Does Local State Capacity Foster Development in Africa? New Data and Analysis

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Abstract

Prominent arguments hold that African states' geography limits state capacity, impedes public service provision, and slows economic development. To test this argument, I collect comprehensive panel data on a proxy of local state capacity, travel times to national and regional capitals. These are computed on a yearly 5×5km grid using time-varying data on roads and administrative units (1966–2016). I use these data to estimate the effect of changes in travel times to capitals on local education provision, infant mortality rates, and nightlight emissions. Within the same location, development outcomes generally improve as travel times to its capitals decrease. These data and results improve the measurement of state capacity and contribute to the understanding of its effects on human welfare.

Keywords: State capacity; Economic development; Africa; Data; GIS

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Introduction

Adverse population distributions, arbitrary colonial borders, and deficient transport networks limit state capacity in Africa and are blamed to impede good governance and economic development on the continent (e.g., Herbst 2000). However, empirical tests of this reasoning lag behind its frequent use. In particular, we lack geographically disaggregated and time-varying data on African states' capacity to estimate its effect on local development. This research note presents new panel data on local state capacity proxied by travel times to post-independence regional and national capitals. With these data, I estimate generally positive effects of state capacity on local development.

The new data of state capacity improves upon previous measures that have, after an initial focus on the country-level (Hendrix 2010), captured important subnational variation in state capacity (Boone 2003). However, their reliance on either surveys (Wig and Tollefsen 2016) or age-heaping in censuses (Lee and Zhang 2017) limits temporal coverage and availability in low-capacity states.[1] As a remedy, I develop and validate a continent-wide, yearly proxy of local state capacity based on travel times to regional and national capitals between 1966 and 2016. I compute these travel times for a 5×5km grid of the continent using new panel data on (1) administrative geographies and (2) road networks digitized from the Michelin map corpus. The measure will made accessible upon publication of this article.

I use the new data to estimate the effect of local state capacity on development. Previous studies provide cross-sectional evidence that locations farther away from capitals experience more conflict (e.g. Tollefsen and Buhaug 2015), suffer from corruption (Campante and Do 2014; Krishna and Schober 2014), and exhibit lower levels of development (Acemoglu, García-Jimeno and Robinson 2015; Henn 2018), an effect that is historically persistent (Pierskalla, Schultz and Wibbels 2017).[2] I improve identification and address the potential endogeneity of administrative geographies by focusing on variation within locations and country-years. The analysis shows that reductions in travel times to capitals generally come with increases in education and infant survival rates, as well as nightlight emissions. These effects are not explained by spurious migration, differential pre-trends and reverse causality, endogenous road construction, improvements in economic market

[1] Surveys also have incomplete spatial coverage and age-heaping may proxy education rather than state capacity (A'Hearn, Baten and Crayen 2009).

[2] Similarly, US counties with a post office in 1896 developed quicker (Rogowski et al. 2019).

access, or ethnic favoritism and conflict.

State capacity and development

State capacity denotes states' ability to enforce their will by monitoring and steering citizens' behavior (Mann 1984; Migdal 1988). It consists of their administrative capacity, military strength, and ability to tax individuals (Hendrix 2010). Physical access to citizens through transport infrastructure is a key determinant of state capacity (Acemoglu, García-Jimeno and Robinson 2015; Boulding 1962; Herbst 2000; Mann 1984).

Four mechanisms link physical accessibility via local state capacity to development. First, low transport costs between states' headquarters and the population enables bureaucrats and police officers to enforce law and order, thereby triggering the developmental effects of centralized state institutions (Campante and Do 2014; Huntington 1968). Second, states' provision of services such as health care and education depends on their capability to monitor demand and control agents, both of which increases with local state capacity (Krishna and Schober 2014; Henn 2018). In addition, citizens' access to specialized services (e.g., hospitals and courts) increases near the administrative capitals that typically harbor them. Third, smooth local accessibility increases citizens knowledge on and ability to tap into private rents from the state such as public sector jobs or subsidies (Ades and Glaeser 1995; Banerjee et al. 2018).

These development-inducing effects are counteracted by the facilitating effect of state capacity on tax collection, which decreases citizens' material welfare. With that, the net effect of state capacity depends on whether the exchange of taxes for public services is generally beneficial for citizens (Timmons 2005) or not (Scott 2017). The empirical analysis sheds light on this question.

Approximating state reach

Because physical accessibility is a necessary (but not sufficient) condition for state capacity, I proxy local state reach with the weighted sum of travel times to a locations' national and regional capitals:[3]

$$\text{total state reach}_{p,t} = \sum_{u=1}^{U} \omega_u \ \text{state reach}_{p,u,t} \tag{1}$$

$$= \sum_{u=1}^{U} -\omega_u \ ln(1 + d_t(p, C_{p,u,t})) \tag{2}$$

where state reach on a level of administrative hierarchy u towards point p at time t is calculated as the travel time (in hours) on the shortest path between p and its capital $C_{p,u,t}$ on the road network at time t.[4] The log-transform[5] captures the convex relation between travel times to capitals and state capacity (Figure 2). Weights ω_u denote the impact of times to capitals on each level u. Because ω_u likely vary across different state activities, I estimate ω_u for each development outcome separately. To measure $\text{state reach}_{p,u,t}$ with time-varying data on regional and national administrative geographies and road networks.[6]

First, I collect comprehensive panel data on the boundaries and capitals of first-level (regional) administrative units since African countries' independence. Drawing on diverse sources, the dataset covers 1763 unique region-periods between independence and 2016 (Appendix A). Data on national borders and capitals comes from Cshapes (Weidmann and Gleditsch 2010).

Second, I transform the Michelin road map corpus into a digital road atlas akin to a time-varying Google Maps.[7] Scanned maps are available at a scale of 1:4 million[8] for 23 years between 1966 and 2014. Using the procedure developed by Müller-Crepon, Hunziker and Cederman (2020), pixels that depict roads are classified with the fully convolutional neural network, vectorized, and transformed into a planar graph that covers the African landmass at a resolution of .0417 decimal degrees (≈5km; Appendix B). Each edge on the network is associated with a travel time derived from the quality of roads observed on the Michelin maps. With these data on roads and administrative units, I cal-

[3]The index does not capture lower levels because no sources comprehensively cover 2[nd] or 3[rd] level administrative units over time.

[4]The relation of travel times with state capacity likely varies by country. This can be reflected by normalizing travel times by country characteristic x_c. The country-year fixed effects in the analysis constitute such a normalization because $log((1 + d_t(p, C_{p,u,t}))/x_c)$ decomposes to $log(1 + d_t(p, C_{p,u,t})) - log(x_c)$.

[5]Adding 1 hour prevents taking the log of 0 in capitals.

[6]Surpassing rail or air transport, road transport is the dominant motorized transport mode in Africa (Jedwab and Storeygard 2018).

[7]Jedwab and Storeygard (2018) use the Michelin maps to measure economic market access.

[8]This corresponds to 1mm per 4km and puts an upper precision limit on the data.

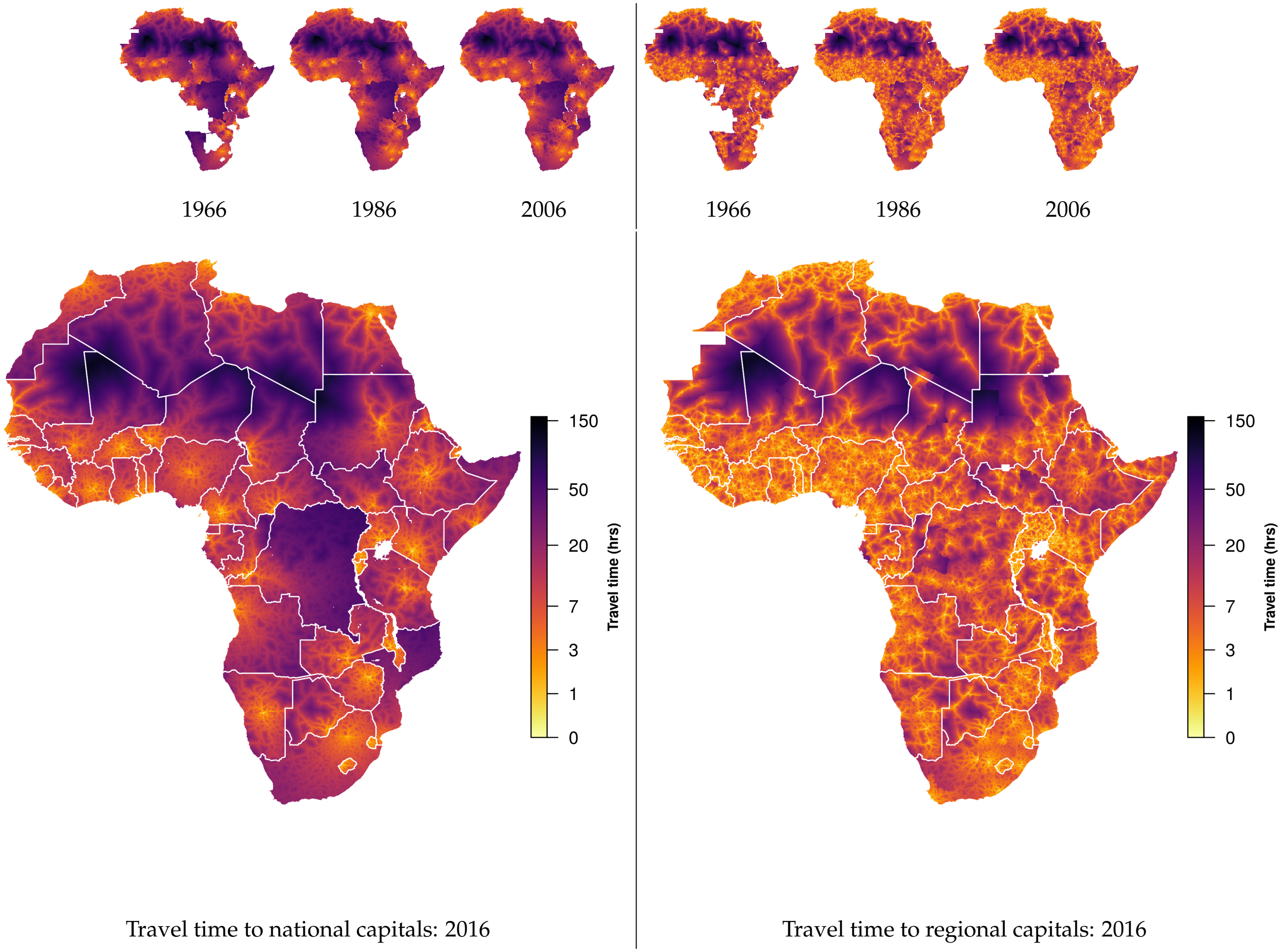


Figure 1: State reach in Africa, 1966–2016.

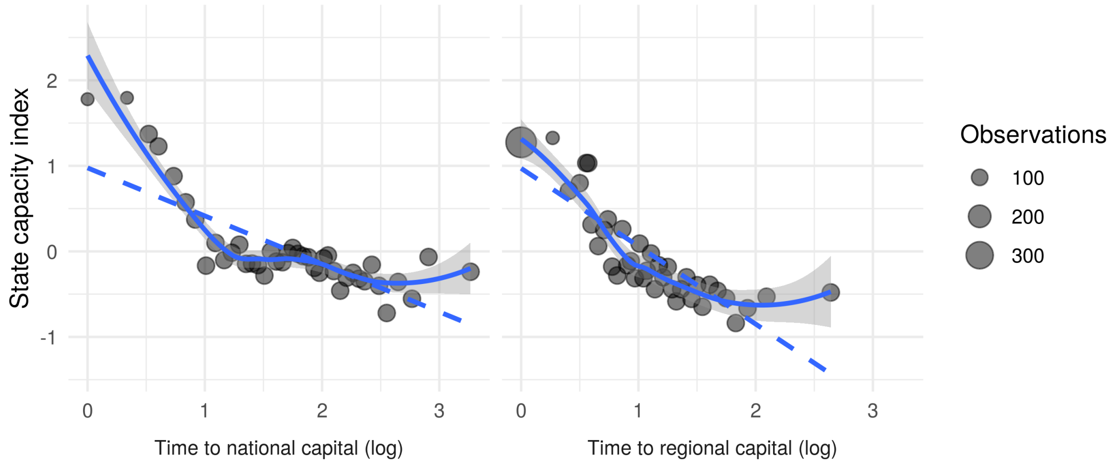


Figure 2: Travel times to national and regional capitals and state capacity index
Values are demeaned by country × survey round and averaged within 40 x-axis quantiles.

culate state $\text{reach}_{p,u,t}$ for the grid cells of a raster with a .0417 decimal degree resolution for every year between 1966 and 2016 (Figure 1).

I validate the utility of the data as a proxy for local state capacity with information on local state presence in the enumeration areas of the Afrobarometer (2018) surveys. Figure 2 shows that travel times to capitals correlate strongly with an index of multiple dimensions of state capacity, in particular the presence of the police and military, post offices, schools, and hospitals, as well as public services such as water, sewage, and electricity. Travel times also fit the index better than mere geodesic, as-the-crow-flies distances (Appendix C.1). In sum, I find the data to be a good proxy of local state capacity.

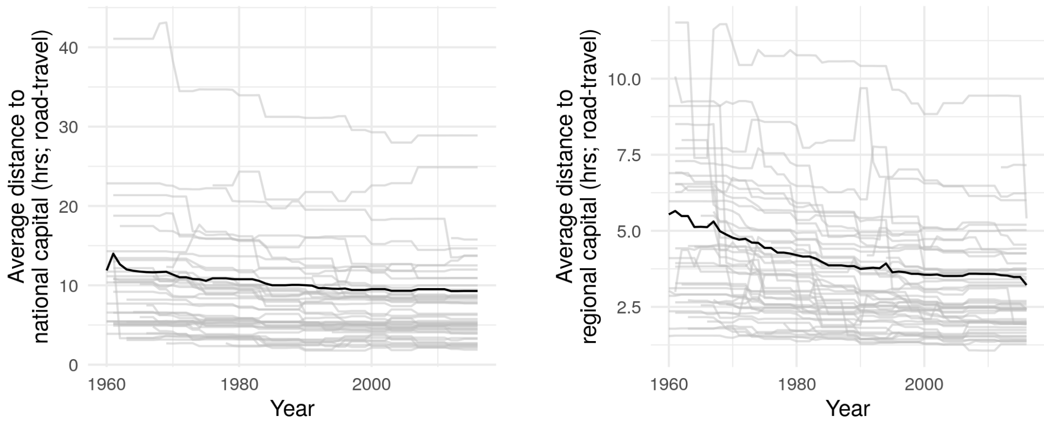
State reach in Africa: weak, growing, and unequal

African states' reach has increased since their independence (Figure 3). Travel times between national capitals and citizens have decreased from a 1966 average of 11.7 hours to 9.3 hours in 2016, a change of 20.8 percent. Travel times to regional capitals decreased from 5.1 hours to 3.5 hours.

Three trends underlie this development (Appendix C.2). First, administrative geographies have changed. Côte d'Ivoire, Nigeria, and Tanzania have relocated their national capitals [9] and most governments have created new administrative regions(Grossman and Lewis 2014; Grossman, Pierskalla and Dean 2017).[10] Second, transport infrastructure has

[9] Abidjan to Yamoussoukro (1983), Lagos to Abuja (1991), and Dar es Salaam to Dodoma (1974, but ministries remain in Dar es Salaam).

