7.41	1.72	-0.73	12.79
Controls: Climate Variables					
Ln(Annual average rainfall in mm)	76335	5.12	0.76	0.13	6.38
Share of district with tropical climate	76335	60.19	47.12	0	100
Share of district with temperate climate	76335	14.32	32.64	0	100
Share of district with dry/arid climate	76335	25.28	42.14	0	100
Controls: Urbanization and Political Economy Variables					
Capital city (1=yes)	76335	0.01	0.11	0	1
Ln (Distance to the capital city in km)	76335	5.47	0.97	0.66	7.54
Ethnic Fractionalization	76335	0.21	0.24	0	0.93
Controls: Infrastructure Variables					
Ln(Paved road density per sq. km (2000))	76335	0.02	0.04	0	0.52
Ln(Railway density per sq. km (2000))	76335	1.01	1.72	0	6.79
Ln(Electric-grid density per sq. km (2000)	76335	0.07	0.17	0	2.25

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 $ln(1+x)$ if x could potentially be equal to 0.

Table 2: Associations between Mineral Production and Night-Lights at District Level

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.024*		-0.061	
	(0.014)		(0.047)	
Ln(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 Ln(0.01+Nighttime Lights Density per sq. km). Column (1) expresses the mineral production value in 1992 constant USD. Column 2 expresses the mineral production value in 1992 constant commodity prices. Column 3 includes both those 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.

Table 3: Where Do Mining Investments Go?

	Grassroots in 2012	Exploration in 2012	Adv. Expl. in 2012	Pre-Feasibility in 2012	Feasibility in 2012	Construction in 2012
	(1)	(2)	(3)	(4)	(5)	(6)
Number of districts at each stage	353	290	203	86	82	19
Ln(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)
Ln(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)
Ln(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)
Ln(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 4: Comparison of Treated and Control Districts (Mineral Production Treatment)

	Treated	Normalized Difference Treated-Control 1 Never mined	Treated-Control 2 Feasibility
	(1)	(2)	(3)
Number of Districts	53	3284	156
Panel A: Time-Invariant Cross-Sectional Variables			
Ln(Altitude in m)	6.18	0.14*	-0.00
Ln(Ruggedness)	4.31	0.14*	-0.04
Share of district with fertile soil	16.09	-0.04	-0.09
Ln(Distance to the Coast in km)	5.76	0.09	0.05
Ln(Land surface area in sq. km)	8.40	0.36***	-0.03
Ln(Average annual rainfall in mm)	4.73	-0.15**	0.03
Share of district with tropical climate	50.88	-0.11*	-0.09
Share of district with dry/arid climate	27.17	0.03	0.00
Share of district with temperate climate	21.94	0.12**	0.11
Capital city (1=yes)	0	-0.11	-0.08
Ln (Distance to the capital city in km)	5.56	0.05	-0.03
Ethnic Fractionalization	0.31	0.24***	0.02
Ln(Paved road density per sq. km in 2000)	0.02	-0.05	0.10
Ln(Railway density per sq. km in 2000)	1.66	0.21***	0.03
Ln(Electric-grid density per sq. km in 2000)	0.06	-0.05	0.16**
Panel B: Trend Comparison			
Ln (0.01+Nighttime Lights Density)			
Pre-treatment growth 1992-2002	0.60	-0.00	0.00
Post-treatment growth 2003-2012	1.33	0.41***	0.53***
Ln (0.01+Nighttime Lights Per Capita)			
Pre-treatment growth 1992-2002	0.40	0.01	0.02
Post-treatment growth 2003-2012	1.17	0.44***	0.55***

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. The control groups are defined as i) districts that never had any mining activity (control group 1) and ii) districts yet without mining but with mineral deposits, which potential is examined in a feasibility study (control group 2). In column (1), coefficients represent the mean value of each variable for the treatment group. In column (2) and (3), we present the normalised 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). ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5: Effect of Mineral Resource Discoveries on 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 refered 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.

Table 6: 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 neighbouring 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 neighbouring 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.

Table 7: Associations between Mineral Production, Discovery and Night-Lights at 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
Ln(Mineral production)	0.018	-0.006						
	(0.018)	(0.019)						
ln(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 Ln(0.01+Nighttime Lights Density per sq. km). 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.

