The Natural Resource Curse Revisited: Evidence based on Tectonic Plate Theory

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Abstract

Research on the resource curse has long been hindered by the challenge of identifying an exogenous change in resource endowments to study the long-run impact on socioeconomic outcomes. We revisit the question of whether natural resources spur or hinder development in the long-run using the mineral endowments of continents that were connected to Africa 250 million years ago as an instrumental variable. We show that higher resource endowments lead to poorer institutional outcomes, as reflected in higher reported corruption, as well as lower human capital investments and higher household poverty. Overall, our results provide causal evidence consistent with a long-run resource curse.

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1 Introduction

The resource curse, which holds that there is a negative impact of natural resource endowments on economic and governance outcomes, is a much-debated conjecture in the political economy of development. There is no shortage of theories of whether and why natural resources are a curse rather than a blessing (e.g., Ploeg, 2011; Ross, 2015; Savoia and Sen, 2021). Evaluating these theories has proven to be considerably more difficult. Credible causal evidence tends to focus on short-run impacts, exploiting exogenous shocks such as resource discoveries or global commodity price fluctuations to isolate the effects of resource abundance and the resultant economic rents (Tsui, 2011; Gallego et al., 2020). While these approaches have advanced our understanding of the political economy of natural resources, they necessarily estimate the consequences of short-run changes in resource rents rather than the long-run effects of resource endowments themselves. Identifying these longer-run effects is challenging because institutions and culture – which influence both economic outcomes and resource exploration – evolve over time and are themselves intertwined with the presence of natural resources.

In this paper, we propose a new identification strategy that allows us to explore the long-run causal impact of natural resource endowments on economic and political outcomes. Our approach takes advantage of the fact that continents now thousands of kilometers apart were conjoined hundreds of millions of years ago and therefore may exhibit positively correlated mineral endowments across historically connected areas. We use the mineral endowments of these previously connected tectonic plates as an instrumental variable to examine whether natural resources are ultimately a long-run curse or blessing for institutional quality and economic prosperity. Because the instrument is based on geological endowments that predate modern institutions, our strategy identifies the long-run effects of underlying resource abundance rather than contemporaneous mining activity.

We begin by demonstrating the validity of our instrument, showing that mineral resource endowments of African coastal areas can be predicted using the endowments of historically

connected regions of now-separated continents. The resulting first-stage relationship is strong and highly robust across alternative specifications.

Turning to our main analysis, we explore the effect of mineral resource endowments on economic and political outcomes, instrumenting for resource endowments using mineral resources in historically connected continents.

We first examine what we see as the outcome most closely allied to theories linking natural resources to political economy outcomes – corruption. That is, the rents created by (government-controlled) resources lead to opportunities for public sector self-enrichment (e.g., Ades and Di Tella, 1999). In our empirical analysis, we measure corruption using responses from the Afrobarometer surveys to questions about the need to pay bribes for access to public services. Instrumenting for African resource endowments using minerals in the "closest match" on a previously-connected continent, we find that natural resources lead to significantly higher bribe payments. The IV estimates are several times higher than the corresponding OLS coefficients. Importantly, these differences are not driven by a weak first stage: throughout the paper, the instrument is strong, with first-stage F-statistics well above conventional thresholds.

Turning from institutional quality to economic consequences, we use both the Afrobarometer and the Demographic and Health Surveys (DHS) to explore households' financial resources and educational outcomes. Focusing first on education, we find consistently poorer outcomes in both survey datasets: higher mineral resources lead to lower educational attainment, as captured by respondents' highest degree obtained.

The results linking mineral resources to households' financial circumstances based on DHS wealth estimates are likewise consistent with a resource curse. Regardless of the measure of household wealth, we find a negative impact of (instrumented) natural resources. Notably, in contrast to our IV findings, the OLS relationship between natural resources and wealth does not exhibit any clear pattern.

Whether these findings can be interpreted causally depends on the validity of our in-

strumental variables strategy. We therefore assess two conceptually distinct threats to our identification strategy: whether the instrument merely proxies for broader geological characteristics preserved through continental drift, or instead captures persistent historical linkages, particularly those arising from the Atlantic slave trade. We find little evidence supporting either explanation, lending support to the interpretation that our instrument isolates exogenous variation in African mineral endowments generated by continental drift.

Our paper contributes to the literatures in economics and political science on the role of natural resources in development. Much of the work in this area focuses on the question of whether natural resources help or hinder development (Ploeg, 2011). A central challenge has been identifying the causal effects of resource abundance itself, rather than the consequences of changes in resource rents. More recent research emphasizes shorter-run effects, as these are more readily identified from plausible exogenous shocks such as global commodity price movements or discoveries of new mineral or oil deposits. For example, Blair et al. (2021) provides a meta-analysis of 46 studies using commodity price shocks to study conflict, while numerous studies also examine the impact of shocks to natural resource prices or resource discoveries on democratic transitions (e.g., Ross, 2015; Brückner et al., 2012). Research linking resource abundance to economic outcomes often argues that there is a more complex dynamic at play, since the impact of resources on economic development depends on political institutions that are themselves endogenous to resource abundance (e.g., Savoia and Sen, 2021; Ross, 2015). Our paper complements this literature by introducing a new identification strategy that isolates exogenous variation in underlying resource endowments, allowing us to estimate their long-run consequences. The resulting evidence suggests that natural resource abundance has persistent adverse effects on institutional quality and economic development, lending support to theories emphasizing the long-run political economy costs of resource wealth.

2 Data

We begin by describing our data and instrument for resource endowments, which is the key innovation of our paper. We then describe the outcomes we examine using responses to the Afrobarometer and DHS surveys.

2.1 Mineral Resource Data and Instrument Construction

Our mineral endowment data come from the 2019 version of S&P's *SNL Metals & Mining Dataset* (*SNL*), a widely used commercial database covering global mining activity. The dataset provides information on mines and mineral projects at all stages of the production lifecycle, from exploration to extraction. Critically for our purposes, it provides information on the exact longitude and latitude of mines worldwide.

Our main empirical innovation is an instrumental variable for resource abundance along the coastal regions of Africa (and, as we note in our conclusion, potentially extendable to other geographies).[1] Our instrument is based on the mineral resource endowments in areas on other continents that, approximately 250 million years ago, were adjacent to these regions in the supercontinent of Pangaea. It is well-established that this shared geological history created correlated present-day resource endowments – indeed, this correspondence is part of the evidence for the existence of Pangaea; see, e.g., Trompette, 2020; Torquato and Cordani, 1981, among many others.[2]

We obtain tectonic plate shape data from 250 million years ago, as provided by Müller et al. (2019), to identify previously-connected areas. Focusing on the African continent, we present in Figure 1 the positions of the African plate and those surrounding it at that time. Africa was primarily connected to South and North America across the Atlantic Ocean, and South Asia across the Red Sea within the Gondwana landmass, one of the two landmasses

[1] Because tectonic continuity can only be established where continental boundaries were once adjacent, we construct the instrument using coastal regions.

[2] We note an important exception to this mineral contiguity below, related to the gold-rich west coast of Africa.

formed when Pangaea began to fragment roughly 200 million years ago.

[Figure 1 here]

To establish the relevance of our instrument, we construct a dataset of mineral resource endowments for coastal Africa in three steps. First, Müller et al. (2019) provides the latitudes and longitudes of 1,394 evenly spaced points along the coast of Africa (excluding Madagascar) as it existed 250 million years ago. At each point, denoted as $\bar{q}$, we draw a circular area with a specified radius, 500 kilometers in our preferred specifications. If this circle overlapped with another present-day continent 250 million years ago, we then project $\bar{q}$ forward to the present, locating the corresponding points q on the African coast and q' on or near the overlapped continent. Finally, we draw circles of the same radius around q and q', and for each of q and q' we define their mineral resource endowments as the number of mines per square kilometer within each circle. This procedure yields matched observations of mineral resource endowments in regions that were adjacent prior to the breakup of Pangaea. (In practice, there are far fewer than 1,394 pairs, since many coastal points were never adjacent to other landmasses, as is evident from Figure 1.)

Figure 2 illustrates this matching procedure. The two red circles, each with a radius of 500 kilometers, are positioned along the coasts of Africa and South America. Because these regions were adjacent 250 million years ago, the two circles would have coincided. The mineral resource densities within these two regions constitute one matched observation in our dataset.

[Figure 2 here]

There is one important exception to this mineral contiguity, as discussed in Torquato and Cordani (1981): the region between $3°W - 3°E$ and $0° - 10°N$, which corresponds to the southern margin of the West African Craton in present-day Ghana, Togo, and Benin. This region shares a pre-Gondwana tectonic linkage with the São Luís cratonic fragment in northern Brazil 250 million years ago. However, while the West African region exhibits

substantial mineral endowment (notably gold in Ghana), the corresponding São Luís region has very few mines. Geological evidence indicates that this disparity stems primarily from the asymmetric distribution of the mineralized structure during continental fragmentation, with the São Luís retaining only a minor fraction of the ore-bearing system, whereas the majority of mineralized units remained within the West African craton. Because this region represents a well-understood tectonic anomaly, we omit it from our analysis.

We next explain how we link our instrument to respondents in the Afrobarometer and DHS surveys. Following prior work, we begin by taking a 50 kilometer radius around the location where the individual or household resides and generate a binary variable denoting whether there is at least one mine within this area (Dreher et al., 2016; Knutsen et al., 2017). As a robustness check, we also use mine density rather than the more commonly-used binary measure.

