Shedding (Night) Lights on Economic Development:
Satellite Luminosity Data and the Persistence of Population Density in Africa

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Abstract

In recent years, scholars have increasingly recognized the importance of historical factors in explaining variation in contemporary development outcomes. Michalopoulos and Pappaioannou (2013) document a strong positive correlation between pre-colonial political centralization in Africa and intensity of night lights, a proxy for economic development. Several mechanisms have been posited to explain this relationship, including accountability of local leadership and the strength of local bureaucracies. Our findings suggest a simpler story: the link between pre-colonial ethnic institutions and night lights is explained almost entirely by the persistence of population density in certain areas over time. After presenting evidence of misspecification, we suggest several alternative models that better characterize the data generating process and reveal the robustness of population density as a predictor of nighttime luminosity. We bolster our interpretation by examining other indicators of development and public goods provision in a handful of countries. Our results have implications not only for the relationship between pre-colonial institutions and contemporary development in Africa, but for the interpretation of results from the many studies that use night lights as a proxy for economic development.

Introduction

History has made a comeback in comparative economic development. After influential studies by Herbst (2000) and Acemoglu, Johnson, and Robinson (2001, 2002), a large amount of empirical work has been devoted to exploring the roots of wealth disparities in Africa and elsewhere (e.g. Gennaioli and Rainer 2007, Nunn 2008, Baldwin 2011, Hariri 2012). These studies document surprisingly persistent effects of pre-colonial politics, the slave trade, and traditional ethnic institutions.

Michalopoulos and Papaioannou (2013) advance this literature by documenting a strong positive relationship between pre-colonial political centralization in Africa and the intensity

of night lights today. The authors overlay satellite images of Africa at night with anthropologist George Murdocks classic map of traditional "ethnic homelands" in Africa. Using data on pre-colonial ethnic groups from Murdocks Ethnographic Atlas, they argue that regions with more hierarchical political organization before colonialism tend to be more developed today. Although very much an empirical paper, Michalopoulos and Papaioannou suggest several possible mechanisms that could explain why historical state centralization is associated with development today: (1) greater accountability of local chiefs, (2) increased bureaucratic efficiency of local institutions charged with providing public goods, (3) more robust legal systems and property rights enforcement, (4) more rapid adoption of western technologies, and (5) closer association with Europeans, who sought out more centralized ethnic groups during the colonial period (116).

This paper builds on the important contribution of Michalopoulos and Papaioannou (2013) by suggesting an alternative channel behind the observed correlation between pre-colonial population density and development today: the persistence of population density. We marshal evidence that the apparent "development premium" on pre-colonial statehood in Africa is driven by the persistent spatial distribution of human settlement over time. Put simply, our argument is as follows: (1) ethnicities with pre-colonial states and complex jurisdictional hierarchies were more likely to live in close proximity than were ethnicities with more decentralized forms of political organization, (2) the spatial distribution of human settlement in Africa appears remarkably stable over time, (3) satellite images more accurately proxy for population density and urbanization than for development per se, and thus (4) the observed correlation between pre-colonial statehood and "development" is driven by the spatial persistence of population density since the pre-colonial period.

This paper is organized as follows. After briefly discussing the data and summarizing key variables, Part 1 diagnoses three types of model misspecification: functional form mischaracterization, omitted variable bias, and post-treatment bias. We analyze the first two types of misspecification in Section 1, which uses binary pixel-level dependent variable that equals 1 if a given pixel is lit and equals 0 otherwise. We reproduce analogous results in Section 2, which instead uses a continuous dependent variable, and also address post-treatment bias using the sequential g-estimator. In Part 2, we investigate the strength

of this relationship in four countries using georeferenced data from the Demographic and Health Surveys.

Data and Summary Statistics

Here we provide a very brief overview of the data used in this paper. We refer readers to Michalopoulos and Papaioannou for a more detailed treatment. Data on precolonial political centralization and population density come from George Murdocks (1967) ethnographic atlas and (1959) ethnolinguistic map of Africa. These materials contain a range of political, economic, and cultural information about the 834 ethnic groups listed on Murdocks map. The two key explanatory variables from Murdock are *Jurisdictional Hierarchy Beyond the Local Community* and *Settlement Patterns*. *Jurisdictional Hierarchy* captures the degree of precolonial political centralization of a given ethnic group in Africa. It equals: 0 for ethnicities with "no political authority beyond community," 1 for "petty chiefdoms," 2 for "paramount chiefdoms," 3 for "states," and 4 for "large states." The median value of Jurisdictional Hierarchy is 1; the mode is 2; and standard deviation is 1.03. This variable has been used in a number of influential studies, including Gennaioli and Rainer (2007).

The second variable, *Settlement Patterns*, we interpret as a proxy for precolonial population density. This variable equals 1 if a tribe is "nomadic or fully migratory," 2 if "seminomadic," 3 if "semisendentary," 4 if "compact but impermanent settlements," 5 if "neighborhoods of dispersed family homesteads," 6 if "separated hamlets, forming a single community," 7 if "compact and reasonably permanent settlements, 8 if complex settlements." *Settlement Patterns* has a median of 6, mode of 7, and standard deviation of 2.20. As we might expect, there is a weak positive correlation between *Settlement Patterns* and *Jurisdictional Hierarchy*.

Although many scholars have used Murdocks map and atlas, these data are not without flaws. Notably, the borders of different ethnic homelands are subject to considerable measurement error. Murdock partitions the continent into non-overlapping spatial subunits. But as anyone who has been to Africa can attest, seldom are borders so clean in reality, and very often mixtures of people from different ethnic backgrounds live in the same ar-

Figure 1: Correlation between the Demographic and Health Surveys (DHS) Wealth Index and log light density within a 10 km radius of a DHS survey cluster. Replicated from Michalopoulos and Papaioannaou (2013).

Table 1: Summary Statistics

Variable	Obs.	Mean	St. Dev.	p25	Median	p75	Min	Max
Panel A: All Observations								
Light density	683	0.368	1.528	0.000	0.022	0.149	0.000	25.140
Log(0.01 + light density)	683	-2.946	1.701	-4.573	-3.429	-1.839	-4.605	3.225
Pixel-level light density	66,570	0.560	3.422	0.000	0.000	0.000	0.000	62.978
Lit pixel	66,570	0.167	0.373	0.000	0.000	0.000	0.000	1.000
Panel B: Stateless Ethnicities								
Light density	176	0.257	1.914	0.000	0.018	0.082	0.000	25.140
Log(0.01 + light density)	176	-3.231	1.433	-4.605	-3.585	-2.381	-4.605	3.225
Pixel-level light density	13,174	0.172	1.556	0.000	0.000	0.000	0.000	55.634
Lit pixel	13,174	0.100	0.301	0.000	0.000	0.000	0.000	1.000
Panel C: Petty Chiefdoms								
Light density	264	0.281	1.180	0.000	0.015	0.089	0.000	13.086
Log(0.01 + light density)	264	-3.187	1.592	-4.605	-3.684	-2.314	-4.605	2.572
Pixel-level light density	20,259	0.283	2.084	0.000	0.000	0.000	0.000	60.022
Lit pixel	20,259	0.129	0.335	0.000	0.000	0.000	0.000	1.000
Panel D: Paramount Chiefdoms								
Light density	167	0.315	0.955	0.002	0.039	0.197	0.000	9.976
Log(0.01 + light density)	167	-2.748	1.697	-4.414	-3.017	-1.574	-4.605	2.301
Pixel-level light density	20,972	0.388	2.201	0.000	0.000	0.000	0.000	58.546
Lit pixel	20,972	0.169	0.375	0.000	0.000	0.000	0.000	1.000
Panel E: Pre-Colonial States								
Light density	76	1.046	2.293	0.012	0.132	0.835	0.000	14.142
Log(0.01 + light density)	76	-1.886	2.155	-3.830	-1.976	-0.168	-4.605	2.650
Pixel-level light density	12,165	1.739	6.644	0.000	0.000	0.160	0.000	62.978
Lit pixel	12,165	0.302	0.459	0.000	0.000	1.000	0.000	1.000

Summary statistics for continuous and binary nightlights variables at different levels of pre-colonial political centralization. Replicated from Michalopoulos and Papaioanna (2013).

eas. Certain ethnic groups, such as the Kuba in the Democratic Republic of Congo, are not correctly coded in Murdocks Atlas. (The Kuba had multiple jurisdictional hierarchies, but are coded as a "paramount chiefdom" in Murdock.) Nonetheless, several scholars have cross-validated of Murdocks map and atlas with other data sources (Nunn and Wantchekon 2008, Gennaioli and Rainer 2007, Michalopoulos and Papaioannou 2012), and in aggregate it provides an acceptable approximation of the traits and spatial distribution of ethnicities before colonialism. Further, this is measurement error on the right-hand side so we should expect attenuated parameter estimates, if anything.

The night-lights data come from the Defense Meteorological Satellite Programs Operational Linescan System. Satellites measure night-time light in a six-bit number from 0 to 63 for every 1-square-kilometer area. The final maps are constructed by overlaying images collected at different times to eliminate cloud cover and light from fires, lightning, and

aurora. A number of papers have noted strong within-country correlations between night lights and economic development (Henderson, Storeygard, and Weil (2012), Doll, Muller, and Morley (2006), Pinkovskiy (2011)). Figure 1, replicated from Michalopoulos and Papaioannou (2013), summarizes this relationship using Demographic and Health Survey data from four African countries. Min (2008) also noted a positive relationship between night lights and access to public goods. The measure also has its detractors (e.g. Chen and Nordhaus 2011), who note its relationship with urbanization and population density but not necessarily more meaningful aspects of development. Nonetheless, it can be a useful additional proxy for economic activity, especially in places with unreliable data.