[10] Similarly, capitals of independent Eritrea and South Sudan moved closer to citizens.



(a) Average time to national capital

(b) Average time to regional capital

Figure 3: Decreasing travel times to regional and national capitals in Africa 1960–2015.
Population-weighted averages based on HYDE population estimates (Goldewijk, Beusen and Janssen 2010) and travel times to capitals.

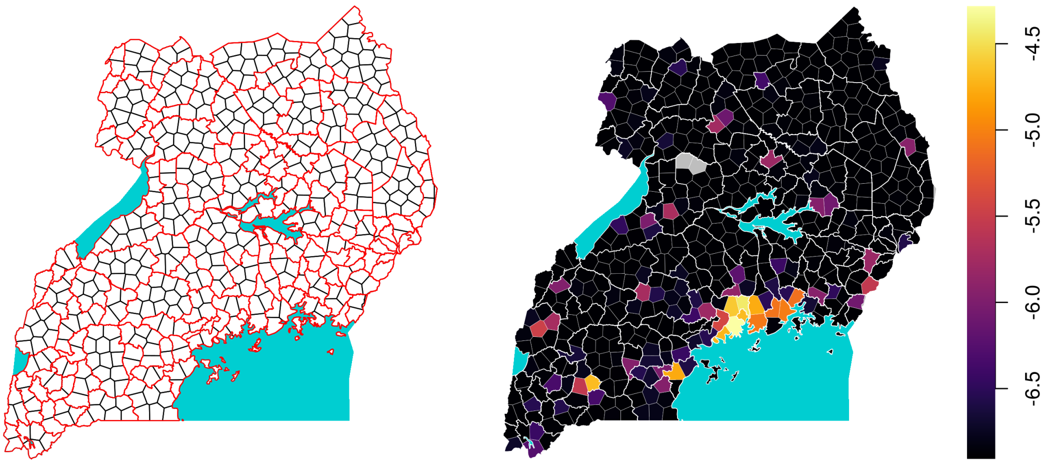
improved, with quality-weighted mileage increasing by about 50 percent since independence. Lastly, many citizens moved closer to capitals as urbanization rates doubled from 20 to 40 percent (World Bank 2018) .

The maps in Figure 1 show that travel times to capitals exhibit substantive variation within and across countries. Travel times within the DR Congo to its capital Kinshasa vary between 0 and 50 hours, with a high median of 34.3 hours, thus reflecting the country's "difficult geography" (Herbst 2000) and sparse infrastructure. Capitals of small countries such as Rwanda are naturally closest to their citizens. Changes in travel times since 1966 are marked by similar variation. States and regions that seceded or relocated their capital experienced the largest improvements. These changes exhibit substantive spatial variation because changes in administrative geographies and road networks have spatially varying effects. My empirical strategy exploits this fact.

Data on local development

The empirical analysis examines whether changes in African states' reach affected local development, measured with data on education, infant mortality, and nightlight emissions.[11] To measure primary education, I rely on the Demographic and Health Survey (DHS 2018). The DHS encodes the educational achievement of all members of sampled households. Assuming that household members live where they were raised, I model

[11]See Appendix D.2 for summary statistics.



(a) Regions and Voronoi cells

(b) Average nightlights per capita 1992–2013 (log)

Figure 4: Voronoi cells, regions, and nightlights in Uganda 1992–2013.

Panel (a) plots all regional borders between 1992 and 2013 (red) and Voronoi cells (black). Unpopulated cells in (b) in grey.

the level of education of 1.9 million individuals older than 15 as having been influenced by the travel time to their capitals at age 6. An 'attended primary school' dummy serves as the main outcome.

The DHS also measures the under-1 mortality of 2.6 million infants born to women aged 15–49. I model infants' deaths as depending on the travel time to their mothers' capitals at their birth. Infant mortality and education rates exhibit local temporal variation because children and household members sampled in the same place are born and schooled at different points in time. In modeling this variation, I assume that migration decisions do not respond to changes in state reach in a manner that correlates with the observed outcomes. I investigate whether effects differ between migrants and non-migrants below.

To mitigate the uneven survey coverage and counter concerns about migration biases, I also proxy local development with nightlight emissions (Weidmann and Schutte 2017) derived from satellite images (1992–2013; National Geophysical Data Center 2014). I measure nightlights within centroidal Voronoi cells (400 km^2)[12] that are nested within administrative regions (Figure 4 and Appendix D.1). In contrast to quadratic cells that frequently overlap with (changing) administrative borders, travel times can be consistently aggregated to the Voronoi cells. Nightlights are log-transformed after adding a

[12]Results are robust to varying cell sizes (Appendix E.7).

constant of .001.[13]

Empirical strategy

The empirical analysis aims to identify the effect of travel times to capitals on development despite endogenous processes such as strategic road, capital, and border placements. To account for any cross-sectional endogeneity and geographical confounders, I only study *temporal* variation in travel times and development within the same location:

$$Y_{i,p,c,t,s} = \alpha_p + \lambda_{c,t} + \mu_s + \beta_1 \, \text{time to nat. cap.}_{p,t} + \beta_2 \, \text{time to reg. cap.}_{p,t} + \delta X_i + \epsilon_{i,p,c,t}, \quad (3)$$

where β_1 and β_2 capture the effects of the travel times to point p's regional and national capitals at time t. In parallel to weights ω_u in Equation 1, the sum of β_1 and β_2 proxies the total effect of state capacity. DHS respondents i are spatially matched to grid-cell p in the travel time rasters of year t.[14] p is synonymous with i where Voronoi cells are the units of analysis. The model controls for all constant attributes of points/units, country-years, and surveys through fixed effects α_p, $\lambda_{c,t}$, and μ_s. Individual-level controls X_i in the education models consist of respondents' sex, age and its square. Infant mortality models include mothers' age at birth and its square, infants' birth-order and its square, as well as female and twin dummies. I add no time-varying covariates to the baseline nightlight model. I cluster standard errors on the point and country-year levels.

Relying on this two-way fixed effect estimator,[15] I assume that changes in travel times to capitals are exogenous to local development outcomes observed thereafter. Robustness checks account for potential violations of this assumption, in particular reverse causation, spurious correlations with changes in economic market access, or potential omitted variables such as ethnic inclusion or civil war.

Results

The results show that reductions in travel times towards regional and national capitals are, first, robustly associated with increasing primary education rates. Second, infant

[13] I drop cells with oil wells that cause bright flares of burning gas (Lujala, Rød and Thieme 2007).
[14] The DHS's random displacement of clusters by up to 10 (2) kilometers in rural (urban) areas adds noise.
[15] Because the 'treatments' are continuous travel times that are subject to multiple positive and negative changes, the setting does not fit a binary difference-in-difference design.

mortality rates improve as travel times to national, but not regional capitals decrease. Lastly, nightlight emissions significantly increase with declining travel times to regional capitals. Their relation to changes in the time to national capitals is of roughly similar size but statistically more unstable. Interpreting the sums of β_1 and β_2 as total effect of state capacity reveals a consistently positive, meaningful, and statistically significant effect on local development.

Table 1: Changes in time to national/regional capital and local development

	Primary educ. (0/100)	Infant mort. (0/100)	Light/capita (log)
	(1)	(2)	(3)
Time to nat. capital (log)	-2.662^{***}	0.932^{***}	-0.052^{*}
	(0.421)	(0.240)	(0.027)
Time to reg. capital (log)	-1.325^{***}	0.138	-0.037^{**}
	(0.323)	(0.160)	(0.019)
$\beta_1 + \beta_2$:	-3.987^{***}	1.069^{***}	-0.089^{***}
	(0.486)	(0.273)	(0.029)
Point FE:	yes	yes	yes
Country-year FE:	yes	yes	yes
Survey FE:	yes	yes	–
Controls:	yes	yes	–
Mean DV:	70	9.9	-6.5
Observations	1,893,067	2,634,209	1,506,991
Adjusted R^2	0.445	0.051	0.836

Notes: OLS linear models. Control variables for models with primary education as the dependent variable consist of responents' age and age squared, as well as a female dummy. Where infant mortality is the dependent variable, models include an infant's mother's age at birth and its square, the birthorder and its square, as well as a female and twin dummy. Standard errors clustered on the point and country-year levels. Significance codes: *p<0.1; **p<0.05; ***p<0.01

Table 1 presents the baseline results. Interpreting coefficients in substantive terms, Model 1 indicates that an decrease in travel times to national (regional) capitals from 2 to 1 hours is associated with a precisely estimated increase in primary education rates by 1.1 (.54) percentage points. Model 2 shows that infant mortality rates decrease by .38 percentage points when the time to the national capital decreases from 2 to 1 hours. In contrast, there is no evidence for a meaningful impact of regional capital accessibility on infant mortality. The respective coefficient is close to zero and statistically insignificant.

Distinguishing the effects of relocations of national capitals[16] from those of road network changes reveals that national capital relocations primarily drive the effects on education and infant mortality rates (Appendix E.1). Changes due to road networks have a smaller, but statistically significant effect on primary education and no effect on infant mortality.

[16]There are very few regional capital relocations.

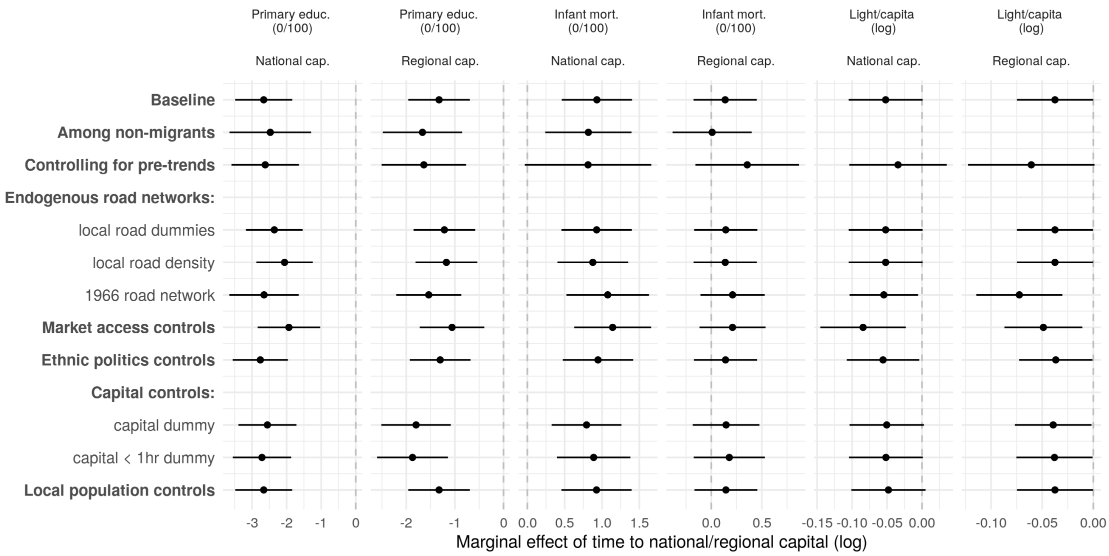


Figure 5: Robustness checks. Coefficient estimates with 95% CIs.

Lastly, Model 3 yields a significant association of travel times to regional capitals with nightlight emissions. As the local distance to the regional capital decreases from two to one hours, per-capita nightlight emissions increase by 1.8 percent. The same change in the distance to its national capital is associated with a similar increase in nightlights, which is however affected by differential pre-trends (Appendix E.3). The estimate's noisiness is related to the short coverage of the data (1992-2013) with changes of national capitals in newly independent South Sudan (2013) and Eritrea (1992), each with only one pre-/post-treatment year. Thus, changes in road networks with their more diffuse impact on development drive the estimate.

Figure 5 presents the results of robustness checks (for details, see Appendix E). First, I find that the effects of travel times to capitals hold among non-migrant DHS respondents. Second and evidence against reverse causality, I find no significant effect of differential pre-trends, except for those that affect the nightlight model. Third, the results are not caused by potentially endogenous road building accounted for by time-varying local road density-measures or by computing travel times on the time-invariant road data from 1966. Fourth, a potentially spurious correlation of travel times to capitals with economic market access to the 1530 biggest African cities does not drive the results. Fifth, the results are not due to potential omitted variables, in particular ethno-political inclusion, exposure to ethnic civil wars, regional and national capital dummies, and population density controls. Lastly, Appendix E.6 demonstrates robustness across alternative outcome specifications.

These analyses show generally positive developmental effects of increases in state capacity as proxied by the sum of the effect of travel times to national and regional capitals. Where national and regional administrations move closer to the citizens they govern, education rates improve. Infant mortality rates increase with travel times to national but not regional capitals. Lastly, nightlights become brighter when regional capitals move closer. Pre-trends partially drive the developmental effects of closer national capital, raising concerns about reverse causality.

Conclusion

One important constraint of states' capacity and their ability to foster development is their physical access to the population (Herbst 2000). Measuring African states' varying success in making their citizens accessible, this research note has introduced new spatio-temporal data on travel times between administrative capitals and citizens as a proxy for post-colonial state capacity. The new data shows a generally positive effect of increases in local state capacity on various indicators of citizens' wealth and well-being. This supports the long-standing argument that difficult geographies with hard-to-access populations impede governance and economic development on the continent. At the same time, the results reject geographic determinism in showing that states can invest in improving their reach and thereby foster local development.

Offering new data and empirical results, this research note opens up avenues for future research. A first set of questions concerns the origins of the manifest variation in the effects of state capacity in the nature of state-provided goods or different institutional settings. Second, there might be important heterogeneity in *when* local state capacity matters most for citizens' welfare. Crises such as droughts, floods, or violent conflicts may exacerbate the effects of weak statehood. Lastly, researchers can use the new measure of state capacity to study state-society interactions more generally, ranging from resource extraction, over accountability, to conflict processes.

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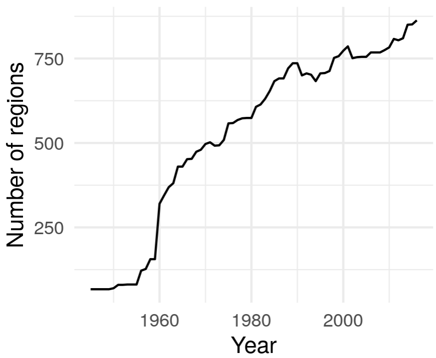
Supporting Information

State Reach and Development in Africa since the 1960s: New data and analysis

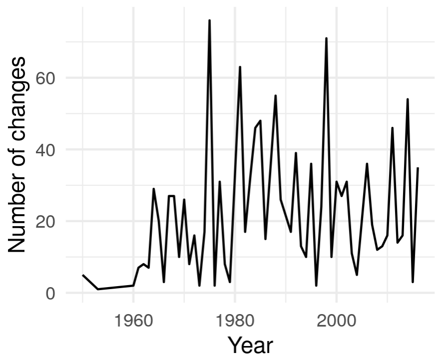
Table of Contents

A Regions in post-colonial Africa

To collect a full panel on the borders and capitals of first-level administrative regions in Africa since countries' independence, I draw on the qualitative accounts of unit changes from the statoids.com database and encode each administrative unit change geographically. I therefore rely primarily on maps from the GAUL database, (FAO 2014). Although this data is contemporary (reaching back until 1990), it allows me to trace back all unit-*splits* – this type of unit-change constitutes the vast majority of cases – by simply merging the units observed after the split which results in the original unit. Where units have been merged or the administrative map of a country has been redrawn completely, I make use of more than 100 digitized maps, mostly from the CIA Base Map series as well as other GIS data, such as the GADM database. Each region-period is associated with its capital, as listed in most cases by statoids.com. Missing capitals are searched on the maps and in secondary sources. The capitals are then geocoded using the geonames.org gazetteer. Changes in the location of capitals within the same boundaries of a region naturally result in new region-periods. Each region-period is associated with a start and end-year. To ensure consistent and temporally non-overlapping coding, region-periods that start after January 1st are coded as starting in the next year. The final data set covers 1763 unique region-periods, covering each African country from independence to 2016. The evolution of the number of regions in the data set is traced in Figure A1. Figure A2 plots the data for the year 2016.