To instrument for this measure of local resource abundance, for each respondent, we consider the nearest African coastal point q, which in turn coincided with point q' on or near another continent 250 million years ago. Our instrument is the number of mines per square kilometer in a 500 kilometer radius around the point corresponding to q' today. Note that it is possible that q' is not directly on or even near the coast of any land mass today. When only a very small fraction of the circle is land, mine density becomes mechanically unstable, since a single mine can generate extremely large density values. We therefore omit any cases in which less than 5% of the circle around q' is on land; we also winsorize the resulting values at the 5% level.

2.2 Political and Economic Outcomes

Individual-level Corruption Data – We measure corruption based on Afrobarometer responses to questions about respondents' personal experiences paying bribes for public services. All questions take the form: "Did you have to pay a bribe, give a gift or do a favor for [*public good*]?" Here, [*public good*] refers to one of the following amenities: school ser-

vices, healthcare, permits, documents, water or sanitation services, police assistance, and court assistance; respondents provide answers ranging from 0 (never) to 3 (often).[3] We use these responses to generate two summary measures of corruption. For our main results, we aggregate these multidimensional responses into a single corruption index, equal to the average of all available responses, where a higher value indicates more frequent bribe payments for public services. We also present an alternative approach, in which the corruption index is defined as the first principal component of these six individual corruption measures, extracted from a principal component analysis (following an approach similar to the measure generated by Kaufmann and Kraay, 2024). This aggregation exercise is complicated by the fact that there are many missing observations for some responses, either because the respondent did not respond to a particular question, or because the set of public services included in the survey varies across waves. For the average, we simply take the mean of all available (non-missing) responses. For the first principal component approach, we use the probabilistic PCA (Tipping and Bishop, 1999) to determine respondents' values.[4] We also present results for the individual components of the indexes, to highlight the consistency of the results across different public services.

Education – Both the Afrobarometer and DHS include measures of educational attainment at the individual level. The Afrobarometer asks respondents about their highest level of education, with responses ranging from 0 (no formal schooling) to 9 (post-graduate training). The DHS records the highest level of education attained by each household member; possible responses include 0 (No education), 1 (Primary), 2 (Secondary), and 3 (Higher). Given the sparsity of higher educational attainment, we collapse the Afrobarometer measure to a 0-3 scale comparable to that of the DHS.[5] For the DHS, we measure education by the

[3]Other potential responses include: no contact; don't know; refused to answer, which we code as missing.

[4]The probabilistic imputation will provide PCA values even if a respondent does not provide answers to any corruption-related questions. Our results are virtually identical if we omit respondents that did not provide any responses.

[5]In practice, given the sparsity of observations above the high school level, this makes little difference to our estimates – we obtain very similar results if we do not make this adjustment.

highest level attained by individual respondents.

Household Wealth – We use the wealth measure generated by the DHS, which is a composite measure of household living standards. The wealth factor is calculated using easy-to-collect data on the ownership of selected assets such as televisions and bicycles; materials used for housing construction; and access to water and sanitation facilities. The wealth factor is the first principal component of these variables.

There has been a wealth factor measure in the DHS dating back to the survey's inception. This original measure has been criticized for making rural households appear relatively poor due to their more limited access to urban infrastructure amenities. To address this shortcoming, the DHS developed separate urban and rural wealth measures (Rutstein, 2008), but these are only available beginning in the DHS Phase VII surveys in the mid-2010s (IPUMS DHS, 2026), reducing the sample size by nearly two-thirds. Given the very high correlation between the two measures ($\rho = 0.762$), we focus on the original wealth factor for our main analysis, presenting the urban/rural distinction as a robustness check.

In Table 1, we present summary statistics for the main variables used in our analysis. In panel A, we report a summary of mines per square kilometer for radii of 300 to 600 kilometers for points along Africa's coast as well as their matched locations on previously-connected continents. Note that the values are lower for the matched locations, which is a direct result of our approach to estimating mining density, since q' can be offshore while q is not. Mining densities are stable across the different radii. Further, note that the number of observations increases for larger radii, since larger circles are more likely to encompass an adjoining continent 250 million years ago. In panels B and C, we provide individual-level summary statistics for the variables we use from the Afrobarometer and DHS surveys, respectively.

[Table 1 here]

3 Historical Correlation in Mineral Endowments: correlation of Mineral Resources Across Previously Connected Continents

A key implication of our instrumental variables strategy is that mine densities in historically connected regions should be positively correlated.

We first assess this prediction using Figure 3, which presents a binned scatterplot of mineral density in the corresponding area on a previously connected continent (x-axis) against mineral density in the corresponding area along Africa's coastline. The scatterplot shows a clear positive relationship. The existence of this first-stage relationship is itself a prediction of plate tectonic theory: regions that were once contiguous should retain correlated mineral endowments despite their present-day geographic separation.

[Figure 3 here]

We next estimate the regression analog of this relationship based on Equation 1:

$$Mine\,Density_q = \gamma_0 + \gamma_1 Mine\,Density_{q'} + \eta_{q,q'} \tag{1}$$

Points q and q' represent two locations that were adjacent 250 million years ago, located today in Africa (q) and a separate landmass (q'). $Mine\,Density_q$ and $Mine\,Density_{q'}$ denote the number of mines per square kilometer within the circular regions around points q and q', respectively. We examine radii ranging from 100 to 900 kilometers. For each radius, we estimate the model using heteroskedasticity-robust standard errors (shown as circles and blue lines) and apply Conley (1999) to account for spatial correlation (shown as diamonds and red lines).

The results are presented in Figure 4, which shows the estimated coefficients on γ_1 across different radii. The connected pairs of regions generally exhibit a positive correlation in mineral density. This relationship is small and insignificant for very small radii, which

reflects the scarcity of mines within 100 kilometers of the coast.[6] The positive correlation becomes larger and more significant as the radius increases. The correlation then diminishes at larger radii, likely because larger circles increasingly average across geologically distinct formations.

[Figure 4 here]

As a complementary validation exercise, we perform a restricted permutation test. Because both our dependent and independent variables are measured along a common geological sequence with inherent autocorrelation, a standard random permutation test would break this structure and generate unrealistic pairings. We therefore employ a constrained permutation test based on cyclic shifts of one series relative to the other, which preserves the sequential order of observations. This yields a null distribution that respects geological continuity and directly tests whether the actual alignment of tectonic plates produces a significantly positive correlation between mineral endowments. These results appear in Figure 5, where we see that our estimated coefficient based on actual historical linkages (labeled with a red line) lies in the extreme right tail of the distribution (within the top 5%) in all cases.[7]

[Figure 5 here]

4 Long-Run Impact of Resource Endowments

4.1 Resources, Rent-Seeking, and Corruption

We begin by revisiting the classic and well-studied question of whether abundant natural resource endowments lead to more corruption, using mineral endowments in historically connected regions as an instrument for local mineral exposure. As a reminder, we measure

[6] Around 34% of the observations have zero mine densities when the radius is 100 km.

[7] If we perform a standard permutation test, we reject even more decisively the null of no relationship between mineral deposits in previously-connected areas.

individual i's exposure to mineral endowments by an indicator variable denoting whether there is a mine within a 50 kilometer circle around the respondent ($\mathbb{1}(MineDens_i > 0)$, also denoted as $HasMine(< 50km)$ in our regression tables). We then instrument for i's exposure to mineral endowments using the mineral density in the historically connected region. Specifically, we identify the closest coastal point q and use the mineral density of the corresponding circle around the historically connected point q' on another continent, which we denote by $MineDens_{q',OC}$. For the baseline analysis, we use a circle of radius 500 km.

We estimate Equation (2) below, employing our instrument for $\mathbb{1}(MineDens_i > 0)$, and Conley (1999) spatial standard errors to account for spatial clustering at the level of "assignment" of our z variable in the 2SLS estimation. We take a conservative approach by allowing for spatial correlation among observations up to 1000 kilometers apart, given the 500-kilometer radius of our instrument. Specifically, our model is given by:

$$y_{it} = \beta \mathbb{1}(MineDens_i > 0) + \alpha_t + \Gamma_i + \epsilon_{it} \tag{2}$$

where the set of controls, Γ_i, includes the respondent's age, age squared, gender, rural/urban residence, and distance to the coast.[8]

Table 2 presents our results relating mineral resource endowments to corruption using our summary measures that encompass bribe payments across a range of government functions. We provide the OLS estimates alongside those from both stages of the IV analysis. Focusing first on the first stage, the instrument is strong, with an F-statistic of approximately 40, whether we measure corruption using a simple average or imputed PCA. Turning to the effect

[8]On our modeling choice, we see two other ways that one might define the individuals' exposure to mineral endowments. First, as a way of accounting for the role of modern political boundaries that are surely relevant for the extent of corruption, we could use province-level mineral endowments as our z variable in the 2SLS estimation. An alternative is to take an approach that is more in line with that of Section 3. Specifically, we may instead simply use the resource endowment for q, the closest coastal point to survey respondent i, and instrument for this value using the connected point q'. In practice, this makes little difference to our analysis. One can easily see that this will be the case, given that the reduced form relating historically connected areas' resource endowments to current corruption is identical. The only difference is the implied treatment of standard errors – if one feels the right model is to measure "treatment" at the province-level, then one may wish to use province-level clustering rather than spatial clustering. In practice, this has no effect on our results.

of resources on corruption, the IV estimates are several times larger than the corresponding OLS coefficients, suggesting – particularly given the strong first stage – a downward bias on the OLS estimates. This pattern is consistent with classical measurement error in our measure of mineral exposure, or reverse causality, which may arise if, for example, weak institutions discourage mineral exploration or the development of mining projects.