Table 1, also replicated from Michalopoulos and Papaioannou, contains summary statistics of several night-lights variables that will be used in the subsequent analysis, across the different categories of Murdocks *Jurisdictional Hierarchy* measure.

Part I: Diagnosing Model Misspecification

Section 1: Binary Dependent Variable

Section 1.1: Comparing Linear Probability and Logit Models

As an initial reality check on the results in Michalopoulos and Papaioannou (2013) using a binary pixel-level outcome variable, we simulated the predicted probabilities from the baseline model (p. 136, Table V, column 1). This is a simple linear probability model with the primary *Jurisdictional Hierarchy* variable on the right-hand side. The dependent variable takes a one if the pixel is lit and zero if it is dark. Our simulations follow the basic logic in King et al (2000). First, we computed the normal maximum likelihood (ML) estimates given the data. Second, exploiting the asymptotic normality of the ML estimator, we accounted for estimation uncertainty by drawing 10,000 sets of parameters from the multivariate normal centered at the ML estimates with dispersion given by the variance-covariance matrix from the previous optimization. Third, we set *Jurisdictional Hierarchy* at specific values {0,1,2,3,4}, corresponding to different levels of pre-colonial political centralization {"stateless society," "petty chiefdom," "paramount chiefdom," "pre-colonial state,"

and "large complex state"}. Fourth and finally, to simulate fundamental uncertainty, we took 10,000 draws from a normal distribution with mean and variance determined by each row of the parameter matrix. The average of these draws is the predicted probability that a pixeli.e. a row in the datasetis lit given its value of *Jurisdictional Hierarchy*.

The top panel of Figure 2 shows the result of these simulations for each value of *Jurisdictional Hierarchy*, using the baseline OLS model. Consistent with Michalopoulos and Papaioannou, the distribution of predicted probabilities shifts right as the level of pre-colonial centralization increases. That is, pixels that fall in the historical homeland of "stateless" ethnicities are less likely to be lit compared to pixels that fall in the homeland of ethnicities with a historical state. However, the figure reveals that the linear regression model predicts probabilities outside of [0,1] for all possible values of *Jurisdictional Hierarchy*. Such nonsensical predictions are a well-known shortcoming of linear probability models; they demonstrate that the linear model does not accurately characterize the data-generating process. Motivated by this finding, we replicated the regressions in Michalopoulos and Papaioannou using a logit model.

Table 2 contains the logit model results alongside the results Michalopoulos and Papaioannou obtain using a linear probability model. When we control for population density in 2000, the coefficient on *Jurisdictional Hierarchy* in the logit specification becomes statistically indistinguishable from zero using double-clustered standard errors (clustering on country and ethno-linguistic family, following the preferred specification in Michalopoulos and Papaioannou).[1] The result is unchanged when we include country fixed effects and a large set of geographic controls. This runs counter to the hypothesis advanced in Michalopoulos and Papaioannaou (2013) that pre-colonial political centralization has a positive effect on night lights independent from its association with population density, i.e. that there is a "development premium" on pre-colonial statehood.

[1]Double-clustered standard errors produced by the replication code for this paper in R are slightly different than those reported here and throughout the paper. This is due to an incongruence between the STATA package used in Michalopoulos and Papaioannaou (2013), cmreg, and the function we use when replicating their results and performing our own analysis in R, mclx. Following the authors, we report double-clustered standard errors produced in STATA. However, in no case does this difference substantially alter our results. Both R and STATA code are available in our replication files.

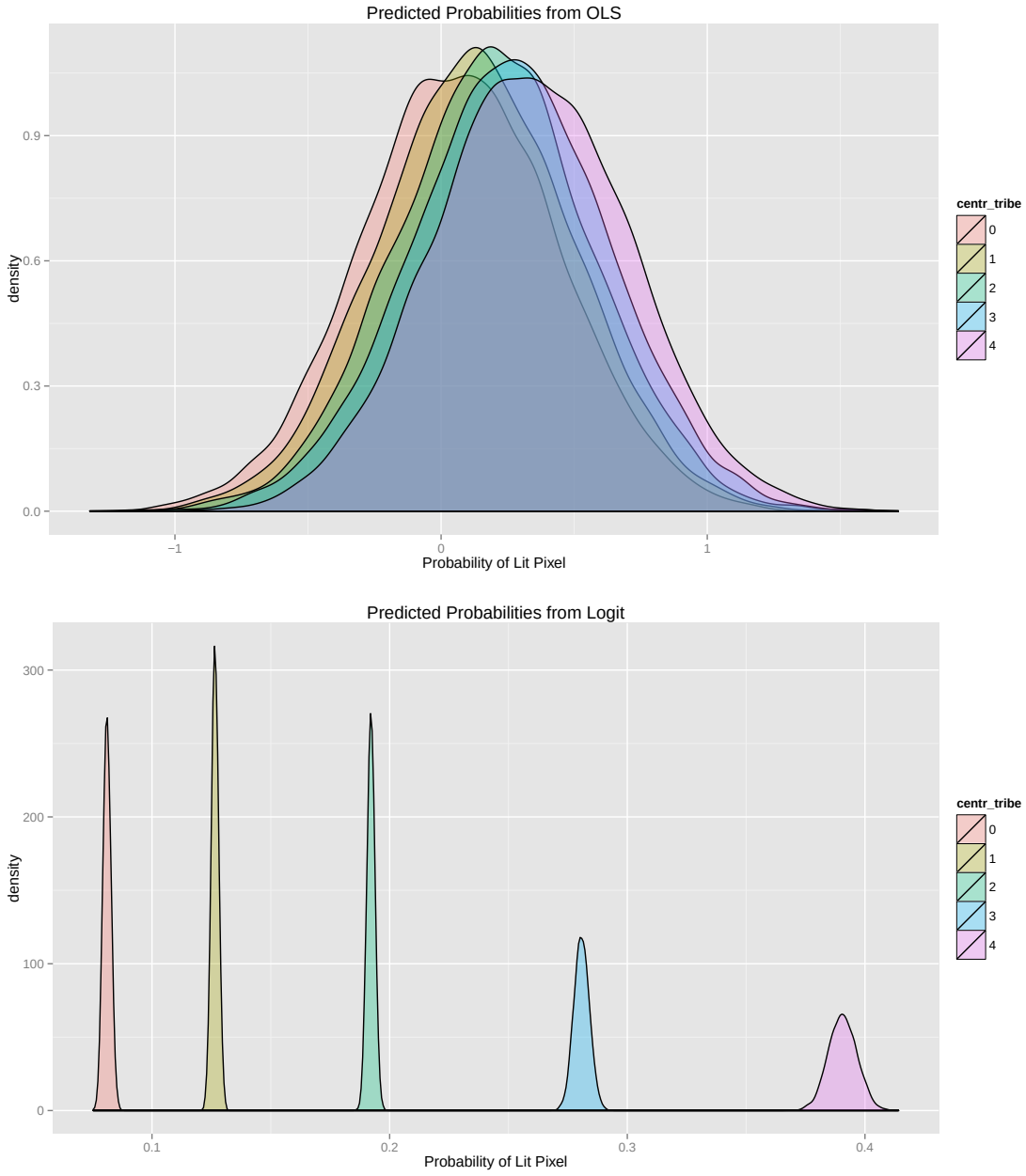

Figure 2: Simulated predicted probabilities of a single pixel being lit within historical ethnic homelands of different pre-colonial political centralization levels, using two different model specifications. Pre-colonial political centralization ranges from 0 ("stateless society") to 4 ("large complex state").

But is the logit model a better fit than the linear probability model? The bottom panel of Figure 2 shows the probabilities predicted by the baseline logit model in Table 2, column 4, obtained following the same procedure outlined above but adapted to a Bernoulli data-generating process and logit link function. All of the predictions fall within [0,1], which is a first sign that this model may be an improvement over the linear model.

