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Isolated and Poor:
The Cost of Remoteness from the Capital City

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Abstract

This paper investigates whether areas isolated from the capital city are less developed economically in Sub-Saharan Africa. We apply a boundary-discontinuity design using national borders that divide pre-colonial ethnic homelands to obtain quasi-experimental variation in distance to the national capital city. Based on nightlights and geocoded surveys, we find that a one percent increase in distance to the capital city causes a decrease in the probability of detecting nightlights by 3 percentage points and a reduction in household wealth corresponding to 3.5 percentiles of the national wealth distribution. Our results suggest that a lower provision of public goods in isolated areas is a key link between remoteness and economic performance. Despite receiving worse services, people who are isolated exhibit a higher level of trust in their political leaders. We interpret this as pointing towards dysfunctional accountability mechanisms that reduce the incentives of state executives to invest into isolated areas.

Keywords: Boundary Discontinuity, Capital City, Economic Growth, Nightlights, Public Goods, Spatial Inequality, Sub-Saharan Africa

JEL: D72, H41, O10, O40, R12

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1 Introduction

Most African capital cities are located either at or close to the coast. This circumstance can be directly linked to colonization. For the Europeans who targeted the extraction of resources but had little access to the hinterlands, coastal trading points constituted suitable locations for colonial headquarters. Over the course of the colonial period, these administrative centers flourished and subsequently persisted as post-colonial national capital cities in modern African states. As a consequence of having coastal rather than centrally located political centers, large parts of the population live far away from the capital city. Being isolated from the capital might have important repercussions on their economic performance. As of today, however, we lack empirical evidence on the role of the location of the capital city with regard to the spatial distribution of economic activity. Exploiting quasi-random variation in treatment at national boundaries, in this study, we establish proximity to the political center within the country, the capital city, as a new important dimension of economic inequality in Sub-Saharan Africa. Furthermore, we provide additional empirical evidence that links these outcomes to a reduced level of public goods provision.
Gaining a better understanding of the patterns of local economic development might be especially helpful in context of Sub-Saharan African growth as the continent still lags far behind economically and features a very high level of (regional) economic inequality (International Monetray Fund, 2015). Yet, the ongoing research on the subject has been largely descriptive (Odusola et al., 2017) rather than seeking to reveal its underlying patterns and mechanisms. Only a limited number of scholars (see for example Hodler and Raschky (2014) or Addison et al. (2017)) have examined spatial patterns and causes of inequality that go beyond the 'urban-rural bias' thematically (Lipton, 1977; Bates, 1981; Bezemer and Headey, 2008; Pierskalla, 2016).

In this paper, we examine the impact of distance from the capital city on economic development using a boundary discontinuity design (BDD). We find that a one percent increase in distance from the capital city reduces the probability of a pixel to be lit by three percentage points (the average probability to be lit is 2.5%) and reduces household wealth corresponding to 3.5 percentiles of the national wealth distribution. We show that the effects associated with isolation from the capital city are unique to isolation from the political center and do not apply to other isolation from other major cities. This finding supports the view that it is in fact the characteristic of hosting the political center that is the driving force behind the effects.

Regarding the economic link between isolation from the capital city and economic performance, we investigate three potential channels: market access, conflict and public goods provision. We show that isolation from capital cities, as opposed to other cities, is linked to a significant drop in the level of public goods provision suggesting that public goods provision is an important force behind the observed patterns. In addition, we provide empirical evidence against alternative explanations related to market access and conflict. With regard to the link between isolation and a lower provision of public services, we examine two potential mechanisms. Firstly, isolated populations might be politically underrepresented and marginalized and thereby unable to secure an equal level of public goods. Secondly, those farther isolated from the capital city might hold politicians less accountable for providing them with public goods. Regarding the former, we find that while isolated citizens are less likely to come from the same region as the head of state, they are more likely to be involved in the ruling coalition in power. Political representation might therefore play a role with regard to the adverse outcomes of remoteness from the capital city but it is ambiguous in which direction the effects go. Regarding the accountability channel, we find that despite being served with a lower level of public goods, people in isolated areas exhibit a higher level of trust in their national political leadership, evaluate their performance better and are less likely to believe that their leaders are corrupt. We interpret this finding as pointing towards dysfunctional feedback and accountability mechanisms. This view is supported by the observation that isolated citizens follow the news less frequently and are less likely to advocate for checks and balances on their leaders in order to hold them accountable for their actions. Consequently, as people farther away from the capital city tend to have less information and more confidence in their state leaders, political agents are left with reduced incentives to provide them with public goods.

The core challenge when seeking to identify the impact of isolation from the capital city is the fact that capital cities are not randomly located in space. There are numerous geographical characteristics, most notably isolation from the coast, that are simultaneously correlated with isolation from the capital city and economic performance and thus confound ordinary regressions. We overcome this obstacle by applying a boundary discontinuity design across national boundaries and comparing places with otherwise similar geographical features but varying distances to their respective capital city. Moving across the boundary might not constitute a valid counterfactual if the switch between countries coincides with other variables that might themselves be linked with development such as ethnicity and culture. We therefore restrict our analysis to boundary segments that divide pre-colonial ethnic homelands into two adjacent countries with different capital cities. Regarding the data input, we combine various remote sensing data sources such as VIIRS (Visible

Infrared Imaging Radiometer Suite) nightlights and use geocoded survey data from the Demographic and Health Surveys (DHS) and the Afrobarometer.
Figure 1 illustrates the intuition of our identification strategy. The figures presents the VIIRS nightlights from 2016 for pixels of around 0.5 km $\times$ 0.5 km in the 25 km boundary area of the Nyanja ethnic homeland that is divided into two adjacent countries, Malawi and Mozambique. We observe that the Malawian side contains more lit pixels and features an overall higher average light density indicating that the Malawian side is more advanced economically. The Mozambiquian side is located 1,262 km from its capital city Maputo, while the Malawian side is situated only 251 km from its capital city Lilongwe. Our identification strategy aims at exploiting this jump in distance from the capital city to explain differences in economic outcomes.

Figure 1: Nyanja Ethnic Homeland Partitioned between Malawi and Mozambique

(a) Lit vs. Not-Lit Pixels (b) Mean Light Density

Previous research on the determinants of regional development has provided ample evidence that local geographical factors have had major impact on the level of economic prosperity today. Nunn and Puga (2012) find that while ruggedness generally constitutes a burden for economic development, it protected relatively rugged countries in Sub-Saharan Africa from the negative long-run implications of the transatlantic slave trade such as reduced levels of trust (Nunn and Wantchekon, 2011). Other research points out that historical institutional framework conditions such as pre-colonial ethnic institutions are a key factor for economic development (Michalopoulos and Papaioannou, 2013). Hodler and Raschky (2014) and Burgess et al. (2015), in turn, show that political factors such as the ethnic affiliation of the incumbent president plays an important role for regional economic growth. The authors document that under weak political institutions, public investments and economic growth are biased in favor of the president's home region. Thus, these studies clearly underline that research on comparative development needs to go beyond the national level and occupy itself with subnational patterns. Moreover, political mechanisms are a key determinant of comparative regional development. These insights are especially relevant in the African context where states have not grown together as one over the centuries and feature very high levels of heterogeneity and ethnic

fractionalization.
Only a small set of papers have looked at the role of the location of the capital city for economic outcomes. Campante and Do (2014) investigate a concept related to this study, namely, the implications of capital cities that are relatively isolated from their respective population. For the sample of US states, the authors find that states with isolated capital cities exhibit higher levels of corruption and lower levels of accountability and public goods provision. Campante et al. (2019) study capital city isolation in a worldwide sample and find that non-democracies (as opposed to democracies) with relatively isolated capitals tend to be associated with misgovernance. Unfortunately, both studies leave the implications of isolated capital cities on economic development untouched. In the Sub-Saharan African context, the importance of the location of capital cities and their limited (institutional) outreach into the hinterlands were theoretically established by Herbst (2000) and empirically investigated by Michalopoulos and Papaioannou (2013). The authors find that national instutions are an important predictor for economic performance in areas relatively close to capital cities but lose their effect in areas farther away. However, the authors leave the economic consequences of isolation from the capital city as well as their impact on public good provision concealed.

The remainder of this paper is organized into six sections. Firstly, Section 2 will introduce the sample and datasets and establish the empirical identification strategy. Secondly, Section 3 will present our empirical results. In Section 4, we conduct a number of robustness tests. Subsequently, in Section 5, we examine the role of public goods provision as mediator between isolation from the capital city and economic performance. In Section 6, we provide additional evidence against alternative potential explanations. Finally, Section 7 will summarize the findings and conclude the paper.

2 Empirical Strategy and Data

2.1 Sample

This study examines isolation from the capital city in Sub-Saharan Africa consisting of 48 countries. However, as the effects of isolation from the capital city are likely to be fundamentally different in (small) island states like Cape Verde, Comoros, São Tomé and Príncipe and Madagascar, we exclude these countries from our sample. We also exclude Sudan and South Sudan due to their recent seperation, as well as Somalia and Somaliland due to the abscense of a stable political power in Somalia and the special role of the government in Somaliland (Eubank, 2012). Furthermore, we exclude South Africa as it has subdivided its three branches of government into three seperate capital cities (Pretoria, Bloemfontein and Cape Town as the executive, judicial and legislative capital respectively). Lastly, we omit Lesotho as it does not share a boundary with any remaining country in the sample. As a result, we are left with a sample of 38 countries as is illustrated in Figure 2.

Figure 2: VIIRS Nightlights Sample

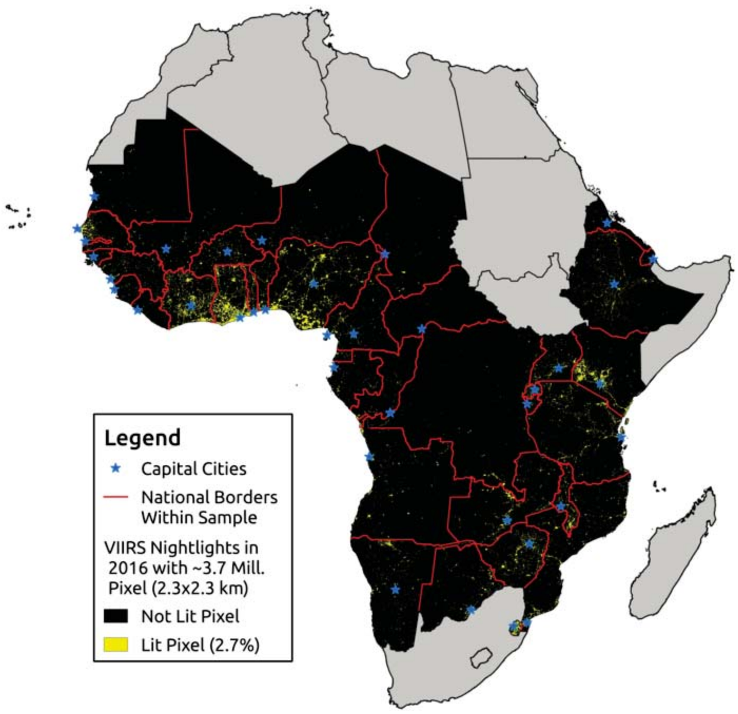
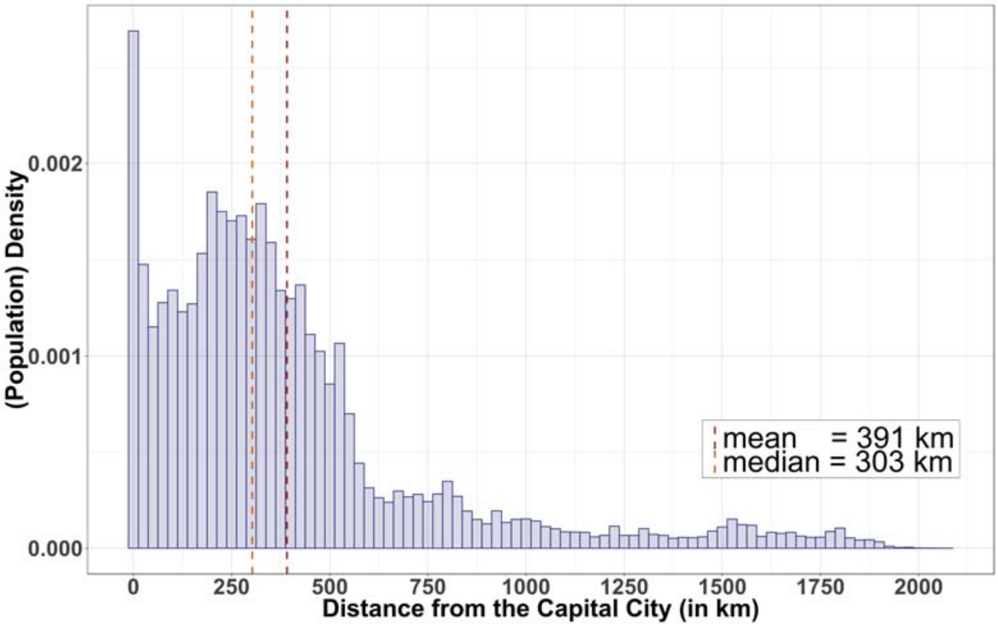


Figure 2 presents the locations of the capital cities (blue stars). For the most part, this assignment is uncontroversial as the majority of capital cities have persisted as such since the colonial era. The exceptions are Ivory Coast and Nigeria where the capital city was ultimately shifted in 1983 from Abidjan to Yamoussoukro and in 1991 from Lagos to Abuja respectively. Tanzania has also been planning to move its capital from Dar es Salaam to Dodoma since 1973. However, up until 2019, only the Tanzanian parliament has relocated to their new headquarter while Dar es Salaam has remained the de-facto seat of the president. We, therefore, keep Dar es Salaam, instead of the new official capital, Dodoma, as national capital of Tanzania.

Figure 3 presents the distribution of isolation from the capital city for the countries under investigation. It becomes clear that isolation from the capital city is not just a phenomenon that only affects small minorities but with a median of 303 km (mean: 391 km) rather represents the common case.

Figure 3: Isolation from the Capital City - Overview



Note: This figure is based on own calculations using the UN-adjusted population density grid for the year 2015 by Worldpop. It displays the density distribution of isolation from the capital city for our sample countries. Please note that this figure includes the population within a range of 20 km from the capital city that is omitted by default from all estimations (see Section 2.4). Each bar represents an intervall of 25 km. The upper limit of isolation from the capital city is 2075 km. The average person lives 391 km (median: 303 km) away from the capital city.

2.2 Measuring Economic Performance Locally

In order to examine the impact of distance from the capital city, we require information on economic activity for small spatial units. Since reliable administrative data on the local level is not available in Sub-Saharan Africa, we use the 2016 VIIRS nighttime light density as our main measure for local economic performance. Additionally, in order to cross-validate our findings and address potential shortcomings of nighttime lights (see below), we complement our analysis using the survey-based DHS wealth index.

Nighttime Lights (VIIRS):

The use of nighttime luminosity data as a proxy for economic activity has greatly increased in recent years. The data has been especially useful for places where national accounts data on GDP is of poor quality, as well as for (small) geographical units where administrative data is simply not available. Several studies have investigated and validated the consistency of nighttime lights as a proxy for GDP. These studies compare GDP estimates from nighttime lights with administrative data for places where both is available. Henderson et al. (2012) show that their estimation for income growth on the national level for a set of 30 countries differed by only up to 3.2% from the actual data. Moreover, Hodler and Raschky (2014: 1030) show for sub-national admin-1 regions across the world that “the relationship

between nighttime lights and GDP is linear and thereby similar across regions with different nighttime light intensity and income levels". Comparing nighttime lights to the wealth index for geocoded DHS respondents in Africa, Michalopoulos and Papaioannou (2013: 122) show that the relationship even holds on the local level. These findings underline that the mechanisms that drive the positive relationship between economic activity and nighttime light emissions are stable across regions and observational units. This also explains why nighttime lights have become so popular among researchers in spatial microeconometric settings.
However, nighttime lights are also subject to limitations. First of all, the relationship between nighttime light density and economic activity on the local pixel level is non-linear (Henderson et al., 2012). As a primary step, it therefore helps to log-transform nightlight intensity in order to obtain a more uniform distribution and reduce the weight of outliers. Moreover, we can adress the concern about the precise functional form by running each regression using an extensive measure of nightlights:

- Intensive approach (the intensity of nightlights using a log-transformation[1]):

$$Y_i = ln(Lights_i + 0.002000212) \tag{1}$$

- Extensive approach (the extent to which cells are lit or not lit):

$$Y_i = \begin{cases} 1 \;\; if \;\; Lights_i > 0 \\ 0 \;\; if \;\; Lights_i = 0 \end{cases} \tag{2}$$

Secondly, Chen and Nordhaus (2011) and Cogneau and Dupraz (2014) point out that the predictive power of nightlights for economic activity is low and noisy for areas of low population and nightlight density. In particular, the ongoing electrification process in Sub-Saharan Africa might confound our estimated relationship between economic activity and remoteness from the capital city. Therefore, attributing the differences between (recently) electrified areas and non-electrified areas to differences in the distance to the capital city might overestimate the actual difference in economic activity. The obstacle is that electrification and economic development are mutually dependent and hard to disentangle. On the one hand, since the returns to electrification are higher in economically more dynamic areas, public decision makers likely prioritize such areas. On the other hand, electrification is itself at least a moderate driver of economic growth (Dinkelman, 2011; Burlig and Preonas, 2016). In a BDD model, electrification as a potential confounding factor is less of a concern as electricity grids often span across boundaries. Moreover, the concern

[1] Since the vast majority of pixels has a light density of 0, we add the minimal observed light density that is greater than zero as a constant term before taking the natural logarithm. The results are stable with regard to alternative added constant terms and hold when for example using 0.0001 or 0.001 instead.

that electrification confounds the estimated relationship rests upon the assumption that the electricity grid expands from the capital city. Yet, this assumption is not in line with the observation that selected cities all around our sample countries emit nightlights. Consequently, electrification is unlikely a major confounder in our models. However, under certain assumptions, we might be overestimating the economic impact of isolation from the capital city. As electrification is endogenous, rather than including it as a 'bad control', we cross-validate our findings using the DHS wealth index as a more concrete alternative measure of economic development.

We combine the nightlights with a wide range of geographical covariates from various remote sensing data sources as is described in Section A.1 in more detail. For the purpose of curbing measurement error and mismatching resulting from small inaccuracies between the datasets and to facilitate the computational intensity of the analysis, the data grids are aggregated to a resolution of 75×75 arcseconds which is equivalent to approximately 2.3×2.3 kilometers at the equator. The nightlight grids have an initial resolution of 15×15 arcseconds which means that 25 original pixels (5×5) constitute a new pixel and inherit the average value of its predecessors. This leaves us with around 3.5 million pixels for the 38 countries in our sample. In order to be able to stack nighttime lights and other geographical covariates together, we interpolate all other grids bilinearly to match the nightlight grid resolution. We further transform our grids from the standard decimal degree CRS 'WGS 84' to 'Africa Sinusoidal' which properly maps distances in Sub-Saharan Africa using the metric system.[2]

Wealth Index (DHS):

The DHS (Demographic and Health Surveys Program) is implemented by ICF International and funded by the United States Agency for International Development (USAID). Since 1984, the program has collected nationally representative data on sociodemographic, economic and health characteristics through more than 400 surveys in over 90 developing and emerging economies including 30 out of the 38 countries in our sample. Aside from the extensive geographical and temporal coverage of the DHS, the advantage of the DHS is that most of its surveys use GPS receivers to record a household's longitude and latitude coordinates which makes the DHS well suited for geospatial analyses.[3] We use the most current household recode survey available for each available country and illustrate the DHS sample in Figure A1a.

[2]See http://spatialreference.org/ref/esri/africa-sinusoidal/ for more information.

[3]Please note that in order to protect the privacy of respondents, the DHS displaces the GPS coordinates randomly up to 2 km for urban clusters and up to 5 km for rural clusters with 1% of rural clusters being displaced up to 10 km. This displacement is restricted such that respondents always stay within the same country and region.

Based on a household's ownership of selected assets (such as car, bicycle, refrigerator, computer, television) and household facilities (such as roof and floor material or type of toilet facility), the DHS estimates a household's 'wealth index' using principal component analysis (PCA).[4] Since the PCA is conducted for each survey (country and year) seperately, the index represents a composite measure of a household's cumulative living standard relative to other households within each country and year. This circumstance limits the applicability of the indicator as measures of absolute wealth between countries or over time are not consistent. Yet, the indicator is perfectly suitable for applications that seek to understand the relative distribution of living standards within countries. We standardize the wealth index for each survey to make a household's wealth index more comparable to the relative position of households in other countries. As a second alternative measure, we rank and assign each household its relative position in the national wealth distribution. While the second measure loses valuable information regarding the absolute difference between two consecutive housholds, its interpretation is more intuitive as differences between housholds can be expressed in terms of percentile changes within the national wealth distribution.

2.3 Further Data Sources for the Channel Analysis

Afrobarometer Survey Data:

The Afrobarometer surveys comprise questions on household characteristics, public goods, public perception, as well as political attitudes and opinion. The surveys are conducted every few years in most African countries and provide the geolocation of their respondents which makes it highly suitable for studies in economic geography. We use rounds 5, 6 and 7 of the Afrobarometer covering 26 out of the 38 countries in our sample as is illustrated in Figure A1b. The data is available upon application at: https://www.afrobarometer.org.

The Afrobarometer is especially useful to investiage the spatial pattern of public goods provision as it contains information on whether the enumeration area (cluster) in which the respondent is located is supplied with certain public goods: paved road, electricity grid, piped water system and sewage system. Moreover, based on the Afrobarometer, we can examine how distance from the capital city affects corruption perception, trust into the political leadership, news readership and other characteristics reflecting how people think about their leaders and the political organization of their country. A complete list of all Afrobarometer survey questions and indicators can be found in Section A.1.

[4] For more information about the construction of the DHS wealth index and which variables and weights are used in each respective country and year please visit: https://dhsprogram.com/topics/wealth-index/Wealth-Index-Construction.cfm.