[Table 2 here]

As can be seen in Table 1, the median respondent reports no bribe payments whatsoever. One straightforward way both to further assess the robustness of our results to alternative specifications and to obtain a coefficient with a more readily interpretable magnitude is to repeat our analysis using a binarized version of our measure of bribe payments, with an indicator variable denoting whether the respondent reports any bribe payment. These results appear in columns 7–9. The coefficient on $\mathbb{1}(MineDens_i > 0)$ of 0.184 (significant at the 10% level) implies that an individual living near mineral resources has an 18.4 percentage point higher probability of reporting a bribe payment, a large magnitude relative to the sample mean of 28.6%.

In Table 3, we present estimates by type of public service. While the point estimates vary, there is a consistent positive relationship between instrumented mineral endowments and corruption across outcomes (panel C). This is particularly notable given the very different samples for each outcome variable: there are only 5,334 observations (out of a total of 148,244 respondents for the survey across all waves overall) for the courts outcome, as most respondents have no interaction with the legal system, while for health there are 86,761 observations — 17 times more observations.

[Table 3 here]

4.2 Human Capital Investment

While we see the relationship between mine density and corruption as the most direct link to the resource curse literature, our findings naturally lead us to consider "downstream" effects on investment and economic development more broadly. There are two natural channels through which resource abundance might affect human capital accumulation. Most obviously, weak institutions may discourage productive investments more generally. Additionally, given the corruption results above, resource abundance may reduce investment in public education through weaker governance.

In this section, we examine the effect of mineral endowments on education outcomes, again following the specification in Equation (2). Note that, for our analyses using the Afrobarometer sample, we report Conley (1999) spatial standard errors using a cutoff radius of 1,000 kilometers. For the DHS individual-level sample, which contains more than 1.5 million observations, computing Conley standard errors is computationally infeasible. Instead, we cluster standard errors at the level of the IV construction circles (defined by the nearest point along the African coastline), since all observations within a circle share the same value of the instrumental variable.

We present our results in Table 4, starting with those based on the DHS survey data. As shown in columns 1–3, greater exposure to mineral resources reduces human capital accumulation, as measured by the highest level of education attained by survey respondents. The IV estimate is substantially larger than the corresponding OLS estimate, suggesting that endogeneity in realized mineral endowments could lead to attenuation bias. Using Afrobarometer data, we also observe a significantly negative effect on respondents' educational attainment, as shown in columns 4–6.

[Table 4 here]

4.3 Wealth accumulation

In our final set of analyses, we examine the effect of mineral resource abundance on wealth. As a reminder, we use two DHS "wealth factor" measures. Our preferred variable is available for the full set of surveys, whereas a measure that separately considers the wealth of urban and rural respondents is available only beginning in the mid-2010s. We present our results using both measures.[9] As before, we provide OLS estimates relating the presence of a mine to wealth along with the first- and second-stage 2SLS results.

We begin in columns 1–3, which use the wealth factor measure that has wider coverage but does not distinguish between urban and rural respondents. Focusing on our 2SLS estimate in column 3, we document a negative effect of mineral endowments on wealth. The point estimate of -0.36 (significant at the 5% level) implies a reduction of about a third of a standard deviation in wealth resulting from proximity to a mine. By contrast, the OLS estimate suggests no relationship between mine proximity and wealth (column 1). The measure that distinguishes between urban and rural respondents yields a substantially larger point estimate but is also much more noisily estimated, reflecting a relatively weak first stage. Again, the OLS estimate is small and statistically insignificant.

[Table 5 here]

Our finding that households located near mineral resources are poorer on average suggests that the adverse consequences of resource abundance extend beyond governance outcomes to household living standards.

Interpreting our estimates causally requires that our instrument affect outcomes only through African mineral endowments. We therefore turn to a series of exercises designed to evaluate the plausibility of this assumption.

[9] We report Conley (1999) spatial standard errors. This is computationally feasible because wealth is measured at the household level, resulting in a substantially smaller sample than in the education analysis, where educational attainment is measured at the individual level.

5 Assessing the Exclusion Restriction

Our identification strategy assumes that mineral endowments in historically connected continents affect present-day outcomes only through their ability to predict local mineral endowments in Africa. Although continental drift is plausibly exogenous with respect to modern political and economic circumstances, the exclusion restriction could fail if historically connected regions share other characteristics that also influence long-run development. In this section, we consider two broad classes of threats. First, continental drift may preserve a broader set of geological characteristics that themselves affect long-run political and economic outcomes. Second, historically connected regions may have experienced correlated patterns of human interaction, most notably through the Atlantic slave trade. [10] We examine each of these possibility in turn.

5.1 Correlated Geological Characteristics

The most immediate challenge to our identification strategy is that continental drift could preserve other geological characteristics other than mineral deposits. Regions that once formed part of the same landmass may, for example, share similarities in topography, elevation, soils, hydrology, biodiversity, and climate. If these broader geographic characteristics themselves affect institutional quality or economic development, then mineral endowments in historically connected continents could violate the exclusion restriction by proxying for these alternative channels.

[10] Some people could argue that colonization activities may also result in this cross-continent linkage. For example, two historically connected regions that share the same colonial power may well inherit the same colonial culture or institution from the colonizers, leading to similar economic and political outcomes as well as similar explored mineral deposits. However, we find it an unlikely alternative explanation, as almost none of the historically connected regions share one colonial power. For West Africa: the major colonizers were France and Britain. The African British colonies were historically connected to Brazilian Portuguese/Dutch colonies; and the African French colonies were historically connected to North American British colonies. Even though Angola and Brazil were both colonized by Portugal, our analysis remains largely unchanged with or without Angola (see Section 6 for details). Similarly, for East Africa: the mass land was colonized by Britain, Portugal, and Italy, whereas its corresponding connected lands were occupied once by France and Holland. See this map for a detailed world map about empires of the modern era from 1492 to 1945. Taken together, the historically connected regions happened to have different colonization histories.

We begin by examining whether this concern is empirically relevant. Specifically, we examine whether our instrument – mineral endowments in historically connected continents – predicts a broad range of geographic and environmental characteristics measured in Africa. We consider 23 characteristics including climate, topography, soils, biodiversity, and related environmental features, as described in Appendix B, using an approach analogous to the proof-of-concept exercise in Section 3. That is, for each African coastal point, we regress each geologically-induced characteristic measured within a 500-kilometer radius on the mineral endowments of the corresponding historically connected region.

We present these results in Figure 6. The results are mixed. Several geographic characteristics that plausibly influence long-run development—including biodiversity, tree cover, and sparse vegetation—are significantly predicted by mineral endowments in historically connected continents. By contrast, other obvious candidates, including temperature, slope, and soil quality, are uncorrelated with the instrument. This is not surprising, as continental drift preserves many aspects of geological history beyond mineral deposits, and historically connected regions should therefore be expected to share broader environmental characteristics as well.

These relationships do not, by themselves, imply a violation of the exclusion restriction. The relevant question is not simply whether our instrument predicts other geological characteristics, but whether those characteristics account for the estimated relationship between mineral endowments and long-run political and economic outcomes.

We therefore ask whether these correlated geographic characteristics explain our results. To do so, we augment our baseline specifications with a rich set of largely predetermined geographic controls, including measures of elevation, slope, temperature, soil quality, and biodiversity. These factors capture many of the most plausible alternative channels through which continental drift could influence modern development independently of mineral resources.

Table 6 reports the results. Across corruption, educational attainment, and household

wealth, the estimated effects of mineral endowments remain very stable. The inclusion of these geographic controls produces only modest changes in the estimated coefficients while leaving the first-stage relationship largely unaffected. Thus, although historically connected regions share broader geological characteristics, these observable similarities do not explain our main findings.

Naturally, it is still possible that other unobserved dimensions of geological similarity could account for the relationship between mineral endowments in historically connected continents and modern-day political economy outcomes. However, the available evidence suggests this is unlikely. After accounting for a broad set of environmental characteristics, several of which are themselves correlated through continental drift, our estimated effects change very little. This suggests that our instrument is not merely a proxy for broad geological similarity. Rather, the evidence is consistent with the identifying variation arising primarily through the correlation in mineral endowments induced by shared tectonic history.

5.2 Historical Linkages: The Slave Trade

A distinct threat to our instrumental variable strategy is that historically connected continents may also have become linked through subsequent patterns of human interaction. Of particular concern, the Atlantic slave trade has been shown to have persistent effects on institutional quality and economic development throughout Africa (Nunn and Wantchekon, 2011). The intuition is straightforward. Regions located on tectonic plates that were historically connected tend to remain geographically closer even after continental drift and were therefore more likely to become linked through Atlantic trading routes. If our instrument captures these historical interactions rather than shared geological history, the exclusion restriction could be violated.[11]

The most natural approach to assessing this concern is to examine whether mineral

[11] We note that it is unlikely that mineral endowments constitute the relevant channel, since demand for enslaved labor was driven primarily by agricultural production rather than mining activities; see Nunn (2008) and Nunn and Wantchekon (2011).

endowments in tectonically-connected areas predict African slave exports. To perform this test, we use the voyage-level slave export data from Nunn (2008), and aggregate it to the port-level. We then take the closest African coastal point q to port p, and find its corresponding point q' on a previously-connected continent. If slave trading routes represent a significant violation of our exclusion restriction, we expect that the mineral endowments around q' will be a significant predictor of slave trade exports from p. We present these results in Appendix Table 7, with $log(1+Slave\ Exports)$ as the outcome. (In practice the one-plus specification is inconsequential – there are only two ports with zero slave exports and our results are identical if we simply remove those observations, or if we use a PPML specification.) Regardless of our treatment of standard errors, the relationship does not approach statistical significance.

