Land Quality*

J. Vernon Henderson, Adam Storeygard and David N. Weil

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Abstract

We develop a new measure of land quality by estimating weights in a Poisson regression of grid-cell population on geographic characteristics and country fixed effects. Aggregating to countries, we construct average land quality (ALQ) and quality-adjusted population density ($QAPD$). We show: First, current income per capita is positively correlated with ALQ. Second, while income today is unrelated to conventional population density, it is strongly negatively related to $QAPD$. Third, this negative relationship was not present in 1820 and emerged because today's lower income countries have experienced faster subsequent population growth. Fourth, countries with higher average land quality began sustained modern economic growth earlier, and this earlier takeoff largely explains the modern income-ALQ relationship. We posit a framework in which land quality induced denser populations in Malthusian equilibrium and, via agglomeration, earlier takeoffs. Less dense countries experienced larger population multipliers during their later demographic transitions due to imported health technologies.

Keywords: Land, land quality, population density, physical geography, economic takeoff, economic growth, demographic transition.
JEL Codes: J10, O13, Q56, R12

*Henderson: London School of Economics. Storeygard: Tufts University. Weil: Brown University. Corresponding author: David_Weil@Brown.edu. A previous version of this paper was titled "Quality-adjusted Population Density." We are grateful to Anna Croley, Joao Garcia, Bo Yeon Jang, Juan Yamin Silva, Raymond Yeo, and Balazs Zelity for excellent research assistance; to Jesus Fernandez Villaverde, Matthew Delventhal, Gajendran Raveendranathan, and Ömer Özak for sharing data; to seminar audiences at Clark University, George Washington University, Louisiana State University, McGill University, Southern Methodist University, the University of Southern Denmark, The Max Planck Institute for Demographic Research, the Second Workshop on Geodata in Economics (Hamburg, 2019), the Federal Reserve Bank of New York, University of Haifa, Hebrew University, and IDC Herzliya for helpful comments; and to Andrew Foster and Joshua Wilde for helpful advice

1 Introduction

Land varies widely in its productivity and amenity value. It is difficult for people to live or produce output in rugged mountains or deep deserts. Similarly, fertile soil, a moderate climate, and access to the coast are conducive to settlement and economic activity. Scholars have long recognized that differences in land characteristics might impact economic outcomes. For example, Smith (1776) stresses the role of access to water transport in facilitating specialization and industrial development. Jones (1981) and Diamond (1997) are among many authors who link the dynamics of long run economic growth to land characteristics. Another obvious place in which land quality matters is in interpreting population density, which is in turn a central measure in the thinking of economists regarding economic growth, population size, agglomeration effects, and the role of natural resources in affecting economic outcomes. For many purposes, though certainly not all, a measure of population size relative to the ability of land to provide support for those people will be more relevant than a simple calculation of people per unit area.

In this paper, we construct a novel measure of the quality of a unit of land, and document several striking relationships between land quality, quality-adjusted population density, and economic outcomes across countries, both contemporaneously and going back to the dawn of modern economic growth. Our novel measure overcomes two main problems. First, land quality has many dimensions, including agricultural suitability, coastal location, ruggedness, and many dimensions of climate. Existing work (Binswanger and Pingali, 1988; Mellinger, Sachs, and Gallup, 2000; Galor and Ozak, 2016) has tended to focus on one of these at a time. Second, empirically assessing the effects of different land characteristics on outcomes such as population density or output requires disentangling the effect of land quality from that of country-level institutions that may be correlated with it, as stressed by Acemoglu, Johnson, and Robinson (2001). To solve both of these problems we estimate a Poisson regression of population in quarter-degree longitude-latitude grid cells on a vector of geographic characteristics and country fixed effects. We then use fitted values that suppress the fixed effects to form a measure of land quality for each grid cell.[1]

[1]Nordhaus (2006) takes an approach similar to that in the current paper, regressing the logs of total output, output per capita, and population at the level of one degree grid cells on country fixed effects and a

Aggregating grid-cell land quality, we construct average land quality (ALQ) for every country. Despite being measured at the country level, ALQ is by construction purged of the effects of country-level institutions or other unobservables. Analogously, we construct total quality-adjusted land area (QAA), and quality-adjusted population density ($QAPD$), which is simply total population divided by the quality-adjusted area. Such measures can be used to quantify intuitions about how land quality adjustments matter. For example, while Canada and the USA have very similar areas, by our measure of quality-adjusted area, the USA is 8.8 times as large as Canada. As part of our analysis, we also discuss the extent of mismatch between countries' current population and their quality-adjusted land areas, and the flows of population that would be required to equalize this ratio across countries.

Examining the relationships between ALQ, $QAPD$, and current economic outcomes, we establish three interesting facts. First, there is a strong and robust positive correlation between countries' average land quality and their level of income per capita. Second, there is no statistical relationship between income per capita and conventionally defined population density. And third, there is a strong negative correlation between income per capita and our measure of quality-adjusted population density.

We then turn to study the historical evolution of income and population over the past 200 years. We show that the relationship between land quality and population density was much stronger historically than it is today. The correlation of income per capita with conventionally-defined population density, which is insignificant today, was significantly positive in the past, while the correlation between quality-adjusted population density and income, which is negative today, was positive in the past. Notably, these facts are inconsistent with standard theories of economic development, natural resources, and population growth. Models going back to Malthus and Ricardo, with more recent examples being Galor and Weil (2000), Hansen and Prescott (2002), and Lucas (2002), predict that population in a pre-industrial equilibrium will be proportional to natural resources, and give no reason to think that the same should not be true of population following industrialization. The key phenomenon that is present in the data but not predicted by existing theories is that there

set of geographic covariates. Our paper differs from his in its specification (log-linear vs. Poisson, as discussed below), population data used, the set of geographic covariates, and most importantly in interpretation, in focusing on re-scaling population density as a function of geographic characteristics.

is a negative correlation between countries' land quality and their level of population growth over the last 200 years.

In the final section of the paper, we develop a model that can explain all of the observed changes in the relationships among density, quality-adjusted density, and income over the last 200 years. There are two key driving forces in our model. First, as noted above, the takeoff into modern economic growth occurred earliest in countries with high land quality. Second, in countries that experienced later takeoffs, the extent of population increase over the course of industrialization was larger than in countries that took off earlier. The source of this greater population multiplication was the rapid transfer of health technology from leading to following countries. In our model, this larger population multiplier results in a permanently higher ratio of population to natural resources in follower countries, and to a persistent gap in income per capita, even when there is full convergence of productive technology.

The rest of this paper is organized as follows. In Section 2, we discuss the data we use as well as a simple model for estimating geographic impacts. Section 3 presents our basic results in terms of geographic predictors and fitted values for land quality at the level of grid cells. Section 4 presents our basic findings on average land quality, quality-adjusted area, and quality-adjusted population density aggregated to the level of countries. This section also examines the relationships between income per capita, on the one hand, and ALQ, $QAPD$, and conventionally defined population density, on the other. Section 5 looks at the historical relationship between land quality, population density, growth of income per capita, and growth of population. Our model for explaining this historical evolution is presented in Section 6. Section 7 concludes.

2 Data and Specification

In this section we first discuss our data on geographic characteristics and the spatial distribution of population, paying particular attention to the choice of population data. We then present a simple model of how population is allocated within a country as a function of geographic characteristics, which we use to motivate our empirical specifications.

2.1 Geographic and Population Data

To measure land quality, our baseline specification combines geographic characteristics from Henderson *et al.* (2018) with agro-climatic data provided by the U.N. Food and Agricultural Organization's Global Agro Ecological Zones version 4 dataset (FAO's GAEZv4), all scaled to the same quarter-degree grid squares (approximately 773 square km at the equator).[2]

From Henderson *et al.* we use elevation, ruggedness, an index of malaria transmission, distance to the coast, and a set of four dummies indicating the presence of a coast, a navigable river, a major lake, and a natural harbor within 25 km of a cell centroid. These variables primarily reflect the potential to trade with other regions and countries. Next we add a selection of 33 characteristics from GAEZ that provide information on the thermal regime, moisture regime, and growing period of each grid square for the time period 1981–2010.[3] Finally, we include suitability indices of 11 major crops for the time period 1971–2000 from GAEZ.[4] These latter two categories primarily reflect agricultural potential, but may also have some amenity value. Finally, we control for latitude. Since our unit of analysis is a latitude-longitude grid square, and grid square sizes decrease with distance from the equator, latitude will mechanically affect our measure of the distribution of population density.[5] These

[2]Data from Henderson *et al.* (2018) are slightly updated. The FAO's GAEZ v4 dataset provides spatial data on more than 180 variables relevant to crop production. These variables are organized into 6 main themes: Land and water resources, agro-climatic resources, agro-climatic potential yield, suitability and attainable yield, actual yields and production, and yield and production gaps. The data can be accessed via the following link: https://gaez.fao.org/

[3]These 33 variables comprise the majority of continuous variables from Theme 2: Agro-climatic resources of GAEZv4. We exclude variables that overlap in definition, are linearly dependent, assume irrigation, indicate beginning dates, are missing data for a significant area of the world, or have a value of 0 for more than 95 percent of observations. The variables that are dropped under these conditions are: annual temperature amplitude, quarterly P/PET ratios, net primary production with irrigation, beginning date of the longest component length of growing period, the beginning date of the earliest growing period, reference evapotranspiration deficit, snow stock at the end of calendar year, soil moisture condition at the end of the calendar year, and number of days with a maximum temperature of 45 degrees Celsius. We further exclude the number of consecutive days with average precipitation greater than 45 mm and the average annual maximum sum of precipitation on such days; these two variables have an exceptionally low ratio of the range in the early agglomerators to the range in the late agglomerators (these categories are defined below).

[4]The 11 crops are the largest in terms of world calorie production: banana, cassava, maize, dryland and wetland rice, soybean, sweet potato, sorghum, wheat, white potato, and yam. The suitability indexes assume a subsistence-based farming system, rain-fed conditions, and no CO2 fertilization; they can be found in Theme 4: Suitability and attainable yield of GAEZv4.

[5]This issue arises when there are points of intense density in space, such as cities and towns. A grid square at the equator that contains a town and no other population will have half the density of a grid cell at 60 degrees latitude that contains a similar town, since the former grid square has half the area of the latter.

53 variables are listed in Table A.3 of the Appendix. An alternate extended specification adds 66 indicators defining classes from 5 climate classifications in GAEZ for the time period 1981–2010.[6] These geographic data are available for 164 countries. While other exogenous natural features are likely useful for human settlement, they are either hard to define, like defendability, or measured based on highly endogenous search, like mineral deposits.

Our primary population dataset is the European Union's Global Human Settlements population layer (GHS-POP), which provides an estimate of population within each 30-arc-second (approximately 1 square km) grid cell. These data are produced in two steps. First, an initial estimate is taken directly from the Gridded Population of the World version 4 (GPWv4). GPWv4 in turn takes population estimates for administrative regions (polygons), typically from censuses circa 2010, and allocates them to cells assuming a uniform distribution. Its effective spatial resolution thus depends on what information individual countries provide, with richer countries typically providing population data for finer regions, down to enumeration units, or even block level data. Of 12.9 million input polygons worldwide, 10.5 million are in the United States. There is substantial variation within countries as well, with higher resolution in more densely populated regions.[7]

In the second step, GHS-POP reallocates GPWv4 estimates within administrative polygons based on a companion dataset, GHS-BUILT, that defines built surface based on Landsat 30-meter resolution satellite data circa 2015. In the rare cases where no built areas are visible in a region, it reverts to the GPWv4 estimates.[8]

GHS-POP's use of building cover to redistribute people within census units is very likely to provide more accuracy than GPWv4's assumption of uniform density within large administrative units. We however avoid more heavily modeled population datasets such as LandScan (Rose and Bright, 2014), primarily due to endogeneity concerns. In the Appendix, we compare these three datasets in greater detail, including what they say about

[6] The 5 climate classifications included are thermal climates, thermal zones, classification by thermal climates and thermal zones, multi-cropping class (rain-fed), permafrost classes, and a thermal classification used in the fallow requirement function.

[7] A grid cell crossing a polygon boundary is assigned a population density that is the areally-weighted average of its constituent polygons.

[8] More information about the GHS data can be found in Florczyk *et al.* (2019). GHS-POP is described in Schiavina *et al.* (2019) and Freire *et al.* (2016). GHS-BUILT is described in Corbane *et al.*, (2018 and 2019). GPWv4 is described in CIESIN (2017).

the key relationship between GDP per capita and quality-adjusted density.

To calculate conventional population density, we follow GHS-POP and divide population by land area from GPWv4, but we first aggregate both to quarter-degree grid squares to match the spatial resolution of our geographic characteristics. We limit the analysis to latitudes between 55 South and 75 North due to data availability. GHS-POP registers 40% of our sample grid squares (35% of the sample area) as having no people, although other information suggests many of these grid squares have some population.[9] Non-zero values begin at a value of 3 people per billion square kilometers. These two issues, many zeroes and very small non-zero values, guide our choice of estimation strategy discussed towards the end of the following section.

2.2 Estimating Land Quality

We outline a simple model of population allocation within a country that leads directly to our econometric specification. Production in region (grid cell) i of country c is given by

$$Y_{i,c} = (A_{i,c} Z_{i,c} B_c)^{1-\alpha} L_{i,c}^{\alpha} \tag{1}$$

where $A_{i,c}$ is a measure of land productivity, $Z_{i,c}$ is the land area, and B_c is a country-level measure of productivity due to non-land factors (institutions, technology, etc.). Differences in physical and human capital per worker could also be incorporated into B_c. Similarly, allowing for agglomeration economies would not affect the key results of the model for our purposes.[10] Although the regions that we use are all quarter-degree squares of latitude and

[9] At least some of the grid squares that are reported in GHS as having zero population are clearly cases of measurement error. Aligning the GHS data with Google Earth and Google Satellite View, we were easily able to find many instances of obvious human habitation, including sheep stations, isolated farm houses, and even some small villages. The largest example we found was the settlement of Tura, Krasnoyarsk Krai, Russia, which Wikipedia lists as having a population of 5,535 in 2010. We believe that the primary driver of this measurement error is the low (30 meter) resolution of the Landsat data used in GHS to distribute population within administrative units.

[10] If we think that agglomeration economies come from density as in the classic Ciccone and Hall (1996) paper or more modern papers such as Combes *et al.* (2017) and Henderson, Kriticos and Nigmatulina (2020), then there should be a multiplicative argument on the right hand side of (1) equal to $(L_{i,c}/Z_{i,c})^{\eta}$. In this case, equation (9) is the same except the $X_{i,c}$ term is multiplied by $(1-\alpha)/(1-\alpha-\eta)$. Using $1-\alpha = 0.25$ or 0.33 from below and $\eta = 0.04$, which is typical in the literature (see Rosenthal and Strange, 2004, or Combes and Gobillon, 2015), this factor is 1.19 or 1.14. While this affects the interpretation of the estimated coefficients in (9), it does not affect the fitted values from this equation that we focus on below.

longitude, they differ in their land areas both because lines of longitude converge away from the equator and because parts of some grid squares are covered with water.

Total labor in the country is

$$L_c = \sum_{i=1}^{N_c} L_{i,c} \tag{2}$$

where N_c is the number of regions in country c. We assume that workers in a region are paid their average product

$$y_{i,c} = \Big(\frac{A_{i,c}Z_{i,c}B_c}{L_{i,c}}\Big)^{1-\alpha} \tag{3}$$

and that labor mobility within a country equalizes income among regions

$$y_{i,c} = y_c \tag{4}$$

We can thus solve for the equilibrium distribution of workers using (2), (3), and (4):

$$L_{i,c} = \frac{A_{i,c}Z_{i,c}}{\sum\limits_{i=1}^{N_c} A_{i,c}Z_{i,c}} L_c \tag{5}$$

Combining the three previous equations, we can solve for the level of income per capita.

$$\ln y_c = (1-\alpha)\Big(\ln B_c - \ln\big(\frac{L_c}{\sum\limits_{i\in c} A_i Z_i}\big)\Big) \tag{6}$$

While we cannot observe $A_{i,c}$ directly, we do observe a set of land characteristics $X = [X_1, X_2, ...]$ that we assume affect productivity[11]:

$$A_{i,c} = exp(X_{i,c}\beta) \tag{7}$$

Previous work (Nordhaus, 2006; Henderson, *et al.*, 2018) estimated the parameters in equation (7) by taking logs and plugging into equation (5) with a log-additive error term:

[11] It is straightforward to allow these characteristics to also affect the amenity value of a location in addition to productivity. Specifically, we can modify (4) so that mobility within a country equalizes the product of income and amenities, rather than just income.

$$\ln(L_{i,c}/Z_{i,c}) = C_c + X_{i,c}\beta + \epsilon_{i,c} \tag{8}$$

where C_c is a country fixed effect and $\epsilon_{i,c}$ is a stochastic error term. There are three key problems with this log-linear specification, however.