Table 2: Baseline Specification Checks: Clustered vs. regular standard errors and LPM vs. Logit

	(1) Lit Pixel	(2) Lit Pixel	(3) Lit Pixel	(4) Lit Pixel	(5) Lit Pixel	(6) Lit Pixel
	OLS	OLS	OLS	Logit	Logit	Logit
Juris. Hier.	0.067**	0.028***	0.027***	0.496***	0.089	0.064
	(0.031)	(0.008)	(0.007)	(0.178)	(0.058)	(0.075)
	{0.001}	{0.001}	{0.001}	{0.011}	{0.016}	{0.017}
Log Pop. 2000		0.069***	0.066***		0.896***	0.908***
		(0.011)	(0.010)		(0.060)	(0.060)
Pixel-level controls	No	No	Yes	No	No	Yes
Ethn.-country controls	No	No	Yes	No	No	Yes
Country FE	No	Yes	Yes	No	Yes	Yes
Observations	66570	66570	66173	66570	66570	66173
(McFadden) R^2	0.034	0.358	0.389	0.038	.403	.426
BIC'	-2298	-28927	-30783	-2283	-23774	-24753

Standard errors in parentheses are clustered by country and language group, following Michalopoulos and Papaioannou. Regular standard errors in curly brackets. R^2 is computed by the usual formula for the OLS models; McFadden's Adjusted R^2 is reported for logit models.
Pixel-level controls include: the distance from the centroid of each pixel to associated capital city, to the sea coast, and to the national border; indicators for pixels that have water (lakes, rivers, streams), for pixels with diamond mines, and for pixels with oil fields; each pixels land suitability for agriculture, mean elevation, average value of a malaria stability index, and log area.
Ethnicity-country-level controls include: the distance of the centroid of each ethnicity-country area from the respective capital city, the distance from the sea coast, the distance from the national border, log(1 + area under water (lakes, rivers, and other streams)), log(surface area), land suitability for agriculture, elevation, a malaria stability index, a diamond mine indicator, and an oil field indicator.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ according to clustered standard errors

As further evidence, the relative difference between clustered and regular standard errors is smaller in the logit specifications than in the linear specifications. That is, following King and Roberts (2014), we interpret a large difference between cluster-robust standard errors and regular standard errors as an indicator of model misspecification. Although we do not formally estimate the information matrix test, which is computationally difficult in the double-clustered case, comparing the standard errors qualitatively is telling. For example, the cluster-robust standard error in the fully specified linear regression in column 3 of Table 2 is seven times larger than the regular standard error. In contrast, the cluster-robust standard error in the analogous logit model (column 6) is roughly four times larger than the regular standard error. This suggests that the logit is a better fit than the linear model in this case. However, the substantial remaining difference in standard errors suggests we still have not found the right model−an issue the next sections will take up in more depth.

Among the logit models, there is some evidence that the fully specified equation in column 6 is the best fit. The adjusted R-squared is higher, though this could reflect the mechanical increase due to adding more parameters. More convincingly, the Bayesian Information Criterion is smallest (most negative) when we include all controls, country fixed effects, and population density in 2000. A likelihood ratio test rejects the hypothesis that this model is not systematically different from the more restricted model in column 4, with a p-value of 0.000.

The logit model also reveals a striking conclusion: the estimated effect of pre-colonial political centralization on night lights disappears when contemporary population density is taken into account. The substantive effect of this change becomes apparent when we compare first differences between the two models. The bivariate logit model (Table 2, column 4) yields an expected increase of 11% in the probability that a pixel is lit when moving from a stateless society (a *Jurisdicational Hierarchy* score of 0) to a paramount chiefdom (a *Jurisdicational Hierarchy* score of 2), holding all else constant. When population density is incorporated into the model, the expected difference shrinks by more than 75%, to 2.7%, and is indistinguishable from zero at a 99% confidence level. Figure 3 shows first differences between stateless societies and paramount chiefdoms generated from the six different models

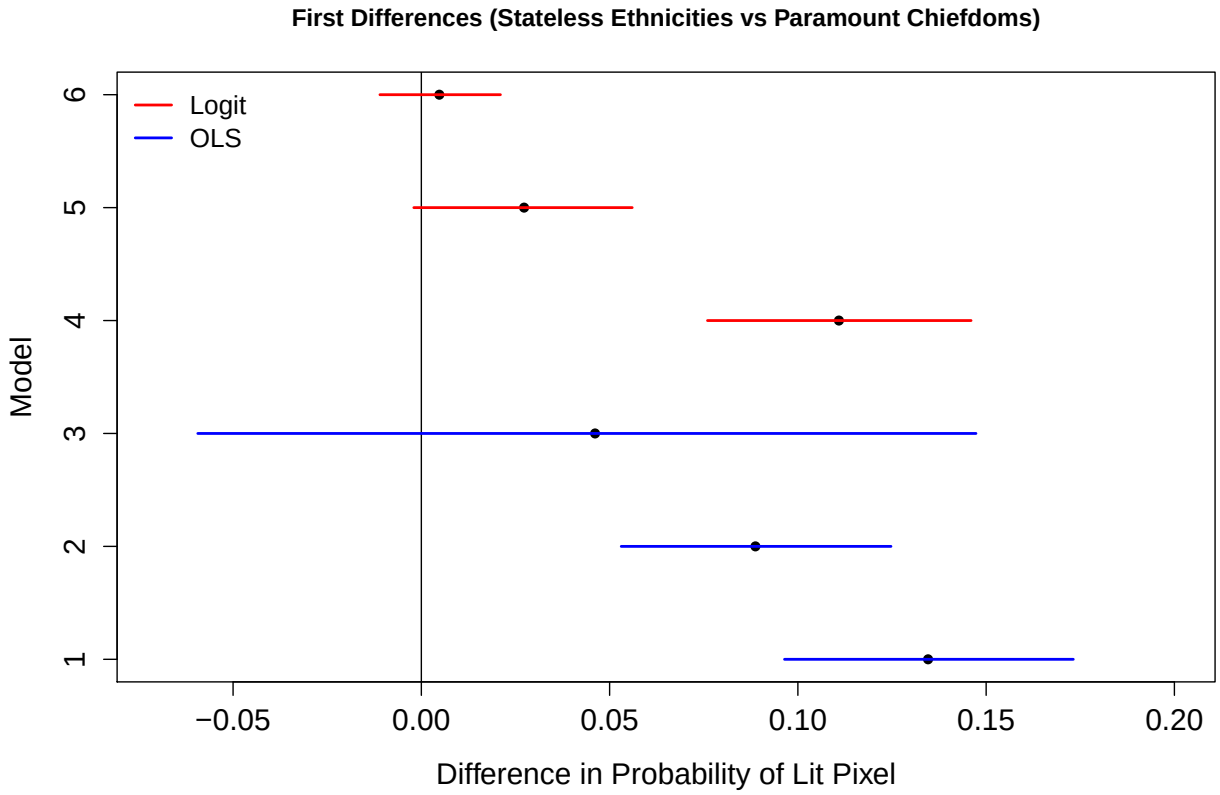

Figure 3: Simulated first differences between stateless societies and paramount chiefdoms for the six different models summarized in Table 1. First differences are obtained by simulating 10,000 expected probabilities from each model for stateless societies and paramount chiefdoms, holding all other variables at their medians, and taking the differences between the two. Line segments indicate 99% confidence intervals. Fixed effects are excluded from all models for the purpose of simulating first differences.

in Table 1.[2] As expected, in both logit specifications that control for log population density in 2000, the difference in the probability of a pixel being lit in the homeland of a stateless ethnicity vs. a paramount chiefdom is indistinguishable from zero. Interestingly, this is also the case for the OLS specification including log population density in 2000 and a set of pixel- and ethnic homeland-level controls (Table 2, column 3), despite the fact that the OLS coefficient on *Jurisdictional Hierarchy* remains significant and positive in the model. This could be due to the exclusion of country fixed effects in the first difference simulation, but in any calls the independent effect of *Jurisdictional Hierarchy* into question.

Taken together, this suggests that population density may be a mediating channel through which *Jurisdictional Hierarchy* affects nighttime lights. If true, this would have significant implications for the conclusions drawn in Michalopoulos and Papaioannou (2013). Instead of interpreting the papers results as evidence of long-run development benefits from

[2]Fixed effects are excluded from all models for the purpose of simulating first differences.

pre-colonial centralization, Table 2 suggests instead a story about the persistence of population density over time. The remainder of this paper will investigate the empirical strength of this alternative hypothesis.

Section 1.2: Omitted Variable Bias

Motivated by the evidence of model misspecification discussed above, this section considers two possible sources of confounding: (1) time-invariant, language-group specific unobservables, and (2) pre-colonial population density.

First, most specifications in Michalopoulos and Papaioannou (2013) include country-level fixed effects, which rule out country-specific, time-invariant factors that could be biasing the results, and restrict the variation used by the OLS estimator to that within countries. They do not, however, similarly control for language-group-level unobservables. This could be a problem if there are relevant time-invariant characteristics shared by members of different language groups that are not picked up by country fixed effects. For example, if certain cultural traits predisposed some tribes to having a hierarchical political system before colonialism and also to living in cities today, then we might expect upward bias on the coefficient on *Jurisdictional Hierarchy*. A cultural effect of this type would likely not be picked up by country fixed effects because language groups are almost never collinear with national boundaries. Often, countries contain multiple language groups. In some cases, language group span multiple countries.

Table 3 summarizes four linear probability models and four logit models. When we include language-group-level fixed effects −in columns 2 and 6, respectively− the estimated marginal effect of *Jurisdictional Hierarchy* on the probability of a lit pixel drops by more than half and loses statistical significance. Adding country fixed effects (in columns 3 and 7) and population density in 2000 (in columns 4 and 8) reduces the magnitude of the estimated coefficient still further. Ordinarily, including both country and language-group fixed effects in the same model would provoke identification concerns because we are estimating more than 150 parameters. However, with over 66,000 pixels, there is still ample within-variation to identify all of the coefficients in the model.