An alternative approach to accounting for the slave trade is simply to include it as a control in our main specifications – both our "proof-of-concept" exercise as well as our main "resource curse" estimates. To implement the first of these tests, we include as a control the (log of) the number of slaves departing from ports within 500 kilometers of the point q on Africa's coast, and for the latter we control for the log of the number of slaves departing from ports within 500 kilometers of the African coastal point to which each individual respondent is closest to. These results appear in Figure 7 and Table 8. In all cases, our point estimates are quite similar to those reported in our main results.

The two exercises in this section address conceptually distinct threats to our instrumental variable strategy. The first asks whether our instrument simply proxies for a broader set of geological characteristics preserved through continental drift; the second asks whether it instead captures persistent historical interactions associated with the Atlantic slave trade. Neither explanation appears capable of accounting for our findings. Taken together, these results strengthen the interpretation that our instrument isolates exogenous variation in African mineral endowments generated by shared tectonic history.

6 Further Robustness Checks

We conclude our analyses by examining the robustness of our results to a number of different samples and specifications. Specifically, we assess how our results are affected by using a continuous measure of mineral endowments rather than the indicator variable more commonly employed in past work; omitting "close" Red Sea neighbors; including observations even if there is very little landmass in our instrumental variable; excluding instances in which tectonic plate theory does a poor job of predicting present-day overlap in mineral density. For each of these robustness checks, we assess how our results are affected for each of our main outcomes: corruption (measured by the average bribery intensity in the Afrobarometer data, shown in Appendix Table A1), education (highest level of education in the Afrobarometer data, shown in Table A2), and wealth (wealth factor in the DHS data, shown in Table A3).

Use continuous measure of mineral endowments To be consistent with prior work (Dreher et al., 2016; Knutsen et al., 2017), our baseline analysis employs an indicator variable denoting the existence of a mine less than 50 kilometers from an individual to capture mineral endowment. This approach plausibly discards useful intensive-margin variation. We thus present results using the number of mines per squared kilometer within this 50 kilmeter radius circle. To make the coefficients readable, we multiply this measure by 10,000. These results in columns 1 and 2 in each of Appendix Tables A1- A3; throughout, the signs and statistical significance in these estimates are consistent with those presented in our baseline results.

Omit close Red Sea neighbors While most previously-adjacent areas are now separated by thousands of kilometers, those situated along the Red Sea, including Egypt, Sudan, Ethiopia, and Eritrea, remain close to previously-connected areas in Saudi Arabia and Yemen, which we use in constructing our instrumental variable. To address the concern that mineral endowments in Saudi Arabia and Yemen could have directly influenced their

adjacent African neighbors, we drop observations in this set of African countries. Again, our results are unaffected by this exclusion (see columns 3 and 4 of Appendix Tables A1- A3).

Include observations in which IV has limited landmass To address the concern that for some areas, the circle used to construct the instrumental variable barely overlaps with previously connected areas, in our baseline analysis we omitted observations for which the instrumental variable is built on circles with less than 5% overlap. Recall that this could occur if the two continents were already some distance apart 250 million years ago (something that happens more often for southern and northern Africa). In columns 5 and 6 of Appendix Tables A1- A3 we do not impose any cutoff. These results appear in columns 5 and 6 of Appendix Tables A1- A3; our results are again largely unchanged. [12]

Outliers of the Tectonic Plate Theory There is a well-documented asymmetry of iron endowments between Africa and Latin America. While there are rich iron mines in Brazilian Belo Horizonte (also known as the Iron Quadrangle), there are very few in the corresponding Cassinga region of Angola. In this section, we draw on existing geological research to explain this asymmetry, and also assess how much this asymmetry influences our baseline results.

Brazil's Iron Quadrangle and Angola's Cassinga share the geological foundations to produce iron ores. Appendix Figure A1 shows that the São Francisco-Congo craton connects the two plates, specifically, East Brazil and the Republic of Guinea, D.R.Congo, Gabon, and Angola in Africa. Moreover, both the iron mines near Belo Horizonte and the iron mines in Cassinga of Angola are Banded Iron Formation (BIF) – a distinctive type of chemical sedimentary rock made of alternating layers (bands) of iron-rich minerals (hematite and magnetite) and silica-rich layers (chert). Importantly, these BIFs were formed in the Precambrain period, well before the Gondwana land split.

However, the two regions evolved under different conditions, and thus very different types

[12] In the "proof-of-concept" analysis, we also find that the results remain generally robust to altering the cutoffs from 0 to 10%.

of BIFs subsequently emerged. The Iron Quadrangle records indicate the deposition of large stable marine basins typical of BIFs of Superior-type (Castro and Azevedo, 2022), while several Angolan deposits are associated with more volcanically active or greenstone-related environments characteristic of BIFs of Algoma-type (Olimpio-Gonzalvez et al., 2021). Compared with rarely seen world-class Superior-type irons, Algoma-type iron deposits are typically smaller, more fragmented, and mixed with volcanic waste rock. This case emphasizes that the asymmetry of mineral endowment across two tectonic plates is not only dictated by the tectonic linkage before they split, but also influenced by geological conditions in the following millions of years. That said, some very newly published papers demonstrate that the Angola iron mines are much less-developed than their potential – precisely the sort of circumstances that emphasize the need for an instrumental variable approach to evaluating the effect of resource endowments. For example, Machadinho et al., 2025 find large potential iron mines beneath Angola. Meanwhile, the Tosyali's subsidiary in Angola (Tosyalı Iron&Steel Angola) announced its intention in 2024 to renew its operation of the mines in the Cassinga region, which "contains the largest reserves of this ore in Angola" (Yermolenko, 2024).

We assess whether the asymmetry in Angolan and Brazilian iron endowments may add noise to our baseline estimates. First, we re-estimate the correlation of mines in Section 3. Figure A2 shows that, when we delete the pairs of circles that contain Belo Horizonte, the estimated relationship is slightly stronger. We next consider our second-stage estimates. Since the Afrobarometer survey does not cover Angola during our sample period, we only provide these results for the DHS sample. We find that dropping Angola's observations improves our first-stage F-statistic. The magnitude, sign, and significance are essentially unchanged (see columns 7 and 8 of Appendix Tables A3).

Overall, we see these results as (a) highlighting the importance of our IV approach, since mineral deposits might go unexploited due to local underdevelopment; and (b) indicating that refinements to based on more detailed geological information could further refine our

instrumental variable.

Robustness to alternative radii Throughout, we focus on mineral resources within a 500 kilometer radius of coastal points to instrument for African mineral endowments. We consider here whether our results are sensitive to this particular cutoff. Specifically, We use alternative radii of 450 kilometers and 550 kilometers as robustness checks in Appendix Tables A4 and A5. The estimates are very similar to our baseline results using a 500 kilometer radius.

7 Conclusion

We propose a new identification strategy to analyze the effect of mineral resource endowments based on plate tectonics, linking the resource endowments of present-day Africa to those of other continents with which it shared a common geological history hundreds of millions of years ago. Since historically connected continents share positively correlated mineral endowments, we use the mineral resources of one continent as an instrument for the endowment of its historically connected counterpart. Using this approach, we revisit the potential long-run consequences of natural resources by examining their impact on institutional and economic outcomes. Our findings provide evidence that mineral resource endowments are, in the long run, more of a curse than a blessing. By addressing endogeneity arising from culture and other institutional factors that influence both resource exploration and economic and political outcomes, our approach provides new evidence on the long-run causal effects of mineral resource endowments on political and economic outcomes.

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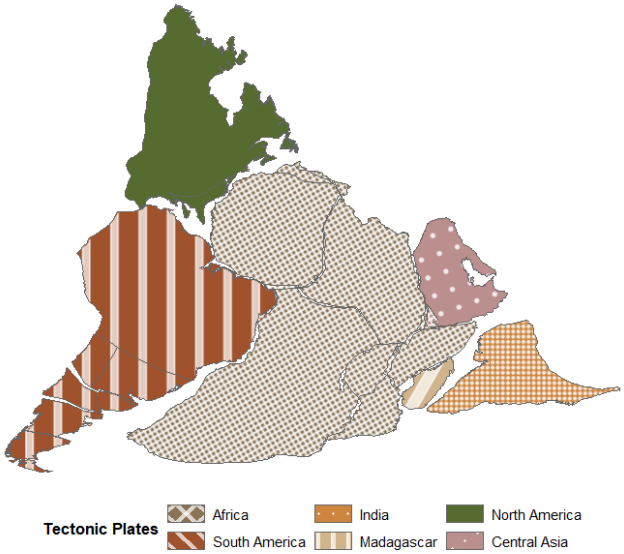
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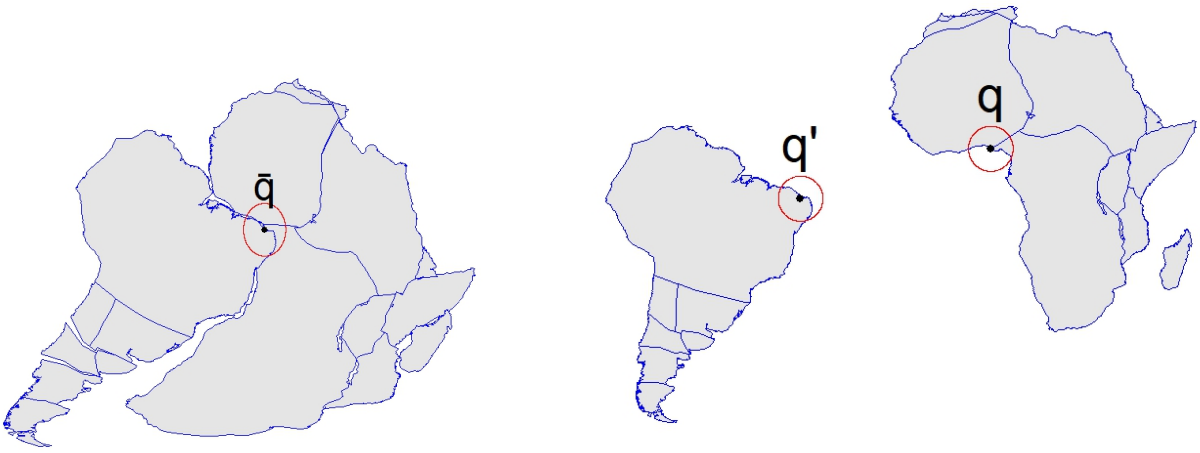
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Figure 1: Historically Connected Landmasses Surrounding Africa 250 Million Years Ago



