The Persistent Effect of the African Slave Trades on Development: Difference-in-difference evidence*

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Abstract

A small economics literature examines the effect of the slave trades on African economies. Extant studies have used geographic variables to instrument for slave exports to identify the causal effect of the slave trades. This paper leverages variation in cultural persistence, rather than geography, to estimate a lower bound on the long-run economic effect of the slave trades. Specifically, I estimate a difference-in-difference model in which I compare productivity across locations with persistent ethnic groups versus those where the dominant ethnic group has changed and across locations with historical participation in the slave trades versus not. Intuitively, if the slave trades affect output through cultural channels, then we would expect the effect to be lower in areas with low cultural persistence. This estimation strategy avoids concerns that geographic instruments predictive of slave exports may also affect economies through other mechanisms. It also allows us to conclude that any measured effect operates through cultural channels and thus pins down a specific causal mechanism. I find a large and negative long-run effect of the slave trades consistent with past research: point estimates indicate that the slave trades decreased long-run GDP per capita by at least 33 log points ($p < .01$) and GDP by at least 20 log points ($p < .1$). Estimates are robust to the inclusion of a rich set of control variables, winzorizing productivity data, and tests for endogeneity in ethnic group persistence. The results indicate that social capital may significantly contribute to economic development and suggest that shocks to social cohesion can be extremely persistent.

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1 Introduction

Despite a recent increase in the growth rates of African countries, parts of the continent remain economically underdeveloped relative to other regions of the world. Many African countries suffer from high rates of poverty and the continent exhibits substantial inequality both across and within nations (United Nations Development Programme, 2017). Emerging evidence indicates that the economic history of the African continent, particularly the slave trades and European colonization, may help explain the economic struggles of certain African nations. This paper contributes to a recent literature that aims to quantify the long-run effects of the slave trades on African economic development.

This paper builds on the existing literature on the African slave trades by employing a novel approach to measuring a lower bound on the long-run effect of the trades on economic development. Areas from which enslaved people were exported differ systematically from those that did not, making it difficult to separate the effect of the slave trades from regional heterogeneity. Past research has addressed this problem by leveraging geographic variables that predict exports of enslaved people. In contrast, I exploit the evolution of ethnic groups from pre-colonial to contemporary times to estimate a difference-in-difference model. If the slave trades affect economies via cultural mechanisms (e.g. low social capital), then we would expect the long-run effect to be larger in areas in which the ethic group from which slaves were historically exported remains predominant compared to areas where the primary ethnic group changed. Therefore, we may compare areas from which enslaved people were exported with high versus low ethnic persistence to estimate the causal effect of interest. However, areas with high versus low ethnic persistence would likely have differing productivity absent the effect of the slave trades. Hence, I estimate a difference-in-difference model in which I compare (1) areas from which enslaved people were exported versus not and (2) areas with high versus low ethnic persistence.

I find that the slave trades had a negative effect on long-run development that is statistically and economically significant. Point estimates indicate that the slave trades reduced GDP by at least 20 log points ($p < .1$) and GDP/capita by at least 32 log points ($p < .01$). These results are qualitatively and quantitatively similar to those reported in prior studies (Nunn, 2008). The estimates reported in this paper are robust to a rich set of control variables, winsorizing outputs, and tests for endogenous ethnic persistence. Results are significant using asymptotic standard errors or randomization inference to calculate p-values. These findings indicate that the long-run effects of the slave trades continue to hinder economic development in regions of Africa from which enslaved people were exported and that a degradation in social capital is an important mechanism through which these effects operate.

There are two reasons why this contribution to literature on the African slave trades is valuable. First, the results validate the findings of past research that shows a negative relationship between the slave trades and long-run income levels using a distinct source of variation. Nunn (2008) instruments for slave exports using proximity to areas in which demand for slaves was high. This approach has two limitations. First, distances to slave markets are a relatively weak predictor of slave exports with first-stage F statistics ranging from $1.82 - 4.55$. This increases uncertainty in the results: the conditional likelihood ratio confidence interval of one of four models reported spans all real numbers. The second limitation is that distance to slave markets may affect economies through other channels. For instance, countries closer to shorelines may have developed more quickly in the absence of slavery because of easier access to international trade routes, although Nunn demonstrates that, outside of Africa, the distance instruments do not have a positive relationship with income.

Nunn and Puga (2012) and Fenske and Kala (2015) present further evidence that the slave trades harmed long-run incomes. Nunn and Puga show that rugged areas protected from slave raids by geography are associated with higher productivity, a positive effect only observed in Africa and that disappears once exports of enslaved people are controlled for. Fenske and Kala demonstrate that areas that experienced negative temperature shocks during the trans-Atlantic slave trade – which lowered the cost of supplying enslaved people – have lower incomes today.

This paper confirms the finding that the slave trades had a statistically significant and economically important effect on long-run economic development using cultural, rather than geographic, variation. This approach is robust to concerns that geography could affect output through other channels and contributes to a growing consensus across data sources and identification strategies that the slave trades affect present income levels. Moreover, this paper relies only on extensive margin variation in the slave trades, so estimates are unbiased if intensive margin slave trade estimates are inaccurate.

Second, this study is the first to isolate the effect of a specific channel through which the slave trades affect output. We may attribute the estimated effect to a reduction in social capital since the identification relies entirely on variation in cultural persistence, holding other consequences of the slave trades constant. So the entire measured effect is driven by the degradation of social ties caused by the slave trades. This helps explain why the long-term effects of the slave trades are so large and persistent. Putnam (2000) and Temple and Johnson (1998) provide evidence that social capital is important to economic growth, and a dense literature demonstrates that social capital affects variables that are known to affect growth such as financial development (Guiso et al., 2004; Karlan, 2005) and institutions (Satyanath et al., 2017). Hence, this study provides further evidence that social capital is important to long-run growth and sheds light on the mechanisms through which the slave trades have affected economies.

The decision to focus on variation in ethnic persistence is rooted in research suggesting that participation in the African slave trades reduced social capital. Whatley and Gillezeau (2011) conclude that the slave trades are associated with greater ethnic stratification at the end of the 19th century, and Nunn and Wantchekon (2011) find that individuals belonging to ethnic groups from which enslaved people were exported are less trusting today. I build on this research by quantifying the contribution of the cultural effects of the slave trades to output today using reduced-form estimates. The results confirm that social capital is an important causal mechanism, and the magnitude of the effects suggests that this may be the primary channel through which the slave trades affect incomes today.

2 History of the African slave trades and colonialism on the continent

Slavery has a long history in Africa, and the existence of markets for exporting enslaved people predates the trans-Atlantic trade. It is estimated that about 6.6 million enslaved people were exported through the trans-Saharan and Red Sea trades between 650 and 1600. Although commercial slave trades existed, evidence suggests that early slave trades were driven by politics. Enslaved people were captured in wars and raids, and over time it became common to enslave prisoners (Lovejoy, 2011).

The expansion of the trans-Atlantic trade caused a shift towards economic motives for slavery. Beginning in around 1600, demand for labor on plantations in the Americas dramatically increased the volume of enslaved people exported from Africa and the price of enslaved people. Lovejoy (2011) estimates that about 1 million people were exported from Africa in the 16th century, close to 3 million in the 17th century, and almost 8 million in the 18th century. About 75% of those exported from Africa between 1500-1800 were sold into the trans-Atlantic trade. Exports fell sharply during the 19th century as abolition gained traction, and by the end of the 19th century the international slave trade was largely eliminated (Falola and Warnock, 2007).

The expansion of the slave trades had significant effects on African political development. Lovejoy (2011) contends that the increased extraction of slaves prevented the establishment of large and unified states as groups raided each other for slaves, eroding ties and thus making it more difficult to unite groups into larger political entities. Whatley and Gillezeau (2011) finds strong econometric evidence in support of this hypothesis.

European colonialism also affected the distribution of ethnic groups. National boundaries imposed by colonial powers were constructed with little regard for existing institutions or ethnic boundaries. As a result, ethnic groups were frequently partitioned by national boundaries. Michalopoulos and Papaioannou (2016) show that partitioned ethnic groups have worse economic outcomes. Blanton et al. (2001) similarly present evidence that characteristics of the power that colonized an area affected ethnic fragmentation. Hence, colonialism represented a significant shock to ethnic identities, and this shock was likely exogenous to the slave trades. Moreover, colonialism occurred predominately after the abolition of the slave trades. We may therefore examine the persistence of ethnic groups from the end of the 19th century to present to obtain variation caused by colonialism that is independent of the slave trades.