First, 40% of grid squares in our data have zero reported population. While a strict application of the model suggests there should be no zeros, we believe the volume of zeros largely reflects measurement error (discussed above) as well as restrictions on where people are permitted to live.[12] A common approach to this problem is to replace these zeros with a small non-zero value.[13] Unfortunately, parameter estimates can be sensitive to the value used for imputation, and are also sensitive to simply dropping zeros. Second, as seen in Figures A1.A and A1.B, about 50% of grid squares have density values less than 0.135 people per square kilometer and about 75% have density less than 12 people per square kilometer. Thus, beyond the problem of zero reported population densities, the specification in (8) puts a lot of weight on regions with extremely low population densities. Given the data construction process described above, it is highly unlikely that the differences between e.g. $3 \cdot 10^{-9}$ and 0.135 people per square kilometer are well-measured. Even if they were well-measured, conceptually they are of less interest than what drives regions to have a density of 12 versus 1000 people per square kilometer. According to the GHS data, 98.5% of the world's population lives in grid squares with density above 12 people per square kilometer. Third, Santos Silva and Tenreyro (2006) show that OLS estimates of (8) are inconsistent (and NLS inefficient) in the presence of heteroskedasticity, which is likely in our context.

For these reasons we estimate a Poisson model. The specific functional form is

$$E(L_{i,c}/Z_{i,c} \mid C_c, X_{i,c}) = exp(C_c + X_{i,c}\beta) \tag{9}$$

[12] According to the United Nations Environment Programme (2016), 14.7% of the world's land area is in "protected areas" such as national parks.

[13] For example, Henderson, *et al.* (2018), which examined lights data, assigned to every reported zero observation the minimum non-zero value in the dataset. In Nordhaus (2006), where output per square kilometer is the dependent variable, 3,170 of 17,409 grid squares in the regression sample have zero values for the dependent variable. Nordhaus imputes values for 618 of these cells based on neighbors, and then assigns the remainder a value of one before taking logs.

The Poisson specification is well-suited for outcome measures with many zeros and tiny values. As shown in Appendix Figure A.2, predicted values of density from a Poisson specification are remarkably robust to using the two alternative population datasets noted above, while log-linear predicted values are not. Similarly, our basic results on the relationship between quality-adjusted population density and income per capita discussed in Section 4.3 are again remarkably similar across the three datasets under the Poisson specification with or without censoring zeros and tiny values, while estimates of the log-linear specification are wildly different (see Table A.2.)

The stochastic component of the Poisson model is crucial for addressing the contingent nature of human settlement. There is a vast literature on multiple equilibria and accidents of history with agglomeration (e.g. Krugman, 1991; Arthur, 1989; Davis and Weinstein, 2002). More recent work has focused on dynamic development subject to stochastic processes that yield particular, unique equilibria as a way of encapsulating these accidents (Michaels, Rauch, Redding, 2012; Desmet and Rappaport, 2017). For example, in a model similar to ours but with a more complex production process, Desmet and Rappaport envision regions as being subject to initial large productivity/resource shocks and then to a series of accumulating independent draws over time. These accidents are important to understanding why, for example, the centre of Kolkata is not 50 kilometers further up or down the Hugli River or on a completely different river in historical Bengal. In that particular case, an initial arbitrary choice of a British East India Company employee, Job Charnock, and then a history of other choices and accumulations over 300 years, anchored that location and induced high density. Our reduced form specification summarizes the cumulative impact of such a succession of shocks. Since we are assuming a Poisson specification overall, we effectively assume that these shocks are a series of Poisson draws.

We estimate the parameter vector β in equation (9). The country fixed effects control for factors like technology and national population relative to national land area. Identification of the determinants of land quality comes solely from within-country variation. In other words, β is not estimated by comparing the land characteristics of more and less densely populated countries, but rather by comparing variation in land characteristics and population density within countries. We judge a country as having high-quality land if it is endowed with more of the characteristics that predict higher within-country population density throughout the world. Given our expression for $A_{i,c}$ in equation (7), our estimate of grid square i's land quality is naturally the fitted value from (9), suppressing country fixed effects:

$$Quality_{i,c} = exp(X_{i,c}\hat{\beta}) \tag{10}$$

3 Cell-level Results on Land Quality

We begin by looking at the explanatory power of equation (9). Poisson regression has no perfect analog to the coefficient of determination (R^2) in OLS. We follow Cameron and Windmeijer (1996) in reporting R^2_{DEV}, which is based on the concept of *deviance*, the difference between the model log-likelihood and the highest possible likelihood for a given dependent variable. It is defined as:

$$R^2_{DEV} = \frac{\sum_i [y_i \ln(\hat{\mu}_i/\bar{y}) - (\hat{\mu}_i - y_i)]}{\sum_i y_i \ln(y_i/\bar{y})} \tag{11}$$

where y_i is the value of the dependent variable for observation i, $\hat{\mu}_i$ is the predicted value for observation i, and $\bar{y}$ is the average of y_i.[14]

In Table 1, we report R^2_{DEV} for the basic specification and a set of alternatives for a Poisson regression using the GHS-POP data.[15] The first row of the table shows that geography and country fixed effects alone each explain similar amounts of variation, but the marginal effect of each is also very high. In the other rows, we examine the robustness of this result with respect to three potential concerns. First, we experiment with dropping the six countries with the largest land area, which contain 54.1% of grid squares and a large share of within-country variation.[16] Second, Henderson, *et al.* (2018) stress that the determinants

[14]This measure applied to Poisson models shares five desirable properties with R^2 applied to OLS: it is bounded within $[0, 1]$; never decreases with additional regressors; can be equivalently expressed based on sum of residual squares or sum of explained squares; relates to joint significance tests of all the slope parameters; and has an interpretation in terms of information content. Other typical pseudo-R^2 measures for Poisson models do not satisfy all these properties.

[15]In Appendix Table A.1 we report the explanatory power of geographic variables and country fixed effects for the Poisson and log-linear specifications for GHS-POP, GPWv4 and LandScan, as well as versions of GPWv4 and GHS-POP that are censored to match the minimum non-zero value in LandScan.

[16]The countries are Russia, Canada, USA, China, Brazil, and Australia. We choose six as our cutoff

of agglomeration differed systematically between early- and late-agglomerating countries. They show that geographic characteristics related to agriculture had a proportionally larger impact on urbanization in the former group, while those characteristics related to trade had a proportionally larger impact in the latter. Migration frictions also may remain larger in the late-agglomerator countries. To test whether these considerations affect our analysis, we re-run the population equation using two complementary sub-samples (early and late agglomerators, based on urbanization in 1950) to estimate the weights on geographic factors. Finally, we estimate the model on a set of countries in which more than 80 percent of the population is descended from people who lived in the country 500 years ago ("*Native*" for short), based on data from Putterman and Weil (2010).[17] This sample comprises about 65% of countries with 82% of world population. Throughout the rest of the paper we often focus on these countries and either drop the others or control for a $Native < 80\%$ indicator. New World countries, where native populations have largely been replaced over the last 500 years, have systematically different population histories than countries of older settlement.

Table 1: Goodness of Fit Under Alternative Samples

	Country Only	Geography Only	Both	N
Full Sample	0.344	0.464	0.566	237,023
Exclude Six Large Countries	0.317	0.366	0.486	108,872
Early Agglomerators Only	0.328	0.526	0.571	134,211
Late Agglomerators Only	0.264	0.443	0.530	102,619
Native >80%	0.337	0.518	0.574	135,057

Notes: All regressions use the GHS dataset and Poisson specification. Goodness of fit measure is R-dev-squared.

Table 1 shows that results are similar across these specifications. While row 2, which drops the six largest countries, has lower overall R^2_{DEV} in each of the columns, considerable explanatory power remains. Rows 3 and 4 indicate that geography has a somewhat stronger role for early agglomerators, but patterns for early and late are similar. Geography also plays a somewhat stronger role when we exclude countries where the native population was replaced over the last 500 years.

because there is a natural break in the distribution of country sizes between the sixth largest (Australia, $7,692,024$ km^2) and the seventh largest (India, $3,287,263$ km^2).

[17] The results reported later are insensitive to using alternative cutoffs or a continuous measure rather than a dummy.

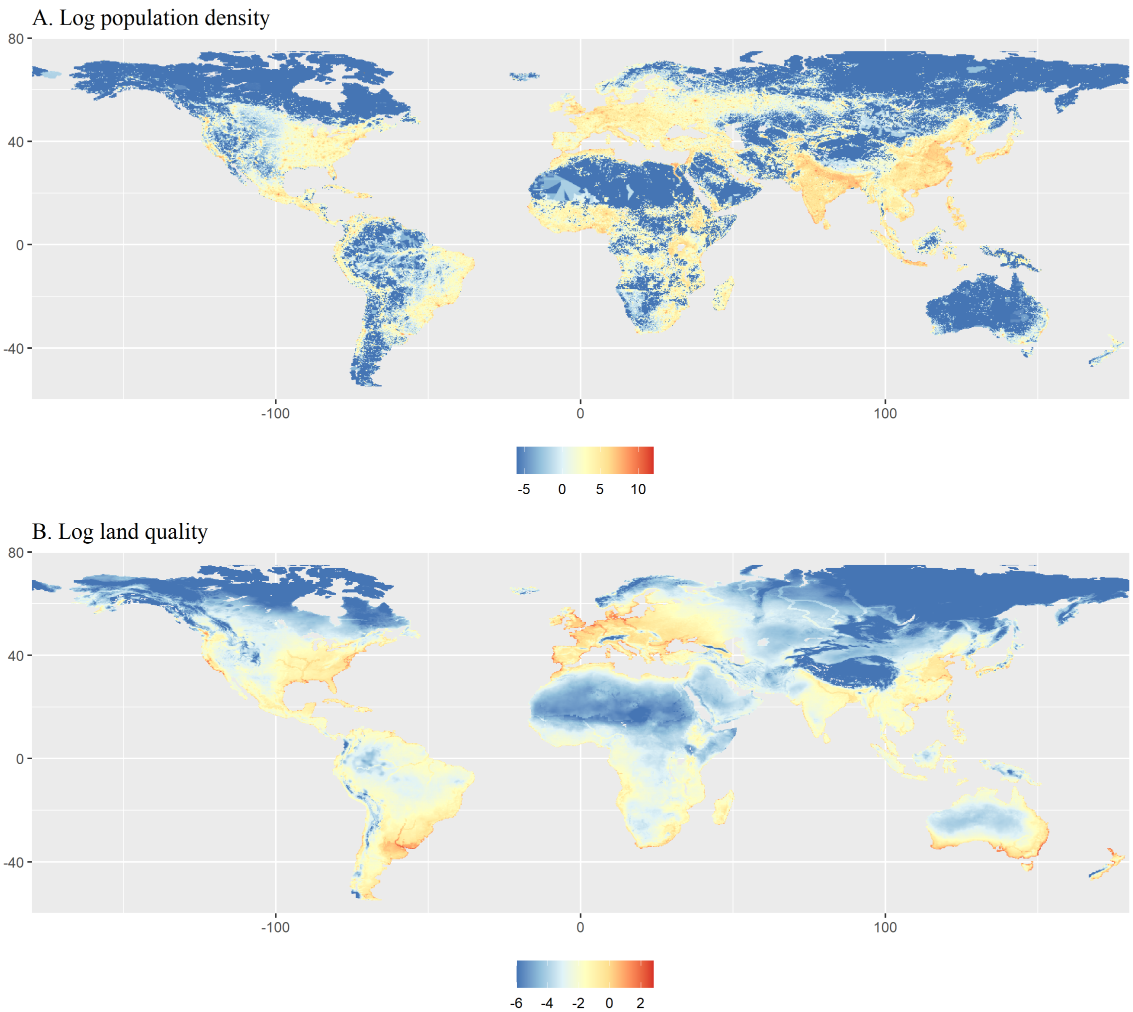
These specifications use the base set of 53 covariates listed earlier. In Appendix B, we experiment with extended sets of up to 951 covariates and a formal method for selecting which ones to include in estimation using Lasso (Tibshirani, 1996). Lasso rarely drops our base covariates, and implies that our 53-variable base specification does not have an overfitting problem. Predictions of key variables used below, like country average land quality, are all highly correlated across the different specifications. We thus limit the analysis to the 53 base covariates for transparency.

Table A.3 in the Appendix shows the coefficient estimates from this baseline specification.[18] With some exceptions particularly among the crop suitability indices, almost all coefficients are highly significant. As an example quantitative interpretation, the coefficient of 0.43 on the coastal dummy implies that coastal cells have $exp(0.43) = 1.54$ times higher population density than non-coastal cells, *ceteris paribus*. Given the subject of this paper, we focus our interpretation on fitted values from this equation, rather than coefficients. Specifically, the fitted values suppressing country fixed effects are what we define in (10) as *Quality*. In our model, if the world were a single country, with the same technology and institutions (B in equation (1)) and with perfect mobility of population, then population density in each grid cell would be proportional to *Quality*.

Figure 1A shows actual population density and Figure 1B shows *Quality*, both at the level of grid cells. The values are on different color scales because the range of *Quality*, a fitted value, is naturally smaller. Visually, there are clear similarities between *Quality* and actual population density, with high values for *Quality* in Europe, northern China, the River Plate basin, and the Ganges delta, among other places. Not surprisingly, *Quality* does a worse job of capturing agglomeration. In Figure 1A, there are more points of intense concentration such as Mexico City, Shanghai, Delhi, or Guangzhou, which do not have particularly high values of *Quality* in Figure 1B in comparison to surrounding areas.

[18] Reported standard errors relax the "equidispersion" assumption of classical Poisson estimation that the variance of the dependent variable is equal to its mean, which is rejected in our data. The quasipoisson model we implement assumes instead that variance is proportional to the mean and estimates the constant of proportionality.

Figure 1: Population Density and Land Quality



4 Country-level Aggregates

The remainder of the paper focuses on country-level aggregates of our cell-level measure of land quality, $exp(X_{i,c}\hat{\beta})$. As explained above, $\hat{\beta}$ is estimated solely using within-country variation. Thus these aggregates are not constructed with any notion of cross-country relationships between land quality and population density, or any other country-level outcome, already baked in. An individual country having a dense population does not necessarily mean it has high land quality. Rather, a country is designated as having high land quality if it has characteristics that predict higher population density within-country on a global basis.

4.1 Quality-Adjusted Area

Multiplying land quality from equation (10) by grid cell area produces what we call *Quality-Adjusted Area* of a grid cell. We can similarly construct quality-adjusted area at the country level, QAA_c:

$$QAA_c = \left[\frac{\sum\limits_{i \in W} Z_{i,c}}{\sum\limits_{i \in W} exp(X_{i,c}\hat{\beta}) Z_{i,c}} \right] \sum_{i \in c} exp(X_{i,c}\hat{\beta}) Z_{i,c} \tag{12}$$

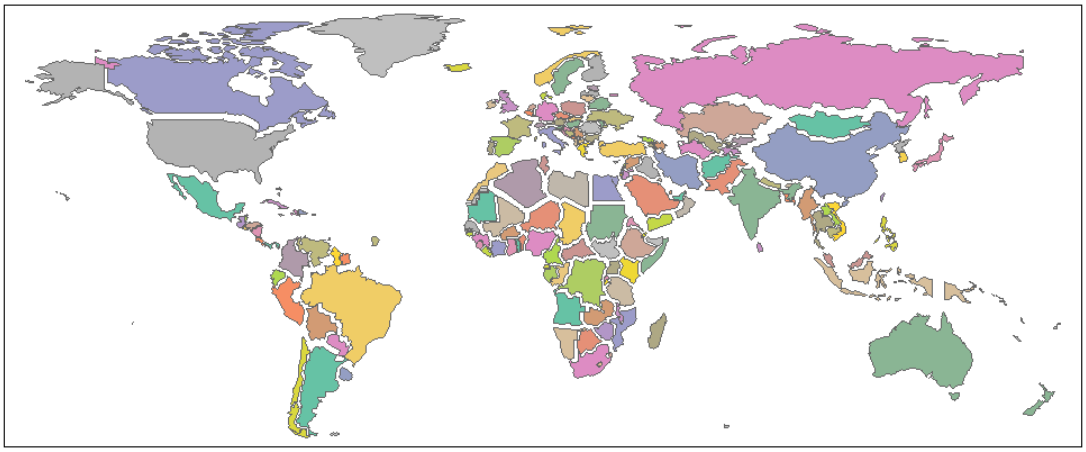
where the term in brackets is a normalization so that QAA_c across countries sums to the actual area of the world (W). In essence, QAA_c is a country's allocation of world land based on its quality of land relative to the world average quality of land.

Figure 2b presents a cartogram in which each country's area is proportional to its quality-adjusted area from equation (12), vs. its actual size in Figure 2a. The corresponding numbers are listed in Appendix Table C.1, columns 2 and 3. In comparing QAA with conventional area, there are a number of interesting rescalings and rank reversals, many of which accord with common sense. For example, in our sample (south of 75 degrees North latitude) Canada has 97% of the conventional area of the United States, but only 11% of its quality-adjusted area. Overall, the figure is notable for showing that Europe expands greatly in size, while Africa contracts. The five countries with the highest quality-adjusted area are the United States, Australia, China, Brazil, and Argentina.