Table 3: Addressing Omitted Variable Bias: Country and Language-Group Fixed Effects

	(1) Lit Pixel	(2) Lit Pixel	(3) Lit Pixel	(4) Lit Pixel	(5) Lit Pixel	(6) Lit Pixel	(7) Lit Pixel	(8) Lit Pixel
	OLS	OLS	OLS	OLS	Logit	Logit	Logit	Logit
Juris. Hier.	0.040***	0.018	0.015	0.012	0.267***	0.061	0.101	0.018
	(0.011)	(0.012)	(0.012)	(0.009)	(0.063)	(0.076)	(0.091)	(0.072)
	{0.002}	{0.002}	{0.002}	{0.002}	{0.016}	{0.021}	{0.022}	{0.025}
Log Pop. 2000				0.063***				0.930***
				(0.010)				(0.069)
Pixel-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethn.-country controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Lang. Grp. FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	66173	66173	66173	66173	66173	66038	66038	66038
(McFadden) R^2	0.031	0.297	0.344	0.400	.309	.297	0.333	0.438
BIC'	-23762	-22038	-26087	-32026	-17781	-16634	-18359	-24610

Standard errors in parentheses are clustered by country and language group, following Michalopoulos and Papaioannou (2013). Regular standard errors in curly brackets. R^2 is computed by the usual formula for the OLS models; McFadden's Adjusted R^2 is reported for logit models. As in other tables, pixel-level controls include: the distance from the centroid of each pixel to associated capital city, to the sea coast, and to the national border; indicators for pixels that have water (lakes, rivers, streams), for pixels with diamond mines, and for pixels with oil fields; each pixels land suitability for agriculture, mean elevation, average value of a malaria stability index, and log area. Ethnicity-country-level controls include: the distance of the centroid of each ethnicity-country area from the respective capital city, the distance from the sea coast, the distance from the national border, log(1 + area under water (lakes, rivers, and other streams)), log(surface area), land suitability for agriculture, elevation, a malaria stability index, a diamond mine indicator, and an oil field indicator.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ according to clustered standard errors

Table 4: Addressing Omitted Variable Bias: Controlling for Precolonial Population Density - Panel A

	(1) Lit Pixel	(2) Lit Pixel	(3) Lit Pixel	(4) Lit Pixel	(5) Lit Pixel	(6) Lit Pixel	(7) Lit Pixel	(8) Lit Pixel
	OLS	OLS	OLS	OLS	Logit	Logit	Logit	Logit
Juris. Hier.	0.037***	0.016	0.015	0.012	0.230***	0.053	0.091	0.017
	(0.010)	(0.012)	(0.012)	(0.009)	(0.070)	(0.080)	(0.091)	(0.072)
	{0.002}	{0.002}	{0.002}	{0.002}	{0.016}	{0.021}	{0.022}	{0.025}
Settl. Patt.	0.018***	0.019**	0.012***	0.004	0.153***	0.126**	0.094***	0.010
	(0.003)	(0.008)	(0.004)	(0.003)	(0.029)	(0.052)	(0.033)	(0.035)
	{0.001}	{0.001}	{0.001}	{0.001}	{0.009}	{0.012}	{0.014}	{0.015}
Log Pop. 2000				0.062***				0.930***
				(0.010)				(0.069)
Pixel-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethn.-country controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Lang. Grp. FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	66173	66173	66173	66173	66173	66038	66038	66038
(McFadden) R^2	0.315	0.300	0.345	0.400	.314	.298	0.333	0.438
BIC'	-24249	-22345	-26181	-32029	-18060	-16739	-18395	-24599

Standard errors in parentheses are clustered by country and language group, following Michalopoulos and Papaioannou (2013). Regular standard errors in curly brackets. R^2 is computed by the usual formula for the OLS models; McFadden's Adjusted R^2 is reported for logit models. As in other tables, pixel-level controls include: the distance from the centroid of each pixel to associated capital city, to the sea coast, and to the national border; indicators for pixels that have water (lakes, rivers, streams), for pixels with diamond mines, and for pixels with oil fields; each pixels land suitability for agriculture, mean elevation, average value of a malaria stability index, and log area. Ethnicity-country-level controls include: the distance of the centroid of each ethnicity-country area from the respective capital city, the distance from the sea coast, the distance from the national border, log(1 + area under water (lakes, rivers, and other streams)), log(surface area), land suitability for agriculture, elevation, a malaria stability index, a diamond mine indicator, and an oil field indicator.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ according to clustered standard errors

Table 5: Addressing Omitted Variable Bias: Controlling for Precolonial Population Density - Panel B

	(1) Lit Pixel	(2) Lit Pixel	(3) Lit Pixel	(4) Lit Pixel	(5) Lit Pixel	(6) Lit Pixel	(7) Lit Pixel	(8) Lit Pixel
	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit
Juris. Hier. Indicator	0.030*	0.018	0.196	0.015				
	(0.017)	(0.013)	(0.131)	(0.104)				
	{0.004}	{0.004}	{0.043}	{0.048}				
Settl. Patt.	0.012***	0.004	0.094***	0.011	0.012***	0.004	0.094***	0.014
	(0.004)	(0.003)	(0.034)	(0.035)	(0.004)	(0.003)	(0.034)	(0.035)
	{0.001}	{0.001}	{0.014}	{0.015}	{0.001}	{0.001}	{0.014}	{0.079}
Log Pop. 2000		0.062***		0.930***		0.062***		0.931***
		(0.010)		(0.069)		(0.010)		(0.069)
Petty Chiefdoms					-0.003	0.007	-0.071	-0.118
					(0.017)	(0.014)	(0.160)	(0.105)
					{0.005}	{0.005}	{0.057}	{0.062}
Paramount Chiefdoms					0.029	0.020	0.136	-0.109
					(0.020)	(0.016)	(0.158)	(0.137)
					{0.005}	{0.005}	{0.063}	{0.069}
Precolonial States					0.027	0.030	0.163	0.024
					(0.042)	(0.033)	(0.299)	(0.226)
					{0.006}	{0.006}	{0.072}	{0.079}
Pixel-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethn.-country controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lang. Grp. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66173	66173	66038	66038	66173	66173	66038	66038
(McFadden) R^2	0.345	0.400	0.333	0.438	0.345	0.400	0.333	0.438
BIC'	-26193	-32015	-18399	-24599	-26171	-31999	-18379	-24584

Standard errors in parentheses are clustered by country and language group, following Michalopoulos and Papaioannou. Regular standard errors in curly brackets. R^2 is computed by the usual formula for the OLS models; McFadden's Adjusted R^2 is reported for logit models. Pixel- and ethnic-country-level controls are as in other tables.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ according to clustered standard errors

The Bayesian Information Criterion (BIC) offers a useful test of whether adding these additional fixed effects may result in over-fitting, as it includes a "punishment term" that compensates the mechanical increase in the likelihood from adding additional parameters to a model. The results indicate that country fixed effects may be individually preferable to language-group fixed effects, but that the combination of both sets of fixed effects is the best of all these models. Moreover, a likelihood ratio test comparing the restricted logit model in column 5 of Table 4 to the fully-specified model in column 8 rejects the null of no systematic difference with a p-value of 0.000. We can therefore conclude with some confidence that adding language-group fixed effects on top of country fixed effects has both improved the models fit and eliminated the possibility that unobservable similarities within language groups are driving the correlation between pre-colonial centralization and night lights.

The second omitted variable worth investigating is population density. The observed instability of the coefficient on *Jurisdictional Hierarchy* while controlling for log population density in 2000 suggests that the results in Michalopoulos and Papaioannou (2013) might operate through a population density channel. To test this hypothesis, we include a second variable from Murdocks ethnographic atlas: *Settlement Patterns*. This variable offers a reasonable proxy for pre-colonial population density. Perhaps surprisingly, it is only weakly correlated with pre-colonial political centralization: a simple regression of *Jurisdictional Hierarchy* on *Settlement Patterns* controlling for country fixed effects estimates a coefficient of 0.07. Nonetheless, this is enough of a positive association for the exclusion of *Settlement Patterns* to be a potential source of omitted variable bias. In addition, given the moderate extent to which these two variables co-vary, we can include them both in our models without worrying about excessive collinearity.

Table 5, which summarizes estimations analogous to those in Table 3 while adding *Settlement Patterns* as a covariate, provides strong support to the hypothesis that the persistence of population density over time is driving the observed correlation between pre-colonial centralization and night lights today. According to these models, *Settlement Patterns* appears to be a more robust predictor of night lights than *Jurisdictional Hierarchy*. In particular, while the statistical significance of *Jurisdictional Hierarchy* vanishes when we

include language-group fixed effects (as in Table 2), the coefficient on *Settlement Patterns* remains positive and significant in both linear probability and logit models. This coefficient decreases and size and becomes indistinguishable from zero when we control for log population density in 2000, which is consistent with the population-persistence hypothesis.

Aside from the statistical significance of the coefficient on *Settlement Patterns* in each of the equations that excludes population density, there is further evidence that controlling for pre-colonial population density has improved the models overall fit. A likelihood ratio test comparing the model in column 7 of Table 3 to the model in column 7 in Table 4−the only difference is the addition of Settlement Patterns−rejects the null hypothesis of no difference with a p-value of 0.000. In addition, the Bayesian Information Criteria for linear probability and logit models in Table 4 are almost uniformly larger (more negative) than those for the analogous models in Table 3, in which *Settlement Patterns* is excluded. The only exception is column 8 (the fully specified logit that includes log population density in 2000) in the two tables: the BIC is slightly more negative in the restricted case. But these models likely suffer from post-treatment bias due to the inclusion of population density in 2000, a problem that we discuss explicitly in Section 2.