Access to Power:

In order to explore whether areas close and far from the capital city are, conditional on their respective population shares, equally represented in the government, we require a dataset on the origins of state executives. Francois et al. (2015) create an extensive dataset on the ethnicity of cabinet ministers in African countries since independence. Based on their analysis, the authors are able to infer that ruling coalitions are large and ethnicities represented proportionally. However, the authors do not study if geographical locations are equally represented. Since their dataset is not geocoded and there exists no complementary dataset that corresponds to their categorization of ethnic groups, we are unable proceed with their database. For this reason, we limit our analysis to the heads of state using and supplementing the database by Dreher et al. (2016: 40-41). We update this list regarding the period of office and region of origin up to the year of 2016 using publicly available information from various sources including Wikipedia.

Yet, solely mapping out the origins of heads of state might be imprecise and not give a holistic image about an area's access to power. Therefore, we complement the analysis with a second dataset comprising the degree of access to power for various politically relevant ethnic groups from 1946 to 2017: the Ethnic Power Relations Core Dataset 2019 (EPR) (Vogt et al., 2015). The advantage of the EPR dataset is that it can be combined with a complementary dataset on the geolocation (polygons) of the respective ethnic groups (Wucherpfennig, 2011). The EPR status indicators categorizes groups as *in power*: 'monopoly', 'dominance', 'senior partner', 'junior partner' as well as *excluded groups*: 'powerless', 'discrimination', 'self-exclusion' and areas that have are not been identified as being politically relevant which are coded as *irrelevant*. To obtain an image of contemporary patterns, we restrict the dataset to the period 2000-2017. We assign each pixel the total number of years in each respective status category as our variable of interest. Since some of the groups are overlapping geographically, we assign each area the status of the respective most powerful group.

Conflict Data (ACLED):

In order to investigate whether conflict is a relevant channel linking remoteness from the capital city and economic development, we use the Armed Conflict Location & Event Data (ACLED) containing the geolocation of conflicts between 1997 and today by type: 'violent events', 'demonstration events' and 'non-violent action' (Raleigh et al., 2010). For more information on the definition of different conflict types please refer to the ACLED homepage at: https://www.acleddata.com/resources/general-guides/. Our conflict event sample comprises 88,853 instances between 01.01.2000 and 27.11.2019 distributed all over our sample countries.

2.4 Identification

Intuition and construction of the BDD Model:

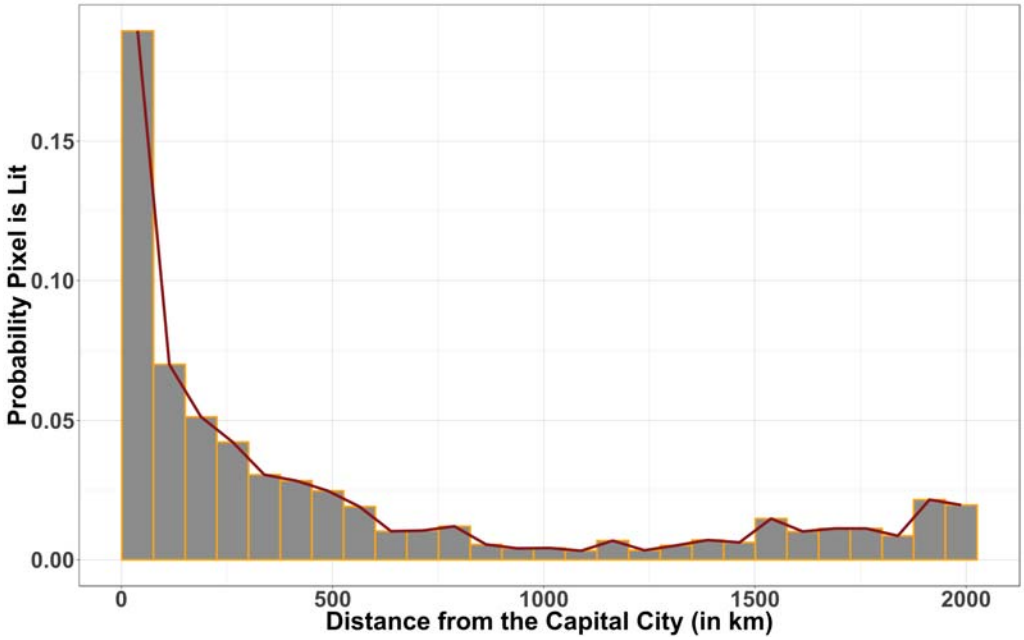
The most intuitive way to assess the effect of isolation from the capital city[5] on local economic development is a simple univariate analysis. In Figure 4, we plot the share of lit pixels over distance from the capital city. The graph reveals that, on average, the probability of detecting nightlights in a pixel decreases exponentially with distance from the respective capital city. Unfortunately, this correlation is hard to interpret as it is shaped by a variety of confounders. Most notably, isolation from the capital city is correlated with a range of location-specific geographical factors, that are themselves determinants of economic performance. For instance, African capitals tend to be located at the coast which means that proximity to capital cities concurrently translates into the advantages of proximity to ports and international trade (Henderson et al., 2017). Moreover, it is highly doubtful whether the relationship actually reverses for very high distance as is indicated by a slightly positive slope starting at around 1,250 km. It is more likely that these pixels just happen to be in economically more dynamic areas such as the mining areas in the South-Eastern part of DR Congo. Hence, local economic framework conditions such as endowments with natural resources or local institutions and culture (Michalopoulos and Papaioannou, 2013) confound the estimated relationship as well. Consequently, simple univariate analyses are highly problematic and do not allow to draw definitive conclusions about the causal impact of remoteness from the capital city.

One way of addressing these shortcomings would be explictly modelling all relevant relationships by including a wide set of geographical covariates as well as country and ethnic homeland characteristics into the model. In the next step, we therefore include: *distance from the coast, elevation, ruggedness, the pixel surface covered with water, annual mean temperature, average minimal temperature in the coldest month, average maximal temperature in the warmest month, caloric suitability index, annual precipitation, latitude, longitude* as geographical characteristics, X_i, for each pixel i and absorb country and ethnic characteristics through fixed effects: b_c and b_e. We log-transform distance to the capital city using the natural logarithm, CAP_i, in order to account for the exponential relationship suggested by Figure 4.[6] Equation

[5]We measure isolation from the capital city as the Euclidean distance between a location (a pixel) and the respective capital city. A drawback of this measure, as opposed to more sophisticated travel time or travel cost estimates, is that it is less precise. However, measures that take into consideration the infrastructure development would induce reverse causality bias. This is due to the fact that places that are more dynamic economically tend to be better connected and are therefore closer to the capital city in terms of travel time. Combes and Lafourcade (2005: 346) underline the consistency of our metric by showing that simple distance measures “do a very good job in capturing transport costs in cross-section analysis”.

[6]The qualitative intuition behind the log-transformation is that the effects of isolation from the

Figure 4: Isolation from the Capital City - Nighttime lights



Note: This figure plots the share of lit pixels over distance from the capital city. Please note that this figure includes the population within a range of 20 km from the capital city that is omitted by default from all estimations (see Section 2.4). Each bar represents an area of 75 km.

3 illustrates the respective model equation where Y_i denotes the outcome variable referring to our measures of *Nightlight Density* in pixel i.

$$Y_i = \beta CAP_i + \gamma X_i + b_c + b_e + \varepsilon_i \tag{3}$$

Yet, since we usually only control for a subset, $\hat{X}_i$, of all relevant location-specific factors ($X_i = \hat{X}_i + \widetilde{X}_i$), CAP_i remains endogenous with $\varepsilon_i = \widetilde{X}_i + u_i$ and $E(\varepsilon_i | CAP_i) \neq 0$. As a result, OLS-estimations based on Equation 3 are usually biased and do not allow for causal inference.

We, therefore, require an estimation approach where omitted relevant location-specific characteristics, $\widetilde{X}_i$, are balanced by construction. A tangible solution is to establish counterfactuals in a BDD model. The idea is that African borders were arbitrarily drawn by the colonial powers and divide pre-colonial ethnic homelands with similar geographical, social and historical traits (Michalopoulos and Papaioannou, 2016). For areas very close to the boundary the assignment to a particular country and its respective capital city can consequently be interpreted as accidental. Hence, national borders constitute an arbitrary cutoff at which we can obtain

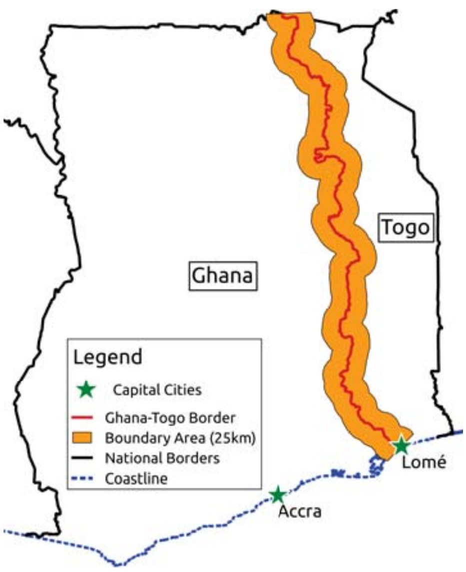
capital city are decreasing with distance from the capital city. Yet, given that the relationship in Figure 4 is strongly confounded and should therefore be taken with caution, we confirm the adequacy of the log-transformation statistically based on the Akaike information criteria applied to our more sophisticated BDD model.

a quasi-random jump in distance from the capital city. However, as opposed to Basten and Betz (2013) or Michalopoulos and Papaioannou (2014), simply pooling areas around boundaries does not remove the heterogeneity in (un-)observables with respect to the treatment intensity. This circumstance is due to the fact that, as opposed to country-wide indicators, isolation from the capital city is autocorrelated i.e. evolves gradually along the boundary which induces a cross-border correlation. This, in turn, causes a spurious relationship between isolation from the capital city and other autocorrelated (un-)observable location-specific factors that concurrently gradually evolve along both sides of the boundary.

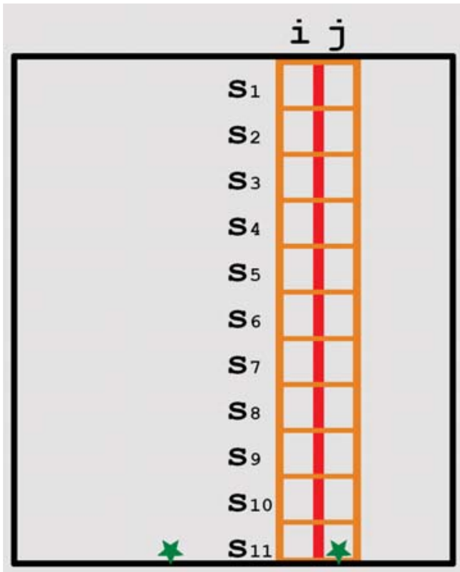
For example, when considering the national boundary between Ghana and Togo (see Figure 5), distance from the capital city increases for both sides from South to North. The problem is that (un-)observable factors such as distance from the coast or climatic conditions simultaneously evolve along the boundary. As a consequence, if we simply pool boundary areas, we are unable to distinguish whether potential differences in outcomes are driven by isolation from the capital city or (un-)observable geographical factors such as a larger distance from the coast and/or drier climate.

Figure 5: The Ghana-Togo Border

(a) Accurate Map - Boundary Area



(b) Schematic Map - Border Segments



In order to overcome this problem, we need to isolate the exogenous variation in distance to the capital city that is induced by arbitrary boundaries using a more elaborate BDD model. The solution is to subdivide shared national boundary areas into smaller segments. In Figure 5, s_1-s_{11} sketch such segments for the example of the Ghana-Togo border schematically. Applying segment fixed effects absorbs the location-specific characteristics of each segment. In other words, these fixed effects partial out anything that equally exists on either side of the boundary. Hence, we are left with the differences between both sides of a boundary segment: a switch in the country and hence the institutional environment that all pixels within a country have in common and which we can therefore absorb using country fixed effects, and a jump in distance from the capital city which we can exploit to study the impact of isolation from the capital city. In Section A.1 we formally show that, under the assumption that (un-)observable location specific characteristics do not differ systematically across the boundary, this procedure is equivalent to taking the difference between counterfactual segment sides. Essentially, this procedure thereby cancels out all (un-)observables location-specific characteristics and allows us to obtain unbiased causal estimates. To satisfy the assumption of balancedness in (un-)observables across the border, we reduce our sample to a small buffer of 25 km around those boundary segments that partition ethnic homelands and entirely nest each segment within one partitioned ethnic homeland p. Thereby, this procudure does not only balance geographical covariates[7] but also historic political and cultural framework conditions. Furthermore, we include polynomials of our running variable *Distance from the Boundary in km* (DFB) for each ethnic homeland in each country separately into our model. These polynomials pick up any potentially remaining heterogeneity within segments. As a result, we essentially analyze how a pixel would have performed economically if the imposed boundary line had been shifted by a few kilometers such that the pixels were on the other side of the border within the same ethnic homeland and the same local economic conditions but with the respective other distance from the capital city. Hence, the BDD model with segment fixed effects in Equation 6 allows us to effectively control for (un-)observed heterogeneity with regard to the treatment intensity and thereby facilitates the isolation of causal estimates.

$$Y_i = \beta CAP_i + \varphi X_i + b_c + b_s + \sum_{n=1}^{3} \lambda_{n,c,p} DFB_i^n + \xi_i \tag{4}$$

<u>*Further technical details:*</u>

In order to identify boundary segments that partition ethnic homelands, we use the ethnographic 'Tribal Map of Africa' on pre-colonial ethnic homelands by Murdock (1959) that is widely used in economics when marking out different ethnicities (Nunn, 2008; Michalopoulos and Papaioannou, 2013, 2014, 2016). Murdock subdivides the entire African continent into 843 distinc polygons that each relate to a

[7] Michalopoulos and Papaioannou (2014: 171) provide an in-depth discussion about the origin of Sub-Saharan African national boundaries and conclude that "differences in geography-ecology, location, and natural resources across the border within partitioned ethnic homelands are small and not systematically linked to differences in national institutions" (Ibid.: 172). Conducting a range of balancing tests, we validate that local (un-)obversable characteristics are also balanced with respect to isolation from the capital city.

local ethnic majority group. The map refers roughly to the era around the Berlin Conference and the establishment of artificial African boundaries. This circumstance makes this map well suited for our purpose as it is free from more recent potentially endogenous migration movements. Moreover, “case study and anecdotal evidence suggest that in spite of population movements ethnic populations tend to reside in their respective historical homelands” (Michalopoulos and Papaioannou, 2014: 162). Since Murdock’s map was originally printed in his book and only later digitized, there might be some inaccuracies with the precise delimination of ethnic homelands (Michalopoulos and Papaioannou, 2013: 143). To account for this potential shortcoming, we restrict each ethnic homeland by (a negative buffer of) -15 km prior to further processing the map.
In the next step, we subdivide all national borders that divide ethnic homelands into segments of 50 km length with a buffer of 25 km (15km, 50 km in sensitivity tests) on each side of the boundary. To verfiy that segments are sufficiently small and homogenous, we conduct a range of balancing tests. In our econometric model, we implicitly assume that both segment sides are of equal size. However, in practice, since national borders are not always straight lines, opposing segment sides are not of equal size in all instances either. Therefore, we weight each pixel such that both segment sides have the same aggregated weight.[8]

For the purpose of preventing that inaccuracies and blooming confound the assignment of nightlights to a segment side (country), we exclude pixels whose centroid is within a range of 3 km (1.5 km in sensitivity tests) from the boundary from all estimations. Further, to account for uninhabitable areas, we exclude pixels that are entirely covered with water or are completely unpopulated. Additionally, in order to ensure that the estimates of isolation from the capital city are not simply capturing the break between the capital city and the hinterland, we exclude pixels within a radius of 20 km (but also 50 km, 75 km and 100 km in sensitivity tests) around the capital city (and placebo city) by default from all estimations.

Last but not least, a potential caveat might stem from the circumstance that isolation from the capital city always simultaneously means isolation from a major city and market. In order to affirm that it is in fact isolation from the political center that is driving the effects of isolation from the capital city, we run placebo tests. The idea is that if hosting the political center is in fact the key characteristic of capital cities with respect to the effects under scrutiny, then the effects of isolation from

[8]We maintain the overall weight of segments relative to each other (proportional to their total segment size). Further, in order to avoid overrepresenting very small segment sides, if a segment side contains less than 20 pixels, we drop the entire segment.

other major cities within the country should be fundamentally different. For this purpose, we create PLC, representing the *log* of *distance from the placebo city (in km)*, as a new variable. A placebo city is defined as the largest city within the country if the capital city is not the largest city and the second largest city otherwise.[9] We then include PLC into Equation 6 and compare the estimated coefficients for capital and placebo city isolation. However, this placebo test might be confounded by the fact that capital cities tend to be the largest city within the country. To this end, we decompose the effect of isolation from a city into a city type (capital vs. placebo city) and city size effect (big vs. small city in terms of city population). We do so by partialing out the size effect by additionally including interactions between CAP and PLC with their respective population counts.

$$\begin{aligned} Y_i = \; & \beta_1 CAP_i + \tau_1 CAP_i \times Pop_{cap,c} + \beta_2 PLC_i + \tau_2 PLC_i \times Pop_{plc,c} \\ & + \varphi X_i + b_c + b_s + \sum_{n=1}^{3} \lambda_{n,c,p} DFB_i^n + \epsilon_i \end{aligned} \tag{5}$$

3 Empirical Analysis

3.1 OLS

The results of the OLS estimations based on Equation 3 for a variety of alternative specifications can be found in Table 1. Columns (1)-(4) refer to the extensive approach (see Equation 2), whereas columns (5)-(8) refer to the intensive approach (see Equation 1). Columns (1)-(2) and (5)-(6) correspond to the simple OLS models while columns (3)-(4) and (7)-(8) include ethnic homeland fixed effects.[10] Further, columns (2), (4), (6) and (8) are restricted to the boundary area within 25 km from the border.[11]

As becomes clear from the table, irrespective of the precise model specification, isolation from the capital city is significantly negativly related to both the probability and the intensity with which a pixel is lit. A one percent increase in distance from the capital city, on average, decreases the probability that a pixel is lit by around 1.5 percentage points and the nightlight density by around 0.07 percent. Figure A5 presents the respective OLS estimates conducted for each country separately. Figure A5a compares the estimates of the full sample to those of the boundary sample using extensive nightlights corresponding to columns (1) and (2). Likewise, Figure

[9] In order to avoid collinearity with the capital city, we further require the placebo city to be at least 50 km away from the capital city.

[10] Note that since the ethnic homeland fixed effects do not only embrace partitioned ethnicities they naturally induce a high level of collinearity with isolation from the capital city.

[11] Note that the boundary area models with ethnicity fixed effects are actually less rigourous hybrids between OLS and BDD estimations.

A5b corresponds to the intensive margin corrsponding to columns (5) and (6). The figures underline that while the aggregated coefficients in the OLS models in Table 1 appear relatively stable, the estimated effects on the country level are very sensitive to alterations in the model specification. This finding suggests that the OLS results are subject to substantial bias and should be taken with caution.

Table 1: OLS Results

	Dependent variable:							
	Probability Pixel is Lit in 2016 (VIIRS)				Log Light Density in 2016 (VIIRS)			
	OLS		Ethnicity FE		OLS		Ethnicity FE	
	All	Border	All	Border	All	Border	All	Border
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Distance from the Capital City	-0.020*** (0.005)	-0.021*** (0.006)	-0.025*** (0.005)	-0.014** (0.005)	-0.068*** (0.021)	-0.083*** (0.026)	-0.101*** (0.023)	-0.065*** (0.024)
Geography Cov.	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	37	37	37	37	37	37	37	37
Ethnicity FE	NO	NO	706	351	NO	NO	706	351
Observations	3,518,146	416,667	3,518,146	416,664	3,518,146	416,667	3,518,146	416,664
R^2	0.080	0.082	0.131	0.134	0.069	0.069	0.126	0.121
Adjusted R^2	0.080	0.082	0.130	0.133	0.069	0.069	0.126	0.120

Note: This table reports OLS and boundary area regression results based on Equation 3. In order to avoid capturing the break between the capital city and the hinterlands, we exclude 20 km around each capital city from our sample. To prevent misassignment of detected nightlights between countries due to blooming, we exclude 3 km on each side of the border. The boundary area regressions ('Border') are restricted to all pixels with centroids within the range of 25 km from shared national borders. The 'Geographical Cov.' include: distance from the coast (in km), ruggedness (in % slope), % surface covered with water, mean annual temperature, minimum average temperature during the coldest month, maximum average temperature during the warmest month (in °C), crop caloric index, annual precipitation (in mm), longitude and latitude (projected in km). The 'Ethnicity FE' are based on the ethnic homelands in the 'Tribal Map of Africa' (Murdock, 1959). Standard errors in paranthesis are clustered by ethnic homeland. *p<0.1; **p<0.05; ***p<0.01

The associated balancing tests, for the example of distance from the coast, can be found in Table A6. In the least restrictive models (columns (1) and (5) in Table 1 and column (1) in Table A6), a one percent increase in isolation from the capital city is correlated to an increase in isolation from the coast by around 18 percent of the sample mean. This imbalance decreases to around 4 percent for the most restrictive models (columns (4) and (8) in Table 1 and column (4) in Table A6). While these results signal that the implemented OLS model restrictions towards the BDD model are effective in tackling heterogeneity in (un-)observables, the imbalances still remain relatively high. And, since we cannot be sure to be controlling for all relevant location-specific factors, the results of the OLS approach are rather descriptive than causal.

