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Spatial Diffusion of Economic Shocks in Networks

Abstract

The aggregate economic impact of any developmental project depends on its effects within the chosen administrative region as well as its economic spillovers into other regions. However, little is known about how these spillovers propagate through geographic, ethnic and road networks. In this paper, we analyze both theoretically and empirically the role of these networks in the spatial diffusion of local economic shocks. We develop a network model that shows how a district's level of prosperity is related to its position in the network. The network model's first-order conditions are used to derive an econometric model of spatial spillovers that we estimate using a panel of 5,944 districts from 53 African countries over the period 1997-2013. To identify the causal effect of spatial diffusion, we exploit cross-sectional variation in the location of mineral mines and exogenous time variation in world mineral prices. Our results show that road and ethnic connectivity are particularly important factors for diffusing economic spillovers over longer distances. We then use the estimated parameters from the econometric model to calculate the key player centralities, which determine which districts are key in propagating local economic shocks across Africa. We further show how counterfactual exercises based on these estimates and the underlying network structure can inform us about the potential gains from policies that increase economic activity in specific districts or improve road connectivity between districts.

JEL-Codes: O130, O550, R120.

Keywords: economic development, networks, spatial spillovers, key player centrality, natural resources, transportation, Africa.

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1 Introduction

In recent decades, the majority of African countries have experienced an unprecedented period of aggregate economic growth. However, the gains from this rise in aggregate income have been unequally distributed between individuals and regions within those countries (Beegle et al., 2016). The reason for this spatial inequality could be a combination of two factors. First, in many African countries, a large fraction of economic activity is concentrated in a few geographic areas.[1] Second, geography, the lack of transport infrastructure and ethnic heterogeneity may limit the extent of spatial economic spillovers (e.g., Easterly and Levine, 1997, Bloom et al., 1998, Brock et al., 2001, Masanjala and Papageorgiou, 2008, Crespo Cuaresma, 2011).

The aim of this paper is to estimate the extent of spatial economic spillovers between African districts and highlight the role of geographic, transport and ethnic networks in the context of regional economic growth in Africa. By doing so, we not only present a novel link between network theory and macro-level measures of prosperity, but (to the best of our knowledge) we are also the first to estimate a well-identified econometric model of spatial economic spillovers across an entire continent.

We first develop a simple theoretical model that describes how one district's prosperity depends on its degree of connectivity with other districts in a multi-district network framework. The first-order conditions are used to estimate an econometric model of spatial spillovers in which the economic prosperity of one district depends on the economic prosperity of neighboring districts, which are defined in terms of geographic, ethnic and road connectivity networks.

We estimate this econometric model using a balanced panel dataset of 5,944 African districts (ADM2, second subnational level) and yearly data from 1997–2013. Our measure of local prosperity is nighttime light intensity. The basic econometric framework is a spatial Durbin model that allows for spatial autoregressive processes in the dependent

[1] Masanjala and Papageorgiou (2008) show that African countries' GDPs heavily rely on mineral exports, which are highly localized. Ades and Glaeser (1995) and Henderson (2002) point out the importance of primate cities in general, while Storeygard (2016) empirically underpins this point for primate cities in Africa.

and explanatory variables. We interpret the estimated coefficient of the spatial lag of the dependent variable in that model as the effect of a district's connectivity on its own prosperity. Our preferred specifications include time-varying controls as well as district and country-year fixed effects to account for all time-invariant differences across districts and country-year specific shocks that affect all districts in a country and year, respectively.

The major empirical challenge is that the estimated parameter is likely to be biased due to reverse causality and time-varying omitted variables. We address this problem by applying an instrumental variables (IV) strategy similar to that of Berman et al. (2017). This strategy relies on cross-sectional variation in the neighboring districts' mining opportunities and fluctuations in the world price of the minerals extracted in these districts as the source of exogenous temporal variation in these districts' prosperity.

One potential threat to our identification strategy is that mineral resources in Africa are often clustered in a number of neighboring districts. Hence, a positive price increase in a particular mineral may not only increase prosperity in a district through spatial spillovers but could also directly impact prosperity in the district if this district happens to have an endowment of that particular mineral itself. Therefore, in our specifications we control for the mineral wealth of the district itself. A second concern is that changes in the neighboring districts' mineral wealth may systematically trigger violent conflict in these districts and these conflicts might spillover to other districts (Berman et al., 2017). We therefore control for conflict in a district and the neighboring districts. A third concern is that spatial spillovers may be fiscal rather than economic. Suppose the central government channels resource-based government revenues back to mining provinces (ADM1, first subnational level). In this case, non-mining districts belonging to a province in which there are some mining districts may well benefit from these government transfers, but we may not want to think of these transfers as economic spillovers. We therefore present specifications in which we compare spillovers to neighboring districts belonging to the same or different provinces.[2]

[2] In addition to these concerns, notice that given this identification strategy, we estimate the local average treatment effect (LATE) of a particular type of economic shock for a particular subset of districts. Among other things, these specific economic shocks could generate both positive and negative spatial spillovers and, as such, we ultimately estimate the total net effect of the economic spillovers. We discuss these

Our estimation results are as follows: Individually, geographic, ethnic and road connectivity all increase local prosperity, but they impact local prosperity in different ways. With respect to geographic connectivity, positive economic shocks only seem to affect other districts within very close geographic proximity. A positive income shock in one district only systematically increases prosperity in districts that are within a 75km radius. The spillover effect is no longer statistically significant beyond this distance. Ethnic connectivity transmits positive economic shocks to other districts that share the same ethnicity but are not necessarily contiguous. Connectivity via primary or secondary roads is the most important determinant of spatial spillovers and positive economic shocks diffuse to districts well beyond 100km if they are connected by better road infrastructure.

Using these estimated coefficients on the spatial lag variable, we are able to calculate different network centrality measures, including betweenness, eigenvector, Katz-Bonacich and key-player network centralities.[3] In particular, based on the key-player centrality, we determine the "key" districts in African countries, i.e., the districts that contribute most to prosperity in Africa. These districts are typically characterized by high local economic activity as well as good connectivity. We further illustrate the usefulness of our approach for evaluating different policies. We conduct counterfactual exercises to show how the estimated coefficients and the underlying network structure can inform us about the aggregate economic effects of policies that increase economic activity in particular districts or improve road connectivity between districts.

We think that our approach and our results have important implications for policymakers in Africa as well as international donors and development agencies. A planner's decision on where to locate a particular developmental project or where to build a road may need to consider many aspects, but one of them should be the potential of this project to generate spatial economic spillovers. For that, she could use the results from our counterfactual policy exercises. Hence, our approach and results could help policymakers to design more informed economic policies.

limitations of our approach below.

[3]Katz-Bonacich and key-player network centralities both require the estimated coefficient of the spatial lag of the dependent variable. In contrast, betweenness and eigenvector centralities are parameter free and only depend on the topology of the network (see e.g., Jackson, 2008).

The rest of the paper is structured as follows. In the next section, we highlight our contribution to the literature. In Section 3, we develop the formal model. We then describe the data in Section 4, discuss the empirical strategy in Section 5, and present the results from our estimates in Section 6. Using these results, we identify the districts that are the most central in Section 7 and discuss counterfactual policy exercises in Section 8. In Section 9, we briefly conclude.

2 Related Literature

Our paper contributes to four different strands of the literature. First, we contribute to the empirical literature on the effects of networks in economics.[4] This literature has so far mostly focused on using micro data to test predictions from network theory (see e.g., Calvó-Armengol et al., 2009, for education or Cawley et al., 2017, for obesity). A major challenge in these studies is the endogeneous sorting of agents in networks and the endogeneous formation of networks (see, in particular, Bramoullé et al., 2009, 2016, and Blume et al., 2011). There are also some recent papers that study network effects from a macroeconomic perspective (see, in particular, Acemoglu et al., 2012, 2015, Carvalho, 2015). These papers study production or supply chain networks and document that the structure of the *production network* (input-output matrix) is key in determining whether and how microeconomic shocks – affecting only a particular firm or technology along the chain – propagate throughout the economy and shape macroeconomic outcomes. For example, localized disturbances such as the 2011 earthquake in Japan, the financial crisis, the 2007–2009 recession (Carvalho, 2015) or natural disasters (Barrot and Sauvagnat, 2016) affect decisions by many firms. These micro decisions then propagate through the production network and the resulting synchronized behavior affects business cycles.

Our contribution to the network literature is twofold. First, compared to the microeconomic strand of the literature, we do not have the problem of endogenous network formation of agents since our unit of analysis is the geographical location of a district

[4]For overviews on the economics of networks, see Ioannides (2012), Jackson (2008, 2014), Jackson and Zenou (2015), Bramoullé et al. (2016), and Jackson et al. (2017).

in a country, which is clearly exogenous.[5] Also, we propose a credible IV strategy that deals with the reflection problem and the endogeneity of the spatial lag variable. Second, compared to the macroeconomic literature, we focus on the geographical location of districts rather than the location of firms in a production network. Moreover, we propose an explicit network analysis and determine the key districts in each country, i.e., the ones that need to be supported if the government wants to maximize total economic growth. In that sense, our paper may be closer to that of König et al. (2017), who present a key player analysis for the conflict in the Democratic Republic of the Congo. We, however, believe that ours is the first study that looks at the role of networks in explaining spatial economic spillovers across an entire continent.

A second literature to which we contribute is the one on the economic effects of natural resource revenues. This literature has traditionally focused on whether and when natural resources are a curse for a country's economic development (e.g., Sachs and Warner, 2001, van der Ploeg, 2011). More recently, the focus of this literature has turned to the local effects of resource extraction. The local economic effects may be positive if the extractive industries hire local workers or if their presence leads to an increase in the demand for locally produced goods and services (e.g., Aragon and Rud, 2013). The effects may also be positive if the central government channels a disproportioned share of the taxes and fees paid by the extractive industry back to the governments of the resource-rich provinces or districts (e.g., Caselli and Michaels, 2013). Resource extraction may have negative effects on the local economy if it causes environmental pollution (e.g., Aragon and Rud, 2016) or conflict (Berman et al., 2017).

In our paper, we focus on spatial spillovers of local economic shocks originating from the mining sector. Positive spatial spillovers may also result from an increased demand or increased fiscal transfers to the province in which the mining activity takes place, while conflict could lead to negative spatial spillovers. To date, there has been little research on spatial spillovers of local resource extraction. A notable exception is Aragon and

[5] The ethnic network that we use is exogenous as well since we rely on maps of traditional ethnic homelands. The road network is exogenous to the extent that the contemporary network of primary and secondary roads in Africa largely originates from roads which were built by colonial powers based on their own needs (Rodney, 1982).

Rud's (2013) study on the spillovers from a large gold mine in Peru. Closer to us, Mamo et al. (2017) look at spatial spillovers from mine discoveries in Africa. They find little evidence for spatial spillovers. Our analysis differs from theirs by focusing on resource price fluctuations rather than less frequent mine discoveries, by using an IV strategy, by using ethnic and road networks in addition to geographic networks, and by letting a network-theoretic framework guide our empirical approach, which allows us to determine key districts.

Third, we contribute to the literature that studies the importance of transport networks for subnational economic development in Africa. Studies in this area often focus on the construction of new highways in, e.g., China or India (Banerjee et al., 2012, Faber, 2014, Alder, 2015). Like us, Storeygard (2016) and Bonfatti and Poelhekke (2017) focus on road networks in Africa. Storeygard (2016) investigates the effect of transportation costs on the income of African cities. Bonfatti and Poelhekke (2017) document that African roads typically connect mines directly to the coast and study how this pattern affects bilateral trade with neighboring versus overseas countries. We differ from these papers by focusing on the importance of roads in shaping the spatial diffusion of economic shocks across Africa.

Fourth, we contribute to the literature on the effects of ethnic diversity on aggregate outcomes (e.g., Easterly and Levine, 1997, Alesina et al., 2003, Alesina and La Ferrara, 2005). Traditionally, this literature has focused on the ethnic composition at the country level. More recently, two strands have developed that take the information about the spatial distribution of different ethnic groups into account. A first strand uses this information to explain differences in economic outcomes across ethnic homelands (e.g., Michalopoulos and Papaioannou, 2013, Burgess et al., 2015, Dimico, 2017, Hodler and Raschky, 2017, De Luca et al., 2018). A second strand is more macro in nature. It uses information about the spatial distribution of ethnic groups to develop country-level measures of ethnic segregation (Alesina and Zhuravskaya, 2011, Hodler et al., 2017) or ethnic inequality (Alesina et al., 2016) and shows how these measures correlate with aggregate economic outcomes. Like these two strands, we also use information on the spatial distribution of economic groups. However, we link the more micro literature to the macro one using subnational regions as units of analysis, but with a focus on how economic shocks propagate through the ethnic network and thereby affect economic development outside these small units.

At a more general level, we relate to the growing number of empirical studies analyzing the differences in economic development between and within subnational units rather than countries (e.g., Gennaioli et al., 2014, Henderson et al., 2018, Michalopoulos and Papaioannou, 2017, and some of the studies cited above). Within this strand of literature, a few studies investigate the role of spatial spillovers on regoinal development using spatial econometric techniques (e.g., Crespo-Cuaresma et al., 2014, Higgins et al., 2006, Mamo et al., 2017). A common problem in this context is the potential endogeneity of the spatial lag variable. To the best of our knowledge, we are the first to address this issue by employing an IV approach to estimate the spatial spillover effects in the context of regional economic development.[6]

3 A simple model

3.1 General case

Consider a network linking different districts. A network (graph) $\boldsymbol{\omega}$ is the pair (N, E) consisting of a set of nodes (here districts) $N = \{1, \ldots, n\}$ and a set of edges (links) $E \subset N \times N$ between them. The neighborhood of a node $i \in N$ is the set $N_i = \{j \in N : (i, j) \in E\}$. The adjacency matrix $\mathbf{\Omega} = (\omega_{ij})$ keeps track of direct links so that $\omega_{ij} \in]0, 1]$ if a link exists between districts i and j and $\omega_{ij} = 0$ otherwise.[7] We assume that the adjacency matrix $\mathbf{\Omega}$ is row-normalized so that the sum of each of its rows is equal to 1, i.e., $\sum_j \omega_{ij} = 1$ for all i.[8] In the data, $\mathbf{\Omega} = (\omega_{ij})$ will capture connectivity based on geography, the road network or ethnicity (see Section 4.2).

[6]Harari and La Ferrara (2018) employ a similar approach in a robustness check. However, they focus on spillovers in conflict rather than economic development.

[7]In spatial econometrics, the adjacency matrix is called the "connectivity matrix." Throughout the paper, we will use these terms interchangeably.

[8]All our theoretical results hold if the adjacency matrix is not row-normalized.

The level of prosperity p_{ict} of a district i belonging to country c is given by:

$$p_{ic} = X_{ic}\lambda_{ic} + \rho\lambda_{ic}\sum_{j=1}^{J}\omega_{ic,jc}\lambda_{jc} + \lambda_{ic}\varepsilon_{ic}$$

where λ_{ic} is the *total activity* in district i belonging to country c, X_{ic} is the marginal effect of district i's total activity on its own prosperity (captured by X_{ic}, the characteristics of the district i), and $\rho > 0$ captures the cross (spillover) effects between own prosperity and the neighbors' activities since

$$\frac{\partial^2 p_{ic}}{\partial\lambda_{ic}\partial\lambda_{jc}} = \rho\omega_{ic,jc}$$

Finally, ε_{ic} is the error term. Observe that it may hold that $\omega_{ic,jc} > 0$ even though district i and district j may belong to different countries. In sum, the prosperity level of a district is determined by the district's *observable* and *unobservable* characteristics, the total activity level of the district, and the spillover effects of the activity of neighboring districts. To ease the presentation, we now omit the subscript c.