To test the robustness of these results further, Table 5 displays eight models that utilize different measures of pre-colonial political centralization. In columns 1-4, we include a binary variable that equals one if a pixel falls in an ethnic homeland that is a paramount chiefdom or pre-colonial state and zero otherwise. Using this coarsened explanatory variable yields estimates quite similar to those in Table 4. *Settlement Pattern* appears a somewhat stronger predictor of night lights than *Jurisdictional Hierarchy* and, as expected, the estimated effect on the former loses significance when we control for population density in 2000. Columns 5-8 disaggregate *Jurisdictional Hierarchy* into four categories to examine where a particular level of political centralization retains an independent effect on night lights. (The omitted category is stateless societies.) Yet, none of these parameters estimated in linear probability and logit models are statistically different from zero.

The models examined thus far suggest that population density may mediate the relationship between pre-colonial political centralization and night lights today. As a reality check, we estimate a sample of these models with population density in 2000 as the de-

Table 6: Contemporary Population Density as the Outcome Variable

	(1) Log Pop. 2000	(2) Log Pop. 2000	(3) Log Pop. 2000	(4) Log Pop. 2000
	OLS	OLS	OLS	OLS
Juris. Hier.	0.211***	0.186**	0.118*	0.047
	(0.081)	(0.074)	(0.071)	(0.075)
	{0.007}	{0.007}	{0.009}	{0.009}
Settl. Patt.		0.148***	0.180***	0.123***
		(0.030)	(0.048)	(0.034)
		{0.004}	{0.005}	{0.005}
Pixel-level controls	Yes	Yes	Yes	Yes
Ethn.-country controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	No	Yes
Lang. Grp. FE	No	No	Yes	Yes
Observations	66173	66173	66173	66173
(McFadden) R^2	0.345	0.359	0.370	0.419
BIC'	-27216	-28629	-29335	-34078

Standard errors in parentheses are clustered by country and language group, following Michalopoulos and Papaioannou. Regular standard errors in curly brackets. R^2 is computed by the usual formula for the OLS models; McFadden's Adjusted R^2 is reported for logit models.
Pixel-level controls include: the distance from the centroid of each pixel to associated capital city, to the sea coast, and to the national border; indicators for pixels that have water (lakes, rivers, streams), for pixels with diamond mines, and for pixels with oil fields; each pixels land suitability for agriculture, mean elevation, average value of a malaria stability index, and log area.
Ethnicity-country-level controls include: the distance of the centroid of each ethnicity-country area from the respective capital city, the distance from the sea coast, the distance from the national border, log(1 + area under water (lakes, rivers, and other streams)), log(surface area), land suitability for agriculture, elevation, a malaria stability index, a diamond mine indicator, and an oil field indicator.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ according to clustered standard errors

pendent variable. Table 6 summarizes the results: *Jurisdictional Hierarchy* and *Settlement Pattern* are strong predictors of contemporary population density, with the latter being more robust to different models and specifications. These findings are consistent with the hypothesis that population density is the channel through which pre-colonial state formation is associated with nighttime lights.

In sum, accounting for language-group-level unobservables and pre-colonial population density in linear probability and logit models offers compelling evidence that the correlation between Jurisdictional Hierarchy and night lights documented in Michalopoulos and Papaioannou (2013) may be driven by omitted variables. In particular, the robustness of *Settlement Patterns* across a number of different specifications suggests that the spatial distribution of population density persists over time: places with more concentrated settlements before colonialism are more likely to have lights at night today.

Section 2: Continuous Dependent Variable

The first section used a binary dependent variable indicating whether pixels were lit or unlit. This section reports similar results using a continuous measure of the luminosity of each pixel. We follow Michalopoulos and Papaioannou (2013) in log-transforming the luminosity because of the large number of outliers in the right tail of the distribution, which correspond to cities with much brighter lights than surrounding regions. After this transformation, the data are sufficiently normal to warrant use of the least squares estimator. This section briefly reproduces the previous sections findings in the continuous case before addressing the issue of post-treatment bias.

Section 2.1: Omitted Variable Bias in the Continuous Case

First, we again focus on possible omitted variable bias due to the exclusion of language-group fixed effects. The first four columns of Table 7 reproduce the substantive findings from Table 3 in the previous section. Namely, once we include language-group fixed effects, the estimated effect of *Jurisdictional Hierarchy* is considerably dampened and no longer significant at conventional levels. The Bayesian Information Criterion (BIC) for the model with both sets of fixed effects (column 3) is smaller (more negative) than that for the previous

two models. The likelihood ratio test rejects the null of no difference between the restricted model in column 1 and the model with both sets of fixed effects with a p-value of 0.000.

Second, columns 5-8 of Table 7 reinforce the findings from Table 3. The stability of *Settlement Patterns* as a predictor of night lights again survives specifications with country fixed effects, language-group fixed effects, both sets of fixed effects, and the inclusion of population density. In contrast, *Jurisdictional Hierarchy* loses statistical significance with the inclusion of language-group fixed effects. Again, the R-squared, likelihood ratio test, and BIC suggest the more fully specified models that include both sets of fixed effects are a better fit of the data. These estimations produce a remarkably similar picture to that from the previous section with the binary dependent variable.

Section 2.2: Post-Treatment Bias

Throughout the analysis thus far, the reader may have questioned the validity of controlling for population density in 2000 if we seek to identify long-run effects of state formation hundreds of years ago. Indeed, this seems like a classic case of post-treatment bias. Michalopoulos and Papaioannou (2013) does not claim causal results, however, and includes this population density measure to identify the mechanism behind the apparent relationship between *Jurisdictional Hierarchy* and night lights. The paper interprets the statistically-significant coefficients on *Jurisdictional Hierarchy* even while controlling for contemporary population density as evidence of an effect of pre-colonial centralization above and beyond that of population density. Theirs is not just a story about people living in higher concentrations today in places where people lived in higher concentrations a hundred years ago; it is a story about how historical states shape long-run economic development.

Although this approach−including a post-treatment covariate to identify the channel of an estimated effectis commony in the literature, it can lead to severely biased results (e.g. Rosenbaum PR 2014). In a causal inference framework, the estimate of the causal effect will suffer from post-treatment bias when controlling for a post-treatment covariate if the "treatment" (*Jurisdictional Hierarchy* in this case) has a direct causal effect on the post-treatment covariate (contemporary population density) and if, in turn, the post-treatment covariate has a direct causal effect on the outcome variable (night lights).

Table 7: Addressing Omitted Variable Bias: Language Group Fixed Effects and Precolonial Population Density

	(1) Pixel Lum.	(2) Pixel Lum.	(3) Pixel Lum.	(4) Pixel Lum.	(5) Pixel Lum.	(6) Pixel Lum.	(7) Pixel Lum.	(8) Pixel Lum.
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Juris. Hier.	0.225***	0.123	0.114	0.098	0.208***	0.109	0.111	0.096
	(0.070)	(0.078)	(0.085)	(0.066)	(0.066)	(0.077)	(0.084)	(0.067)
	{0.007}	{0.009}	{0.009}	{0.008}	{0.007}	{0.009}	{0.009}	{0.008}
Log Pop. 2000				0.319***				0.315***
				(0.069)				(0.069)
Settl. Patt.					0.104***	0.137**	0.091***	0.052**
					(0.026)	(0.062)	(0.029)	(0.022)
					{0.004}	{0.005}	{0.005}	{0.005}
Pixel-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethn.-country controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Lang. Grp. FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	66173	66173	66173	66173	66173	66173	66173	66173
R^2	0.377	0.356	0.415	0.482	0.384	0.363	0.418	0.483
BIC'	-30509	-27803	-33702	-41731	-31328	-28597	-34009	-41837

Standard errors in parentheses are clustered by country and language group, following Michalopoulos and Papaioannou.
Regular standard errors in curly brackets. As in other tables, pixel-level controls include: the distance from the centroid of each pixel to associated capital city, to the sea coast, and to the national border; indicators for pixels that have water (lakes, rivers, streams), for pixels with diamond mines, and for pixels with oil fields; each pixels land suitability for agriculture, mean elevation, average value of a malaria stability index, and log area. Ethnicity-country-level controls include: the distance of the centroid of each ethnicity-country area from the respective capital city, the distance from the sea coast, the distance from the national border, log(1 + area under water (lakes, rivers, and other streams)), log(surface area), land suitability for agriculture, elevation, a malaria stability index, a diamond mine indicator, and an oil field indicator.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ according to clustered standard errors

Table 8: Addressing Post-Treatment Bias: The Sequential G-Estimator

	(1) Pixel Lum.	(2) Pixel Lum.	(3) Pixel Lum.	(4) Pixel Lum.	(5) Pixel Lum.	(6) Pixel Lum.	(7) Pixel Lum.	(8) Pixel Lum.
G-estimator	No OLS	Yes OLS	No OLS	Yes OLS	No OLS	Yes OLS	No OLS	Yes OLS
Juris. Hier.	0.098	0.098	0.096	0.096				
	(0.066)	(0.068)	(0.067)	(0.068)				
	{0.008}	{0.008}	{0.008}	{0.008}				
Log Pop. 2000	0.319***		0.315***		0.318***		0.315***	
	(0.069)		(0.069)		(0.069)		(0.069)	
Settl. Patt.			0.052**	0.052**			0.055**	0.054**
			(0.022)	(0.023)			(0.023)	(0.025)
			{0.005}	{0.005}			{0.005}	{0.005}
Petty Chiefdoms					0.006	0.006	-0.006	-0.005
					(0.076)	(0.076)	(0.077)	(0.078)
					{0.020}	{0.020}	{0.020}	{0.020}
Paramount Chiefdoms					0.138	0.138	0.129	0.128
					(0.092)	(0.096)	(0.097)	(0.099)
					{0.022}	{0.022}	{0.022}	{0.022}
Precolonial States					0.239	0.239	0.238	0.238
					(0.226)	(0.225)	(0.229)	(0.227)
					{0.027}	{0.027}	{0.027}	{0.027}
Pixel-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethn.-country controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lang. Grp. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66173	66173	66173	66173	66173	66173	66173	66173
R^2	.482	0.388	0.483	0.389	0.482	0.388	0.483	0.389
BIC'	-41731	-30731	-41837	-30835	-41693	-30693	-41810	-30808

Standard errors in parentheses are clustered by country and language group, following Michalopoulos and Papaioannou.