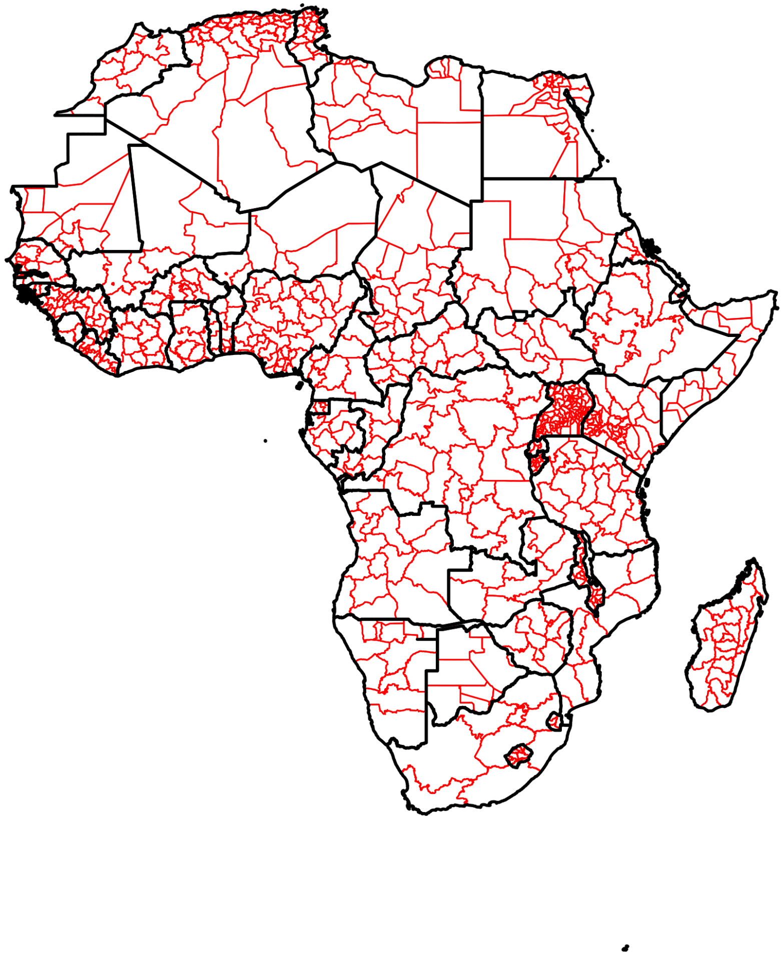


(a)

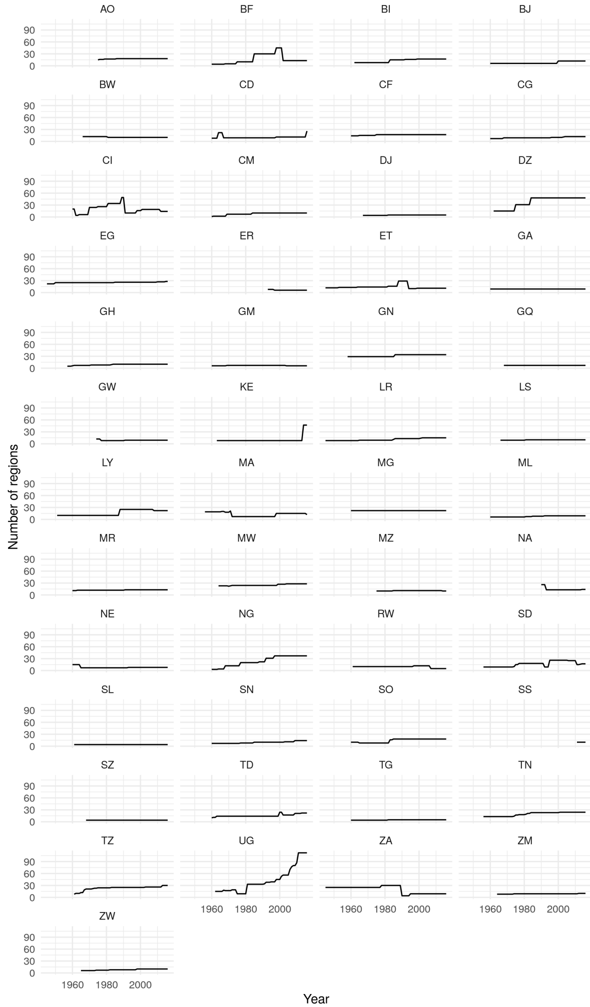


(b)

Figure A1: Description of newly collected data on first-level administrative units in Africa.



(a) First-level administrative units in Africa 2016



(b) Number of admin-1 units by country and year

Figure A2: Overview over first-level administrative unit data.

B Road data from the Michelin map corpus

This section provides the details on how I digize the Michelin map corpus, building on the procedure that was developed by Müller-Crepon, Hunziker and Cederman (2020). Compared to Müller-Crepon, Hunziker and Cederman (2020), data collection has been extended for the purpose of this article from the initial 6 to 23 road map cross-sections. Subsection B.1 describes the map corpus, Subsection B.2 summarizes the digitization procedure, Subsection B.3 describes the construction of travel speeds, and Subsection B.4 discusses the construction of the final road network data.

B.1 The Michelin map corpus

The source for road network data for post-colonial Africa is the African Michelin map corpus, a collection of large topographical maps at a resolution of 1:4,000,000. Each map shows detailed information on road infrastructure with a consistent cartographic symbology for about a third of the continent (see Figure A3). While coverage before the 1960s is sporadic, Michelin has covered the entire African continent at intervals of approximately 5 years beginning in 1964 (see Figure A4). This makes the Michelin corpus an unparalleled source for time-variant road-network information. I digitize 34 map sheets published between 1964 and 2017, which combine into 23 maps of the entire continent.

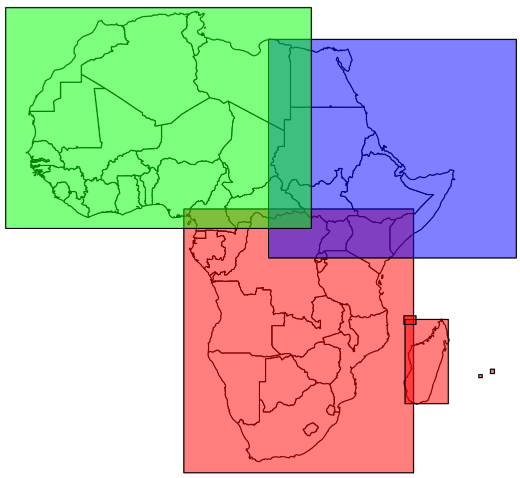


Figure A3: Spatial coverage of Michelin Map types.

Note that Madagascar is not covered in 1966. Green: North-West. Blue: North-East. Red: Center-South.

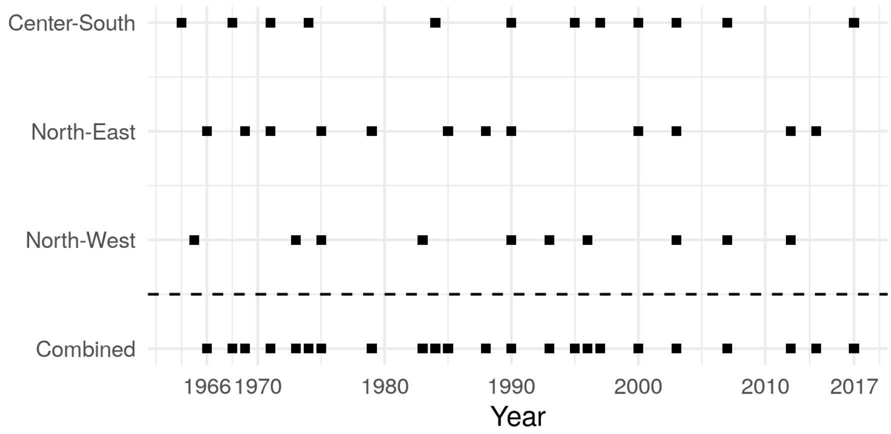


Figure A4: Temporal coverage of Michelin Maps

B.2 Map digitization

I use the Fully Convolutional Neural Network (FCNN) and post-processing algorithms developed by Müller-Crepon, Hunziker and Cederman (2020) to transform the scanned and georeferenced Michelin Maps into spatial road network data. In short, the FCNN is based on the methodology developed by Shelhamer, Long and Darrell (2017) and yields pixel-level predictions of road-types for the map scans. These predictions are fed into a four-step algorithm to transform pixels into vector data by (1) thinning lines made up of pixels, (2) tracing lines to transform them into vectors, (3) filling small, unlikely gaps in the resulting network of lines, and (4) smoothing road-type information to reduce noise from small missclassifications. Müller-Crepon, Hunziker and Cederman (2020) demonstrate that the procedure yields an excellent digitization of road networks: over 98.8% of all extracted roads are present in the Michelin maps, and 98.6% of all Michelin roads are extracted. Take road categories into account, the respective percentages are somewhat lower, but still 88.8 and 96.4, respectively. Ordinal missclassification errors are however small, on average (among errors) amounting to 1.38 on the ordinal road-type scale. These errors will thus only marginally affect travel time estimates and will do so in a presumably random manner.

B.3 Retrieving travel speeds

I follow Müller-Crepon, Hunziker and Cederman (2020) and obtain travel speeds for each of the six main road categories in the Michelin data[17] from the Michelin website (`www.viamichelin.com`. For each road category, I use data on a random selection of trips on roads of that category, and record the travel speed returned by the Michelin querying tool (see Figure A6a).[18] I define traveling speed on foot-paths as 6 km (about 4 miles) per

[17]The 16 types of roads in the Michelin data are collapsed into the 6 main categories.

[18]Note that the average speed returned for 'highways' is somewhat lower than that returned for 'hard surface' roads. Highways are almost non-existent in Africa. They constitute only .06 percent of the total

hour. This corresponds to walking-time estimates on www.maps.google.com (see also Jedwab and Storeygard 2018).

B.4 Network construction

I transform the road data from the Michelin map corpus into planar graphs that uniformly cover geographic space. I do so in a step-wise manner:

1. **Foot-path network:** The basis of the planar graphs consist of network of 8-connected 'foot-paths', shown for the case of Uganda in Figure A5a. The graph's nodes are the centroids of a raster of population estimates from the HYDE 3.1 data (Goldewijk, Beusen and Janssen 2010) for 1960 at a resolution of $.04167 \times .04167$ decimal degrees (or ca. 5 km at the equator). Each node is connected with a foot-path to its 8 nearest neighbors using queen moves. This setup allows for much more flexible applications than travel-query APIs such as Google Maps which do not process queries from/to points that are too distant from the next road.

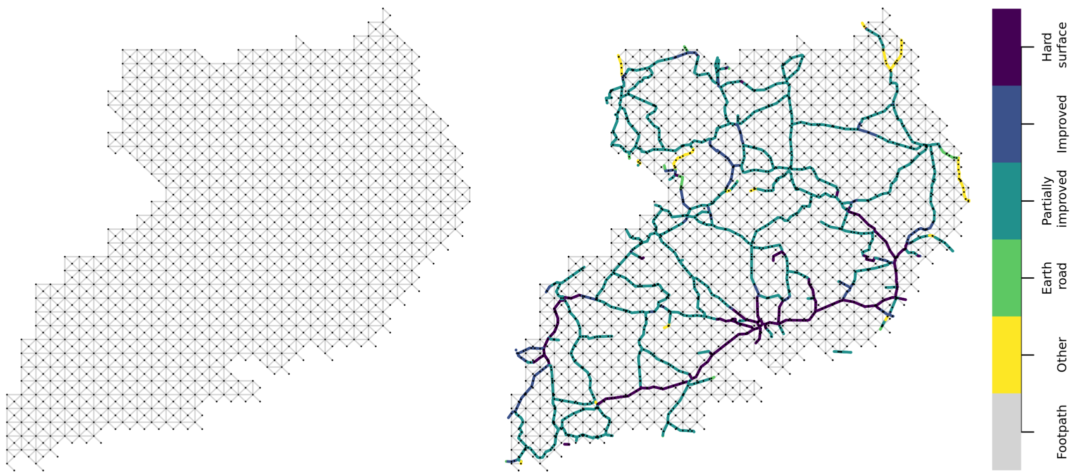
2. **Adding roads:** I then overlay the basic foot-path network with the spatial lines extracted from each map corpus (see Figure A5b) after aligning them all to the last and most extensive network observed in 2017.[19] I create additional nodes wherever two roads or foot-paths cross, thus retaining the planar graph property. These additional nodes' purpose is to serve as intersections. They are not associated with any population data. Hence, travel between two populated nodes will typically start by taking a foot-path to a road, and end by traveling from a road to the target node on another foot-path. Note that the occasional imperfect spatial alignment of road networks observed in consecutive Michelin maps causes variation in the length of these first or last foot-paths of some trips. The resulting variation in travel travel times is however deemed negligible and, importantly, random.

3. **Calculating edge weights:** Each edge on the network is associated with an edge weight which is equivalent to the estimated time it takes to traverse the edge (see Subsection B.3).

Müller-Crepon, Hunziker and Cederman (2020) demonstrate that the road networks thus constructed yield very similar travel time estimates as the Google Maps API. Their validation results are reproduced in Figure A6b.

road mileage observed in 1966 and cluster in the immediate neighborhood of large cities where speed is slowed by congestion. To preserve the rank-ordering of roads (which is important for our road simulation), we recode all highways as hard surface roads.