3 Leveraging variation in ethnic persistence to estimate the effect of the slave trades

Historical and economic evidence indicate that the long-run effects of the slave trades are likely to operate through cultural channels. Historically, Lovejoy (2011) contends that slave raids engendered mistrust and eroded social ties. Whatley and Gillezeau (2011) present quantitative evidence that the slave trades caused ethnic fragmentation, and

Nunn and Wantchekon (2011) demonstrate that members of ethnic groups from which enslaved people were exported are less trusting today. This suggests that variation in ethnic persistence may be leveraged to estimate the economic effect of the slave trades. In areas where the historical ethnic group persisted to the present, we would expect the cultural effects of the slave trades to remain. Traditions, stories, identity, local power structures, and patterns of interaction are all likely to transmit memories of the slave trades, the accompanying mistrust, and thin social networks. In contrast, we would expect the transmission of the cultural effects of the slave trades to be comparably weak in areas where the historical ethnic group did not persist because individuals born today have no memory of the events, there are fewer social structures to transmit the knowledge, and potentially serially correlated social features such as the density of social networks were not exposed to the shock of the slave trades. So both types of areas were exposed to the slave trades, but transmission of the effect into the present varies in areas where the historical ethnic group persisted versus not.

If the persistence of ethnic groups were orthogonal to productivity, we could thus estimate a lower bound of the effect of the slave trades on output by comparing areas from which enslaved people were exported and the historical ethnic group persisted to those that exported slaves but where the historical ethnic group did not persist. However, ethnic persistence is likely related to productivity. For instance, wealthy areas may have more stable ethnic groups due to social stability or less stable groups if globalization increases ethnogenesis and growth. In this case, a regression of productivity on persistence would produce a biased estimate of the effect of the slave trades on output. However, we may estimate what the productivity difference between persistent versus not areas would have been absent the slave trades by considering areas from which no enslaved people were exported. Hence, a difference-in-difference estimate may be used to estimate the effect of the slave trades.

3.1 Conceptual framework

Before presenting the data and empirical specification employed in this paper, I formalize the intuitive arguments made in the prior section into a simple conceptual framework that illustrates how the cultural effects of the slave trades on output may be estimated using a difference-in-difference approach.

Let Y_i denote output for observation i, ST_i indicate whether enslaved people were exported from observation i, EP_i be a binary variable indicating whether the dominant ethnic group i persisted, and SC_i denote social capital. Suppose that

$$Y_i = a + bST_i + cSC_i + e_i \tag{1}$$

and

$$SC_i = \tau + \theta ST_i + \kappa EP_i + \delta ST_i \times EP_i + \epsilon_i \tag{2}$$

θ captures differences in social capital between areas involved in the slave trade versus not and κ absorbs differences in areas that persisted versus not. Assuming that the long-run effects of the slave trades on social capital are smaller in non-persistent areas, δ gives a lower bound on the effect of the slave trades on social capital.

A lower bound on the cultural effect of the slave trades on output is thus given by $c \cdot \delta \equiv \gamma$ and b captures effects of the slave trades that operate through other channels.[1] The total effect of the slave trades on output is given by $c\dot{\delta} + b$. Assuming $b \leq 0$, that is that the slave trades did not increase output, γ gives a lower bound on the effect of the slave trades on productivity.

Set $\mathbf{Z} = (ST_i, EP_i, ST_i \times EP_i)'$. Suppose that the following assumptions are satisfied:

$$\mathbb{E}[e_i|\mathbf{Z}] = 0 \tag{3a}$$

$$\mathbb{E}[\epsilon_i|\mathbf{Z}] = 0 \tag{3b}$$

Then $c * \delta$ is identified through a difference-in-difference estimate of Y_i on ST_i and EP_i:

$$\begin{aligned}
\Delta_{DD} &= (\mathbb{E}[Y_i|ST_i = 1, EP_i = 1] - \mathbb{E}[Y_i|ST_i = 1, EP_i = 0]) - (\mathbb{E}[Y_i|ST_i = 0, EP_i = 1] - \mathbb{E}[Y_i|ST_i = 0, EP_i = 0]) \\
&= [(a + b + c(\tau + \theta + \kappa + \delta)) - (a + b + c(\tau + \theta))] - [(a + c(\tau + \kappa)) - (a + c(\tau))] \\
&= c * \delta \equiv \gamma
\end{aligned} \tag{4}$$

Hence, we may estimate the reduced-form effect of the slave trades on output, through cultural channels, using a difference-in-difference specification.

3.2 Data

The unit of observation for this paper is given by pre-colonial ethnic boundaries. As a result, geospatial data sources are used so that statistics can be calculated based on non-standard boundaries. This section describes the data source and processing of key variables. A detailed list of each data source is presented in Appendix Table 1.

[1] ST_i may be correlated with e_i, and so b cannot be estimated consistently using OLS.

3.2.1 Ethnic boundaries

Pre-colonial ethnic boundaries are from Murdock (1959). The data was digitized by Nunn (2008), and the version used in this paper is from Nunn and Wantchekon (2011). Murdock details the boundaries of ethno-linguistic groups in Africa in the late 19th century prior to the onset of European colonial rule. Hence, the data reflect ethnic boundaries at roughly the time the slave trades ended. The data contains 843 entries. Eight historically uninhabited regions were dropped, leaving 835 polygons that are the unit of observation for this study.

I also examine contemporary ethno-linguistic boundary data. I use data from Felix and Meur (2001) digitized by the Harvard Center for Geographic Analysis. Of the 835 ethno-linguistic groups identified in the data from Murdock (1959), 736 (88%) have a close match in the Felix and Meur (2001) data, defined as a token set ratio similarity score (a measure of textual similarity) above 0.8 between the Murdock name and either the primary or variant name in Felix and Meur, and 423 observations (51%) perfectly match. Hence, there is strong consistency between the two data sources, and differences between the data thus seem to be reflective of evolving ethnic boundaries and not differences in cartography.

I construct an indicator called "Persistent" that takes on a value of 1 if the Murdock ethnic group is still the dominant ethnic group in the geographic area in the Felix and Meur (2001) data. In particular, for each ethnic boundary in the pre-colonial data, I calculate the percent overlap with each of the contemporary ethnic boundaries. If the contemporary ethnic group with the highest percent overlap is the same as that which historically occupied the land, I code the variable to 1. A new ethnic group may occupy an area due to migration or ethnogenesis. Colonialism affected the dynamics by which ethnic groups came to occupy areas by partitioning and weakening certain ethnic groups. It is also believed to have increased the rate of ethnogenesis, for instance by introducing new power structures, religions, and languages (Kurien, 1994; Mahoney, 2003).

The variable "Persistent" records whether the most prevalent ethnic group changed. An alternative approach would be to measure persistence continuously as the share of its historical land an ethnic group still occupies. The binary measure of ethnic persistence is employed because variations in cartography may create measurement error in the continuous measure, but the maps appear sufficiently consistent to determine whether the dominant ethnic group changed. In addition, estimates are robust to a non-linear relationship between ethnic persistence and output. However, Appendix Table 3 demonstrates that results are similar using the continuous measure.

There are two potential issues with this measurement of ethnic persistence. The first is that variation in measured ethnic persistence may be driven by cartographic differences. This would cause attenuation bias and is thus unlikely to drive the relationship between the slave trades and productivity. The consistency of the two maps, particularly the ethnic groups reported, also suggests that cartographic differences are not the primary source of variation between the maps. Moreover, I show in Section 4 that ethnic persistence has intuitive relationships with variables such as malaria incidence and colonizer fixed effects. As a final robustness check, I present p-values using both asymptotic standard errors and randomization inference. Randomization inference simulates the type of persistence assignment one would expect to see if the variable were a product of cartographic differences and thus quantifies the likelihood that the measure of persistence does not reflect a real historic process. The second potential issue is that variation in ethnic persistence may be affected by the slave trades. This concern is addressed in Section 4.

3.2.2 Slave trade data

Data on the slave trades was initially compiled and digitized in Nunn (2008), and the version used in this paper was obtained from Nunn and Wantchekon (2011). Nunn and Wantchekon matched data on slave exports from the trans-Atlantic and Indian slave trades to the ethnic groups identified in Murdock (1959). Data from the trans-Saharan and Red Sea trades is not included because adequate ethnicity data is not available. The omission of trans-Saharan and Red Sea data is unlikely to affect results given that the trans-Atlantic trade was much larger than the other three trades combined. In addition, Nunn and Wantchekon (2011) show that the estimates used in this paper are consistent with historical sources describing from where slaves were taken.

Nunn and Wantchekon (2011) reports estimates of the number of enslaved people exported from each ethnic group. However, the difference-in-difference approach employed in this paper only leverages extensive margin variation to estimate the average effect of the slave trades. Hence, I construct an indicator called “Slave trade” that is coded to 1 if any enslaved people were exported from an ethnic group and is otherwise equal to zero. The difference-in-difference estimate is thus unbiased if exports of enslaved people are mismeasured at the intensive margin. There are records of slave exports from 299 of the 835 ethnic groups identified in Murdock (1959). About half (153) of these ethnicities were persistent. Of the 536 ethnic groups from which no slaves were sold, 203 persisted (Appendix Figure 1).