We assume the total activity in district i to be a constant elasticity of substitution (CES) composite of both locally $l_i \geq 0$ and nationally chosen activity $\overline{L}_i \geq 0$, i.e.

$$\lambda_i = \left[\alpha l_i^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\,\overline{L}_i^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where $\sigma > 0$ and $\alpha \geq 0$. The idea here is that the total activity of district i, λ_i, depends on its own activity l_i and how much activity or money $\overline{L}_i$ is given to district i by the national government. $\overline{L}_i$ is exogenous in the model.

Each district i (or more exactly the local politician in charge of the district) decides its own activity level l_i, taking as given the choices of its neighbors and $\overline{L}_i$. The utility function of district i is given by:

$$\begin{aligned} U_i &= p_i - \frac{1}{2}l_i^2 \\ &= X_i\lambda_i + \rho\lambda_i\sum_{j=1}^{J}\omega_{ij}\lambda_j + \lambda_i\varepsilon_i - \frac{1}{2}l_i^2 \end{aligned}$$

where λ_i is given by (1). The first-order condition yields:

$$l_i = \frac{\partial \lambda_i}{\partial l_i}\left[X_i + \rho \sum_{j=1}^{J} \omega_{ij}\lambda_j + \varepsilon_i\right]$$

where

$$\frac{\partial \lambda_i}{\partial l_i} = \left(\frac{\sigma}{\sigma - 1}\right)\left[\alpha l_i^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\,\overline{L}_i^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} \alpha \left(\frac{\sigma-1}{\sigma}\right) l_i^{-\frac{1}{\sigma}}$$

By plugging this last expression into the first-order condition, we obtain:

$$l_i^{\frac{\sigma+1}{\sigma}} = \left(\frac{\sigma}{\sigma - 1}\right)\left[\alpha l_i^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\,\overline{L}_i^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} \alpha \left(\frac{\sigma-1}{\sigma}\right)\left[X_i + \rho \sum_{j=1}^{J} \omega_{ij}\lambda_j + \varepsilon_i\right] \tag{2}$$

Since $\rho > 0$, we have a game with strategic complementarities, and the existence of equilibrium is usually not an issue (as one can apply the Brouwer fixed point theorem). Also, it is easily verified from (2) that the equilibrium l_i is always strictly positive, so we do not have to worry about corner solutions. Using the results of Allouch (2015) or Zenou and Zhou (2018), who both deal with network games with non-linear best responses, it is relatively easy to impose a bound on the slope of the best responses to obtain uniqueness of the equilibrium.

3.2 The linear case

Let us study the linear case when $\alpha = 1$. In that case, $\lambda_i = l_i$, so that only own activity affects the prosperity of district i. The utility function can then be written as:

$$U_i = X_i l_i + \rho l_i \sum_{j=1}^{J} \omega_{ij} l_j + \lambda_i \varepsilon_i - \frac{1}{2} l_i^2 \tag{3}$$

The first-order condition yields:

$$l_i = \rho \sum_{j=1}^{J} \omega_{ij} l_j + X_i + \varepsilon_i \tag{4}$$

or in matrix form

$$\mathbf{l} = (\mathbf{I} - \rho\mathbf{\Omega})^{-1} (\mathbf{X} + \boldsymbol{\varepsilon}) =: \mathbf{C}^{BO}_{\mathbf{X}+\boldsymbol{\varepsilon}}(\rho, \boldsymbol{\omega}) \tag{5}$$

where $\mathbf{l}$ is a column-vector of l_is, $\mathbf{I}$ is the identity matrix, and $\mathbf{X}$ and $\boldsymbol{\varepsilon}$ are the vectors corresponding to the X_is and ε_is, respectively. In (5), $\mathbf{C}^{BO}_{\mathbf{X}+\boldsymbol{\varepsilon}}(\rho, \boldsymbol{\omega})$, whose ith row is $C^{BO}_{i,X_i+\varepsilon_i}(\rho, \boldsymbol{\omega})$, is the weighted *Katz-Bonacich centrality* (due to Bonacich, 1987, and Katz, 1953), where the weights are determined by the sum of X_i and ε_i for each district i. Denote by $\mu_1(\mathbf{\Omega})$ the spectral radius of $\mathbf{\Omega}$. Then, if $\rho\mu_1(\mathbf{\Omega}) < 1$, there exists a unique interior equilibrium given by (4) or (5). Since the adjacency matrix $\mathbf{\Omega}$ is assumed to be row-normalized, it holds that $\mu_1(\mathbf{\Omega}) = 1$. Thus, the condition for existence and uniqueness can be written as $\rho < 1$.

Interestingly, ρ has an easy interpretation. In social networks, it is called the social or network multiplier. Here, it is the strength of spillovers in terms of nighttime lights between neighboring districts. To illustrate this, consider the case of a dyad (two districts, i.e., $N = 2$). For simplicity, assume that the two districts are ex ante identical so that $X_1 + \varepsilon_1 = X_2 + \varepsilon_2 = X + \varepsilon$. In that case, if there were no network (empty network) so that the two districts were not linked, the unique Nash equilibrium would be given by:

$$l_1^{empty} = l_2^{empty} = X + \varepsilon$$

Consider now a network where the two districts are linked to each other (i.e., $g_{12} = g_{21} = 1$). Then, if $\rho < 1$, the unique interior Nash equilibrium is given by:

$$l_1^{dyad} = l_2^{dyad} = \frac{X + \varepsilon}{1 - \rho}$$

In other words, because of complementarities, in the dyad, the level of activity of each district is much higher than when the districts are not connected. The factor $1/(1-\rho) > 1$ is the *network multiplier*.[9]

[9] Observe that if we keep the ex ante heterogeneity, we have that, if $\rho < 1$, then the unique interior Nash equilibrium is equal to:

$$\begin{pmatrix} l_1 \\ l_2 \end{pmatrix} = \frac{1}{(1-\rho^2)} \begin{pmatrix} X_1 + \varepsilon_1 + \rho\,(X_2 + \varepsilon_2) \\ X_2 + \varepsilon_2 + \rho\,(X_1 + \varepsilon_1) \end{pmatrix}$$

So far, we have assumed that $\rho > 0$, which implies strategic complementarities. However, it may be the case, especially in Africa, that there are negative spillovers on neighboring districts so that $\rho < 0$. For example, if a district i has a high activity level, then it may be that the neighboring districts are negatively affected by this because their residents may move to district i, which is more prosperous. In the linear case, the equilibrium nighttime lights are still given by (4) or (5). In that case, the condition for the existence and uniqueness of equilibrium is no longer given by $\rho\mu_1(\mathbf{\Omega}) < 1$ but by $\rho\mu_{\min}(\mathbf{\Omega}) > -1$, where $\mu_{\min}(\mathbf{\Omega})$ is the *lowest* eigenvalue of $\mathbf{\Omega}$.

3.3 The case of multiple spillover effects

Consider the linear case where $\alpha = 1$, $\lambda_i = l_i$ and $\rho > 0$. We have assumed that the level of prosperity p_{ic} of a district i belonging to country c was given by (for the linear case):

$$p_{ic} = X_{ic}l_{ic} + \rho l_{ic}\sum_{j=1}^{J}\omega_{ic,jc}l_{jc} + l_{ic}\varepsilon_{ic}$$

where l_{ic} is the *total activity* in district i belonging to country c. In the real world, each district is affected by more than one dimension of the spillovers. For example, in some of our specifications (see below), we use different adjacency matrices $\mathbf{\Omega} = (\omega_{ij})$ that keep track of the (inverse) distance between districts, the road network and the proximity in terms of ethnicity between districts. As a result, we now assume that:[10]

$$p_{ic} = X_{ic}l_{ic} + \rho_1 l_{ic}\sum_{j=1}^{J}\omega_{1,ic,jc}l_{jc} + \rho_2 l_{ic}\sum_{j=1}^{J}\omega_{2,ic,jc}l_{jc} + \rho_3 l_{ic}\sum_{j=1}^{J}\omega_{3,ic,jc}l_{jc} + l_{ic}\varepsilon_{ic} \quad (6)$$

where we now have three adjacency matrices $\mathbf{\Omega}_1 = (\omega_{1,ij})$, $\mathbf{\Omega}_2 = (\omega_{2,ij})$ and $\mathbf{\Omega}_3 = (\omega_{3,ij})$, which are all assumed to be row-normalized. This means that the prosperity of a district is affected differently by the different ways we measure the "proximity" between neighborhoods. Remember that $\mu_1(\mathbf{A})$ denotes the spectral radius of a matrix $\mathbf{A}$. Thus, we have the following result:

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[10]Our analysis straightforward extends to the case of n adjacency matrices.

Proposition 1. *Consider a model where the prosperity of a district is given by (6). Then, if* $\mu_1(\rho_1\mathbf{\Omega}_1 + \rho_2\mathbf{\Omega}_2 + \rho_3\mathbf{\Omega}_3) < 1$, *there exists a unique interior equilibrium given by:*

$$l_i = \rho_1 \sum_{j=1}^{J} \omega_{1,ij} l_j + \rho_2 \sum_{j=1}^{J} \omega_{2,ij} l_j + \rho_3 \sum_{j=1}^{J} \omega_{3,ij} l_j + X_i + \varepsilon_i \tag{7}$$

or, in matrix form,

$$\mathbf{l} = (\mathbf{I} - \rho_1\mathbf{\Omega}_1 - \rho_2\mathbf{\Omega}_2 - \rho_3\mathbf{\Omega}_3)^{-1} (\mathbf{X} + \boldsymbol{\varepsilon})$$

Proof: We need to show that $\mathbf{I}-\mathbf{A}$ is non-singular (i.e., invertible), where $\mathbf{A} \equiv \rho_1\mathbf{\Omega}_1 + \rho_2\mathbf{\Omega}_2 + \rho_3\mathbf{\Omega}_3$. We know that $\mathbf{I}-\mathbf{A}$ is non-singular if $\mu_1(\mathbf{A}) := \mu_1(\rho_1\mathbf{\Omega}_1 + \rho_2\mathbf{\Omega}_2 + \rho_3\mathbf{\Omega}_3) < 1$ (see, e.g., Meyer, 2000, page 618). From the first-order condition (7), we see that the solution is always interior. ▮

In terms of empirical implications, the two models are very different, as we discuss in detail when interpreting the results of our econometric model of spatial spillovers (see Section 6.1).

4 Data

Our units of observation are administrative units at the second subnational level (ADM2), which we call districts.[11] The final dataset consists of yearly observations for 5,944 districts from 53 African countries[12] over the period 1997–2013.[13] The average (median) size of a district is 39km^2 (6km^2) and the average (median) population is around 150,000 (55,000).

For our purpose, there are a number of advantages of using administrative units rather than other grid cells (e.g., Berman et al., 2017, Henderson et al., 2018) or ethnic homelands (Michalopoulos and Papaioannou, 2013, 2014). First and foremost, policymakers operating within a country's administrative framework typically take their project allo-

[11]The shapefile containing the ADM boundary polygons comes from the GADM database of Global Administrative Areas, version 1, available at http://gadm.org. Boundary polygons at the ADM2 level are available for all African countries, except Egypt and Libya, for which they are only available at the ADM1 level.

[12]For the exact list of all the African countries with the number of districts each country has, see Table A1 in the Online Appendix.

[13]Figure A1 in the Online Appendix shows the boundaries of each district in Africa.

cation decisions based on administrative units. Second, changes in economic activity in the African hinterland, e.g., agricultural production or mining, may often be reflected by changes in nighttime lights in a district's urban hub. We thus want to ensure that a district's urban hub belongs to the same spatial units as its hinterland. Third, our measure for road connectivity relies on primary and secondary roads. Using grid cells would result in a large number of seemingly unconnected cells, whereas in reality they might have direct access to primary/secondary roads via a short trip on a small road.

4.1 Dependent variable: Nighttime lights

Satellite data on the intensity of nighttime lights comes from the the National Oceanic and Atmospheric Administration (NOAA). Weather satellites from the US Air Force circle the earth 14 times per day and measure light intensity. The NOAA uses evening observations during the dark half of the lunar cycle in seasons when the sun sets early, but removes observations affected by cloud coverage, or northern or southern lights. It further processes the data by setting readings that are likely to reflect fires, other ephemeral lights or background noise to zero.[14] The objective is that the reported nighttime lights are primarily man-made. The NOAA then provides annual data for the time period from 1992 onwards for output pixels that correspond to less than one square kilometer. The data come on a scale from 0 to 63, with higher values implying more intense nighttime lights.

Nighttime lights are a proxy for economic activity, as most forms of consumption and production in the evening require light. Moreover, public infrastructure is often lit at night. It is, therefore, not surprising that Henderson et al. (2012) and Hodler and Raschky (2014) find a high correlation between changes in nighttime light intensity and GDP at the level of countries and subnational administrative regions, respectively. Using data from Gennaioli et al. (2014), we also find a high correlation between nighttime lights and subnational GDP for 82 subnational administrative regions from nine African countries

[14]Readings due to fires and other ephemeral lights are identified by their high brightness and infrequent occurrence. Background noise is identified by setting light intensity thresholds based on areas expected to be free of detectable lights (Baugh et al., 2010).

(see Table B1 in the Online Appendix).

To construct our dependent variable, $Light_{ict}$, we take the logarithm of the average nighttime light pixel value in district i of country c in year t. To avoid losing observations with a reported nighttime light intensity of zero, we follow Michalopoulos and Papaioannou (2013, 2014) and Hodler and Raschky (2014) in adding 0.01 before taking the logarithm.

4.2 Connectivity matrices

We construct three connectivity matrices to measure spatial spillovers.

4.2.1 Ethnic connectivity

Africa is known for its ethnic diversity. Members of the same ethnic group share similar cultural traits and behavioral norms, which may influence their ability to cooperate and their willingness to maintain economic relations. The work by Murdock (1958) documents the spatial distribution of ethnic homelands in Africa and subdivides the continent into over 800 ethnic homelands.[15]

To measure ethnic connectivity between districts, we first overlay the district (ADM2) boundaries with the boundaries of the ethnic homelands from Murdock. Each district is assigned the ethnicity of the ethnic homeland in which it is located. For districts that fall into more than one ethnic homeland, we assign the ethnicity of the ethnic homeland that covers the largest part of the district. We then construct our ethnic connectivity matrix, $\omega_{ic,jc}$, where elements are 1 if the ethnicity in district i is the same as the ethnicity in district j, and 0 otherwise.

4.2.2 Geographic connectivity

We base the weighting matrix for geographic connectivity on geographic distance. We construct this weighting matrix as follows: First, we calculate the centroid of each district. Second, we calculate the geodesic distance $d_{ic,jc}$ connecting the centroids of districts i and

[15] Figure A2 in the Online Appendix shows the digitized version of Murdock's original map.

j. Third, following Acemoglu et al. (2015), we measure the variability of altitude, $e_{ic,jc}$, along the geodesic connecting the centroids of districts i and j. We use elevation data from GTOPO30. Finally, we calculate the inverse of the altitude-adjusted geodesic distance as $\tilde{d}_{ic,jc} = 1/d_{ic,jc}(1 + e_{ic,jc})$.

Defining geographic connectivity using the inverse altitude-adjusted distance as opposed to contiguity proves advantageous on three accounts.[16] First, by incorporating all districts within a given radius, connectivity is extended to districts beyond those merely sharing a common border or a point. Second, by incorporating variability in altitude, $e_{ic,jc}$, we account for the topology of the landscape. Districts separated by a mountainous terrain, for example, receive a lower connectivity weight, as opposed to districts connected via a flat surface. Third, measuring geographic connectivity based on geodesic distance allows truncation at different distances, enabling the determination of the extent of spillovers. Leveraging this advantage, we construct different weighting matrices by varying the distance considered in defining a district's neighbors. The main specification will use a cutoff of 75km (for reasons made explicit below). In this case, we set the spatial weight as $\omega_{ic,jc} = 1/\tilde{d}_{ic,jc}$ if the geodesic distance $d_{ic,jc}$ is less than 75km, and $\omega_{ic,jc}$=0 otherwise.