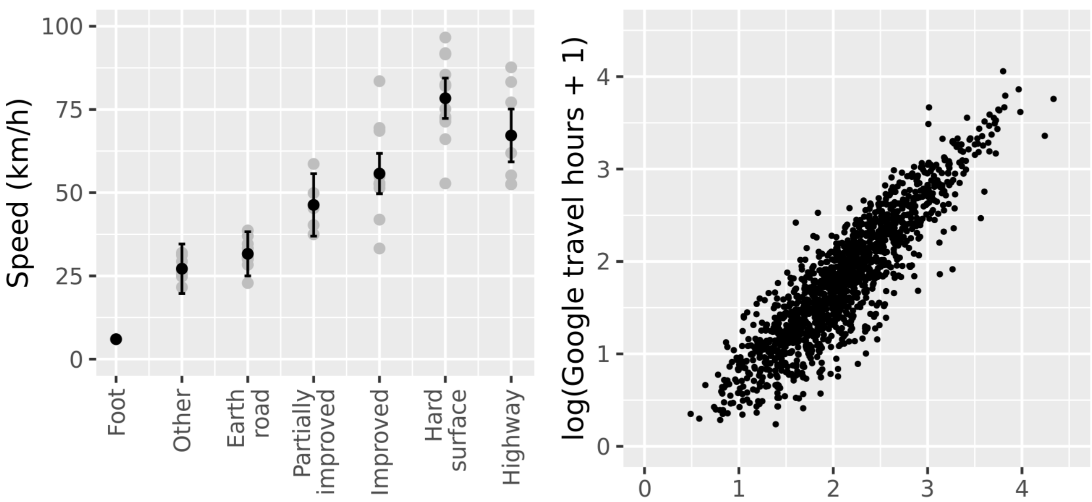
[19]This alignment is necessary to preclude small 'jumps' in the location of roads, caused by the digitization procedure, to introduce random noise into the measure and downwards bias the estimation results. The alignment of roads is computed via ArcGIS's align_feature function.



(a) Foot-path network

(b) ... adding Michelin roads observed in 1966

Figure A5: Constructing road networks that regularly cover geographical space. Additional vertices are added to the graph where foot-paths and roads intersect.



(a) Estimate of travel speed on different road types

(b) Comparison of travel times on the Michelin-based road network (roads from 2003) and travel times queried from the Google Maps API.

Figure A6: Construction and validation of edge-weights.

C Travel times to capitals as proxy for state reach: Data description and validation

C.1 Validation

I use data from the Afrobarometer (2018) surveys to validate travel times to national and regional capitals as proxies for subnational state capacity. In particular, the surveys contain information provided by the enumerators about the presence of state organs and services in each enumeration area (EA). The respective items range from the local provision of electricity, water and sewage, over the presence of a school, clinic, or post office, to the presence of police and military forces. All variables are coded as dummies. I combine them into a joint index of local state capacity by taking their first principal component, which explains 36.2 percent of the variation in its constitutive parts. Furthermore, I compute for each EA the time to its regional and national capital at the time of the survey.[20]

Figure A7 plots the association between EA's travel times to their regional and national capital and each indicator, demeaned by country. All indicators correlate with travel times to capitals, which I take as a first indication of their quality as proxies for local state capacity.

Table A1 goes a step further and compares the association between travel times and the local state capacity index with the correlation between mere geodesic distances to capitals. The results show that both distance measures correlate with the index. However, once both are included in Models 3 and 6, the coefficient of geodesic distances becomes much smaller and looses significance in Model 3. I take this as evidence that travel times are superior to simply taking geodesic distances. After all, state agents typically rely on earth bound vehicles and do not fly as crows.

C.2 Description

Three main factors influence the difficulties of a state to reach out to its population: the location of administrative borders and capitals, and the structure of the transportation network that links the state to its subjects, and the geographic distribution of its population. By changing their geography along each of these three dimensions, states can increase their reach and improve their capacity to govern. First, states can optimize the location of its headquarters, open new branches of state agencies, and shift the boundaries of administrative units (Fesler 1949). Since independence, the Côte d'Ivoire, Nigeria, and Tanzania have relocated their national capitals[21] and most have increased the number of administrative units (Figure A8a, see also Grossman and Lewis 2014; Grossman, Pierskalla and Dean 2017).[22] Similarly, the independence of Eritrea and South Sudan has

[20]To do so, I use the geocodes provided by Ben Yishay, Ariel Rotberg et al. (2017).

[21]Côte d'Ivoire (Abidjan to Yamoussoukro in 1983), Nigeria (Lagos to Abuja in 1991), and Tanzania (Dar es Salaam to Dodoma in 1974). The change in Tanzania was less de facto than de jure. Until today, all ministries are located in Dar es Salaam.

[22]Note the case of Uganda being the outlier with the steepest increase in Figure A8a.

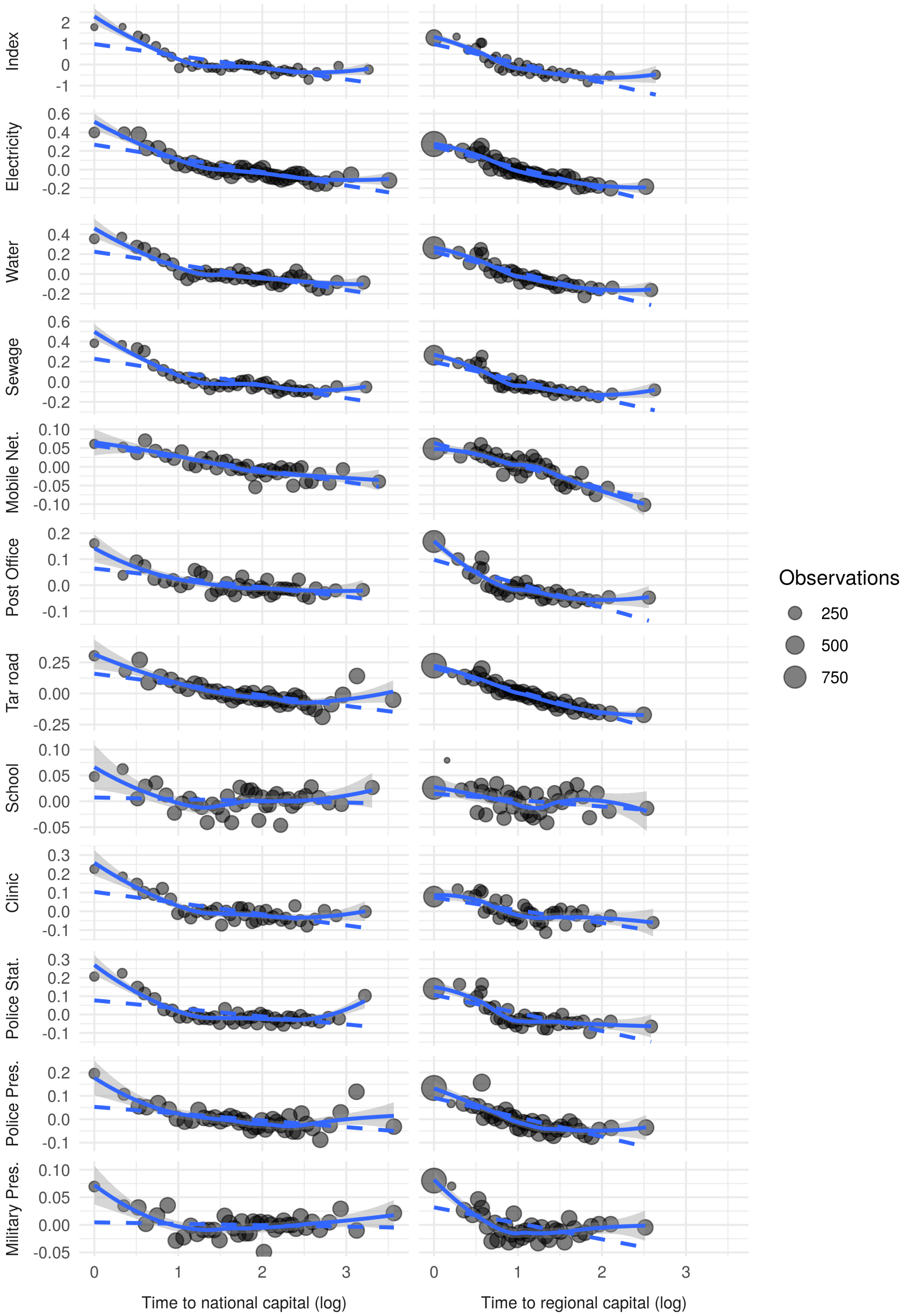


Figure A7: Correlation between travel times to national and regional capitals and state capacity index

The state capacity index is constructed from enumeration area level data in the Afrobarometer survey. The plot shows values of the index that are demeaned by country $\times$ survey round and averaged within 40 quantiles of the travel time to regional and national capitals.

Table A1: Logged distances to national and regional capitals correlate with state capacity index

	State capacity index					
	(1)	(2)	(3)	(4)	(5)	(6)
Nat. capital: geodesic	-0.295^{***}		-0.026			
	(0.037)		(0.056)			
Nat. capital: time		-0.635^{***}	-0.588^{***}			
		(0.080)	(0.117)			
Reg. capital: geodesic				-0.414^{***}		-0.199^{***}
				(0.029)		(0.043)
Reg. capital: time					-1.006^{***}	-0.608^{***}
					(0.059)	(0.080)
Unit:	EA	EA	EA	EA	EA	EA
Survey FE:	yes	yes	yes	yes	yes	yes
Mean DV:	-0.0042	-0.0042	-0.0042	-0.0042	-0.0042	-0.0042
Std.-dev. DV:	2	2	2	2	2	2
Observations	11,302	11,302	11,302	11,302	11,302	11,302
Adjusted R^2	0.311	0.317	0.317	0.348	0.351	0.356
Note:	*p<0.1; **p<0.05; ***p<0.01					

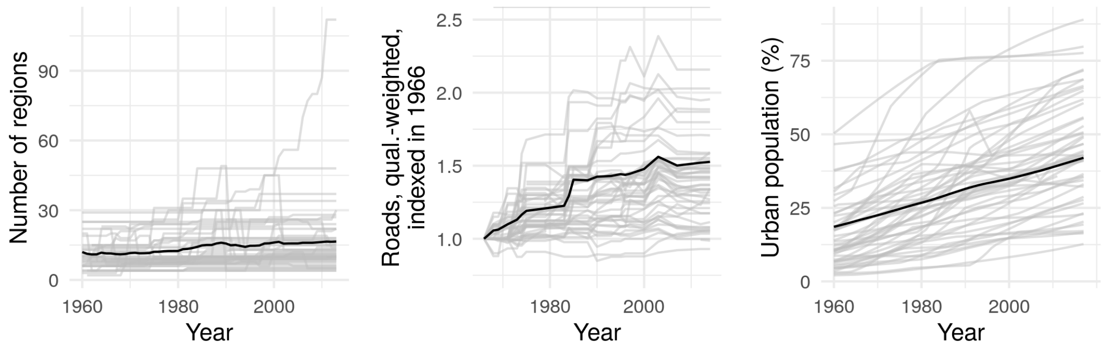
reduced the distance between their population and the capital.[23]

Second, states can improve transport networks to access certain areas. Although the main backbones of African road networks are of colonial origin, the networks' extent has increased by about 50 percent since independence (Figure A8b). While this figure is not necessarily impressive (Herbst 2000), it has shortened the distance between states and their citizens.

Lastly, states can incentivize their population to concentrate and urbanize, thereby increasing governments' economies of scale of reaching out to a particular populated place (e.g. Scott 2017). While in 1960 only about 20% of Africans have lived in cities, the proportion of urban residents in 2016 has risen above 40% (Figure A8c). Among other social changes brought about by this development, rural-urban migrants experience a steep increase in state reach since administrations and state institutions are typically based in cities. Equivalent state-led population concentration also occurred in the countryside. In particular villagization programs, such as the resettlement of millions of Tanzanians into so-called 'Ujamaa-Villages' in the 1970s (e.g. Miguel 2004), have made rural populations more accessible to the state.

Together, administrative unit changes, road building, and population concentration since the 1960s have decreased the distance between the state's headquarters and citizens, thereby extending states' reach over the continent. As seen in Figure A9, the average travel time between African national capitals and citizens has decreased from 11.7 hours in 1966 to 9.3 hours in 2016, a change of about 20.8 percent. Moving to the level of regional administrations where changes in the design of units are more common, we observe a

[23]Their independence of course also affected other dimensions of the distance between the state and citizens, in particular the ethnic distance.



(a) Number of administrative regions (b) Quality-weighted road mileage in Africa (c) Urban population

Figure A8: Drivers of expanding state reach in Africa 1960–2015.

Sources: (a) own data; (b) Michelin road map corpus; (c) World Development Indicators (World Bank 2018).

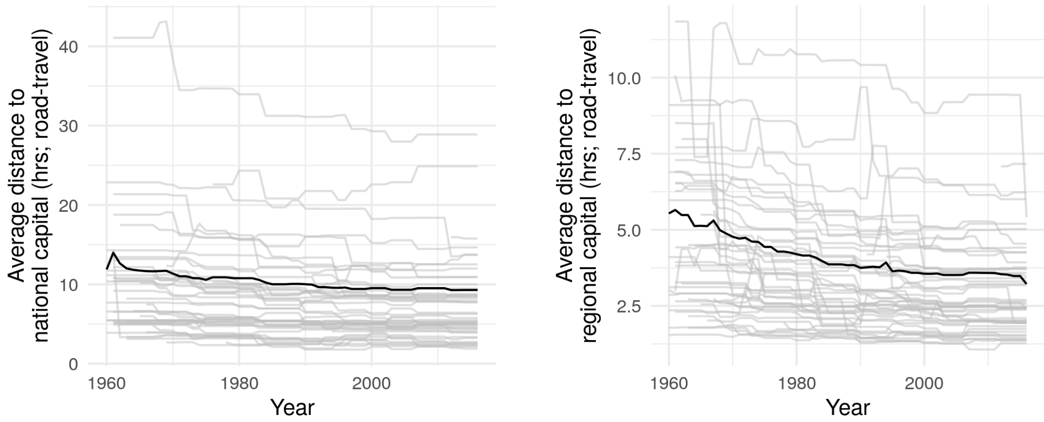
steeper trend. While citizens in 1966 had an average travel time of 5.1 hours to their regional capital, they had to travel 'only' 3.5 hours in 2016 – a decrease of 32.2 percent.

As expected from the large diversity of countries and their geographies, these continent-wide aggregates mask substantial heterogeneity across and within states. Figure A11 visualizes this variation and plots population-weighted densities of travel times to national capitals for five countries in 2016 and their change since 1966. From a cross-sectional perspective, Subfigure A11a shows how states differ in their reach towards their population. Capitals of countries with "difficult geographies" (Herbst 2000) and poor infrastructure such as the DR Congo are farthest away from their median inhabitant (34.3 hours). In the mid-range, we find Mali where one travels 7.2 hours from Bamako to the median citizen. Lastly, capitals of small countries such as Rwanda naturally are closest to their median citizen (2.6 hours). Similar variation marks changes in the accessibility of the population since 1966 (Subfigure A11b). Here, the populations of states that seceded (Eritrea, Namibia, and South Sudan) and of those that relocated their capital (Nigeria, Côte d'Ivoire, Tanzania) profited the most. Other states, such as the DR Congo, significantly improved their reach in absolute term. However, in relative terms, these improvements look less impressive.

Even more striking than the variation across countries is the variation observed within countries. The density plots in Subfigure A11a visualize high levels of inequality in state reach in some countries. In particular states that Herbst (2000) associates with 'difficult geographies'[24] exhibit large variation in travel times – to the point where the distribution of travel times in the DR Congo is heavier in its right than left tail. Similarly, new roads, borders, and capitals do not have a geographically uniform effect. For example, relocating the Nigerian capital from Lagos to Abuja in 1991 increased state reach towards the northern areas of the country, while decreasing it around Lagos in the southwest (Figure

[24] Angola, DR Congo, Ethiopia, Mozambique, Namibia, Nigeria, Senegal, Somalia, Sudan (borders of 2000), Tanzania. Cf. Herbst (2000, p. 161).

A10).