Regular standard errors in curly brackets. Pixel and ethnic-country-level controls are as in other tables.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ according to clustered standard errors

However, post-treatment bias can be a problem even when causal inference is not the explicit aim, as in Michalopoulos and Papaioannaou (2013). In particular, adding an intermediate variable to a regression will create bias if there are unobserved confounders that are also affected by the key explanatory variable. For example, if population density is correlated with omitted variables that affect night lights and are also shaped by pre-colonial political centralization, then the estimated direct effect of *Jurisdictional Hierarchy* will be biased. One candidate for such a variable is agricultural practices. If (1) pre-colonial states were more likely to practice intensive agriculture, (2) intensive agriculture is associated with population density over time, and (3) places with intensive agriculture historically are today more brightly-lit at night, then the coefficient on *Jurisdictional Hierarchy* will be biased when controlling for population density.

To mitigate post-treatment bias concerns, we use the sequential g-estimator, adapted from the biostatistics literature in political science by Acharya et al (2014). This method proceeds in three steps. First, estimate the effect of the post-treatment variable (population density in 2000) on the dependent variable (night lights), while controlling for the full set of covariates from the initial regression. Second, subtract the estimated effect of the post treatment variable from the dependent variable. Third, estimate the effect of the explanatory variable of interest (*Jurisdictional Hierarchy*) on the transformed dependent variable. This procedure isolates the direct effect of pre-colonial political centralization. We satisfy the selection-on-observables assumption by including a rich set of geographic and location-based controls.

Table 8 compares results from estimating the effect of *Jurisdictional Hierarchy* while including 2000 population density in the model compared to analogous models that using the sequential g-estimator . The coefficients on *Jurisdictional Hierarchy* are almost exactly the same across the two versions of these different models, and the standard errors are marginally larger. On the whole, though, the results are largely unchanged, suggesting that there is not a great deal of post-treatment bias caused by including logged population density in 2000 in previous models. Furthermore, we see the same pattern of results in Table 5, suggesting again that the strength of *Settlement Patterns* is not an artifact of the binary data examined in the previous section.

Section 3: Ethnic-Homeland-Level Analysis

As a further robustness check on the results presented thus far, this section examines the ethnic-homeland level. Instead of the fine-grained pixel-level analysis of the previous two sections, we take the mean luminosity across each ethnic homeland in Murdocks Ethnographic Atlas. Following Michalopoulos and Papaioannou (2013), we use two continuous dependent variables: log(0.01 + luminosity) and log(luminosity). The first is constructed to not be dropped if a pixel has zero detectable luminosity, while the second does drop in this case. We again log-transform the outcome variable to mitigate the effect of outliers to the far right of the distribution. Given the structure of these data, the normal linear regression model is again a good choice.

Tables presenting the results from this section are included in the Appendix. Including language-group fixed effects, in columns 2 and 4 of Table 13, has the by now familiar effect of reducing the magnitude of the coefficients on *Jurisdictional Hierarchy*, and rendering it statistically insignificant. In Table 14, we test how strongly pre-colonial population density predicts night lights and reach similar conclusions. The results are somewhat less strong here than using the pixel-level data. For example, the estimated coefficient on *Settlement Patterns* in the model in column 2 is not statistically significant. As in the pixel-level results, models using only country fixed effects tend to have lower BIC scores and higher R-squared values. Although we found previously that models including both sets of fixed effects generally had better fit, the ethnic-homeland-level data have too few observations to accommodate more than 150 parameters. Hence, in this section we consider country and language group fixed effects one at a time.

Table 16 reproduces the models estimated in Table 8, again using the g-estimator to mitigate the effects of post-treatment bias. There is more evidence that including logged population density in 2000 does artificially inflate the estimated effect of *Jurisdictional Hierarchy* in this case. For example, the coefficient on *Jurisdictional Hierarchy* drops from .149 in column 5 to .142 in column 6, where the g-estimator has removed the effect of population density. This is not a massive source of bias, but it is not trivial either. The rest of the results are consistent with the preceding analysis. The lack of statistical significance on *Settlement Patterns* is expected here because, as noted, the dependent variable has

been transformed to take out the direct effect of population density. Finally, in Table 17 we again see that both *Jurisdictional Hierarchy* and *Settlement Patterns* are predictors of contemporary population density.

Part II: Within-Country Analysis

As a further test of the development benefits of pre-colonial statehood, we pursue within-country analysis in four countries using data from the Demographic and Health Surveys (DHS), following Michalopoulos and Papaioannou (2013). This approach has several advantages. First, it lets us examine the long-run effects of pre-colonial political centralization at a more micro level, holding constant country-specific factors. Second, it lets us consider alternative indicators of development. If truly there is a development premium from pre-colonial statehood, we should be able to detect it using alternative measures, such as education, health, and public infrastructure, even when controlling for population density.

Section 1: Data and Analytic Strategy

In this section, we hone in one four countries, one in each major region of Africa: the Democratic Republic of the Congo (DRC), Nigeria, Tanzania, and Zambia. The first three, along with Zimbabwe, are used in Michalopoulos and Papaioannou (2013) to test the correlation between night lights and household wealth (see Figure 1). We substitute neighboring Zambia for Zimbabwe due to the fact that only five ethnic homelands intersect Zimbabwe, making it difficult to explore micro-level within-country variation. For each of these four countries, we overlaid geo-coded DHS survey clusters onto a digitized version of Murdocks Ethnographic Atlas and identified survey clusters that fell within each ethnic homeland using ArcGIS software.[3] To maintain respondent confidentiality, DHS incorporates random error in to the GPS coordinates of survey clusters. Urban clusters are displaced with an error of between 0 and 2 km. Ninety-nine percent of rural clusters are displaced between 0 and 5 km, while the remaining one-percent are displaced between 0 and 10 km. To account for this, as well

[3]Ethnic homelands without corresponding DHS data were dropped from the sample. In only one case, Nigeria, did this lead to statistically-significant imbalance on jurisdictional hierarchy.

as for potential error in the designation of ethnic homeland boundaries in the digitized Murdock map, we re-run our main within-country analysis excluding survey clusters that fall within 5 km of each ethnic homeland border. Re-running the analysis excluding clusters that fall within a 10 km band does not substantially change our results. Ethnic homelands were assigned to countries according to the classifications used in by Michalopoulos and Papaioannou.[4]

We use six development indicators in our analysis intended to represent different aspects of development. The first, the DHS wealth index, is a country-specific composite indicator of relative household wealth incorporating information such as housing material, toilet facilities, and the possession of certain assets. Access to piped water and electricity serve as indicators of relatively local public goods provision, while education and literacy are included as rough measures of national-level public goods. Finally, we include child mortality as a proxy for the quality of health services.

For each country, we first examine the simple bivariate relationship between jurisdictional hierarchy and each of our six dependent variables. We then control for log population density in 2000 to further test our argument that population concentration provides a channel through which pre-colonial political centralization affects development outcomes. As discussed in previous sections, log population density appears subject to mild omitted variable bias in some specifications. However, in no case was this bias found to be extremely problematic, and estimating it using the g-estimator in this case is not possible because we are unable to satisfy the selection-on-observables assumption in the current data.[5]

We collapse DHS survey data into cluster-level means and inverse-weight clusters ac-

[4]There are many cases of ethnic homelands partitioned by country borders. In these cases, Michalopoulos and Papaioannou classify the ethnic group separately within each country and assign light density and population density scores of the portion of the ethnic homeland that falls within each country (124). Partitioned ethnic groups do not present a problem in our case, as we are examining only within-country variation, our main outcome variables of interest (from DHS) fall within the portion of the ethnic homeland that is within a particular country and our main independent variable of interest, jurisdictional hierarchy, applies to an entire ethnic homeland.

[5]Specifically, we lack cluster-specific values for many of the ethnic-homeland controls used elsewhere in the analysis

cording the number of households or individuals in each cluster. We estimate standard errors using a block bootstrap procedure, in which ethnic groups are randomly sampled with replacement 1,000 times, and the analysis is performed using the clusters within the ethnic groups selected in each iteration. The standard error is estimated by taking the standard deviation of the sampling distribution of the coefficient estimate. Block bootstrap estimators have been shown to perform better than cluster-robust standard errors in clustered data with small numbers of clusters, or ethnic groups in this case (Cameron et al 2008). Furthermore, this strategy takes into account spatial autocorrelation between survey clusters, as well as other unobservable similarities between clusters within the same ethnic homeland.