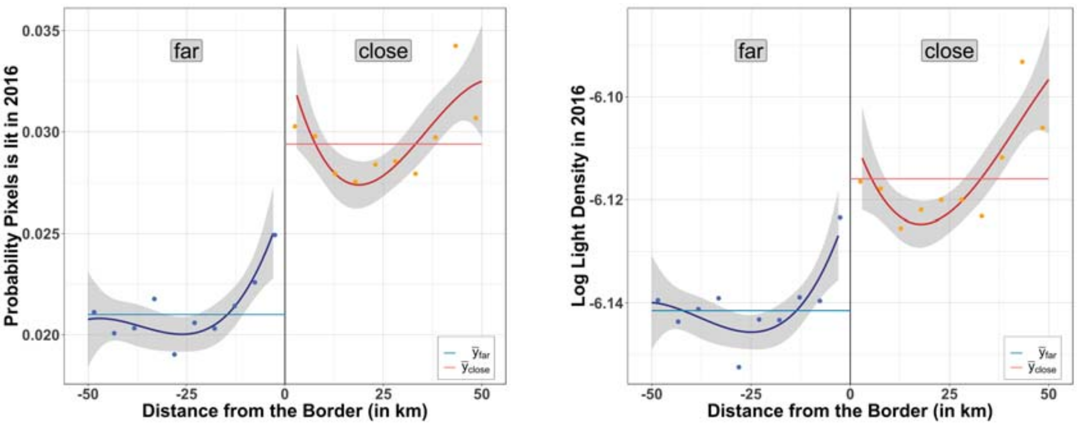
3.2 Border Discontinuity Graphs

In the next step, the goal is to overcome the imbalance in location-specific characteristics with respect to the treatment intensity of isolation from the capital city. Yet, prior to moving to the most elaborate BDD model based on Equation 6, we undertake a simplified, yet more intuitive, graphical approach.

We begin by subdividing all national boundaries into segments of 50 km line lenght with a buffer of 50 km on either side (see A2 for an illustrative map).[12] Each segment side belongs to a different country (and capital city). Next, we determine the average distance to the capital city for each segment side and assign them into the group 'close' if they are relatively closer to their capital city as their opposing boundary segment and into the group 'far' otherwise. Through this procedure, we obtain two groups that are balanced with respect to location-specific covariates but with systematically different distances from their respective capital cities. Thereby, this procedure enables us to assess the impact of crossing the boundary from 'far' to 'close' to the capital city on nightlight density while keeping geographical factors constant.

Figure 6: Boundary Discontinuity Graphs

(a) Extensive (b) Intensive



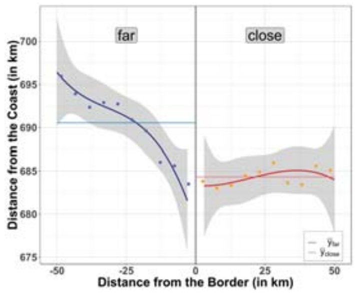
Note: The graphs illustrate the graphical BDD. The grey buffer around the lines represent the 95% confidence intervall. The bins on the left-hand side are, with an average distance of 830 km, relatively far from the capital city and represent a total of 241,241 pixels. In contrast, pixels on the right-hand side are, with an average of around 430 km, relatively close to the capital city and represent 238,908 pixels.

Figure 6 plots the border discontinuity graphs with 6a referring to the extensive and 6b to the intensive scale of nightlights. Areas on the left are on average 830 km and areas on the right 430 km away from the capital city. The graph indicates a large jump of around 25% in the probability with which pixels are lit when moving from relatively remote to areas near the capital city.

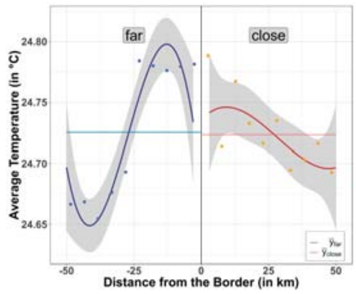
[12] To obtain balanced subgroups, we drop segments where the minimum distance from the border on either side is greater than 5 km or the maximum distance less than 45 km (which occurs mostly around very uneven boundaries). This reduces our sample from 729,093 to 480,149 pixels.

Figure 7: Discontinuity Balancing Graphs: Capital City

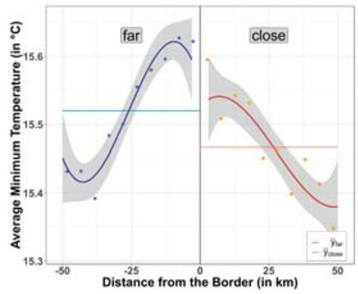
(a) Distance from Coast



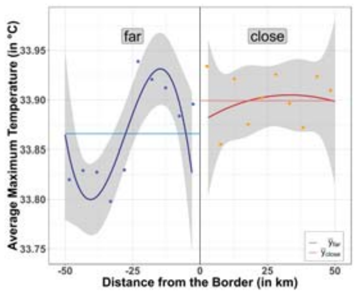
(b) Mean Temperature



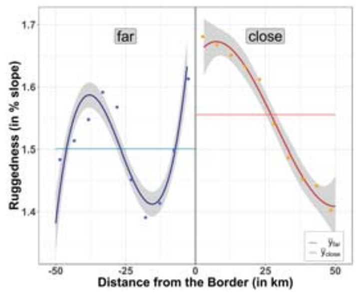
(c) Min Temperature



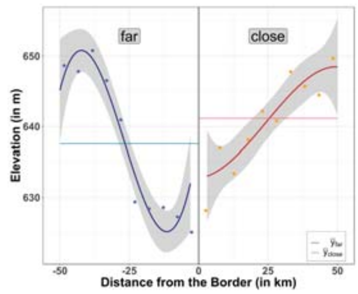
(d) Max Temperature



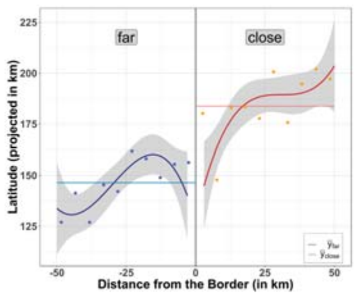
(e) Ruggedness



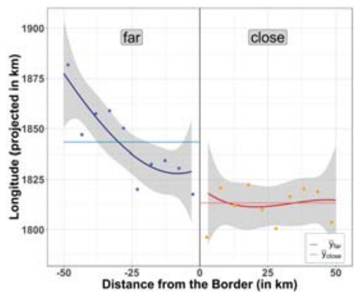
(f) Elevation



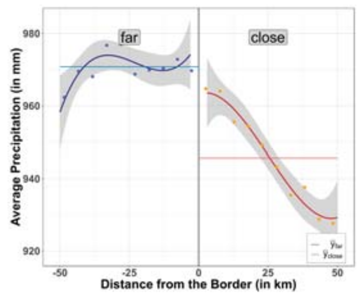
(g) Latitude



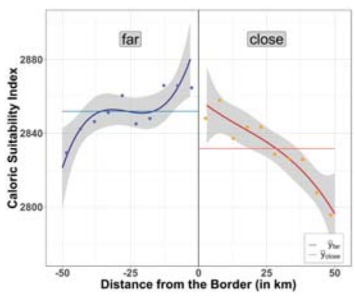
(h) Longitude



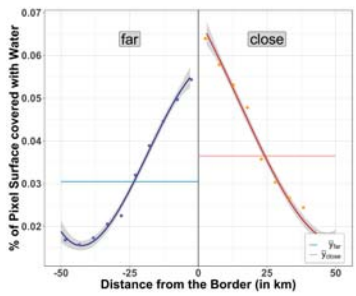
(i) Precipitation



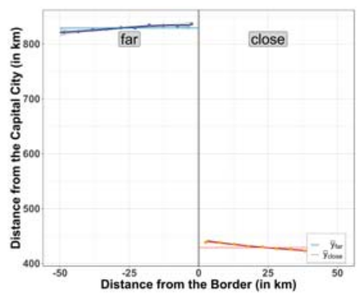
(j) Crop Suitability



(k) Water Bodies



(l) Distance Capital City



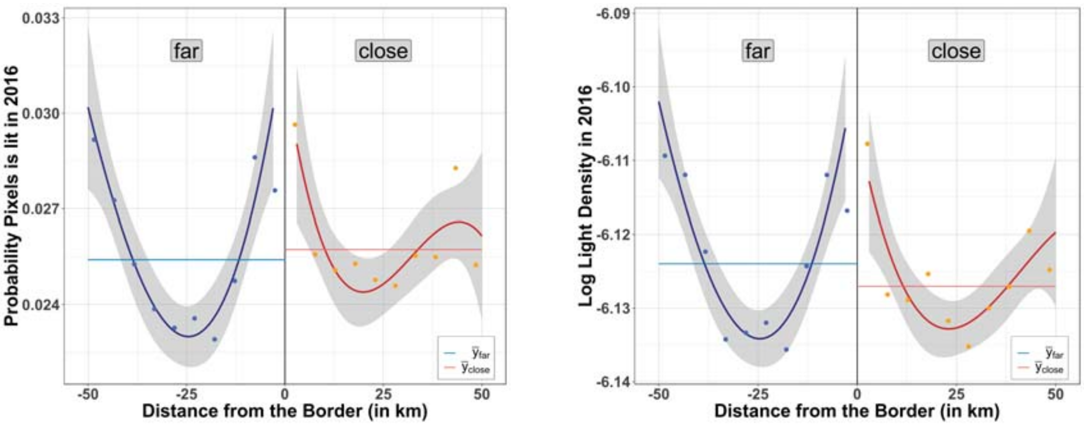
Note: The graphs illustrate the graphical balancing tests corresponding to Figure 6. The grey buffer around the lines represent the 95% confidence intervall. The bins on the left-hand side are, with an average distance of 830 km, relatively far from the capital city and represent a total of 241,241 pixels. In contrast, pixels on the right-hand side are, with an average of around 430 km, relatively close to the capital city and represent 238,908 pixels.

Even if (un-)observable geographical factors should by construction be balanced between the two regimes ('far' and 'close'), this needs to be emprically confirmed. Figure 7 illustrates the respective graphs for a range of geographical indicators. All covariates, except for distance from the capital city, move smoothly across the threshold and do not exhibit significant discontinuities at the cutoff. Based on the balancing tests, we can thus conclude that the jump in nightlight density stems from difference in isolation from the capital city.

A remaining concern is that the results might be confounded by country characteristics. For example, supposing that small countries perform better economically, and given that small countries tend to constitute the 'close' group, we would expect to see comparable patterns even in the absence of effects induced by isolation from the capital city. Moreover, it might be that the effects are a result of isolation from a major city rather than isolation from the political center. Yet, if either of the two concerns were valid, we would observe a similar result when deploying the location of other major cities. Figure 8 depicts the graphs when conducting the analogous analysis but for isolation from the placebo city.

Figure 8: Boundary Discontinuity Graphs - Placebo

(a) Placebo City Isolation - Extensive (b) Placebo City Isolation - Intensive



Note: The graphs illustrate the placebo tests regarding the graphical BDD. A placebo city is the largest city if the capital is not the largest city and the second largest city otherwise. The grey buffer around the lines represent the 95% confidence intervall. The bins on the left-hand side are, with an average distance of 820 km, relatively far from the placebo city and represent a total of 238,980 pixels. In contrast, pixels on the right-hand side are, with an average of around 440 km, relatively close to the placebo city and represent 237,153 pixels.

As it turns out, the placebo graphs clearly indicate that there are no effects associated with isolation from other cities.[13] Yet, despite these highly encouraging results, at this stage, we cannot be entirely sure that the estimated effects are causal. While the graphical BDD, balancing and placebo tests give strong support to our hypothesis, in the next step, we need to properly account for the switch between countries and ethnic homelands at the cutoff.

[13]The respective balancing graphs, once again, indicate that (un-)observable geographical factors are balanced and move smoothly across the cutoff (see Figure A4).

3.3 Boundary Regression Discontinuity

In order to tackle the remaining shortcomings pointed out in Section 3.2, we move to a more sophisticated BDD regression model based on Equation 6. In this setting, the switch between countries at the boundary cutoff is accounted for using country fixed effects. Furthermore, we identify arbitrary borders by exclusively using border pieces that divide ethnic homelands. Additionally, we nest our boundary segments within the restricted partitioned ethnic homelands to prevent ethnic shifts within segments (see Section 2.4).

Table 2: Boundary Discontinuity Estimation

	Dependent variable:							
	Probability Pixel is Lit in 2016 (VIIRS)				Log Light Density in 2016 (VIIRS)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Distance from the Capital City	-0.023** (0.010)	-0.025** (0.010)	-0.031** (0.012)	-0.031** (0.013)	-0.104** (0.048)	-0.112** (0.048)	-0.137** (0.058)	-0.143** (0.061)
	Polynomials for: distance from the border $\times$ country $\times$ ethnicity (305 groups)							
2nd order	x	x	-	-	x	x	-	-
3rd order	-	-	x	-	-	-	x	-
4th order	-	-	-	x	-	-	-	x
Geography Cov.	NO	YES	YES	YES	NO	YES	YES	YES
Country FE	36	36	36	36	36	36	36	36
Segment FE	569	569	569	569	569	569	569	569
Observations	168,620	168,620	168,620	168,620	168,620	168,620	168,620	168,620
R^2	0.181	0.183	0.189	0.193	0.161	0.162	0.169	0.173
Adjusted R^2	0.175	0.177	0.182	0.185	0.155	0.156	0.161	0.164

Note: This table reports our main BDD regression results corresponding to Equation 6. In order to avoid capturing the break between the capital city and the hinterlands, we exclude 20 km around each capital city from our sample. To prevent misassignment of detected nightlights between countries due to blooming, we exclude 3 km on each side of the boundary. The 'Geographical Cov.' include: distance from the coast (in km), ruggedness (in % slope), % surface covered with water, mean annual temperature, minimum average temperature during the coldest month, maximum average temperature during the warmest month (in °C), crop caloric index, annual precipitation (in mm), longitude and latitude (projected in km). Boundary segments corresponds to a buffer of 25 km around border pieces of 50 km line length and are entirely nested within a restricted ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). The observations are weighted such that each segment side has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by boundary segment. *p<0.1; **p<0.05; ***p<0.01

Table 2 presents the BDD results for the extensive (columns (1)-(4)) and intensive (columns (5)-(8)) scales of nightlight density. Columns (1) and (5) exclude all geographical covariates and serve as a reference to assess the extend to which potentially omitted location-specific characteristics might confound our estimates. When comparing column (1) to (2) and column (5) to (6), it becomes clear that our identification strategy proves to be effective. The omission of an extensive set of geographical covariates impacts the magnitude of our estimates only by a small and statistically insignificant margin. With the exception of ruggedness, all balancing tests confirm that in our BDD model, (un-)observable factors are balanced with respect to treatment intensity - the coefficients are either insignificant and/or very close to zero and economically negligible (see Table A7). The models in columns (2)-(4) as well as (6)-(8) feature an increasing number of polynomials of the running variable, distance from the border. In order to allow for a sufficient degree of flexibility regarding the dynamics of nightlights around the boundary, we choose third order polynomials as our default option. Consequently, applying our BDD estimation framework, we can verify that isolation from the capital city has a negative causal impact on economic development. A one percent increase in distance from the capital city decreases the probability of a pixel to be lit by 3 percentage points and the nightlight intensity by 0.14 percent. The causal estimates are therefore of a slightly higher absolute magnitude than the OLS and boundary area estimates (see Table 1). This differential is likely triggered by the fact that OLS estimates are confounded by local economic conditions. One such example are the economically high performing mining areas in the South-Eastern part far away from the capital of DR Congo.

3.4 Placebo Tests

In this section, we use our BDD framework to test whether the driving characteristic of isolation from the capital city is rooted in isolation from the political center or, alternatively, based on isolation from a major city within the country. In order to answer this question we compare the effects of isolation from the capital city to isolation from other major cities within the country, the placebo cities, using our estimation approach specified in Equation 5.

The results in Table 3 indicate very clearly that the effects of isolation from the capital city differ fundamentally from those of isolation from the placebo city. While, the impact of isolation from the capital city is significantly negative across all model specifications[14], the effects associated with placebo city isolation are insignificant and very close to zero. This result holds when decomposing isolation from a city into a city type and city size effect (see column (6) and (8) where we additionally control for the interactions of capital and placebo city isolation with their respective population counts). These results imply that the type of a city (capital vs. other cities) is much more important than the city size. We conclude that hosting the political center of the country is the driving force behind the effects of remoteness from the capital city.

[14]Due to some collinearity between capital and placebo city isolation, the coefficient of isolation from the capital city is slightly lower as compared to Table 2.

Table 3: Placebo Tests

	Dependent variable:							
	Boundary Area Regression				Boundary Discontinuity Regression			
	Probability Pixel is Lit in 2016 (VIIRS)		Log Light Density in 2016 (VIIRS)		Probability Pixel is Lit in 2016 (VIIRS)		Log Light Density in 2016 (VIIRS)	
	OLS	Ethn FE	OLS	Ethn FE	BDD	City Size	BDD	City Size
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Distance from the Capital City	-0.022***	-0.014**	-0.087***	-0.065***	-0.018**	-0.019**	-0.070*	-0.072*
	(0.006)	(0.005)	(0.027)	(0.025)	(0.009)	(0.009)	(0.037)	(0.037)
Log Distance from the Placebo City	-0.008	-0.009	-0.035	-0.038	-0.005	-0.010	-0.041	-0.065
	(0.005)	(0.007)	(0.024)	(0.030)	(0.018)	(0.017)	(0.081)	(0.073)
CAP $\times$ SIZE$_{CAP}$	-	-	-	-	-	0.001	-	0.004
	-	-	-	-	-	(0.001)	-	(0.005)
PLC $\times$ SIZE$_{PLC}$	-	-	-	-	-	0.006	-	0.029
	-	-	-	-	-	(0.010)	-	(0.047)
	Polynomials for: distance from the border $\times$ country $\times$ ethnicity (299 groups)							
3rd order	-	-	-	-	x	x	x	x
Geography Controls	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	37	37	37	37	35	35	35	35
Ethnicity FE	NO	351	NO	351	-	-	-	-
Segment FE	-	-	-	-	554	554	554	554
Observations	414,879	414,876	414,879	414,876	164,337	164,337	164,337	164,337
R^2	0.083	0.134	0.071	0.123	0.186	0.186	0.164	0.164
Adjusted R^2	0.083	0.133	0.071	0.122	0.179	0.179	0.156	0.156

Note: This table reports our boundary area and BDD placebo test based on Equation 5. In order to avoid capturing the break between the capital or placebo cities and the hinterlands, we exclude 20 km around each capital and placebo city from our sample. To prevent misassignment of detected nightlights between countries due to blooming, we exclude 3 km on each side around shared national boundaries. The 'Geographical Cov.' include: distance from the coast (in km), ruggedness (in % slope), % surface covered with water, mean annual temperature, minimum average temperature during the coldest month, maximum average temperature during the warmest month (in °C), crop caloric index, annual precipitation (in mm), longitude and latitude (projected in km). Columns (1)-(4) constitute boundary area regressions and columns (2) and (4) additionally include ethnicity fixed effects. Boundary segments corresponds to a buffer of 25 km around border pieces of 50 km line length and entirely nested within a restricted ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). Columns (6) and (8) include interactions between isolation from the capital and placebo city and their respective population counts. The observations in columns (5)-(8) are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by ethnic homeland in columns (1)-(4) and border segment in columns (5)-(8) *p<0.1; **p<0.05; ***p<0.01

4 Sensivity Analysis

4.1 Robustness

In this section, we examine whether the results from Section 3.3 are robust to variations in the precise model specification. Firstly, we reduce the bandwith of the segments around the boundary from 25 km to 15 km. Simulataneously, we only exclude pixels within 1.5 km, instead of 3 km, around the boundary. In addition, we run the regressions with a varying degree of up to fourth order polynomials of the running variable. As can be clearly seen in Table A11, the results are very similar to the previous findings in direction, magnitude and significance.
We then investigate whether the effects of isolation from the capital city are limited to areas close to the capital city. Therefore, in the next step, we increase the sample restriction from excluding 20 km (default) around the capital city to 50, 75 and 100 km. Once again, the results in Table A11 reveal that the estimated effects are very stable with respect to this modification. This finding implies that isolation from the capital city is a more general phenomenon that is relevant for wide areas within the country.

In the subsequent step, we test whether the estimated effects of isolation from the capital city are driven by individual countries or boundaries. To this end, in Figure A6, we iteratively exclude both sides of boundary segments adjoining a particular country and compare the estimated coefficient to our unrestricted baseline coefficients (in Table 2 columns (3) and (7)). The figures clearly illustrate that the estimated coefficients are highly robust to excluding particular countries/boundaries. Even when excluding large amounts of border segments for large or centrally located countries, all confidence bands overlap clearly with that of the baseline estimate.
While the coefficients prove themselves to be very stable to excluding even large parts of the sample, it might be that the deviations in the estimated coefficients are systematic. Therefore, we test whether there are heterogeneities with respect to the implications of isolation from the capital city depending upon a country's level of decentralization, democratization or overall level of development. For this purpose we categorize all boundaries as either delimiting two relative decentralized[15] (democratic[16], developed[17]) or two relatively non-decentralized (autocratic,

[15] We define countries as decentralized if they exceed the median decentralization value (based on a decentralization index by Thomas Bijl for J. Vernon Henderson (LSE processed)).

[16] Democratic countries are defined as having a Polity2 index score of greater than zero (Marshall et al., 2017).

[17] Since there is no obvious cutoff for distinguishing between relatively developed and underdeveloped countries, we categorize them as such depending on whether they exceed the sample median or mean GDP level based on estimates by the World Bank (2016).

underdeveloped) countries or one of each. We then run regressions allowing for heterogenous coefficients for the different boundary pair cateogries and compare the coefficients using F-tests (see Table A13).[18] The results for decentralization in Table A13 in columns (1)-(4) are ambiguous and we cannot reject the hypothesis that the effects are the same for relatively decentralized and non-decentralized countries. In contrast, columns (5)-(8) reveal that the average effect in democracies is higher than in autocracies where they are consistently very close to zero. The difference is statistically significant for the 20-year average measure of democracy. Regarding GDP per capita, irrespective of whether we split the countries by the median or mean GDP per capita, the results consistently indicate that the effect are significantly stronger in less developed countries. We conclude that the implications of isolation from the capital city seem to be more relevant under democratic, as opposed to autocratic, institutional framework conditions and more relevant in relatively underdeveloped countries. Yet, these results should be interpreted with caution as the patterns might be confounded by other characteristics these groups of countries have in common.