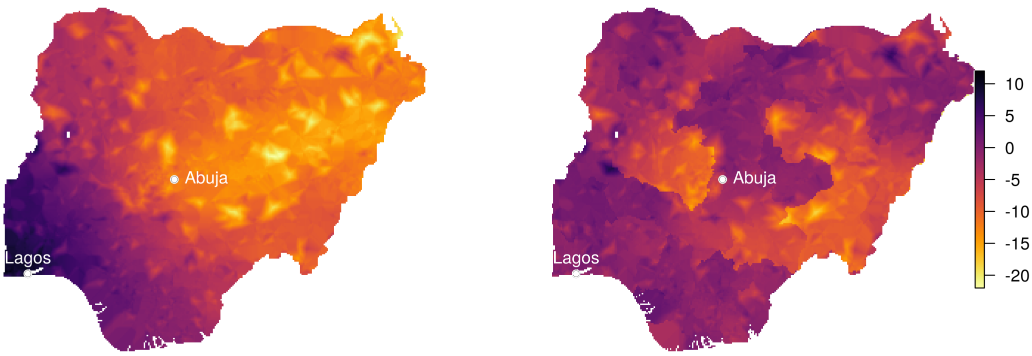


(a) Average time to national capital

(b) Average time to regional capital

Figure A9: Decreasing travel times to regional and national capitals in Africa 1960–2015.

All averages are population weighted. Sources: Own calculations based on HYDE population estimates (Goldewijk, Beusen and Janssen 2010), Michelin-based road networks, Cshapes (Weidmann and Gleditsch 2010), and own data on administrative regions and their capitals.



(a) Change in travel time to the national capital

(b) ... to regional capitals

Figure A10: Change of travel times to capitals in Nigeria 1966–2016.

Note: Brighter colors indicate a decrease of travel times, thus an improvement in state reach. Sources: See Figure A9.

(a) Travel time to national capital 2016

(b) Change in travel time to national capital 1966–2016

Figure A11: Population-weighted distribution of state reach in Africa in 2016 and development since 1966.

Note: Brighter colors identify better outcomes. To calculate population-weighted distributions for single countries, I fix the spatial distribution of the population and the borders of countries to their status in 2016. For areas that became independent after 1966 no change can be calculated. Sources: Own calculations based on 2016 WorldPop population estimates, Michelin-based road networks, and country-borders from 2016 from Cshapes (Weidmann and Gleditsch 2010).

D Data and summary statistics

D.1 Units of the nightlight analysis: Voronoi cells

In order to divide an arbitrary geographical space into units of roughly equal size and high levels of compactness (i.e. similarity to a circle),[25] this section introduces a spatial clustering algorithm that is combines the advantages of the k-means clustering algorithm (Lloyd 1982) that requires a finite sample of points to cluster, and the Voronoi tesselation that is used to transform the centers of the k-means clusters into continuous areas. The algorithm proceeds as follows:

1. Draw a large number of points P from the area of polygon t in set T. T is defined in the present application as the constitutive parts of all administrative regions observed between 1992 and 2013. These polygons are computed as cutting the territory of each country with all regional borders existing between 1992 and 2013. The resulting polygons are strictly nested within all regional boundaries. Points are sampled from these polygons on the basis of a raster with a resolution of ≈1km (.01 decimal degrees).

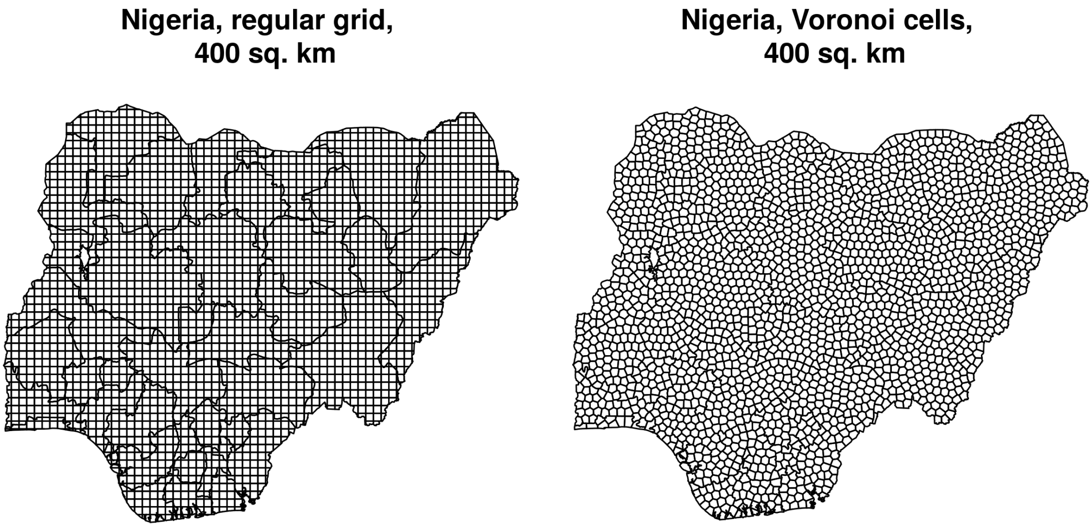
2. Conduct a k-means clustering (Lloyd 1982) of points P into N clusters, with $N = round(A_T/A_{target})$, thus N being the number of units to create so that the average area of each unit comes closest to the target size of units. For the main analysis, the target size is 400 km^2, further variations are conducted in the robustness check presented below in Subsection E.7. For best results, I initialize the k-means algorithm with a random spatial sample of N points from P.

3. Take the centroids of the clusters thus computed and conduct a Voronoi tesselation around them.

4. Crop the resulting Voronoi polygons with the target polygon T.

We can now compare the Voronoi cells with the more commonly used quadratic grid cells. Across various target sizes, the Voronoi cells resulting from the relatively simple (and fast) algorithm significantly improve over the quadratic grid cells, both in terms of their distribution around the target size and in terms of their level of compactness. First, Figure A13 shows that many regular quadratic grid cells are smaller than the target size – this occurs wherever a cell is cut by a regional border or the coast line. Thus, the heterogeneity in units' sizes is correlated with their closeness to the coast and border, a feature which might introduce slight bias into an analysis. Second, Figure A14 proves that Voronoi cells are much more compact than grid cells, which – as quadratic shapes and in particular where cut by borders – are shaped in a more irregular and less "circle-like" manner.

[25]The shape that can continuously cover an area with the highest level of compactness is the hexagon. However, where the honeycomb reaches a border, hexagonal cells must be cut or reshaped, thus deviating from the requirements of uniform size and compactness.



(a) Regular grid cells

(b) Voronoi cells

Figure A12: Regular grid and Voronoi cells for Nigeria with regional borders observed in 1992–2013.

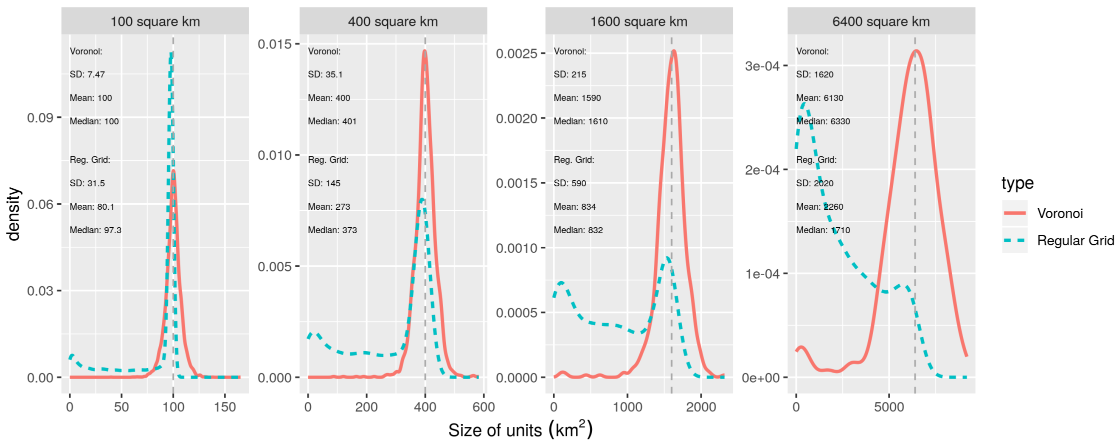


Figure A13: Size of Voronoi and regular grid cells for varying target sizes.

Vertical dashed line indicates the target size of units. Cells are constructed for all countries in mainland Africa, using borders from the year 2000.

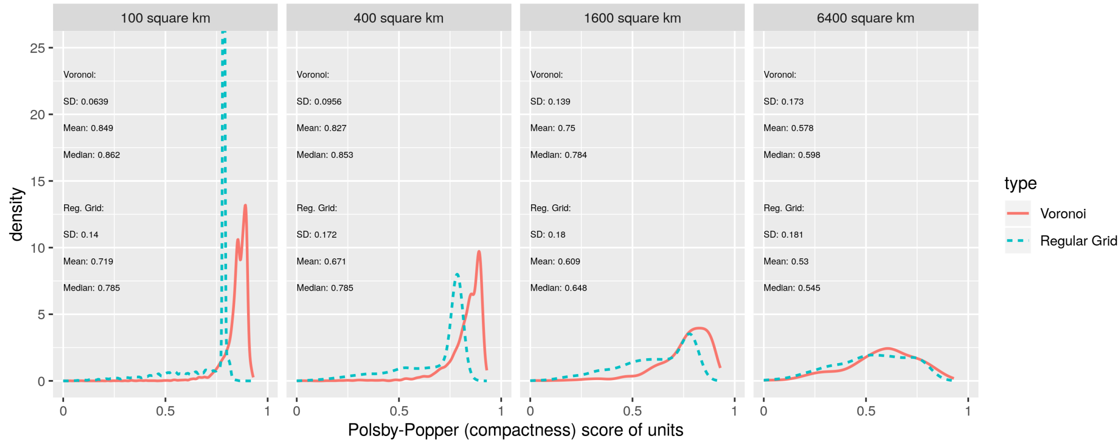


Figure A14: Compactness of Voronoi and regular grid cells for varying target sizes.

The compactness of each unit is calculated according to Polsby and Popper (1991, p. 349) as: $(4\pi A_i)/P_i^2$, where A_i is the size of unit i and P_i its perimeter. Cells are constructed for Nigeria, using regional borders observed between 1992 and 2013. Note that densities above 25 are censored to improve the readability of the graphs.

D.2 Summary statistics

Table A2: Summary statistics: DHS education data (Personal Recode)

Statistic	N	Mean	St. Dev.	Min	Max
Primary educ. (0/100)	1893067	70.22	45.73	0	100
Female	1893067	0.53	0.50	0	1
Age	1893067	27.92	9.66	15	57
Time to nat. capital (log)	1893067	1.92	0.81	0.00	4.32
Time to reg. capital (log)	1893067	1.17	0.65	0.00	3.93

Table A3: Summary statistics: DHS infant mortality data (Children Recode)

Statistic	N	Mean	St. Dev.	Min	Max
Infant mort. (0/100)	2644591	9.89	29.86	0	100
Female	2644591	0.49	0.50	0	1
Birth-order	2644591	3.30	2.25	1	18
Twin	2644591	0.03	0.18	0	1
Mother's age at birth	2634666	24.64	6.42	10	49
Time to nat. capital (log)	2644591	1.94	0.72	0.00	4.26
Time to reg. capital (log)	2644591	1.21	0.62	0.00	3.93

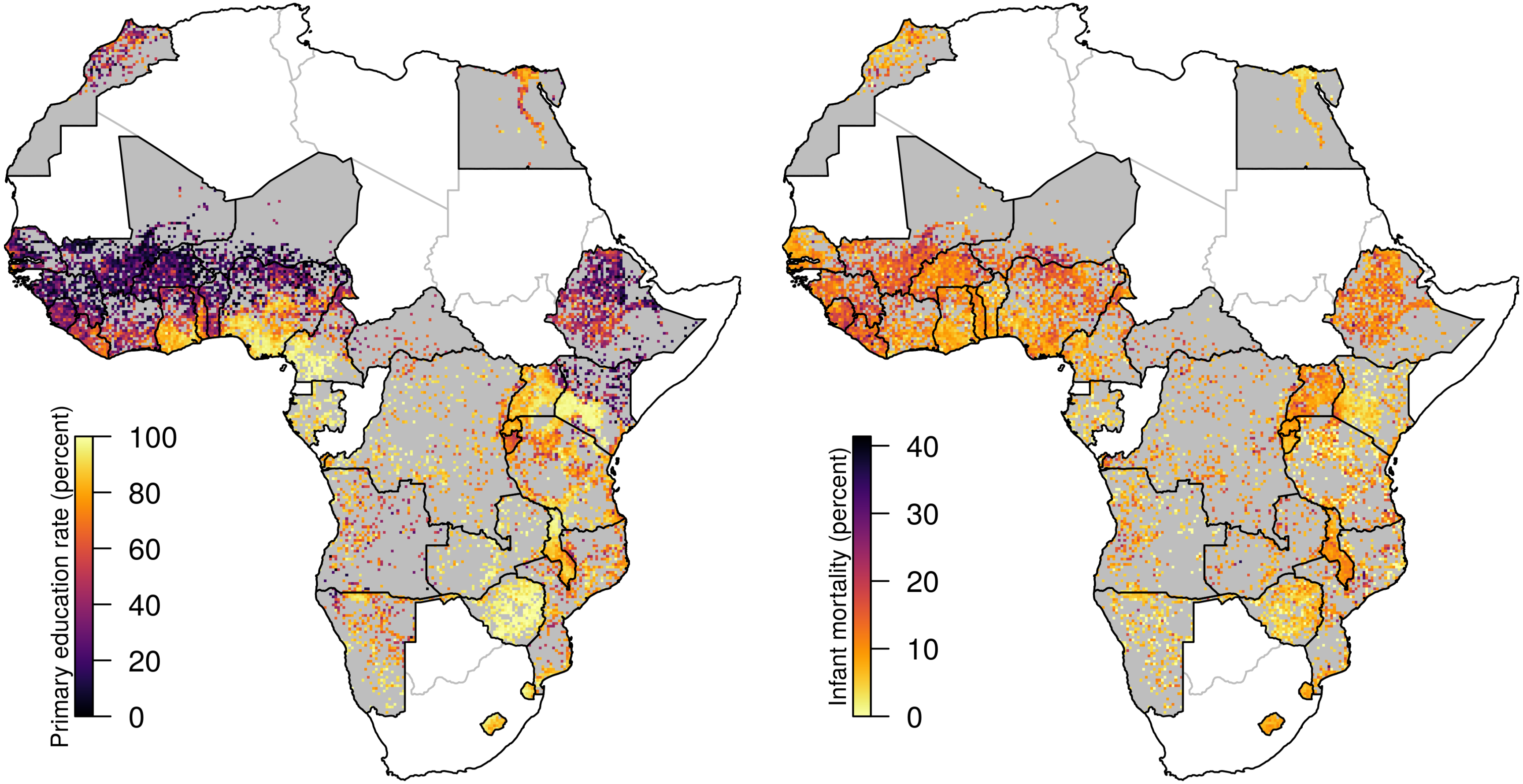
Table A4: Summary statistics: Nightlight data (Voronoi cells, 400 km^2)