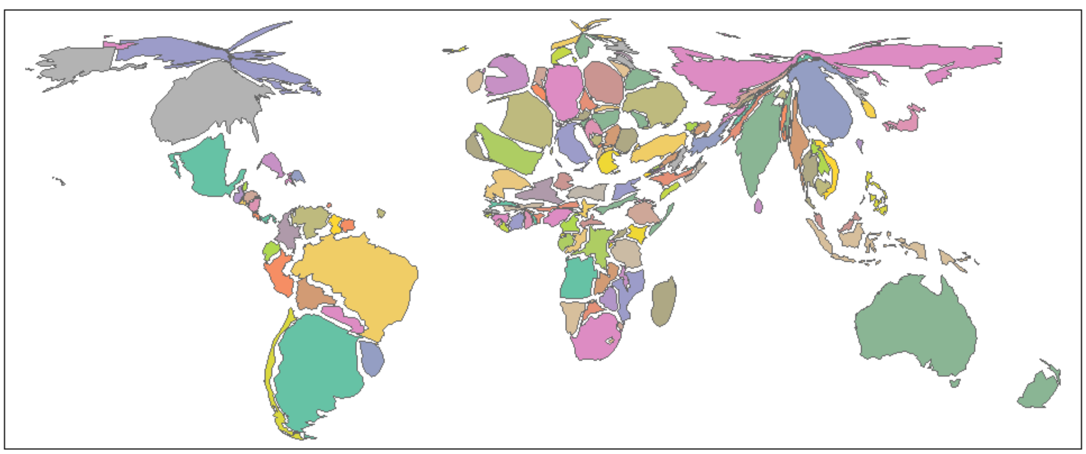
For a corresponding perspective, we ask what each country's population would be if the world's population were reallocated such that country populations were proportional to quality-adjusted areas. This involves replacing the numerator of the term in square brackets in equation (12), world land area, with total world population. Figure 3 shows actual (in blue) and reallocated (in red) log populations for the 80 countries with the largest quality-adjusted areas, with numbers taken from Table C.1. The distance between the red and blue dots represents the proportional gain or loss this reallocation would entail. The five countries

Figure 2: Country Level Quality-Adjusted Area

(a) Countries by Land Area

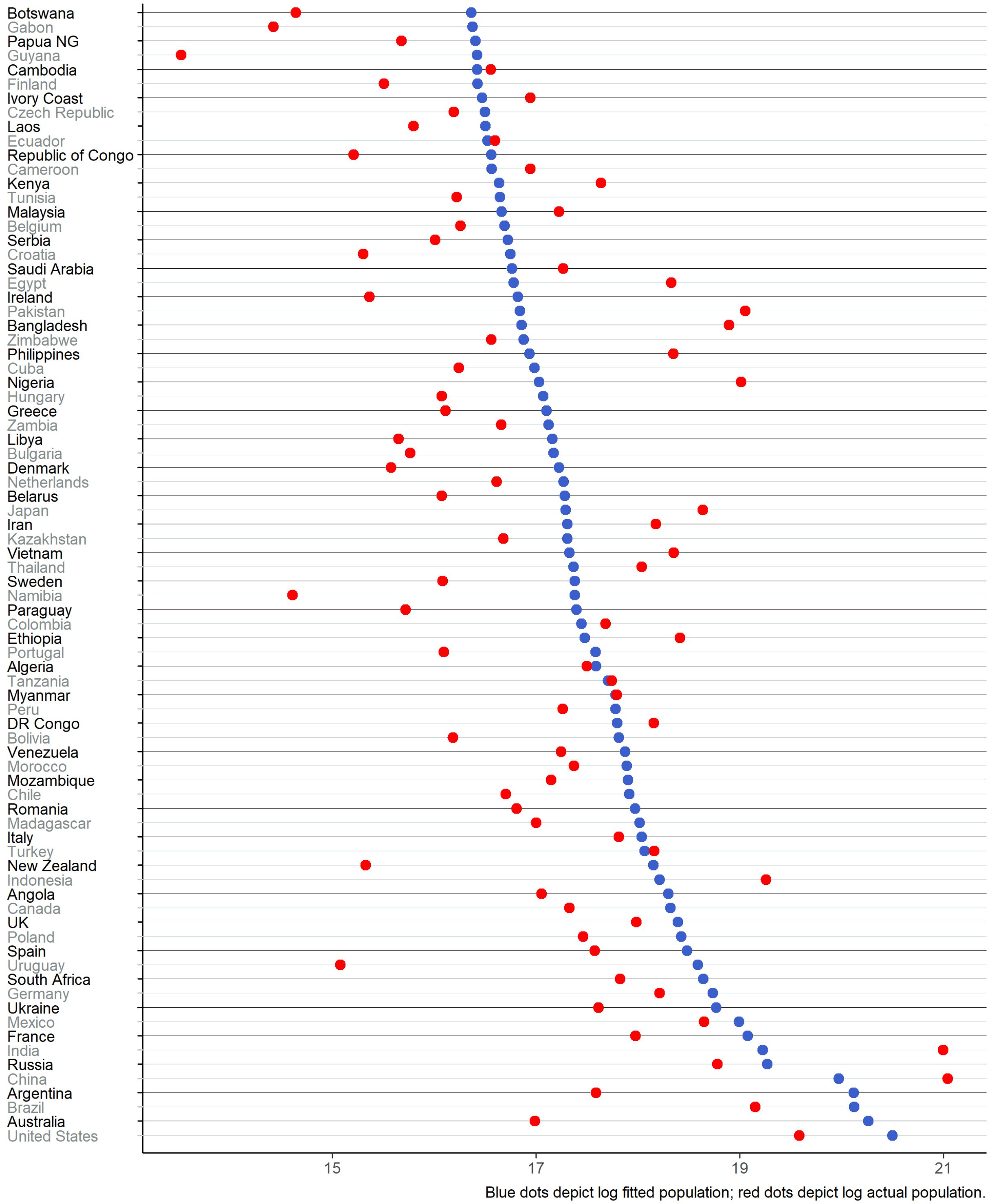


(b) Countries by Quality-Adjusted Area



with the biggest gains in absolute population size would be Australia (adding 605 million), Argentina (502 million), the United States (479 million), Brazil (341 million), and France (129 million). By contrast, the countries with the biggest absolute declines following such a reallocation would be India (losing 1.09 billion), China (903 million), Pakistan (167 million), Nigeria (156 million), and Indonesia (149 million).

Figure 3: Top 80 Countries by Fitted Population



4.2 Average Land Quality

Next we can calculate average land quality of a country using normalized QAA_c:

$$ALQ_c = \frac{QAA_c}{Z_c} \tag{13}$$

where $Z_c = \sum_{i=1}^{N_c} Z_{i,c}$. Average land quality values are in column 1 of Appendix Table C.1. Similar to the thought experiment above, if the world had uniform institutions/technology and there was perfect international population mobility, then the population density of countries would be proportional to their average land quality. The five countries with the highest average land qualities are the Netherlands, Denmark, Uruguay, Belgium and Portugal.

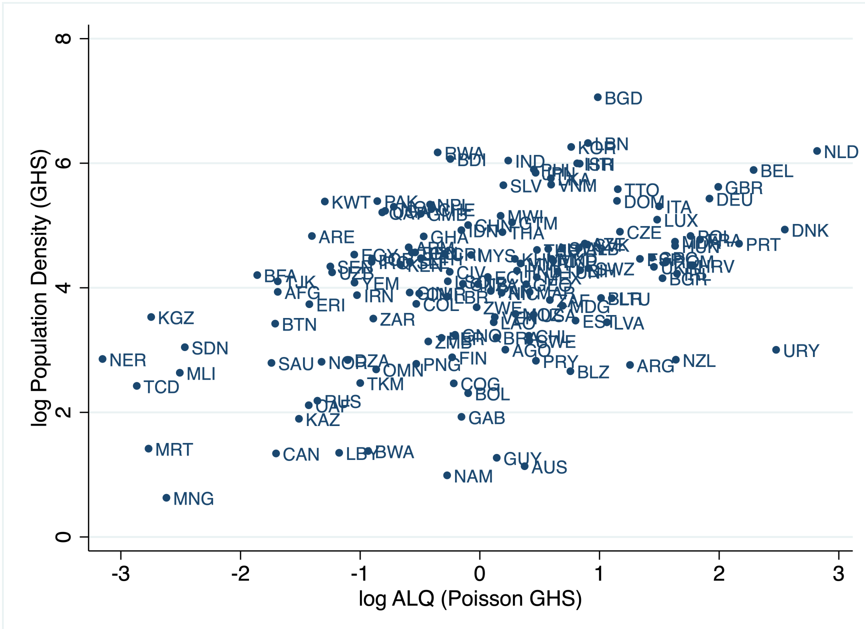
4.2.1 Average Land Quality and Population Density

A natural starting point for assessing our measure of land quality is to look at how it relates to population density. Recall that land quality at the grid cell level is constructed from a regression with country fixed effects, but that these fixed effects are suppressed in forming the fitted values that measure land quality. Thus in principle it would be possible for the fitted values to have a low or even negative correlation with actual population density. Figure 4 shows that looking across countries the correlation is in fact positive. Further below (Table 5) we show this result in regression form and discuss how it has changed historically.

4.2.2 Average Land Quality and Income per Capita

While a positive relationship between land quality and population density would be predicted by just about any model, the relationship between land quality and income per capita is more complicated. The idea that good geography should make a country richer goes back to at least Smith (1776). But there has always been a logical problem with this view: Since Malthus (1798), economists have understood that if population density increases the congestion of natural resources and if population is endogenous, due to either migration or a feedback from the standard of living to net reproduction, then better geography should make a country or sub-national region have more people in it, but not make those people better off. Looking within a country like the United States, this phenomenon is obvious.

Figure 4: log Conventional Density and log ALQ



For example, the states of Idaho and South Carolina have almost exactly the same levels of Gross State Product per capita, but differ in average land quality by a factor of 9.5 and in population density by a factor of 7.6.

Empirically, a good deal of the literature supporting the contention that better geography makes countries richer (e.g. Mellinger, Gallup, and Sachs, 2000) comes from cross-country regressions of income per capita on geographic variables. Such evidence is hardly dispositive, however, because of the well-known correlation of geography with institutions and colonial history (e.g. Acemoglu, Johnson, and Robinson, 2001). Further, as we show below, several existing measures of land quality that are not constructed from cross-country regressions are actually negatively correlated with income per capita. We thus view the relationship between land quality and income as worthy of both further empirical study and theoretical exploration.

Examining the relationship between income and land quality requires us to reduce the sample size from 164 to 148 countries. This is the main sample which we maintain in all of the work that follows.[19] Figure 5 shows a striking positive correlation between ALQ and

[19]We call the 148 countries our main sample. Eight of 164 countries do not have a GDP measure; 3 have area under 1500 sq km, approximately two cells, and therefore have no real within-country geographic variation; and 10 have no Putterman-Weil index of the fraction of the current population descended from

Figure 5: log GDP per capita and log ALQ

income per capita. It is notable that many of the outliers in this figure appear to be special cases such as hydrocarbon producers (Qatar, Kuwait, Saudi Arabia, United Arab Emirates) or small countries with large banking sectors (Switzerland, Luxembourg). Table 2 shows corresponding regression results.[20] For the reasons discussed above, we control for a dummy that takes the value one where $Native < 0.8$.[21] The key finding of Table 2 is that there is a strong, positive relationship between ALQ and income per capita. The baseline elasticity of 0.43 in column (1) implies that a two standard deviation increase in log ALQ is associated with a rise in GDP of 1.01 in log points, or about 170%.

The other columns of Table 2 focus solely on the agricultural dimension of land quality. In column (2), we construct our measure of land quality starting from a grid cell regression that includes only country fixed effects, latitude, and the 33 measures of land characteristics

people present 500 years ago, which we emphasize later. Several are missing more than one of these.

[20] Because ALQ and its variants defined below are generated regressors, their OLS standard errors are inconsistent (Pagan, 1984; Murphy and Topel, 1985). To address this, we estimate bootstrapped standard errors in all regressions that include them. Specifically, we sample countries with replacement, and then estimate (9) on the set of all cells in the sampled countries. We use these estimates in (12) and (13) to calculate ALQ for the sampled countries, and estimate the regression of interest for the same sample. We do this 500 times to generate 500 sets of regression coefficients. The reported standard errors are the sample standard deviations of these coefficient estimates.

[21] All coefficients change by less than 6% with the addition of the $Native < 80\%$ control.

Table 2: Land Quality Measures and Income

	(1)	(2)	(3)	(4)
	Dependent variable: log GDP per capita			
Land quality measure:	log ALQ	log ALQ, agricultural	log calories per hectare	log land suitability
Land quality measure	0.430**	0.270	-0.673***	-0.0222
	(0.158)	(0.184)	(0.168)	(0.0462)
Native<80%	0.241	0.282*	0.250	0.277
	(0.162)	(0.133)	(0.191)	(0.204)
Constant	8.946***	8.895***	14.96***	8.638***
	(0.0878)	(0.130)	(1.501)	(0.662)
Observations	148	148	146	148
R-squared	0.180	0.0542	0.0911	0.0133

Notes: Column (2) uses the analogue of our *ALQ* measure, but constructed from a grid-cell regression that only includes country fixed effects, the 33 characteristics from GAEZ, the 11 suitability indices, and latitude. Column (3) is the log of million calories of agricultural production potential per hectare per year at intermediate input technology, from Galor and Ozak (2016). Column (4) calculates the log of land suitability from Ramankutty et al. (2002). Standard errors are reported in parentheses. Standard errors in columns (1)-(3) are bootstrapped. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

and 11 suitability indices from the GAEZ dataset. This purely agricultural measure has a positive relationship with GDP per capita, although the effect is smaller in magnitude than that of our full-fledged measure, and is not statistically significant. No positive association exists between GDP per capita and two alternative measures of agricultural land quality: calories of agricultural potential unit per area (Galor and Ozak 2016; column 3) and land suitability for agriculture per unit area (Ramankutty *et al.* 2002; column 4).[22] In fact, the Galor-Ozak measure has a significantly negative relationship with GDP per capita. These findings suggest, first, that our agricultural measures may provide a more nuanced assessment of agricultural productivity than the uni-dimensional indices used in previous work, and second, that the inclusion of additional geographic variables that go beyond agriculture, such as ruggedness, elevation, and access to water for transport, is important for assessing land's overall quality.

Table 3 probes the robustness of this result that higher average land quality is associated with higher income today to different specifications of the grid-cell regression that we used to measure land quality. Column 1 shows our baseline result, where the elasticity of GDP

[22] This is the weighted average of the Ramankutty index for each grid square, where the weights are grid-square areas.

with respect to ALQ per capita is 0.43. Columns 2–4 correspond to rows 2–4 in Table 1. In column 2, we drop the 6 largest countries in the grid square regression (equation (9)), but still predict ALQ for them using the estimated coefficients. In column 3 we estimate land quality parameters in a grid-cell regression run only in early agglomerating countries and predict ALQ for all countries from those coefficients. Column 4 repeats this exercise for late agglomerators, and column 5 for $Native > 80\%$ countries. In all these specifications, the income-ALQ elasticity remains large, from 74% to 101% of the baseline.

Table 3: Robustness of ALQ and Income Relationship

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: log GDP per capita				
Grid cell regression	Baseline	Drop 6 Largest	Only Early Agglomerators	Only Late Agglomerators	Native >0.8
ALQ measure	0.430**	0.340***	0.320***	0.422**	0.440***
	(0.158)	(0.0839)	(0.0967)	(0.144)	(0.0826)
Native<80%	0.241	0.204	0.216	0.271***	0.241
	(0.162)	(0.288)	(0.111)	(0.0630)	(0.174)
Constant	8.946***	8.951***	9.103***	9.071***	8.965***
	(0.0878)	(0.116)	(0.0823)	(0.955)	(0.197)
Observations	148	148	148	148	148
R-squared	0.180	0.108	0.175	0.278	0.195

Note: We restrict the sample in these regressions to exclude countries with areas below 1,500 km^2. Bootstrapped standard errors are reported in parentheses. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The findings of Tables 2 and 3 clearly show that countries with higher quality land are on average richer. This in turn raises the question of why the prediction of the simple population equilibrium model is not borne out, to which we return below.

4.3 Quality-Adjusted Population Density

Finally, we can use land quality to create a new measure of population density. We define Quality-Adjusted Population Density ($QAPD_c$) simply as country population divided by normalized QAA_c, or equivalently as conventional population density divided by ALQ_c:[23]

[23]Ignoring the normalization in (12), $QAPD$ can written as

$$QAPD = \frac{L_c}{\sum\limits_{i \in c} exp(X_{i,c}\hat{\beta})Z_{i,c}}.$$

$$QAPD_c = \frac{L_c}{QAA_c} = \frac{L_c}{Z_c ALQ_c} = \frac{PD_c}{ALQ_c} \tag{14}$$

Column 7 of Appendix Table C.1 shows values of log $QAPD$, which is measured in units of population per quality-adjusted square kilometer. For the world as a whole, $QAPD$ is 56.6, which is, by construction, the same as conventional population density for our geographic sample covering most of the world. The five countries with the highest levels of quality-adjusted population density are Kuwait (797), Rwanda (683), Burundi (553), Kyrgyzstan (533), and Pakistan (517) (excluding the city-states of Hong Kong and Singapore, as well as countries with populations of less than one million). The five countries with the lowest $QAPD$ are Uruguay (1.70), Australia (2.14), New Zealand (3.35), Namibia (3.54) and Argentina (4.51). Among the other interesting findings in this table are that China, with $QAPD$ 2.9 times the world average, has noticeably lower quality-adjusted density than India, which is 5.9 times the world average. The United Kingdom (37.6) and Germany (33.6) have higher $QAPD$ than the United States (22.6). However, the United States, despite being in the New World, has higher quality-adjusted density than France (18.8) or Ireland (13.2).