3.2.3 Long-run economic development

The primary outcome examined in this paper is long-run economic development. Incomes are measured using night-time light data because the unit of observation is non-standard, so official estimates of GDP are not available. In addition, luminosity data is consistently measured across geographies, so errors are orthogonal to the effectiveness of government institutions which may be correlated with the slave trades. Multiple studies such as Henderson et al. (2012) and Chen and Nordhaus (2011) demonstrate that luminosity data is an effective proxy for GDP.

I begin with monthly composites that have been processed to remove stray light, and then take the median pixel value across each satellite image from a year. Due to processing (e.g. moonlight corrections), areas with no stable light can sometimes have negative pixel values. These pixels are coded to zero, indicating there is no stable light, to avoid issues when logarithms are taken. I use night lights data from 2014-2018 to limit the influence of stray lights and fluctuations in GDP. For each year and each observation in Murdock (1959), the sum of night lights values contained in each polygon is calculated.

The nightlights and nightlights per capita data is next scaled to $\log(GDP)$ and $\log(GDP/capita)$ units. Since GDP data is not available for the ethnic boundaries, I calibrate a linear model using national level GDP data. The slope and intercept are allowed to vary from year to year to account for changing spacecrafts. The log of GDP is estimated from the log of 1 plus night lights readings. To estimate the log of GDP per capita, the night lights readings are normalized by population, and then the log is taken after adding 1. Appendix Table 2 and Appendix Figure 2 demonstrate that the luminosity data is an effective proxy for GDP, and the relationship between the variables is approximately linear. In the appendix, I show that results are similar using raw luminosity data instead of predicted GDP.

3.2.4 Control variables

Several regressions include controls for the number of diamond and gold deposits contained within the ethnic group's boundary, an indicator for whether the area includes known oil deposits, temperature suitability for two strains of malaria (P. vivax and P. falciparum), and annual rainfall. The source of each of these data sources is described in Appendix Table 1. The number of neighbors – in the pre-colonial boundaries – is also calculated from the Murdock (1959) data. In analysis examining factors affecting the persistence of ethnicities, indicators are created to capture whether each European colonial power had a presence in the area, and the number of powers that occupied an area.[2]

3.3 Empirical methodology

I estimate the average effect of the slave trades on long-run economic development using the difference-in-difference specification

$$Y_{it} = \alpha_t + \beta_0 ST_i + \beta_1 EP_i + \gamma ST_i \times EP_i + \lambda' X_i + \epsilon_{it} \tag{5}$$

where Y_{it} is the log of GDP (or GDP/capita) measured in pre-colonial ethnic boundary i in year t, α_t are year fixed-effects, ST_i indicates whether enslaved people were exported from the ethnic group, EP_i indicates ethnic persistence, and X_i is a vector of control variables. The coefficient γ is the difference-in-difference estimate of the long-run effect of slavery on economic development.

I estimate a panel regression with annual GDP data from 2014-2018 to reduce the influence of temporary lights or business cycles on GDP measurements. Since there is no variation in the independent variables across years, a more direct approach would be to average GDP measurements across time and estimate cross-sectional regressions. However, the satellites used to measure GDP vary, so GDP measurements cannot be easily aggregated. Estimating panel regressions with year fixed effects addresses this problem since the time effects capture changing satellites.

[2]This variable is designed to capture whether an area was partitioned by national boundaries, and so "Independent" is treated as a colonial power in these calculations.

The use of geospatial data may introduce spatial correlation between observations. Hence, I report spatial HAC standard errors that are robust to spatial correlation and serial correlation from repeated nightlight measurements in each entity (Conley, 1999, 2016). Details are reported in Appendix A. I also report p-values calculated using randomization inference as a robustness check.

γ estimates a lower bound on the effect of the slave trades on output under the parallel trends assumption that the difference in long-run productivity between areas where the pre-colonial ethnic group persisted versus not would not be larger in areas from which enslaved people were exported versus not had the slave trades not occurred. One limitation of this identification strategy is that the parallel trends assumption cannot be directly tested because historical productivity data is limited, so we cannot examine whether the effect of persistence was equal in areas that exported slaves versus not before the slave trades were established. However, robustness tests demonstrate that estimates are not sensitive to control variables or the use of predicted ethnic persistence in place of observed persistence.

The estimated parameter is a lower bound on the effect of the slave trades because it isolates a specific causal mechanism and the slave trades may still affect social capital in areas where the historical ethnic group did not persist. In addition, if the historical ethnic group was supplanted more recently in one area than another, we would expect the level of output to be lower today because the social capital effects of the slave trades inhibited growth for a longer period of time. Hence, γ is likely underestimating the effect of the slave trades, so it may be interpreted as a lower bound.

4 Results

4.1 Summary statistics

I begin by reporting summary statistics, along with t-tests for equality between areas from which enslaved people were exported versus not and areas where the ethnic group was persistent versus not, in Table 1. Column (1) reports the mean and standard deviation across the full sample, column (2) across observations from which $ST_i = 0$, and column (4) across observations for which $EP_i = 0$. Column (3) reports the difference in means between areas from which enslaved people were exported versus not. Column (5) is similar, but examines persistence.

Areas from which enslaved people were exported are more prone to malaria, had more neighbors in pre-colonial times, have higher annual rainfall, and have a higher contemporary population. We can reject the hypothesis that areas from which enslaved people were exported versus not would be comparable absent the slave trades: the p-value on an F-test of joint orthogonality is well below 0.01. Hence, simple cross-sectional comparisons are likely to return biased results, and the difference-in-difference approach is necessary.

We similarly see that areas in which ethnic groups persisted vary systematically from those where they did not. Persistent areas are, on average, less susceptible to malaria, have lower rainfall, and had more neighbors in pre-colonial times. These differences support the interpretation that the measure of persistence records true variation, not cartographic variation.

4.2 Cross-sectional comparisons of productivity

Table 2 presents OLS regressions examining the difference in long-run productivity in areas from which enslaved people were exported versus not. Without including any control variables, point estimates indicate that GDP/capita is over 36 log points lower in areas from which enslaved people were sold ($p < .01$). There is no statistically significant difference in GDP. Once including controls, the estimated effect of the slave trades on GDP is statistically 0, and GDP is 39 log points higher in areas from which slaves were captured ($p < .01$). The dramatic change in estimates when controls are added reflects the importance of systematic differences between areas where the slave trades operated versus not. Hence, difference-in-difference estimation is necessary to isolate the effect of the slave trades from regional heterogeneity.

4.3 The effect of the slave trades on long-run development

Difference-in-difference estimates indicate that the slave trades had an economically large and statistically significant negative effect on long-run economic development in Africa. Table 3 presents estimates of the lower bound of the effect on the log of GDP/capita (columns (1) and (3)) and GDP (columns (2) and (4)). The best estimate is given in column (3). The point estimate indicates that the slave trades reduced GDP/capita by at least 33 log points ($p < .01$), and the 95% confidence interval ranges from a 17 to 50 log point reduction in GDP/capita. Estimates are robust to the inclusion of control variables. The results also indicate that the slave trades reduced GDP, but the result in column (4) is only marginally significant. Results remain statistically significant if we consider randomization inference p-values, reported in brackets, instead of asymptotic standard errors. Appendix Table 4 demonstrates that results are similar if we use raw luminosity data.

These results are similar to those reported in Nunn (2008), although the point estimates in this paper are somewhat smaller, consistent with the lower bound interpretation. OLS estimates in Nunn indicate that a one unit increase in $log(exports/area)$ is associated with a decrease in $log(GDP/capita)$ of $0.076 - 0.128$. The mean of $\log(exports/area)$ reported in Nunn (2008) is 3.26. Hence, Nunn's OLS estimates suggest that, on average, per capita income is $25 - 42$ log points lower in areas from which enslaved people were exported. Instrumental variable estimates indicate that the causal effect of the slave trades was potentially larger: point estimates of the coefficient on $\log(exports/area)$ range from -0.201 to -0.286.

In Appendix Table 5, I report difference-in-difference estimates using outcome data winsorized at the 5th and 95th percentiles. The results are qualitatively similar, although the estimates are about $1/3$ smaller in magnitude. One may thus conclude that the reported effect of the slave trade is not entirely attributable to outlying growth in a small number of areas from which no enslaved people were exported (e.g. South Africa).

4.4 Predicting persistence

Perhaps the most serious threat to identification is an endogenous relationship between ethnic persistence and the slave trades. There are two potential mechanisms by which the relationship could be endogenous. The first is by selection. The type of ethnic groups that persist may be more or less common in areas from which enslaved people were exported. This does not threaten identification since the slave trade fixed-effect absorbs these differences.