4.2.3 Road connectivity

Roads are, arguably, a key form of connectivity between districts. Roads enable non-contiguous districts to connect with one another and allow connectivity to extend to greater distance. Moreover, while the inverse distance matrix assumes that all districts within a given (altitude-adjusted) distance are by default connected, the road network presents an actual mechanism of connectivity, which can lead to a more realistic quantification of spillovers.

To construct connectivity via the road network we obtained data from OpenStreetMap

[16] As an alternative we construct a weighting matrix for geographic connectivity based on contiguity. The contiguity matrix indicates whether districts i and j share a common border or, at least, a common point along their borders. We report estimates based on the contiguity matrix in Table D1 in the Online Appendix. Further, we report estimates based on geodesic distances but without adjustment for the variability in altitude in Table E1 in the Online Appendix.

(OSM).[17] We accessed the OSM data in early 2016 and extracted information about primary (e.g., highways and motorways) and secondary roads for the African continent.[18] We intersect these roads with the district boundary polygons and generate a network graph of the road network.[19] In a first step, the road polylines are split into segments whenever they intersect with a district boundary. For each segment (edge), we then calculate the road travel distance in km between each intersection (node).[20] In the second step, we identify the shortest path on the road segments between each district and calculate the distance on that path. If districts A and B are adjacent and connected via a primary or secondary road, we assign a distance value of 1km. If districts A and B are not adjacent, but connected via the road network, they are assigned the road distance between the closest road and district boundary node of A and the closest road and district boundary node of B (i.e., the road travel distance through all the district that one has to cross to get from district A to district B).

The road connectivity matrix assigns a value equal to the inverse of the road distance in km between districts i and j if they are connected via a primary or secondary road, and 0 if they are not connected. We again construct different weighting matrices by truncating at different distance cutoffs.

4.3 Mining data and instrumental variables

Our identification strategy makes use of cross-sectional information on the location of mining projects and temporal variation in the world prices of the corresponding minerals. We describe the construction of the respective variables in turn.

Our information on mining activity comes from the SNL Minings & Metals database.

[17]OSM is an open-source mapping project where information about roads (and other objects) is crowd-sourced by over two million volunteers worldwide, who can collect data using manual surveys, handheld GPS devices, aerial photography, and other commercial and government sources. (See https://openstreetmap.org for more information and https://geofabrik.de for the shapefiles.) We opted for the OSM instead of the World Bank's African Infrastructure Country Diagnostic (AICD) database because the AICD data does not contain information for countries with Mediterranean coastline as well as Djibouti, Equatorial Guinea, Guinea-Bissau, and Somalia.

[18]Figure A3 in the Online Appendix shows the road network.

[19]The road connectivity analysis between ADM2 polygons was conducted in ArcMap 10.2 using arcpy. The python scripts are available upon request.

[20]If the road starts/ends in a district, we calculate the distance between the start/end point and the intersection.

This database covers 3,487 mining projects across Africa that were active during our sample period. For each project, it contains information about the point location, i.e., the geographic coordinates, and the (potentially multiple) resources extracted at this location.[21]

We use the point locations to assign the mining projects to districts and identify all districts where a mine was active for at least one year during our sample period. Across Africa, 4% of all districts are mining districts. The indicator variable $Mine^r_{ic}$ is equal to one if district i of country c has a mining project that extracts resource r and is active for at least one year during our sample period. Following Berman et al. (2017), the underlying idea is that this time-invariant variable should capture a district's suitability for mining, in particular its geology, rather than endogenous decisions on production or the opening and closing of mines.[22]

Data on world prices of minerals are sourced from the World Bank, IMF, USGS and SNL (see Table A2 in the Online Appendix for more information on the data sources). $Price^r_t$ is the logarithm of the yearly nominal average price of resource r in USD.

4.4 Control variables

Our main time-varying control variable at the district level is $Population_{ic}$. It measures a district's total population (in logs) and is derived based on the population data from the Center for International Earth Science Information Network (CIESIN).

In most specifications, we further control for conflicts using data extracted from the PRIO/Uppsala Armed Conflict Location and Event Database (ACLED). This is a geo-referenced database on dyadic conflict from 1997 to 2015. It includes nine different types of conflict-related events, including battles and violence against civilians as well as some non-violent events. We use the indicator variable $Conflict_{ict}$, which takes a value of one if any conflict-related event occurred in district i in year t, and zero otherwise.

Table 1 provides the descriptive statistics for our key variables.

[21] Figure A4 in the Online Appendix shows the spatial distribution of mining projects across Africa.

[22] Berman et al. (2017) restrict their sample to grid cells where a mine operates in all years or no year. This methodology significantly reduces the number of mining districts in our case and thus weakens the relevance of the instrumental variable.

[Table 1 about here]

5 Empirical strategy

The aim of the empirical analysis is to estimate equation (7) from the theoretical model. By inserting county subscript c and time subscript t, the equation can be written as:

$$l_{ict} = \rho_1 \sum_{j=1}^{J} \omega_{1,ic,jc} l_{jct} + \rho_2 \sum_{j=1}^{J} \omega_{2,ic,jc} l_{jct} + \rho_3 \sum_{j=1}^{J} \omega_{3,ic,jc} l_{jct} + X_{ict} + \varepsilon_{ict} \tag{8}$$

where $\omega_{1,ic,jc}$ is the (ic, jc) cell of the adjacency matrix based on geographic connectivity, $\omega_{2,ic,jc}$ is the (ic, jc) cell of the adjacency matrix based on road connectivity, and $\omega_{3,ic,jc}$ is the (ic, jc) cell of the adjacency matrix based on ethnic connectivity. For the sake of the exposition, we rewrite equation (8) in a more compact form:

$$l_{ict} = \sum_{k=1}^{3} \sum_{j=1}^{J} \rho_k \omega_{k,,ic,jc} l_{jct} + X_{ict} + \varepsilon_{ict}, \tag{9}$$

Denote by $\mathbf{X}_{ict} = \left(X_{ict}^1, ..., X_{ict}^M\right)$ the $(1 \times M)$ vector of time-variant, district-level characteristics and by $\boldsymbol{\beta} = \left(\beta^1, ..., \beta^M\right)^T$ a $(M \times 1)$ vector of parameters. Then, using $Light_{ict}$ to measure the level of economic activity l_{ict} and adding district and country-year fixed effects to equation (9), we get the following econometric specification:

$$Light_{ict} = \sum_{k=1}^{3} \sum_{j=1}^{J} \rho_k \omega_{k,ic,jc} Light_{jct} + \mathbf{X}_{ict} \boldsymbol{\beta} + \alpha_i + CT_{ct} + \epsilon_{ict} \tag{10}$$

where α_i and CT_{ct} are district and country-year fixed effects, respectively, and ϵ_{ict} is an error term that is assumed to be $\epsilon_{ict} \sim N(0, \sigma^2 I_n)$. As is standard in spatial econometrics, we row-normalize the adjacency matrices, i.e., we normalize them so that the sum of each row becomes equal to 1.

The specification in equation (10) assumes that local spillovers to other districts only operate through the spatial lag of the dependent variable. However, it is possible that spillover effects occur due to spatial autoregressive processes in the explanatory variables as well. To account for this, we extend the model in equation (10) to a Spatial Durbin Model by including spatial lags of the explanatory variables, $\omega_{k,ic,jc}X^{m}_{jct}$:

$$Light_{ict} = \sum_{k=1}^{3}\sum_{j=1}^{J}\rho_k\omega_{k,ic,jc}Light_{jct} + \mathbf{X}_{ict}\boldsymbol{\beta} + \sum_{k=1}^{3}\sum_{j=1}^{J}\sum_{m=1}^{M}\rho^{m}_{k}\omega_{k,ic,jc}X^{m}_{jct} + \alpha_i + CT_{ct} + \epsilon_{ict} \tag{11}$$

where ρ^{m}_{k} are the coefficients of the spatial lags.

In the spatial context, spillovers might not only run from district j to i but also from i to j. In addition, economic activity (and therefore $Light_{jct}$) might also be simultaneously determined by other unobserved shocks. Therefore, estimating equation (11) using OLS can yield biased and inconsistent estimates.

Traditionally, scholars have either used a quasi-maximum likelihood estimation procedure (e.g., Anselin, 1988, Lee, 2004) or a GMM instrumental variable (IV) approach that uses internal instruments (including higher order spatial lags of contiguity matrices) and estimates the model using a standard 2SLS approach (e.g., Kelejian and Prucha, 1998, Kelejian and Robinson, 1993). However, Gibbons and Overman (2012) criticize both approaches because the validity assumption is often unlikely to hold. They propose the use of exogenous instruments (as opposed to internal instruments) in a standard spatial IV specification.

We follow their suggestion and estimate a 2SLS model that exploits exogenous variation in the economic value of mineral resources in the mining districts. The idea is that more valuable mining districts increase spillover effects such that the level of economic activity in neighboring districts will be positively affected. In particular, in the first stage we use interaction terms between time-invariant indicators of mining activity and time-variant exogenous world prices for minerals as instrumental variables:

$$Light_{jct} = \gamma MP_{jct} + \mathbf{X}_{jct}\boldsymbol{\beta} + \sum_{k=1}^{3}\sum_{i=1}^{J}\sum_{m=1}^{M}\rho^{m}_{k}\omega_{k,jc,ic}X^{m}_{ict} + \alpha_j + CT_{ct} + u_{jct} \tag{12}$$

where

$$MP_{jct} \equiv \frac{1}{R_{jc}}\sum_{r=1}^{R_{jc}}(Mine^{r}_{jc} \times Price^{r}_{t}) \tag{13}$$

with $R_{jc} = \sum_r Mine^r_{jc}$ being the number of different minerals extracted in district j of country c. Hence, for each mining region, this instrumental variable captures the average of the world prices (in logs) of all the minerals that are extracted in this district at some time during the sample period. For all other districts, this instrumental variable is zero.

This IV strategy was used by Berman et al. (2017), who focus on the effect of exogenous variation in the economic value of mines on the likelihood of local conflict. The use of the time-invariant indicator $Mine^r_{jc}$ addresses the potential endogeneity between economic activity and mining activity. Hence, our identification strategy operates as a differences-in-differences estimator, which exploits between-variation in a district's suitability for extracting specific minerals, combined with the exogenous time variation in the world price of these minerals.

For this instrument to be relevant, it is key that fluctuations in world mineral prices have a first-order effect on the mining districts' economies. Even though only 4% of all districts are mining districts, minerals account for a large proportion of export earnings in many African countries, especially strategically important minerals such as diamonds, gold, uranium and bauxite. For example, in countries such as Botswana and Congo, minerals account for over 80% of export income (USGS, 2014). Given the small number of mining districts and the importance of minerals at the country level, it seems plausible to assume that fluctuations in world mineral prices are relevant for mining districts.

With respect to the instrument's validity, our identification strategy rests upon the assumption that price shocks in the mining sector in district j affects $Light_{ict}$ in district i only through $Light_{jct}$. We take a number of measures to mitigate the risk that the exclusion restriction is violated. First, we include district fixed effects in equation (12), which absorbs all time-invariant characteristics at the district level, including suitability for mining activity. The vector of country-year fixed effects accounts for any time-variant factors that might simultaneously drive mineral prices and aggregated economic development. Second, the work by Berman et al. (2017) shows that mining activity could lead to increased conflict as parties dispute over ownership of lucrative mines. This, in turn, could adversely affect economic activity. Therefore, we control for district-level conflict events in our specifications. Third, the exclusion restriction also relies on the assumption of exogeneity of world prices, i.e., no single district can affect the world price of a commodity. For this reason, we conduct a robustness check of our specification by excluding countries in the top ten list of producers for any mineral.

An analysis of spatial spillovers at the subnational level also requires accounting for potential spatial clustering in the standard errors. Therefore, all our specifications use the method proposed by Conley (1999) and Hsiang (2010) to allow for both cross-sectional spatial clustering and location-specific serial correlation in the standard errors.[23]

Our setting implies that we estimate the local average treatment effect (LATE) of a particular type of economic shock, i.e., increases in mineral wealth, and for a particular subset of districts, i.e., districts within a certain proximity to mineral districts. Income shocks related to windfalls in natural resource rents and their resulting spatial spillovers may have very particular effects on consumption, investment and government expenditure. Moreover, the subset of districts in Africa that drive our results might systematically differ from the average African district. Therefore, one needs to be careful when drawing more general policy conclusions based on the estimated spatial spillover effects.

In addition, it is a priori unclear whether mining-related income shocks only generate positive spillover effects for other districts. Windfalls in natural resource rents in one district could lead to migration of labor and capital from other, connected, districts into the mining district. A mining boom could also lead the government to shift public expenditure and infrastructure projects away from nearby districts into the mining district. As such, the estimated parameters of the spatial lags represent the net effect from mining-related economic shocks in connected districts.

[23]This procedure was implemented in Stata 14 using Thiemo Fetzer's "reg2hdfespatial" command, which extends the routine from Hsiang (2010) to multidimensional fixed effects.

6 Estimation results

6.1 Main results

Table 2 presents our estimates of equations (11) and (12).[24]

[Table 2 about here]

We start with specifications that include each weighting matrix individually. First, we analyze the spillover effects using the spatial weighting matrix based on ethnic connectivity. Column (1) provides the results of the OLS estimates, while column (2) provides the comparable IV estimates. Both columns include district fixed effects and country-year fixed effects to filter out time-invariant district-specific features and country-specific time-varying characteristics. The OLS estimates show that coefficient ρ_1, i.e., the coefficient on $Ethnicity\,W\,Light_{jct}$, is positive and statistically significant at the 1% level, suggesting that economic activity in districts inhabited by the same ethnic group indeed has a positive impact on economic activity in district i. However, endogeneity concerns restrict us from drawing causal inference based on these OLS estimates. In column (2), we thus present comparable IV estimates. The coefficient of interest in the *first stage* of the IV estimate, γ, is positive and statistically significant at the 1% level. This, along with the high F statistics of the first stage, indicates that our instrumental variable is a strong predictor of economic activity in district j. The coefficient of interest of the *second stage*, ρ_1, is positive and statistically significant at the 10% level, suggesting that economic activity in districts inhabited by the same ethnic group may exert a positive causal impact on a district's own economic activity. Moreover, coefficient ρ_1 is lower in column (2) than in column (1), indicating that OLS leads us to over-estimate the true causal effect.

Second, in columns (3) and (4), we focus on geographic connectivity and therefore use the weighting matrix based on the inverse of the altitude-adjusted geodesic distance between districts i and j, truncating the matrix at 75km. The coefficient of interest,

[24]Table 2 only reports the coefficients on the variables of main interest to improve the readability of the table. Table C1 in the Online Appendix reports the coefficients on the control variables as well.

ρ_2, is positive and statistically significant at the 1% level in both the OLS and the IV estimates. As in Figure 1, the coefficient of interest from the IV estimates declines in magnitude in the cutoff distance and become statistically insignificant for cutoff distances beyond 75km.

[Figure 1 about here]

Third, in columns (5) and (6), we focus on road connectivity based on our matrix of inverse road distances, again truncating the matrix at 75km. The coefficient of interest, ρ_3, is positive and statistically significant at the 1% level in both the OLS and the IV estimates. As in Figure 1, the coefficient of interest from the IV estimates would remain positive and statistically significant for cutoff distances of 100km and beyond, indicating that the extent of positive spillovers spreads farther when focusing on actual transport infrastructure rather than just geography.