Next, we study whether the effects of isolation from the capital city had been relevant at some point in the past and have persisted until today or, alternatively, whether the effects are still ongoing and relevant today. For this exercise, we exclude all pixels that have already been lit in 1992[19] from the sample and thereby focus on the pattern of newly emerging nightlights (see Table 4). While the coefficients are, as expected, slightly lower as in Table 2, they are still strong in magnitude and highly significant which underlines the present-day importance of the effects.
Further, we want to examine whether a potential shift in the role of the ethnicity within the country distorts our findings. One factor that we have not accounted for in our identification strategy is that a partitioned ethnic homeland might represent a minority group in one but a majority group in another country. This circumstance makes it necessary to include a measure of ethnic representation within a country into our model. In columns (3) and (4) in Table 4 we include the *log* of the number of pixels belonging to the own ethnic homeland within the country. In contrast, in columns (5) and (6) we include the share of pixels of an ethnic homeland in the overall number of pixels within a country. While both measures are closely related, the former emphasizes the absolute size of an ethnicity while the latter explicitly targets an ethnic homeland's share within a country. The results indicate that ethnic representation does not confound the effects of isolation from the capital city.

[18]As policy indicators usually have a lot of fluctuations, we conduct the analysis based on the most recent snapshot of the indicators as well as a 20-year average.

[19]We use the earliest available DMSP-OLS nightlight grid from 1992 as VIIRS nightlights only date back to 2012.

Table 4: Border Discontinuity Estimation - Robustness

	Dependent variable: Nightlight Density in 2016 (Prob/Log/PC)								
	Exclude Pixels Lit in 1992		Accounting for Minority vs. Majority Jumps at the Boundary				Population Density		Log Lights Per Capita
	Prob	Log	Prob	Log	Prob	Log	Prob	Log	Log pc
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Distance from the Capital City	-0.022*** (0.008)	-0.085*** (0.031)	-0.032*** (0.012)	-0.142** (0.058)	-0.032*** (0.012)	-0.142** (0.058)	-0.026** (0.011)	-0.107** (0.049)	-0.263** (0.115)
	Polynomials for: distance from the border × country × ethnicity (305 groups)								
3rd order	x	x	x	x	x	x	x	x	x
Population Density	No	No	No	No	No	No	YES	YES	No
Log Ethnicity Area	No	No	YES	YES	No	No	No	No	No
Ethnicity Share	No	No	No	No	YES	YES	No	No	No
Geography Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	36	36	36	36	36	36	36	36	36
Segment FE	569	569	569	569	569	569	569	569	569
Observations	167,841	167,841	168,620	168,620	168,620	168,620	168,620	168,620	168,620
R^2	0.172	0.149	0.189	0.169	0.189	0.169	0.221	0.258	0.186
Adjusted R^2	0.165	0.141	0.182	0.161	0.182	0.161	0.214	0.251	0.179

Note: This table reports robustness tests for our main BDD regression results in Table 2 and extends the model in Equation 6. In order to avoid capturing the break between the capital city and the hinterlands, we exclude 20 km around each capital city from our sample. To prevent misassignment of detected nightlights between countries due to blooming, we exclude 3 km on each side of the national boundary. The 'Geographical Cov.' include: distance from the coast (in km), ruggedness (in % slope), % surface covered with water, mean annual temperature, minimum average temperature during the coldest month, maximum average temperature during the warmest month (in °C), crop caloric index, annual precipitation (in mm), longitude and latitude (projected in km). Boundary segments corresponds to a buffer of 25 km around border pieces of 50 km line length and are entirely nested within a restricted ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). In columns (1)-(2), we exclude pixels that were already lit in 1992. In columns (3)-(4), we account for the log of the area of the ethnicity wihin the home country and, in columns (5)-(6), we include the share of the ethnicity with respect to the total area of the country. In columns (7)-(8), we include population density as a covariate and in column (9), we use the log of lights per capita as our dependent variable. The observations are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by boundary segment. *p<0.1; **p<0.05; ***p<0.01

Since increased economic activity is directly associated to increased population density, either through higher net fertility or migration, it is difficult to disentangle the two. Moreover, population density maps do not exhibit a very high accuracy on the very fine pixel level and are themselves usually based on indicators of economic activity such as schools, hospitals, roads or even nightlights. Keeping these caveats in mind, in columns (7) and (8), we control for population density in 2015 to get an impression of the impact of isolation from the capital city when partialling out patterns of population density. An alternative and slightly more explicit test corresponding to GDP per capita is to use the log of the light density per capita as dependent variable (column (9)). The results in columns (7)-(9) suggest that the implications of isolation from the capital city go beyond population agglomeration and hold robust with respect to per capita estimates.

Finally, we cross-validate our results using the DHS wealth index as an alternative data source for measuring the spatial distribution of economic performance. For this purpose, we combine the latest available round for each country in our dataset. While the DHS comprises a geocoded wealth index for the vast majority of coun-

Table 5: DHS Wealth Index

	Dependent variable:			
	DHS Wealth Index (z-score)		DHS Wealth Rank (percentile)	
	(1)	(2)	(3)	(4)
Log Distance from the Capital City	-0.121*** (0.045)	-0.121** (0.052)	-0.035* (0.018)	-0.033* (0.019)
	Polynomials for: distance from the border			
3rd order	-	x	-	x
Household Cov.	YES	YES	YES	YES
Geography Cov.	YES	YES	YES	YES
Country FE	28	28	28	28
Segment FE	107	107	107	107
Observations	24,582	24,582	24,582	24,582
R^2	0.456	0.458	0.392	0.394
Adjusted R^2	0.426	0.381	0.453	0.455

Note: This table reports the BDD regressions results on household wealth using the DHS sample. The z-score of the wealth index constitutes the dependent variable in columns (1)-(2). The percentile rank within the country constitutes the dependent variable in columns (3)-(4). The 'Geographical Cov.' include: age of household head, age of houshold head squared, number of household members. The 'Household Cov.' include: distance from the coast (in km), mean annual temperature, minimum average temperature during the coldest month, maximum average temperature during the warmest month (in °C), annual precipitation (in mm), longitude and latitude (projected in km) and whether the household is in an urban or rural setting. Boundary segments corresponds to a buffer of 25 km around border pieces of 50 km line length and are entirely nested within a restricted ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). The observations are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by DHS cluster and boundary segment. *p<0.1; **p<0.05; ***p<0.01

tries and land areas in SSA, eight of the sample countries are not covered (see Fiugre A1a). Since the granularity of the data structure differs from nightlight grids, we have to implement some simplifications compared to the estimation framework of Table 2. Firstly, due to the lower sample size, we restrict the ethnic homelands by a negative buffer 5 km rather than 15 km. Secondly, the geographical accuarcy of the DHS is lower than remote sensing sources. DHS households are clustered with an average of 26 households sharing the same coordinate pair leaving us with a minimum of one and a median of seven clusters per segment side. Additionally, the assigned geolocation is randomized by up to 10 km. As a consequence, there is too little variation and too much noise in the data to model the running variable disaggregated for each ethnicity in each country separately. As an alternative, we include distance from the border in an aggregated form. Thirdly, as the observational unit are housholds, we include household level control variables: age of head of houshold, age of head of household squared and number of de jure houshold members. Lastly, since there are some concerns about the comparability of the DHS wealth index with regard to urban vs. rural households, we include a urban/rural dummy variable in our model. Yet, whether a location is urban or rural is endogenous as it is an outcome of economic development. As a consequence, our the magnitude of our estimated coefficients in Table 5 constitute lower bounds estimates.

The results in Table 5 confirm our finding about the adverse economic consequences of remoteness from the capital city. A one percent increase in distance from the capital city results in a drop of household wealth by around 0.12 standard deviations. This corresponds to a drop of 3.5 percentiles of the national wealth distribution. The respective balancing tests in columns (1)-(6) in Table A8 underline valid inference. The respective placebo tests in columns (7)-(8) in Table A8 once again validate that the effects are specific to isolation from the capital city and do not hold for other cities.

Based on the wide range of sensivity analyses that we conducted in this section, we conclude that our results are highly robust to a wide range of alternative specifications and robustness tests which confirm our estimated negative causal impact of remoteness from the capital city on economic performance.

5 Mechanisms

So far, we have shown that isolation from the political center within the country, the capital city, has strong adverse causal net effects on local economic performance. Since isolation from the capital city itself is not an economic variable, there must be a more concrete economic link between remoteness from the capital city and economic performance.

The provision of public goods is a fundamental driver of economic development (Besley and Ghatak, 2006; Dittmar and Meisenzahl, 2019). Campante and Do (2014) find that US states with isolated capital cities provide less public goods. These results might reflect aggregations of the microdynamics that are under scrutiny in this study. In this section, we will provide empirical support for the view that the level of public goods provision consitutes an important mediator. In a subsequent step, we then seek to shed light into the causes of the lower public goods provision in remote areas. In this context, we investigate political representation and accountability as potential mechanisms. While the results on political representation are ambiguous, the results on accountability clearly suggest that dysfunctional feedback and accountability mechanisms are relevant with regard to the effects.

5.1 Public Goods

Based on rounds 5, 6 and 7 of the Afrobarometer, we generate an index on the provision of public goods reflecting whether a cluster is provided with paved roads, electricity grid access, piped water and a sewage system. The public goods index is the average of binary responses about the availability of the respective provisions. Consequently, the index can take the values of 0, 0.25, 0.5, 0.75 and 1 corresponding to the respective share of public goods being present. Table 6 combines the results of OLS, boundary area and BDD regression models, similar to those in Section 3. We include a range of household and geography controls by default into all models. This includes a dummy variable corresponding to whether the respondent is located in an urban or rural area. However, since the degree of urbanization is an outcome of remoteness and thereby endogenous to the model, the estimated absolute magnitudes constitute lower bound estimates.[20] Furthermore, it should be noted that the Afrobarometer dataset has less observations than the nightlights sample. In order to avoid the sample size from getting too small, we do not restrict the ethnic homelands with a negative buffer before defining the boundary segments. Moreover, since Afrobarometer respondents are clustered in enumeration areas, with in some cases just one or two clusters per segment side, we do not account for distance from the boundary disaggregated but rather focus on capturing the general trend.

A one percent increase in isolation from the capital city decreases the probability index of public goods provision by around 10 percentage points.[21] This relationship also holds, albeit with a slight upward bias, for the OLS and boundary area regressions. Conducting balancing tests (see Table A9) exhibits that the BDD model is an effective way to reduce imbalances to an economically negligible margin. We conclude that people in areas isolated from the capital city receive significantly less public goods and services from their political leaders as compared to those closer to the capital city. Public goods are therefore likely to be an important mediator between isolation from the capital city and economic develpment.

However, it is not obvious why the provision of public goods in isolated areas is reduced. With regard to this puzzle, we empirically investigate two potential explanations. Firstly, geographical isolation potentially translate into political isolation

[20] In this context, it is important to account for population agglomeration as it is directly related to public goods provision. Since the urban/rural dummy is highly correlated with population density, it implicitly accounts for it. Additionally or alternatively including the mean population density in a 5 or 10 km buffer around the respondent has no significant impact on the estimated coefficient.

[21] The corresponding placebo tests and associated F-tests indicate that the effects are indeed specific to isolation from the capital city and do not hold for placebo cities.

Table 6: Channel Analysis: Public Goods Provision (Afrobarometer)

	Dependent variable: Public Goods Index		
	OLS	Boundary Area	BDD
	(1)	(2)	(3)
Log Distance from the Capital City	-0.019** (0.007)	-0.041*** (0.014)	-0.095*** (0.036)
	Polynomials for: distance from the border		
3rd order	-	-	x
Household Cov.	YES	YES	YES
Geography Cov.	YES	YES	YES
Country × Round FE	73	72	71
Segment FE	-	-	140
Observations	92,247	15,233	8,249
R^2	0.482	0.443	0.614
Adjusted R^2	0.481	0.440	0.604

Note: This table reports the regressions on the impact of isolation from the capital city on the level of public goods provision using the Afrobarometer survey. The 'Household Cov.' include: age, age squared and sex of respondent. The 'Geographical Cov.' include: distance from the coast (in km), longitude and latitude (projected in km) and whether the household is in an urban or rural setting. Column (1) correspond to the full sample OLS regression, columns (2) to the 25 km boundary area regression and column (3) to the BDD regression. Boundary segments corresponds to a buffer of 25 km around border pieces of 50 km line length and are entirely nested within an ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). In column (1), the observations are weighted according to the Afrobarometer survey weights. In column (3), the observations are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by Afrobarometer cluster and ethnic homeland (columns (1) and (2)) and Afrobarometer cluster and boundary segment (column (3)). *p<0.1; **p<0.05; ***p<0.01

and thereby exclusion from government resources. For example, isolated areas might be less represented within the incumbent government and therefore benefit less from ethnic or regional favoritism (Hodler and Raschky, 2014; Dreher et al., 2019). Another explanation is that public goods might be lower due to dysfunctional feedback and accountability mechanisms. Political agents might simply lack the incentives to provide those in isolated areas with public goods.

5.2 Public Goods and Political Representation

We start by investigating whether political representation and 'political favoritism' are relevant in this context and test whether segment sides farther away from the capital city exhibit a lower access to power. For this purpose, we examine whether the national leaders are more likely to come from segment sides closer to the capital city using an updated version of the database by Dreher et al. (2016: 40-41). Since measuring an area's political representation and access to power solely based on the head of state might not sufficiently reflect the overall power access, we complement the analysis using the Ethnic Power Relations Core Dataset 2019 (EPR) (Vogt et al.,

2015) and combine it with spatial information about the location of the respective politically relevant groups (Wucherpfennig, 2011). The results in Table A10 indicate that a one percent increase in distance from the capital city decreases the probability that the incumbent political leader comes from the same region by 9 percentage points. In contrast, it turns out that a one percent increase in isolation increases the number of years participated in the ruling government by 3.6 years (within a period of 18 years since 2000).[22] Since the results go in opposite directions, it remains ambiguous which of the two outweights the other.

5.3 Public Goods and Accountability

Next, we investigate whether accountability might be relevant to the mechanism between isolation and public goods provision. The idea behind this potential channel is that, public leaders might have reduced the incentives to invest into isolated areas. One reason for this might be that the threat of collective action is limited in isolated areas (Johnson and Thyne, 2018; Campante et al., 2019). Similarly, Pierskalla (2016) uses this argument in context of the 'urban-rural bias'. Political leaders might simply neglect the demands and hazard the consequences of dissatisfied isolated citizens. We therefore begin the analysis by examining how people in different geographical locations relate to their political leaders. Given the reduced provision of public goods, we might expect that isolated groups demonstrate mistrust towards their government. However, as it turns out, people farther isolated from the capital exhibit a significantly higher level of trust into their political leadership (see column (1) in Table 7). The results in Table A14 demonstrate that the increased trust in politicians is associated with the ruling party but not with the opposition party suggesting that the reason for the higher trust does not stem from a generally higher level of trust or credulity in isolated areas. Rather, it seems that the increased trust in state leaders is a result of a lower perceived corruption as well as a higher performance evaluation of national leaders (see columns (1) and (2) in Table 7). The augmented approval rate of national leaders in isolated areas is in contrast to the idea that the national governments simply neglect the demands from people in isolated areas. The higher voter turnout in remote areas also contradicts the view that isolated citizens feel left out and politically disenchanted (see Table A14).

These patterns rather support the view that isolated citizens are not aware of their disadvantaged position and therefore do not demand a higher provision of public services. Yet, this does not seem to be a matter of education or asymetric identity

[22] A simple explanation for this phenomenon might be that incumbent governments tend to include isolated groups into the government to counteract secessive aspirations. Another possible reason could be that isolated groups are striving to have an impact politically and overcompensate for their geographical isolation.

Table 7: Channel Analysis: Perception of Political Leadership and Accountability

	BDD Model with dependent variable z-score of:					
	Trust in Political Leaders	Government Corruption Perception	Government Performance Evaluation	Education Level	Frequency of News Consumption	Advocate Checks and and Balances
	(1)	(2)	(3)	(4)	(5)	(6)
Log Distance from the Capital City	0.191***	-0.078*	0.171***	0.064	-0.139**	-0.094**
	(0.061)	(0.043)	(0.064)	(0.056)	(0.066)	(0.041)
	Polynomials for: distance from the border					
3rd order	x	x	x	x	x	x
Household Cov.	YES	YES	YES	YES	YES	YES
Geography Cov.	YES	YES	YES	YES	YES	YES
Country × Round FE	70	71	71	71	71	71
Segment FE	140	140	140	140	140	140
Observations	7,812	6,705	6,593	8,310	8,113	7,763
R^2	0.202	0.191	0.229	0.312	0.192	0.160
Adjusted R^2	0.178	0.164	0.202	0.293	0.169	0.135

Note: This table reports the regressions on the impact of isolation from the capital city on the perception of political leaders and accountability. The 'Household Cov.' include: age, age squared and sex of respondent. The 'Geographical Cov.' include: distance from the coast (in km), longitude and latitude (projected in km) and whether the household is in an urban or rural setting. Columns (1)-(3) correspond to trust, corruption perception and performance evaluation of their national political leadership. Column (4) corresponds to the educational level, column (5) to the frequency of news consumption and column (6) to the extent to which respondents are advocating a system of checks and balances to monitor the actions of their political leaders. All models are BDD regressions using 'Segment FE' for boundary segments of 50 km length with a buffer of 25 km that are nested within an ethnic homelands based on the 'Tribal Map of Africa' (Murdock, 1959). All observations are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by Afrobarometer cluster and boundary segment. *p<0.1; **p<0.05; ***p<0.01

because these characteristics are balanced between areas close and far from the capital (see Tables 7 and A14). In contrast, we find significant imbalances with regard to the frequency of news consumption which is considerably smaller in isolated areas (see Table 7). Hence, isolated citizens might trust their national leaders more because they know less about them. This factor has important repercussions on the functioning of effective accountability mechanisms that keep the actions of political agents aligned with the interest of the people. Since isolated citizens know less about the actions of their political agents and their reduced provision with public goods, national leaders are left with lower incentives to providing them with services. The hypothesis of dysfunctional accountability mechanisms in isolated areas is also consistent with the observation that isolated citizens are less inclined to advocate for checks and balances on the government. The corresponding placebo tests indicate that these patterns are specific to isolation from the capital city and do not hold for other major cities (see Table A15).

To conclude, our analysis suggests that public goods provision is a important mediator between remoteness from the capital city and economic performance. Furthermore, our results support the view that dysfunctional accountability mechanisms are important regarding the reduced level of public goods provision.

6 Alternative Explanations

In this section, we investigate two alternative potential channels that might constitute important mediators between distance from the capital city and economic development: Market access and conflict. We show that neither market access nor conflict is likely to be relevant with regard to the observed patterns.

6.1 Market Access and Trade

As an alternative potential channel, distance to the capital city might affect economic growth through reduced market access (Redding and Sturm, 2008; Bosker and Garretsen, 2012; Donaldson and Hornbeck, 2016; Gibbons and Wu, 2017). Places that are farther away from the capital city might face higher costs when buying and selling intermediate and final goods and services. This, in turn, might have major repercussions on the opportunities for economies of scale and productivity growth. Since capital cities constitute important markets within the country, these effects might be significant. Yet, if a reduced market access was indeed an important channel, we should observe similar effects for remoteness from other major markets within the country. The fact that, even when accounting for city and hence market size, the coefficients associated with placebo cities are insignificant (see Table 3) raises doubt on the relevance of market access in this context. A potential explanation could be that the capital or placebo cities only represent one of multiple market agglomerations within the country which decreases their individual impact.

Another way of testing for this channel makes use of the fact that the shared national boundaries in our sample feature different degrees of border permeability with regard to trade. If borders did not constitute barriers for trade, in our BDD design, counterfactual pixels on both sides of the boundary would by construction have the same market access. Therefore, if market access was indeed a relevant channel, we should observe that the effects of remoteness from the capital city are strongest at restrictive borders and lower at relatively open national boundaries. In Table 8, we therefore test whether the impact of isolation from the capital city is lower at boundaries within trade blocs such as within free trade agreements (FTA), customs and monetary unions. For this purpose, we include interactions between *Log Distance from the Capital City* and dummies identifying low barrier boundaries into our main BDD model (see Equation 6). In columns (1) and (2) in Table 8, we use boundaries within FTAs. The results suggest that the effects are stronger within FTAs than at more restrictive boundaries which is in contrast to the idea that market access is driving the results. In columns (3) and (4), we tighten the criterion for relatively open borders and only consider customs unions and in columns (5) and

Table 8: Channel Analysis: Market Access and Trade

	Dependent variable: VIIRS Nightlights in 2016 (Prob/Log)					
	Prob	Log	Prob	Log	Prob	Log
	(1)	(2)	(3)	(4)	(5)	(6)
Log Distance from the Capital City	-0.013 (0.011)	-0.067 (0.044)	-0.037*** (0.014)	-0.164** (0.068)	-0.035** (0.014)	-0.158** (0.066)
CAP × FTA	-0.028*** (0.011)	-0.113*** (0.044)	-	-	-	-
CAP × Customs Union	-	-	0.023 (0.015)	0.098 (0.061)	-	-
CAP × Customs Union and Monetary Union	-	-	-	-	0.018 (0.015)	0.083 (0.060)
	Polynomials: dist. to border × country × ethnicity (305 groups)					
3rd order	x	x	x	x	x	x
Geography Cov.	YES	YES	YES	YES	YES	YES
Country FE	36	36	36	36	36	36
Segment FE	569	569	569	569	569	569
Observations	168,620	168,620	168,620	168,620	168,620	168,620
R^2	0.189	0.169	0.189	0.169	0.189	0.169
Adjusted R^2	0.182	0.161	0.182	0.161	0.182	0.161

Note: Standard errors in paranthesis are clustered by border segment.
*p<0.1; **p<0.05; ***p<0.01

Note: This table reports the tests for heterogeneities at boundaries that are less restrictive to trade and extend the model in Equation 6. In order to avoid capturing the break between the capital city and the hinterlands, we exclude 20 km around each capital city from our sample. To prevent misassignment of detected nightlights between countries due to blooming, we exclude 3 km on each side of the border. The 'Geographical Cov.' include: distance from the coast (in km), ruggedness (in % slope), % surface covered with water, mean annual temperature, minimum average temperature during the coldest month, maximum average temperature during the warmest month (in °C), crop caloric index, annual precipitation (in mm), longitude and latitude (projected in km). Boundary segments corresponds to a buffer of 25 km around border pieces of 50 km line length and are entirely nested within a restricted ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). We include interactions of *CAP* (*Log Distance to the Capital City*) and a dummy for boundaries between countries with FTAs (columns (1)-(2)), customs unions (columns (3)-(4)) and those that additionally share a common currency (columns (5)-(6)). The observations are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by boundary segment. *p<0.1; **p<0.05; ***p<0.01

(6) only those that also share a common currency. In both cases, we cannot reject the hypothesis that the effects at relatively open boundaries are any different than at restrictive ones. Consequently, based on the results in this section, we conclude that it is very unlikely that market access and trade constitute the missing economic link between remoteness from the capital city and economic performance.