Statistic	N	Mean	St. Dev.	Min	Max
Light/capita (log)	1506991	−6.51	1.28	−6.91	10.12
Time to nat. capital (log)	1506991	2.92	0.77	0.26	4.97
Time to reg. capital (log)	1506991	2.30	0.83	0.26	4.94

Table A5: Samples across data sources, DHS rounds and nightlight observations

Country	Adults	Children	Households	Nightlight-cells
Algeria				1992–2013
Angola	7.1	6.1, 7.1	5.1, 6.1, 7.1	1992–2013
Benin	4.1, 6.1	4.1, 6.1	6.1	1992–2013
Botswana				1992–2013
Burkina Faso	2.1, 3.1, 4.1, 6.1	2.1, 3.1, 4.1, 6.1	4.1, 6.1, 7.1	1992–2013
Burundi	6.1, 6.2, 7.1	6.1, 6.2, 7.1	6.1, 6.2, 7.1	1992–2013
Cameroon	2.1, 4.1, 6.1	2.1, 4.1, 6.1	4.1, 6.1	1992–2013
Central African Republic	3.1	3.1		1992–2013
Chad				1992–2013
Congo				1992–2013
Côte D'Ivoire	3.1, 3.2, 6.1	3.1, 3.2, 6.1	6.1	1992–2013
Djibouti				1992–2013
DR Congo	5.1, 6.1	5.1, 6.1	5.1, 6.1	1992–2013
Egypt	2.1, 3.1, 4.1, 4.2, 5.1, 5.2	2.1, 3.1, 4.1, 4.2, 5.1, 5.2	5.1, 5.2	1992–2013
Equatorial Guinea				1992–2013
Eritrea				1993–2013
Ethiopia	4.1, 5.1, 6.1, 7.1	4.1, 5.1, 6.1, 7.1	5.1, 6.1, 7.1	1992–2013
Gabon	6.1	6.1	6.1	1992–2013
Gambia				1992–2013
Ghana	3.1, 4.1, 4.2, 5.2, 7.1	3.1, 4.1, 4.2, 5.2, 7.1	4.2, 5.2, 7.1, 7.2	1992–2013
Guinea	4.1, 5.1, 6.1	4.1, 5.1, 6.1	5.1, 6.1	1992–2013
Guinea Bissau				1992–2013
Kenya	4.1, 5.1, 7.1	4.1, 5.1, 7.1	4.1, 5.1, 7.1, 7.2	1992–2013
Lesotho	4.1, 6.1, 7.1	4.1, 6.1, 7.1	4.1, 6.1, 7.1	1992–2013
Liberia	5.1, 6.2	0.1, 5.1, 5.2, 6.1, 6.2	5.1, 5.2, 6.1, 6.2, 7.1	1992–2013
Libya				1992–2013
Malawi	4.1, 4.2, 6.1, 7.2	4.1, 4.2, 6.1, 6.2, 7.2	4.2, 6.1, 6.2, 7.1, 7.2	1992–2013
Mali	3.1, 4.1, 5.1, 6.2	3.1, 4.1, 5.1, 6.2	5.1, 6.2, 7.1	1992–2013
Mauritania				1992–2013
Morocco	4.1	4.1	4.1	1992–2013
Mozambique	5.1, 6.1, 7.1	6.1, 7.1	5.1, 6.1, 7.1	1992–2013
Namibia	4.1, 5.1, 6.1	4.1, 5.1, 6.1	5.1, 6.1	1992–2013
Niger	2.1, 3.1	2.1, 3.1		1992–2013
Nigeria	2.1, 4.2, 5.1, 6.1, 6.2, 7.1	2.1, 4.2, 5.1, 6.1, 6.2	4.2, 5.1, 6.1, 6.2, 7.1	1992–2013
Rwanda	5.1, 6.1, 7.1	5.1, 5.2, 6.1, 7.1	5.1, 5.2, 6.1, 7.1	1992–2013
Senegal	2.1, 4.2, 6.1, 6.2	2.1, 3.1, 4.2, 5.2, 6.1, 6.2	4.2, 5.2, 6.1, 6.2	1992–2013
Sierra Leone	5.1, 6.1	5.1, 6.1	5.1, 6.1, 7.1	1992–2013
Somalia				1992–2013
South Africa				1992–2013
South Sudan				2011–2013
Sudan				1992–2013
Swaziland	5.1	5.1	5.1	1992–2013
Tanzania	4.1, 4.2, 5.1, 6.1, 6.2	4.1, 5.1, 6.1, 6.2	4.2, 5.1, 6.1, 6.2	1992–2013
Togo	3.1, 6.1	0.1, 3.1, 6.1	6.1	1992–2013
Tunisia				1992–2013
Uganda	4.1, 5.1, 6.1, 6.2	4.1, 5.1, 5.2, 6.1	5.1, 5.2, 6.1, 6.2	1992–2013
Zambia	5.1	5.1	5.1	1992–2013
Zimbabwe	4.1, 5.1, 6.1	4.1, 5.1, 6.1	5.1, 6.1	1992–2013

Note that the divergence between the samples used from the DHS stems from the fact that not all surveys enlist the level of education of household members, come with the Child Recode file needed to derive infant mortality rates, or include the DHS wealth index.



(a) Primary education rate in sample

(b) Infant mortality in sample

Figure A15: Primary education and infant mortality in the DHS Data, aggregated to .25 raster cells.

E Robustness checks

This section describes additional analyses that probe the robustness of the analysis of the effects of changes in the distance to national and regional capitals on local development. Figure A16 provides an overview over the various robustness checks. All additional models are described in detail below. Where Figure A16 captures the main insights from an additional analysis, I do not report detailed results as a table. However, the reader may note that all results will be made available as tables with the replication data.

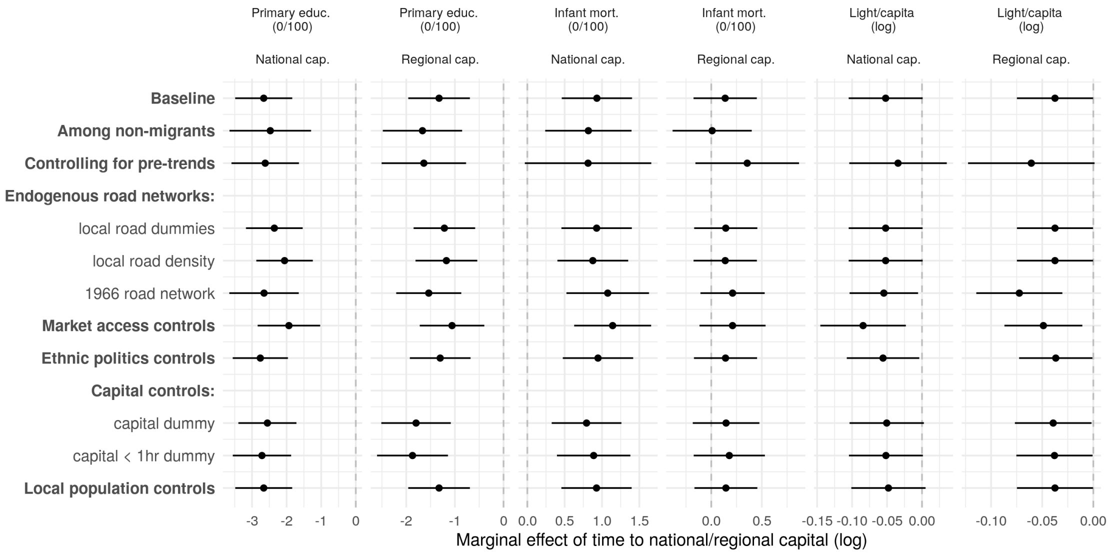


Figure A16: Panel analysis: Summary of robustness checks.

E.1 Re-locations of national capitals vs. road-network development:

One main concern of the analysis of changes in travel times to national capitals is that we observe only very few relocations of capitals that drive the results. In the sample of DHS respondents, capital re-locations have occurred in Côte d'Ivoire (Abidjan to Yamassoukro), Nigeria (Lagos to Abuja), and Tanzania (the de jure move from Dar es Salaam to Dodoma). The data on nightlights include the secessionist cases of Eritrea and South Sudan. In order to gauge whether the baseline estiamtes are due to these relocations and secessions or whether they are driven by changes in the road networks that link national capitals to their citizens, Table A6 presents the results of estimating the baseline panel specification on the split samples. For primary education rates we observe a larger effect in the sample of DHS respondents from countries with capital relocations, than from those without. However, also in the latter case the estimate is substantive and statistically significant, meaning that improved road connections to national capitals come with increases in local primary education rates. In the case of infant mortality rates, the results show them to be driven by capital relocations rather than road network improvements. Lastly and consistent with the baseline results, the results show only insignificant effects of either better road connections or new capitals on nightlight emissions. Note however, that the secessionist cases of Eritrea and South Sudan are each only observed one year pre-/post-treatment. We would hardly expect the new capitals to have such an immediate and sudden effect on nightlight emissions, in particular since both cases where riven by civil war before (and after, in the case of South Sudan) their secession.

Table A6: Changes in time to national/regional capital and local development: Cases where national capitals changed

	Primary educ. (0/100)		Infant mort. (0/100)		Light/capita (log)	
	(1)	(2)	(3)	(4)	(5)	(6)
Time to nat. capital (log)	-1.409^{**}	-3.392^{***}	0.105	1.484^{***}	-0.044	-0.054
	(0.645)	(0.523)	(0.306)	(0.318)	(0.034)	(0.037)
Time to reg. capital (log)	-1.617^{***}	-0.784	0.051	1.065^{**}	-0.039^{*}	-0.039^{*}
	(0.379)	(0.614)	(0.169)	(0.462)	(0.021)	(0.023)
$\beta_1 + \beta_2$:	-3.026^{***}	-4.176^{***}	0.156	2.549^{***}	-0.083^{**}	-0.094^{**}
	(0.674)	(0.778)	(0.31)	(0.574)	(0.034)	(0.039)
Cap.-re-loc. cases:	drop	only	drop	only	drop	only
Point FE:	yes	yes	yes	yes	yes	yes
Country-year FE:	yes	yes	yes	yes	yes	yes
Survey FE:	yes	yes	yes	yes	–	–
Controls:	yes	yes	yes	yes	–	–
Mean DV:	70	71	9.7	11	-6.5	-6.8
Observations	1,583,837	309,230	2,246,915	387,294	1,467,083	39,908
Adjusted R^2	0.445	0.446	0.051	0.049	0.838	0.395

Notes: OLS linear models. Control variables for models with primary education as the dependent variable consist of responents' age and age squared, as well as a female dummy. Where infant mortality is the dependent variable, models include an infant's mother's age at birth and its square, the birthorder and its square, as well as a female and twin dummy. Standard errors clustered on the point and country-year levels. Significance codes: *p<0.1; **p<0.05; ***p<0.01

E.2 Migration

Over their lifetime, DHS respondents might have moved towards or away from changing regional (and national) capitals in a manner correlated with their level of education and wealth. Such migration patterns might bias the results. If that was the case, we should see differential effects of travel times among migrants and non-migrants. In particular, if migrants were driving the results, no effect of changes in the travel time towards capitals should be visible among non-migrants. Table A7 demonstrates that this is not the case. The effect of travel times on education rates is significantly larger for migrants than for non-migrants. In the case of infant mortality rates, the difference between the two sample is mostly insignificant, except for Model (4), which suggest that longer travel times to regional capitals have a more *negative* effect on infant mortality rates among migrant- than non-migrant mothers. Their absolute effect is however insignificantly different from zero in both cases (see also the lead-analysis above, Table A9).

Table A7: Changes in time to national/regional capital and local development: Migrants and non-migrants

	Primary educ. (0/100)		Infant mort. (0/100)	
	(1)	(2)	(3)	(4)
Time to nat. capital (log)	-2.472^{***}	-2.362^{***}	0.818^{***}	0.643^{**}
	(0.602)	(0.591)	(0.295)	(0.288)
Time to reg. capital (log)	-1.666^{***}	-1.582^{***}	0.009	-0.004
	(0.416)	(0.413)	(0.200)	(0.207)
Migrant	-3.903^{***}	-13.391^{***}	0.654^{***}	1.965^{***}
	(0.783)	(2.290)	(0.243)	(0.363)
Migrant×Time to nat. capital (log)	0.652^{**}	0.567^{*}	0.224^{*}	0.207
	(0.312)	(0.308)	(0.132)	(0.136)
Migrant×Time to reg. capital (log)	1.542^{***}	1.308^{***}	-0.151	-0.154
	(0.264)	(0.266)	(0.154)	(0.154)
Non-migrants: $\beta_1 + \beta_2$:	-4.138^{***}	-3.944^{***}	0.826^{**}	0.639^{**}
	(0.704)	(0.694)	(0.325)	(0.322)
Migrant × controls	no	yes	no	yes
Point FE:	yes	yes	yes	yes
Country-year FE:	yes	yes	yes	yes
Survey FE:	yes	yes	yes	yes
Controls:	yes	yes	yes	yes
Mean DV:	67	67	11	11
Observations	673,335	673,335	1,485,168	1,495,445
Adjusted R^2	0.479	0.480	0.052	0.034

Notes: OLS linear models. Control variables for models with primary education as the dependent variable consist of responents' age and age squared, as well as a female dummy. Where infant mortality is the dependent variable, models include an infant's mother's age at birth and its square, the birthorder and its square, as well as a female and twin dummy. Standard errors clustered on the point and country-year levels. Significance codes: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

E.3 Testing for pre-trends and reverse causality

As highlighted in the main text, one important threat to inference in the panel analysis is that the baseline estimates may be biased by differential pre-trends in local development that reversely cause the extension of state reach. I here present the full details of the empirical test that accounts for such trends. In particular, I re-estimate the baseline specification, adding measures of future travel times to capitals in $t + x$. These leads of the main treatments capture differential changes in local development that occur before changes in travel times affect localities. More specifically, for the analysis of local primary education rates, which are affected by state reach during age 6 to 11 of respondents, I estimate the effect of the average travel time to capitals during age 6-11, and add five separate controls for the travel times to capitals at age 12 to 16. For infant mortality rates, which are affected only in the year of an infants' birth, I add the time to capitals at age 2 to 6. Similarly, for local nightlight emissions, I add the respective variables for

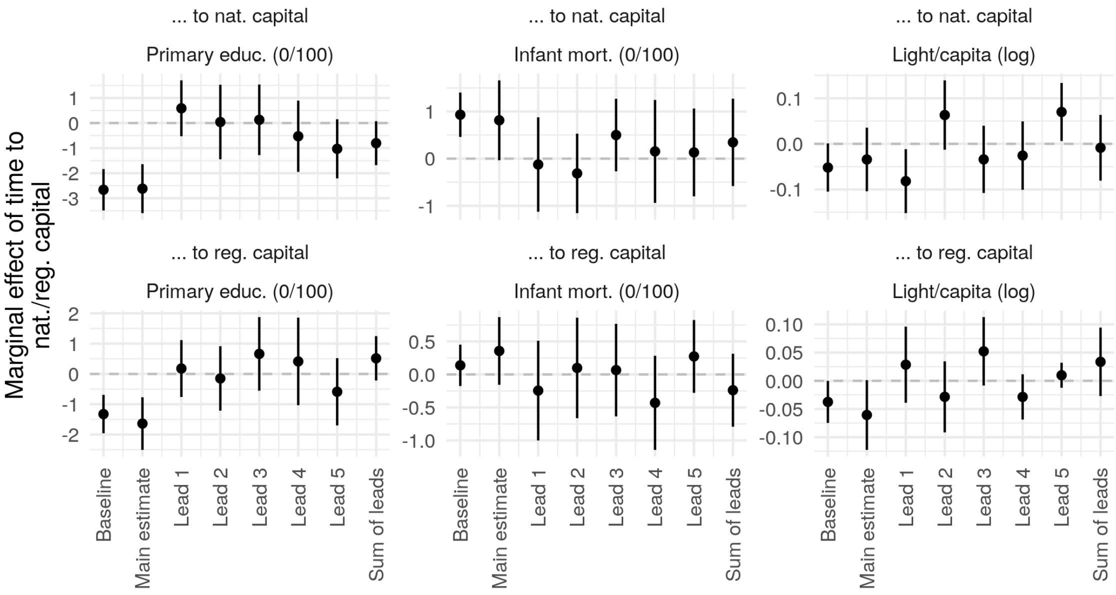


Figure A17: All leads, based on Table A8.