Figure 6 compares conventional population density to $QAPD$ in logs using our main 148-country sample. The two measures of density are highly correlated, but there are notable differences. For example, while Mongolia is the lowest density country in the world and the Netherlands is one of the highest, the two countries have nearly identical levels of $QAPD$.

Figures 7A and 7B plot the bivariate relationships between GDP per capita and (respectively) conventional population density and our measure of quality-adjusted population density. Visually, there is little association between GDP per capita and conventional pop-

In our grid-cell level regression, the country fixed effect is given by (again, ignoring the normalization)

$$\hat{C}_c = \ln\left(\frac{\sum\limits_{i \in c} \frac{L_{i,c}}{Z_{i,c}}}{\sum\limits_{i \in c} exp(X_{i,c}\hat{\beta})} \right).$$

The difference between these expressions is that the expression for the fixed effect divides the items in the numerator by grid square land area Z_i before summing, while in constructing $QAPD$ the Z_i terms are in the denominator sum. As noted earlier, these areas vary within a country both due to the convergence of longitude lines away from the equator and the exclusion of surface water area. If all grid cells in a country had the same area, the country fixed effect that we estimate would just be the log of quality-adjusted population density, ignoring the normalization. In practice, the correlation of the fixed effect and the log of quality-adjusted population density across countries is 0.98, so that the two measures are almost interchangeable.

Figure 6: Conventional and Quality-Adjusted Population Density Across Countries

ulation density, while GDP per capita and quality-adjusted density appear to be negatively correlated. It is also notable that the largest outliers in Figure 7b are again hydrocarbon producers or small countries with large banking sectors.

Table 4: GDP per Capita, Population Density, and $QAPD$ in 2010

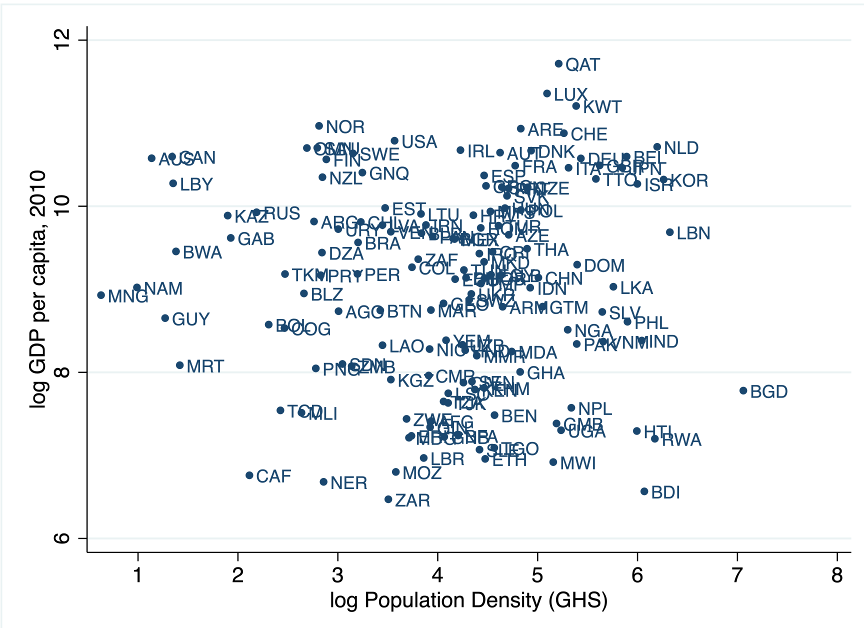
	(1)	(2)	(3)	(4)
Dependent Variable	log 2010 GDP per Capita			
log Population Density	0.0360 (0.0840)	0.0905 (0.116)		
log QAPD			-0.352*** (0.0962)	-0.515*** (0.0921)
Native<80%	0.299 (0.212)		0.0259 (0.205)	
Constant	8.787*** (0.373)	8.553*** (0.503)	10.46*** (0.456)	11.17*** (0.396)
Observations	148	96	148	96
R-squared	0.0128	0.00648	0.138	0.212

Columns (2) and (4) restrict the sample to countries where Native is greater than or equal to 80%. Standard errors are reported in parentheses. Standard errors in columns 3 and 4 are bootstrapped. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

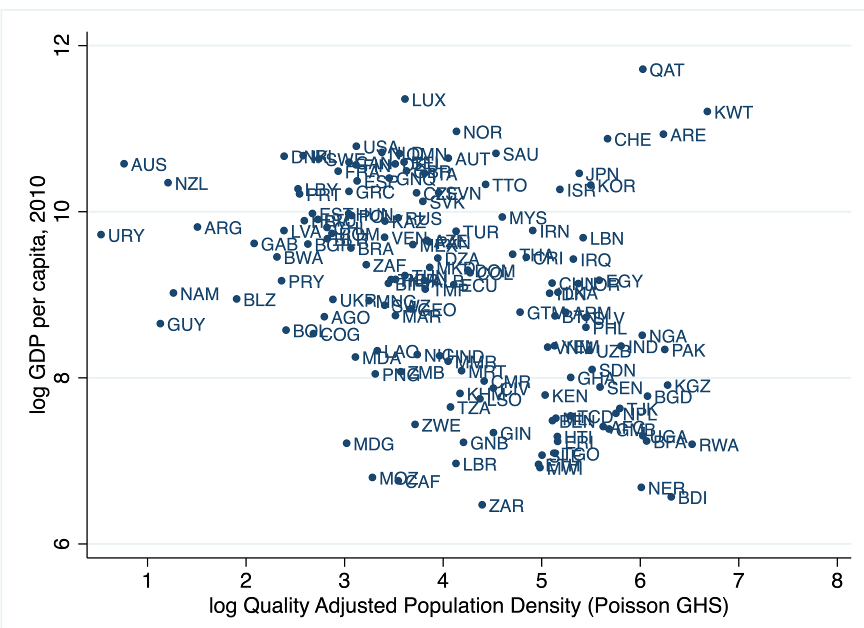
Table 4 probes this result further in a regression context. As above, we control for the

Figure 7: Density and GDP per Capita

(a) Conventional Population Density and GDP per Capita



(b) Quality-Adjusted Population Density and GDP per Capita



$Native < 0.8$ dummy and present results excluding countries where $Native < 0.8$. The table confirms that there is no correlation between conventional population density and income per capita, but a strong negative relationship between $QAPD$ and income per capita.[24] Using the coefficient in column (3) of the table, a decrease in the log of quality-adjusted density by one standard deviation (1.29) is associated with an increase in GDP per capita of 57%.

This negative relationship between $QAPD$ and income is surprising. As mentioned above, existing models of the role of natural resources in economic development predict that population in a preindustrial equilibrium will be proportional to natural resources, and give no reason to think that the same should not be true of population following industrialization. Thus income and $QAPD$ should have no correlation. If one thought that the source of income differences among countries was differences in productivity or the quality of institutions, then with endogenous population, we would expect to see a *positive* relationship between income and quality-adjusted density. It is true that one would expect to see a negative correlation between $QAPD$ and income if differences in population were generated primarily by differences in fertility preferences. However, embracing this explanation would raise the question of why countries with preference for high fertility have systematically lower land quality than those with preferences for low fertility.[25] Further, this story is inconsistent with several of the historical regularities we show in the next section, most notably that the currently observed income-$QAPD$ relationship did not exist historically.

[24]In Table A.2 and the discussion in Appendix A, we explore the result in Table 4, column 3, using the different sources of population data discussed in Section 2 and comparing a Poisson and log-linear specification to Equation (9). Results for the Poisson are similar across data sets and specifications, but log-linear results differ by data set and specification.

[25]Such a story also has a quantitative problem. Equation (6) implies that a regression of log income on log $QAPD$ would yield a negative coefficient equal in absolute value to the natural resource share in the production function, $(1-\alpha)$. Estimates of this share tend to have one-third as a maximum value (see discussion in Appendix D). The coefficient on log $QAPD$ in column 3 of Table 4, -0.352, is slightly larger in absolute value than is consistent with this range. However, in column (4) of the table, focusing on countries where the native population was not displaced, the coefficient (-0.515) is too large in absolute value to be consistent with pure resource congestion. It is also notable that these coefficients are biased toward zero due to measurement error.

5 Historical Evolution of Population and Income

To assess the historical development of population and income we use data from the Maddison project.[26] The underlying source for this data is historical national and regional accounts, wages, and other records. As an alternative to the Maddison data, we conduct a parallel analysis using data from the Gapminder project. This covers a significantly larger number of countries but relies much more heavily on statistical modeling and interpolation than does the Maddison data. Corresponding to our Tables 5–9 are Appendix Tables C.2–C.6 using Gapminder data. The patterns of results are the same in all cases.

5.1 The Effect of Land Quality on Density and Development

Figure 4 showed the relationship across countries between our measure of average land quality and population density in data for 2010. Columns (1) and (4) of Table 5 show the same relationship in regression form. It is hardly a surprise that the coefficient is highly significant.

Table 5: *ALQ* and Conventional Population Density

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	all			exclude native< 80%		
Dependent Variable	log Population Density					
Year	2010	2010	1820	2010	2010	1820
log ALQ	0.463***	0.515***	0.768***	0.498***	0.561***	0.891***
	(0.116)	(0.134)	(0.130)	(0.117)	(0.153)	(0.129)
Native<80%	-0.668*	-0.611	-2.190***			
	(0.263)	(0.371)	(0.513)			
Constant	4.311***	4.241***	2.217***	4.311***	4.224***	2.172***
	(0.109)	(0.171)	(0.167)	(0.109)	(0.172)	(0.171)
Observations	148	77	77	96	50	50
R-squared	0.254	0.289	0.563	0.313	0.385	0.577
Coefficient equality test						
$\chi^2(1)$		9.26			10.69	
p-value		0.002			0.001	

Bootstrapped standard errors are reported in parentheses. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The first question we take up in this section is whether the nature of this relationship has changed over time. Columns (2) and (5) of Table 5 show the regression of conventional

[26] Reported on the Gapminder website (https://www.gapminder.org/tag/maddison/).

density on ALQ in contemporary data for samples that match the countries for which Maddison's historical data are available. There is little change in the coefficient on ALQ from Columns (1) and (4). Columns (3) and (6) then repeat the regression using population density from 1820 as the dependent variable.

Using the 1820 data on population, the value of the coefficient on the log of land quality is relatively close to one, and in Column (6) we cannot reject the coefficient being equal to one. This is the value that we would expect in a simple model where population was proportional to land quality. By contrast, the coefficient on land quality when we use modern population data much smaller, significantly different from the 1820 value, and significantly different from one. In other words, land quality had a bigger effect on density in the past than it does today. An additional finding is that the coefficient on the dummy variable for $Native < 80\%$ is negative and three times as large in absolute value in the 1820 data as it is in modern data. This is consistent with the observation that countries in which native populations were replaced were relatively underpopulated as of that year, and have been converging to the density pattern of the rest of the world since then.

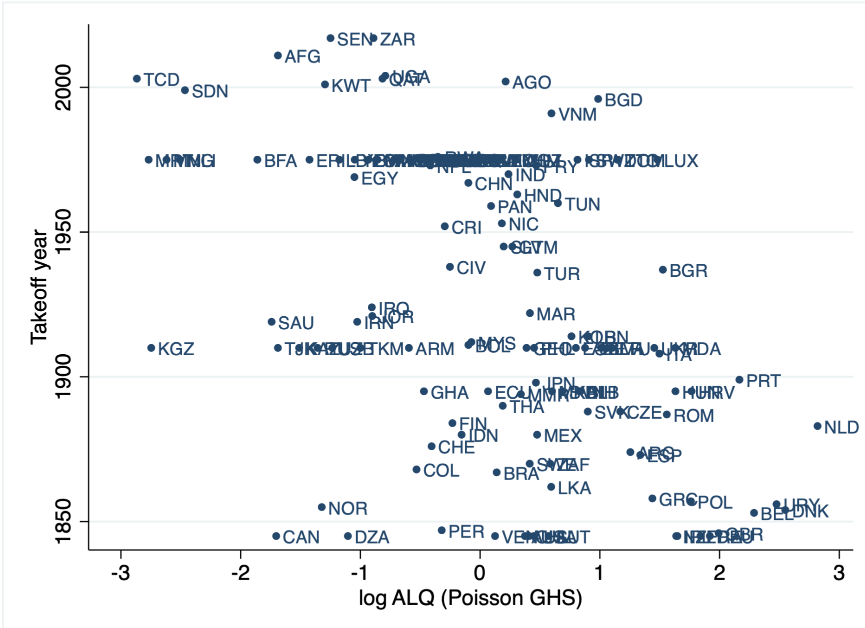
In a mechanical sense, the results in Table 5 suggest that population growth has been faster in countries with low ALQ than in those with higher land quality—something that we will look at directly in a later section. More generally, they suggest that there is a relationship between land quality and the broad processes of economic development and demographic transition which have produced large increases in population throughout the world. We probe this issue more directly in the next section.

5.1.1 Average Land Quality and the Takeoff into Growth

A common observation is that today's rich countries began to experience economic growth before countries that are poorer. This idea is formalized by Lucas (2000), among many others. In searching for an explanation of the positive relationship between average land quality and current income, then, a natural starting point is to look at the relationship between land quality and the timing of takeoff into modern growth.

To operationalize this idea we start by using the methodology of Costa, Kehoe, and Raveendranathan (2016) to identify takeoff dates, which we update using Maddison project

Figure 8: Takeoff Year and log ALQ



data. In their classification scheme, a country moves from stage 0 (Malthusian) to stage 1 (first time sustained growth) when it has experienced a 25 year period of income per capita growth averaging 1% per year. Countries can revert from stage 1 to stage 0 if they have 25 years of slow growth, and can then take off again. We look at the first episode of takeoff. Information on takeoff dates is available for 148 countries, of which 137 are in our main sample.[27] Figure 8 shows that there is a negative relationship between takeoff date and log ALQ. That is, countries with better land on average took off earlier. Note that data on the bottom edge of the figure are truncated at 1845 because that is 25 years after 1820, which is the start of the income data used by Costa *et al.* Other horizontally-aligned groups of points in the graph are also related to the differential availability of income data across countries.

Table 6A reports regression results using these data on takeoff year. Column 1 repeats the regression of income on ALQ from Column 1 of Table 2, but for the slightly smaller sample of countries where takeoff dates are available. The coefficient is almost unchanged. Column 2 then regresses takeoff dates on ALQ, producing a highly significant negative coefficient.

[27] The takeoff dates that we derive are mostly the same as in the Costa *et al.* paper. In all but three cases, differences arise from updates of or extension to the GDP data. In three cases (Kuwait, the Netherlands, and Qatar), we were unable to match their takeoff dates even using their underlying data. In the case of four countries that were subsequently splintered — the Soviet Union, Ethiopia, Czechoslovakia, and Yugoslavia — we calculate takeoff dates for the mother country and assign this date for all of the daughter countries.

A one standard deviation reduction in log of ALQ predicts a delay in the takeoff date of 28 years. Comparing the country with the highest quality (Netherlands; $\log ALQ = 2.82$) to the lowest (Niger, $\log ALQ = -3.15$), the predicted difference in takeoff dates is 140 years. Column 3 shows in turn that takeoff date is a strong predictor of current income. Taking off into growth one century earlier implies a current income advantage of a factor of 5.4. Finally, Column 4 includes both land quality and takeoff date on the right hand side. Columns 5–8 repeat this analysis for countries where greater than 80% of the population is descended from people present 500 years ago. Looking at the two "horserace" columns (4 and 8), the coefficient on takeoff date is reduced in magnitude only slightly compared to when it was entered alone on the right hand side, and it remains highly statistically significant. The coefficient on ALQ falls by a much greater percentage of its value when entered alone on the right hand side, and is no longer significant. This finding is suggestive of a mechanism in which the most important channel by which land quality affects current income is through its effect on the takeoff date.

5.1.2 Average Land Quality and Economic Development as of 1820

While the data that we use to measure takeoff dates begin in 1820, and thus the first takeoff date is 1845, we know that in fact modern economic growth began in many places earlier than that. One way to get a handle on this earlier growth is simply to look at levels of income per capita as of that year. If at some point countries all had the same level of income per capita, then a country being richer in 1820 is evidence of its having grown faster at some point in history. Figure 9 illustrates the relationship between the ALQ and 1820 GDP per capita using data from Maddison. There is a strong, positive correlation, as well as significant variation in income. This strong correlation holds (although with less variation in income) for the smaller sample of 14 countries where there is data for 1700.