The second mechanism by which an endogenous relationship could exist is if the slave trades had a causal effect on ethnic persistence. Suppose that there are some ethnic groups that always persist ("always persistent"), some that never persist ("never persistent"), and some that persist if and only if they are exposed to the slave trades ("sometimes persistent"). Then the variable "Persistent" captures the difference in productivity between always and sometimes persistent groups versus never persistent groups in areas from which enslaved people were exported. But it measures the difference in output between always persistent groups versus sometimes persistent and never persistent groups in areas from which no enslaved people were exported. Hence, the difference-in-difference estimator compares a different set of ethnic groups between areas from which enslaved people were exported versus not.

This may be understood as error-in-variables bias using the conceptual framework presented in section 3.1. We may think of EP_i as denoting which ethnic groups would have persisted had they never been exposed to the slave trades. If exposure to the slave trades changed the persistence outcome of some ethnic groups, then we observe $EP_i^* = EP_i + \eta_i$ where $\text{Cov}(\eta_i, ST_i \times EP_i) \neq 0$. If $\text{Cov}(\eta_i, ST_i \times EP_i) \cdot \text{Cov}(\eta_i, Y_i) < 0$, the difference-in-difference estimate is overstating the effect of the slave trades on output and is not a valid lower bound.

The data used to calculate ethnic persistence was selected to limit the probability that the slave trades affected persistence. Pre-colonial ethnic boundary data was collected by Murdock (1959) at the end of the 19th century. Hence, this paper is using variation in persistence from after the slave trades concluded, so persistence is less likely determined by the slave trades. However, it is still possible that the slave trades affected ethnic persistence. For instance, areas from which enslaved people were exported may be more prone to cultural turnover due to the cultural pressures of slavery, or less prone to cultural evolution if areas become resistant to engaging with other groups. Hence, I turn to the data to examine the relationship between the slave trades and ethnic persistence.

Table 4 reports regressions of ethnic persistence on slave trade variables. Columns (1) and (2) use the an indicator for any exports from an area. The relationship is positive and statistically significant: point estimates indicate that ethnic groups from which enslaved people were exported are $13.3 - 16.2$ percentage points more likely to persist, relative to a base of 37.8 percentage points. But this result does not indicate whether this relationship is due to the fact that areas from which enslaved people were exported differ from those where they were not or is a consequence of the slave trades.

In fact, we see that the effect is no longer present if we consider variation at the intensive margin. In columns (3) and (4), the number of enslaved people exported from each ethnicity, normalized by land area, is used in the regression instead of an indicator, and the coefficients are statistically zero. In columns (5) and (6), the sample is restricted to ethnic groups from which enslaved people were exported to isolate the intensive margin effect and there is again no relationship. If the greater rate of persistence in areas involved in the slave trades were a consequence of the slave trades, as opposed to selection, we would expect persistence to be related to intensive margin variation since this captures the intensity of the slave trade in the area. As such, the results suggest that ethnic persistence is related to the slave trade indicator due only to selection effects. However, attenuation bias could also drive the results in columns (3) - (6), so this test does not completely rule out a causal relationship between the slave trades and persistence.

4.5 Difference-in-difference estimation using predicted persistence

To further test for bias due to the slave trades affecting persistence, I estimate the model using a proxy for ethnic persistence. The proxy, $\hat{EP}$, is constructed using a random forest classifier. I randomly split the data into 5 folds. For each fold, I train a random forest to predict persistence using the observations for which $ST_i = 0$ among the other four folds. The trained model is then used to predict persistence for all observations in the fold. Hence, $\hat{EP}_i$ is predicted using a model that was not trained using data from observation i, and the models were not trained using data from areas in which the slave trade operated. To further ensure that $\hat{EP}_i$ is not influenced by the slave trades, I only use variables that were implausibly affected by the slave trades: indicators for diamond and oil deposits, the number of gold deposits, temperature suitability for malaria, rainfall, land surface feature classification, latitude, longitude, colonial power fixed effects, and the number of colonizers that occupied the area.

Intuitively, the machine learning algorithm partitions observations into high versus low persistence groups. Since persistence is predicted using variables unaffected by the slave trades, and the models were trained on the subset of observations from which no enslaved people were exported, the proxy is not likely affected by the slave trades. Hence, $\hat{EP}_i = EP_i + \xi_i$ where $\text{Cov}(\xi_i, ST_i \times EP_i) = 0$, and so imperfect prediction is only likely to introduce attenuation bias which does not threaten the lower bound interpretation of the coefficient. So long as the parallel trends assumption holds for the groupings constructed by the random forests, a difference-in-difference estimate using the proxy variable will return a valid lower bound on the effect of the slave trades.

Table 5 presents results using the proxy variable. The table reports p-values calculated using a block bootstrapping procedure that aims to capture uncertainty from both the estimation of the proxy and the difference-in-difference estimation using the proxy variable. I begin by selecting a block bootstrapped sample, train the random forests on this sample, estimate $\hat{EP}_i$, and then estimate each of the regressions reported in Table 5.

The estimated effect of the slave trade on long-run economic development remains negative and statistically significant in columns (1) and (2), supporting the validity of the initial results. Point estimates indicate that the slave trades reduced per capita GDP by over 48 log point ($p = 0.033$) and GDP by over 69 log points ($p = 0.019$). However, the results are somewhat sensitive to control variables, with estimates dropping to 31 and 48 log points once they are added. The coefficient on GDP remains statistically significant ($p = 0.012$) but not for GDP/capita ($p = 0.119$). This is potentially driven by overlap between the control variables and the variables used to predict persistence, but could indicate that $\hat{EP}_i$ is an invalid proxy. Overall, this test provides further evidence that a causal relationship between ethnic persistence and the slave trades is not likely driving the results presented in the paper.

5 Conclusion

Using variation in the persistence of ethnic groups from pre-colonial to contemporary times, I find that the African slave trades had a large and statistically significant negative effect on long-run economic development. I estimate that the slave trade reduced long-run per capita GDP by about 33 log points and can reject effect sizes below 17 log points with 95% confidence. The estimates are robust to the inclusion of a rich set of controls, and tests indicate that endogeneity in the relationship between ethnic group persistence and the slave trades is not likely a source of bias in the estimates. These results confirm the findings of Nunn (2008) that the long-run effect of the African slave trades on the areas from which enslaved people were exported is negative and economically meaningful. The magnitude of the effect of the slave trades is striking. This suggests that slavery remains an important contributor to poverty and inequality in parts of Africa from which enslaved people were exported over 100 years after the abolition of international slave trades.

This study also provides insight into the mechanisms through which the slave trades affect present day productivity. The identification strategy leverages variation in ethnic persistence, and one can thus attribute the estimated effect entirely to cultural channels of transmission. The results indicate that a reduction in social capital is a significant avenue through which the slave trades hinder economic development. The findings demonstrate that shocks to social capital can drive significant income differences over long time horizons.

These findings contribute to a growing body of research indicating that mistrust, transmitted through ethnic groups, can have important effects on economic outcomes. For instance, Lowes and Montero (2021) demonstrate that the historical exposure of one's ethnic group to colonial medical campaigns lowers their likelihood of being vaccinated and their trust in medicine today. The methodology employed in this paper – estimating ethnic persistence from the evolution of maps and then leveraging ethnic persistence to disentangle cultural from geographic effects – is to my knowledge novel. Maps documenting the historical distribution of ethnic groups are quite common, and so this approach could be utilized to isolate the cultural effects of other historical events or policies on contemporary outcomes.

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Tables

Table 1: Summary statistics

	(1) Full sample	(2) ST = 0	(3) ST: 1 - 0	(4) Persistent = 0	(5) Persistent: 1 - 0
Diamond deposits	0.516	0.397	0.332*	0.468	0.114
	[2.448]	[2.128]	(0.192)	[2.302]	(0.175)
Oil	0.105	0.108	-0.008	0.088	0.042*
	[0.307]	[0.311]	(0.022)	[0.283]	(0.022)
Gold deposits	0.631	0.793	-0.452	0.835	-0.478
	[4.886]	[5.967]	(0.275)	[6.349]	(0.298)
Malaria (Pf)	0.440	0.409	0.085***	0.457	-0.040***
	[0.174]	[0.175]	(0.012)	[0.173]	(0.012)
Malaria (Pv)	0.588	0.547	0.113***	0.607	-0.045***
	[0.205]	[0.209]	(0.014)	[0.201]	(0.014)
Annual rainfall (mm/day)	2.925	2.539	1.079***	3.048	-0.287***
	[1.587]	[1.546]	(0.106)	[1.575]	(0.111)
Neighbors	5.468	5.278	0.531***	5.194	0.643***
	[2.503]	[2.297]	(0.190)	[2.387]	(0.176)
Colonizers (number)	1.388	1.364	0.068	1.370	0.043
	[0.571]	[0.547]	(0.042)	[0.563]	(0.040)
Population (2014, mil)	1.427	1.182	0.657***	1.139	0.628**
	[3.976]	[4.306]	(0.252)	[2.452]	(0.286)
Belgium (colonized by)	0.132	0.125	0.019	0.129	0.005
	[0.338]	[0.331]	(0.025)	[0.336]	(0.024)
Britain	0.491	0.519	-0.077**	0.520	-0.068*
	[0.500]	[0.500]	(0.036)	[0.500]	(0.035)
France	0.321	0.319	0.005	0.282	0.092***
	[0.467]	[0.466]	(0.034)	[0.450]	(0.033)
Germany	0.228	0.188	0.109***	0.246	-0.044
	[0.419]	[0.391]	(0.031)	[0.431]	(0.029)
Italy	0.038	0.058	-0.054***	0.038	0.002
	[0.192]	[0.233]	(0.011)	[0.190]	(0.013)
Portugal	0.078	0.037	0.113***	0.061	0.041**
	[0.268]	[0.190]	(0.022)	[0.239]	(0.019)
Spain	0.022	0.030	-0.023***	0.015	0.016
	[0.145]	[0.170]	(0.009)	[0.120]	(0.011)
Observations	835	536	835	479	835
p-val joint orthogonality			0.000		0.000