Notes: This figure shows the location of tectonic plates 250 million years ago. The figure includes the landmass that is modern-day Africa, as well as neighboring landmasses that were adjacent to Africa prior to the breakup of Pangaea, which are used in constructing our instrumental variable.

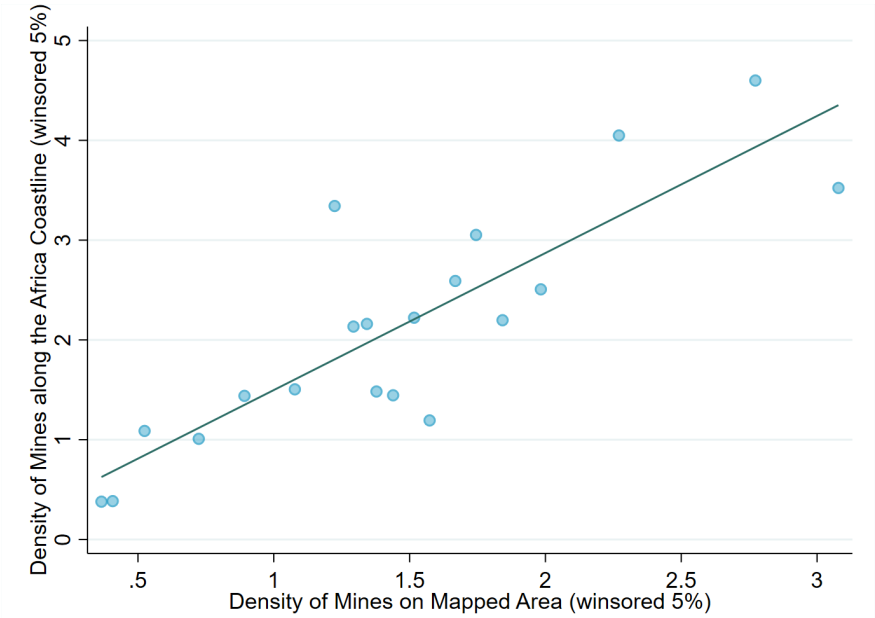
Figure 2: Illustration of Matching Historically Connected Regions



(a) 250 million years ago: $\bar{q}$ (b) Present day: q and q'

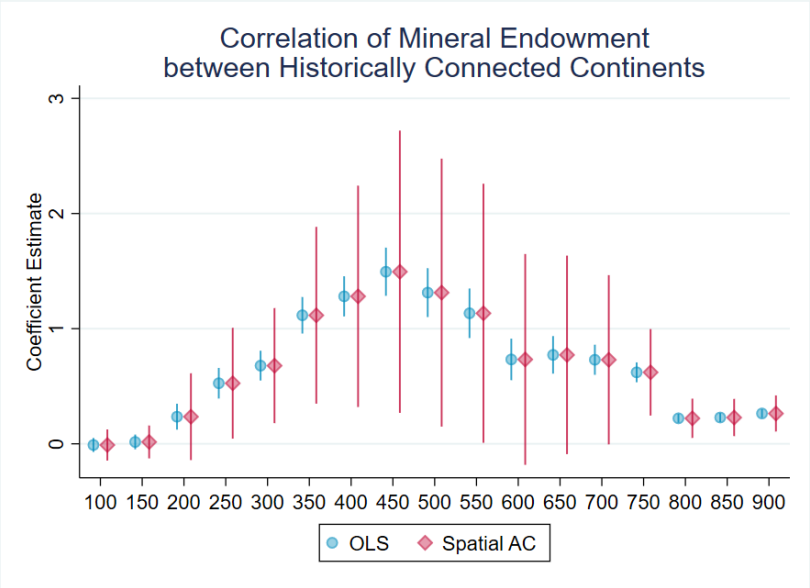
Notes: This figure illustrates the construction of the instrumental variable. Panel (a) presents a circle centered at $\bar{q}$, a point situated on the African coastline roughly 250 million years ago. Panel (b) maps the present-day counterparts of this circle – one centered at q adjacent to the African continent, and the other centered at q' off the coast of South America. The mineral density measured within the circle around q' serves as the basis for constructing the instrumental variable for African mineral resources.

Figure 3: Correlation in Mine Densities Across Historically Connected Regions



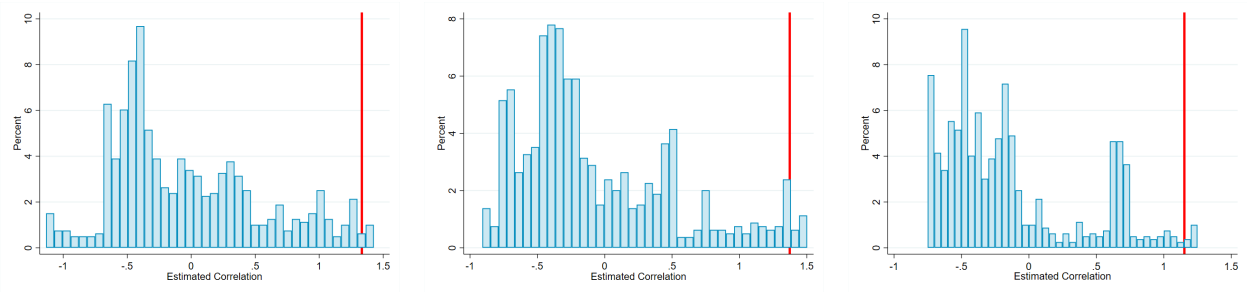
Notes: This figure provides a binned scatterplot of the relationship between mine density for Africa's coastline and mine density for the corresponding areas on a previously connected continent, with the data partitioned into 20 equal-sized groups.

Figure 4: First-Stage Estimates Across Alternative Radii



Notes: This plot provides the estimated first-stage coefficient from a regression relating the mineral densities of two historically connected regions across continents for differing radii. For each radius, the figure shows the estimated relationship and 95% confidence intervals with heteroskedasticity-robust standard errors (circles and blue lines), and applies Conley (1999) to account for spatial correlation (diamonds and red lines).

Figure 5: Permutation Test for Correlation in Mineral Endowments



(a) Radius = 450 km (b) Radius = 500 km (c) Radius = 550 km

Notes: This figure provides the results of Monte Carlo simulations in which historically adjacent points on the African coast and another continent are randomly permuted. Because both our dependent variable and independent variable are measured along a common geological sequence with inherent autocorrelation, a standard random permutation test would break this structure and generate unrealistic pairings. We therefore employ a constrained permutation test that preserves the sequential order of observations, specifically cyclic shifts of one series relative to the other. The observed estimate is labeled on each graph with a red line.