Finally, the last two columns of Table 2 include spatial lags with weights based on ethnic, geographic *and* road connectivity. That is, they report our estimates of the whole model as described in equations (11) and (12). We observe that three coefficients of interest, i.e., ρ_1, ρ_2 and ρ_3, are all positive and statistically significant at the 1% level in the OLS estimates. The same holds true for the IV estimates except that the spatial spillovers via purely geographic connectivity are only statistically significant at the 10% level. The coefficient estimates further suggest that geographic connectivity tends to be less important than ethnic and road connectivity.

Figure 1 presents the coefficient estimates for ρ_2 and ρ_3, i.e., the coefficients on $Inv\ Dist\ W\ Light_{jct}$ and $Inv\ Road\ W\ Light_{jct}$, and the corresponding 90% confidence intervals from re-running our main IV specification (corresponding to column (8) of Table 2) for various cutoff distances. Spatial spillovers via purely geographic connectivity are decreasing in the cutoff distance and become statistically insignificant for cutoffs above 75km, while spatial spillovers via the road network remain large in magnitude and statistically significant even for considerably larger cutoff distances. For the subsequent analysis, we use IV estimates that are based on the largest cutoff distance at which the three coefficients of interest, i.e., ρ_1, ρ_2 and ρ_3, are all positive and statistically significant at the

10% level. That is, we use the estimates from column (8) in Table 2, where the cutoff distance is at 75km.

To better interpret the magnitude of the coefficients in this specification, we provide a simple example with three districts, labeled 1, 2 and 3. First, however, let us consider a model with only one adjacency matrix $\mathbf{\Omega}$. Denote the initial matrix by $\widetilde{\mathbf{\Omega}}$ and the row-normalized one by $\mathbf{\Omega}$. Assume that the network is *complete*. We have:

$$\widetilde{\mathbf{\Omega}} = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix} \text{ so that } \mathbf{\Omega} = \begin{pmatrix} 0 & 1/2 & 1/2 \\ 1/2 & 0 & 1/2 \\ 1/2 & 1/2 & 0 \end{pmatrix}$$

Assume $\rho = 0.271$ (which corresponds to the estimated ρ_1 for the ethnic network in column (2) of Table 2) so that $\rho = 0.271 < \mu_1(\mathbf{\Omega}) = 1$. Then, given the districts' observable and unobservable characteristics, a 10% increase of the nighttime lights in district $i = 1, 2, 3$ increases the nighttime lights in each of the other two districts by 1.355%.

Consider, now, the case of three adjacency matrices $\mathbf{\Omega}_1$, $\mathbf{\Omega}_2$ and $\mathbf{\Omega}_3$ and assume that the networks are different so that each row-normalized network is equal to:

$$\mathbf{\Omega}_1 = \begin{pmatrix} 0 & 1/2 & 1/2 \\ 1/2 & 0 & 1/2 \\ 1/2 & 1/2 & 0 \end{pmatrix}, \mathbf{\Omega}_2 = \begin{pmatrix} 0 & 1/2 & 1/2 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix} \text{ and } \mathbf{\Omega}_3 = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \tag{14}$$

$\mathbf{\Omega}_1$ represents an ethnicity network in which all districts share the same ethnicity; $\mathbf{\Omega}_2$ is a geographic network in which the geodesic distance between district 1 and each of the other districts is within 75km, whereas the distance between districts 2 and 3 exceeds 75km; and $\mathbf{\Omega}_3$ is a road network with a single road between districts 1 and 2.[25] Using the estimates from column (8) of Table 2, assume $\rho_1 = 0.364$, $\rho_2 = 0.162$ and $\rho_3 = 0.446$. It

[25] This is a simple theoretical example. In the data, the adjacency matrices $\mathbf{\Omega}_2$ and $\mathbf{\Omega}_3$ are weighted by the inverse distance between the two districts.

is easily verified that

$$\rho_1 \mathbf{\Omega}_1 + \rho_2 \mathbf{\Omega}_2 + \rho_3 \mathbf{\Omega}_3 = \begin{pmatrix} 0 & 0.709 & 0.263 \\ 0.790 & 0 & 0.182 \\ 0.344 & 0.182 & 0 \end{pmatrix}$$

so that

$$\mu_1 \left(\rho_1 \mathbf{\Omega}_1 + \rho_2 \mathbf{\Omega}_2 + \rho_3 \mathbf{\Omega}_3\right) = 0.881 < 1$$

Let us now interpret equation (7). For district 1, we have:

$$l_1 = (0.364 + 0.162) \left(\frac{l_2 + l_3}{2}\right) + 0.446\, l_2 + X_1 + \varepsilon_1 = 0.709\, l_2 + 0.263\, l_3 + X_1 + \varepsilon_1$$

Similarly, for the two other districts, we obtain:

$$\begin{aligned} l_2 &= 0.364 \left(\frac{l_1 + l_3}{2}\right) + (0.162 + 0.446)\, l_1 + X_2 + \varepsilon_2 = 0.790\, l_1 + 0.182\, l_3 + X_2 + \varepsilon_2 \\ l_3 &= 0.364 \left(\frac{l_1 + l_2}{2}\right) + 0.162\, l_1 + X_3 + \varepsilon_3 = 0.344\, l_1 + 0.182\, l_2 + X_3 + \varepsilon_3 \end{aligned}$$

We can now interpret the different coefficients as follows. Given the observable and unobservable characteristics of districts 2 and 3, a 10% increase of the nighttime lights in district 1 increases the nighttime lights by 7.90% and 3.44% in districts 2 and 3, respectively. The increase in nighttime lights is larger in district 2 because it is better connected to district 1 due to the road connecting these two districts.

6.2 Robustness checks

We perform a number of robustness checks, the results of which are presented in the Online Appendix. Let us briefly discuss these robustness checks.

First, our main results rely purely on spatial lags and assume that spatial spillovers occur in the contemporary period. One could, however, argue that spillovers may occur in the future periods. Therefore, in Table F1 in the Online Appendix, we add a temporal lag to the spatial lag of the explanatory variable. Results remain quantitatively similar.

Second, in our IV estimates, we exploit the variation of world mineral prices as a source of exogenous shocks, which is then propagated amongst neighbors based on different levels of connectivity. Our identification relies on the assumption that mining activity in a single unit does not influence world mineral prices. Given that our units are subnational districts, this assumption appears reasonable. Nevertheless, in Table G1 in the Online Appendix, we exclude the districts which belong to countries that are among the top ten producers for any mineral under consideration. Results remain quantitatively similar, but the impact of geographic connectivity decreases slightly.

Finally, we show that our results are not driven by fiscal spillovers. Fiscal spillovers would occur if non-resource-extractive districts benefit from economic activity in resource-extractive districts belonging to the same province purely because government revenues get channeled to resource-rich provinces. To control for fiscal spillovers, we add an additional connectivity matrix that captures whether two districts belong to the same province. The results are reported in Table H1 in the Online Appendix. They suggest that the spatial lag related to this new connectivity matrix matters as well and, therefore, that fiscal spillovers may be present. More importantly for our purpose, we see that the spatial lags of our three main connectivity matrices remain quantitatively similar even when controlling for fiscal spillovers.

7 Most central districts

We now present different centrality measures by separating those that are not microfounded from those that are. Using the results of the previous sections, especially the estimation of the spillover effects, we are able to calculate these centrality measures and determine the districts that play a key role in African economies due to their connectivity.

7.1 Theory: Different definitions of node centralities

7.1.1 Non micro-founded centrality measures

There are different centrality measures (see Jackson, 2008, for an overview). We provide the definition of the two most commonly used individual-level measures of network centrality: (*i*) betweenness centrality and (*ii*) eigenvector centrality.

The *betweenness centrality*, $C_i^{BE}(\boldsymbol{\omega})$, describes how well located an individual district in the network in terms of the number of shortest paths between other districts that run through it. Denote the number of shortest paths between districts j and k that district i lies on as $P_i(jk)$, and let $P(jk)$ denote the total number of shortest paths between districts j and k. The ratio $P_i(jk)/P(jk)$ tells us how important district i is for connecting districts j and k to each other. Averaging across all possible jk pairs gives us the betweenness centrality measure of district i:

$$C_i^{BE}(\boldsymbol{\omega}) = \sum_{j \neq k : i \notin \{j,k\}} \frac{P_i(jk)/P(jk)}{(n-1)(n-2)/2}$$

It has values in $[0, 1]$.

The *eigenvector centrality*, $C_i^E(\boldsymbol{\omega})$, is defined using the following recursive formula:

$$C_i^E(\boldsymbol{\omega}) = \frac{1}{\mu_1(\boldsymbol{\Omega})} \sum_{j=1}^{n} g_{ij} C_j^E(\boldsymbol{\omega}) \tag{15}$$

where $\mu_1(\boldsymbol{\Omega})$ is the largest eigenvalue of $\boldsymbol{\Omega}$. According to the Perron-Frobenius theorem, using the largest eigenvalue guarantees that $C_i^E(\boldsymbol{\omega})$ is always positive. In matrix form, we have:

$$\mu_1(\boldsymbol{\Omega})\, \mathbf{C}^E(\boldsymbol{\omega}) = \boldsymbol{\Omega}\mathbf{C}^{\mathbf{E}}(\boldsymbol{\omega}) \tag{16}$$

The eigenvector centrality of a district assigns relative scores to all districts in the network based on the concept that connections to high-scoring districts contribute more to the score of the district in question than equal connections to low-scoring agents.

7.1.2 Micro-founded centrality measure: the Katz-Bonacich centrality

In our theoretical model (Section 3), we have shown that the unique Nash equilibrium of our game in terms of nighttime lights is equal to the *Katz-Bonacich centrality* of the district. As a result, the level of nighttime lights in district i is given by its weighted Katz-Bonacich centrality, defined in (5), i.e.

$$\mathbf{C}^{BO}_{\mathbf{X}+\boldsymbol{\varepsilon}}(\rho, \boldsymbol{\omega}) =: (\mathbf{I} - \rho\boldsymbol{\Omega})^{-1} (\mathbf{X} + \boldsymbol{\varepsilon})$$

Importantly, in order to calculate the Katz-Bonacich centrality of each district i, we need to know the value of ρ. We will use the estimated value of ρ (IV estimates). We also need to check that the condition $\rho\mu_1(\boldsymbol{\Omega}) < 1$ is satisfied.

7.1.3 The intercentrality measure (key player)

The Katz-Bonacich centrality was based on the outcome of a Nash equilibrium. Let us now focus on the planner's problem. The key question is as follows: Which district, once removed, will reduce total nighttime lights the most? In other words, which district is the key player? Ballester et al. (2006) have proposed a measure (the *key-player centrality*) that answers this question.[26] For that, consider the game with strategic complements developed in the theory section (Section 3) for which the utility is given by (3), and denote $L^*(\boldsymbol{\omega}) = \sum_{i=1}^{n} l_i^*$ the total equilibrium level of activity in network $\boldsymbol{\omega}$, where, assuming $\phi\mu_1(\boldsymbol{\omega}) < 1$, l_i^* is the Nash equilibrium effort given by (4) or (5). Also, denote by $\boldsymbol{\omega}^{[-i]}$ the network $\boldsymbol{\omega}$ without district i. Then, in order to determine the *key player*, the planner will solve the following problem:

$$\max\{L^*(\boldsymbol{\omega}) - L^*(\boldsymbol{\omega}^{[-i]}) \mid i = 1, ..., n\} \tag{17}$$

Then, the *intercentrality* or the *key-player centrality* $C_i^{KP}(\rho, \boldsymbol{\omega})$ of district i is defined as follows:

$$C^{KP}_{i,u_i}(\rho, \boldsymbol{\omega}) = \frac{C^{BO}_{i,u_i}(\rho, \boldsymbol{\omega}) \sum_j m_{ji}(\rho, \boldsymbol{\omega})}{m_{ii}(\rho, \boldsymbol{\omega})} \tag{18}$$

[26]For an overview of the way the key player is determined in different areas, see Zenou (2016).

where $C^{BO}_{i,u_i}(\rho, \boldsymbol{\omega})$ is the weighted Katz-Bonacich centrality of district i (see equation (5)) and $m_{ij}(\rho, \boldsymbol{\omega})$ is the (i, j) cell of the matrix $\mathbf{M}(\rho, \boldsymbol{\omega}) = (\mathbf{I} - \rho\boldsymbol{\Omega})^{-1}$. Ballester et al. (2006, 2010) have shown that the district i^* that solves (17) is the key player if and only if i^* is the district with the highest *intercentrality* in $\boldsymbol{\omega}$, that is, $C^{KP}_{i^*,u_i}(\rho, \boldsymbol{\omega}) \geq C^{KP}_{i,u_i}(\rho, \boldsymbol{\omega})$, for all $i = 1, ..., n$. The intercentrality measure (18) of district i is the sum of i's centrality measures in $\boldsymbol{\omega}$, and its contribution to the centrality measure of every other district $j \neq i$ also in $\boldsymbol{\omega}$. It accounts both for one's exposure to the rest of the group and for one's contribution to every other exposure. This means that the key player i^* in network $\boldsymbol{\omega}$ is given by $i^* = \arg\max_i C^{KP}_{i,u_i}(\rho, \boldsymbol{\omega})$, where[27]

$$C^{KP}_{i^*,u_i}(\rho, \boldsymbol{\omega}) = L^*(\boldsymbol{\omega}) - L^*\left(\boldsymbol{\omega}^{[-i]}\right). \tag{19}$$

7.2 Empirical results

We compute these four different centrality measures for all 5,444 districts from the 53 African countries in our sample. Table 3 presents information on the ten most central districts (according to the key-player centrality) for two large countries that feature prominently in the literature: Nigeria and Kenya.[28]

[Table 3 about here]

Column (4) of Table 3 presents the main ranking of interest, i.e., the key-player ranking based on the geographic network, the road network *and* the ethnicity network. The underlying computation thus uses the coefficient estimates, in particular the estimated ρ's, reported in column (8) of Table 2. The district with the highest key-player centrality is Ikeja, which is part of the Lagos metropolitan area (often simply called Lagos) and the capital of Lagos State (province). Lagos is the primate city of Nigeria and its economic

[27] Ballester et al. (2006) define the key player in (18) only when the adjacency matrix $\boldsymbol{\Omega}$ is not row-normalized. Since we use row-normalized adjacency matrices when estimating the ρs, we will determine the key player numerically based on its definition in (19).

[28] Table I1 in the Online Appendix presents information on the ten most central districts for the five most populous African countries besides Nigeria. These countries are (in decreasing order of their population): Ethiopia, Egypt, the Democratic Republic of the Congo, South Africa, and Tanzania. The rankings for all other African countries are available upon request.

hub. Seven other districts belonging to the top-ten key districts of Nigeria are also part of Lagos State. The two remaining districts in the key-player ranking belong to the Kano metropolitan area (often simply Kano) in Kano State. Kano is the second largest metropolitan area in Nigeria and the economic hub of the country's northern part.

Nigeria is no exception in this respect. The key district in Kenya is Nairobi, which is the capital and the primate city. It is followed by Mombassa, which is Kenya's second largest city and home to Kenya's largest seaport. The key districts encompass or are part of the primate city in many other African countries as well, including Ethiopia (Addis Ababa) and South Africa (Johannesburg). The overall pattern suggests that *primate cities* tend to be the key districts for economic development in Africa. This finding resonates with findings on the importance of primate cities for development. Ades and Glaeser (1995) and Henderson (2002) point out the importance of primate cities in general, while Storeygard (2016) empirically highlights the importance of primate cities in Africa. In addition, Henderson et al. (2017) document high spatial inequality in late-developing countries, with one or a few urban areas being much more economically developed than the rest of these countries. The finding that primate cities are the key districts suggests that they are not only characterized by higher local economic activity but that they also tend to cause more spatial economic spillovers than other districts.