While this may seem like a conservative approach that biases us against finding a significant relationship, we believe it makes the most sense given the nature of our data. The most conservative approach would be to collapse our development indicators to ethnic homeland means, as in the cross-sectional ethnic homeland analysis in Michalopoulos and Papaioannou (2013), discussed in the previous section. However, this is not feasible given that we have as few as 17 ethnic homelands per country in the four countries we examine, and it involves throwing away much of the variation in the DHS data. A slightly less conservative approach would be to collapse to cluster-level means without taking cluster size into account.

Two less conservative alternatives that would conceivably allow greater exploitation of the variation in the DHS data would be 1) to treat individual people or households as independent within cluster and 2) to treat clusters as independent within ethnic homelands. The first option makes little sense given that households within the same survey cluster live close to one another and are likely to have similar outcomes, especially for public goods that are often provided at the community level, such as piped water and electricity. The second, as noted above, does not account for unobservable shared characteristics between communities in the same ethnic homeland, nor does it account for intra-homeland correlation produced by geographic distance. However, for the sake of transparency, we include regular standard errors alongside block bootstrap standard errors in our results.

Section 2: Results

The results of this analysis are presented in Tables 9-12. Looking closely within countries, the relationship between pre-colonial jurisdictional hierarchy and modern day development is far from straightforward. In Nigeria and DRC, pre-colonial jurisdictional hierarchy is not a significant predictor of any of the six development outcomes we examine. In fact, in DRC, though non-significant using the bootstrap standard errors, the coefficients on all but child mortality are negative. In Zambia, *Jurisdictional Hierarchy* initially appears to be a significant predictor of access to piped water, but the effect becomes insignificant when population density in 2000 is included.

In the specifications that include population density for these three countries, population density, but not *Jurisdictional Hierarchy*, is a significant predictor of the various development outcomes. Tanzania provides an interesting contrast to the other three. Pre-colonial centralization is associated with higher levels of literacy and education, even when controlling for population density, while population density does not independently predict any of the outcomes we examine. These mixed results suggest a need for further investigation of country-specific determinants of the nature of the relationship between pre-colonial political centralization and modern day development. Using this limited data, for example, we find that when an outlier among the DRC ethnic groups, the Teke tribe, is removed, many of the coefficients become positive (but remain insignificant even using regular standard errors). The Teke are classified according to the Murdoch map as a "petty chiefdom" (a *Jurisdictional Hierarchy* score of 1), but have high values on all development outcomes. This group spans from western DRC into Congo-Brazzaville and Gabon and counts among its members the ruling family in Gabon, suggesting a potential story about political elites providing support to their coethnics across country borders.

Detailed case analysis is beyond the scope of this paper and there is only so much that can be gleaned given the limited nature of our data. However, what does emerge almost consistently is the importance of population density as a channel through which pre-colonial centralization affects development.

Table 9: Within-Country Analysis: Democratic Republic of Congo

	Wealth Index		Piped Water		Electricity		Education		Literacy		Child Mortality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Juris. Hier.	−0.417	−0.163	−0.124	−0.035	−0.131	−0.053	−0.195	−0.100	−0.218	−0.130	0.017	0.009
	(0.346)	(0.237)	(0.122)	(0.084)	(0.118)	(0.077)	(0.165)	(0.129)	(0.157)	(0.127)	(0.011)	(0.008)
	{0.094}	{0.094}	{0.033}	{0.032}	{0.028}	{0.028}	{0.043}	{0.046}	{0.044}	{0.048}	{0.006}	{0.006}
Log Pop. 2000		0.555*		0.196*		0.171		0.181		0.168		−0.014
		(0.236)		(0.082)		(0.084)		(0.136)		(0.130)		(0.016)
		{0.085}		{0.029}		{0.025}		{0.041}		{0.043}		{0.006}
Observations	186	186	186	186	186	186	186	186	186	186	186	186
R^2	0.096	0.266	0.072	0.253	0.106	0.287	0.103	0.187	0.117	0.183	0.045	0.073

Block bootstrap standard errors in parentheses, regular OLS standard errors in curly brackets. Significance levels are based on block bootstrap estimates, blocking on ethnic homeland. Observations refers to the number of DHS survey clusters.

*p<0.1; **p<0.05; ***p<0.01

Table 10: Within-Country Analysis: Nigeria

	Wealth Index		Piped Water		Electricity		Education		Literacy		Child Mortality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Juris. Hier.	0.057	−0.057	−0.014	−0.018	0.016	−0.009	0.035	−0.063	0.053	−0.034	0.013	0.020
	(0.204)	(0.154)	(0.018)	(0.020)	(0.054)	(0.044)	(0.169)	(0.118)	(0.152)	(0.106)	(0.014)	(0.010)
	{0.052}	{0.050}	{0.009}	{0.010}	{0.019}	{0.019}	{0.034}	{0.029}	{0.031}	{0.026}	{0.003}	{0.003}
Log Pop. 2000		0.643***		0.024		0.150***		0.624***		0.548***		−0.044***
		(0.190)		(0.024)		(0.049)		(0.176)		(0.152)		(0.011)
		{0.065}		{0.013}		{0.025}		{0.037}		{0.034}		{0.004}
Observations	582	582	582	582	582	582	582	582	582	582	582	582
R^2	0.002	0.146	0.004	0.010	0.001	0.061	0.002	0.327	0.005	0.312	0.025	0.188

Block bootstrap standard errors in parentheses, regular OLS standard errors in curly brackets. Significance levels are based on block bootstrap estimates, blocking on ethnic homeland. Observations refers to the number of DHS survey clusters.

*p<0.1; **p<0.05; ***p<0.01

Table 11: Within-Country Analysis: Tanzania

	Wealth Index		Piped Water		Electricity		Education		Literacy		Child Mortality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Juris. Hier.	0.043	0.044	0.028	0.029	−0.002	−0.0004	0.084*	0.085*	0.100**	0.099**	−0.003	−0.004
	(0.100)	(0.109)	(0.039)	(0.038)	(0.013)	(0.014)	(0.040)	(0.042)	(0.038)	(0.040)	(0.009)	(0.009)
	{0.068}	{0.068}	{0.021}	{0.021}	{0.014}	{0.014}	{0.021}	{0.021}	{0.028}	{0.028}	{0.004}	{0.004}
Log Pop. 2000		−0.019		−0.016		−0.015		−0.008		0.009		0.007
		(0.149)		(0.045)		(0.021)		(0.043)		(0.048)		(0.008)
		{0.082}		{0.025}		{0.017}		{0.026}		{0.035}		{0.005}
Observations	243	243	243	243	243	243	243	243	243	243	243	243
R^2	0.002	0.002	0.007	0.009	0.0001	0.003	0.064	0.064	0.051	0.051	0.003	0.010

Block bootstrap standard errors in parentheses, regular OLS standard errors in curly brackets. Significance levels are based on block bootstrap estimates, blocking on ethnic homeland. Observations refers to the number of DHS survey clusters.

*p<0.1; **p<0.05; ***p<0.01

Table 12: Within-Country Analysis: Zambia

	Dependent variable:											
	Wealth Index		Piped Water		Electricity		Education		Literacy		Child Mortality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Juris. Hier.	0.055	−0.002	0.087*	0.075	0.030	0.017	0.059	0.043	0.126	0.109	0.007	0.007
	(0.276)	(0.288)	(0.050)	(0.058)	(0.045)	(0.041)	(0.087)	(0.106)	(0.117)	(0.147)	(0.010)	(0.013)
	{0.131}	{0.130}	{0.046}	{0.046}	{0.033}	{0.033}	{0.051}	{0.052}	{0.057}	{0.057}	{0.007}	{0.007}
Log Pop. 2000		0.236***		0.049		0.056**		0.069**		0.073*		0.001
		(0.251)		(0.064)		(0.049)		(0.10)		(0.125)		(0.009)
		{0.087}		{0.031}		{0.022}		{0.034}		{0.038}		{0.005}
Observations	173	173	173	173	173	173	173	173	173	173	173	173
R^2	0.001	0.043	0.021	0.035	0.005	0.041	0.008	0.031	0.028	0.049	0.006	0.006

Block bootstrap standard errors in parentheses, regular OLS standard errors in curly brackets. Significance levels are based on block bootstrap estimates, blocking on ethnic homeland. Observations refers to the number of DHS survey clusters.

*p<0.1; **p<0.05; ***p<0.01

Conclusion

This paper has taken a closer look at the observed correlation, in Michalopoulos and Papaioannou (2013), between precolonial political centralization and development. We have presented evidence that this correlation may in fact be driven by the persistence of population density over time. Regions with more complex political organization in the precolonial period were also likely to have more densely concentrated settlements. These same regions, our results indicate, are more likely to have night lights today. The estimated coefficient on *Settlement Patterns*, a proxy for precolonial population density, remains stable to the inclusion of a rich set of controls, fixed effects, and alternative functional forms. Only the inclusion of contemporary population density erodes the statistical significance of this parameter, which is consistent with our hypothesis. The estimated coefficient on *Jurisdictional Hierarchy*, however, tends to drop in magnitude and lose statistically meaningful difference from zero when we control for language group fixed effects or precolonial population density. Furthermore, within-country analysis demonstrates that *Jurisdictional Hierarchy* has little predictive power over other development outcomes. The few robust correlations we estimate are wiped away upon inclusion of population density.