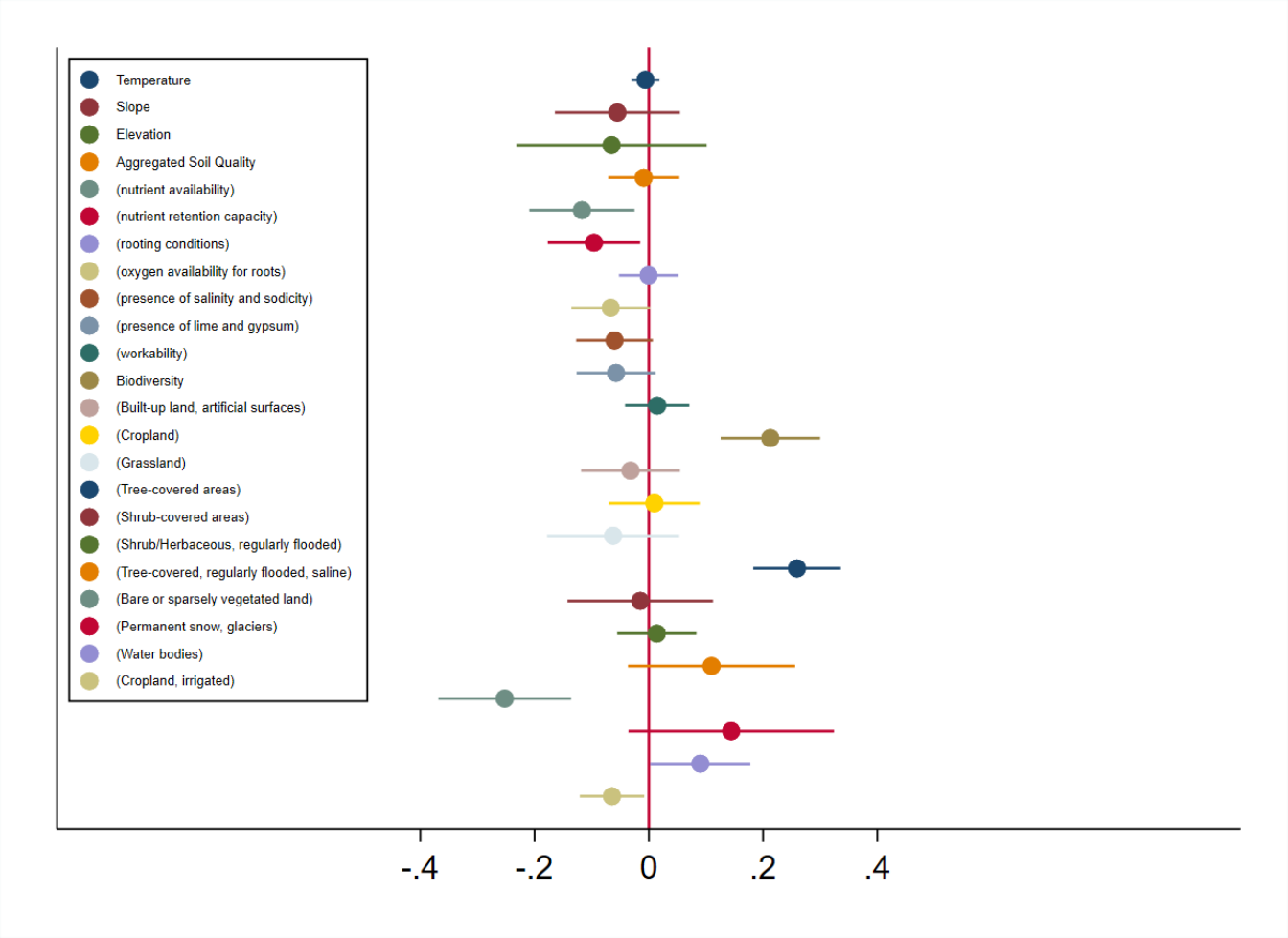
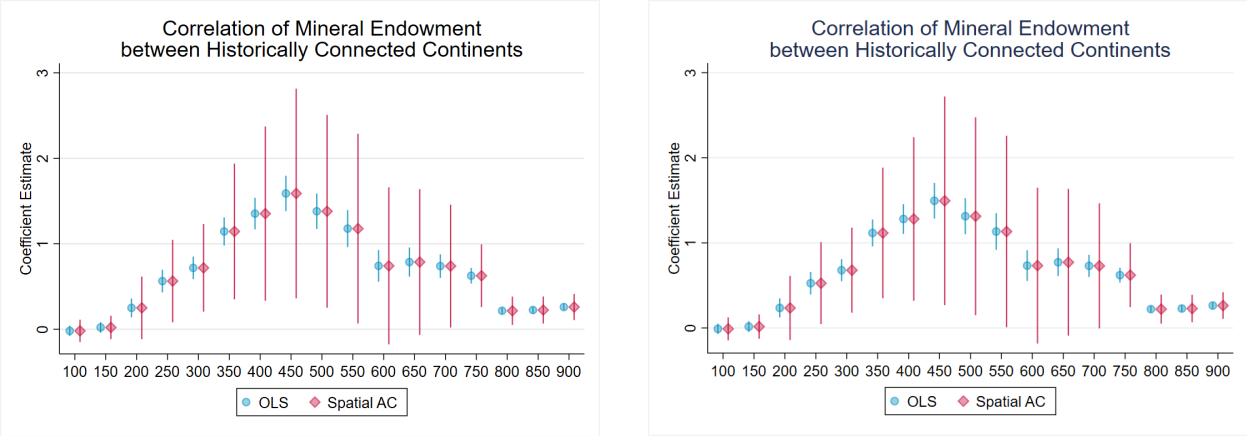


Figure 6: Relationship Between the Instrument and Geographic and Environmental Characteristics

Note: This figure presents the estimated coefficients after regressing a range of environmental and geological characteristics measured in Africa on our instrumental variable. We consider 23 characteristics, covering five environmental dimensions: temperature, topography, soil quality, biodiversity, and land cover. Within these dimensions, soil quality has 7 measures for different soil qualities and one aggregate index; land cover includes the share of 11 types of surfaces. These subcategories are listed in Appendix B and are labeled in the figure within the round brackets. We use an approach analogous to the validation exercise in Section 3. That is, for each African coastal point, we regress each geologically-induced characteristic measured within a 500-kilometer radius on the mineral endowments of the corresponding historically connected region. To show the confidence intervals, we use the Conley (1999) to estimate the standard errors to account for spatial correlation, as is consistent with our analysis in Section 3.

Figure 7: First-Stage Estimates With and Without Controlling for Slave Exports



Notes: This figure reports the first-stage estimates relating mineral densities in historically connected regions across continents for alternative radii. The left panel additionally controls for the log of slave exports from ports within 500 kilometers of each African coastal point, while the right panel reproduces the baseline estimates from Figure 4 for comparison. Points denote coefficient estimates and horizontal lines indicate 95% confidence intervals computed using Conley (1999) standard errors.

Table 1: Summary Statistics

Panel A: Proof of Concept						
	African Continent			**Connected Continent**		
Radius	Mean	SD	N	Mean	SD	N
300 km	1.990	2.276	707	1.417	0.933	691
350 km	1.913	2.041	728	1.381	0.785	720
400 km	1.883	1.823	740	1.403	0.727	740
450 km	2.079	1.908	783	1.429	0.736	783
500 km	2.156	2.015	815	1.448	0.754	815
550 km	2.178	2.014	830	1.440	0.741	830
600 km	2.190	2.029	856	1.580	1.329	856
Panel B: Afrobarometer						
	Mean	SD	Median	Min	Max	N
Has Mine (50km Circle)	0.584	0.493	1	0	1	148244
Bribery Experience (Mean)	0.290	0.594	0	0	3	135658
Bribery Experience (PCA)	.403	.949	0	0	6.599	148,244
Bribery Experience (Dummy)	0.286	0.452	0	0	1	120651
Highest Education Degree	3.345	2.175	3	0	9	168831
Panel C: DHS						
	Mean	SD	Median	Min	Max	N
Has Mine (<50km)	0.531	0.500	1	0	1	915240
Wealth Factor	-0.013	1.377	-0.264	-20.154	39.785	856809
Wealth Factor (Urban/Rural)	0.005	0.972	-0.050	-4.056	10.825	303353
Highest Education Degree	0.794	0.821	1	0	3	3315861

Table 2: Mineral Resource Endowments and Corruption

	Simple Average			Principal Component Analysis			Ever Pay Bribe		
	(1) OLS	(2) First-Stg	(3) IV	(4) OLS	(5) First-Stg	(6) IV	(7) OLS	(8) First-Stg	(9) IV
Has Mine (<50km)	0.0902***		0.343**	0.133***		0.580**	0.0519**		0.184*
	(0.0344)		(0.150)	(0.0493)		(0.249)	(0.0228)		(0.109)
Mineral Density of Connected Continent		0.272***			0.267***			0.272***	
		(0.0415)			(0.0438)			(0.0415)	
N obs	39239	39239	39239	48955	48955	48955	39239	39239	39239
Weak IV F-stat		42.94			37.16			42.94	

Notes: Columns 1–3 examine the relationship between mineral endowments and the average of responses to the question: *"Did you have to pay a bribe, give a gift or do a favor for [public good]?"*. In each case, answers range from 0 (never) to 3 (often); we average these values across all public goods for which we have responses for a given respondent. Columns 4-6 use the first principal component of the bribery measures. Columns 7-9 use an indicator variable for whether the respondent reports ever paying a bribe for at least one public good. All regressions include demographic controls for age, age squared, distance to coastline, rural or urban residence, gender, and year of survey. We report Conley (1999) spatial standard errors using a cutoff radius of 1,000 kilometers.