Panel B of Table 6 pursues this point. The structure is the same as in Panel A, but this time using the log of GDP per capita in 1820, rather than the takeoff date, as an indicator of early development. Columns (1) and (5) show that there is a still a positive relationship between average land quality and current income in this much smaller sample, though it is only significant, at 10%, in the $Native < 80\%$ subsample. Columns (2) and (6) in turn

Table 6: Economic Development and Land Quality

(a) ALQ and Takeoff Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	all				exclude native< 80%			
Dependent Variable	log 2010 GDP	Takeoff Year	log 2010 GDP	log 2010 GDP	log 2010 GDP	Takeoff Year	log 2010 GDP	log 2010 GDP
log ALQ	0.431**	-19.97***		0.194	0.518***	-20.61***		0.180
	(0.166)	(2.324)		(0.188)	(0.141)	(1.966)		(0.231)
Takeoff year			-0.0139***	-0.0119***			-0.0188***	-0.0164**
			(0.00172)	(0.00264)			(0.00158)	(0.00557)
Native<80%	0.366*	-1.441	0.364	0.349**				
	(0.183)	(9.267)	(0.188)	(0.134)				
Constant	8.957***	1929.8***	35.86***	31.90***	8.955***	1929.8***	45.25***	40.55***
	(0.0742)	(3.066)	(3.303)	(5.140)	(0.0710)	(3.063)	(3.029)	(10.82)
Observations	137	137	137	137	90	90	90	90
R-squared	0.200	0.212	0.368	0.395	0.275	0.279	0.553	0.578

Standard errors are reported in parentheses. Standard errors in columns 1-2, 4-6, and 8 are bootstrapped. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

(b) ALQ and Historical GDP

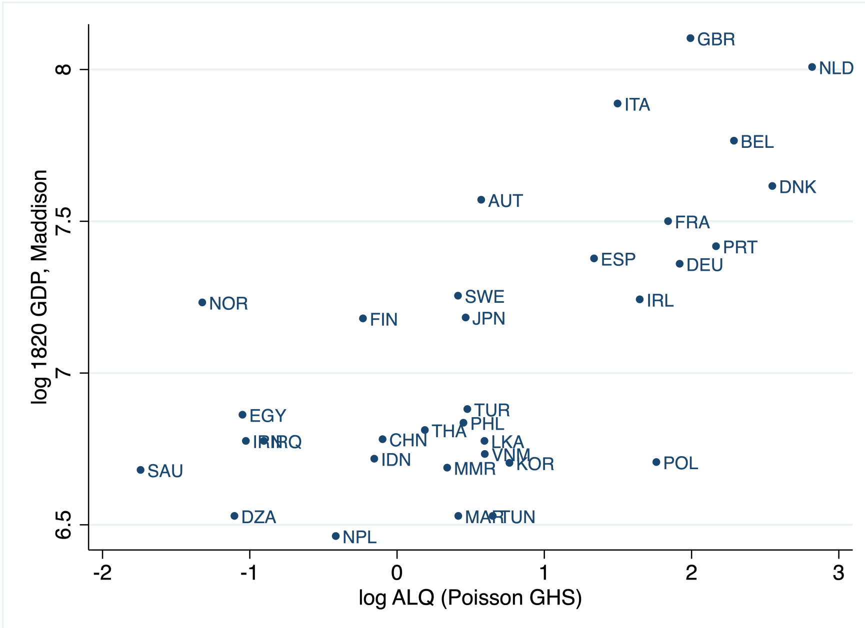
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	all				exclude native< 80%			
Dependent Variable	log 2010 GDP	log 1820 GDP	log 2010 GDP	log 2010 GDP	log 2010 GDP	log 1820 GDP	log 2010 GDP	log 2010 GDP
log ALQ	0.207	0.223***		-0.0903	0.260	0.260***		-0.169
	(0.160)	(0.0417)		(0.162)	(0.136)	(0.0344)		(0.218)
log 1820 GDP,			1.196***	1.336***			1.356***	1.651**
Maddison			(0.201)	(0.303)			(0.247)	(0.507)
Native<80%	0.0398	-0.0153	0.0738	0.0602				
	(0.267)	(0.157)	(0.174)	(0.212)				
Constant	9.710***	6.943***	1.371	0.437	9.679***	6.920***	0.236	-1.745
	(0.241)	(0.0449)	(1.480)	(2.218)	(0.233)	(0.0411)	(1.798)	(3.611)
Observations	49	49	49	49	33	33	33	33
R-squared	0.0893	0.348	0.429	0.440	0.124	0.453	0.500	0.528

Standard errors are reported in parentheses. Standard errors in columns 1-2, 4-6, and 8 are bootstrapped. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

show that average land quality is a good predictor of GDP per capita in 1820. Columns (3) and (7) show that GDP per capita in 1820 is a good predictor of GDP per capita in 2010. Finally, columns (4) and (8) show that when both 1820 GDP and ALQ appear on the right hand side, the former retains its magnitude and significance but the latter becomes smaller and even slightly negative. The two panels of Table 6 are thus both consistent with a story in which land quality affects the date of takeoff into growth, but has little effect on current income through other channels.

Using other measures of early economic development or nascent takeoff into modern growth reinforces the link of these phenomena with land quality. As stressed by Pomeranz (2000), the region of the Yangtze River delta was marked by a level of technological and economic development on par with the most advanced regions of Europe as of 1750. Defining

Figure 9: *ALQ* and Historical GDP per Capita



the delta region to be the modern provinces of Anhui, Jiangsu, and Zhejiang plus the city of Shanghai gives an area of $337,265$ km^2, which is ten times the size of the Netherlands. The log of average land quality for this region is 1.39, which would place it at the 87th percentile in our sample of countries. By contrast, the log of *ALQ* for China as a whole is -0.098. Similarly, in the late eighteenth century, Bengal was viewed as among the richest, if not the richest, region in India, although modern economic historians continue to debate exactly where it stood relative to Europe of the time.[28] The region that was historical Bengal is roughly congruent with modern Bangladesh and the Indian state of West Bengal. The average land quality for this region is 1.04, which would place it at the 81st percentile of our sample of countries. By contrast, the value of log *ALQ* for modern India as a whole is 0.237.

Using literacy as an indicator of early development paints a similar picture. Reis (2005) gives values of literacy for males for European countries circa 1800, with the highest values being the German states of Hesse (91%) and Lower Saxony (80%), the Netherlands (73%), Scotland (65%), England (60%), and Belgium (60%). Land quality for all of these regions and countries is quite high: Hesse (log *ALQ* of 1.59), Lower Saxony (2.12), Netherlands

[28] Parthasarathi (2005), Roy (2010).

(2.82), Scotland (1.27), England (2.30), and Belgium (2.29).[29]

5.1.3 Historical Population Density and Income

Recall that in Table 4 we looked at the relationship between current income, on the one hand, and conventional density and $QAPD$, on the other. The finding there was that as of 2010, there was no significant relationship between income and population density, while there was a significant negative relationship between income and quality-adjusted density.

Table 7 repeats this analysis on income and population from 1820. Columns 1–2 cover all countries, while columns 3–4 are restricted to the sample where $Native > 80\%$. The results in Table 7 are dramatically different from Table 4. While modern income is significantly negatively associated with $QAPD$, there is no significant association between 1820 income and 1820 $QAPD$. However, in Table 7 there is a strong *positive* association between population density in 1820 and income in 1820. By contrast, in modern data population density and income are not significantly related.

Table 7: GDP per Capita, Population Density, and $QAPD$ in 1820

	(1)	(2)	(3)	(4)
Dependent Variable	log 1820 GDP per Capita, Maddison			
log 1820 Population Density	0.119**	0.200***		
	(0.0406)	(0.0465)		
log 1820 QAPD			-0.0321	0.00760
			(0.0553)	(0.120)
Native<80%	0.290		-0.164	
	(0.152)		(0.170)	
Constant	6.742***	6.515***	7.146***	7.059***
	(0.105)	(0.112)	(0.142)	(0.274)
Observations	49	33	49	33
R-squared	0.159	0.354	0.0150	0.000194

Columns (2) and (4) restrict the sample to countries where Native is greater than or equal to 80%. Standard errors in parentheses. Standard errors in columns 3 and 4 are bootstrapped. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The emergence of a negative relationship between $QAPD$ and income over the last 200 years is a significant (and we would argue, underappreciated) aspect of the process of global

[29]Reis gives the literacy number for "Saxony" rather than "Lower Saxony," but the source he uses (Hofmeister *et al.*, 1998) seems to refer to the latter. The log of ALQ for the states of Saxony, Lower Saxony, and Saxony-Anhalt, taken together, is 2.03.

economic growth. In the next subsection, we look directly at population growth, which is what drove the change in $QAPD$, and is thus part of the story of the changing correlation between $QAPD$ and income. Then in Section 6, we present a model of the joint evolution of income and population that generates both the historical and contemporaneous correlations observed in the data.

5.2 Population Growth and its Determinants, 1820 to 2010

Finally, we bring together the analysis of the previous two subsections to examine the relationship between average land quality, takeoff dates, and population growth. Table 8 shows regressions of the change in log population since 1820 on the year of takeoff in the Madison dataset. As in many previous tables, we present results both controlling for $Native < 0.8$ and dropping observations in which the native population was replaced. The coefficient on $Native < 0.8$ is large and significant, showing that population growth has been faster in countries where the native population was largely displaced.

Table 8: The Effects of Takeoff Year on Population Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	all				exclude native< 80%			
Dep. Var.	Pop. Growth	Takeoff	Pop. Growth	Pop. Growth	Pop. Growth	Takeoff	Pop. Growth	Pop. Growth
log ALQ	-0.252**	-19.39***		-0.202*	-0.333***	-22.08***		-0.232**
	(0.0936)	(4.930)		(0.0845)	(0.0858)	(3.208)		(0.0890)
Takeoff year			0.00469**	0.00259*			0.00790***	0.00457*
			(0.00158)	(0.00123)			(0.00188)	(0.00215)
Native<80%	1.624***	-15.34	1.713***	1.664***				
	(0.161)	(8.601)	(0.173)	(0.188)				
Constant	2.007***	1919.0***	-7.058*	-2.957	2.036***	1920.0***	-13.19***	-6.745
	(0.116)	(5.228)	(3.057)	(2.388)	(0.114)	(4.647)	(3.616)	(4.196)
Observations	75	75	75	75	49	49	49	49
R-squared	0.599	0.215	0.574	0.610	0.267	0.317	0.231	0.320

Standard errors are reported in parentheses. Standard errors in columns 1-2, 4-6, and 8 are bootstrapped. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Columns (1) and (5) show that there is a strong negative effect of land quality on population growth. To interpret the magnitude of the effect, looking at the sample of countries where the native population was not displaced, the coefficient on log ALQ is -0.341. An increase of two standard deviations in log ALQ (for this sample of countries) is associated with a decline in annual population growth of 0.45 percentage points per year over this 190-year period, which would in turn produce a difference in population size by a factor of 2.3.

Columns (2) and (6) replicate the finding of Table 6 (for this slightly different sample) that land quality is also a good predictor of takeoff dates into modern growth, while columns (3) and (7) show that takeoff dates in turn negatively predict population growth rates. The coefficient in column (7), 0.0079, implies that a one century delay in takeoff is associated with population growth higher by 0.42 percentage points per year over this 190-year period.

In Columns (4) and (8), the effect of ALQ remains sizable when takeoff year is included. This result is different from our analysis of GDP growth, where including the takeoff year reduced the coefficient on ALQ substantially, rendering it insignificant in some specifications. This result is not surprising since takeoff year in this table is defined in terms of income growth. As will be seen below in Table 9, when we look at an analogue of early takeoff that is more appropriate to population, specifically, the speed with which life expectancy increased, we find that it indeed dominates ALQ as a predictor of population growth.

6 Pulling Together the Pieces: An Illustrative Model

Sections 4 and 5 establish a number of empirical regularities regarding the interrelationships of land quality, population growth, and income, both in the world today and historically. In this section we develop a stylized economic-demographic model that encompasses these regularities. We focus on the following regularities:

- Economic growth took off first in countries with high levels of land quality, and these countries remain richest today.

- Population growth over the two centuries for which we have data is a negative function of the level of average land quality.

- Historically, there was a positive relationship between income per capita and population density, but no significant relationship between income per capita and quality-adjusted density.

- By contrast in the world today, there has been a reversal. There is a strong negative relationship between quality-adjusted population density and income per capita, and no significant relationship between conventionally defined population density and income per capita.

The model is detailed in Appendix D; here we outline its features. The model extends standard theories of population and economic growth by explicitly taking into account the role of health technology in the demographic transition.

A starting point for any analysis of the relationship between land characteristics, population, and economic growth is the Malthusian model. As argued by Galor and Weil (2000), this model characterized economic-population equilibrium for most of human history. In the steady state of a Malthusian model, differences in land quality affect population density but do not affect the standard of living. The literature argues that sometime prior to the Industrial Revolution, there was rough equality of income among countries, compared to the vast income gaps we see today.[30] We presume that, when time starts in our model, all countries are in Malthusian steady states with the same income per capita.

Of course, the Malthusian model no longer characterizes most of humanity. The departure from that equilibrium involved the dual processes of economic takeoff and demographic transition. In the model of Lucas (2000), the richest countries in the world today are those that took off first into modern economic growth. In Lucas (2000), there is a lead country that takes off into growth, with trailing countries that take off at later dates, a characterization we adopt. Although the Lucas model is silent on what factors determine a country's takeoff into growth, it is not a far stretch to associate that takeoff with land quality, via the route of population density and its effect on technological progress.

6.1 Economic Growth

Land quality plays two roles in the model. First, it appears directly in the production function as in Equation (1). In the Malthusian steady state prior to takeoff, conventionally defined population density will just be proportional to land quality. Second, land quality

[30] Bourguignon and Morrisson (2002), Howitt and Weil (2010).

determines the date of takeoff. Concretely, we set the relationship between ALQ and takeoff to be the one estimated in the text, with a one log unit decrease in ALQ leading to a takeoff that is 26 years later. Although we do not model it explicitly, we assume that the underlying mechanism is through agglomeration and Marshallian externalities. Ciccone and Hall (1996) first established a link between population density and productivity across US states. Recent work has extended this result at a more microgeographic level, with papers estimating high returns to increased density in China (Combes *et al.*, 2020; Chauvin *et al.*, 2017) and a set of African countries (Henderson *et al.*, 2021). A direct link between higher density and increased innovation was established in Carlino *et al.* (2007), with a recent work by Roche (2020) showing how dense urban neighborhoods foster innovation.

The next element of the model is technological progress, which we base on Lucas (2000). Prior to takeoff in the lead country, technology is stagnant and equal everywhere in the world. We then assume that, in the lead country, technology grows at a constant rate of 2% per year following takeoff. After their own takeoff dates, follower countries experience faster technological growth: that baseline 2% per year plus a bonus proportional to the gap between the lead country technology level and theirs. This spillover is important in promoting convergence and narrowing the gap in technology levels over time.

These elements explain why countries with high land quality are the richest today, since they started growing first, and technological convergence is not yet complete. They also explain the positive relationship between income per capita and population density at the beginning of our historical data in 1820. That year was after some countries (those with higher quality land and denser populations) had begun their economic takeoffs, but before less dense countries had done so.

However, the mechanism just described, on its own, cannot explain several facts regarding population: first, that quality-adjusted population density is higher today in poor than rich countries, and second, that population growth has been faster in countries with low land quality than in countries with high land quality. One might have expected the population history of late-takeoff countries (those with lower land quality) to simply parallel that of early-takeoff countries but starting at a later date. However, this has not been the case. Further, while a simple model of resource congestion could theoretically justify the negative correlation of current income per capita with quality-adjusted population density (for example, if countries differed in their fertility preferences), our discussion in Section 4.3 suggested that more was at work. And if countries differed exogenously in productivity, with population responding positively to income, then we would expect to see a positive correlation between income and quality-adjusted density, not the negative correlation we observe in the data.

6.2 The Demographic Transition

To explain these facts, we need to model the process of demographic transition that has paralleled economic growth in the last two centuries. Demographic transition refers specifically to the transition from a regime in which fertility and mortality were both high and roughly equal, toward one in which both of these vital rates are significantly reduced and again roughly equal. In early developing countries, this process took about two centuries and is mostly complete. But in late developers, the process is still ongoing.

6.2.1 Life Expectancy

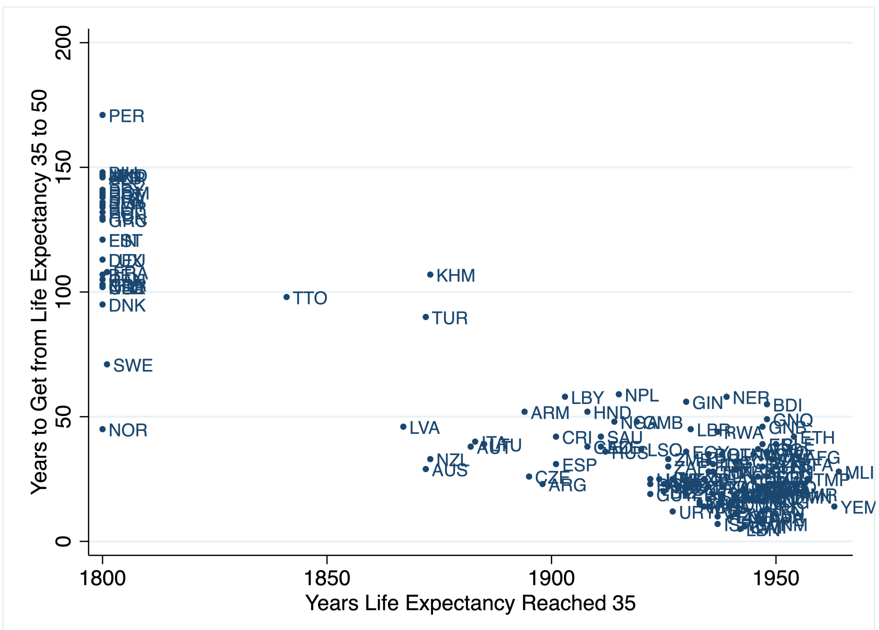
In the interplay between the fertility and mortality rate, one key feature is that the decline in mortality temporally precedes the decline in fertility, and the gap between the two is responsible for the increase in population over the demographic transition, what Chesnais (1990) refers to as the population multiplier.[31] Further, the dominant driver of decline in mortality is improvements in health technology (Deaton, 2014).[32] In our model we follow Deaton's perspective that improvements in life expectancy primarily flowed from the same scientific progress that allowed for higher productivity. We assume life expectancy in all countries is 30 years prior to takeoff. In the lead country, life expectancy then increases in a linear fashion at a rate of three months per year (Oeppen and Vaupel, 2002). Over two centuries, life expectancy rises from 30 to 80 years.