Table 8: Mine Closure and Development

	(1)	(2)	(3)
District has been mined	0.722***	0.725***	0.722***
	(0.162)	(0.161)	(0.162)
Shutdown	-0.491*	-0.224	-0.224
	(0.264)	(0.137)	(0.137)
Shutdown and not reopened by 2012		-0.837	-0.531
		(0.700)	(0.787)
Population density & Rainfall	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes
N	76,335	76,335	76,314
N(Districts/Regions/Countries)	3,635/519/42	3,635/519/42	3,634/519/42
R-squared adj.	0.947	0.947	0.947

Notes: This table shows association between a stop in mining activities and night-lights in a panel of district-year observations for the period 1992-2012. Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). "District has been mined" is a dummy variable equal to 1, once a district had at least one producing mine. "Shutdown" is a dummy variable equal to 1, if all mines in a district shut down (it may be temporary or persisent). "Shutdown and not reopened by 2012" is a dummy variable equal to 1 if all mines in a district shut down and none has reopened by 2012. Column (1) and (2) include all districts. Column (3) excludes Bonthe District in Sierra Leone, where the closure was reportedly caused by rebels during the civil war. Data from MinEx. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Appendices

A Online Appendix: Additional Tables

Table A.1: Placebo Test for Pre-discovery Trends in Night-Lights

	MD_{dt-j}: Mineral discovery made in year $t-j$	First Discoveries 2002-2012 (1)	First Discoveries 1997-2007 (2)
Pre-Discovery	$j=-10$	0.030	
		(0.101)	
	$j=-9$	0.063	
		(0.083)	
	$j=-8$	-0.059	
		(0.110)	
	$j=-7$	-0.047	
		(0.088)	
	$j=-6$	-0.016	
		(0.090)	
	$j=-5$	-0.064	-0.037
		(0.092)	(0.179)
	$j=-4$	0.020	0.027
		(0.055)	(0.214)
	$j=-3$	0.022	0.037
		(0.061)	(0.199)
	$j=-2$	-0.033	0.042
		(0.043)	(0.202)
	$j=-1$	-0.048	-0.004
		(0.046)	(0.201)
Post-Discovery	$j=0$		0.016
			(0.215)
	$j=1$		0.048
			(0.217)
	$j=2$		0.037
			(0.220)
	$j=3$		0.033
			(0.220)
	$j=4$		0.050
			(0.220)
	$j=5$		0.072
			(0.213)
	Population density & Rainfall	Yes	Yes
	Year Fixed Effects	Yes	Yes
	District Fixed Effects	Yes	Yes
	F-test of joint significance of pre-discovery dummies (p-val)	0.15	0.59
	N	73,106	73,253
	N Discoveries	34	42
	N(Districts/Regions/Countries)	3,497/514/42	3,505/515/42
	R-squared adj.	0.944	0.944

Notes: This table tests for pre-treatment effects in mineral discoveries (shown in Table 4). Because information on discoveries post-2012 is unavailable, we apply the following symmetric pre-/post discovery windows. Column (1) shows 10-year pre-discovery trends for discoveries that were made between 2002 and 2012. Column (2) shows trends in night-lights 5-years pre-/ post-discovery for discoveries that were made between 1997 and 2007. 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.

Table A.2: Effect of Mineral Resource Discoveries on 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)
$j=0$	-0.138	-0.138	-0.236	-0.095
	(0.129)	(0.129)	(0.235)	(0.151)
$j=1$	-0.057	-0.041	-0.032	-0.063
	(0.128)	(0.129)	(0.209)	(0.154)
$j=2$	-0.027	-0.009	0.142	-0.101
	(0.136)	(0.136)	(0.222)	(0.160)
$j=3$	-0.002	0.015	0.073	-0.035
	(0.129)	(0.132)	(0.230)	(0.146)
$j=4$	-0.004	0.011	0.208	-0.092
	(0.115)	(0.115)	(0.184)	(0.146)
$j=5$	0.076	0.081	0.309	-0.034
	(0.121)	(0.119)	(0.209)	(0.150)
$j=6$	0.172	0.190	0.476**	0.016
	(0.124)	(0.121)	(0.209)	(0.167)
$j=7$	0.250**	0.254**	0.484**	0.130
	(0.124)	(0.126)	(0.225)	(0.161)
$j=8$	0.399***	0.409***	0.675***	0.236
	(0.146)	(0.151)	(0.228)	(0.198)
$j=9$	0.430***	0.455***	0.673***	0.271
	(0.146)	(0.150)	(0.236)	(0.187)
$j=10$	0.460***	0.491***	0.730***	0.265
	(0.142)	(0.151)	(0.214)	(0.190)
Pop. density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Region 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.	0.756	0.756	0.757	0.756