6.2 Conflict

There is vast empirical evidence that conflict has negative implications for economic developement (see for example Ray and Esteban (2017) for a general overview and

Serneels and Verpoorten (2015) or Besley and Reynal-Querol (2014) for evidence from the African continent). Further, there are multiple ways in which isolation from the capital city might affect conflict, hence ultimately economic performance. Since a conflict or protest farther away from the capital represents a lower threat to a government (Johnson and Thyne, 2018), the state might be less inclined to prevent or resolve such isolated conflicts. Also, the capacity of a state to counter conflicts in isolated areas might simply be restricted. This circumstance might even attract conflict parties to target remote areas. Moreover, a potentially lower state presence might impact the propensity for ethnic cleavages and conflict. Lastly, conflict might be a result of inequalities between areas close and far from the capital city and thereby reinforce the adverse implications of isolation from the capital city.

Table 9: Channel Analysis: Conflict

	Dependent variable: Conflict frequency (ACLED)							
	Viol	Demo	Non-V	All	Viol	Demo	Non-V	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Distance from the Capital City	0.356 (0.720)	0.061 (0.632)	0.130 (0.146)	0.547 (1.344)	0.413 (0.732)	0.186 (0.573)	0.151 (0.149)	0.751 (1.318)
Population Count in Segment Side	-	-	-	-	0.026 (0.021)	0.056** (0.026)	0.010* (0.006)	0.092* (0.050)
Country FE	35	35	35	35	35	35	35	35
Segment FE	568	568	568	568	568	568	568	568
Observations	1,138	1,138	1,138	1,138	1,138	1,138	1,138	1,138
R^2	0.726	0.558	0.620	0.684	0.730	0.648	0.648	0.709
Adjusted R^2	0.415	0.055	0.188	0.325	0.423	0.247	0.246	0.377

Note: This table reports the balancing tests on conflict with regard to isolation from the capital city. The observational unit in these models are the BBD boundary segments. The dependent variables are instances of conflict by type in the respective side of the boundary segment in the period between 01.01.2000 and 27.11.2019. Column (1) refers to 'violent conflicts', column (2) to 'demonstrations', column (3) to the number of 'non-violent actions' and column (4) aggregates all three kinds of conflict (for more information on these categories please refer to the ACLED homepage at: https://www.acleddata.com/resources/general-guides/). Boundary segments corresponds to a buffer of 25 km around border pieces of 50 km line length and are entirely nested within a restricted ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). Standard errors in paranthesis are clustered by boundary segment. *p<0.1; **p<0.05; ***p<0.01

In order to assess whether conflict is actually relevant in this context, we test whether there is any pattern of increased or perhaps even decreased conflict in isolated areas. To this end, we use our ACLED dataset of conflicts by type (Violent Events, Demonstration Events and Non-Violent Action) (Raleigh et al., 2010). Out of the total 88,853 conflict events in our sample countries between 01.01.2000 and 27.11.2019, a total of 3,446 fall into the area of our boundary segments. We aggregate the frequency of conflict that fall within each segment side and run BDD regressions with segment sides as the observational unit (see Table 9). Since conflict frequency might directly increase with population density, in columns (5)-(8), we additionally account for the total population count in each segment side. Our results demonstrate that there is no significant relationship between the frequency any conflict type (or all types of conflicts aggregated) and distance from the capital city. As a consequence, we have no reason to believe that conflict is relevant with regard to the implications of isolation from the capital city.

7 Conclusion

Using extensive remote sensing data on the very fine pixel level and large collections of geocoded surveys from the DHS and the Afrobarometer, we investigate the impact of isolation from the capital city on economic development in Sub-Saharan Africa. We obtain quasi-random variation in treatment at arbitrarily set national borders that divide ethnic homelands with similar geographical, social and historical factors. Conducting our analysis in a BDD regression framework, we deliver tangible evidence that isolation from the capital city imposes strong adverse causal net effects on the level of local economic capacity. We perform a series of alternative specifications, balancing and robustness tests that underline that our estimates are in fact causal. Moreover, comparing the effects of isolation from the capital city to isolation from other major cities confirms that hosting the political center is the driving force behind the effects.

In addition, we investigate potential channels through which isolation from the capital city might affect economic performance: public goods provision, market access and conflict. We show that the latter two, market access and conflict, are unlikely to be the link between isolation and economic development. In contrast, we document that remoteness from the capital city, as opposed to other major cities, is linked to a significant drop in the level of public goods provision. This finding suggest that the provision of public goods and services constitutes a key mediator between isolation and prosperity. In order to understand the imbalances in public goods, we explore two potential explanations. Firstly, we hypothesize that geographical isolation might translate into political isolation and thereby exclusion from government resources and, secondly, that politicians are not being held accountable by isolated citizens and therefore have reduced incentives to provide them with public goods. Our findings regarding political representation are ambiguous - the head of state is more likely to come from regions closer to the capital city but remote regions are more often part of the coalition in power. In contrast, our findings provide clear support for the accountability channel. Our analyses indicate that isolated populations, despite receiving less public goods, have more trust into their political leaders, evaluate their performance better, believe less that they are corrupt or that their actions should be monitored. At the same time, people in isolated areas follow the news less frequently. We interpret this as reflecting an asymmetry in information about political affairs between areas far and close from the capital. We conclude that these findings point at dysfunctional accountability mechanism that are at the root of the decreased levels of public goods and ultimately hamper economic growth.

Our findings are novel in the literature and provide new insights into the political economy of the location of the capital city (Campante and Do, 2014; Campante et al., 2019). Furthermore, we add to the literature regarding the limited institutional outreach of the state beyond the capital city (Michalopoulos and Papaioannou, 2013) and the literature on power sharing and political representation in SSA (Francois et al., 2015). Last but not least, by identifying proximity to the capital as an important dimension of spatial inequality, we contribute to the debate about the causes of the very high levels of economic inequality in the Sub-Saharan African context.

The results of this study underline the importance for targeted investments into public goods that are currently undersupplied in areas distant from the capital city. An alternative policy approach would be to strengthen the accountability mechanisms that foster a more equal distribution of public goods indirectly. Our analyses suggest that increasing the connectivity between the capital and the hinterland - with regard to physical transportation as well as media and communication - could increase accountability. Future research needs to analyze to what extend infrastructure upgrading, that reduces the meaning of distance, alleviates the adverse implications of remoteness from the capital city - and perhaps makes them ultimately disappear altogether.

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A Appendix

A.1 Data Sources and Description

In the following, we present the various datasets that we collected from different sources and merged into the final dataset for the remote sensing analysis including an URL for download:

Remote Sensing Grids

Regarding nighttime luminosity data, there are currently two products: the 'new' VIIRS (Visible Infrared Imaging Radiometer Suite) by the Suomi National Polar Partnership between NOAA and NASA and the 'old' Version 4 DMSP-OLS (Defense Meteorological Satellite Program - Operational Linescan System) by the U.S. Air Force and the National Oceanic and Atmospheric Administration (NOAA). The VIIRS images are more recent and are superior to the DMSP-OLS with regard to their accuracy and resolution (Elvidge et al., 2013). We use the latest cleaned annual VIIRS product from 2016 that underwent extensive filtering including outlier (such as fires or ephemeral lights) and background (non-lights) removal as our main proxy for economic activity (see Elvidge et al. (2017) for details on the alogrithms used to pre-process and filter the annual VIIRS images). This dataset is publicly available and can be downloaded from: https://www.ngdc.noaa.gov/eog/viirs/download_dnb_composites.html. The drawback of the VIIRS is that the earliest available grids (unfiltered and monthly) are available for April 2012 while the DMSP-OLS span from 1992-2013. Therefore, in order to obtain an 'early' disaggregated proxy for economic activity, we will supplement our dataset with the annaul DMSP-OLS nighttime lights from 1992 (available for download at: https://www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html#AVSLCFC).

The water surface grid (5×5 arcseconds) is aggregated to reflect the percentage of the surface that is covered with water and was obtained from the European Space Agency (ESA). It is publicly available for download at: http://maps.elie.ucl.ac.be/CCI/viewer/index.php.

The land elevation (in m) grid (30×30 arcseconds) by the NASA in context of the Shuttle Radar Topography Mission (SRTM) based on the work of Jarvis et al. (2008) is available for download at: http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1.

A measure for terrain ruggedness measured in degree of slope with an initial resolution of (20 × 20 arcseconds) based on Nunn and Puga (2012) was obtained from: https://diegopuga.org/data/rugged/.

The 'Crop Caloric Index', a measure of agricultural suitability containing the potential agricultural caloric output per year and hectar (excluding zero yields) based on Galor and Özak (2016) was obtained from https://ozak.github.io/Caloric-Suitability-Index/.

Annual precipitation (in mm), annual mean temperature, minimum temperature in the coldest month and maximum temperature in the warmest month (all in °C) based on Karger et al. (2017) were obtained from http://chelsa-climate.org/downloads/.

The population grid (30 × 30 arcseconds) for 2015 was obtained from Worldpop (available for download at: http://www.worldpop.org.uk/data/summary/?doi=10.5258/SOTON/WP00004) and contains the (UN-adjusted) total number of inhabitants per pixel.

Vectorized Data

The list of cities including their population size were obtained from various sources including United Nations Department of Economic and Social Affairs Population Division (2018) (https://population.un.org/wup/Download/), CityPopulation (see here for further information: https://www.citypopulation.de/) and WorldPopulationReview (see here for further information: http://worldpopulationreview.com/). In a next step, these cities were geocoded in R using an OpenStreetMap (https://www.openstreetmap.org/) interface.

The country shapefiles were obtained from GADM (currently Version 3.6) and are available for download at: https://gadm.org/data.html.

Based on the above sources we have calculated the following indicators on the pixel level using the projected coordinate reference system 'Africa Sinusoidal' which properly maps distances in Sub-Saharan Africa using the metric system (in km): distance from the capital city, distance from the placebo city, distance from the coast, distance from shared national boundaries, latitude and logitude.

The ethnographic 'Tribal Map of Africa' based on Murdock (1959) was recently digitized by Nathan Nunn and is available for download at: https://worldmap.harvard.edu/data/geonode:murdock_ea_2010_3.

Afrobarometer Data:

In the following, we provide details about the construction of the indicators that are based on the Afrobarometer survey data from round 5, 6 and 7 including extracts from the underlying questions in the Afrobarometer codebook (Isbell, 2017). Note that respondents who answered 'Do not know', 'Refused to answer' or 'Missing' are excluded from the sample for the respective indicator.

Public Goods Index

Average of responses to each of the following questions (responed by the interviewee prior to approaching the individual households within the cluster/ enumeration area):

Piped Water System: Are the following services present in the primary sampling unit/ enumeration area: Piped water system that most houses could access? Value Labels: 0=No, 1=Yes.

Electricity Grid: Are the following services present in the primary sampling unit/ enumeration area: Electricity grid that most houses could access? Value Labels: 0=No, 1=Yes.

Paved Road: Thinking of your journey here: Was the road at the start point in the primary sampling unit/ enumeration area paved/ tarred/ concrete? Value Labels: 0=No, 1=Yes.

Sewage System: Are the following services present in the primary sampling unit/ enumeration area: Sewage system that most houses could access? Values Labels: 0=No, 1=Yes.

Trust into the Political Elite

Average of responses to each of the following questions (see parenthesis): How much do you trust each of the following, or have you not heard enough about them to say: *The President (Parliament)*? Value Labels: 0 = Not at all, 1 = Just a little, 2 = Somewhat, 3 = A lot.

Corruption Perception of Political Leadership

Average of responses to each of the following questions (see parenthesis): How many of the following people do you think are involved in corruption, or haven't you heard enough about them to say: The President and Officials in his Office (Members of Partliament, Government Officials)? Value Labels: 0 = Not at all, 1 = Just a little, 2 = Somewhat, 3 = A lot.

Evaluation of Government Performance

Average of responses to each of the following questions (see parenthesis):

Now let's speak about the present government of this country. How well or badly would you say the current government is handling the following matters, or haven't you heard enough to say: Managing the economy (handling improving living standards of the poor, handling creating jobs, handling keeping prices down, handling narrowing income gaps, handling reducing crime, handling improving basic health services, handling addressing educational needs, handling providing water and sanitation services, handling ensuring enough to eat, handling fighting corruption, handling and maintaining roads and bridges, handling providing reliable electric supply)? Value Labels: 1 = Very badly, 2 = Fairly badly, 3 = Fairly well, 4 = Very well.

Voter Turnout

Understanding that some people were unable to vote in the most recent national election in [20xx], which of the following statements is true for you? Value Labels: 0 = You were not registered to vote Or you decided not to vote Or you could not find the polling station Or you were prevented from voting Or you did not have time to vote Or you did not vote because you could not find your name in the voters' register Or Did not vote for some other reason, 1 = You voted in the elections

National vs. Ethnic Identity

Let us suppose that you had to choose between being a [ENTER NATIONALITY] and being a [Respondent's Ethnic Group]. Which of the following best expresses your feelings? Value Labels: 1 = I feel only (Respondent's ethnic group), 2 = I feel more (Respondent's ethnic group) than [ENTER NATIONALITY], 3 = I feel equally [ENTER NATIONALITY] and (Respondent's ethnic group), 4 = I feel more [ENTER NATIONALITY] than (Respondent's ethnic group), 5 = I feel only [ENTER NATIONALITY].

Educational Level

What is your highest level of education? Value Labels: 0 = No formal schooling, 1 = Informal schooling only (including Koranic schooling), 2 = Some primary schooling, 3 = Primary school completed, 4 = Intermediate school or Some secondary school / high school, 5 = Secondary school / high school completed, 6 = Post-secondary qualifications, other than university e.g. a diploma or degree from a polytechnic or college, 7 = Some university, 8 = University completed, 9 = Post-graduate.

Advocate Check and Balances

Average of support for statement 2 in the two respective questions:

Checks by citizens:

Statement 1: It is more important to have a government that can get things done, even if we have no influence over what it does.
Statement 2: It is more important for citizens to be able to hold government accountable, even if that means it makes decisions more slowly.

Checks by parliament:

Statement 1: The President should be able to devote his full attention to developing the country rather than wasting time justifying his actions.
Statement 2: Parliament should ensure that the President explains to it on a regular basis how his government spends taxpayers' money.

Value Labels: 1 = Agree very strongly with Statement 1, 2 = Agree with Statement 1, 3 = Agree with Statement 2, 4 = Agree very strongly with Statement 2, 5 = Agree with neither.

News Consumption

How often do you get news from any of the following sources: Radio, Television, Newspaper or Internet? 0 = Never, 1 = Less than once a month, 2 = A few times a month, 3 = A few times a week, 4 = Every day.

Table A1: **Summary Statistics - Remote Sensing Data - Arithmetic Mean by Country 1/2**

Country Name	Light Density VIIRS 2016	Share Lit Pixels	Distance to the Capital	Distance to the Placebo	Distance to the Coast	Elevation (in m)	Ruggedness (in %)	% Surface covered in Water	Mean Temperature	Min Temperature	Max Temperature	Crop Caloric Index	Annual Precipitation	Longitude projected (in km)	Latitude projected (in km)
Angola	.024	1	700	477	476	1,071	2.3	.29	21	12	30	3,492	1,061	1,906	-1,360
Benin	.015	6	373	179	367	268	.38	.21	27	19	36	3,974	1,076	257	1,070
Botswana	.0095	1.9	422	479	784	1,035	.49	.082	22	6.8	32	1,549	390	2,453	-2,454
Burkina Faso	.0069	2.8	226	345	736	300	.64	.34	28	18	39	3,575	773	-189	1,358
Burundi	.0047	3.9	86	96	1,015	1,523	4.3	7.2	20	15	27	3,510	1,238	3,322	-375
Cameroon	.0045	2	353	447	433	650	1.4	.84	24	18	31	2,969	1,673	1,411	631
CAF	.0001	.075	453	457	1,221	600	.53	.2	25	18	33	3,482	1,366	2,265	728
Chad	.0035	.19	650	842	1,286	521	1.1	.28	27	13	39	1,432	312	2,000	1,700
Congo	.0079	.83	443	599	515	420	.41	.97	24	20	28	2,532	1,602	1,696	-91
Djibouti	.0036	1.7	91	91	37	441	6.5	2	28	19	39	11	180	4,638	1,302
DR Congo	.0037	.33	1,056	1,131	1,129	688	1.2	1.8	23	18	29	3,110	1,620	2,623	-318
Equat. Guinea	.034	6	299	107	84	494	1.3	1.2	23	20	27	2,003	2,519	1,155	183
Eritrea	.0018	.6	197	544	101	752	6.6	.85	27	18	36	831	283	4,169	1,702
Ethiopia	.0071	1.9	428	486	475	1,256	4.2	.68	23	15	31	3,035	861	4,357	954
Gabon	.032	1.5	330	370	219	379	.58	1.4	24	20	27	2,246	1,833	1,312	-69
Gambia	.0072	5.2	145	88	64	24	.91	3.9	28	19	37	3,488	797	-1,654	1,487
Ghana	.1	24	326	232	284	181	.59	2.8	27	21	35	3,625	1,242	-134	883
Guinea	.0078	2.8	370	403	287	443	2	.65	26	18	36	3,731	1,746	-1,198	1,156
Guinea Bissau	.0008	1.8	102	89	48	38	1.3	5.2	28	20	36	4,109	1,574	-1,631	1,328
Ivory Coast	.054	14	233	355	286	262	.59	.88	26	20	33	3,302	1,280	-613	844
Kenya	.016	6.1	364	584	451	785	1.7	2.1	25	19	32	3,007	630	4,210	62
Liberia	.0021	1.1	205	146	102	217	.7	.64	25	21	30	2,482	2,558	-1,028	712
Malawi	.015	8.7	214	310	508	854	2.2	21	22	13	30	4,062	1,113	3,716	-1,457
Mali	.0019	.43	808	822	1,038	320	.38	.28	29	14	42	1,086	309	-375	1,921
Mauritania	.0012	.26	724	776	534	263	.31	.089	28	13	42	233	101	-1,079	2,242
Mozambique	.014	2.5	1,110	634	209	354	1.6	2	24	15	31	3,767	1,020	3,775	-1,908
Namibia	.0088	1.9	391	646	330	1,088	2.5	.66	21	7.3	32	1,143	283	1,773	-2,450
Niger	.0017	.41	920	582	1,173	463	.48	.031	27	12	41	611	134	996	1,928
Nigeria	.13	8.1	382	675	499	330	.83	1.1	27	18	36	3,399	1,161	888	1,061
Rwanda	.031	13	68	117	1,056	1,688	8	6.4	19	14	25	3,327	1,173	3,332	-220
Senegal	.02	6.3	354	224	179	53	.64	1.8	29	18	38	2,861	658	-1,559	1,588
Sierra Leone	.0035	1.5	184	118	110	202	1.3	1.3	25	20	33	2,834	2,686	-1,297	948
Swaziland	.17	53	65	68	117	622	8.6	.41	19	8	27	3,934	820	3,138	-2,940
Tanzania	.0084	3.2	589	544	490	1,019	1.7	6.4	22	15	30	4,027	1,005	3,849	-693
Togo	.02	12	272	144	265	258	.74	.46	27	20	35	3,786	1,195	107	945
Uganda	.0067	4.1	217	242	977	1,155	2.1	15	22	18	28	3,873	1,214	3,604	141
Zambia	.019	2.9	443	411	942	1,120	1.4	1.8	21	11	32	3,960	1,015	3,009	-1,489
Zimbabwe	.013	6	292	295	517	973	3.2	1.2	21	8.9	30	3,330	680	3,144	-2,102
Overall	.016	2.5	615	627	716	671	1.4	1.5	24	15	34	2555	887	1,857	198

Note: This table reports the arithmetic mean of remote sensing variables by country excluding 20 km around the capital and placebo cities based on own calculations.