Standard deviations in brackets. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (1) reports the mean and standard deviation of the indicated variable across the full sample. Column (2) reports the mean and standard deviation among the restricted sample of ethnic groups that did not participate in international slave trades. Column (4) is the similar but the sample is instead restricted to non-persistent ethnic groups. Column (3) reports the difference in mean of each variable among groups that did participate in the slave trades relative to those that did not, and standard errors of this pairwise t-test. Column (5) reports similar results, but based on ethnicity persistence instead of slave trade participation.

Table 2: Correlations between output and the slave trade

	(1) $\log(GDP/capita)$	(2) $\log(GDP)$	(3) $\log(GDP/capita)$	(4) $\log(GDP)$
Slave trade	-0.364***	0.108	-0.063	0.390***
	(0.058)	(0.081)	(0.063)	(0.071)
Diamond deposits			0.046***	0.042***
			(0.010)	(0.012)
Oil			0.760***	1.207***
			(0.130)	(0.120)
Gold deposits			0.006*	0.033***
			(0.003)	(0.006)
Malaria (Pf)			1.680*	0.775
			(0.978)	(1.100)
Malaria (Pv)			-1.558*	-1.684*
			(0.908)	(0.960)
Annual rainfall (mm/day)			-0.248***	-0.201***
			(0.032)	(0.028)
Neighbors			-0.015	0.129***
			(0.011)	(0.011)
Time FE	Yes	Yes	Yes	Yes
Observations	4,175	4,175	4,175	4,175
R^2 within	0.025	0.002	0.239	0.420
Entities	835	835	835	835
Time periods	5	5	5	5

Spatial HAC standard errors in parenthesis (Conley, 1999, 2016). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable in columns (1) and (3) is the log of GDP/capita estimated using the log of night lights per capita measured using VIIRS luminosity data. In columns (2) and (4), the log of GDP is the dependent variable and is estimated using the log of night lights. All variables are calculated over the historical ethnic boundaries presented in Murdock (1959). The variable “Slave trade” is an indicator recording whether the ethnic group historically participated in the slave trade.

Table 3: Difference-in-difference estimate of the effect of the slave trade on output

	(1) $\log(GDP/capita)$	(2) $\log(GDP)$	(3) $\log(GDP/capita)$	(4) $\log(GDP)$
Slave trade	-0.255***	0.097	0.054	0.424***
	(0.074)	(0.105)	(0.086)	(0.088)
	[0.008]	[0.352]	[0.508]	[0.000]
Persistent ethnicity	0.467***	0.653***	0.337***	0.426***
	(0.103)	(0.106)	(0.078)	(0.067)
	[0.000]	[0.000]	[0.000]	[0.000]
Slave trade x Persistent	-0.334***	-0.149	-0.329***	-0.202*
	(0.122)	(0.148)	(0.115)	(0.106)
	[0.021]	[0.370]	[0.007]	[0.101]
Diamond deposits			0.046***	0.042***
			(0.011)	(0.012)
Oil			0.726***	1.167***
			(0.128)	(0.113)
Gold deposits			0.008**	0.035***
			(0.003)	(0.006)
Malaria (Pf)			1.879*	1.116
			(0.983)	(1.114)
Malaria (Pv)			-1.678*	-1.894**
			(0.906)	(0.965)
Annual rainfall (mm/day)			-0.242***	-0.190***
			(0.031)	(0.028)
Neighbors			-0.018	0.122***
			(0.012)	(0.011)
Time FE	Yes	Yes	Yes	Yes
Observations	4,175	4,175	4,175	4,175
R^2 within	0.054	0.064	0.253	0.442
Entities	835	835	835	835
Time periods	5	5	5	5

Spatial HAC standard errors in parenthesis (Conley, 1999, 2016). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Randomization inference p-values in brackets.

The dependent variable in columns (1) and (3) is the log of GDP/capita estimated using the log of night lights per capita measured using VIIRS luminosity data. In columns (2) and (4), the log of GDP is the dependent variable and is estimated using the log of night lights. All variables are calculated over the historical ethnic boundaries presented in Murdock (1959). The variable "Slave trade" is an indicator recording whether the ethnic group historically participated in the slave trade. The variable "Persistent" indicates whether the ethnic group that historically occupied the area is still the dominant ethnicity in the area. The coefficient on the interaction between "Slave trade" and "Persistent" is the difference-in-difference estimate of the effect of the slave trade on output.

Table 4: The relationship between ethnic group persistence and participation in the slave trade

	Full sample				Participants in the slave trade	
	(1) Indicator	(2) Indicator	(3) # Enslaved	(4) # Enslaved	(5) # Enslaved	(6) # Enslaved
Slave trade	0.133***	0.162***				
	(0.036)	(0.039)				
Slaves/area			22.039	61.157	-22.683	-14.965
			(52.543)	(58.378)	(53.569)	(54.988)
Diamond deposits		0.000		0.001		0.003
		(0.006)		(0.006)		(0.009)
Oil		0.062		0.066		0.067
		(0.056)		(0.058)		(0.090)
Gold deposits		-0.006***		-0.006***		0.007
		(0.002)		(0.002)		(0.021)
Malaria (Pf)		-1.376*		-1.728**		-0.800
		(0.713)		(0.729)		(1.174)
Malaria (Pv)		0.974		1.305**		0.365
		(0.643)		(0.656)		(1.077)
Annual rainfall (mm/day)		-0.827**		-0.514		-0.783
		(0.374)		(0.384)		(0.616)
Neighbors		0.022***		0.026***		0.020*
		(0.007)		(0.007)		(0.011)
Colonizers (number)		0.035		0.017		0.100
		(0.070)		(0.069)		(0.145)
Belgium (colonized by)		0.000		-0.024		-0.144
		(0.083)		(0.082)		(0.153)
Britain		-0.059		-0.053		-0.008
		(0.073)		(0.073)		(0.148)
France		0.045		0.072		-0.004
		(0.077)		(0.075)		(0.154)
Germany		-0.098		-0.087		-0.043
		(0.073)		(0.073)		(0.147)
Italy		-0.061		-0.054		-0.819***
		(0.121)		(0.121)		(0.300)
Portugal		0.029		0.086		0.037
		(0.092)		(0.091)		(0.156)
Spain		0.078		0.055		-0.593***
		(0.122)		(0.122)		(0.227)
Observations	835	835	835	835	299	299
Adjusted R^2	0.015	0.060	-0.001	0.041	-0.003	0.040

Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable in each regression is an indicator that takes on a value of 1 if the dominant ethnic group in an area is the same ethnicity that historically occupied the land. In columns (1) and (2), the dependent variable is regressed on an indicator for whether members of the historical ethnic group were sold into the slave trade. In columns (3) - (6) the independent variable is the total number of slaves from the ethnic group sold into the trans-Atlantic and Indian slave trades normalized by land area. Columns (1) - (4) examine the entire sample. Columns (5) - (6) are restricted to ethnicities from which a strictly positive number of people were sold into the slave trade.