Notes: This table is a re-estimation of Table 4, using region fixed effects instead of district fixed effects. The 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 refered to by each dummy variable may vary. Coefficients in column (1) and (2) show the same order of magnitude as Table 4. In contrast, coefficients in column (3) and (4) indicate a somewhat larger and smaller effect respectively. All regressions include year and region 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.

Table A.3: Associations between Mineral Production and Night-Lights at District Level (Dropping light pixels emanating from the industry)

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.022		-0.075	
	(0.014)		(0.048)	
Ln(Mineral production in 1992 commodity prices)		0.037**	0.115*	
		(0.018)	(0.058)	
Mineral production (1=yes)				0.466***
				(0.106)
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 is a re-estimation of Table 2. 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. sum of nighttime lights density) excludes lights emanating from the mining industries (i.e deleting pixel values of the light data around 2km radius of mining industries). Column (1) expresses the mineral production value in 1992 constant USD. Column (2) expresses the mineral production value in 1992 constant commodity prices. Column (3) includes both those indicators. Column (4) 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.

Table A.4: Effect of Mineral Resource Discoveries on Night-Lights in Virgin Districts (Deleting lights emanating from the industry)

MD_{dt-j}: Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j = 0$	0.031	-0.003	0.032	-0.008
	(0.109)	(0.067)	(0.111)	(0.084)
$j = 1$	0.102	0.041	0.133	0.013
	(0.121)	(0.078)	(0.119)	(0.095)
$j = 2$	0.081	0.007	0.114	-0.030
	(0.117)	(0.082)	(0.105)	(0.102)
$j = 3$	0.111	0.022	0.088	0.022
	(0.131)	(0.091)	(0.132)	(0.099)
$j = 4$	0.206	0.079	0.146	0.042
	(0.138)	(0.105)	(0.170)	(0.106)
$j = 5$	0.249	0.108	0.197	0.102
	(0.160)	(0.112)	(0.193)	(0.116)
$j = 6$	0.318*	0.222*	0.384	0.145
	(0.164)	(0.121)	(0.240)	(0.118)
$j = 7$	0.288*	0.223*	0.418	0.136
	(0.173)	(0.132)	(0.262)	(0.117)
$j = 8$	0.384**	0.386***	0.519**	0.323**
	(0.170)	(0.143)	(0.253)	(0.153)
$j = 9$	0.434**	0.396***	0.529*	0.337**
	(0.188)	(0.153)	(0.269)	(0.159)
$j = 10$	0.418**	0.409***	0.556**	0.337**
	(0.191)	(0.155)	(0.272)	(0.159)
Pop. density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
N	73,428	74,178	73,150	73,828
N(Districts/Regions/Countries)	3,560/516/42	3,557/516/42	3,493/515/42	3,530/515/42
R-squared adj.	0.943	0.944	0.944	0.943

Notes: This table is a re-estimation of Table 4. 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. sum of nighttime lights density) excludes lights emanating from the mining industries (i.e deleting pixel values of the light data around 2km radius of mining industries). 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.