$t+1...5$.

$$Y_{i,p,c,t,s} = \alpha_p + \lambda_{c,t} + \mu_s + \beta_1 \text{ time to nat. cap.}_{p,t} + \beta_2 \text{ time to reg. cap.}_{p,t} + \delta X_i + \sum_{l=1}^{5} \gamma_l \text{ time to nat. cap.}_{p,t+l} + \sum_{l=1}^{5} \zeta_l \text{ time to reg. cap.}_{p,t+l} + \epsilon_{i,p,c,t}, \tag{4}$$

Consistently significant estimates for $gamma_l$ and $zeta_l$ or their sum that point in the same direction as the main result would reject the null-hypothesis of an absence of pre-trends. Table A8 and Figure A17 show the results of these demanding[26] specifications. The first thing to note is that the main estimates of the effects of travel times to capitals are only marginally and insignificantly different from those obtained in the baseline specification. This is a first sign that these are not affected by differential pre-trends. Second however, and as Table A8 shows, the sum of leads is negative and marginally significant in the estimation of the effect of travel times to national capitals on education rates. This suggests that education rates increase before capitals move closer to a location through roads or relocation. The leads in the infant mortality analysis are in sum close to zero and show few signs of divergent pre-trends. The leads in the nightlight analysis have very heterogeneous estimates, but are, for the most part statistically insignificant and in sum not different from zero. Both patterns suggest that the main estimate is not systematically affected by differential pre-trends.

One reason for the negative and marginally significant lead effect of travel times to national capitals on primary education rates consists in biased migration patterns by which

[26]The specifications are demanding because of the high correlations between the actual treatments and its leads.

Table A8: Changes in time to national/regional capital and local development: Controlling for leads

	Primary educ. (0/100)	Infant mort. (0/100)	Light/capita (log)
	(1)	(2)	(3)
Time to nat. capital (log)	-2.618^{***}	0.813^{*}	-0.034
	(0.498)	(0.432)	(0.036)
Time to reg. capital (log)	-1.638^{***}	0.356	-0.061^{*}
	(0.443)	(0.262)	(0.032)
$\beta_1 + \beta_2$:	-4.256^{***}	1.169^{***}	-0.095^{***}
	(0.629)	(0.444)	(0.036)
Sum of leads (nat. cap.):	-0.804^{*}	0.346	-0.009
	(0.447)	(0.473)	(0.037)
Sum of leads (reg cap.):	0.516	-0.24	0.034
	(0.373)	(0.282)	(0.031)
Time to cap.$_{t+1,\ldots,t+5}$:	yes	yes	yes
Point FE:	yes	yes	yes
Country-year FE:	yes	yes	yes
Survey FE:	yes	yes	–
Controls:	yes	yes	–
Mean DV:	70	10	-6.5
Observations	1,887,591	2,561,533	1,369,902
Adjusted R^2	0.445	0.050	0.840

Notes: OLS linear models. Control variables for models with primary education as the dependent variable consist of responents' age and age squared, as well as a female dummy. Where infant mortality is the dependent variable, models include an infant's mother's age at birth and its square, the birthorder and its square, as well as a female and twin dummy. Standard errors clustered on the point and country-year levels. Significance codes: *p<0.1; **p<0.05; ***p<0.01

individuals select in and out of treatment after having gone to school. These patterns can be picked up by the lead effects because I attribute travel times on the basis of the current location of DHS respondents. In order to test for this possibility, I re-estimate the respective specification, now interacting the treatment variables and their leads with a dummy for migrants.[27] The respective variable is only available for the reduced sample of DHS respondents that have gone through the entire interview and is based on whether they have 'always' lived in their current place of residence.[28]

Reassuringly, the results in Table A9 show that the lead effects are only negative for the migrants in the sample, but positive for the non-migrants. Both sums of leads are statistically insignificant, presumable due to the smaller sample size. Furthermore, the main effect associated with travel times to national and regional capitals is much larger in the non-migrant sample than in the migrant sample, which is consistent with the fact that non-migrants' primary education is affected by local state reach to greater extent than that of migrants. The results for the respective analysis of the mortality of infants of non-migrant mothers mirror those described above, albeit with the caveat that the

[27]The baseline results for this migrant $\times$ travel times interaction without the leads is reported below in Subsection E.2.

[28]Note that the respective question does not allow to distinguish individuals who have moved within the same neighborhood from those who have migrated from one place to another. The migrant dummy therefore overestimates migration.

children of migrant mothers are slightly – but only weakly significantly – more likely to survive close to capitals than those of non-migrant mothers.

Table A9: Changes in time to national/regional capital and local development: Controlling for leads, migrants and non-migrants

	Primary educ. (0/100)	Infant mort. (0/100)
	(1)	(2)
Migrant	-3.483^{***}	0.720
	(0.810)	(0.535)
Non-migrants: Time to nat. capital (log)	-1.730^{***}	0.144
	(0.622)	(0.363)
Non-migrants: Time to reg. capital (log)	-3.971^{***}	0.641^{***}
	(0.795)	(0.247)
Migrants: Time to nat. capital (log)	-1.988^{**}	-0.023
	(0.825)	(0.871)
Migrants: Time to reg. capital (log)	0.050	-0.037
	(0.809)	(0.552)
Non-migrants: $\beta_1 + \beta_2$:	-5.213^{***}	0.864
	(0.996)	(0.578)
Non-migrant leads:		
Sum of leads (nat. cap.):	0.137	0.36
	(0.697)	(0.586)
Sum of leads (reg. cap.):	-0.236	-0.133
	(0.533)	(0.388)
Migrant leads:		
Sum of leads (nat. cap.):	-0.655	1.365
	(0.705)	(0.897)
Sum of leads (reg. cap.):	-0.473	-0.146
	(0.761)	(0.555)
Time to cap.$_{t+1,\dots,t+5}$:	yes	yes
Point FE:	yes	yes
Country-year FE:	yes	yes
Survey FE:	yes	yes
Controls:	yes	yes
Mean DV:	67	11
Observations	671,851	1,465,462
Adjusted R^2	0.479	0.052

Notes: OLS linear models. Control variables for models with primary education as the dependent variable consist of responents' age and age squared, as well as a female dummy. Where infant mortality is the dependent variable, models include an infant's mother's age at birth and its square, the birthorder and its square, as well as a female and twin dummy. Standard errors clustered on the point and country-year levels. Significance codes: *p<0.1; **p<0.05; ***p<0.01

E.4 Potentially endogenous road building

The main results might also be driven by roads that are built at the local level around specific towns and villages. Because such road building inherently lowers the distance to all capitals, it might lead to spurious results if it was caused by increasing levels of development in these areas. To exclude such omitted variable bias, I employ two strategies. First, I control for the mileage of roads in the geographic neighborhood of respondents

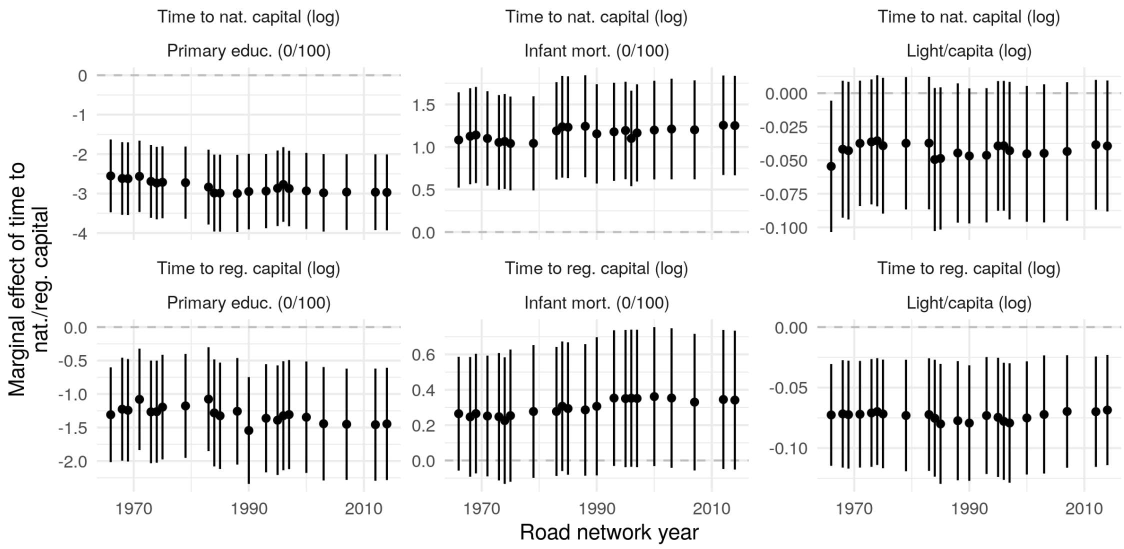


Figure A18: Estimating the baseline models with constant road networks from varying years

(20km) / in a Voronoi cell (see Figure A16). This is similar to the strategy of Donaldson and Hornbeck (2016) in that the variation left stems from changes in the road network outside a particular point's neighborhood. The second and more stringent test is to re-estimate all models with non-time variant road networks. In such a setting, all variation within points stems solely from changes in the administrative design of a country – that is the location of boundaries and capitals. I do so with each Michelin network that I observe. The results, plotted in Figure A18, are insensitive towards these changes – it appears that the magnitude of baseline results are unaffected by purging the model of temporal variance induced through changes in road networks. If at all, the absolute size of the estimates slightly increases.

E.5 Omitted variables and spurious correlations

Controlling for spuriously correlated economic market access Travel times to regional and national capitals might not only proxy for transaction costs between governments and citizens, but more broadly transaction costs between the participants of economic markets. Variation in economic market access might lead to spurious results, since it results in higher levels of economic activity and development (e.g. Donaldson 2018; Donaldson and Hornbeck 2016; Eaton and Kortum 2002; Jedwab and Moradi 2016; Jedwab and Storeygard 2018). I thus follow the economic literature on the effect of market access on economic growth and calculate, for each year, the road-network based access to national and international markets. Following Donaldson (2018) and Eaton and Kortum (2002), I define the measure as:

$$MA_{p,t} = \sum_{m=1}^{M} c_{p,m,t}^{-\theta} * P_{m,t},$$

where the market access of point p in year t is the sum of the market potential P of a market m in year t multiplied by the travel time between p and m calculated on the road network and discounted by a trade elasticity θ. Because Donaldson (2018) and Eaton and Kortum (2002) estimate different trade elasticity measures ($\theta = 8.28$ and 3.2 respectively), I construct the market access measure for both parameters. Because the effects of access to national and international markets might differ, I calculate MA separately for markets inside and outside of p's country. I define markets as the 1530 biggest cities and towns in Africa. These are all cities that ever reached more then 50'000 inhabitants since 1950[29]. Each city's market potential P is approximated by its population as measured in each decade. Controlling for the four resulting variables in Table A10 indicates does not affect the magnitude of the effects associated with the measures of state reach. This indicates that a low distance towards capital cities increases local development above and beyond the effect of the economic markets they harbor. The effect of market access on education rates is slightly positive, once we take the sum of the respective coefficients. They have a mixed effect of infant mortality and nightlight emissions.

Controlling for ethnic politics and war: Ethnic politics are an important driver of both, development and state reach. Research on administrative unit reforms has found that they can reward government allies (Green 2010; Hassan 2016; Gottlieb et al. 2019) or harm opponents (Resnick 2017), strategies which may well be used in processes of ethnic accommodation or exclusion. At the same time, ethnic and regional favoritism of governments has been found to affect investments into road infrastructure (Burgess et al. 2015) and local development in general (Franck and Rainer 2012; Hodler and Raschky 2014). To capture such dynamics, I draw on the most comprehensive and geocoded data on ethnic power dynamics in Africa since independence, the Ethnic Power Relations data set (Vogt et al. 2015).[30] I use the geodata of ethnic groups to map respondents and Voronoi cells to the database's coding of ethnic inclusion and exclusion as well as the occurrence and history of ethnic civil wars. Table A11 shows the results from the baseline analysis with the resulting variables as additional controls. The additional controls do not affect the results. While in particular the time since the last ethnic civil war positively affects education rates, ethnic inclusion has a positive effect on infant survival rates and nightlight emissions.

[29]Data comes from `Africapolis.org`.
[30]All data can be freely downloaded from `growup.ethz.ch`.