Table 5: Difference-in-difference estimate of the effect of the slave trade on output
Predicted persistence

	(1) $\log(GDP/capita)$	(2) $\log(GDP)$	(3) $\log(GDP/capita)$	(4) $\log(GDP)$
Slave trade	-0.152	0.374**	0.074	0.566***
	[0.177]	[0.011]	[0.512]	[0.000]
Predicted persistence	0.742***	0.719***	0.591***	0.515***
	[0.000]	[0.000]	[0.000]	[0.000]
Slave trade x Predicted persistence	-0.485**	-0.691**	-0.313	-0.480**
	[0.033]	[0.010]	[0.119]	[0.012]
Diamond deposits			0.043**	0.042**
			[0.037]	[0.039]
Oil			0.633***	1.083***
			[0.001]	[0.000]
Gold deposits			0.010	0.036**
			[0.118]	[0.019]
Malaria (Pf)			2.623*	1.510
			[0.073]	[0.327]
Malaria (Pv)			-2.283*	-2.257*
			[0.095]	[0.100]
Annual rainfall (mm/day)			-0.235***	-0.190***
			[0.000]	[0.000]
Neighbors			-0.012	0.132***
			[0.537]	[0.000]
Time FE	Yes	Yes	Yes	Yes
Observations	4,175	4,175	4,175	4,175

Block bootstrapped p-values in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable in columns (1) and (3) is the log of GDP/capita estimated using the log of night lights per capita measured using VIIRS luminosity data. In columns (2) and (4), the log of GDP is the dependent variable and is estimated using the log of night lights. All variables are calculated over the historical ethnic boundaries presented in Murdock (1959). The variable "Slave trade" is an indicator recording whether the ethnic group historically participated in the slave trade. The variable "Predicted persistence" is a random forest prediction of whether the ethnic group that historically occupied the area is still the dominant ethnicity in the area. The random forest model was trained using the subset of ethnic groups that did not participate in the slave trade. Persistence was predicted using the number of diamond deposits, an indicator for oil deposits, temperature suitability for malaria transmission, the number of neighbors, area, the number of powers that colonized the area, and indicators for whether each colonial power colonized the area in question. The random forest produced a precision score (true positives over true positives plus false positives) of 0.56 relative to a baseline value of 0.39 from random assignment. The coefficient on the interaction between "Slave trade" and "Predicted persistence" is the difference-in-difference estimate of the effect of the slave trade on output.

6 Appendix A: Standard error calculation

Productivity likely exhibits limited spatial dependence since historical ethnic groups often fall within the same national boundaries and unobserved variables that affect output may vary geographically. OLS produces consistent coefficient estimates in the presence of limited spatial dependence, but standard errors must account for the lack of independence. Hence, this paper report spatial HAC standard errors that are robust to spatial correlation across ethnic boundaries and serial correlation from repeated nightlight measurements in each entity (Conley, 1999, 2016). In particular, let S_{it} denote an observation and define

$$K_N\left(S_{it}, S_{jk}\right) = \begin{cases} 0 & i \neq j \wedge t \neq k \\ 1 & i = j \wedge t \neq k \\ 0 & d(S_{it}, S_{jk}) > 1,500 \wedge t = k \\ 1 & d(S_{it}, S_{jk}) \leq 1,500 \wedge t = k \end{cases} \tag{6}$$

where $d(S_{it}, S_{jk})$ denotes the distance, in kilometers, between the centroids of the two observations. Under the assumption that observations further than $1,500$ km from each other are not spatially correlated, Conley (1999) and Conley (2016) show that the asymptotic distribution of $\hat{\beta}$, where β is the population vector of regression coefficients and $\mathbf{x_{it}}$ is a vector of covariates, is given by

$$\hat{\beta} \overset{A}{\sim} \mathcal{N}\left(\beta, \frac{1}{TN}\left(\frac{1}{TN}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{x_{it}}\mathbf{x_{it}}'\right)^{-1}\hat{V}_N\left(\frac{1}{TN}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{x_{it}}\mathbf{x_{it}}'\right)^{-1}\right) \tag{7}$$

I estimate

$$\hat{V}_N = \frac{1}{TN}\sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{j=1}^{N}\sum_{k=1}^{T} K_N\left(S_{it}, S_{jk}\right)\hat{u_{it}}\hat{u_{jk}}\mathbf{x_{it}}\mathbf{x_{jk}}' \tag{8}$$

where $\hat{u_{it}}$ are the OLS residuals. Note that these standard errors allow for arbitrary serial correlation within entities across time, and if we used a distance cutoff near 0 km instead of $1,500$ km we would be estimating standard errors clustered by historical ethnic group.

Appendix B: Figures

Appendix Figure 1: Pre-colonial ethnic boundaries:
Slave trade participation and persistence

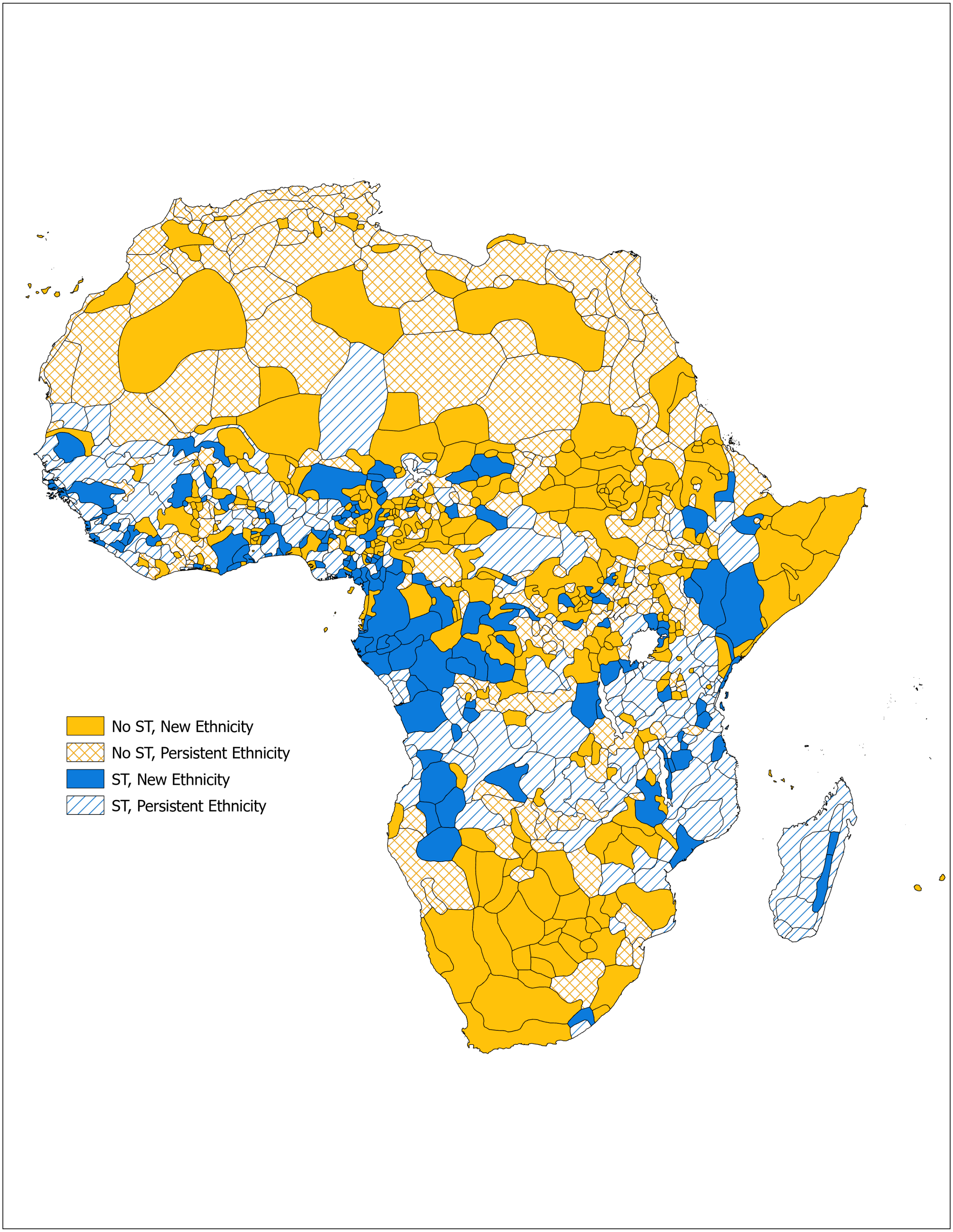
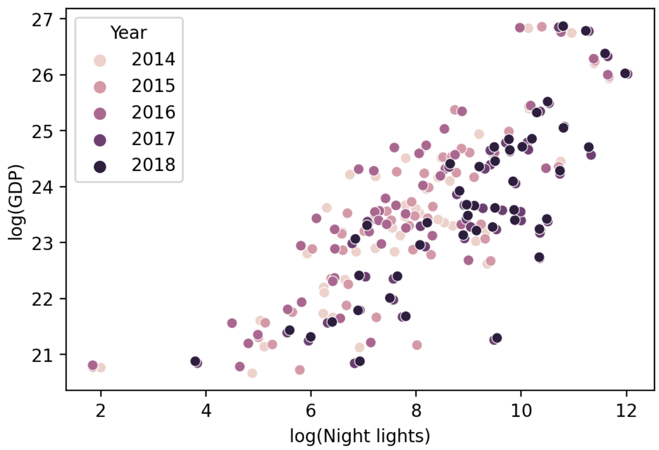