Table A.5: Association between mineral production and nightlights in a country's major cities

	Capital city	Capital city	Two brightest cities in 1992	Two brightest cities in 1992
	(1)	(2)	(3)	(4)
Capital City x Ln(Mineral exports value)	-0.007			
	(0.011)			
Capital city x (Mineral rents as % of GDP)		-0.010		
		(0.006)		
Country's two brightest cities in 1992 x Ln(Mineral exports value)			-0.003	
			(0.013)	
Country's two brightest cities in 1992 x (Mineral rents as % of GDP)				-0.008
				(0.009)
Pop. density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
N	69,569	74,781	69,569	74,781
N(Regions/Districts)	494/ 3,524	503/ 3,561	494/ 3,524	503/ 3,561
Adjusted R-squared	0.949	0.947	0.949	0.947

Notes: This table shows the correlation between a country's mining activities and nightlights in a country's major cities using a panel of district-year observations. Column (1) reports the interaction effect between being the capital city and the natural log of total value of mineral exports. Instead of export values, column (2) uses mineral rents as a percentage of GDP. Column (3) and (4) examine the patterns in the two highest lit districts as of 1992 instead of the capital city. Estimator is OLS. All regressions include population density, rainfall and year and district fixed effects. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

B Online Appendix: Robustness Tests

Table B.1: Associations between Mineral Production and Night-Lights at District Level (District-year observations dropped if production data is missing)

	Intensive margin		
	(1)	(2)	(3)
Ln(Mineral production value in 1992 USD)	0.040**		-0.083
	(0.018)		(0.065)
Ln(Mineral prod. value in 1992 commodity prices)		0.079**	0.163*
		(0.032)	(0.088)
Population density & rainfall	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes
N	776	776	776
N(Districts/Regions/Countries)	126/77/28	126/77/28	126/77/28
R-squared adj.	0.985	0.985	0.986

Notes: In the main analysis we replaced missing values in production quantities by linear interpolation. This may affect estimates of the intensive margin. This table is a re-estimation of Table 2 in the main text. It shows associations between mining activities and night-lights in a panel of district-year observations for the period 1992-2012. In this table, district-year observations are dropped if production quantity is missing for at least one commodity for one mine in that district. This results in an unbalanced panel and fewer observations. Coefficients in this table are larger and more significant, which can be attributed to selection and measurement error. Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). Column (1) expresses the mineral production value in 1992 constant USD. Column 2 expresses the mineral production value in 1992 constant commodity prices. Column 3 includes both those indicators. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.2: Associations between Mineral Production and Night-Lights at District Level (Excluding sparsely populated districts with less than four people per square kilometre)

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.032*		-0.011	
	(0.016)		(0.039)	
Ln(Mineral production in 1992 commodity prices)		0.039*	0.050	
		(0.020)	(0.049)	
Mineral production (1=yes)				0.567***
				(0.131)
Population density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
N	1,579	1,579	1,579	70,615
N(Districts/Regions/Countries)	121/71/ 27	121/71/ 27	121/71/ 27	3410/496/42
R-squared adj.	0.980	0.980	0.980	0.947

Notes: This table is a re-estimation of Table 2 in the main text. It shows associations between mining activities and night-lights in a panel of district-year observations for the period 1992-2012. In this table, district-year observations are dropped if the population density is less than 4 (i.e. sparsely populated districts are excluded). Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). Column (1) expresses the mineral production value in 1992 constant USD. Column 2 expresses the mineral production value in 1992 constant commodity prices. Column 3 includes both those indicators. Column 4 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.

Table B.3: Associations between Mineral Production and Night-Lights at District Level (Excluding districts with zero luminosity from the sample)

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.021*		-0.065	
	(0.011)		(0.045)	
Ln(Mineral production in		0.035**	0.102*	
1992 commodity prices)		(0.016)	(0.056)	
Mineral production (1=yes)				0.343***
				(0.087)
Population density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
N	1,772	1,772	1,772	51,609
N(Districts/Regions/Countries)	136/79/28	136/79/28	136/79/28	3182/516/42
R-squared adj.	0.983	0.983	0.983	0.959

Notes: This table is a re-estimation of Table 2 in the main text. It shows associations between mining activities and night-lights in a panel of district-year observations for the period 1992-2012. In this table, district-year observations are dropped if the sum of light intensity values for the district is zero. Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). Column (1) expresses the mineral production value in 1992 constant USD. Column 2 expresses the mineral production value in 1992 constant commodity prices. Column 3 includes both those indicators. Column 4 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.

Table B.4: Associations between Mineral Production and Night-Lights at District Level (Weighting districts by district population size)

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.024*		-0.061	
	(0.014)		(0.047)	
Ln(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.	0.973	0.974	0.974	0.935

Notes: This table is a re-estimation of Table 2 in the main text. 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 is light density minus log population density (i.e. log luminosity per capita) based on Cogneau and Dupraz (2014). Column (1) expresses the mineral production value in 1992 constant USD. Column 2 expresses the mineral production value in 1992 constant commodity prices. Column 3 includes both those indicators. Column 4 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.