*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table 3: Frequency of Bribe Payments for Various Public Goods and Services

	Public Goods			Administrative and Legal Services		
	(1) education	(2) health	(3) water	(4) permits	(5) police	(6) courts
Panel A: OLS						
Has Mine (<50km)	0.0897***	0.103***	0.0466	0.0490*	0.0699*	0.183**
	(0.0310)	(0.0378)	(0.0326)	(0.0291)	(0.0369)	(0.0842)
N obs	36412	47720	29917	43163	33463	3248
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: First Stage						
Mineral Density of Connected Continent	0.181***	0.189***	0.203***	0.190***	0.198***	0.382***
	(0.0484)	(0.0466)	(0.0492)	(0.0424)	(0.0464)	(0.0743)
N obs	36412	47720	29917	43163	33463	3248
Weak IV F-stat	14.04	16.50	17.04	20.17	18.15	26.43
Panel C: IV						
Has Mine (<50km)	0.564**	0.888***	0.309*	0.0896	0.409	0.509
	(0.275)	(0.313)	(0.178)	(0.185)	(0.275)	(0.318)
N obs	36412	47720	29917	43163	33463	3248

Notes: This table examines the relationship between mineral endowments and responses to the question: *"Did you have to pay a bribe, give a gift or do a favor for [public good]?"*. For each type of public service, answers range from 0 (never) to 3 (often). All regressions include demographic controls for age, age squared, distance to coastline, rural or urban residence, gender, and year of survey. We report Conley (1999) spatial standard errors using a cutoff radius of 1,000 kilometers. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table 4: Mineral Resource Endowments and Educational Attainment

	DHS Education Degree			Afrobarometer Education Degree		
	(1) OLS	(2) First-stage	(3) IV	(4) OLS	(5) First-stage	(6) IV
Has Mine (<50km)	-0.0989***		-0.655***	-0.137**		-0.553**
	(0.0357)		(0.143)	(0.0623)		(0.248)
Mineral Density of Connected Continent		0.258***			0.267***	
		(0.0506)			(0.0438)	
N obs	1532960	1532960	1532960	48780	48780	48780
Weak IV F-stat		26.11			37.22	

Notes: This table examines the relationship between mineral endowments and respondents' educational attainment measured using the Afrobarometer and DHS surveys. We harmonize responses into a discrete variable with four possible outcomes: No education, Primary, Secondary, and Higher. For the Afrobarometer data, we include demographic controls such as age, age squared, distance to coastline, rural or urban residence, gender, and survey year fixed effects. For the Afrobarometer sample, we report Conley (1999) spatial standard errors using a cutoff radius of 1,000 kilometers. For the DHS individual-level sample, Conley standard errors are computationally infeasible because of the sample size. We therefore cluster standard errors at the level of the IV construction circles, the level at which the instrumental variable varies.
*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table 5: Mineral Resource Endowments and Household Wealth

	Wealth Factor			Wealth Factor (Urban/Rural)		
	(1) OLS	(2) First-Stg	(3) IV	(4) OLS	(5) First-Stg	(6) IV
Has Mine (<50km)	0.0061		-0.359**	-0.0208		-1.488*
	(0.0408)		(0.1657)	(0.0509)		(0.875)
Mineral Density of Connected Continent		0.249***			0.134**	
		(0.0414)			(0.0676)	
N obs	413427	413427	413427	150658	150658	150658
Weak IV F-stat		36.32			3.930	

Notes: Columns 1-3 show results using the DHS wealth factor. Columns 4-6 show results using the DHS wealth factor calculated separately for urban and rural households. All regressions control for family structure, household size, number of children, urban or rural residence, distance to coast, and survey-year fixed effects. We report Conley (1999) spatial standard errors using a cutoff radius of 1,000 kilometers.
*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table 6: Robustness to Geographic and Environmental Controls

	Corruption		Education		Wealth	
	(1)	(2)	(3)	(4)	(5)	(6)
	First-Stg	IV	First-Stg	IV	First-Stg	IV
Mineral Density	0.217***		0.210***		0.225***	
of Connected Continent	(0.0474)		(0.0482)		(0.0397)	
Has Mine (<50km)		0.359**		-1.096***		-0.592**
		(0.146)		(0.248)		(0.228)
Slope	0.0977***	0.0241	0.103***	0.140***	0.056***	-0.047**
	(0.0212)	(0.0193)	(0.0212)	(0.0489)	(0.0191)	(0.0231)
Temperature	0.0158	-0.0278***	0.0138	-0.0201	0.0117	-0.0058
	(0.0109)	(0.00921)	(0.0108)	(0.0221)	(0.00934)	(0.0208)
Soil Quality	-0.0426***	0.00982	-0.0457***	-0.0601***	-0.0266	-0.0476*
	(0.0146)	(0.0118)	(0.0146)	(0.0229)	(0.0178)	(0.0268)
Elevation	-0.102	-0.225***	0.123	0.259*	-0.0557	0.380***
	(0.0835)	(0.0759)	(0.0839)	(0.152)	(0.0585)	(0.0962)
Biodiversity	0.00183	0.168	0.0184	0.177	0.00986	0.380***
	(0.0815)	(0.105)	(0.0868)	(0.140)	(0.0756)	(0.127)
N obs	39239	39239	48780	48780	413427	413427
Weak IV F-stat	21.05		19.08		32.21	

Notes: This table shows the first-stage and IV estimates controlling for average slope, temperature, soil quality, elevation, and biodiversity within the 50 kilometer circle around each individual. Elevation and biodiversity are divided by 1,000 to make their coefficients readable. Columns 1–4 show results for corruption and education using Afrobarometer individual-level data. All regressions control for age, squared age, gender, urban or rural residence, distance to coast, and survey-year fixed effects. Columns 5 and 6 show results for wealth, using the DHS household survey data. All regressions control for family structure, household size, number of children, urban or rural residence, distance to coast, and survey-year fixed effects. We report Conley (1999) spatial standard errors using a cutoff radius of 1,000 kilometers.

*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table 7: Previously-Connected Mineral Endowments and African Slave Exports

	log(1+slaves)	log(1+slaves)	log(slaves)
Has Mine (<50km)	0.134	0.134	0.232
	(0.380)	(0.306)	(0.301)
N obs	141	141	139
Standard Errors	Heteroskedasticity	Conley Spatial	Conley Spatial

Notes: This table shows the relationship between port-level African slave purchases and the mineral endowment of the corresponding location on the ports' historically connected continents (see text for details). Columns 1-2 uses the natural logarithm of the number of slaves + 1 as our dependent variable, assuming heteroskedasticity-robust standard errors (column 1) and Conley (1999) spatial standard errors with a radius of 1,000 kilometers (column 2). Column 3 uses the natural log of the number of slaves as our dependent variable, which results in the loss of two observations, since two ports recorded zero slave exports, again assuming Conley (1999) spatial standard errors.
*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table 8: Robustness to Controlling for Slave Trade

	Corruption		Education		Wealth	
	OLS	IV	OLS	IV	OLS	IV
Has Mine (<50km)	0.0784**	0.346**	-0.123*	-0.553**	-0.0162	-0.562***
	(0.0335)	(0.147)	(0.0632)	(0.247)	(0.0374)	(0.155)
log(1+slaves)	0.00905*	0.00487	-0.0100	-0.00276	0.0266***	0.0336***
	(0.00528)	(0.00617)	(0.00921)	(0.00985)	(0.00412)	(0.00514)
N obs	39239	39239	48780	48780	413349	413349
Weak IV F-stat		45.84		40.73		31.19

Notes: This table shows the OLS and IV estimates controlling for the natural logarithm of the number of slaves exported, measured by the number of slaves purchased within 500 kilometers of the African coastal point to which each individual is the closest. Columns 1-4 show results for corruption and education using Afrobarometer individual-level data. All regressions control for age, squared age, gender, urban or rural residence, distance to coast, and survey-year fixed effects. Columns 5 and 6 show results for wealth, using the DHS household survey data. All regressions control for family structure, household size, number of children, urban or rural residence, distance to coast, and survey-year fixed effects. We report Conley (1999) spatial standard errors using a cutoff radius of 1,000 kilometers.
*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Appendix - for online publication

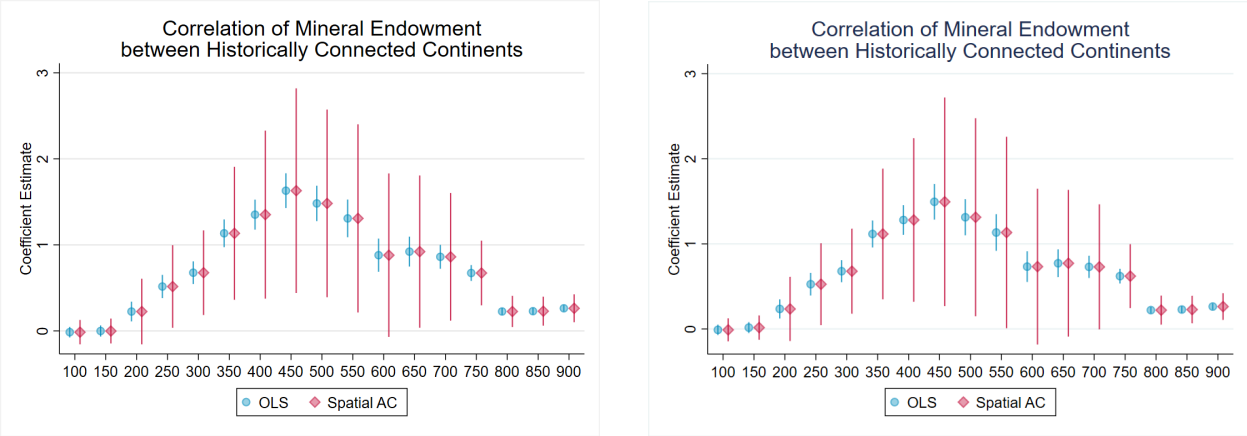
A Additional Figures and Tables

Figure A1: Map of Relevant African and South American Cratons



Notes: This figure shows the map of cratons on the Gondwana landmass, marked by shaded areas. Cratons are large, ancient, and exceptionally stable sections of continental lithosphere, typically found in the interior of tectonic plates, which have remained relatively unchanged for billions of years since the Precambrian era. Gold mines in Ghana are found on the West Africa craton, which is only related to a very small fracture in São Luís in Brazil. This explains why the mineral correlation is poor for Ghana and its previously connected neighbors. Additionally, the São Francisco-Congo craton connects Brazil and the West African countries, leading to a shared basis for generating iron mines. However, tectonic activities in Brazil in subsequent millennia made the iron mines extremely productive in Brazil relative to the corresponding region in Africa. This figure is a simplified version of Figure 1 from Moretti et al. (2026).