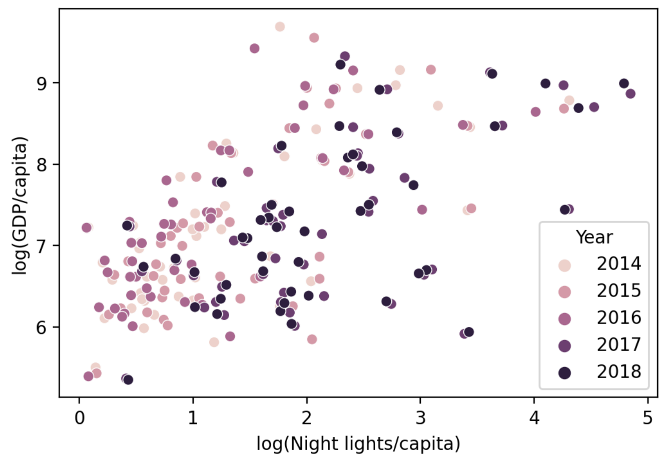
Figure Appendix Figure 1 plots pre-colonial ethnic boundaries as presented in Murdock (1959). The territories are colored green if no members of the ethnicity were documented as being sold into the trans-Atlantic or Indian slave trades and red if at least one member of the ethnic group was sold into slavery. The polygons are solid if the pre-colonial ethnic group is not the current dominant ethnic group in the area. They are hashed if the pre-colonial ethnic group is the dominant contemporary ethnic group.

Appendix Figure 2: African national output versus night lights

(a) A. $\log(GDP)$ vs $\log(NL)$



(b) B. $\log(GDP/capita)$ vs $\log(NL/capita)$



Panel A presents a scatter plot of the natural log of GDP vs the natural log of luminosity readings for 48 countries in Africa using annual observations from 2014-2018. Panel B plots (the log of) GDP/capita and night lights per capita. Night light data is from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB). Night lights values were constructed using the Google Earth Engine beginning with stray light corrected monthly composites. Values were then clipped below at 0 and the sum of all luminosity values observed in the boundaries of a country was calculated for each composite, then the median was taken across each image obtained in a year.

Appendix Figure 3: ROC plots of persistence model performance

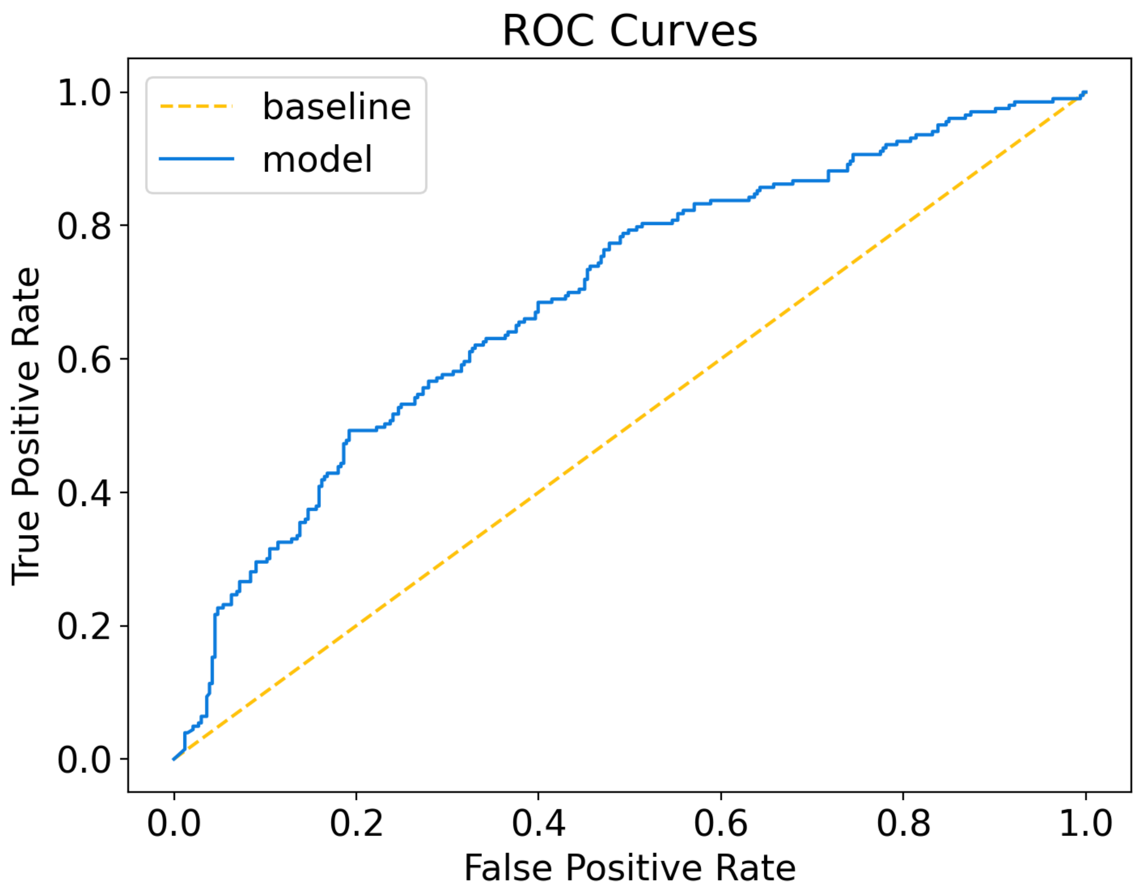


Figure Appendix Figure 3 plots ROC curves from the random forest classifier used to predict ethnic group persistence. The random forest model was trained using the subset of ethnic groups that did not participate in the slave trade. Persistence was predicted using the number of diamond deposits, an indicator for oil deposits, temperature suitability for malaria transmission, rainfall, land surface classification, latitude, longitude, the number of powers that colonized the area, and indicators for whether each colonial power colonized the area in question. The ROC curve plots the true vs false positive rates with different cutoff probabilities. The performance of the model is plotted against a baseline of random assignment which is the 45 degree line.

Appendix C: Tables

Appendix Table 1: Data sources

Description	Source	Processing
Pre-colonial ethnic boundaries	The pre-colonial ethnic boundaries were originally constructed by Murdock (1959). The version used in this paper was downloaded from the replication data for Nunn and Wantchekon (2011).	Data from areas that were unpopulated in pre-colonial times are omitted from analysis.
Contemporary ethnic boundaries	Data on contemporary ethnic boundaries is from Felix and Meur (2001). The data was digitized by Harvard University's AfricaMap project.	The Python package "Geopandas" was used to identify persistent ethnic groups as discussed in Section 3.2.
Slave trade data	Data on the trans-Atlantic and Indian slave trades was originally compiled on Nunn (2008). The data used in this paper was downloaded from the replication files for Nunn and Wantchekon (2011).	An indicator variable "Slave trade" is coded to 1 if at least one slave was exported from an ethnic group in the raw data. The variable "Total slaves" records the sum of all enslaved people exported from an ethnic group across all years and trades.
Nighttime lights data	VIIRS Stray Light Corrected Nighttime Day/Night Band Composites Version 1 accessed from the Google Earth Engine	Luminosity data was processed on the Google Earth Engine. The median value was calculated for each pixel across all images from a year for the years 2014-2018. Pixels with a value below 0 were recoded to 0, then the sum of all pixels contained in each polygon from the Murdock (1959) was calculated.
Population data	LandScan Global rasters from Oak Ridge National Laboratory	The total number of people contained in each polygon from Murdock (1959) was calculated by summing each pixel contained in each polygon. Calculations were performed in Python using the "rasterstats" package.
Petroleum	Lujala et al. (2007)	An indicator was constructed in Python using the package "Geopandas" that is coded to 1 if an oil reserve intersects with the boundaries of a polygon from Murdock (1959).
Diamonds	Gilmore et al. (2005)	The number of diamond deposits contained in each polygon from Murdock (1959) was calculated in Python using the "Geopandas" package.
Gold	United States Geological Survey Mineral Resource Data System	The number of gold deposits contained in each polygon was calculated using Python.
Malaria	The temperature suitability indices for P. falciparum and P. vivax transmission were downloaded from the Malaria Atlas Project	The average index value was calculated separately for each index across each Murdock (1959) observation using Python.
Rainfall	GPM: Global Precipitation Measurement (GPM) v6	Average rainfall value was calculated across each year and each polygon using the Google Earth Engine.
GIS data on colonizers of Africa	The data was uploaded by Bucknell University on ArcGIS and is available under the name "Colonial Africa" for download.	Python was used to determine which colonial powers occupied each polygon from Murdock (1959). An indicator was constructed to indicate if each power occupied the area, and the number of colonizers was recorded.
National GDP/capita and population data	World Development Indicators	Used for evaluating night lights data and estimating GDP from luminosity. GDP was calculated by multiplying GDP by population.
Africa Land Surface Forms	USGS	The data classifies each pixel into a land surface form (e.g. flat/smooth plain, low mountains) based on elevation data. I first reduce the resolution of the image in ArcGIS pro using a majority aggregation approach, then calculated the majority surface form type for each polygon.