Table B.5: Associations between Mineral Production and Night-Lights at District Level (Weighting districts by the inverse of total number of districts in the country)

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.019		-0.089	
	(0.017)		(0.070)	
Ln(Mineral production in 1992 commodity prices)		0.036*	0.128*	
		(0.019)	(0.077)	
Mineral production (1=yes)				0.898***
				(0.204)
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.	0.941	0.941	0.942	0.896

Notes: This table is a re-estimation of Table 2 in the main text. 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. sum of nighttime lights density) is weighted by the inverse total number of the districts within a country. Column (1) expresses the mineral production value in 1992 constant USD. Column 2 expresses the mineral production value in 1992 constant commodity prices. Column 3 includes both those indicators. Column 4 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.

Table B.6: Associations between Mineral Production and Night-Lights at District Level (Grid-year observations)

	Intensive margin			Extensive margin
	(1)	(2)	(3)	(4)
Ln(Mineral production)	0.106***		0.086	
	(0.034)		(0.086)	
Ln(Mineral production in 1992 commodity prices)		0.116***	0.025	
		(0.038)	(0.094)	
Mineral production (1=yes)				0.701***
				(0.096)
Population density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
N	1,200	1,200	1,200	171,633
N(Grids/Regions/Countries)	170/80/29	170/80/29	170/80/29	8173/366/41
R-squared adj.	0.957	0.957	0.957	0.934

Notes: In the main analysis we used district level administrative boundaries as units of interest. Administrative boundaries are endogenous by construction, as it is likely to be determined by local geographic and demographic characteristics.This table is a re-estimation of Table 2 in the main text using grid level boundaries corresponding to a spatial resolution of 0.5 x 0.5 degrees latitude and longitude. It shows associations between mining activities and night-lights in a panel of district-year observations for the period 1992-2012. Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). Column (1) expresses the mineral production value in 1992 constant USD. Column 2 expresses the mineral production value in 1992 constant commodity prices. Column 3 includes both those indicators. Robust standard errors clustered by region are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.7: Effect of Mineral Resource Discoveries on Night-Lights in Virgin Districts (Excluding sparsely populated districts with less than four people per square kilometre)

MD_{dt-j}: Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	-0.019	-0.029	-0.040	-0.029
	(0.115)	(0.068)	(0.098)	(0.081)
$j=1$	0.075	0.030	0.088	-0.011
	(0.127)	(0.082)	(0.111)	(0.091)
$j=2$	0.061	0.000	0.063	-0.052
	(0.118)	(0.088)	(0.107)	(0.098)
$j=3$	0.065	0.019	-0.032	0.030
	(0.142)	(0.096)	(0.131)	(0.094)
$j=4$	0.202	0.078	0.070	0.059
	(0.151)	(0.114)	(0.167)	(0.112)
$j=5$	0.244	0.140	0.128	0.110
	(0.161)	(0.119)	(0.174)	(0.115)
$j=6$	0.298*	0.214*	0.296	0.123
	(0.166)	(0.128)	(0.221)	(0.118)
$j=7$	0.318*	0.245*	0.324	0.180
	(0.179)	(0.139)	(0.235)	(0.123)
$j=8$	0.415**	0.433***	0.465*	0.319*
	(0.175)	(0.158)	(0.236)	(0.162)
$j=9$	0.480**	0.447***	0.456*	0.343**
	(0.197)	(0.168)	(0.248)	(0.172)
$j=10$	0.468**	0.460***	0.514**	0.359**
	(0.198)	(0.168)	(0.253)	(0.167)
Pop. density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
N	68,140	68,830	67,914	68,592
N(Districts/Regions/Countries)	3298/494/42	3347/495/42	3289/496/42	3326/497/42
R-squared adj.	0.946	0.946	0.946	0.946

Notes: This table is a re-estimation of Table 4 in the main text. It reports the effect of mineral resource discoveries on night-lights in a panel of district-year observations. In this table, district-year observations are dropped if the population density is less than 4 (i.e. sparsely populated districts are excluded). Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). 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.