Table A2: **Summary Statistics - Remote Sensing Data - Arithmetic Mean by Country 2/2**

Country Name	Capital Name	Capital Pop.	Placebo Name	Placebo Pop.	Decentralized In 2010	Decentralized 1990-2010	Democracy 2016	Democracy 1996-2016	GDP per capita 2016 (median)	GDP per capita 2016 (mean)	Number of Observations
Angola	Luanda	7,265	Huambo	620	0	0	0	0	1	1	238,832
Benin	Cotonou	683	Djougou	299	0	0	1	1	1	0	21,546
Botswana	Gaborone	269	Francistown	100	0	1	1	1	1	1	116,273
Burkina Faso	Ouagadougou	2,306	Bobo Dioulasso	794	1	1	1	0	0	0	51865
Burundi	Bujumbura	797	Muyinga	101	0	0	0	1	0	0	4,631
Cameroon	Yaounde	3,273	Douala	3,112	1	0	0	0	1	0	87,276
CAF	Bangui	815	Bimbo	268	0	0	1	1	0	0	116,642
Chad	N'Djamena	1,230	Moundou	138	0	1	0	0	0	0	246,434
Congo	Brazzaville	2,044	Pointe-Noire	1,047	1	1	0	0	1	1	63,746
Djibouti	Djibouti	541	Ali Sabieh	14	1	0	1	1	1	1	3,899
DR Congo	Kinshasa	12,100	Lubumbashi	2,101	0	0	0	1	0	0	437,353
Equat. Guinea	Malabo	297	Bata	332	0	0	0	0	1	1	4,781
Eritrea	Asmara	833	Assab	21	0	0	0	0	0	0	22,990
Ethiopia	Addis Ababa	4,040	Dire Dawa	344	1	1	0	0	0	0	213,500
Gabon	Libreville	769	Port-Gentil	148	0	1	1	0	1	1	49,380
Gambia	Banjul	426	Farafenni	103	1	1	0	0	0	0	1,790
Ghana	Accra	2,338	Kumasi	2,758	0	0	1	1	1	1	44,707
Guinea	Conakry	1,756	Nzerekore	195	1	1	1	1	0	0	46,305
Guinea Bissau	Bissau	516	Bafata	35	NA	NA	1	1	0	0	6,056
Ivory Coast	Yamoussoukro	231	Abidjan	4,659	0	0	1	1	1	0	60,325
Kenya	Nairobi	4,065	Mombasa	1,139	1	1	1	1	1	0	109,423
Liberia	Monrovia	1,318	Gbarnga	46	0	0	1	1	0	0	17,712
Malawi	Lilongwe	945	Blantyre	831	0	0	1	1	0	0	22,198
Mali	Bamako	2,292	Sikasso	320	1	1	1	1	0	0	245,165
Mauritania	Nouakchott	1,105	Nouadhibou	118	0	0	0	0	1	0	207,455
Mozambique	Maputo	1,100	Nampula	707	0	0	1	1	0	0	154,023
Namibia	Windhoek	380	Rundu	63	1	1	1	1	1	1	165,977
Niger	Niamey	1,143	Zinder	393	0	0	1	1	0	0	231,640
Nigeria	Abuja	2,591	Lagos	12,634	1	1	1	1	1	1	172,110
Rwanda	Kigali	986	Butare	90	1	0	0	0	0	0	4,323
Senegal	Dakar	2,830	Touba	753	1	1	1	1	1	0	37,753
Sierra Leone	Freetown	1,073	Bo	174	1	0	1	1	0	0	13,435
Swaziland	Mbabane	76	Big Bend	10	0	1	0	0	1	1	3,156
Tanzania	Dar es Salaam	5,409	Mwanza	890	1	1	1	0	1	0	176,892
Togo	Lome	1,671	Sokode	118	1	1	0	0	0	0	10,444
Uganda	Kampala	2,707	Gulu	150	1	1	0	0	0	0	44,715
Zambia	Lusaka	2,294	Kitwe	602	0	0	1	1	1	0	143,985
Zimbabwe	Harare	1,505	Bulawayo	645	0	1	1	0	1	0	76,778

Note: This table reports the arithmetic mean of remote sensing variables by country excluding 20 km around the capital and placebo cities based on own calculations. The population (Pop.) in the respective capital and placebo cities is in thousands of inhabitants.

Table A3: **Summary Statistics - DHS - Arithmetic Mean by Country**

Country Name	Z-Wealth Index	Distance to the Capital	Distance to the Coast	Urban Pop. Share	Longitude projected (in km)	Latitude projected) (in km)	Age of head of household	Number of household members	Mean Temp-erature	Min Temp-erature	Max Temp-erature	Precip-itation Index	Elevation (in m)	Number of Obser-vations
Angola	-0.33	482	242	0.39	1,686	-1,290	43	4.7	21	15	28	73	1,164	9,933
Benin	-0.27	214	204	0.33	243	904	45	5.3	28	23	33	78	187	10,161
Burkina Faso	-0.21	195	750	0.17	-216	1,365	45	5.6	29	22	35	66	311	10,643
Burundi	-0.27	87	1,017	0.045	3,326	-356	45	4.8	20	15	26	109	1,595	11,240
Cameroon	-0.069	412	398	0.48	1,306	742	46	5.1	26	21	31	117	513	8,824
CAF	-0.28	303	892	0.24	1951	603	42	4.6	25	19	31	123	605	2705
Chad	-0.19	287	1,028	0.13	1,761	1,192	43	5.8	28	21	36	71	414	7,797
DR Congo	-0.081	1,170	1,067	0.25	2,721	-251	43	5.2	23	18	29	122	864	8,655
Ethiopia	-0.28	335	521	0.19	4,231	982	44	4.8	21	14	28	93	1,863	8,967
Gabon	0.26	216	124	0.68	1,165	-12	47	4.2	26	22	30	124	210	4,849
Ghana	0.073	217	173	0.48	-120	766	44	3.5	28	23	32	84	184	8,416
Guinea	-0.32	308	211	0.18	-1,269	1,130	49	6.1	26	20	32	165	470	5,240
Ivory Coast	0.15	204	147	0.51	-562	708	44	5.1	27	22	32	104	167	6,829
Kenya	0.041	216	506	0.28	4,040	-46	45	4.1	21	15	27	115	1,539	30,365
Liberia	-0.15	176	106	0.35	-1,054	738	44	5.1	26	20	32	187	203	6,583
Malawi	-0.17	177	407	0.12	3,725	-1,605	43	4.5	23	17	29	73	907	19,326
Mali	-0.35	264	802	0.11	-692	1,442	47	5.6	29	22	36	65	314	6,018
Mozambique	-0.39	1,113	161	0.23	3,822	-1,931	43	4.4	25	19	30	72	375	9,906
Namibia	-0.25	486	445	0.36	1,812	-2,135	48	4.5	23	15	32	23	1,140	6,877
Niger	-0.31	487	885	0.12	691	1,533	45	5.9	29	22	36	38	356	4,694
Nigeria	-0.011	388	401	0.42	777	996	44	4.7	27	22	33	92	296	28,009
Rwanda	-0.26	68	1,062	0.09	3,323	-226	45	4.3	19	14	25	119	1,685	9,567
Senegal	0.075	211	88	0.36	-1,700	1,608	52	9.1	28	21	35	54	33	4,071
Sierra Leone	-0.31	181	99	0.19	-1,294	926	46	6	27	22	32	226	160	10,159
Swaziland	-0.18	60	121	0.28	3,135	-2,940	46	4.7	21	14	28	50	622	3,987
Tanzania	-0.19	586	483	0.23	3,863	-593	46	5	23	17	28	84	1,101	8,665
Togo	-0.31	219	210	0.23	114	889	46	4.8	28	23	33	83	223	6,611
Uganda	-0.14	198	962	0.16	3,604	116	43	4.7	23	17	29	121	1,211	14,324
Zambia	-0.34	452	830	0.18	3,173	-1,509	44	5.3	23	16	30	58	1,119	7,048
Zimbabwe	-0.27	243	457	0.26	3,205	-2,101	45	4.1	22	14	29	35	1,092	8,145
Overall	-0.18	336	511	0.26	1625	69	45	5.1	25	19	31	92	717	288,614

Note: This table reports the arithmetic mean of the Demographic and Health Survey (DHS) variables excluding 20 km around the capital cities based on own calculations.

Table A4: **Summary Statistics - Afrobarometer - Arithmetic Mean by Country 1/2**

Country Name	Public Goods Index	Wealth Index	Trust into Leaders	Corruption Perception Index	Evaluation of Leadership Performance	Trust Ruling Party	Trust Oppos. Party	Voter Turnout	National vs. Ethnic Identity	Education Level	Frequency of News Consumption	Advocate Monitoring of Leaders
Benin	.4	.35	1.7	1.5	2.2	1.5	1.2	.85	3.5	2	2.9	3
Botswana	.61	.38	2	1.1	2.6	1.9	1.1	.75	3.3	3.7	3	3
Burkina Faso	.2	.28	2	1.1	2.2	1.7	1.6	.73	3.7	1.3	2.8	2.9
Burundi	.2	.16	2.3	.82	2.3	2.1	1.1	.91	4.5	1.9	2.6	2.8
Cameroon	.67	.46	1.6	1.6	2.2	1.2	.87	.6	3.7	4.2	3.2	2.8
Gabon	.54	.42	1.1	1.9	1.6	.74	.95	.58	4.1	4.4	3.4	2.8
Gambia	.36	.43	2.1	1	2.5	1.7	1.4	.67	3.9	3.1	3.3	3.3
Ghana	.61	.44	1.6	1.5	2.2	1.5	1.5	.85	3.6	3.2	3.4	3.1
Guinea	.27	.28	1.7	1.3	1.9	1.5	1.3	.84	4.4	1.8	2.8	2.8
Ivory Coast	.53	.4	1.7	1.2	2.3	1.3	1.2	.62	3.7	3.3	3	2.8
Kenya	.41	.3	1.7	1.5	2.1	1.6	1.2	.82	3.8	3.8	3.4	2.8
Liberia	.15	.27	1.5	1.7	2.1	1.5	1.2	.83	3.2	3.1	2.9	2.8
Malawi	.21	.2	1.6	1.4	2.1	1.4	1.5	.85	3.4	2.5	2.4	2.8
Mali	.19	.29	1.7	1.4	2.1	1.6	1.2	.73	3.6	1.1	2.9	3
Mozambique	.26	.29	2.1	1.1	2.4	2	1.4	.79	3.7	3	2.9	2.6
Namibia	.43	.44	2.1	.98	2.4	2	1.2	.8	3.7	4.1	3.5	2.6
Niger	.24	.23	2.1	1.1	2.3	2	1.6	.82	4	1.2	2.5	2.8
Nigeria	.56	.49	1.1	1.7	2	1.1	.96	.71	3.2	4.4	3.4	2.6
Senegal	.52	.49	1.9	1.2	2.2	1.5	1.2	.7	3.7	2.1	3.4	2.9
Sierra Leone	.22	.26	1.8	1.4	2.2	1.7	1.5	.83	3.8	2.6	2.7	2.8
Swaziland	.47	.4	1.6	1.4	2.4	NA	NA	.69	3.6	4	3.4	3
Tanzania	.32	.33	2.2	.93	2.2	2	1.5	.82	4.1	3	3	2.7
Togo	.34	.35	1.5	1.6	2.1	1.2	1.1	.87	3.7	3.1	2.9	3
Uganda	.2	.29	2	1.4	2.2	1.9	1.2	.83	3.2	3	3.1	2.9
Zambia	.33	.33	1.8	1.3	2.2	1.7	1.2	.71	3.5	3.5	3	2.8
Zimbabwe	.37	.39	1.8	1.4	2.1	1.7	1	.75	3.8	4	2.6	2.8
Overall	.37	.34	1.8	1.3	2.2	1.6	1.3	.77	3.7	2.9	3	2.8

Note: This table reports the arithmetic mean of the Afrobarometer variables excluding 20 km around the capital cities based on own calculations.

Table A5: **Summary Statistics - Afrobarometer - Arithmetic Mean by Country 2/2**

Country Name	Distance to the Capital	Distance to the Placebo	Distance to the Coast	Population Density	Age of Respondent	Share of Women	Rural Pop. Share	Longitude projected (in km)	Latitude projected (in km)	Number of Observations
Benin	222	241	213	291	39	0.5	0.6	250	914	2,928
Botswana	331	313	708	18	41	0.5	0.78	2,643	-2,487	1,567
Burkina Faso	192	309	739	96	43	0.5	0.85	-215	1,354	3,136
Burundi	81	85	1,020	400	38	0.5	0.9	3,321	-360	2,160
Cameroon	395	394	392	323	39	0.5	0.53	1,305	727	3,182
Gabon	315	338	199	55	35	0.5	0.35	1,286	-84	1,168
Gambia	119	93	51	196	38	0.48	0.63	-1,687	1,480	688
Ghana	234	177	183	432	38	0.5	0.52	-123	775	6,193
Guinea	313	418	226	150	43	0.5	0.75	-1,252	1,132	3,185
Ivory Coast	201	236	169	918	38	0.5	0.49	-584	729	3,527
Kenya	236	548	497	410	41	0.5	0.73	4,051	-51	5,378
Liberia	187	131	105	66	40	0.5	0.73	-1,044	729	2,510
Malawi	177	192	428	251	45	0.5	0.9	3,722	-1,581	4,993
Mali	326	348	813	62	41	0.5	0.88	-686	1,489	2,976
Mozambique	1,137	540	132	108	65	0.52	0.71	3,864	-1,925	6,384
Namibia	474	476	409	35	37	0.5	0.62	1,781	-2,164	2,896
Niger	453	365	889	105	42	0.5	0.88	651	1,545	3,295
Nigeria	379	518	346	1,099	35	0.5	0.57	776	934	6,303
Senegal	219	149	88	248	41	0.5	0.67	-1,697	1,598	2,759
Sierra Leone	166	105	93	171	41	0.51	0.71	-1,308	930	2,910
Swaziland	58	67	123	76	39	0.5	0.84	3,134	-2,940	2,936
Tanzania	586	487	481	171	41	0.5	0.76	3,868	-609	6,481
Togo	239	170	231	151	38	0.5	0.75	113	910	2,595
Uganda	205	258	979	255	41	0.5	0.86	3,583	113	5,408
Zambia	379	332	888	88	40	0.5	0.64	3,107	-1,486	2,890
Zimbabwe	277	275	480	95	40	0.5	0.73	3,171	-2,136	4,904
Overall	316	304	427	263	41	0.5	0.71	1,286	3.7	93,352

Note: This table reports the arithmetic mean of the Afrobarometer variables excluding 20 km around the capital cities based on own calculations.

Formal Identification

1. Let s be a segment consisting of pixels closely around both sides of a boundary d between country c and country k. We denominate pixels belonging to country c by i while pixels belonging to country k are denominated by j. We assume that, within a segment, pixels i and j are equally represented, have homogenous geographical characteristics, $E(X_i) = E(X_j) = E(X_s)$, and belong to the same ethnicity e.

   From Equation 3 we get:

$$\overline{Y_s} = \beta\overline{CAP_s} + \gamma\overline{X_s} + b_{c,k} + b_e + \varepsilon_s \tag{6}$$

$$\frac{\overline{Y_i} + \overline{Y_j}}{2} = \beta\frac{\overline{CAP_i} + \overline{CAP_j}}{2} + \gamma\frac{\overline{X_i} + \overline{X_j}}{2} + \frac{b_c + b_k}{2} + \frac{b_e + b_e}{2} + \frac{\varepsilon_i + \varepsilon_j}{2} \tag{7}$$

$$\overline{Y_i} + \overline{Y_j} = \beta(\overline{CAP_i} + \overline{CAP_j}) + \gamma(\overline{X_i} + \overline{X_j}) + b_c + b_k + 2b_e + \varepsilon_i + \varepsilon_j \tag{8}$$

2. Applying segment fixed effects to Equation 3: $E[Y_i - \overline{Y_s}] = E[2Y_i - 2\overline{Y_s}] = E[2\text{Equation 3} - \text{Equation 8}]$:

$$\begin{aligned} E\Big[2Y_i - \overline{Y_i} - \overline{Y_j}\Big] = E\Big[&\beta(2CAP_i - \overline{CAP_i} - \overline{CAP_j}) + \gamma(2X_i - \overline{X_i} - \overline{X_j}) \\ &+ (2b_c - b_c - b_k) + (2b_e - 2b_e) + (2\varepsilon_i - \varepsilon_i - \varepsilon_j)\Big] \end{aligned} \tag{9}$$

$$\begin{aligned} E\Big[Y_i - Y_j\Big] &= E\Big[\beta(CAP_i - CAP_j) + \gamma(X_i - X_j) \\ &\quad + (b_c - b_k) + (\varepsilon_i - \varepsilon_j)\Big] \end{aligned} \tag{10}$$

$$E\Big[\Delta Y_{i,j}\Big] = E\Big[\beta\Delta CAP_{i,j} + \gamma\Delta X_{i,j} + b_b + \Delta\varepsilon_{i,j}\Big] \tag{11}$$

3. Under the assumption that (un-)observable factors are balanced across the boundary, the (un-)observable covariates cancel each other out:

$$E(\Delta X_{i,j}) = E(X_i - X_j) = 0 \tag{12}$$

   ,thus:

$$E\Big[\Delta Y_{i,j}\Big] = E\Big[\beta\Delta CAP_{i,j} + b_b + \Delta\varepsilon_{i,j}\Big] \tag{13}$$

4. Furthermore, the larger a segment, the variation of isolation from the capital city or location-specific characteristics within a segment side, the higher the endogeneity bias. Therefore, segments sides need to be sufficiently small and homogenous to eliminate the correlation between isolation from the capital city and geographical covariates.

$$\lim_{s \to i \cup j} Cov\Big[\Delta CAP_{i,j} \quad , \Delta\varepsilon_{i,j}\Big] \tag{14}$$

$$= \lim_{s \to i \cup j} Cov\Big[(CAP_i - CAP_j) \quad , (\widetilde{X}_i - \widetilde{X}_j)\Big] = 0 \tag{15}$$

Figure A1: Mapping Survey Respondents

(a) DHS Sample

(b) Afrobarometer Round 5, 6 + 7 Sample

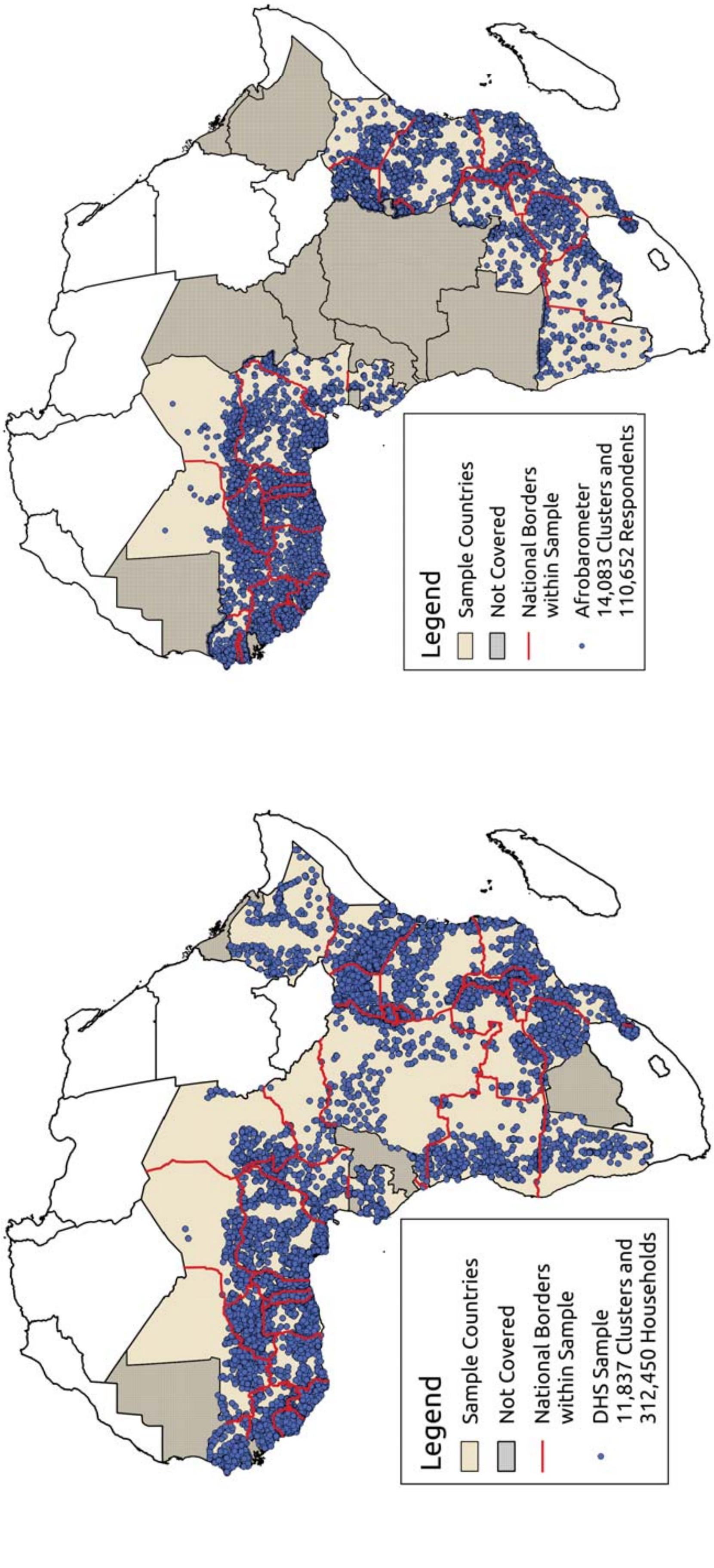
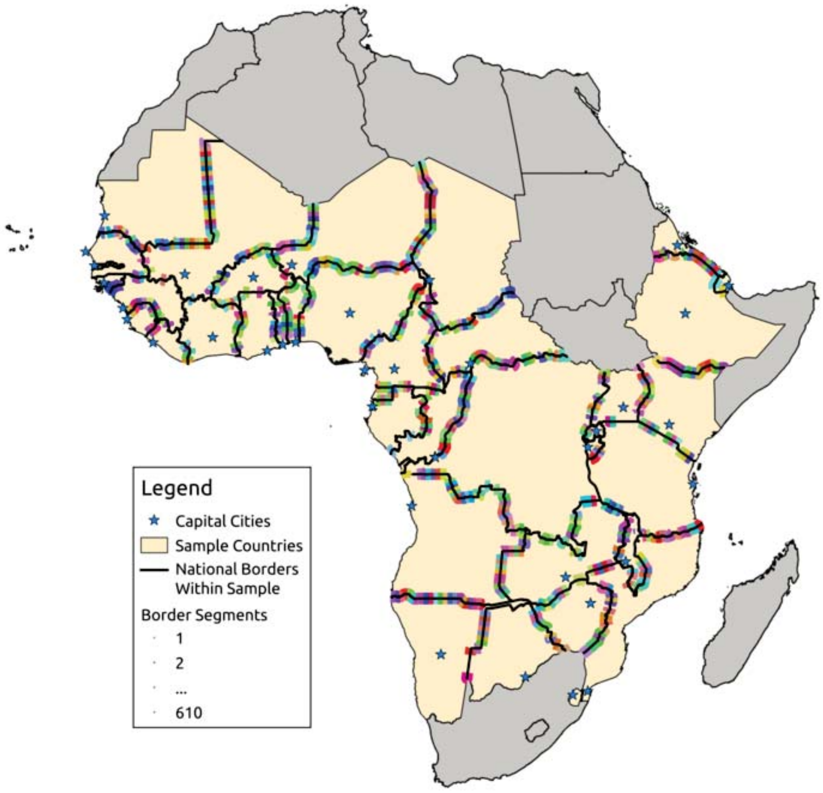