Figure A2: First-Stage Estimates Excluding Iron-Asymmetric Regions



Notes: This figure reports first-stage coefficients relating mineral density in African locations to mineral density in their historically connected regions across alternative radii. The right panel reproduces the baseline estimates from Figure 4. The left panel excludes observations whose historically connected circles in Latin America include Belo Horizonte, an area whose subsequent geological history makes it a poor fit for the instrumental-variables strategy.

Table A1: Robustness of Corruption Results

	Use Continuous Xvar		Drop Red Sea Neighbors		Add Less Than 5% Coverage	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Has Mine (<50km)	0.00760**	0.0215**	0.110***	0.405**	0.0883***	0.394**
(or Mineral Density)	(0.00334)	(0.00868)	(0.0338)	(0.168)	(0.0328)	(0.157)
N obs	39239	39239	37221	37221	41319	41319
Weak IV F-stat		116.9		31.21		30.78

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: The dependent variable in all specifications is the average response to the question: *"Did you have to pay a bribe, give a gift or do a favor for [public good]?"* Responses range from 0 (never) to 3 (often), and we average them across all public goods for which the respondent provided an answer. Columns 1 and 2 report OLS and IV estimates using a continuous measure of African mineral endowments: the number of mines per square kilometer within a 50 km radius of the respondent. For readability, this measure is multiplied by 10,000. Columns 3 and 4 exclude observations in Egypt and Sudan. Columns 5 and 6 add back observations whose historically connected circles overlap another continent by less than 5 percent—that is, locations for which the landmasses were already largely separated 250 million years ago. All regressions control for age, age squared, gender, urban or rural residence, distance to the coast, and survey-year fixed effects. We report Conley (1999) spatial standard errors using a cutoff radius of 1,000 kilometers.
*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table A2: Robustness of Education Results

	Use Continuous Xvar		Drop Red Sea Neighbors		Add Less Than 5% Coverage	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Has Mine (<50km)	-0.0127***	-0.0343**	-0.185***	-0.730***	-0.166***	-0.841***
(Or Mineral Density)	(0.00485)	(0.0153)	(0.0605)	(0.261)	(0.0594)	(0.280)
N obs	48780	48780	46073	46073	51356	51356
Weak IV F-stat		98.19		25.49		27.56

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: The dependent variable is respondents' educational attainment, measured using the Afrobarometer question *"What is your highest level of education?"*. We harmonize responses into a discrete variable with four possible outcomes: No education, Primary, Secondary, and Higher. Columns 1 and 2 report OLS and IV estimates using a continuous measure of African mineral endowments: the number of mines per square kilometer within a 50 km radius of the respondent. For readability, this measure is multiplied by 10,000. Columns 3 and 4 exclude observations in Egypt and Sudan. Columns 5 and 6 add back observations whose historically connected circles overlap another continent by less than 5 percent. Afrobarometer regressions control for age, age squared, gender, urban or rural residence, distance to the coast, and survey-year fixed effects. We report Conley (1999) spatial standard errors using a cutoff radius of 1,000 kilometers for the Afrobarometer regressions.
*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table A3: Robustness Checks for Wealth

	Use Continuous Xvar		Drop Red Sea Neighbors		Add Less Than 5% Coverage		Drop Iron-Asymmetry Region	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Has Mine (<50km)	-0.00438	-0.0211**	-0.0436	-0.7423***	0.00649	-0.3151*	0.0021	-0.3027**
(Or Mineral Density)	(0.00269)	(0.00945)	(0.0420)	(0.1833)	(0.0394)	(0.181)	(0.0421)	(0.1525)
N obs	405627	405627	353343	353343	432877	432877	406993	406993
Weak IV F-stat		49.96		32.16		19.89		49.72

Notes: The dependent variable in all specifications is the DHS wealth factor measure of wealth. Columns 1 and 2 show the OLS and IV estimates using a continuous measure of African mineral endowments, which is the number of mines per square kilometer in a 50 kilometer radius around the respondent. For readability of coefficients, this measure is multiplied by 10,000. Columns 3 and 4 show the OLS and IV estimates after excluding observations in Egypt and Sudan. Columns 5 and 6 show the OLS and IV estimates after adding back observations for which the instrumental variable is built on circles that overlap with another continent by less than 5% (i.e., the landmasses were already well separated 250 million years ago). Columns 7 and 8 show the OLS and IV estimates after dropping observations in Angola. All regressions control for family structure, household size, number of children, urban or rural residence, distance to coast, and survey-year fixed effects. We report Conley (1999) spatial standard errors using a cutoff radius of 1,000 kilometers.
*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table A4: Robustness to Using a 450 kilometer Radius

	Corruption		Education		Wealth	
	OLS	IV	OLS	IV	OLS	IV
Has Mine (<50km)	0.0886**	0.349**	-0.140**	-0.537**	-0.00661	-0.373**
	(0.0363)	(0.155)	(0.0662)	(0.256)	(0.0439)	(0.169)
N obs	36779	36779	45700	45700	388930	388930
Weak IV F-stat		44.30		39.50		32.74

Notes: This table reports OLS and IV estimates using a 450 km radius rather than the 500 km radius used in the main analysis. Columns 1–4 report results for corruption and education using Afrobarometer individual-level data. These regressions control for age, age squared, gender, urban or rural residence, distance to the coast, and survey-year fixed effects. Columns 5 and 6 report results for wealth using DHS household-level data. These regressions control for family structure, household size, number of children, urban or rural residence, distance to the coast, and survey-year fixed effects. We report Conley (1999) spatial standard errors using a cutoff radius of 1,000 kilometers.
*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table A5: Robustness to Using a 550 kilometer Radius

	Corruption		Education		Wealth	
	OLS	IV	OLS	IV	OLS	IV
Has Mine (<50km)	0.0908***	0.338**	-0.144**	-0.598**	0.0193	-0.252*
	(0.0326)	(0.135)	(0.108)	(0.407)	(0.0618)	(0.251)
N obs	41808	41808	50440	50440	437918	437918
Weak IV F-stat		46.04		38.58		38.78

Notes: This table reports OLS and IV estimates using a 550 km radius rather than the 500 km radius used in the main analysis. The sample therefore includes locations within 550 km of the coastline, and mineral endowments in historically connected regions are measured within circles of radius 550 km. Columns 1–4 report results for corruption and education using Afrobarometer individual-level data. These regressions control for age, age squared, gender, urban or rural residence, distance to the coast, and survey-year fixed effects. Columns 5 and 6 report results for wealth using DHS household-level data. These regressions control for family structure, household size, number of children, urban or rural residence, distance to the coast, and survey-year fixed effects. We report Conley (1999) spatial standard errors using a cutoff radius of 1,000 kilometers.
*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

B The Geographic and Environmental Characteristics

We examine 23 geographic and environmental characteristics to assess the plausibility of the exclusion restriction assumption underlying our instrumental variable. These characteristics capture five dimensions of the natural environment: climate, topography, soil properties, biodiversity, and land cover. Specifically, we include average annual temperature between 2000 and 2020, elevation, and slope. To characterize soil conditions, we include seven dimensions of soil quality—nutrient availability, nutrient retention capacity, rooting conditions, oxygen availability for roots, salinity and sodicity constraints, lime and gypsum accumulation, and soil workability—as well as an aggregate soil quality index. To characterize land cover, we include the shares of land covered by different surface types, including water bodies, cropland, tree-covered areas, regularly flooded tree-covered areas, grassland, shrub-covered areas, regularly flooded shrub/herbaceous areas, bare or sparsely vegetated land, snow, and artificial land.

We focus on these characteristics for two reasons. First, a large literature in economics has documented that geographic and environmental conditions influence a wide range of economic and political outcomes. Climate affects productivity, disease prevalence, and long-run economic development (Dell et al., 2012; Gallup et al., 1999). Topographic features, including elevation and terrain ruggedness, influence agricultural suitability, transportation costs, and the extent of state penetration (Nunn and Puga, 2012). Soil characteristics influence agricultural productivity (Easterly and Levine, 2003), and biodiversity influences ecosystem services and resource availability (De Perthuis and Jouvet, 2015).

Second, geological evidence suggests that some of these environmental characteristics may exhibit similarity across historically connected landmasses. Ancient orogenic belts and inherited crustal structures formed before continental rifting can generate long-lasting similarities in elevation and terrain characteristics across formerly connected regions (Porada, 1989). Similarly, deep geological inheritance shapes soil properties through its influence on parent materials and mineral composition. Consequently, soil characteristics, including

salinity, sodicity, lime, and gypsum accumulation, may display spatial continuity across regions that shared a common geological history (Pankhurst, 2008). Accordingly, correlations between our instrument and these characteristics would raise concerns about the exclusion restriction.

Our primary source of data is the Global Agro-Ecological Zones (GAEZ), Version 5, an open-access platform developed by the Food and Agriculture Organization (FAO) and the International Institute for Applied Systems Analysis (IIASA). From this database, we obtain measures of temperature, slope, elevation, soil quality, and land cover with spatial resolutions ranging from 30 arc-seconds (approximately 1 km $\times$ 1 km at the equator) to 5 arc-minutes (approximately 10 km $\times$ 10 km at the equator). Additionally, we obtain biodiversity measures from the EarthEnv project. EarthEnv provides global measures of habitat heterogeneity based on textural features extracted from Enhanced Vegetation Index (EVI) imagery collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) (Tuanmu and Jetz, 2015). Following the existing literature, we use the range of EVI values as a proxy for biodiversity, as greater vegetation heterogeneity is associated with greater habitat diversity and species richness.