Table A10: Changes in time to national/regional capital and local development: Controlling for market access

	Primary educ. (0/100)	Infant mort. (0/100)	Light/capita (log)
	(1)	(2)	(3)
Time to nat. capital (log)	-1.933^{***}	1.143^{***}	-0.084^{***}
	(0.461)	(0.263)	(0.031)
Time to reg. capital (log)	-1.059^{***}	0.210	-0.049^{**}
	(0.339)	(0.167)	(0.019)
MA, internat. (log; $\theta = 3.8$)	2.204^{***}	0.465^{*}	-0.146^{***}
	(0.511)	(0.257)	(0.018)
MA, nat. (log; $\theta = 3.8$)	-0.840^{***}	-0.049	0.082^{***}
	(0.179)	(0.084)	(0.008)
MA, internat. (log; $\theta = 8.28$)	0.489	0.248	-0.009
	(0.343)	(0.190)	(0.012)
MA, nat. (log; $\theta = 8.28$)	-0.150	-0.102	0.034^{***}
	(0.123)	(0.078)	(0.006)
$\beta_1 + \beta_2$:	-2.992^{***}	1.353^{***}	-0.133^{***}
	(0.561)	(0.313)	(0.035)
Point FE:	yes	yes	yes
Country-year FE:	yes	yes	yes
Survey FE:	yes	yes	–
Controls:	yes	yes	–
Mean DV:	70	9.9	-6.5
Observations	1,889,905	2,634,150	1,506,991
Adjusted R^2	0.446	0.051	0.836

Notes: OLS linear models. Control variables for models with primary education as the dependent variable consist of responents' age and age squared, as well as a female dummy. Where infant mortality is the dependent variable, models include an infant's mother's age at birth and its square, the birthorder and its square, as well as a female and twin dummy. Standard errors clustered on the point and country-year levels. Significance codes: *p<0.1; **p<0.05; ***p<0.01

Table A11: Changes in time to national/regional capital and local development: Controlling for ethnic representation and civil war

	Primary educ. (0/100)	Infant mort. (0/100)	Light/capita (log)
	(1)	(2)	(3)
Time to nat. capital (log)	-2.760^{***}	0.946^{***}	-0.056^{**}
	(0.407)	(0.241)	(0.026)
Time to reg. capital (log)	-1.302^{***}	0.141	-0.037^{**}
	(0.318)	(0.159)	(0.018)
Ethnic inclusion (0/1)	0.861	-0.589^{**}	0.084^{***}
	(0.708)	(0.231)	(0.025)
Ethnic exclusion (0/1)	0.837	-0.348	0.036^{*}
	(0.702)	(0.219)	(0.020)
Ethnic civil war (0/1)	0.358	-0.043	0.037^{***}
	(0.786)	(0.222)	(0.010)
Eth. war since indep. (0/1)	0.613	-0.357	-0.048^{***}
	(0.900)	(0.311)	(0.017)
Time since eth. war	0.431^{***}	0.013	-0.001
	(0.151)	(0.037)	(0.001)
Time since eth. war^2	-0.014^{***}	0.001	0.00000
	(0.004)	(0.001)	(0.00002)
$\beta_1 + \beta_2$:	-4.062^{***}	1.087^{***}	-0.092^{***}
	(0.477)	(0.274)	(0.029)
Point FE:	yes	yes	yes
Country-year FE:	yes	yes	yes
Survey FE:	yes	yes	–
Controls:	yes	yes	–
Mean DV:	70	9.9	-6.5
Observations	1,893,067	2,626,280	1,506,991
Adjusted R^2	0.445	0.051	0.836

Notes: OLS linear models. Control variables for models with primary education as the dependent variable consist of responents' age and age squared, as well as a female dummy. Where infant mortality is the dependent variable, models include an infant's mother's age at birth and its square, the birthorder and its square, as well as a female and twin dummy. Standard errors clustered on the point and country-year levels. Significance codes: *p<0.1; **p<0.05; ***p<0.01

Controlling for capitals: Another potential danger is that as some cities may become, for a variety of reasons, richer with time, and then benefit from a political upgrade and get their own administrative unit. In such cases, changes in state reach in that city would be endogenous to local development. In an additional robustness check I therefore include dummies for whether an interview-location was (1) in and (2) closer than 1 hour to a regional and national capital in time t. For the Voronoi units, I create analagous measures when they either contain a capital or have an average distance to a capital of below 1 hour. The results in Table A12 highlight that changes in distances towards capitals in locations which are not capitals themselves drive the baseline patterns. Above and beyond the effect associated with a reduction in travel times, becoming a regional capital is associated with *lower* education rates, and more mixed patterns in the other outcomes. Relocations of national capitals are associated with reductions of infant mortality rates in the new capitals.

Table A12: Changes in time to national/regional capital and local development: Controlling for capitals

	Primary educ. (0/100)		Infant mort. (0/100)		Light/capita (log)	
	(1)	(2)	(3)	(4)	(5)	(6)
Time to nat. capital (log)	-2.555^{***}	-2.712^{***}	0.793^{***}	0.888^{***}	-0.050^{*}	-0.052^{*}
	(0.428)	(0.430)	(0.238)	(0.251)	(0.027)	(0.027)
Time to reg. capital (log)	-1.798^{***}	-1.871^{***}	0.147	0.178	-0.039^{**}	-0.038^{**}
	(0.364)	(0.372)	(0.168)	(0.180)	(0.019)	(0.019)
National capital (0/1)	-0.364		-5.790^{**}		0.200	
	(3.426)		(2.331)		(0.271)	
Regional capital (0/1)	-3.194^{***}		-0.003		-0.049	
	(1.135)		(0.457)		(0.053)	
Time to nat. cap. $<$ 1hr		-0.594		-0.217		0.099^{**}
		(0.631)		(0.396)		(0.044)
Time to reg. cap $<$ 1hr		-1.283^{***}		0.093		-0.028
		(0.390)		(0.180)		(0.033)
$\beta_1 + \beta_2$:	-4.353^{***}	-4.584^{***}	0.94^{***}	1.067^{***}	-0.09^{***}	-0.09^{***}
	(0.501)	(0.512)	(0.275)	(0.29)	(0.029)	(0.029)
Point FE:	yes	yes	yes	yes	yes	yes
Country-year FE:	yes	yes	yes	yes	yes	yes
Survey FE:	yes	yes	yes	yes	–	–
Controls:	yes	yes	yes	yes	–	–
Mean DV:	70	70	9.9	9.9	-6.5	-6.5
Observations	1,893,057	1,893,067	2,634,195	2,634,209	1,506,991	1,506,991
Adjusted R^2	0.445	0.445	0.051	0.051	0.836	0.836

Notes: OLS linear models. Control variables for models with primary education as the dependent variable consist of responents' age and age squared, as well as a female dummy. Where infant mortality is the dependent variable, models include an infant's mother's age at birth and its square, the birthorder and its square, as well as a female and twin dummy. Standard errors clustered on the point and country-year levels. Significance codes: *p<0.1; **p<0.05; ***p<0.01

E.6 Varying education- and health-related outcomes:

Lastly, two sets of additional analyses gauge whether the results are applicable to alternative education and health care outcomes. First, Table A13 shows very similar effects of the travel time to regional and national capitals on (1) whether a respondent has spent any time in school, (2) on her years of schooling – logged and linear, and (3) on a simple secondary education dummy. The main deviation from the baseline model is that the distance to the national capital does not seem to impact secondary education levels. With regard to infant mortality, Table A14 indicates that increased infant mortality in regions of low state reach can indeed be related to a lower availability of professional prenatal assistants. Similarly, changes in travel times to national capitals come with an increased chance that a child is born in a public clinic and positively relate to the receipt of professional assistance during delivery. Conversely, if children are born under low levels of state reach from the national capital, assistance is given more often in traditional manner. Consistent with the earlier results, the distance to regional capitals does not have any significant effect on the receipt of professional prenatal or birth assistance. Regarding local development measured through nightlight emissions, Table A15 shows that the choice of outcomes – whether nightlights per capita (log), absolute nightlights (log), or a dummy for whether a Voronoi cell exhibits any nightlight emissions does not produce different conclusions. In all three cases, changes in travel times to capitals are in sum associated with more nightlights. The estimated effect of changes in travel times towards national capitals are statistically significant, with the exception of their effect on the logged amount of absolute nightlight emissions.

Table A13: Changes in time to national/regional capital and various education outcomes

	Any educ. (0/100)	Educ. years (linear)	Educ. years (log)	Sec. educ. (0/100)
	(1)	(2)	(3)	(4)
Time to nat. capital (log)	-2.655^{***}	-0.227^{***}	-0.054^{***}	-0.070
	(0.421)	(0.048)	(0.009)	(0.441)
Time to reg. capital (log)	-1.301^{***}	-0.075^{**}	-0.026^{***}	-0.955^{***}
	(0.327)	(0.034)	(0.007)	(0.334)
$\beta_1 + \beta_2$:	-3.956^{***}	-0.303^{***}	-0.081^{***}	-1.025^{**}
	(0.487)	(0.054)	(0.011)	(0.511)
Point FE:	yes	yes	yes	yes
Country-year FE:	yes	yes	yes	yes
Survey FE:	yes	yes	yes	yes
Controls:	yes	yes	yes	yes
Mean DV:	70	5.4	1.5	35
Observations	1,890,391	1,890,391	1,890,391	1,615,848
Adjusted R^2	0.443	0.459	0.483	0.356

Notes: OLS linear models. Control variables include respondents' age and age squared, as well as a female dummy. Standard errors clustered on the point and country-year levels. Significance codes: *p<0.1; **p<0.05; ***p<0.01

Table A14: Changes in time to national/regional capital and quality of prenatal care and birth assistance (in percent)

	Prof. prenatal care	Birth in public inst.	Prof. birth assist.	Trad. birth assist.
	(1)	(2)	(3)	(4)
Time to nat. capital (log)	-9.605^{***}	-3.138^{**}	-7.310^{***}	4.057^{**}
	(2.457)	(1.284)	(2.024)	(1.586)
Time to reg. capital (log)	0.268	0.482	0.512	0.921
	(1.056)	(1.084)	(1.019)	(0.742)
$\beta_1 + \beta_2$:	-9.338^{***}	-2.656^{*}	-6.798^{***}	4.977^{***}
	(2.661)	(1.435)	(2.179)	(1.663)
Point FE:	yes	yes	yes	yes
Country-year FE:	yes	yes	yes	yes
Survey FE:	yes	yes	yes	yes
Controls:	yes	yes	yes	yes
Mean DV:	81	21	54	18
Observations	419,768	579,787	578,573	573,685
Adjusted R^2	0.450	0.543	0.444	0.307

Notes: OLS linear models. Control variables include an infant's mother's age and age squared, the birthorder and its square, as well as a female and twin dummy. Standard errors clustered on the point and country-year levels. Significance codes: *p<0.1; **p<0.05; ***p<0.01

Table A15: Changes in time to national/regional capital and various nightlight measures

	Light/capita (log)	Light (log)	Any Light (0/100)
	(1)	(2)	(3)
Time to nat. capital (log)	-0.052^{*}	-0.113	-1.215^{**}
	(0.027)	(0.073)	(0.601)
Time to reg. capital (log)	-0.037^{**}	-0.112^{*}	-0.870^{*}
	(0.019)	(0.063)	(0.510)
$\beta_1 + \beta_2$:	-0.089^{***}	-0.225^{***}	-2.085^{***}
	(0.029)	(0.072)	(0.583)
Unit FE:	yes	yes	yes
Country-year FE:	yes	yes	yes
Controls:	–	–	–
Mean DV:	-6.5	-5.4	12
Observations	1,506,991	1,506,991	1,506,991
Adjusted R^2	0.836	0.838	0.784

Notes: OLS linear models. Standard errors clustered on the point and country-year levels. Significance codes: *p<0.1; **p<0.05; ***p<0.01

E.7 Additional robustness checks:

Country-weights: Because the DHS has not regularly sampled all African countries, the weights each country receives in the baseline specifications vary considerably. If the effects of state capacity on development vary systematically with the number and size of survey the DHS by countries, the results would be biased towards the most-sampled set of countries. Table A16 addresses this caveat by weighting each observation by the inverse of the number of observations from its country (Models 1 and 3) and from the respective cohort in the same country (Models 2 and 4). The latter serves to prevent that the biggest cohorts drive the results at the expense of dynamics in smaller cohorts observed in the data.[31] Though coefficients slightly change, the results remain generally consistent with those reported at the baseline. Lastly, Model 5 addresses the potential problem that until now I have treated all Voronoi cells in the same manner, thus giving equal weight to areas with many and few inhabitants. Weighting the Voronoi units by their population roughly doubles the estimated effect of the travel time to regional capitals on nightlight emissions. This is reassuring, since it shows that the results above are not driven by areas with very low population densities that are prone to produce outliers in the per-capita nightlight measure. As in some previous results, the effect of the travel time to national capitals, is statistically insignificant.

Table A16: Changes in time to national/regional capital and local development: Alternative weights

	Primary educ. (0/100)		Infant mort. (0/100)		Light/capita (log)
	(1)	(2)	(3)	(4)	(5)
Time to nat. capital (log)	-1.908^{***}	-2.538^{***}	0.593^{**}	0.768^{*}	-0.031
	(0.440)	(0.489)	(0.249)	(0.407)	(0.040)
Time to reg. capital (log)	-1.508^{***}	-1.609^{***}	0.143	0.194	-0.089^{**}
	(0.322)	(0.339)	(0.170)	(0.366)	(0.037)
$\beta_1 + \beta_2$:	-3.417^{***}	-4.147^{***}	0.735^{***}	0.962^{*}	-0.12^{**}
	(0.5)	(0.546)	(0.279)	(0.525)	(0.049)
Weights	country	country cohort	country	country cohort	population
Point FE:	yes	yes	yes	yes	yes
Country-year FE:	yes	yes	yes	yes	yes
Survey FE:	yes	yes	–		
Controls:	yes	yes	–		
Mean DV:	70	70	9.9	9.9	-6.5
Observations	1,893,067	1,893,067	2,634,209	2,634,209	1,506,991
Adjusted R^2	0.427	0.422	0.054	0.155	0.949

Notes: OLS linear models. Control variables for models with primary education as the dependent variable consist of responents' age and age squared, as well as a female dummy. Where infant mortality is the dependent variable, models include an infant's mother's age at birth and its square, the birthorder and its square, as well as a female and twin dummy. Standard errors clustered on the point and country-year levels. Significance codes: *p<0.1; **p<0.05; ***p<0.01

Varying the size of Voronoi units: This last robustness check assesses the impact of the choice of the size of Voronoi units used in the baseline analysis (400km^2). Figure A19 plots the results of the baseline specification estimated with units with exponential increases in their size from 100 to 6400km^2. Reassuringly, the Figure shows that small units generally give rise to smaller estimated and standardized effects. The increases in the respective effects that comes with larger units might be due to the unit constant added to the nightlight measure, which has a larger effect in small units in which more units have no observed nightlight emissions. Throughout, decreases in travel times to regional cap-

[31] Because of the sampling scheme of the DHS and attrition-by-death, cohorts close to the date of the survey are bigger than those in the past.

itals are associated with more nightlights. Decreases in travel times to national capitals are only associated with more nightlights in large units. This result adds to the uncertainty discussed in the main text on whether travel times to national capitals are indeed related to local nightlight emissions or not.

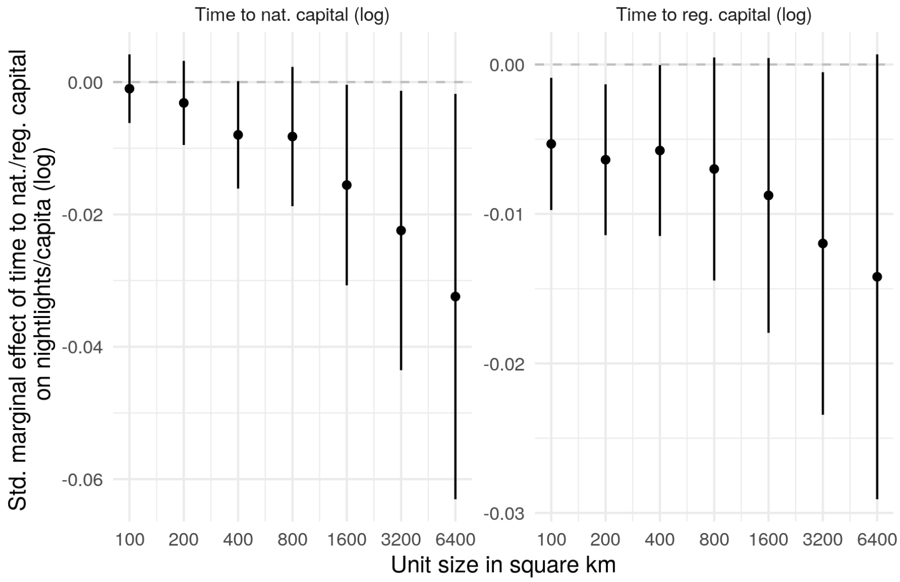


Figure A19: Effect of travel times to national and regional capitals on nightlight emissions in Voronoi units of increasing size.

Estimated coefficients and their 95% CI are standardized by dividing them by the mean dependent variable (log(.001 + nightlight p.c.)).

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