Table B.8: Effect of Mineral Resource Discoveries on Night-Lights in Virgin Districts (Excluding districts with zero luminosity from the sample)

MD_{dt-j}: Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	-0.015	-0.003	-0.007	-0.029
	(0.075)	(0.062)	(0.100)	(0.081)
$j=1$	0.014	0.011	0.104	-0.012
	(0.101)	(0.075)	(0.112)	(0.093)
$j=2$	-0.090	-0.054	0.085	-0.062
	(0.109)	(0.083)	(0.107)	(0.101)
$j=3$	-0.086	-0.059	0.006	0.017
	(0.126)	(0.086)	(0.133)	(0.097)
$j=4$	0.047	0.058	0.111	0.044
	(0.108)	(0.088)	(0.170)	(0.114)
$j=5$	0.073	0.024	0.159	0.090
	(0.124)	(0.093)	(0.175)	(0.118)
$j=6$	0.049	0.073	0.342	0.108
	(0.120)	(0.090)	(0.222)	(0.121)
$j=7$	0.075	0.078	0.372	0.164
	(0.123)	(0.100)	(0.238)	(0.127)
$j=8$	0.104	0.150	0.502**	0.310*
	(0.118)	(0.102)	(0.237)	(0.162)
$j=9$	0.213	0.275**	0.496**	0.340*
	(0.131)	(0.115)	(0.251)	(0.175)
$j=10$	0.170	0.244*	0.551**	0.342**
	(0.138)	(0.126)	(0.260)	(0.171)
Pop. density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
N	49,063	49,620	48,919	49,597
N(Districts/Regions/Countries)	3,058/513/42	3,107/513/42	3,048/512/42	3,085/512/42
R-squared adj.	0.959	0.959	0.959	0.959

Notes: This table is a re-estimation of Table 4 in the main text. It reports the effect of mineral resource discoveries on night-lights in a panel of district-year observations. In this table, district-year observations are dropped if the sum of light intensity values for the district is zero. Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). 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.

Table B.9: Effect of Mineral Resource Discoveries on Night-Lights in Virgin Districts (Weighting district areas by its population size i.e. population density times surface area)

MD_{dt-j}: Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	-0.024	-0.028	-0.032	-0.024
	(0.106)	(0.063)	(0.098)	(0.081)
$j=1$	0.060	0.024	0.100	-0.005
	(0.118)	(0.075)	(0.111)	(0.091)
$j=2$	0.046	-0.008	0.075	-0.043
	(0.111)	(0.081)	(0.106)	(0.098)
$j=3$	0.048	0.006	-0.015	0.039
	(0.132)	(0.087)	(0.131)	(0.094)
$j=4$	0.174	0.068	0.085	0.070
	(0.141)	(0.104)	(0.167)	(0.111)
$j=5$	0.212	0.114	0.146	0.122
	(0.151)	(0.109)	(0.174)	(0.114)
$j=6$	0.257	0.190	0.314	0.134
	(0.157)	(0.118)	(0.220)	(0.118)
$j=7$	0.277	0.218*	0.342	0.190
	(0.169)	(0.126)	(0.235)	(0.123)
$j=8$	0.363**	0.391***	0.484**	0.331**
	(0.167)	(0.147)	(0.235)	(0.161)
$j=9$	0.427**	0.402***	0.477*	0.355**
	(0.187)	(0.155)	(0.247)	(0.171)
$j=10$	0.430**	0.431***	0.538**	0.373**
	(0.187)	(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	73,428	74,178	73,150	73,828
N(Districts/Regions/Countries)	3,560/516/42	3,557/516/42	3,493/515/42	3,530/515/42
R-squared adj.	0.933	0.933	0.933	0.933

Notes: This table is a re-estimation of Table 4 in the main text. It reports the effect of mineral resource discoveries on night-lights in a panel of district-year observations. In this table, the dependent variable is light density minus log population density (i.e. log luminosity per capita) based on Cogneau and Dupraz (2014). 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.