Column (5) in Table 3 shows the ranking for the Katz-Bonacich centrality, again based on the estimates taking the geographic network, the road network and the ethnicity network into account. We see that the districts that rank high in terms of key-player centrality also tend to rank high in terms of Katz-Bonacich centrality in Nigeria, but not in Kenya. This is because Katz-Bonacich and key-player centralities capture different aspects of centrality. The former is a recursive measure highlighting the importance of being connected to central districts while the latter is a welfare measure that also takes into account the negative impact of cutting links on neighboring districts.

Columns (6) and (7) show the rankings for the two other centrality measures: betweenness and eigenvector centrality. Looking at Nigeria, we see that the districts from Lagos State that are top ranked in terms of key-player centrality tend to rank poorly in terms of these alternative centrality measures. This is not surprising given that the betweenness and eigenvector centralities are pure topological measures, which capture either the number of paths that go through a district (betweenness centrality) or the links to other central districts (eigenvector centrality), and Lagos State is situated at the coast in the country's south-east bordering Benin. For other countries, including Kenya, the districts that rank high in terms of key-player centrality also tend to rank high in terms of eigenvector centrality, but less so in terms of betweenness centrality. These findings suggest that it is not easy to determine the key districts with simple topological measures since the key-player centrality depends on the districts' local economic activity, i.e., their nighttime lights, *and* the spatial spillovers they generate to connected districts.

Columns (8)-(10) also give rankings of key-player centrality, but in each of these columns we compute the ranking based on the coefficient estimates from regressions including one network only. Ikeja, which is top ranked in Nigeria when looking at all three networks jointly, is also top ranked when focusing just on the road network (column (9)). It is also highly ranked when focusing just on the ethnicity network (column (8)) or the geographic network (column (10)). More generally, we see that all Nigerian districts that rank high in overall key-player centrality also rank high in any type of single-network key-player centrality. This pattern holds true for many other countries, including Kenya. This suggests that most key districts are important due to their geographic, ethnic *and* road connectivity. For many countries, including Nigeria but not Kenya, the overall key-player centrality is most highly correlated with the key-player centrality based on the road network, which indicates that road connectivity may be of particular importance.

8 Policy experiments

The key-player rankings are valuable in showing which districts are most economically important. However, relying on key-player rankings for policymaking has two disadvantages. First, the key districts are typically economically active and well connected while policymakers may be interested in the benefits from either promoting local economic activity or improving the network structure, e.g., by building roads. Second, key-player rankings capture the total effect of having a particular district while policymakers are generally better advised to focus on the “marginal” effects of increasing local economic activity or improving the network structure. In this section, we thus illustrate how our approach allows for counterfactual exercises that can inform policymakers.

At a general level, there are two types of counterfactual exercises that we can pursue. First, we can study how changes within one or more districts propagate through the geographic, ethnic and road networks and, thereby, how these changes affect all other districts. Such an exercise provides insights that go beyond the sometimes more narrow policy evaluations that only focus on the local benefits of local policies. In Section 8.1, we perform such an analysis by computing the aggregate effect of increasing economic activity, i.e., nighttime lights, in each single district, one at a time. The second type of counterfactual exercise is based on changing the network structure. In Section 8.2, we study the aggregate economic effect of linking neighboring districts by a primary or secondary road.

A few comments are in order before presenting these two policy experiments: First, the socially optimal location of a development project depends on costs and benefits, and our approach does not take into account the fact that the costs of implementing a certain project or building a certain road may differ across districts. Second, it is impossible to compare the benefits of different development projects or different project locations without an underlying social welfare function. Here, as in the previous section, we (implicitly) measure social welfare in a district by the logarithm of the average nighttime light pixel value, and we give equal weight to all districts when computing aggregate social welfare. Needless to say, one could apply our approach using alternative social welfare functions.

8.1 Policy experiment 1: Increasing local economic activity

The first policy experiment consists in increasing economic activity, i.e., nighttime lights, in each district, one at a time. This experiment may mimic large public investments within the given districts.

We proceed as follows: First, we add the value of 10 to the average nighttime light pixel value in the treatment district, which corresponds to an increase of one standard deviation. Second, we take the logarithm of the now higher average nighttime light pixel value and recalculate the spatially lagged dependent variables with the new values, but keep the estimated ρ's from Table 2 (column (8)). Third, we recalculate the predicted nighttime lights (in logs) for each African district and compute the sum across all African districts. Fourth, we compare this sum, which includes the increase in nighttime lights in one district and the subsequent spatial spillovers, with the sum of the district-level nighttime lights (in logs) across Africa from the baseline, i.e., in the absence of any policy intervention. We repeat this exercise for each of the 5,944 districts.[29]

Table 4 presents the ten districts in Nigeria and Kenya where this counterfactual increase in economic activity would have the largest overall impact.[30]

[**Table 4 about here**]

There are various types of districts where the overall impact is particularly high. First, for both Nigeria and Kenya, the top-ten list includes districts that have high key-player centrality because they are economically active and well connected, such as the districts from Lagos State. Second, in Nigeria, the top-ten list includes some districts in Bayelsa and Delta, which are both oil-producing states in the Niger Delta. These districts are economically quite active and well connected but have a low key-player centrality because they are conflict-ridden. An increase in economic activity, however, has a positive impact exactly because of the dense network in the Niger Delta. Third, in Kenya, the top-ten list includes three poor districts that rank at the bottom in terms of key-player centrality because of their low nighttime light values. In these districts, an increase in absolute nighttime lights leads to a large overall impact, mainly because we measure economic benefits using the logarithm of nighttime lights. Our use of logged values implies that an increase in economic activity is more valuable in poorer districts.

[29] In all steps and for all districts, we average the variables used over the sample period.

[30] Table J1 in the Online Appendix presents the same ranking for the five most populous African countries besides Nigeria.

8.2 Policy experiment 2: Improving road connectivity

The second policy experiment consists in increasing the road connectivity of each district, again one at a time. This experiment mimics improvements in the road infrastructure.

We proceed as follows: First, for any given district, we determine the set of contiguous districts with which the given district is not yet linked via a primary or secondary road, and we then choose the district with the highest average nighttime light value from this set of districts. Second, we add a link between these two districts (with a value of 1) in the non-normalized road connectivity matrix. Third, we re-normalize the road connectivity matrix and then recalculate the spatially lagged dependent and independent variables using this new matrix. Fourth, we recalculate the predicted nighttime lights (in logs) for each African district and compute the sum across all African districts. Finally, we again compare this sum with the sum of nighttime lights (in logs) across Africa from the baseline. We repeat this exercise for each of the 5,944 districts to identify, for each country, the districts that have the largest overall impact when improving their road connectivity.

Table 5 presents the ten districts in Nigeria and Kenya where this counterfactual improvement of the road connectivity would have the largest overall impact.[31]

[Table 5 about here]

The top-ten districts in Nigeria are all in the Niger Delta. The top two, Boony and Orika, are both islands with intense nighttime lights but poor road connectivity. Improving their road connectivity would lead to positive economic spillovers from these two districts to other districts in the Niger Delta and beyond. The top-ten list for Kenya again includes many districts with high key-player centrality. In addition, it includes some very dark/poor districts (Machakos, Wajir and Meru), where an increase in economic activity from better road connectivity would be particularly valuable.

[31] Table K1 in the Online Appendix presents the same ranking for the five most populous African countries besides Nigeria.

9 Concluding remarks

In this paper, we study the role of geographical, ethnic and road networks for the spatial diffusion of local economic shocks. We first develop a simple network model that describes how a district's level of prosperity is determined by the district's observable and unobservable characteristics, the total activity level of the district, and the spillover effects of the activity of neighboring districts. Using a panel dataset of 5,944 districts from 53 African countries over the period 1997–2013, we estimate the model's first-order conditions using an econometric model of spatial spillovers. To identify the causal effect of spatial diffusion, we exploit cross-sectional variation in the location of mineral mines and time variation in world mineral prices.

We then use the estimated parameters to calculate various network centrality measures for each district. In particular, we calculate the key-player centralities by performing a counterfactual exercise, which consists of removing a district and all its direct "links" (in the adjacency matrices representing the geographical, ethnic and road networks) from the map of Africa. We can thereby identify the economic loss to an average African district if any single district were "wiped out." We find that primate cities are indeed key for a country's economic development due to their high economic activity and good connectivity, suggesting that policies focusing on the major cities are justified from a growth perspective.

We go one step further by conducting two more counterfactual exercises based on our estimates and the underlying network structure. The first looks at the aggregate effects of increasing economic activity in each district, one at a time, and the second at the aggregate effects from improving each district's road connectivity. These counterfactual exercises illustrate the potential of our approach for informing policymakers.

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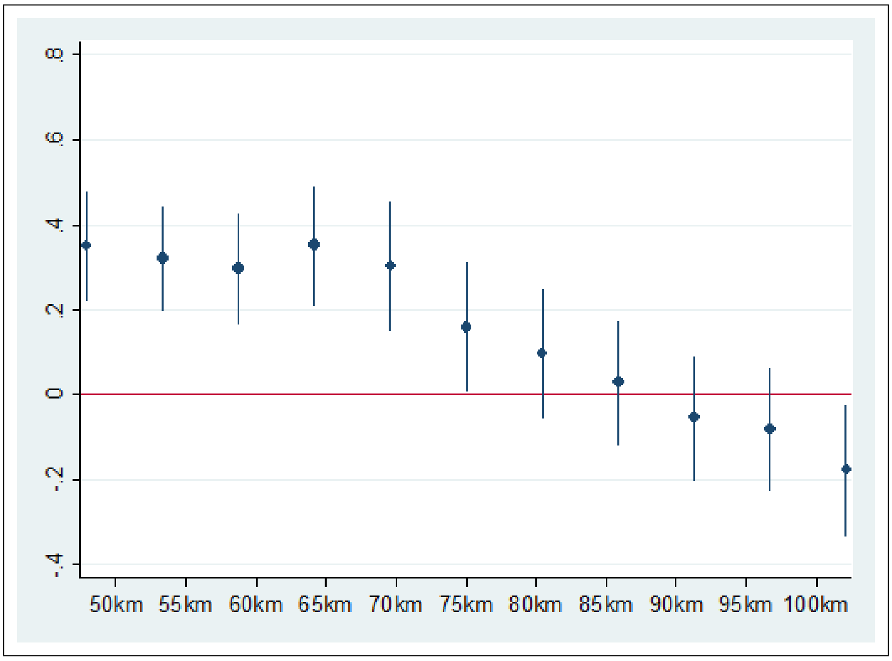
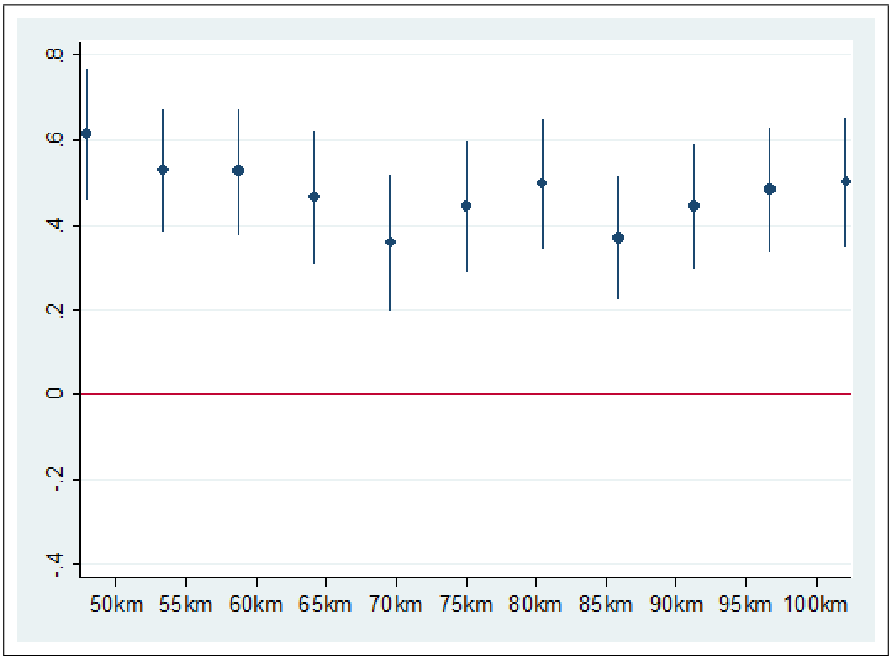
Figures and Tables

Figure 1: Coefficients on the Spatial Lag of the Dependent Variable



(a) Coefficient on $Inv\,Dist\,W\,Light_{jct}$



(b) Coefficient on $Inv\,Road\,W\,Light_{jct}$

Notes: Dots show the coefficients on $Inv\,Dist\,W\,Light_{jct}$ and $Inv\,Road\,W\,Light_{jct}$ from the second-stage regression reported in Table 2, column (8), when applying different distance cutoffs for the weighting matrices for geographic and road connectivity. The vertical lines show the 90% confidence interval based on Conley (1999) standard errors, allowing for spatial correlation up to the distance cutoff and for infinite serial correlation.

Table 1: Descriptive statistics

Variable	**Observations**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
$Light_{ict}$	101,048	-1.257	2.703	-4.605	4.143
$Conflict_{ict}$	101,048	0.126	0.332	0	1
$Population_{ict}$	101,048	10.782	1.799	3.423	16.204
MP_{ict}	101,048	0.218	1.233	-2.161	11.133

Notes: See Section 4 for the definitions of all variables. Note that $Light_{ict}$ and $Population_{ict}$ are in logs.

Table 2: Connectivity based on ethnicity, geography and roads

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	Dependent variable: $Light_{ict}$							
Ethnicity W $Light_{jct}$	0.552***	0.271*					0.156***	0.364***
	(0.013)	(0.149)					(0.011)	(0.092)
Inv Dist W $Light_{jct}$			0.563***	0.535***			0.255***	0.162*
			(0.010)	(0.107)			(0.010)	(0.094)
Inv Road W $Light_{jct}$					0.557***	0.288***	0.392***	0.446***
					(0.010)	(0.110)	(0.011)	(0.095)
First stage:	Dependent variable: $Light_{jct}$							
MP_{jct}		0.121***		0.119***		0.123***		0.122***
		(0.013)		(0.013)		(0.013)		(0.013)
First-stage F-stat		87.98		80.89		85.99		85.16
Observations	101,048	101,048	101,048	101,048	101,048	101,048	101,048	101,048
District FE	YES	YES	YES	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES	YES	YES	YES
Additional controls	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Even columns report standard fixed effects regressions with district and country-year fixed effects, and odd columns report IV estimates. See Section 4 for the definitions of all variables. *Ethnicity W* $Light_{jct}$ is weighted $Light_{jct}$, with weights based on the row-normalized ethnicity matrix. *Inv Dist W* $Light_{jct}$ (*Inv Road W* $Light_{jct}$) is weighted $Light_{jct}$, with weights based on the row-normalized matrix of the inverse altitude-adjusted geodesic distances (inverse road distances) truncated at 75km. Additional control variables are population, conflict and MP_{ict} as well as weighted population and conflict in districts $j \neq i$. MP_{jct} is an interaction term based on cross-sectional information on the location of mines and time-varying world prices of the commodities produced in these mines (see equation (13)). The first stage further includes the control variables indicated in equation (12). Conley (1999) standard errors are in parentheses, allowing for spatial correlation up to 75km and for infinite serial correlation. ***, **, * indicate significance at the 1, 5 and 10% level, respectively.