[31]This population multiplier is defined by Chesnais (1990) as "the number by which the population is multiplied during the transition between the pre-transitional phase (high mortality, high fertility) and the post-transitional phase (low mortality, low fertility)."

[32]Also, a very significant component of fertility decline is a fall in *desired* family size due to changes in the structure of the economy, including the return to skill, urbanization, and the gender wage differential as discussed in Galor and Weil (2000), Dyson (2011), and Galor and Weil (1996).

For a follower country, we model life expectancy as a weighted average of life expectancy in the lead country and life expectancy that would be justified by the follower country's own productive technology. This allows for spillover of health technologies from the leader to the follower, and for life expectancy in follower countries to rise before their economic takeoffs. As in the literature, our modeling has the spillover from leader to follower of health technologies being stronger than the spillover of productive technologies. Acemoglu and Johnson (2007) show that convergence of life expectancy among countries is much faster than convergence of income per capita. Similarly, "health miracles" in developing countries have been far more common than "growth miracles" (Deaton, 2014).

Figure 10: Time to Get from Life Expectancy of 35 to 50



This rapid transfer of health technologies produced a demographic transition in which mortality fell both more quickly, and at lower income levels, than had been the case in early developing countries. We can illustrate the importance of this transfer of health technology for population growth in our data. Figure 10 shows the length of time it took countries to go from life expectancy at birth of 35 years to 50 years.[33] Richer countries that reached life expectancy of 35 in the 19th century generally took more than 100 years to reach life expectancy of 50; those that reached 35 in the middle of the 20th century took less than half

[33]Source: Gapminder Life Expectancy (Ola Rosling), Version 9 (October, 2017).

as long.[34] This suggests late takeoff countries had high rates of health technology transfer and adoption, lowering death rates.

Table 9 looks at the effect of this faster life expectancy gain on population growth. The first column repeats the regression of population growth on average land quality, for the sample of countries where life expectancy data are available. The second column then shows the positive effect of land quality on "life expectancy improvement time" (the variable on the vertical axis of Figure 10), which is highly statistically significant. Column (3) shows that life expectancy improvement time, in turn, has a significant effect on the degree to which population increased between 1820 and 2010. Column (4) shows that when both ALQ and life expectancy improvement time are included on the right-hand side, the ALQ coefficient falls by nearly half and loses significance, while the life expectancy improvement measure remains highly significant, with a much smaller drop in magnitude.

Table 9: The Effects of Life Expectancy Improvement on Population Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	all				exclude native< 80%			
Dependent Variable	Pop. Growth	LE Imp. Time	Pop. Growth	Pop. Growth	Pop. Growth	LE Imp. Time	Pop. Growth	Pop. Growth
log ALQ	-0.254**	15.79**		-0.152	-0.329***	21.14***		-0.136
	(0.0920)	(4.862)		(0.0896)	(0.0833)	(2.487)		(0.105)
Life-expectancy Improvement Time			-0.00800***	-0.00646***			-0.0114***	-0.00915***
			(0.00162)	(0.00181)			(0.00176)	(0.00234)
Native<80%	1.579***	-20.60	1.426***	1.446***				
	(0.173)	(13.15)	(0.169)	(0.185)				
Constant	2.024***	57.72***	2.439***	2.397***	2.052***	55.75***	2.653***	2.562***
	(0.104)	(10.88)	(0.151)	(0.135)	(0.104)	(10.23)	(0.158)	(0.157)
Observations	77	77	77	77	50	50	50	50
R-squared	0.585	0.205	0.624	0.646	0.257	0.345	0.397	0.426

Standard errors are reported in parentheses. Standard errors in columns 1-2, 4-6, and 8 are bootstrapped. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Columns 5–8 of the table repeat the exercise for the sample of countries where the native population was not replaced, thus excluding countries where immigration played an important role in population dynamics. Here the effect is even stronger. Using the estimate in column (7) of the table, a one century speed-up in the time it took to get from life expectancy

[34] In fact, the data as shown actually understate this effect, since a number of countries had already passed life expectancy of 35 years by 1800, which is when our data begin. A related fact is that increases in life expectancy have been achieved at lower and lower levels of income over time. This is generally discussed under the rubric of the Preston Curve. See Preston (1975) and Deaton (2014). Weil (2014), Figure 3.7, shows that over the course of the 20th century, life expectancy at a fixed level of income per capita rose by approximately 20 years

of 35 to life expectancy of 50 led to a population increase that was larger by a factor of 3.1.[35]

6.2.2 Fertility

In the model, the fertility rate in the pre-takeoff period is set equal to the mortality rate. Following Hansen and Prescott (2002), for the lead country, we model the relationship between income and fertility as being composed of three segments: First, there is an upward sloping segment, in which higher income raises fertility. Then there is a downward sloping segment in which higher income lowers fertility. Finally, above a fixed level of income, fertility is fixed at the rate consistent with zero population growth. Hansen and Prescott model the specific timing of onset of each segment, based on current income relative to the initial Malthusian level. We follow them, with minor modifications.

In carrying over the analysis to countries that are not the lead country, we maintain the effect of income on fertility calibrated to the lead country. Since these trailing countries have lower mortality (for a given level of income) than does the lead country, they will in turn experience faster population growth at any level of income than did the lead country. We think of this change as being particularly appropriate for looking at population growth in late-starting countries, which indeed experienced higher levels of peak population growth than those that took off first.

6.2.3 Results

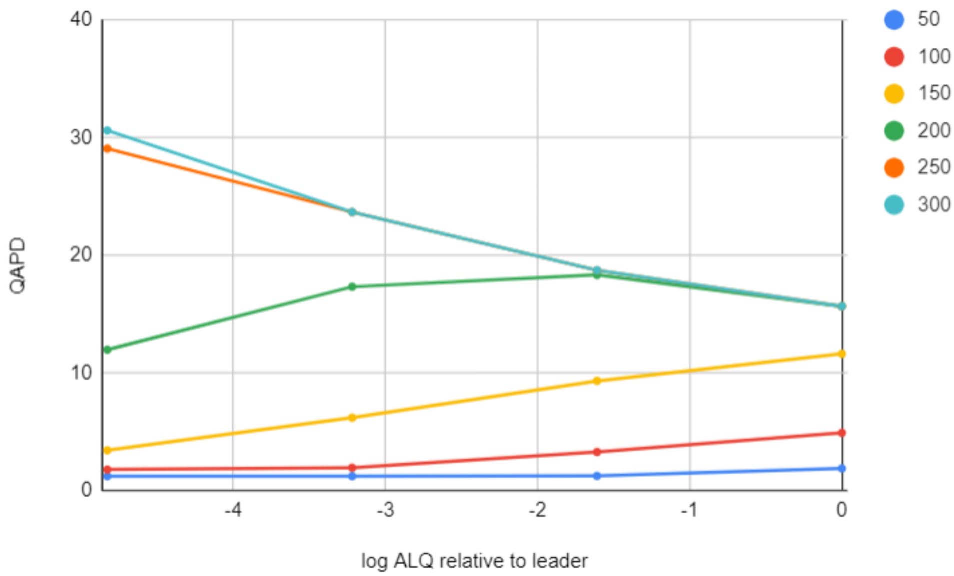
We summarize the results of our model with two figures. In both of them, the horizontal axis measures the log of ALQ relative to the leader, which is normalized to zero. The low value on the axis is -4.83, corresponding to a value of average land quality that is $1/125$ that of the leader. This is a slightly smaller range of values than what we found in the data.

Figure 11A shows $QAPD$ on the vertical axis. Each line corresponds to a cross section of countries ordered by ALQ at the point in time indicated in the legend, measured as years

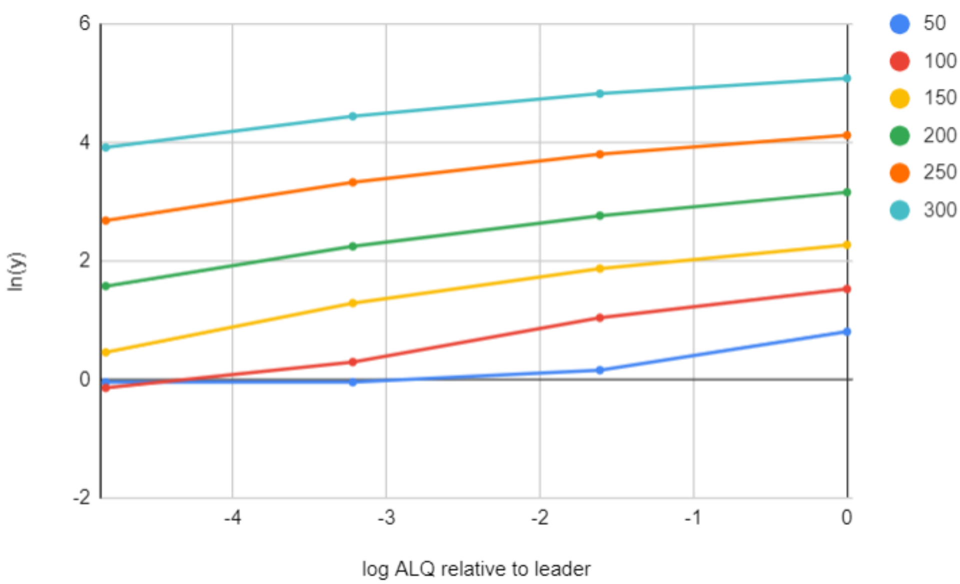
[35] These findings match results from Chesnais (1990), who showed the relation of the population multiplier to the speed of transition and the gap between birth and death rates. He noted that countries and regions that went through the transition later in time tended to reach higher maximal rates of population growth, and also (in his limited data) showed that on average countries that started the transition later had larger multipliers

Figure 11: Model Results

(a) Quality-Adjusted Population Density



(b) Income per Capita



since takeoff in the first country. The figure shows that there is a reversal over time in the relationship between $QAPD$ and land quality (there is a similar reversal in the relationship between $QAPD$ and income). Prior to any country taking off, quality-adjusted density is equal in all countries as a result of the Malthusian mechanism. In the early years of the simulation, countries that have taken off first experience more rapid population growth due both to higher income and lower mortality than the trailing countries. As a result, quality-adjusted density rises with income. However, once trailing countries do take off, they experience faster population growth than did the leaders, as a result of which the relationship between land quality and quality-adjusted population density changes sign. (For the simulation shown, the peak rate of population growth in the last country to take off is 2.7% per year, compared to a peak rate of 2% per year in the first country to take off.)

Given our normalization of initial quality-adjusted density to be one, $QAPD$ at any point in time is equal to the "population multiplier," that is, current population in a country as a multiple of its population before the first takeoff. It is notable that countries that are late to take off have permanently higher population multipliers. Since pre-takeoff population in every country was proportional to land quality, this means that higher population relative to land quality is a permanent feature of late-starting countries.

Figure 11B shows the log of income per capita on the vertical axis. In the early years of the simulation, income rises only in countries that have taken off. In countries that have not, income even falls slightly due to the spillover of health technology that raises population growth without affecting productivity. The gap in income between high and low ALQ countries reaches its peak around 150 years after the first country has taken off. Growth in late takeoff countries is initially slowed by resource congestion due to rising population. However, after a time, income in these trailing countries rises high enough that population growth is reduced, while the force of technological catch-up (as in the Lucas model) remains. However, unlike the Lucas model, late starting countries do not catch up all the way to early starters. This is because, as mentioned above, the population multiplier relating post-transition population to population in the Malthusian regime is higher in the countries that started later, and thus late starting countries face a permanently higher level of resource congestion than countries that took off first.

7 Conclusion

In this paper we construct a new measure of land quality, which we define as the suitability of a piece of land for human habitation and economic activity. Our starting point is a Poisson regression of population density in quarter degree longitude-latitude grid cells on a vector of geographic characteristics and country fixed effects. By incorporating these fixed effects, we avoid bias from any correlation of country-level institutions with geographic characteristics. The fitted values from this regression, suppressing the fixed effects, are our measure of quality. This measure can then be aggregated to sub-national units, regions, or continents, although for this paper we focus on countries.

The new country-level measures we create are quality-adjusted area (QAA), average land quality (ALQ) and quality-adjusted population density ($QAPD$). The last is just the total population of a country divided by QAA. We also establish a number of facts, some of which are not unexpected and others of which are inconsistent with standard macro-demographic models of historical economic growth.

Average land quality is highly correlated with population density, which is hardly surprising. More interesting is that average land quality is correlated with income per capita. We also find that income per capita is uncorrelated with conventionally measured population density, but is strongly negatively correlated with $QAPD$.

Turning to historical data, we find that the effect of ALQ on population density in data from 1820 was much stronger than the same effect measured in modern data. Further, while population density is uncorrelated with income in modern data, it was positively correlated with income in historical data, and similarly while there is a negative correlation between income and $QAPD$ in modern data, there is no correlation in historical data. The mechanism that ties all of these facts together is that population growth since 1820 was systematically higher in countries that have low values of ALQ. Finally, we find that average land quality is a good predictor (with a negative sign) of the date on which countries took off into modern economic growth, and further that once one controls for that takeoff date, the statistical effect of ALQ on current income is greatly diminished.

Taken together, these facts are at variance with the predictions of standard theories of economic and population growth. Malthusian models of the pre-industrial period predict that population will be proportional to natural resources, which is what we find. Models of agglomeration can also explain why the takeoff of economic growth and the exit from the Malthsuian equilibrium took place first in areas with better land and denser populations. But neither of these mechanisms gives any reason to expect that population growth since the exit from the Malthusian equilibrium would have been higher in countries that had lower levels of resources, as we see in the data, and they thus provide no explanation for the signal fact that quality-adjusted population density is negatively correlated with income. This negative correlation could be explained if there were variation across countries in preferences toward children, as in Lucas (2002), but we argue that the magnitude of the effect we find is larger than this channel would justify. Finally, if productivity varied among countries (due to e.g. to institutional quality or technology), standard models predict that there would be a positive correlation between income per capita and $QAPD$, rather than the negative correlation that we see in the data.

To explain all of the observed facts, we present a simple macro-demographic model where the takeoff into modern economic growth occurred earliest in countries with high land quality, for the agglomeration reasons just mentioned, and population growth over the course of industrialization was larger in late-takeoff countries (those with lower land quality) because of the transfer of health technology from countries that started to grow first. The model predicts that a high ratio of population to resources will be a permanent feature of late takeoff countries, even after they have fully caught up with the leaders in terms of productivity.

Beyond the analysis of historical income and population growth that we have undertaken here, we expect that our new measures of land quality will be useful in many other contexts. For example, having estimated the weights on different geographic characteristics in determining quality, we are in a position to discuss the effects of climate change on quality and thus on the degree of population pressure on natural resources. Our measures of average land quality and quality-adjusted area are useful for studying the effects of population pressure on outcomes like food imports, political conflict or migration both within and between countries, among other issues.[36]

[36]In a supplemental analysis (available upon request), we compare the results of regressing net food im-

We certainly don't expect that our measure of quality-adjusted population density will displace conventionally-measured population density; rather, we see it as giving a complementary perspective. For example, if one is interested in Marshallian externalities or agglomeration effects, then a conventional measure of local density is appropriate since that is more closely related to how far apart people live from each other and how easy it is for them to interact. The same would be true if one were concerned about disease transmission. By contrast, if one is interested in the ecological services provided by the geo-physical environment, then an adjusted measure like ours is more useful.

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ports per capita averaged over the period 2010-2015 on the log of either conventional population density or $QAPD$. Conventional density has an insignificant effect on imports, while quality-adjusted density significantly increases imports, whether or not we also include controls for GDP per capita and openness (total trade divided by country GDP). The effects are large: a 2 standard deviation increase in log $QAPD$ is associated with an increase in net food imports of 85% of 1 standard deviation.