Figure A2: Unrestricted Segments

(a) Simple Border Segments



(b) Simple Border Segments - Magnified

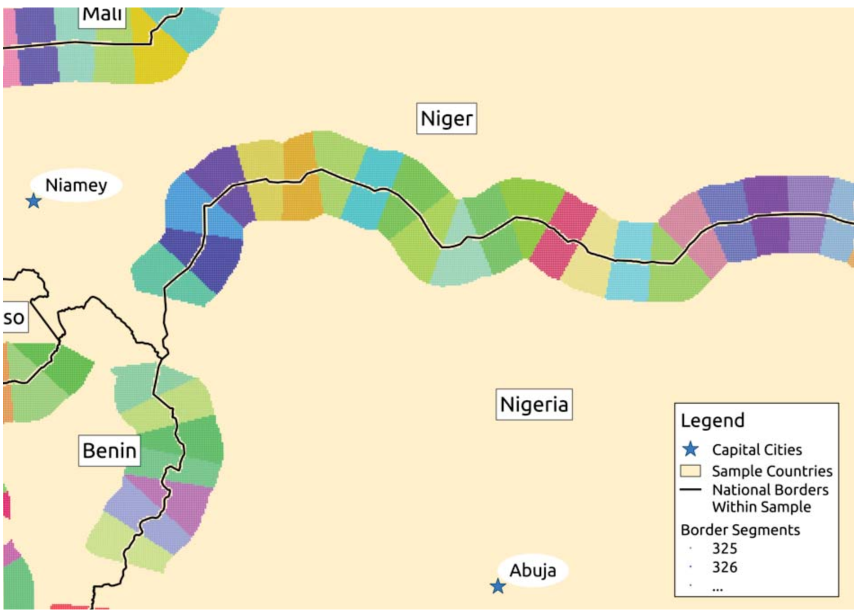
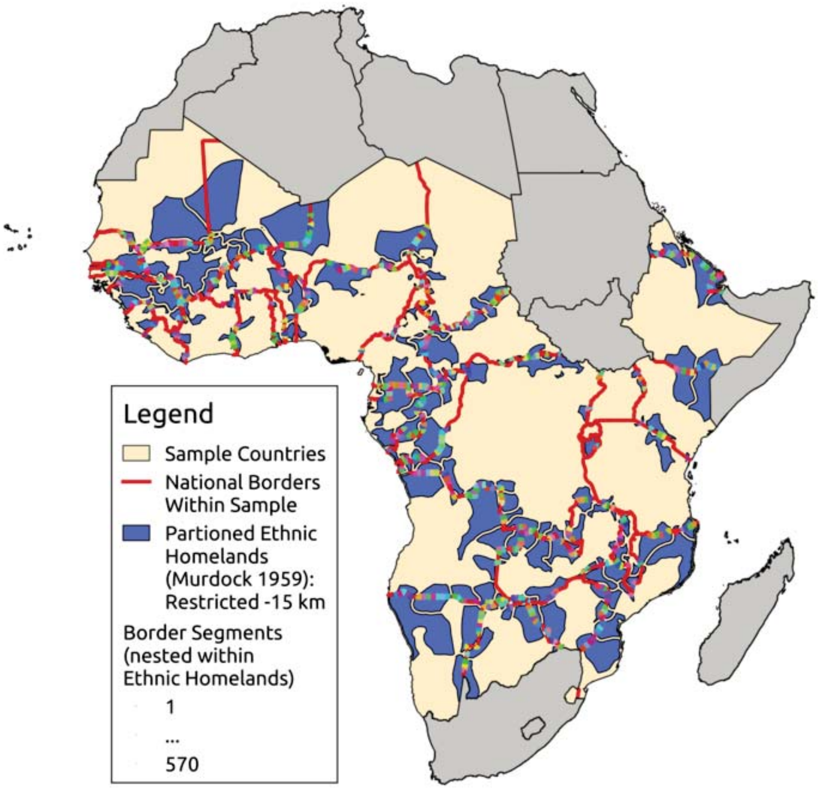
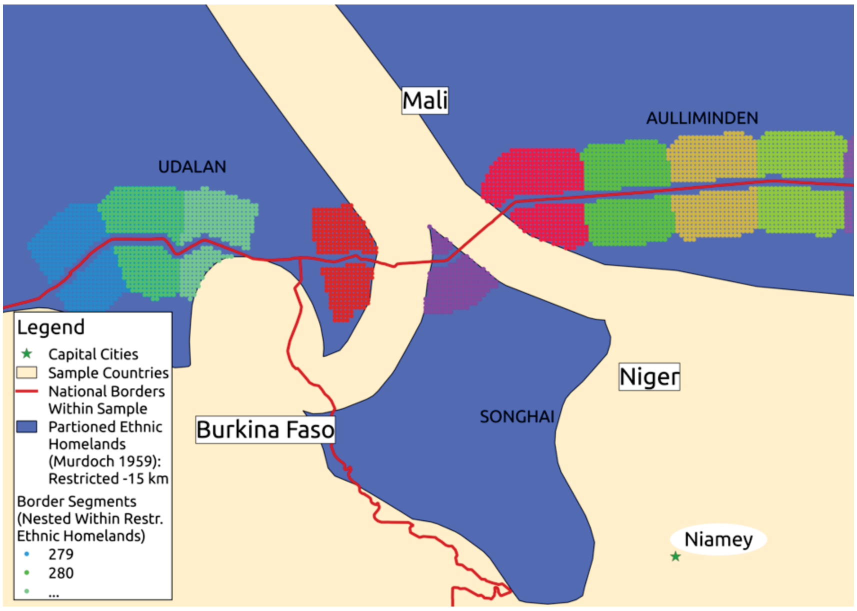


Figure A3: Restricted Segments

(a) Border Segments nested within Restricted Parioned Ethnic Homelands



(b) Border Segments nested within Restricted Parioned Ethnic Homelands - Magnified



A.2 Balancing Tests

Table A6: OLS - Balancing Tests

	Dependent variable: Normalization of							
	Distance from the Coast				Crop Caloric Index			
	All Pixels		Border Area		All Pixels		Border Area	
	OLS	Ethnicity FE	OLS	Ethnicity FE	OLS	Ethnicity FE	OLS	Ethnicity FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Distance from the Capital City	0.178***	0.077***	0.152***	0.044***	-0.137***	-0.042*	-0.046*	0.008
	(0.022)	(0.016)	(0.029)	(0.013)	(0.022)	(0.022)	(0.024)	(0.014)
Geography Cov.	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	37	37	37	37	37	37	37	37
Ethnicity FE	-	706	-	351	-	706	-	351
Observations	3,518,146	3,518,146	416,667	416,664	3,518,146	3,518,146	416,667	416,664
R^2	0.838	0.974	0.792	0.980	0.785	0.935	0.670	0.930
Adjusted R^2	0.838	0.974	0.792	0.980	0.785	0.935	0.670	0.930

Note: This table reports the balancedness tests for the examples of distance from the coast (in km) and crop caloric index corresponding to the OLS and boundary area regressions in Table 1 based on Equation 3. We normalize the dependent variables by dividing them by their sample mean. In order to avoid capturing the break between the capital city and the hinterlands, we exclude 20 km around each capital city from our sample. To prevent misassignment of detected nightlights between countries due to blooming, we exclude 3 km on each side of the border. The boundary area regressions ('Border') are restricted to all pixels with centroids within the range of 25 km from shared national borders. The 'Geographical Cov.' include: distance from the coast (in km), ruggedness (in % slope), % surface covered with water, mean annual temperature, minimum average temperature during the coldest month, maximum average temperature during the warmest month (in °C), crop caloric index, annual precipitation (in mm), longitude and latitude (projected in km) - except for when the respective variable is the dependent variable itself. The 'Ethnicity FE' are based on the ethnic homelands in the 'Tribal Map of Africa' (Murdock, 1959). Standard errors in paranthesis are clustered by ethnic homeland. *p<0.1; **p<0.05; ***p<0.01

Table A7: Border Discontinuity Estimation - Balancing Tests

	Dependent variable: Normalization of								
	Dist. Coast	Elevation	Water	Rugged.	∅ Temp.	Crop	Precip.	Lon.	Lat.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Distance from the Capital City	0.008***	0.006	-0.002	-0.367**	0.000	-0.005	0.010	0.006***	0.018**
	(0.003)	(0.004)	(0.004)	(0.156)	(0.000)	(0.006)	(0.017)	(0.001)	(0.009)
	Polynomials for: distance from the border × country × ethnicity (305 groups)								
3rd order	x	x	x	x	x	x	x	x	x
Geography Cov.	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	36	36	36	36	36	36	36	36	36
Segment FE	569	569	569	569	569	569	569	569	569
Observations	168,620	168,620	168,620	168,620	168,620	168,620	168,620	168,620	168,620
R^2	1.000	0.999	0.317	0.683	1.000	0.990	0.972	1.000	1.000
Adjusted R^2	1.000	0.999	0.311	0.680	1.000	0.990	0.971	1.000	1.000

Note: This table reports the balancedness tests corresponding to our main BDD regressions in Table 2 based on Equation 6. We normalize the dependent variables by dividing them by their sample mean. In order to avoid capturing the break between the capital city and the hinterlands, we exclude 20 km around each capital city from our sample. To prevent misassignment of detected nightlights between countries due to blooming, we exclude 3 km on each side of the national boundary. The 'Geographical Cov.' include: distance from the coast (in km), ruggedness (in % slope), % surface covered with water, mean annual temperature, minimum average temperature during the coldest month, maximum average temperature during the warmest month (in °C), crop caloric index, annual precipitation (in mm), longitude and latitude (projected in km) - except for when the respective variable is the dependent variable itself. Boundary segments corresponds to a buffer of 25 km around border pieces of 50 km line length and entirely nested within a restricted ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). The observations are weighted such that each segment side has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by boundary segment. *p<0.1; **p<0.05; ***p<0.01

Table A8: DHS - Balancing and Placebo Tests

	Dependent variable:							
	Balancing Tests: Normalization of						Placebo Tests	
	Distance to Coast	Longitude	Latitude	Elevation	Mean Temperature	Precip-itation	DHS wealth index (z-score)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Distance from the Capital City	0.000 (0.004)	0.000 (0.001)	0.029 (0.092)	-0.035 (0.029)	-0.000** (0.000)	-0.008 (0.010)	-0.094* (0.054)	-0.086 (0.061)
Log Distance from the Placebo City	-	-	-	-	-	-	0.071 (0.064)	0.082 (0.065)
Placebo Tests							Coef_{CAP}=Coef_{PLC}	
F-Statistic	-	-	-	-	-	-	8.76***	8.40***
	Polynomials for: distance from the border							
3rd order	x	x	x	x	x	x	-	x
Household Cov.	YES	YES	YES	YES	YES	YES	YES	YES
Geography Cov.	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	36	36	36	36	36	36	36	36
Segment FE	569	569	569	569	569	569	569	569
Observations	24,582	24,582	24,582	24,582	24,582	24,582	23,671	23,671
R^2	1.000	1.000	1.000	0.974	1.000	0.985	0.467	0.469
Adjusted R^2	1.000	1.000	1.000	0.974	1.000	0.985	0.464	0.465

Note: This table reports the DHS balancing (columns (1)-(6)) and placebo tests (columns (7)-(8)) corresponding to Table 5. In columns (1)-(6), we normalize the dependent variables by dividing them by their sample mean. Regarding the placebo tests, we report the respective F-tests on the equality of the coefficients. The 'Geographical Cov.' include: age of household head, age of houshold head squared, number of household members. The 'Household Cov.' include: mean annual temperature, minimum average temperature during the coldest month, maximum average temperature during the warmest month (in °C), annual precipitation (in mm), longitude and latitude (projected in km) and whether the household is in an urban or rural setting - except for when the respective variable is the dependent variable itself. Boundary segments corresponds to a buffer of 25 km around border pieces of 50 km line length and are entirely nested within a restricted ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). The observations are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by DHS cluster and boundary segment. *p<0.1; **p<0.05; ***p<0.01

Table A9: Channel Analysis: Afrobarometer Balancing Tests

	Dependent variable: Normalization of								
	Distance from the Coast			Longitude			Latitude		
	OLS	Boundary	BDD	OLS	Boundary	BDD	OLS	Boundary	BDD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Distance from the Capital City	0.154***	0.204***	0.015***	0.036***	0.061***	0.001	-0.185	-0.228	0.057***
	(0.023)	(0.050)	(0.005)	(0.010)	(0.013)	(0.001)	(0.128)	(0.229)	(0.020)
	Polynomials for: distance from the border								
3rd order	-	-	x	-	-	x	-	-	x
Household Cov.	YES	YES	YES	YES	YES	YES	YES	YES	YES
Geography Cov.	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country × Round FE	73	72	71	73	72	71	73	72	71
Segment FE	-	-	140	-	-	140	-	-	140
Observations	93,242	15,419	8,347	93,242	15,419	8,347	93,242	15,419	8,347
R^2	0.856	0.891	0.999	0.991	0.994	1.000	0.988	0.989	1.000
Adjusted R^2	0.856	0.891	0.999	0.991	0.994	1.000	0.988	0.989	1.000

Note: This table reports the Afrobarometer balancing tests for distance from the coast (in km), latitude and longitude (in km) corresponding to Table 6, 7 and A14. We normalize the dependent variables by dividing them by their sample mean. The 'Household Cov.' include: age, age squared and sex of respondent. The 'Geographical Cov.' include: distance from the coast (in km), longitude and latitude (projected in km) and whether the household is in an urban or rural setting - except for when the respective variable is the dependent variable itself. The segments are entirely nested within an ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). In the full sample OLS regressions, the observations are weighted according to the Afrobarometer survey weights. In the BDD regressions, the observations are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by Afrobarometer cluster and ethnic homeland in the OLS and boundary area regressions and Afrobarometer cluster and boundary segment in the BDD regressions. *p<0.1; **p<0.05; ***p<0.01

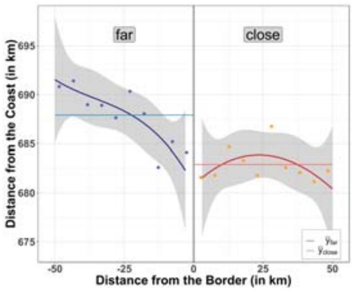
Table A10: Channel Analysis: Political Representation Balancing Tests

	Dependent variable: Political Representation							
	Region of Birth of Leader (1/0)			EPR Power Coalition Status (in years since 2000)				
	All	Since 2000	Ongoing	Irrelevant	Powerless	Junior	Senior	In Power
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Distance from the Capital City	-0.026	-0.152***	-0.091***	-2.569***	-1.096**	2.278***	1.386**	3.664***
	(0.039)	(0.032)	(0.027)	(0.838)	(0.530)	(0.785)	(0.667)	(0.909)
Population Share of Region	1.232***	1.188***	0.837***	-	-	-	-	-
	(0.308)	(0.247)	(0.224)					
Country FE	35	35	35	33	33	33	33	33
Segment FE	568	568	568	531	531	531	531	531
Observations	1,138	1,138	1,138	1,064	1,064	1,064	1,064	1,064
R^2	0.738	0.695	0.649	0.751	0.862	0.739	0.819	0.796
Adjusted R^2	0.438	0.347	0.248	0.468	0.704	0.442	0.612	0.564

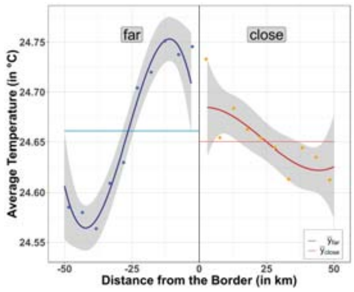
Note: This table reports the balancing tests on political representation with regard to isolation from the capital city. The observational unit in these models are the BBD boundary segments. The dependent variables in column (1)-(3) are dummies indicating whether a head of state came from the same admin-1 region as the boundary segment side (since independence, since 2000 and only refering to incumbent state leaders). The dependent variables in columns (4)-(8) correspond the total number of years a segment side has spent under the respective power access status in the period between 2000 and 2018 (for more information on these categories please refer to Section 2.3). Boundary segments corresponds to a buffer of 25 km around border pieces of 50 km line length and are entirely nested within a restricted ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). Standard errors in paranthesis are clustered by boundary segment. *p<0.1; **p<0.05; ***p<0.01

Figure A4: Discontinuity Balancing Graphs: Placebo City

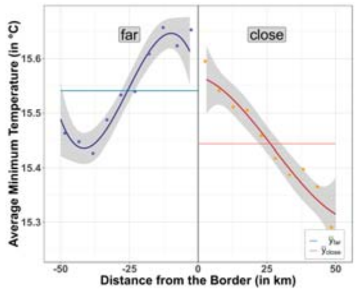
(a) Distance from Coast



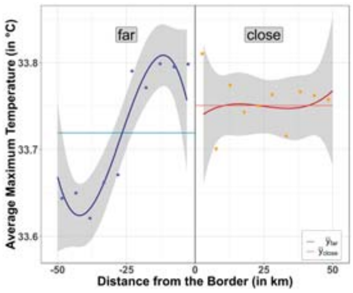
(b) Mean Temperature



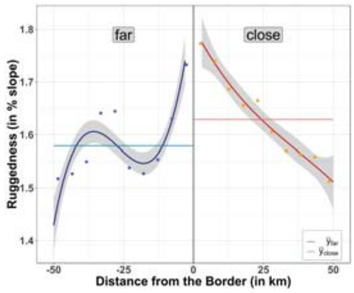
(c) Min Temperature



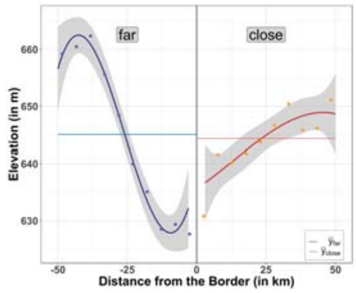
(d) Max Temperature



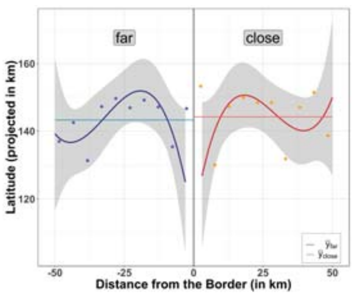
(e) Ruggedness



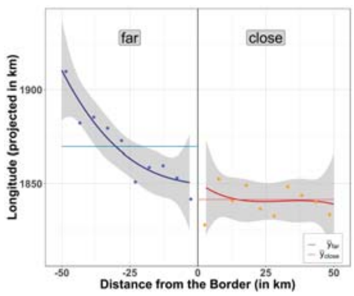
(f) Elevation



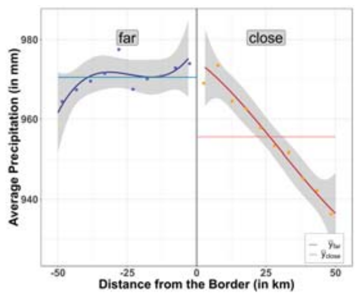
(g) Latitude



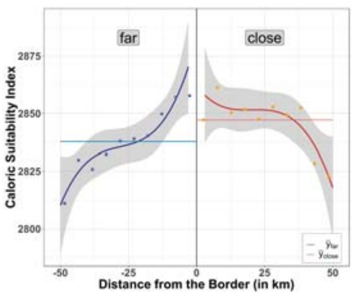
(h) Longitude



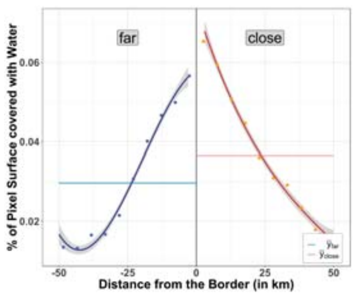
(i) Precipitation



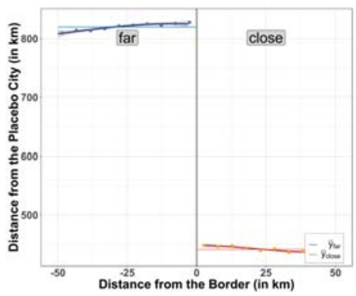
(j) Crop Suitability



(k) Water Bodies



(l) Distance Capital City

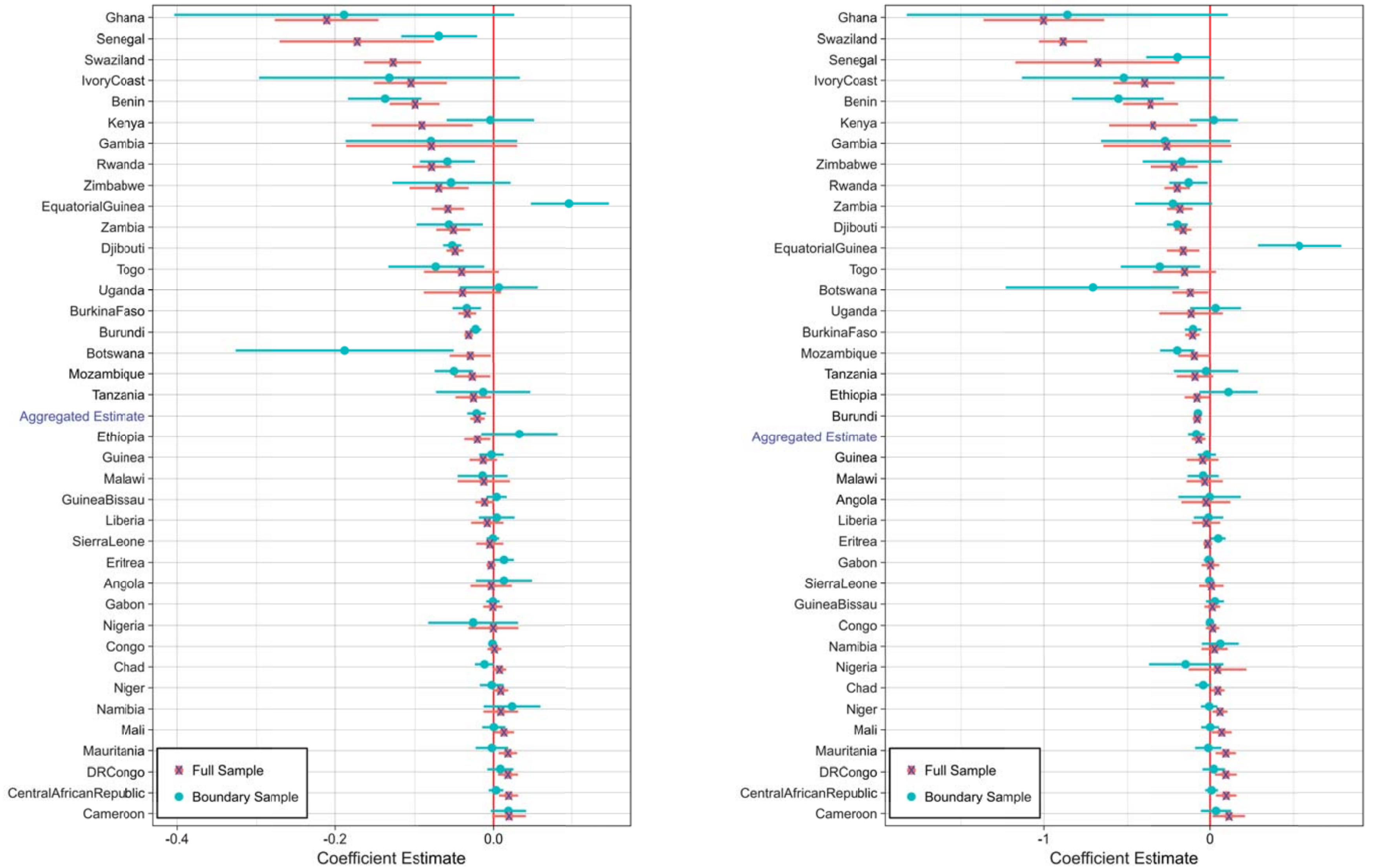


Note: The graphs illustrate the graphical placebo balancing tests corresponding to Figure 8. The grey buffer around the lines represent the 95% confidence intervall. The bins on the left-hand side are, with an average distance of 820 km, relatively far from the capital city and represent a total of 238,980 pixels. In contrast, pixels on the right-hand side are, with an average of around 440 km, relatively close to the capital city and represent 237,153 pixels.