Although perhaps more prosaic than a story about lasting development benefits from historical statehood, the persistence of the spatial distribution of human settlement in Africa over a significant time period is striking. It adds a spatial dimension to path-dependent view of history, one that must be factored into analyses of long-run economic development. Our results also suggest caution in interpreting night lights as indicative of broad-based economic development. These data remain a useful tool in comparative political economy, but they should be bolstered with other available economic data before making confident claims about the landscape of development. Investigating the within-country relationship between population density, night-time light, and other development indicators remains a fruitful avenue for further research.

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Appendix: Ethnic Homeland-Level Analysis Results

Table 13: Addressing Omitted Variable Bias: Country versus Language Group Fixed Effects

	(1) Mean Lum.	(2) Mean Lum.	(3) Mean Lum.	(4) Mean Lum.
	OLS	OLS	OLS	OLS
Juris. Hier.	0.177***	0.111	0.149**	0.100
	(0.050)	(0.090)	(0.072)	(0.112)
	{0.047}	{0.062}	{0.069}	{0.093}
Log Pop. 2000	0.437***	0.460***	0.682***	0.663***
	(0.062)	(0.072)	(0.135)	(0.099)
Geog. controls	Yes	Yes	Yes	Yes
Loc. controls	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	No
Lang. Grp. FE	No	Yes	No	Yes
Observations	683	683	519	519
R^2	0.662	0.659	0.673	0.661
BIC'	-350	-49	-204	89

Standard errors in parentheses are clustered by country and language group, following Michalopoulos and Papaioannou. Regular standard errors in curly brackets. The dependent variable is log(0.01+ luminosity) in columns 1-2, and log(luminosity) in columns 3-4. This latter variable excludes homelands with zero luminosity, which explains the difference in N across specifications. Geographic controls include: log(1 + area under water (lakes, rivers, and other streams)), log(surface area), mean agricultural suitability, mean elevation, malaria suitability, a diamond mine indicator, and an oil field indicator. Location-based controls include: the distance from the centroid of each homeland to the respective capital city, to the sea coast, and to the national border.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ according to cluster-robust standard errors

Table 14: Addressing Omitted Variable Bias: Language Group Fixed Effects and Precolonial Population Density

	(1) Pixel Lum.	(2) Pixel Lum.	(3) Pixel Lum.	(4) Pixel Lum.	(5) Pixel Lum.	(6) Pixel Lum.	(7) Pixel Lum.	(8) Pixel Lum.
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Juris. Hier.	0.225***	0.123	0.114	0.098	0.208***	0.109	0.111	0.096
	(0.070)	(0.078)	(0.085)	(0.066)	(0.066)	(0.077)	(0.084)	(0.067)
	{0.007}	{0.009}	{0.009}	{0.008}	{0.007}	{0.009}	{0.009}	{0.008}
Log Pop. 2000				0.319***				0.315***
				(0.069)				(0.069)
Settl. Patt.					0.104***	0.137**	0.091***	0.052**
					(0.026)	(0.062)	(0.029)	(0.022)
					{0.004}	{0.005}	{0.005}	{0.005}
Pixel-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethn.-country controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Lang. Grp. FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	66173	66173	66173	66173	66173	66173	66173	66173
R^2	0.377	0.356	0.415	0.482	0.384	0.363	0.418	0.483
BIC'	-30509	-27803	-33702	-41731	-31328	-28597	-34009	-41837

Standard errors in parentheses are clustered by country and language group, following Michalopoulos and Papaioannou.
Regular standard errors in curly brackets. As in other tables, pixel-level controls include: the distance from the centroid of each pixel to associated capital city, to the sea coast, and to the national border; indicators for pixels that have water (lakes, rivers, streams), for pixels with diamond mines, and for pixels with oil fields; each pixels land suitability for agriculture, mean elevation, average value of a malaria stability index, and log area. Ethnicity-country-level controls include: the distance of the centroid of each ethnicity-country area from the respective capital city, the distance from the sea coast, the distance from the national border, log(1 + area under water (lakes, rivers, and other streams)), log(surface area), land suitability for agriculture, elevation, a malaria stability index, a diamond mine indicator, and an oil field indicator.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ according to clustered standard errors

Table 15: Addressing Omitted Variable Bias: Controlling for Precolonial Population Density

	(1) Mean Lum.	(2) Mean Lum.	(3) Mean Lum.	(4) Mean Lum.
	OLS	OLS	OLS	OLS
Juris. Hier.	0.272***	0.176	0.319***	0.189
	(0.082)	(0.124)	(0.102)	(0.123)
	{0.054}	{0.071}	{0.076}	{0.104}
Settl. Patt.	0.093**	0.056	0.192***	0.206***
	(0.038)	(0.054)	(0.053)	(0.070)
	{0.031}	{0.045}	{0.044}	{.066}
Geog. controls	Yes	Yes	Yes	Yes
Loc. controls	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	No
Lang. Grp. FE	No	Yes	No	Yes
Observations	683	683	519	519
R^2	0.549	0.540	0.581	0.576
BIC'	-152	155	-76	205

Standard errors in parentheses are clustered by country and language group, following Michalopoulos and Papaioannou. Regular standard errors in curly brackets. The dependent variable is log(0.01+ luminosity) in columns 1-2, and log(luminosity) in columns 3-4. This latter variable excludes homelands with zero luminosity, which explains the difference in N across specifications. Geographic controls include: log(1 + area under water (lakes, rivers, and other streams)), log(surface area), mean agricultural suitability, mean elevation, malaria suitability, a diamond mine indicator, and an oil field indicator. Location-based controls include: the distance from the centroid of each homeland to the respective capital city, to the sea coast, and to the national border.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ according to cluster-robust standard errors

Table 16: Addressing Post-Treatment Bias: The Sequential G-Estimator

	(1) Mean Lum.	(2) Mean Lum.	(3) Mean Lum.	(4) Mean Lum.	(5) Mean Lum.	(6) Mean Lum.	(7) Mean Lum.	(8) Mean Lum.
G-estimator	No OLS	Yes OLS	Yes OLS	Yes OLS	No OLS	Yes OLS	Yes OLS	Yes OLS
Juris. Hier.	0.177***	0.173***	0.170***	0.112	0.149**	0.142*	0.136*	0.089
	(0.050)	(0.054)	(0.053)	(0.093)	(0.072)	(0.073)	(0.070)	(0.109)
	{0.047}	{0.045}	{0.047}	{0.062}	{0.069}	{0.067}	{0.067}	{0.093}
Log Pop. 2000	0.437***				0.682***			
	(0.062)				(0.135)			
Settl. Patt.			0.031	-0.004			0.083	0.066
			(0.039)	(0.043)			(0.056)	(0.063)
			{0.027}	{0.039}			{0.039}	{0.059}
Geog. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loc. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Lang. Grp. FE	No	No	No	Yes	No	No	No	Yes
Observations	683	683	683	683	519	519	519	519
R^2	0.662	0.578	0.579	0.574	0.673	0.573	0.577	0.558
BIC'	-350	-204	-199	102	-204	-72	-71	226

Standard errors in parentheses are clustered by country and language group, following Michalopoulos and Papaioannou.
Regular standard errors in curly brackets. The dependent variable is log(0.01+ luminosity) in columns 1-4, and log(luminosity) in columns 5-8. This latter variable excludes homelands with zero luminosity, which explains the difference in N across specifications. Geographic controls include: log(1 + area under water (lakes, rivers, and other streams)), log(surface area), mean agricultural suitability, mean elevation, malaria suitability, a diamond mine indicator, and an oil field indicator. Location-based controls include: the distance from the centroid of each homeland to the respective capital city, to the sea coast, and to the national border.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ according to cluster-robust standard errors

Table 17: Population Density as the Outcome Variable

	(1)	(2)	(3)
	Log Pop. 2000	Log Pop. 2000	Log Pop. 2000
	OLS	OLS	OLS
Juris. Hier.	0.235**	0.223**	0.142
	(0.110)	(0.109)	(0.129)
	{0.064}	{0.063}	{0.079}
Settl. Patt.		0.137***	0.133*
		(0.048)	(0.079)
		{0.036}	{0.050}
[1em] Geog. controls	Yes	Yes	Yes
Loc. controls	Yes	Yes	Yes
Country FE	Yes	Yes	No
Lang. Grp. FE	No	No	Yes
Observations	683	683	683
R^2	0.557	0.567	0.601
BIC'	-171	-179	58

Standard errors in parentheses are clustered by country and language group, following Michalopoulos and Papaioannou. Regular standard errors in curly brackets.
Geographic controls include: log(1 + area under water (lakes, rivers, and other streams)), log(surface area), mean agricultural suitability, mean elevation, malaria suitability, a diamond mine indicator, and an oil field indicator. Location-based controls include: the distance from the centroid of each homeland to the respective capital city, to the sea coast, and to the national border.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ according to cluster-robust standard errors