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Online Appendix

Appendix A: Comparison of population datasets and cell-level specifications

In this appendix we first compare the distribution of population density in our main population data source, GHS-POP, to two alternatives, GPWv4 and LandScan. We then compare regression results using our baseline Poisson specification and a log-linear alternative, using all three datasets — a total of six variants. Specifically, we compare goodness of fit and fitted values in a regression of population on geographic characteristics. We also show the robustness of one key result, the negative correlation between Quality-Adjusted Population Density and income per capita, to the choice of dataset and specification. All three global datasets report population counts for 30-arc-second by 30 arc-second pixels in Plate Carrée (latitude/longitude) projection. The area of a pixel is 0.86 square km at the equator, decreasing with the cosine of latitude.

The Gridded Population of the World version 4 (GPWv4; CIESIN 2017) is the simplest of the three. The underlying data are population estimates for administrative regions (polygons) from censuses circa 2010. When there is no census in exactly 2010, values are extrapolated or interpolated from multiple censuses. Population is assumed to be distributed evenly within an administrative region. GPWv4's effective spatial resolution thus depends on what information individual countries provide, with richer countries typically providing data for finer regions, down to enumeration units, or even block level data . There is substantial variation within countries as well, with higher resolution in more densely populated regions. Of 12.9 million input polygons worldwide, only 2.4 million are from outside the United States. A grid cell crossing a polygon boundary is assigned a population density that is the areally-weighted average of its constituent polygons.

The European Union's Global Human Settlements population layer (GHS-POP; Schiavina *et al.* 2019; Freire *et al.* 2016) reallocates GPWv4 estimates within administrative polygons based on a companion dataset, GHS-BUILT (Corbane *et al.*, 2018, 2019) that defines built-up pixels as seen in Landsat 30-meter resolution satellite data circa 2015. In the rare cases where there is no built-up area visible in a region, it reverts to the GPWv4 estimates. Its land area measures are taken directly from GPWv4. More information about the GHS data can be found in Florczyk *et al.* (2019).

LandScan uses a proprietary algorithm to provide population estimates based on a much wider set of inputs that include census population data and satellite imagery at higher resolution than Landsat. While the algorithm is not publicly documented and changes from year to year, in the recent past input data have also included information on elevation, slope, and land cover, as well as locations of road and rail networks, hydrologic features and drainage systems, utility networks, airports, and populated urban places. LandScan reports estimates of ambient population averaged throughout the day, whereas the other two datasets report nighttime (residential) population estimates. A recent explanation of LandScan for an academic audience can be found in Rose and Bright (2014).

We rely on GHS-POP as our primary source, and consider GPWv4 and LandScan for robustness here. GHS-POP's use of building cover to redistribute people within census units is very likely to provide more accuracy than GPWv4's assumption of uniform density within large administrative units.

LandScan aims to achieve the same goal of redistributing population based on built cover. However, as noted, it uses other information in making assessments, including higher resolution satellite imagery. LandScan may thus do a better job of finding the built environment in rural locations and it may have greater accuracy in dense but low income cities with coarse population data.

However LandScan has four main drawbacks. First, it has historically used coarse census data as a benchmark outside of the United States.[37] While better satellite imagery can better define the built environment, to convert that to population one still needs fine grained census population data. Second and more importantly, LandScan's algorithm uses physical features like elevation directly to predict population density. This raises the possibility that our regressions will end up simply predicting LandScan's algorithm rather than true population density. Third, LandScan's algorithm changes from year to year and is not documented. Finally LandScan measures the ambient population over the 24 hours of a day, making inferences about where people work and for how many hours of the day, without, as we understand it, much if any spatial economic census data which are unavailable for many developing countries anyway. This seems likely to add error without benefit for our purposes.

Figure A.1 Panel A reports the cumulative distribution function (CDF) of log population density according to the three datasets, with zeros in each dataset replaced with that dataset's minimum nonzero value before logging. In this and all other subnational empirical work, our unit of analysis is a quarter-degree grid square, a 30-by-30 array of 30-arc-second pixels.

The figure shows that the three data sets treat grid squares with tiny densities very differently. For example GHS-POP registers about 40% of cells as having no people, with nonzero densities starting at $0.0000000033/km^2$, while LandScan registers only about 24% of grid squares at 0, with non-zero densities starting at about 0.0013/km2. By population densities of about $50/km^2$ ($exp(3.9)$), the three lines converge, at which point about 85% of pixels have been accounted for. Panel B of Figure A.1 analogously reports cumulative population by density. It shows that less than 10% of the world population lives at a density under $50/km^2$. However, since our unit of analysis is the grid square, these tiny densities potentially play an important role.

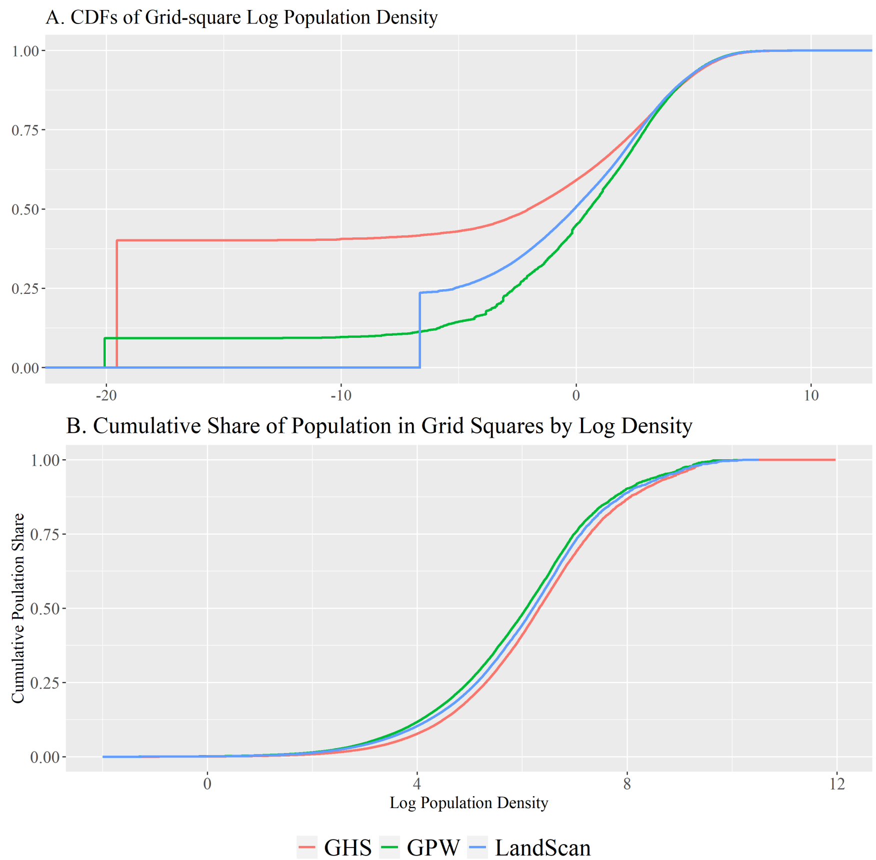
We now further flesh out the log-linear specification, in order to compare it to our main Poisson specification. Given the log-linear specification from (8), $\ln(L_{i,c}/Z_{i,c}) = C_c + X_{i,c}\beta + \epsilon_{i,c}$, the corresponding OLS estimate of the country constant is

$$\hat{C}_c = \frac{1}{N_c}\left(\sum_{i\in c}\ln\Big(\frac{L_{i,c}}{Z_{i,c}}\Big) - \Big(\sum_{i\in c}X_{i,c}\hat{\beta}_{OLS}\Big)\right) \tag{15}$$

Our OLS estimate of cell i's log population density when setting all the country fixed effects to zero to equalize all factors that vary at the country level is $\widehat{\ln(\frac{L_{i,c}}{Z_{i,c}})} = X_{i,c}\hat{\beta}_{OLS}$. The

[37]LandScan has not released details about its current census data, but as of its 2009 version: "Outside the USA LandScan used 79,590 administrative units for ambient modeling. By contrast, GPWv3 uses 338,863 units outside of the US." Source: https://sedac.uservoice.com/knowledgebase/articles/41665-what-are-the-differences-between-gpw-grump-and-la

Figure A.1: Population Distributions by Grid Square Worldwide



analogous estimate of population density level is $\widehat{\frac{L_{i,c}}{Z_{i,c}}} = exp(X_{i,c}\hat{\beta}_{OLS} + \frac{\hat{s}^2}{2})$ where $\hat{s}^2$ is the variance of the error term in the estimated equation (which we assume to be homoskedastic across countries). Fitted national population is then:

$$\widehat{L}_c = \sum_{i \in c} exp(X_{i,c}\hat{\beta}_{OLS} + \frac{\hat{s}^2}{2})Z_{i,c} \tag{16}$$

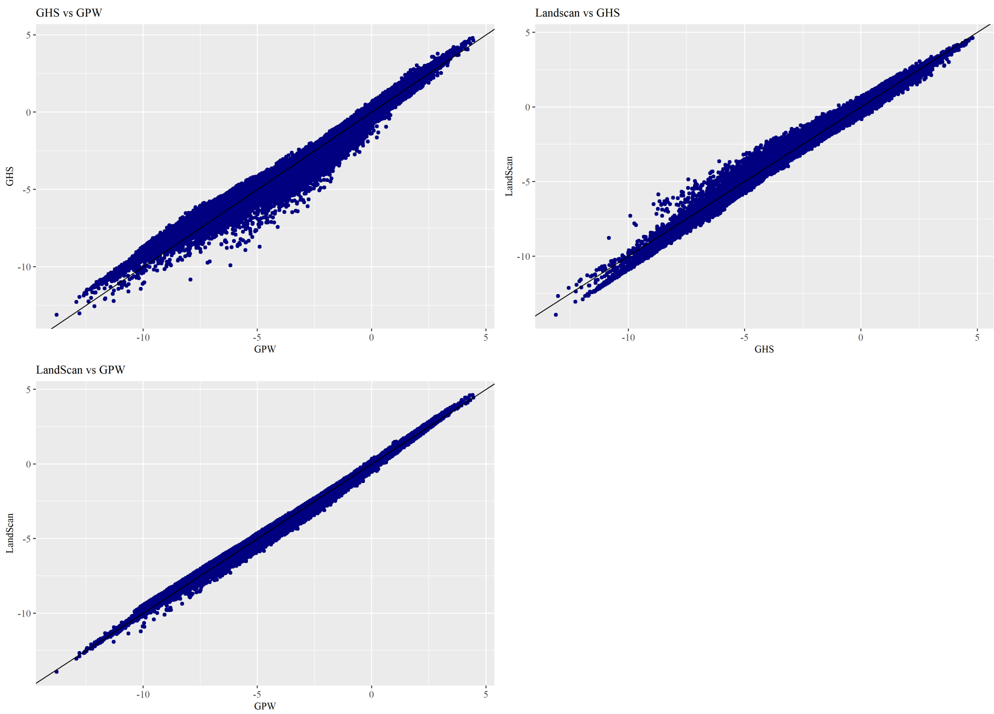
Finally, we can calculate the ratio of actual to expected population, where the latter is based on the fitted value suppressing country fixed effects. This is what we have been calling quality-adjusted population density.

$$QAPD_c = \frac{\sum_i L_{i,c}}{\sum_{i \in c} exp(X_{i,c}\hat{\beta}_{OLS} + \frac{\hat{s}^2}{2})Z_{i,c}} \tag{17}$$

An obvious problem with this approach is that, as discussed above, there are a significant number of grid cells with zero measured population in our data. In implementing the log-linear specification, we assigned to such cells the population density of the least dense non-zero cell in the dataset before logging. We also experimented with creating versions of the logged GPWv4 and GHS-POP datasets in which cells with zero density are assigned the minimum nonzero density value in LandScan. As shown in Figure A.1, LandScan's minimum value is much larger than the minimum non-zero density in the other two datasets.

Figure A.2: Predicted Values

(a) Poisson Specification



(b) Log Linear Specification

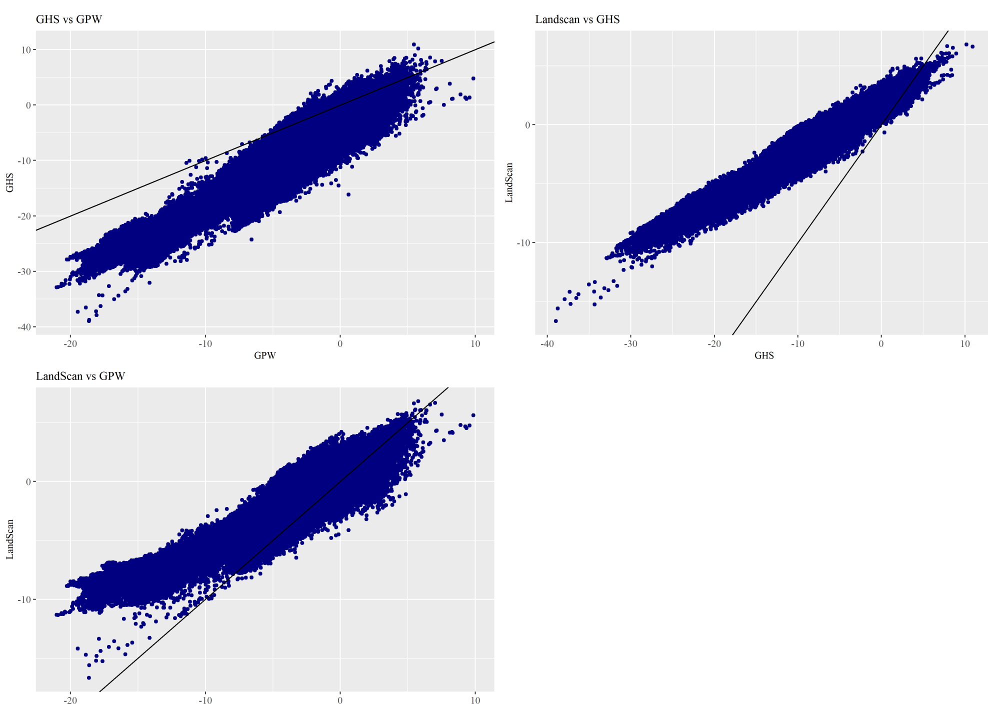


Figure A.2 compares cell-level predicted values across the three datasets. Using the Poisson specification (Equation (9)), Panel A shows that all three data sets give very similar predicted values. This is because the Poisson specification makes little distinction between cells that have moderately low density and those that have extremely low density. By contrast, in Panel B, there are large differences across datasets when using the log-linear specification (Equation (8)), driven by the differing treatments of low density regions.

Table A.1 reports goodness of fit measures for geographic variables, country fixed effects, and both, analogously to Table 1, Row 1, for the six variants. In the first 3 rows zeros are assigned their dataset-specific minimum non-zero value. In rows 4 and 5 zeros in GHS-POP and GPWv4 are assigned the LandScan minimum value. Results across all data sets and specifications are generally similar.

Table A.1: Goodness of Fit for Grid Cell Level Regressions

	Log-linear Specification			Poisson Specification		
	Country Only	Geography Only	Both	Country Only	Geography Only	Both
GHS	0.359	0.537	0.597	0.344	0.464	0.566
GPW	0.551	0.520	0.758	0.390	0.504	0.620
LandScan	0.482	0.630	0.738	0.364	0.479	0.593
GHS Censored	0.411	0.574	0.658	0.344	0.464	0.566
GPW Censored	0.557	0.606	0.800	0.390	0.504	0.620

Notes: The table reports R-squared values for the log-linear regressions annd R-dev-squared for the Poisson specification.

Table A.2 reports ten variants of Table 4, column 3, each corresponding to a variant reported in Table A.1. Log-linear results in columns 1, 3 and 5 vary enormously across datasets, while Poisson results in columns 2, 4 and 6 do not. Columns 7–10 censor at the Landscan minimum. Poisson results (columns 8 and 10) are also insensitive to this, while log-linear results (columns 7 and 9) are much more sensitive.

Finally Table A.3 reports the main grid square Poisson estimation of equation (9).