Table 3: Top-Ten Key Player Rankings

(1) Country	(2) Province	(3) District Rank	(4) Overall KP Rank	(5) Overall Katz-Bon Rank	(6) Overall Betw. Rank	(7) Overall Eig. Rank	(8) Ethnicity KP Rank	(9) Road KP Rank	(10) Inv.Dist KP Rank
Nigeria									
Nigeria	Lagos	Ikeja	1	25	644	428	4	1	2
Nigeria	Kano	Fagge	2	107	54	492	5	4	7
Nigeria	Lagos	LagosIsland	3	11	691	423	32	3	17
Nigeria	Lagos	Agege	4	26	515	427	8	13	8
Nigeria	Lagos	Mainland	5	9	687	430	1	2	1
Nigeria	Kano	Tarauni	6	108	555	492	14	9	11
Nigeria	Lagos	Surulere	7	12	642	430	3	6	6
Nigeria	Lagos	Ajeromi/Ifelodun	8	8	605	439	6	14	10
Nigeria	Lagos	Shomolu	9	13	688	430	2	5	3
Nigeria	Lagos	Amuwo Odofin	10	20	518	441	26	8	12
Kenya									
Kenya	Nairobi	Nairobi	1	26	41	4	1	1	1
Kenya	Coast	Mombasa	2	41	45	9	2	2	2
Kenya	Coast	Kwale	3	33	9	9	17	48	3
Kenya	Rift Valley	Nakuru	4	23	3	26	8	5	5
Kenya	Central	Kiambu	5	24	40	4	4	3	4
Kenya	Rift Valley	Narok	6	18	12	30	23	42	34
Kenya	Central	Murang'a	7	21	29	3	5	6	7
Kenya	Eastern	Machakos	8	30	17	6	9	46	6
Kenya	Central	Nyeri	9	22	19	25	7	7	8
Kenya	Central	Kirinyaga	10	20	31	7	19	9	11

Notes: Overall KP Rank is based on the ρs estimated in column (8) of Table 2. Overall Katz-Bonacich Rank is based on the ρs estimated in column (8) of Table 2 and a weighting vector of 1. Ethnicity KP Rank is based on ρ_1 estimated in column (2) of Table 2. Inv.Dist KP Rank is based on ρ_2 estimated in column (4) of Table 2. Road KP Rank is based on ρ_3 estimated in column (6) Table 2. Nigeria has 775 districts, and Kenya has 48 districts.

Table 4: Top-Ten Rankings from Policy Experiment 1 – Nighttime Lights

(1) Country	(2) Province	(3) District	(4) Overall Rank	(5) Overall Key-Player Rank
		Nigeria		
Nigeria	Lagos	Surulere	1	7
Nigeria	Lagos	Mainland	2	5
Nigeria	Lagos	Shomolu	3	9
Nigeria	Lagos	Amuwo Odofin	4	10
Nigeria	Lagos	Alimosho	5	15
Nigeria	Lagos	Oshodi/Isolo	6	11
Nigeria	Lagos	Kosofe	7	18
Nigeria	Delta	Warri South-West	8	772
Nigeria	Bayelsa	Nembe	9	771
Nigeria	Bayelsa	Brass	10	770
		Kenya		
Kenya	Coast	Lamu	1	48
Kenya	Coast	Kilifi	2	46
Kenya	Central	Machakos	3	47
Kenya	Coast	Kwale	4	3
Kenya	Central	Kiambu	5	5
Kenya	Eastern	Machakos	6	8
Kenya	Eastern	Embu	7	17
Kenya	Central	Murang'a	8	7
Kenya	Central	Kirinyaga	9	10
Kenya	Rift Valley	Nakuru	10	4

Notes: Overall rank reflects the district's overall impact from increasing its average nighttime light pixel value by 10 on average nighttime lights across African districts (see Section 8.1 for a more detailed explanation). This counterfactual exercise is based on the ρs estimated in column (8) of Table 2. Nigeria has 775 districts, and Kenya has 48 districts.

Table 5: Top-Ten Rankings from Policy Experiment 2 – Roads

(1) Country	(2) Province	(3) District	(4) Overall Rank	(5) Overall Key-Player Rank
		Nigeria		
Nigeria	Rivers	Bonny	1	756
Nigeria	Rivers	Okrika	2	21
Nigeria	Delta	Burutu	3	71
Nigeria	Rivers	Khana	4	104
Nigeria	Delta	Warri North	5	79
Nigeria	Rivers	Andoni/O	6	130
Nigeria	Delta	Ughelli South	7	43
Nigeria	Rivers	Abua/Odu	8	46
Nigeria	Rivers	Akukutor	9	767
Nigeria	Bayelsa	Yenegoa	10	30
		Kenya		
Kenya	Central	Machakos	1	47
Kenya	Eastern	Wajir	2	27
Kenya	Eastern	Meru	3	42
Kenya	Central	Nyeri	4	9
Kenya	Central	Kirinyaga	5	10
Kenya	Eastern	Machakos	6	8
Kenya	Central	Murang'a	7	7
Kenya	Rift Valley	Narok	8	6
Kenya	Coast	Kwale	9	3
Kenya	Rift Valley	Nakuru	10	4

Notes: Overall rank reflects the district's overall impact from adding a road link to the contiguous district with the highest average nighttime light pixel value to which there exists no road link (see Section 8.2 for a more detailed explanation). This counterfactual exercise is based on the ρs estimated in column (8) of Table 2. Nigeria has 775 districts, and Kenya has 48 districts.

Online Appendix: Spatial Diffusion of Economic Shocks in Networks

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Contents

A Additional Data Description

A.1 Subnational Districts and Countries

Our analysis focuses on 5944 subnational districts, i.e., ADM2 regions, in 53 countries across the African continent. The list of countries and the number of subnational regions belonging to each country appear in Table A1. The geographic dispersion of subnational regions is graphically represented in Figure A1.

Figure A1: Districts in Africa

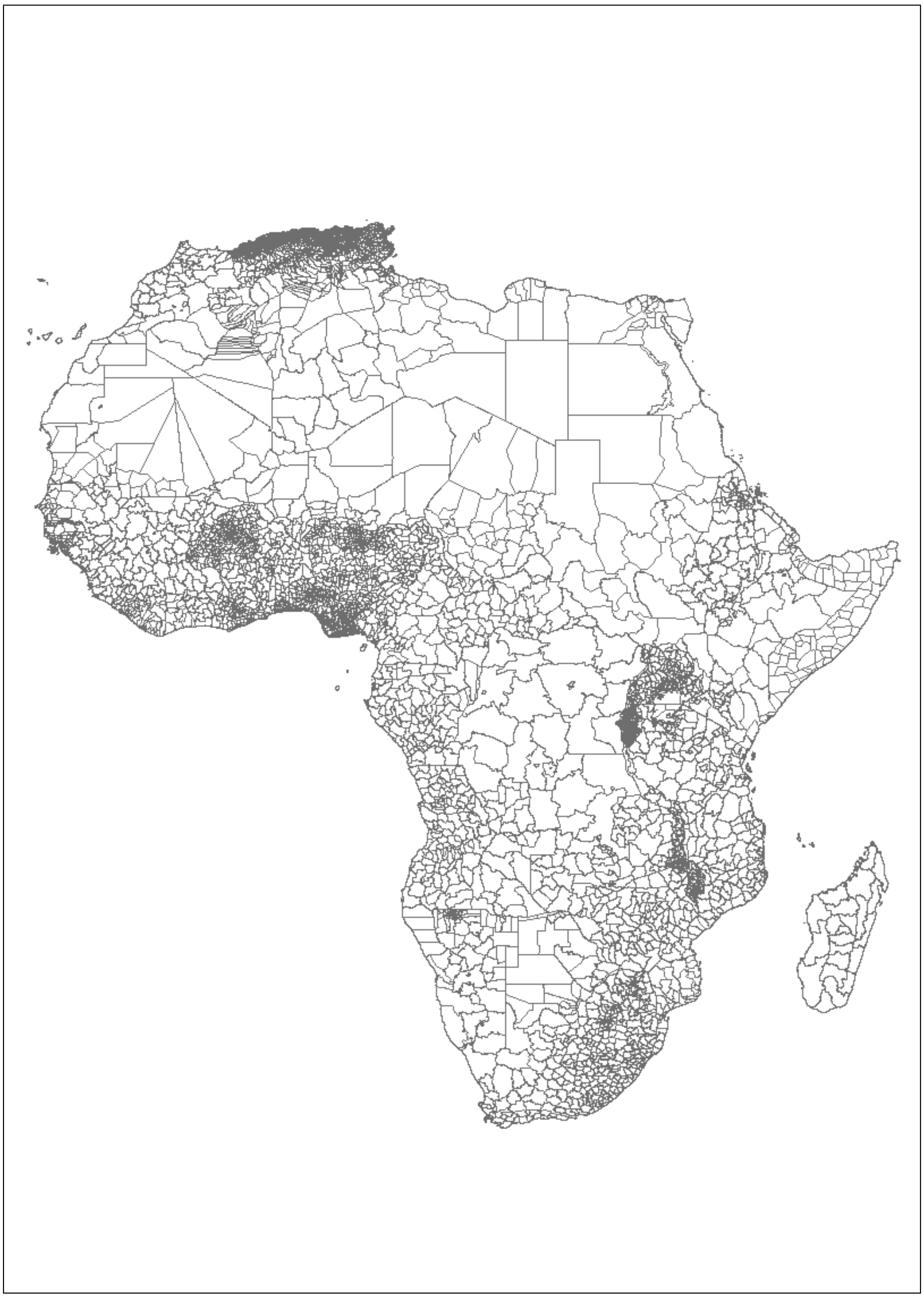


Table A1: List of Countries

	Country	No. of districts
1	Algeria	1,504
2	Angola	163
3	Benin	76
4	Botswana	25
5	Burkina Faso	301
6	Burundi	133
7	Cameroon	58
8	Cape Verde	16
9	Central African Republic	51
10	Chad	53
11	Comoros	3
12	Ivory Coast	50
13	Democratic Republic of the Congo	38
14	Djibouti	11
15	Egypt	26
16	Equatorial Guinea	6
17	Eritrea	50
18	Ethiopia	72
19	Gabon	37
20	Gambia	13
21	Ghana	137
22	Guinea	34
23	Guinea-Bissau	37
24	Kenya	48
25	Lesotho	10
26	Liberia	66
27	Libya	32
28	Madagascar	22
29	Malawi	253
30	Mali	51
31	Mauritania	44
32	Mauritius	10
33	Morocco	54
34	Mozambique	128
35	Namibia	107
36	Niger	36
37	Nigeria	775
38	Republic of Congo	46
39	Rwanda	142
40	Sao Tome and Principe	2
41	Senegal	30
42	Sierra Leone	14
43	Somalia	74
44	South Africa	354
45	Sudan	26
46	Swaziland	4
47	Tanzania	136
48	Togo	21
49	Tunisia	267
50	Uganda	162
51	Western Sahara	4
52	Zambia	72
53	Zimbabwe	60

A.2 Ethnic Homelands

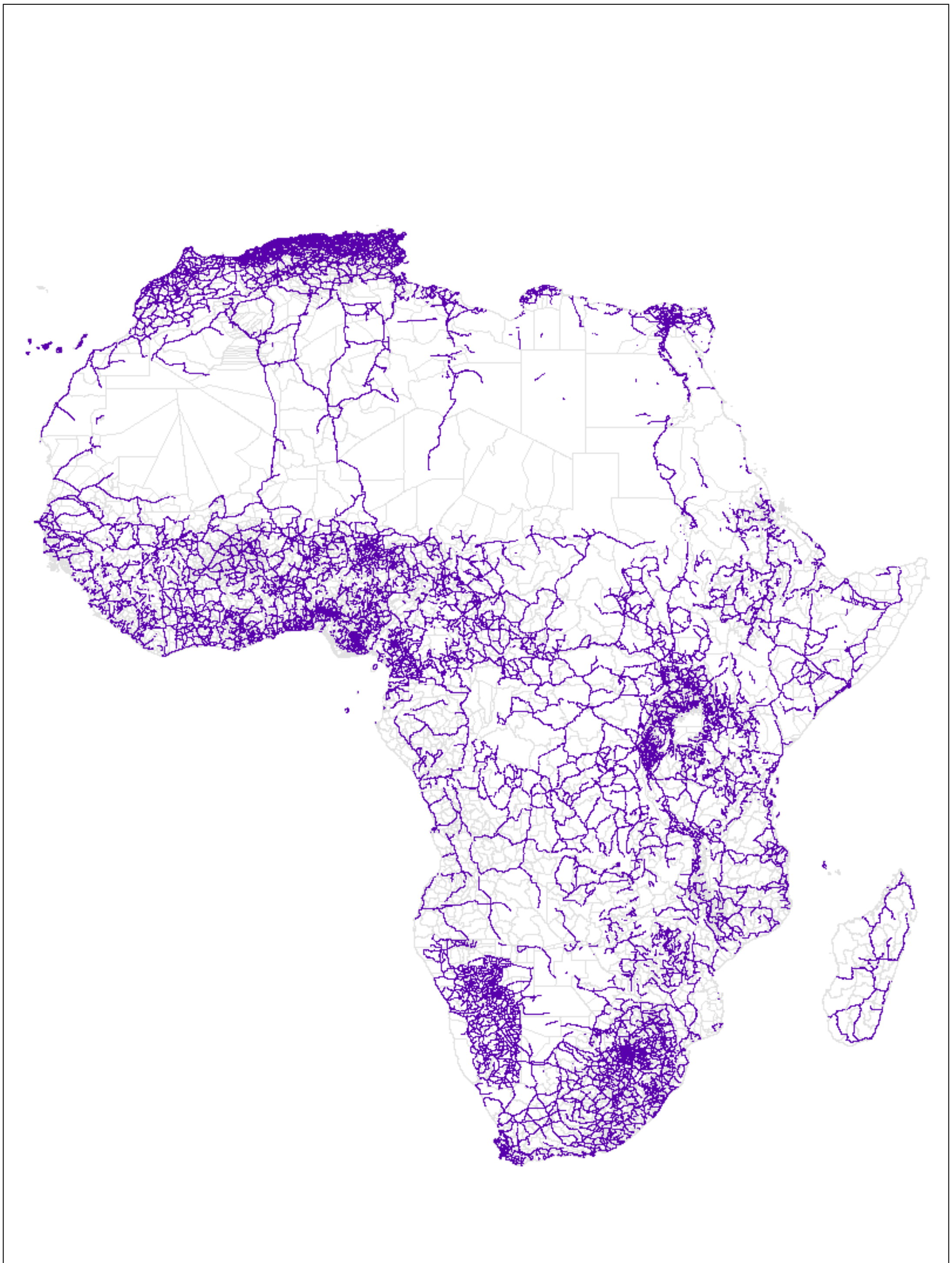
The ethnic connectivity matrix is based on the digitized map version of the Murdock (1958) map of the boundaries of ethnic homelands in Africa shown in Figure A2. Using the spatial overlay tool in ArcMap 10.2, we combined the ADM2 polylines from Figure A1 with the ethnic homeland polylines from Figure A2 to assign each district the ethnicity of the ethnic homeland that covers the largest area of this district.

Figure A2: Ethnic Homelands in Africa

A.3 Road Network

Figure A3 shows the network of primary and secondary roads (in purple) from the OpenStreetMap data, with the district boundaries in the background (in light-gray).

Figure A3: Primary and Secondary Roads in Africa



A.4 Mines & Minerals

Figure A4 shows the location of mines from the SNL Minings & Metals database, with the district boundaries in the background. Table A2 lists the different types of minerals covered in this database as well as the source for the information on the world market price of these minerals.