A.3 Additional Results

Figure A5: 'Naive' OLS Estimates by Country

(a) OLS β - Coefficients (extensive)　　(b) OLS β - Coefficients (intensive)



Note: On the left, Figure A5a present the OLS estimates by country based on columns (1) and (2) in Table 1. Likewise, Figure A5b corresponds to those of columns (5) and (6). Please note that the estimates corresponding to the boundary sample of Swaziland were omitted. The reason is that Swaziland only has relatively few observations and little variance in isolation from the capital city in the boundary area approach which inflates the standard errors and depreciates the readabiliy of the graph. Standard errors are clustered by ethnic homeland.

Table A11: Border Discontinuity Estimation - Robustness Bandwidth

	Dependent variable:									
	Probability Pixel is Lit in 2016 (VIIRS)					Log Light Density in 2016 (VIIRS)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Distance from the Capital City	-0.009	-0.019**	-0.031***	-0.033***	-0.035***	-0.051*	-0.078**	-0.124***	-0.149***	-0.159***
	(0.006)	(0.008)	(0.010)	(0.011)	(0.012)	(0.029)	(0.036)	(0.045)	(0.054)	(0.059)
	Polynomials for: distance from the border × country × ethnicity (325 groups)									
1nd order	-	x	-	-	-	-	x	-	-	-
2nd order	-	-	x	-	-	-	-	x	-	-
3rd order	-	-	-	x	-	-	-	-	x	-
4th order	-	-	-	-	x	-	-	-	-	x
Geography Cov.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	36	36	36	36	36	36	36	36	36	36
Segment FE	608	608	608	608	608	608	608	608	608	608
Observations	106,746	106,746	106,746	106,746	106,746	106,746	106,746	106,746	106,746	106,746
R^2	0.176	0.206	0.217	0.224	0.229	0.166	0.194	0.204	0.212	0.217
Adjusted R^2	0.171	0.198	0.207	0.212	0.215	0.161	0.187	0.194	0.200	0.203

Note: This table reports robustness tests on our main BDD regression results in Table 2 based on Equation 6 and feature variations on the boundary thickness, boundary buffer and the number of polynomials of the running variable. In order to avoid capturing the break between the capital city and the hinterlands, we exclude 20 km around each capital city from our sample. To prevent misassignment of detected nightlights between countries due to blooming, we exclude 1.5 km (instead of 3 km) on each side of the national boundary. The 'Geographical Cov.' include: distance from the coast (in km), ruggedness (in % slope), % surface covered with water, mean annual temperature, minimum average temperature during the coldest month, maximum average temperature during the warmest month (in °C), crop caloric index, annual precipitation (in mm), longitude and latitude (projected in km). Boundary segments corresponds to a buffer of 15 km (instead of 25 km) around border pieces of 50 km line length and are entirely nested within a restricted ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). The observations are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by boundary segment. *p<0.1; **p<0.05; ***p<0.01

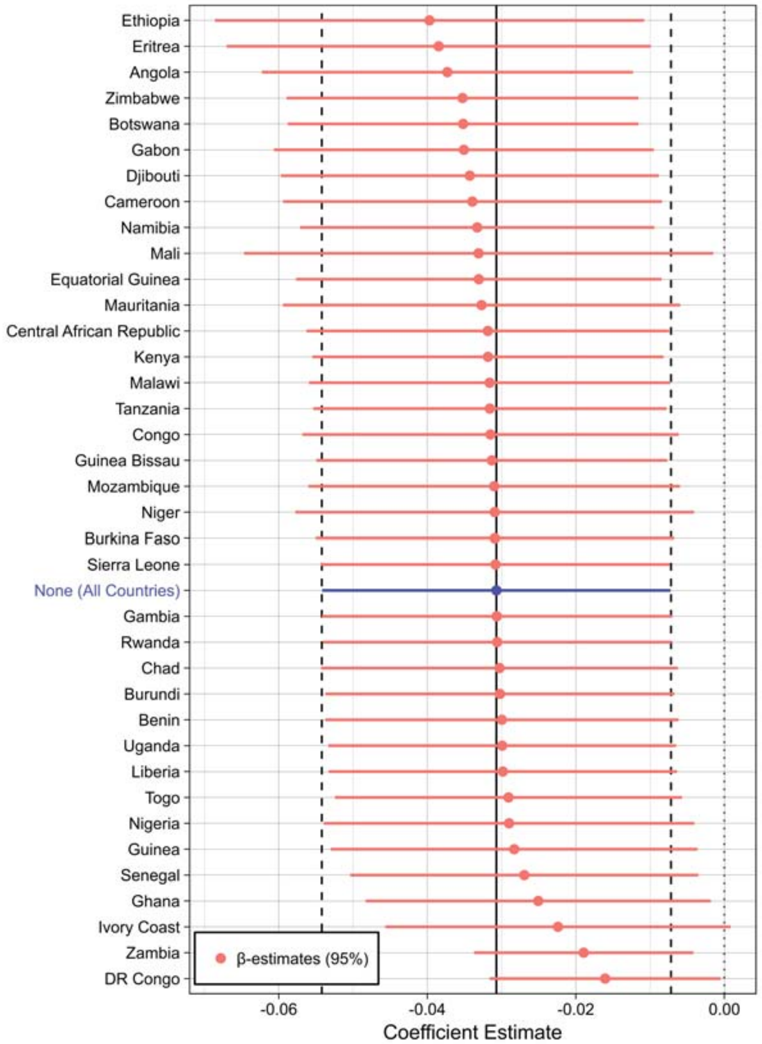
Table A12: Border Distcontinuity Estimation: Robustness - Capital City Buffer

	Dependent variable: VIIRS Nightlights 2016					
	Exclude all Pixels with a Distance from the Capital City					
	< 50 km		< 75 km		< 100 km	
	Prob	Log	Prob	Log	Prob	Log
	(1)	(2)	(3)	(4)	(5)	(6)
Log Distance from the Capital City	-0.030**	-0.135**	-0.034**	-0.151**	-0.037**	-0.164**
	(0.012)	(0.060)	(0.014)	(0.067)	(0.016)	(0.077)
	Polynomials for: distance from the border × country × ethnicity					
	305 groups		295 groups		290 groups	
3rd order	x	x	x	x	x	x
Geography Cov.	YES	YES	YES	YES	YES	YES
Country FE	36	36	36	36	36	36
Segment FE	563	563	548	548	531	531
Observations	166,741	166,741	163,014	163,014	158,033	158,033
R^2	0.187	0.168	0.186	0.167	0.178	0.159
Adjusted R^2	0.180	0.160	0.179	0.160	0.170	0.152

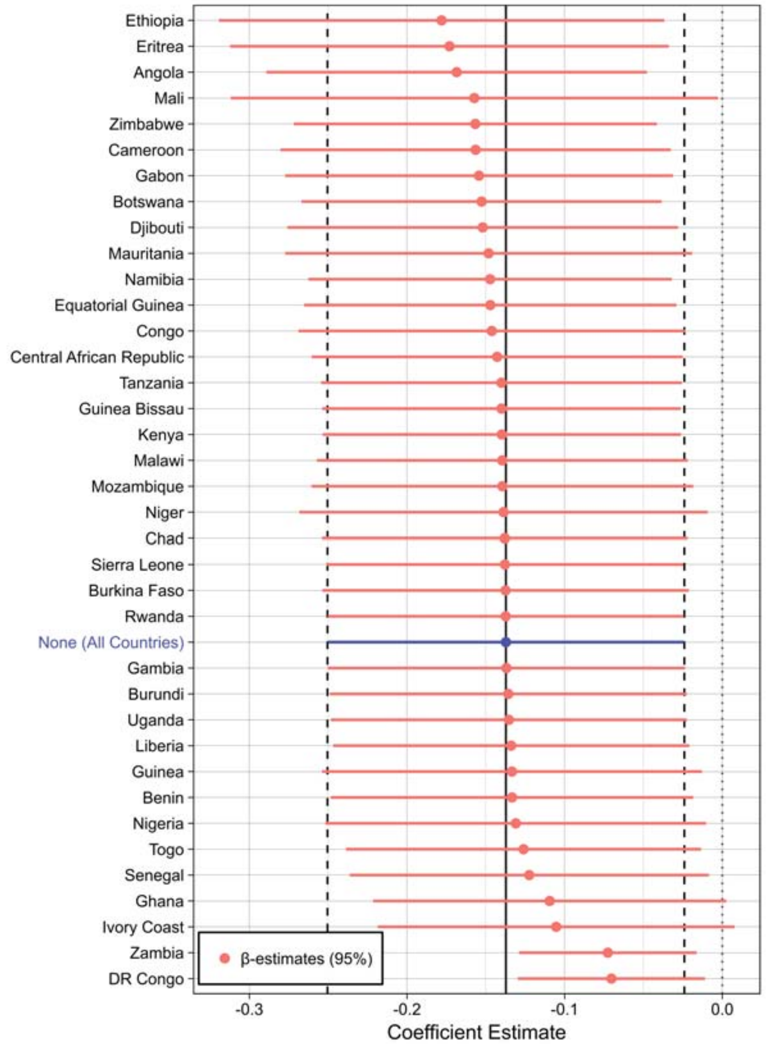
Note: This table reports robustness tests on our main BDD regression results in Table 2 based on Equation 6 and includes some variations on the exclusion around the capital city. In order to avoid capturing the break between the capital city and the hinterlands, we exclude 50, 75 and 100 km (instead of 20 km) around each capital city from our sample. To prevent misassignment of detected nightlights between countries due to blooming, we exclude 3 km on each side of the national boundary. The 'Geographical Cov.' include: distance from the coast (in km), ruggedness (in % slope), % surface covered with water, mean annual temperature, minimum average temperature during the coldest month, maximum average temperature during the warmest month (in °C), crop caloric index, annual precipitation (in mm), longitude and latitude (projected in km). Boundary segments corresponds to a buffer of 25 km around border pieces of 50 km line length and are entirely nested within a restricted ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). The observations are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by boundary segment. *p<0.1; **p<0.05; ***p<0.01

Figure A6: Robustness - Dropping Countries Iteratively

(a) Extensive



(b) Intensive



Note: The graphs illustrate the estimated coefficients and 95% confidence bands associated with isolation from the capital city based on Equation 6 when iteratively excluding all boundaries of individual countries. Since we are conducting a BDD, whenever we drop all segments of a country, we also drop a significant amount of pixels of adjacent countries. The change in the coefficient can therefore not be solely attributed to one particular country. The vertical solid black line corresponds to the baseline estimates of the full sample and the two vertical dashed black lines demarcate the respective 95% confidence interval. Standard errors are clustered by boundary segment.

Table A13: Border Discontinuity Estimation - Heterogeneity

	Dependent variable: Nightlight Density in 2016 (Prob/Log)											
	Decentralization				Democracy (Polity2)				GDP per capita (World Bank 2016)			
	Mean 1990-2010		2010		Mean 1996-2016		2016		Split at median		Split at mean	
	Prob	Log	Prob	Log	Prob	Log	Prob	Log	Prob	Log	Prob	Log
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CAP × Non-Decentr.	-0.045*	-0.229*	-0.041	-0.217	-	-	-	-	-	-	-	-
	(0.024)	(0.125)	(0.028)	(0.146)								
CAP × Decentralized	-0.031	-0.121*	-0.055***	-0.204***	-	-	-	-	-	-	-	-
	(0.021)	(0.070)	(0.017)	(0.060)								
CAP × Mixed	-0.026**	-0.107**	-0.025***	-0.101***	-	-	-	-	-	-	-	-
	(0.010)	(0.047)	(0.008)	(0.032)								
CAP × Autocracy	-	-	-	-	-0.001	0.007	-0.017	-0.041	-	-	-	-
					(0.010)	(0.042)	(0.013)	(0.049)				
CAP × Democracy	-	-	-	-	-0.064***	-0.292**	-0.027*	-0.117**	-	-	-	-
					(0.023)	(0.114)	(0.014)	(0.051)				
CAP × Mixed	-	-	-	-	-0.019	-0.089*	-0.041*	-0.206*	-	-	-	-
					(0.013)	(0.053)	(0.023)	(0.117)				
CAP × Underdeveloped	-	-	-	-	-	-	-	-	-0.033***	-0.140***	-0.041***	-0.177**
									0.011)	(0.049)	0.015	0.072
CAP × Developed	-	-	-	-	-	-	-	-	0.012	0.013	0.020	0.046
									(0.021)	(0.083)	0.022	0.096
CAP × Mixed	-	-	-	-	-	-	-	-	-0.049***	-0.210**	-0.027*	-0.114**
									(0.017)	(0.083)	0.014	0.057
Coefficient Tests	Non-Decentralized = Decentralized				Autocracy = Democracy				High GDP = Low GDP			
F-Statistic	0.23	0.68	0.21	0.01	6.66**	6.15**	0.27	1.18	4.67**	3.66**	5.62**	3.71*
	Polynomials for: distance from the border × country × ethnicity (302 groups columns (1)-(4) and 305 groups columns (5)-(12))											
3rd order	x	x	x	x	x	x	x	x	x	x	x	x
Geography Cov.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	35	35	35	35	36	36	36	36	36	36	36	36
Segment FE	563	563	563	563	569	569	569	569	569	569	569	569
Observations	166,833	166,833	166,833	166,833	168,620	168,620	168,620	168,620	168,620	168,620	168,620	168,620
R^2	0.190	0.169	0.190	0.169	0.189	0.169	0.189	0.169	0.189	0.169	0.189	0.169
Adjusted R^2	0.182	0.162	0.182	0.162	0.182	0.161	0.182	0.161	0.182	0.161	0.182	0.161

Note: This table reports the heterogeneity test corresponding to our main BDD regression results based on Equation 6. For this purpose we categorize all boundaries as either delimiting two relatively decentralized, democratic or developed countries and interact the respective dummies with log distance from the capital city. In columns (1)-(4), we group boundaries based on the 20-year arithmetic and 2010 level of the decentralization index, in columns (5)-(8) based on the 20-year mean and 2016 level of the Polity2 score and in columns (9)-(12) based on the median and the mean of the 2016 GDP per capita value. We report the F-tests on the equality of the respective coefficients. In order to avoid capturing the break between the capital city and the hinterlands, we exclude 20 km around each capital city from our sample. To prevent misassignment of detected nightlights between countries due to blooming, we exclude 3 km on each side of the border. The 'Geographical Cov.' include: distance from the coast (in km), ruggedness (in % slope), % surface covered with water, mean annual temperature, minimum average temperature during the coldest month, maximum average temperature during the warmest month (in °C), crop caloric index, annual precipitation (in mm), longitude and latitude (projected in km). Boundary segments corresponds to a buffer of 25 km around border pieces of 50 km line length and are entirely nested within a restricted ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). The observations are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by boundary segment. *p<0.1; **p<0.05; ***p<0.01

Table A14: Channel Analysis: Supplementary Results on Political Attitude

	BDD Model with dependent variable z-score of:			
	Trust in Ruling Party	Trust in Opposition Party	Voter Turnout	National (vs Ethnic) Identity
	(1)	(2)	(3)	(4)
Log Distance from the Capital City	0.169***	0.023	0.232***	0.039
	(0.060)	(0.052)	(0.051)	(0.049)
	Polynomials for: distance from the border			
3rd order	x	x	x	x
Household Cov.	YES	YES	YES	YES
Geography Cov.	YES	YES	YES	YES
Country × Round FE	67	67	70	68
Segment FE	140	140	140	140
Observations	7,794	7,809	7,702	8,007
R^2	0.186	0.083	0.112	0.137
Adjusted R^2	0.163	0.057	0.086	0.113

Note: This table reports the supplementary regressions on the impact of isolation from the capital city on the perception of political leaders and accountability. The 'Household Cov.' include: age, age squared and sex of respondent. The 'Geographical Cov.' include: distance from the coast (in km), longitude and latitude (projected in km) and whether the household is in an urban or rural setting. Columns (1) and (2) correspond to trust into the ruling and opposition party respectively. Column (3) to voter turnout and column (4) to the extent to which the respondent identifies with the nation rather than the ethnicity. All models are BDD regressions using 'Segment FE' for boundary segments of 50 km length with a buffer of 25 km that are nested within an ethnic homelands based on the 'Tribal Map of Africa' (Murdock, 1959). All observations are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by Afrobarometer cluster and boundary segment. *p<0.1; **p<0.05; ***p<0.01

Table A15: Channel Analysis: Afrobarometer Placebo Tests

	BDD Model with dependent variable z-score of:										
	Public Goods	Trust Leader	Corrupt Percept	Perform Eval	Trust Rule	Trust Oppos	Voter Turnout	National Identity	Educ Level	News Reader	Checks Balance
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Log Distance from the Capital City	-0.064*	0.173**	-0.070	0.226**	0.177**	0.064	0.122***	0.070	0.064	-0.092	-0.147**
	(0.038)	(0.071)	(0.068)	(0.105)	(0.081)	(0.070)	(0.027)	(0.068)	(0.090)	(0.083)	(0.059)
Log Distance from the Placebo City	0.059*	-0.024	0.023	0.080	0.012	0.062	0.041	0.037	0.003	0.097	-0.077
	(0.031)	(0.071)	(0.074)	(0.124)	(0.076)	(0.066)	(0.028)	(0.061)	(0.083)	(0.070)	(0.055)
Placebo Tests	$\text{Coef}_{CapitalCity} = \text{Coef}_{PlaceboCity}$										
F-Statistic	15.50***	8.49***	4.27**	3.51*	7.00***	0.0	9.82***	0.46	1.29	11.90***	2.16
	Polynomials for: distance from the border										
3rd order	x	x	x	x	x	x	x	x	x	x	x
Household Cov.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Geography Cov.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country × Round FE	70	70	71	71	67	67	70	68	71	71	71
Segment FE	70	138	138	138	138	138	138	138	138	138	138
Observations	8,053	7,601	6,525	6,414	7,590	7,598	7,501	7,802	8,096	7,902	7,556
R^2	0.624	0.207	0.190	0.229	0.192	0.085	0.114	0.135	0.315	0.197	0.163
Adjusted R^2	0.614	0.183	0.162	0.202	0.168	0.058	0.087	0.110	0.296	0.173	0.137

Note: This table reports the BDD placebo tests corresponding to the Afrobarometer regressions in Table 6, 7 and A14. We report the respective F-tests on the equality of the coefficients. The 'Household Cov.' include: age, age squared and sex of respondent. The 'Geographical Cov.' include: distance from the coast (in km), longitude and latitude (projected in km) and whether the household is in an urban or rural setting. The BDD sample is restricted to a buffer of 25 km around the shared national boundaries. The 'Segment FE' are nested within an ethnic homeland based on the 'Tribal Map of Africa' (Murdock, 1959). The observations are weighted such that each side of a segment has the same aggregated weight as its counterfactual. Standard errors in paranthesis are clustered by Afrobarometer cluster and boundary segment. *p<0.1; **p<0.05; ***p<0.01