Appendix Table 2: Predicting GDP with luminosity data

	(1) log(GDP)	(2) log($GDP/capita$)
Constant	18.291***	6.292***
	(0.564)	(0.144)
Night lights	0.666***	0.719***
	(0.073)	(0.102)
2015	-0.039	-0.005
	(0.189)	(0.065)
NL x 2015	-0.007	-0.040
	(0.022)	(0.045)
2016	0.147	0.095**
	(0.124)	(0.041)
NL x 2016	0.012	0.049
	(0.016)	(0.040)
2017	-0.896***	-0.156
	(0.316)	(0.158)
NL x 2017	0.018	-0.191**
	(0.037)	(0.087)
2018	-0.935***	-0.142
	(0.326)	(0.170)
NL x 2018	0.027	-0.185*
	(0.038)	(0.094)
Observations	237	237
Adj R^2	0.660	0.396
Entities	48	48
Time periods	5	5

Clustered standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (1) reports the results of a regression of the natural log of GDP on the log of the sum of night lights values recorded in the boundary of each country. Column (2) reports the results of a regression of the log of GDP/capita on the log of night lights per capita. Night light data is from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB). Night lights values were constructed using the Google Earth Engine beginning with stray light corrected monthly composites. Values were then clipped below at 0 and the sum of all luminosity values observed in the boundaries of a country was calculated for each composite, then the median was taken across each image obtained in a year. The log VIIRS value used in column 1 is defined as the log of 1 plus the raw luminosity calculation, and in column 2 the log of 1 plus 10,000 times the raw nightlights per capita value is considered.

Appendix Table 3: Difference-in-difference estimate of the effect of the slave trade on output
Continuous persistence

	(1) $\log(GDP/capita)$	(2) $\log(GDP)$	(3) $\log(GDP/capita)$	(4) $\log(GDP)$
Slave trade	-0.202**	0.146	0.083	0.453***
	(0.082)	(0.116)	(0.095)	(0.096)
	[0.042]	[0.185]	[0.352]	[0.000]
Persistence	0.838***	1.098***	0.530***	0.689***
	(0.178)	(0.178)	(0.139)	(0.125)
Slave trade x Persistence	-0.650***	-0.350	-0.569***	-0.385**
	(0.213)	(0.263)	(0.203)	(0.192)
	[0.011]	[0.203]	[0.006]	[0.052]
Diamond deposits			0.046***	0.041***
			(0.011)	(0.011)
Oil			0.706***	1.139***
			(0.128)	(0.110)
Gold deposits			0.008**	0.036***
			(0.003)	(0.006)
Malaria (Pf)			1.894*	1.187
			(0.981)	(1.106)
Malaria (Pv)			-1.676*	-1.930**
			(0.902)	(0.956)
Annual rainfall (mm/day)			-0.242***	-0.189***
			(0.031)	(0.028)
Neighbors			-0.015	0.128***
			(0.011)	(0.011)
Time FE	Yes	Yes	Yes	Yes
Observations	4,175	4,175	4,175	4,175
R^2 within	0.060	0.066	0.252	0.441
Entities	835	835	835	835
Time periods	5	5	5	5

Spatial HAC standard errors in parenthesis (Conley, 1999, 2016). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Randomization inference p-values in brackets.

The dependent variable in columns (1) and (3) is the log of GDP/capita estimated using the log of night lights per capita measured using VIIRS luminosity data. In columns (2) and (4), the log of GDP is the dependent variable and is estimated using the log of night lights. All variables are calculated over the historical ethnic boundaries presented in Murdock (1959). The variable “Slave trade” is an indicator recording whether the ethnic group historically participated in the slave trade. The variable “Persistence” measures the share of its historical boundaries each ethnic group now occupies.

Appendix Table 4: Difference-in-difference estimate of the effect of the slave trade on luminosity

	(1) log($NL/capita$)	(2) log(Night lights)	(3) log($NL/capita$)	(4) log(Night lights)
Slave trade	-0.415***	0.144	0.051	0.629***
	(0.117)	(0.156)	(0.132)	(0.131)
	[0.005]	[0.351]	[0.687]	[0.000]
Persistent ethnicity	0.703***	0.968***	0.507***	0.631***
	(0.152)	(0.157)	(0.118)	(0.100)
	[0.000]	[0.000]	[0.000]	[0.000]
Slave trade x Persistent	-0.505***	-0.221	-0.500***	-0.300*
	(0.187)	(0.219)	(0.176)	(0.158)
	[0.023]	[0.367]	[0.009]	[0.100]
Diamond deposits			0.070***	0.063***
			(0.016)	(0.017)
Oil			1.065***	1.732***
			(0.185)	(0.169)
Gold deposits			0.010*	0.053***
			(0.005)	(0.008)
Malaria (Pf)			2.560*	1.706
			(1.498)	(1.655)
Malaria (Pv)			-2.234	-2.851**
			(1.387)	(1.434)
Annual rainfall (mm/day)			-0.376***	-0.282***
			(0.046)	(0.042)
Neighbors			-0.026	0.181***
			(0.018)	(0.016)
Time FE	Yes	Yes	Yes	Yes
Observations	4,175	4,175	4,175	4,175
R^2 within	0.057	0.063	0.255	0.441
Entities	835	835	835	835
Time periods	5	5	5	5

Spatial HAC standard errors in parenthesis (Conley, 1999, 2016). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Randomization inference p-values in brackets.

The dependent variable in columns (1) and (3) is the log of night lights per capita measured using VIIRS luminosity data. The dependent variable is columns (2) and (4) is the log of night lights. All variables are calculated over the historical ethnic boundaries presented in Murdock (1959). The variable "Slave trade" is an indicator recording whether the ethnic group historically participated in the slave trade. The variable "Persistent" indicates whether the ethnic group that historically occupied the area is still the dominant ethnicity in the area. The coefficient on the interaction between "Slave trade" and "Persistent" is the difference-in-difference estimate of the effect of the slave trade on luminosity.

Appendix Table 5: Difference-in-difference estimate of the effect of the slave trade on output
Winsorized data

	(1) $\log(GDP/capita)$	(2) $\log(GDP)$	(3) $\log(GDP/capita)$	(4) $\log(GDP)$
Slave trade	-0.234***	0.081	0.017	0.379***
	(0.067)	(0.098)	(0.076)	(0.079)
	[0.004]	[0.392]	[0.807]	[0.000]
Persistent ethnicity	0.347***	0.553***	0.248***	0.349***
	(0.077)	(0.095)	(0.060)	(0.062)
	[0.000]	[0.000]	[0.000]	[0.000]
Slave trade x Persistent	-0.225**	-0.067	-0.224**	-0.122
	(0.102)	(0.140)	(0.098)	(0.101)
	[0.067]	[0.659]	[0.036]	[0.282]
Diamond deposits			0.044***	0.042***
			(0.009)	(0.011)
Oil			0.601***	0.991***
			(0.095)	(0.092)
Gold deposits			0.009***	0.029***
			(0.003)	(0.005)
Malaria (Pf)			1.707*	1.147
			(0.895)	(1.057)
Malaria (Pv)			-1.446*	-1.791*
			(0.818)	(0.924)
Annual rainfall (mm/day)			-0.200***	-0.179***
			(0.026)	(0.026)
Neighbors			-0.019*	0.115***
			(0.010)	(0.010)
Time FE	Yes	Yes	Yes	Yes
Observations	4,175	4,175	4,175	4,175
R^2 within	0.047	0.061	0.238	0.435
Entities	835	835	835	835
Time periods	5	5	5	5

Spatial HAC standard errors in parenthesis (Conley, 1999, 2016). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Randomization inference p-values in brackets.

The dependent variable in columns (1) and (3) is the log of GDP/capita estimated using the log of night lights per capita measured using VIIRS luminosity data. In columns (2) and (4), the log of GDP is the dependent variable and is estimated using the log of night lights. Both variables were winsorized at the 5th and 95th percentiles. All variables are calculated over the historical ethnic boundaries presented in Murdock (1959). The variable "Slave trade" is an indicator recording whether the ethnic group historically participated in the slave trade. The variable "Persistent" indicates whether the ethnic group that historically occupied the area is still the dominant ethnicity in the area. The coefficient on the interaction between "Slave trade" and "Persistent" is the difference-in-difference estimate of the effect of the slave trade on output.