Figure A4: Distribution of Mines in Africa

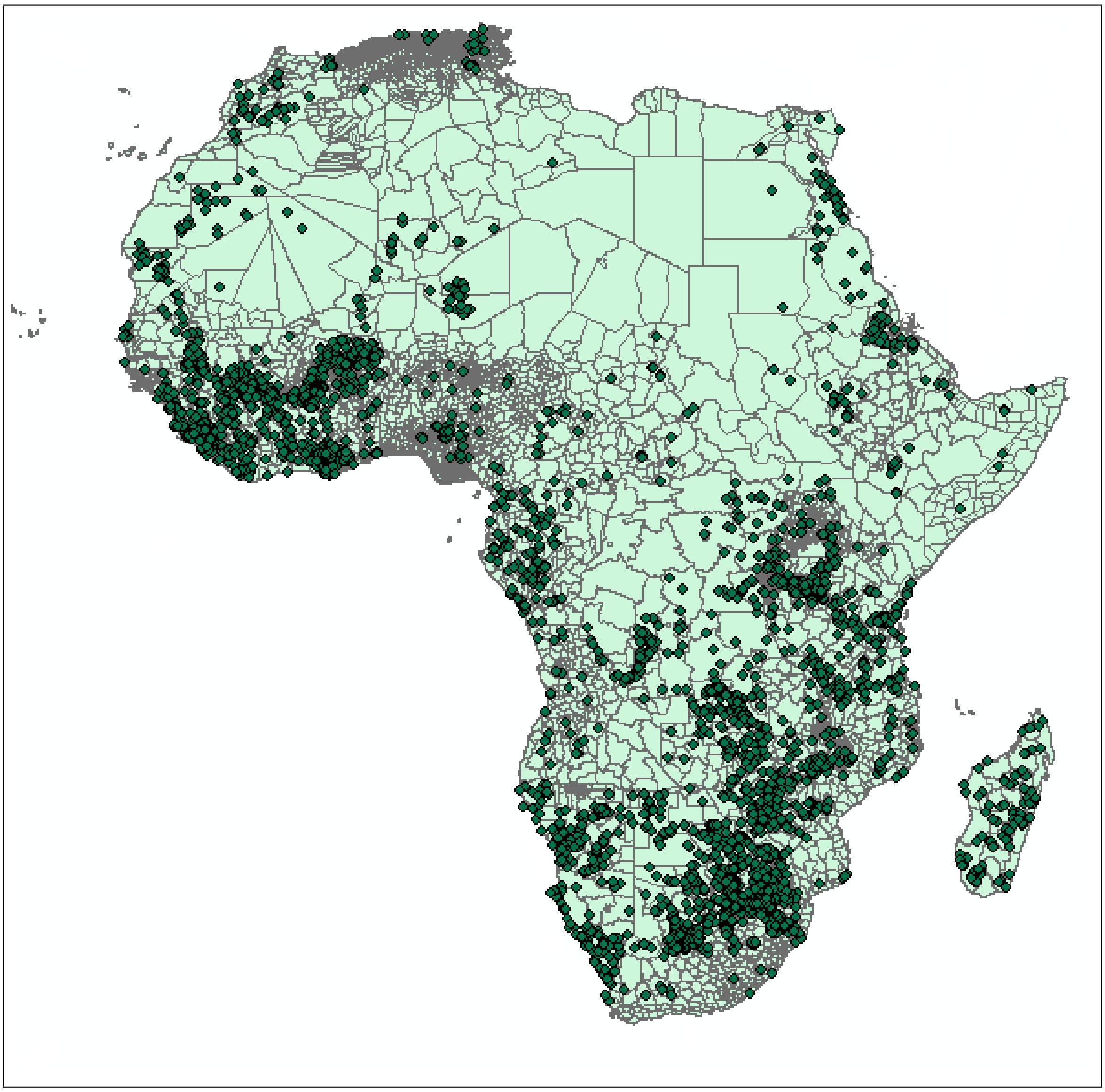


Table A2: List of Minerals

	Name	Measure	Source
1	Antimony	Tonnes	USGS Commodity Prices
2	Bauxite	Tonnes	USGS Commodity Prices
3	Chromite	Tonnes	USGS Commodity Prices
4	Coal	Tonnes	World Bank
5	Cobalt	Tonnes	USGS Commodity Prices
6	Copper	Tonnes	SNL-Thomas Reuters
7	Diamond	Carats	USGS Commodity Prices
8	Gold	Ounces	SNL-Thomas Reuters
9	Graphite	Tonnes	USGS Commodity Prices
10	Ilmenite	Tonnes	USGS Commodity Prices
11	Iron	Tonnes	World Bank
12	Lanthanide	Tonnes	USGS Commodity Prices
13	Lead	Tonnes	World Bank
14	Lithium	Tonnes	USGS Commodity Prices
15	Managanese	Tonnes	USGS Commodity Prices
16	Nickel	Tonnes	World Bank
17	Niobium	Tonnes	USGS Commodity Prices
18	Palladium	Ounces	SNL-Thomas Reuters
19	Phosphate	Tonnes	World Bank
20	Platinum	Ounces	SNL-Thomas Reuters
21	Potash	Tonnes	World Bank
22	Rutile	Tonnes	USGS Commodity Prices
23	Silver	Ounces	World Bank
24	Tin	Tonnes	SNL-Thomas Reuters
25	Tantalum	Tonnes	USGS Commodity Prices
26	Tungsten	Tonnes	USGS Commodity Prices
27	Uranium Oxide	Pounds	International Monetary Fund
28	Vanadium	Tonnes	USGS Commodity Prices
29	Yttrium	Tonnes	SNL-Thomas Reuters
30	Zinc	Tonnes	SNL-Thomas Reuters
31	Zircon	Tonnes	USGS Commodity Prices

B Correlation between Subnational GDP and Subnational Nighttime Lights in Africa

Hodler and Raschky (2014, Appendix B) document a strong correlation between GDP per capita and nighttime lights in subnational administrative regions using the subnational GDP data by Gennaioli et al. (2014). In Table B1, we replicate their analysis using their data, but restricting the sample to the 82 subnational regions from the nine African countries for which Gennaioli et al. (2014) provide subnational GDP data. These countries are: Benin, Egypt, Kenya, Lesotho, Morocco, Mozambique, Nigeria, South Africa, and Tanzania. Comparing the results reported in Table B1 with those in Hodler and Raschky (2014) suggests that the relation between subnational GDP per capita and subnational nighttime lights is very similar in Africa as elsewhere.

Table B1: Subnational GDP and Nighttime Lights in Africa

	(1)	(2)
$Light_{ict}$	0.291***	0.354***
	(0.005)	(0.047)
R-squared	0.688	0.688
Observations	1,200	1,200
Region FE	NO	YES

Notes: Dependent variable is the logarithm of regional GDP per capita. OLS regressions. $Light_{ict}$ is the logarithm of average nighttime lights. Robust standard errors in parentheses. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.

C Main Results with Full Set of Controls

Table C1: Connectivity based on ethnicity, geography and roads

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
	Dependent variable: $Light_{ict}$							
$Ethnicity\ W\ Light_{jct}$	0.552***	0.271*					0.156***	0.364***
	(0.013)	(0.149)					(0.011)	(0.092)
$Inv\ Dist\ W\ Light_{jct}$			0.563***	0.535***			0.255***	0.162*
			(0.010)	(0.107)			(0.010)	(0.094)
$Inv\ Road\ W\ Light_{jct}$					0.557***	0.288***	0.392***	0.446***
					(0.010)	(0.110)	(0.011)	(0.095)
$Population_{ict}$	0.243***	0.179***	0.157***	-0.031	0.162***	-0.100***	0.081***	-0.226***
	(0.028)	(0.030)	(0.026)	(0.031)	(0.026)	(0.032)	(0.026)	(0.034)
$Conflict_{ict}$	-0.011**	-0.012**	-0.010**	-0.010*	-0.010**	-0.012**	-0.008	-0.006
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
$Ethnicity\ W\ Population_{jct}$	-0.377***	0.096*					-0.169***	-0.263***
	(0.043)	(0.054)					(0.038)	(0.047)
$Ethnicity\ W\ Conflict_{jct}$	-0.031**	-0.043***					-0.020*	-0.019
	(0.013)	(0.015)					(0.012)	(0.015)
$Inv\ Dist\ W\ Population_{jct}$			-0.191***	0.442***			0.029	0.293***
			(0.038)	(0.043)			(0.035)	(0.040)
$Inv\ Dist\ W\ Conflict_{jct}$			-0.017	-0.024*			-0.008	-0.017
			(0.011)	(0.013)			(0.011)	(0.013)
$Inv\ Road\ W\ Population_{jct}$					-0.129***	0.582***	0.040	0.465***
					(0.035)	(0.044)	(0.036)	(0.043)
$Inv\ Road\ W\ Conflict_{jct}$					-0.004	-0.018	0.005	0.003
					(0.009)	(0.011)	(0.010)	(0.012)
MP_{ict}	0.125***	0.118***	0.120***	0.115***	0.111***	0.112***	0.114***	0.106***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)
First stage:	Dependent variable: $Light_{jct}$							
MP_{jct}		0.121***		0.123***		0.119***		0.122***
		(0.013)		(0.013)		(0.013)		(0.013)
First-stage F-stat		87.98		85.99		80.89		85.16
Observations	101,048	101,048	101,048	101,048	101,048	101,048	101,048	101,048
District FE	YES	YES	YES	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES	YES	YES	YES
Additional controls	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table corresponds to Table 2 in Section 6, but reports the coefficient estimates on all (second-stage) control variables. Even columns report standard fixed effects regressions with district and country-year fixed effects, and odd columns IV estimates. See Section 4 for the definitions of all variables. The first stage further includes the control variables indicated in Section 5. Conley (1999) standard errors are in parentheses, allowing for spatial correlation up to the stipulated distance cutoff and for infinite serial correlation. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.

D Robustness: Contiguity Network

Table D1: Connectivity based on contiguity

	(1) OLS	(2) IV
	Dependent variable: $Light_{ict}$	
$Contiguity\ W\ Light_{jct}$	0.746***	0.607***
	(0.009)	(0.166)
First stage:	Dependent variable: $Light_{jct}$	
MP_{jct}		0.127***
		(0.014)
First-stage F-Stat		88.91
Observations	101,048	101,048
District FE	YES	YES
Country-year FE	YES	YES
Additional controls	YES	YES

Notes: Column (1) reports the standard fixed effects regression with district and country-year fixed effects, and column (2) the IV estimates. See Section 4 for the definitions of all variables. $Contiguity\, W\, Light_{jct}$ is weighted $Light_{jct}$ with weights based on the row-normalized contiguity matrix. Additional control variables are population, conflict and MP_{ict} as well as weighted population and conflict in districts $j \neq i$. MP_{jct} is an interaction term based on cross-sectional information on the location of mines and time-varying world prices of the commodities produced in these mines (see equation (13)). The first stage further includes the control variables indicated in equation (12). Conley (1999) standard errors are in parentheses, allowing for spatial correlation up to 75km and for infinite serial correlation. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.

E Robustness: Geodesic Distances without Adjustment for Variability in Altitude

Table E1: Geodesic Distances without Adjustment for Variability in Altitude

	(1) OLS	(2) IV	(3) OLS	(4) IV
	Dependent variable: $Light_{ict}$			
$Ethnicity\ W\ Light_{jct}$			0.102***	0.436***
			(0.011)	(0.095)
$Inv\ Dist\ W\ Light_{jct}$	0.686***	0.734***	0.394***	0.282***
	(0.010)	(0.125)	(0.012)	(0.104)
$Inv\ Road\ W\ Light_{jct}$			0.324***	0.492***
			(0.011)	(0.094)
First stage:	Dependent variable: $Light_{jct}$			
MP_{jct}		0.127***		0.124***
		(0.013)		(0.013)
First-stage F-stat		91.36		87.96
Observations	101,048	101,048	101,048	101,048
District FE	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES
Additional controls	YES	YES	YES	YES

Notes: Even columns report standard fixed effects regressions with district and country-year fixed effects, and odd columns IV estimates. See Section 4 for the definitions of all variables. $Ethnicity\,W\,Light_{jct}$ is weighted $Light_{jct}$ with weights based on the row-normalized ethnicity matrix. $Inv\,Dist\,W\,Light_{jct}$ ($Inv\,Road\,W\,Light_{jct}$) is weighted $Light_{jct}$ with weights based on the row-normalized matrix of the inverse geodesic distances without adjustment for the variability in altitude (inverse road distances) truncated at 75km. Additional control variables are population, conflict and MP_{ict} as well as weighted population and conflict in districts $j \neq i$. MP_{jct} is an interaction term based on cross-sectional information on the location of mines and time-varying world prices of the commodities produced in these mines (see equation (13)). The first stage further includes the control variables indicated in equation (12). Conley (1999) standard errors are in parentheses, allowing for spatial correlation up to 75km and for infinite serial correlation. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.

F Robustness: Temporal and Spatial Lags

Table F1: Temporal and Spatial Lag

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
				Dependent variable: $Light_{ict}$				
$Ethnicity\ W\ Light_{jct-1}$	0.350***	0.457***					0.109***	0.367***
	(0.013)	(0.169)					(0.013)	(0.095)
$Inv\ Dist\ W\ Light_{jct-1}$			0.346***	0.572***			0.159***	0.201**
			(0.011)	(0.113)			(0.011)	(0.098)
$Inv\ Road\ W\ Light_{jct-1}$					0.334***	0.286**	0.226***	0.421***
					(0.010)	(0.114)	(0.011)	(0.098)
First stage:				Dependent variable: $Light_{jct}$				
MP_{jct}		0.110***		0.113***		0.111***		0.113***
		(0.014)		(0.014)		(0.014)		(0.014)
First-stage F-stat		65.92		66.13		63.84		65.96
Observations	101,048	101,048	101,048	101,048	101,048	101,048	101,048	101,048
District FE	YES	YES	YES	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES	YES	YES	YES
Additional controls	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Even columns report standard fixed effects regressions with district and country-year fixed effects, and odd columns IV estimates. See Section 4 for the definitions of all variables. $Ethnicity\,W\,Light_{jct}$ is weighted $Light_{jct}$ with weights based on the row-normalized ethnicity matrix. $Inv\,Dist\,W\,Light_{jct}$ ($Inv\,Road\,W\,Light_{jct}$) is weighted $Light_{jct}$ with weights based on the row-normalized matrix of the inverse altitude-adjusted geodesic distances (inverse road distances) truncated at 75km. Additional control variables are population, conflict and MP_{ict} as well as weighted population and conflict in districts $j \neq i$. MP_{jct} is an interaction term based on cross-sectional information on the location of mines and time-varying world prices of the commodities produced in these mines (see equation (13)). The first stage further includes the control variables indicated in equation (12). Conley (1999) standard errors are in parentheses, allowing for spatial correlation up to 75km and for infinite serial correlation. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.