Table B.10: Effect of Mineral Resource Discoveries on Night-Lights in Virgin Districts (Weighting districts by the inverse of total number of districts in the country)

MD_{dt-j}: Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	-0.039	-0.051	0.126	-0.095
	(0.235)	(0.135)	(0.306)	(0.167)
$j=1$	0.131	0.043	0.487	-0.107
	(0.279)	(0.191)	(0.309)	(0.218)
$j=2$	0.240	-0.023	0.500	-0.205
	(0.289)	(0.195)	(0.330)	(0.214)
$j=3$	0.042	0.083	0.179	0.155
	(0.315)	(0.192)	(0.328)	(0.199)
$j=4$	0.249	0.008	0.273	-0.006
	(0.318)	(0.226)	(0.404)	(0.223)
$j=5$	0.296	0.173	0.554	0.108
	(0.339)	(0.220)	(0.392)	(0.223)
$j=6$	0.464	0.348	0.692	0.218
	(0.298)	(0.214)	(0.421)	(0.190)
$j=7$	0.445	0.420*	0.747*	0.321
	(0.322)	(0.241)	(0.428)	(0.231)
$j=8$	0.709**	0.677**	0.939**	0.540*
	(0.331)	(0.264)	(0.442)	(0.277)
$j=9$	0.672*	0.529	0.801*	0.417
	(0.380)	(0.326)	(0.485)	(0.366)
$j=10$	0.706*	0.658**	0.950*	0.520
	(0.384)	(0.316)	(0.484)	(0.344)
Pop. density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
N	73,428	74,178	73,150	73,828
N(Districts/Regions/Countries)	3,560/516/42	3,557/516/42	3,493/515/42	3,530/515/42
R-squared adj.	0.892	0.892	0.892	0.892

Notes: This table is a re-estimation of Table 4 in the main text. 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. sum of nighttime lights density) is weighted by the inverse total number of the districts within a country. 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.

Table B.11: Effect of Mineral Resource Discoveries on Night-Lights in Virgin Districts (Grid-year observation)

MD_{dt-j}: Mineral discovery made in year $t-j$	First Discoveries (1)	Single, First Discoveries (2)	Giant Discoveries (3)	Major Discoveries (4)
$j=0$	0.160*	0.078	0.088	0.071
	(0.090)	(0.055)	(0.111)	(0.061)
$j=1$	0.234***	0.153**	0.078	0.152**
	(0.088)	(0.065)	(0.097)	(0.074)
$j=2$	0.289***	0.144*	-0.050	0.162**
	(0.108)	(0.075)	(0.129)	(0.082)
$j=3$	0.271**	0.187**	-0.113	0.240***
	(0.109)	(0.079)	(0.123)	(0.092)
$j=4$	0.335***	0.181**	-0.124	0.246**
	(0.126)	(0.091)	(0.131)	(0.101)
$j=5$	0.409***	0.308***	0.157	0.385***
	(0.144)	(0.100)	(0.106)	(0.118)
$j=6$	0.457***	0.323***	0.259*	0.389***
	(0.138)	(0.099)	(0.134)	(0.121)
$j=7$	0.435***	0.385***	0.415***	0.416***
	(0.148)	(0.114)	(0.151)	(0.145)
$j=8$	0.667***	0.654***	0.695***	0.656***
	(0.147)	(0.119)	(0.180)	(0.152)
$j=9$	0.647***	0.681***	0.777***	0.657***
	(0.173)	(0.137)	(0.219)	(0.176)
$j=10$	0.695***	0.742***	0.907***	0.681***
	(0.158)	(0.130)	(0.221)	(0.163)
Pop. density & Rainfall	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Grid Fixed Effects	Yes	Yes	Yes	Yes
N	168,244	169,203	167,949	168,861
N(Grids/Regions/Countries)	8,022/366/41	8,088/366/41	8,009/366/41	8,059/366/41
R-squared adj.	0.932	0.932	0.932	0.932

Notes: In the main analysis we used district level administrative boundaries as units of interest. Administrative boundaries are endogenous by construction, as it is likely to be determined by local geographic and demographic characteristics. This table is a re-estimation of Table 4 in the main text using grid level boundaries corresponding to a spatial resolution of 0.5 x 0.5 degrees latitude and longitude. It reports the effect of mineral resource discoveries on night-lights in a panel of district-year observations. Dependent variable is Ln(0.01+Nighttime Lights Density per sq. km). 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.