G Robustness: Dropping Large Players

Table G1: Dropping Large Players

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
	Dependent variable: $Light_{ict}$							
Ethnicity W $Light_{jct}$	0.546***	0.394***					0.154***	0.362***
	(0.013)	(0.108)					(0.011)	(0.079)
Inv Dist W $Light_{jct}$			0.561***	0.525***			0.252***	0.120
			(0.011)	(0.102)			(0.011)	(0.088)
Inv Road W $Light_{jct}$					0.554***	0.427***	0.391***	0.477***
					(0.010)	(0.089)	(0.012)	(0.079)
First stage:	Dependent variable: $Light_{jct}$							
MP_{jct}		0.211***		0.213***		0.208***		0.210***
		(0.017)		(0.018)		(0.017)		(0.018)
First-stage F-stat		151.49		147.42		142.62		143.18
Observations	95,030	95,030	95,030	95,030	95,030	95,030	95,030	95,030
District FE	YES	YES	YES	YES	YES	YES	YES	YES
Country-year FE	YES	YES	YES	YES	YES	YES	YES	YES
Additional controls	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Sample is restricted to districts of countries that do not belong to the top ten producers for any mineral under consideration over the period 1997–2013 (see Table A2). Even columns report standard fixed effects regressions with district and country-year fixed effects, and odd columns IV estimates. See Section 4 for the definitions of all variables. *Ethnicity W* $Light_{jct}$ is weighted $Light_{jct}$ with weights based on the row-normalized ethnicity matrix. *Inv Dist W* $Light_{jct}$ (*Inv Road W* $Light_{jct}$) is weighted $Light_{jct}$ with weights based on the row-normalized matrix of the inverse altitude-adjusted geodesic distances (inverse road distances) truncated at 75km. Additional control variables are population, conflict and MP_{ict} as well as weighted population and conflict in districts $j \neq i$. MP_{jct} is an interaction term based on cross-sectional information on the location of mines and time-varying world prices of the commodities produced in these mines (see equation (13)). The first stage further includes the control variables indicated in equation (12). Conley (1999) standard errors are in parentheses, allowing for spatial correlation up to 75km and for infinite serial correlation. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.

H Robustness: Fiscal Channel

Table H1: Controlling for Connectivity based on ADM1 Networks

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
				$Light_{ict}$				
Ethnicity W $Light_{jct}$	0.314***	0.274*					0.122***	0.321***
	(0.012)	(0.149)					(0.011)	(0.095)
Inv Dist W $Light_{jct}$			0.399***	0.443***			0.218***	0.157*
			(0.010)	(0.101)			(0.010)	(0.087)
Inv Road W $Light_{jct}$					0.442***	0.405***	0.358***	0.462***
					(0.011)	(0.109)	(0.012)	(0.092)
$ADM1$ *W* $Light_{jct}$	0.434***	0.256	0.326***	0.699***	0.270***	0.236*	0.142***	0.258***
	(0.012)	(0.215)	(0.012)	(0.114)	(0.012)	(0.125)	(0.012)	(0.099)
First stage:				$Light_{jct}$				
MP_{jct}		0.123***		0.125***		0.122***		0.124***
		(0.013)		(0.013)		(0.013)		(0.013)
First-stage F-stat		89.28		87.71		84.95		87.27
Observations	101,048	101,048	101,048	101,048	101,048	101,048	101,048	101,048
District FE	YES	YES	YES	YES	YES	YES	YES	YES
Country Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Additional Controls	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Even columns report standard fixed effects regressions with district and country-year fixed effects, and odd columns IV estimates. See Section 4 for the definitions of all variables. *Ethnicity W* $Light_{jct}$ is weighted $Light_{jct}$ with weights based on the row-normalized ethnicity matrix. *Inv Dist W* $Light_{jct}$ (*Inv Road W* $Light_{jct}$) is weighted $Light_{jct}$ with weights based on the row-normalized matrix of the inverse altitude-adjusted geodesic distances (inverse road distances) truncated at 75km. $ADM1$ *W* $Light_{jct}$ is weighted $Light_{jct}$ with weights based on the row-normalized ADM1 matrix, which identifies whether districts belong to the same ADM1 unit. Additional control variables are population, conflict and MP_{ict} as well as weighted population and conflict in districts $j \neq i$. MP_{jct} is an interaction term based on cross-sectional information on the location of mines and time-varying world prices of the commodities produced in these mines (see equation (13)). The first stage further includes the control variables indicated in equation (12). Conley (1999) standard errors are in parentheses, allowing for spatial correlation up to 75km and for infinite serial correlation. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.

I Top-Ten Key Player Rankings for Populous Countries

Table I1: Top-Ten Key Player Rankings for Populous Countries

(1) Country	(2) Province	(3) District Rank	(4) Overall KP Rank	(5) Overall Katz-Bon Rank	(6) Overall Betw. Rank	(7) Overall Eig. Rank	(8) Ethnicity KP Rank	(9) Road KP Rank	(10) Inv.Dist KP Rank
Ethiopia									
Ethiopia	Addis Ababa	Zone 4*	1	3	47	14	2	2	1
Ethiopia	Addis Ababa	Zone 3*	2	4	39	49	6	4	4
Ethiopia	Addis Ababa	Zone 2*	3	5	40	49	3	3	5
Ethiopia	Addis Ababa	Addis Ababa*	4	2	38	14	1	1	2
Ethiopia	Addis Ababa	Zone 5*	5	6	44	14	4	6	3
Ethiopia	Addis Ababa	Zone 6*	6	7	62	49	11	11	10
Ethiopia	Oromia	North Shewa (K4)	7	11	48	58	29	8	6
Ethiopia	Tigray	Mekele	8	8	52	70	5	7	7
Ethiopia	Amhara	Oromia Zone	9	13	62	52	12	29	26
Ethiopia	Amhara	West Gojam	10	21	10	9	18	9	8
Egypt									
Egypt	Al Qalyubiyah		1	8	17	4	1	1	1
Egypt	Al Minufiyah		2	7	16	6	2	3	3
Egypt	Ash Sharqiyah		3	6	6	2	6	5	5
Egypt	Al Gharbiyah		4	5	12	1	3	4	6
Egypt	Ad Daqahliyah		5	2	8	5	9	11	2
Egypt	Dumyat		6	1	23	19	8	9	11
Egypt	Al Buhayrah		7	11	7	7	13	10	7
Egypt	Al Qahirah*		8	9	15	8	10	6	4
Egypt	Kafr ash Shaykh		9	3	20	11	12	13	15
Egypt	Bani Suwayf		10	14	13	12	15	16	12
Democratic Republic of the Congo (DRC)									
DRC	Kivu	Sud-Kivu	1	9	6	3	20	1	20
DRC	Bas-Congo	Matadi	2	20	29	2	2	2	2
DRC	Bas-Congo	Boma	3	2	26	37	4	7	1
DRC	Kasaï-Oriental	Tshilenge	4	8	28	3	17	37	5
DRC	Kasaï-Oriental	Mbuji-Mayi	4	6	31	3	3	5	4
DRC	Katanga	Lubumbashi	6	4	31	3	1	3	3
DRC	Kivu	Bukavu	7	1	30	38	6	8	6
DRC	Kinshasa City	Kinshasa*	8	15	17	3	5	6	7
DRC	Bas-Congo	Bas-Fleuve	9	3	25	1	18	10	8
DRC	Kasaï-Occidental	Kananga	10	7	31	3	15	15	12
South Africa (SA)									
SA	Gauteng	Johannesburg*	1	75	281	5	1	1	1
SA	Western Cape	Kuils River*	2	121	328	241	10	3	5
SA	Gauteng	Roodepoort*	3	80	304	13	4	11	4
SA	Western Cape	Mitchells Plain*	4	117	329	241	8	2	9
SA	KwaZulu-Natal	Durban	5	11	181	197	9	4	8
SA	Gauteng	Benoni*	6	78	257	8	7	10	10
SA	Gauteng	Boksburg*	7	76	173	1	2	8	3
SA	Gauteng	Kempton Park*	8	79	240	6	17	6	7
SA	Gauteng	Soweto*	9	77	298	9	3	7	2
SA	Gauteng	Soshanguve*	10	191	131	27	14	12	15

				Tanzania					
Tanzania	Dar-Es-Salaam	Kinondoni	1	47	38	7	4	1	1
Tanzania	Dar-Es-Salaam	Ilala	2	56	40	10	5	3	2
Tanzania	Arusha	Arusha	3	61	105	95	3	2	4
Tanzania	Dar-Es-Salaam	Temeke	4	53	121	8	7	4	5
Tanzania	Arusha	Arumeru	5	60	112	94	24	8	11
Tanzania	Kilimanjaro	Moshi Rural	6	49	28	91	21	15	26
Tanzania	Kilimanjaro	Moshi Urban	7	45	104	90	6	5	6
Tanzania	Mwanza	Nyamagana	8	29	87	107	2	6	3
Tanzania	Kaskazini-Unguja	Kaskazini 'B'	9	7	110	5	25	15	12
Tanzania	Iringa	Iringa Urban	10	87	122	28	9	9	7

Notes: Overall key-player (KP) rank is based on the ρs estimated in column (8) of Table 2. Overall Katz-Bonacich rank is based on the ρs estimated in column (8) of Table 2 and a weighting vector of 1. Ethnicity KP rank is based on ρ_1 estimated in column (2) of Table 2. Inverse distance KP rank is based on ρ_2 estimated in column (4) of Table 2. Road KP rank is based on ρ_3 estimated in column (6) Table 2. * indicate districts that are (part off) capital cities. South Africa has three capital cities i.e. Pretoria (Gauteng), Bloemfontein (Free State) and Cape Town (Western Cape). The number of districts per country are: Ethiopia 72, Egypt 26 (ADM1 level), DRC 38, South Africa 354, and Tanzania 136.

J Top-Ten Rankings from Policy Experiment 1 (Nighttime Lights) for Populous Countries

Table J1: Top-Ten Rankings from Policy Experiment 1 (Nighttime Lights) for Populous Countries

(1) Country	(2) Province	(3) District	(4) Overall Rank	(5) Overall KP Rank
Ethiopia				
Ethiopia	Amhara	West Gojam	1	10
Ethiopia	Addis Ababa	Addis Ababa	2	4
Ethiopia	Oromia	East Shewa	3	70
Ethiopia	Oromia	West Shewa	4	66
Ethiopia	Afar	Zone 5	5	68
Ethiopia	Addis Ababa	Zone 5	6	5
Ethiopia	Amhara	North Shewa (K3)	7	69
Ethiopia	Addis Ababa	Zone 4	8	1
Ethiopia	Addis Ababa	Zone 2	9	3
Ethiopia	Addis Ababa	Zone 3	10	2
Egypt				
Egypt	Al Jizah		1	25
Egypt	Suhaj		2	18
Egypt	Asyut		3	19
Egypt	Qina		4	20
Egypt	Al Minya		5	22
Egypt	Matruh		6	26
Egypt	As Suways		7	23
Egypt	Al Bahr al Ahmar		8	24
Egypt	Al Wadi al Jadid		9	13
Egypt	Aswan		10	21
Democratic Republic of the Congo (DRC)				
DRC	Katanga	Haut-Shaba	1	37
DRC	Kivu	Sud-Kivu	2	1
DRC	Équateur	Sud-Ubangi	3	38
DRC	Kivu	Nord-Kivu	4	11
DRC	Katanga	Lubumbashi	5	6
DRC	Kinshasa City	Kinshasa	6	8
DRC	Bandundu	Mai-Ndombe	7	36
DRC	Bas-Congo	Cataractes	8	35
DRC	Bas-Congo	Matadi	9	2
DRC	Bas-Congo	Boma	10	3

South Africa (SA)				
SA	Western Cape	Wynberg	1	11
SA	Gauteng	Kempton Park	2	8
SA	Gauteng	Germiston	3	13
SA	Gauteng	Pretoria	4	20
SA	Gauteng	Wonderboom	5	36
SA	Gauteng	Randburg	6	16
SA	Gauteng	Bronkhorstspruit	7	341
SA	Gauteng	Johannesburg	8	1
SA	Gauteng	Alberton	9	21
SA	Mpumalanga	KwaMhlanga	10	345
Tanzania				
Tanzania	Zanzibar West	Magharibi	1	135
Tanzania	Morogoro	Morogoro Rural	2	136
Tanzania	Mwanza	Ilemela	3	134
Tanzania	Iringa	Iringa Rural	4	129
Tanzania	Pwani	Mafia	5	132
Tanzania	Arusha	Arumeru	6	5
Tanzania	Kilimanjaro	Moshi Rural	7	6
Tanzania	Zanzibar South and Central	Zansibar Central	8	22
Tanzania	Kaskazini-Unguja	Kaskazini 'B'	9	9
Tanzania	Manyara	Simanjiro	10	126

Notes: Overall rank is based on counterfactual analysis described in Section 8.1 and the ρs estimated in column (8) of Table 2. Overall key-player (KP) rank is based on the ρs estimated in column (8) of Table 2 as well. The number of districts per country are: Ethiopia 72, Egypt 26 (ADM1 level), DRC 38, SA 354, and Tanzania 136.

K Top-Ten Rankings from Policy Experiment 2 (Roads) for Populous Countries

Table K1: Top-Ten Rankings from Policy Experiment 2 (Roads) for Populous Countries

(1) Country	(2) Province	(3) District	(4) Overall Rank	(5) Overall KP Rank
		Ethiopia		
Ethiopia	Tigray	Central Tigray	1	15
Ethiopia	Tigray	Easetern Tigray	2	16
Ethiopia	Afar	Zone 5	3	68
Ethiopia	SNNP*	Basketo Special Woreda	4	48
Ethiopia	SNNP*	Amaro Special Woreda	5	58
Ethiopia	Afar	Zone 4	6	71
Ethiopia	Tigray	Southern Tigray	6	65
Ethiopia	Amhara South Gonder	8	64	
Ethiopia	Amhara	West Gojam	8	10
Ethiopia	SNNP*	Konso Special Woreda	10	26
**Southern Nations, Nationalities and Peoples*				
		Egypt		
Egypt	Ad Daqahliyah		1	5
Egypt	Al Qalyubiyah		2	1
Egypt	Kafr ash Shaykh		3	9
Egypt	Asyut		4	19
Egypt	Al Iskandariyah		5	12
Egypt	Al Gharbiyah		6	4
Egypt	Al Buhayrah		7	7
Egypt	Al Isma'iliyah		8	15
Egypt	Al Fayyum		9	11
Egypt	Suhaj		10	18
		Democratic Republic of the Congo (DRC)		
DRC	Bas-Congo	Bas-Fleuve	1	9
DRC	Bas-Congo	Boma	2	3
DRC	Bas-Congo	Matadi	3	2
DRC	Kivu	Sud-Kivu	4	1
DRC	Bas-Congo	Cataractes	5	35
DRC	Kasaï-Occidental	Lulua	6	33
DRC	Kivu	Nord-Kivu	7	11
DRC	Kasaï-Occidental	Kasaï	8	21
DRC	Équateur	Équateur	9	15
DRC	Orientale	Ituri	10	15

South Africa (SA)				
SA	Orange Free State	Botshabelo	1	25
SA	Orange Free State	Bloemfontein	2	106
SA	Orange Free State	Thaba'Nchu	3	84
SA	Orange Free State	Dewetsdorp	4	294
SA	Mpumalanga	Moutse	5	67
SA	Gauteng	Cullinan	6	331
SA	Mpumalanga	Mdutjana	7	44
SA	Mpumalanga	Moretele	8	351
SA	Mpumalanga	Mbibana	9	131
SA	Limpopo	Bochum	10	348
Tanzania				
Tanzania	Kilimanjaro	Mwanga	1	130
Tanzania	Kilimanjaro	Same	2	117
Tanzania	Kagera	Bukoba Rural	3	50
Tanzania	Morogoro	Ulanga	4	83
Tanzania	Manyara	Karatu	5	101
Tanzania	Manyara	Simanjiro	6	126
Tanzania	Mwanza	Lake Victoria	7	37
Tanzania	Mwanza	Nyamagana	8	8
Tanzania	Manyara	Mbulu	9	75
Tanzania	Mtwara	Masasi	10	73

Notes: Overall rank is based on counterfactual analysis described in Section 8.2 and the ρs estimated in column (8) of Table 2. Overall key-player (KP) rank is based on the ρs estimated in column (8) of Table 2 as well. The number of districts per country are: Ethiopia 72, Egypt 26 (ADM1 level), DRC 38, SA 354, and Tanzania 136.