Table A.2: Cross-country regressions of GDP per capita on QAPD: Robustness to Alternative Grid Cell Datasets and Specifications

Grid cell regression	log-linear GPW	Poisson GPW	log-linear Land Scan	Poisson Land Scan	log-linear GHS	Poisson GHS	log-linear GPW Censored	Poisson GPW Censored	log-linear GHS Censored	Poisson GHS Censored
log QAPD	0.101	-0.323**	0.0464	-0.357***	-0.0360	-0.352***	0.0499	-0.323***	-0.0258	-0.352**
	(0.196)	(0.109)	(0.0854)	(0.101)	(0.0430)	(0.0962)	(0.143)	(0.0608)	(0.0675)	(0.122)
Native<80%	0.404	0.0453	0.308	0.0127	0.254	0.0259	0.319	0.0453	0.256	0.0259
	(0.230)	(0.183)	(0.197)	(0.0993)	(0.170)	(0.205)	(0.334)	(0.227)	(0.136)	(0.184)
Constant	8.377***	10.30***	8.724***	10.46***	9.252***	10.46***	8.707***	10.30***	9.081***	10.46***
	(0.994)	(0.493)	(0.473)	(0.401)	(0.438)	(0.456)	(0.678)	(0.346)	(0.327)	(0.502)
Observations	148	148	148	148	148	148	148	148	148	148
R-squared	0.0344	0.109	0.0150	0.141	0.0226	0.138	0.0148	0.109	0.0131	0.138

Note: The dependent variable is log GDP per capita. Bootstrapped standard errors are reported in parentheses. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Grid square results on the geographic determinants of population

	Baseline
Ruggedness (000s)	-2.7e-06***
	(1.2e-07)
Malaria (index)	-0.0298***
	(0.0027)
Abs(Latitude)	0.023***
	(0.0037)
Elevation (m)	-2.5e-04***
	(4.2e-05)
Distance to coast (000 km)	-7.7e-07***
	(3.4e-08)
Coast dummy	0.434***
	(0.0276)
Harbor dummy	0.829***
	(0.0244)
Navigable river dummy	0.752***
	(0.0291)
Lake dummy	0.808***
	(0.146)
Adjusted LGP for evaluating agro-climatic constraints	3.3e-04
	(2.1e-04)
Length of longest component LGP	-0.0015
	(0.0041)
Longest consecutive dry days in LGPt=5	-0.0021***
	(1.1e-04)
Number of dry days during LGPt=5	0.0016***
	(1.8e-04)
Total number of growing period days	-2.08
	(2.46)
Total number of LGP days in component LGPs > 20 days	1.73
	(2.34)
Net primary production (rain-fed)	0.0059***
	(5.5e-04)
Annual P/PET ratio (*100)	0.0022***
	(3.9e-04)
P/PET (*100) for days with mean temperature > 5 deg. C	-0.007***
	(0.0011)
Seasonal P/PET ratio (*100) in summer	0.0038**
	(0.0013)
Seasonal P/PET ratio (*100) in winter	0.0193***
	(0.0031)
Number of consecutive days with average precipitation > 30 mm	-0.0055
	(0.0028)
Total number of rain days (days with precipitation > 1 mm)	-6.9e-04
	(8.1e-04)
Modified Fournier Index (mm)	-8.2e-04*
	(3.9e-04)
Annual precipitation (mm)	0.001**
	(3.5e-04)
Mean max. sum of precipitation on consecutive > 30 mm average daily precipitation days	-0.0083***
	(0.0014)

Reference actual evapotranspiration (using AWC=100 mm/m)	-6.5e-04
	(3.9e-04)
Reference potential evapotranspiration (using AWC=100 mm/m)	-0.0081***
	(0.0014)
Number of days with max temperature > 35 deg. C	0.0506
	(0.122)
Number of days with max temperature > 40 deg. C	-3.8e-05***
	(3.0e-06)
Number of days with min temperature < 0 deg. C	-1.1e-04
	(1.3e-04)
Number of days with min temperature < 10 deg. C	3.8e-04***
	(3.4e-05)
Number of days with min temperature < 15 deg. C	-.0227***
	(.0022)
Number of days with mean temperature > 10 deg. C (LGPt=10)	0.0086**
	(.0027)
Number of days with mean temperature > 5 deg. C (LGPt=5)	-0.0031***
	(6.3e-04)
Annual temperature amplitude (deg. C)	-0.0019***
	(3.8e-04)
Mean annual temperature (deg. C)	-0.0011***
	(3.0e-04)
Snow-adjusted cold temperature limit	-0.0625***
	(0.0127)
Temperature of coolest month (deg. C*100)	0.459***
	(0.0347)
Annual temperature sum for days with mean temperature > 10 deg. C	-0.0027***
	(3.9e-04)
Annual temperature sum for days with mean temperature > 5 deg. C	0.0016***
	(3.8e-04)
Air frost number	-0.0011**
	(4.3e-04)
Snow-adjusted air frost number	0.0038***
	(7.7e-04)
Maize suitability index; low input, rain-fed, no CO2 fertilization	1.1e-05
	(1.3e-05)
Dryland rice suitability index; low input, rain-fed, no CO2 fertilization	-1.8e-06
	(8.2e-06)
Wetland rice suitability index; low input, rain-fed, no CO2 fertilization	3.1e-06
	(8.5e-06)
Wheat suitability index; low input, rain-fed, no CO2 fertilization	-4.4e-06
	(1.0e-05)
Cassava suitability index; low input, rain-fed, no CO2 fertilization	-2.3e-05*
	(1.1e-05)
Soybean suitability index; low input, rain-fed, no CO2 fertilization	4.5e-05***
	(1.1e-05)
White potato suitability index; low input, rain-fed, no CO2 fertilization	2.0e-05
	(1.2e-05)
Sorghum suitability index; low input, rain-fed, no CO2 fertilization	2.6e-05*
	(1.0e-05)
Sweet potato suitability index; low input, rain-fed, no CO2 fertilization	5.5e-05***
	(1.0e-05)
Yam suitability index; low input, rain-fed, no CO2 fertilization	-1.5e-04***
	(1.2e-05)

Banana suitability index; low input, rain-fed, no CO2 fertilization	2.2e-05*
	(9.9e-06)
Observations	237,023
R-dev-squared	0.566

Note: LGP is the length of the growing period; LGPt=n is the temperature growing period, which provides the number of days with mean temperature over n degrees Celsius. P/PET is the ratio of precipitation to potential evapotranspiration. Goodness of fit measure is R-dev-squared. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix B. Choice of geographic variables

GAEZ provides more than a hundred variables that may be relevant to predicting land quality or population density; the baseline specification adopted in the main text includes only a limited subset of such variables. We verify that the baseline specification performs sufficiently well compared to alternate combinations of covariates using the Least Absolute Shrinkage and Selection Operator (Lasso) estimator.

Lasso is a regularization technique that adds a penalty term to coefficients. In the Poisson context, it solves the following minimization problem (Friedman *et al.*, 2010):

$$min_{\beta} - \frac{1}{N} l(\beta \mid X, Y) + \lambda \sum_{i=0}^{N} |\beta_i| \tag{18}$$

where the log likelihood is

$$l(\beta \mid X, Y) = \sum_{i=0}^{N} (y_i \beta^T x_i) - e^{\beta^T x_i} \tag{19}$$

We fit Poisson models with Lasso on three sets of possible covariates: baseline specification, expanded baseline specification, and fully interacted specification. The baseline is identical to the specification used in the main text and includes 53 variables; the expanded baseline adds to the baseline 66 climate class indicators for a total of 119 variables; and the fully interacted specification adds to the expanded baseline the squares of all continuous non-crop suitability variables as well as all nonzero two-way interactions between such variables for a total of 951 variables.

In order to allow for random samples to be stratified by country, we restrict the sample to countries that include more than 10 grid cells; this excludes Hong Kong, Liechtenstein, Luxembourg, Palestine, and Singapore. The country grid data are then randomly split into training and testing data so that we can assess the out-of-sample performance of each specification. 10 sets of 75% training and 25% testing samples were generated.

We identify optimal values of λ and fit Poisson models via 5-fold cross-validated Lasso for each specification on the 10 training sets. The folds are stratified by country, and country fixed effects are not allowed to be excluded from the set of covariates. Two λs are defined as "optimal": the λ that yields minimum deviance and the largest λ with deviance within one standard error of the optimum (1SE λ). The latter is used to select more parsimonious models against overfitting, as per the "One Standard Error Rule." Once the appropriate λs are found, the fitted models for each specification are applied to the corresponding test set to calculate the R^2_{DEV} of out-of-sample predictions for each specification. Final fitted values were then generated by using the optimal λ to refit the models on the full grid-cell dataset that excludes countries with fewer than 10 grid cells. To generate comparison out-of-sample predictions, we also fit each specification using the standard maximum-likelihood Poisson regression on the 10 training sets.

Panels A and B of Appendix Table B.1 shows summary statistics for R^2_{DEV} and the number of covariates chosen from each specification over 10 sets of training and test splits. We find that the out-of-sample R^2_{DEV} for either s in all specifications are not notably different from that of the baseline regression estimated with standard Poisson. Lasso regressions rarely drop any of the base 53 covariates. Compared to the baseline out-of-sample R^2_{DEV} of 0.563, the maximum out-of-sample R^2_{DEV} from Lasso is 0.587, not a substantial improvement, given the exponential increase in the number of covariates. It must be noted that plotted deviations were extremely flat near the beginning of the tested λ sequences for most Lasso regressions; it may be that the dimensions of our data are insufficient for Lasso.

The final fitted values generated for each specification are then aggregated on the country level. 10 variant ALQs are thus generated for each Lasso specification, for which we calculate the pairwise correlation with the baseline ALQ. We further generate ALQs for each specification fitted with the standard maximum likelihood Poisson, which do not differ across the 10 runs. Panel C of Table B.1 displays the mean and standard deviation of these pairwise correlation coefficients; these alternate specifications and use of Lasso yield results that are highly correlated with the baseline specification ALQ used in the main text.

Table B.1: Lasso Summary

A. Mean of Results from 10 Draws.

Specification	Nonlasso				Min. Dev. Lasso			1SE Lasso		
	Train	Test	Full	# Coef.	Train	Test	# Coef.	Train	Test	# Coef.
Baseline	0.565	0.558	0.563	53	0.563	0.558	44.3	0.526	0.525	16.7
Expanded Baseline	0.574	0.566	0.572	119	0.572	0.566	79.2	0.536	0.536	28.4
Fully Interacted	0.693	0.616	0.674	951	0.644	0.587	265	0.588	0.568	83.6

Note: The Fully Interacted specification only includes 9 out of the 10 draws; the training-test split for one draw generated nonsensical out-of-sample R^2_{dev} results. Results of individual train-test draws are available upon request.

B. Standard Deviation of Results from 10 Draws.

Specification	Nonlasso				Min. Dev. Lasso			1SE Lasso		
	Train	Test	Full	# Coef.	Train	Test	# Coef.	Train	Test	# Coef.
Baseline	0.00666	0.0222	0.00144	0	0.0064	0.0214	1.77	0.013	0.0187	2.58
Expanded Baseline	0.00635	0.0216	0.00152	0	0.00632	0.0211	9.25	0.0124	0.0195	3.53
Fully Interacted	0.00283	0.0316	0.0104	0	0.00644	0.0467	35.5	0.0164	0.0214	23.3

Note: The Fully Interacted specification only includes 9 out of the 10 draws; the training-test split for one draw generated nonsensical out-of-sample R^2_{dev} results. Results of individual train-test draws are available upon request.

C. Summary Statistics of Pairwise Correlations With baseline log ALQ.

Specification		Mean	Standard deviation
Nonlasso	Baseline	1.000	0.000
	Expanded baseline	0.992	0.000
	Fully Interacted	0.817	0.000
Min. Dev.	Baseline	0.999	0.000
	Expanded baseline	0.992	0.000
	Fully Interacted	0.922	0.015
1SE Dev.	Baseline	0.891	0.030
	Expanded baseline	0.918	0.019
	Fully Interacted	0.952	0.007

Note: Pairwise correlations are of country-level log ALQ for the main sample with baseline log ALQ in the main text. All specifications were estimated on the grid-cell dataset excluding countries with 10 or fewer observations.

Appendix C: Other Results

Table C.1 reports log Average Land Quality (ALQ), log conventional area, log Quality-adjusted Area (QAA), log conventional population density, and log Quality-adjusted population density ($QAPD$), for each country in the grid-cell-level estimation (Tables 1 and 2). It also reports whether they appear in the country-level sample and the 1820 sample, and their value of ($Native < 0.8$). Tables C.2-C.6, repeat Tables 5-9 in the text using the Gapminder data.

Table C.1: Country-Level Measures

Country Name	log ALQ	log Area (conventional)	log QAA	Actual Population	Fitted Population	log Population Density (conventional)	log QAPD	Country-level Sample	Pop. 1820	Native < 0.8
Afghanistan	-1.689	13.372	11.683	3.28e+07	6707250	3.935	5.624	1	1	0
Albania	0.827	10.223	11.051	2841868	3564790	4.637	3.809	1	1	0
Algeria	-1.104	14.656	13.551	3.97e+07	4.34e+07	2.841	3.946	1	1	0
Angola	0.213	14.046	14.259	2.55e+07	8.82e+07	3.007	2.794	1	0	0
Argentina	1.255	14.826	16.081	4.35e+07	5.45e+08	2.761	1.507	1	1	1
Armenia	-0.595	10.309	9.715	3138061	937076.3	4.650	5.244	1	0	0
Australia	0.374	15.850	16.224	2.38e+07	6.29e+08	1.136	0.762	1	1	1
Austria	0.571	11.295	11.867	8194625	8059722	4.624	4.052	1	1	0
Azerbaijan	0.876	11.308	12.184	9045611	1.11e+07	4.710	3.834	1	0	0
Bangladesh	0.986	11.833	12.819	1.60e+08	2.09e+07	7.059	6.074	1	1	0
Belarus	1.013	12.234	13.247	9540904	3.20e+07	3.837	2.825	1	0	0
Belgium	2.288	10.365	12.653	1.15e+07	1.77e+07	5.891	3.603	1	1	0
Belize	0.757	10.047	10.804	330484.7	2785437	2.661	1.904	1	0	1
Benin	-0.541	11.672	11.131	1.13e+07	3863529	4.569	5.109	1	0	0
Bhutan	-1.710	10.530	8.820	1149519	382915	3.425	5.135	1	0	0
Bolivia	-0.098	13.873	13.776	1.07e+07	5.44e+07	2.308	2.406	1	1	1
Bosnia and Herzegovina	0.839	10.844	11.683	3713176	6709126	4.283	3.444	1	0	0
Botswana	-0.933	13.260	12.327	2280547	1.28e+07	1.380	2.313	1	0	1
Brazil	0.138	15.948	16.086	2.08e+08	5.48e+08	3.202	3.064	1	1	1
Brunei	-0.248	8.761	8.513	437312.5	281907.6	4.227	4.475	0	0	
Bulgaria	1.527	11.607	13.134	6996386	2.86e+07	4.154	2.627	1	1	0
Burkina Faso	-1.860	12.521	10.661	1.84e+07	2413989	4.204	6.065	1	0	0
Burundi	-0.247	10.137	9.890	1.09e+07	1116706	6.068	6.315	1	0	0
Cambodia	0.293	12.091	12.384	1.55e+07	1.35e+07	4.464	4.171	1	1	0
Cameroon	-0.507	13.032	12.525	2.28e+07	1.56e+07	3.909	4.416	1	0	0
Canada	-1.703	15.985	14.282	3.35e+07	9.02e+07	1.341	3.044	1	1	1
Central African Republic	-1.430	13.347	11.917	5189272	8480344	2.115	3.545	1	0	1
Chad	-2.867	14.058	11.191	1.44e+07	4100449	2.425	5.292	1	0	0
Chile	0.409	13.469	13.878	1.79e+07	6.03e+07	3.230	2.821	1	1	1
China	-0.098	16.034	15.936	1.37e+09	4.72e+08	5.008	5.106	1	1	0
Colombia	-0.531	13.938	13.406	4.77e+07	3.76e+07	3.742	4.274	1	1	1
Costa Rica	-0.295	10.839	10.544	4814606	2147052	4.548	4.843	1	1	1
Croatia	1.766	10.946	12.711	4424145	1.88e+07	4.357	2.591	1	0	1
Cuba	1.356	11.589	12.945	1.13e+07	2.37e+07	4.649	3.293	0	0	1
Czech Republic	1.171	11.291	12.462	1.08e+07	1.46e+07	4.901	3.730	1	0	0
Democratic Republic of the Congo	-0.890	14.648	13.758	7.66e+07	5.34e+07	3.506	4.396	1	0	0
Denmark	2.548	10.641	13.189	5812939	3.03e+07	4.935	2.386	1	1	0
Djibouti	-1.873	10.009	8.136	946672.3	193257.5	3.752	5.625	0	0	
Dominican Republic	1.146	10.778	11.924	1.06e+07	8536849	5.396	4.250	1	1	1
Ecuador	0.066	12.419	12.485	1.61e+07	1.50e+07	4.174	4.108	1	1	1
Egypt	-1.050	13.794	12.744	9.11e+07	1.94e+07	4.533	5.583	1	1	0
El Salvador	0.197	9.981	10.177	6124157	1488219	5.647	5.451	1	1	1
Equatorial Guinea	-0.207	10.129	9.921	643085	1152360	3.245	3.453	1	0	1
Eritrea	-1.425	11.694	10.269	5027255	1630774	3.737	5.162	1	0	0

Estonia	0.800	10.624	11.424	1325524	5175995	3.473	2.674	1	0	1
Ethiopia	-0.493	13.935	13.443	9.90e+07	3.90e+07	4.475	4.968	1	0	0
Finland	-0.231	12.620	12.389	5414596	1.36e+07	2.885	3.116	1	1	0
France	1.840	13.200	15.040	6.40e+07	1.93e+08	4.775	2.935	1	1	0
French Guiana	-0.039	11.332	11.292	267631.9	4539322	1.166	1.205	0	0	
Gabon	-0.154	12.493	12.339	1832193	1.29e+07	1.928	2.082	1	0	1
Gambia	-0.494	9.206	8.712	1784434	343798.2	5.189	5.683	1	0	0
Georgia	0.388	11.145	11.532	4004654	5770629	4.058	3.671	1	0	0
Germany	1.919	12.780	14.699	8.12e+07	1.37e+08	5.433	3.514	1	1	0
Ghana	-0.469	12.351	11.882	2.88e+07	8184653	4.825	5.294	1	0	0
Greece	1.439	11.628	13.067	9929615	2.68e+07	4.483	3.044	1	1	0
Guatemala	0.269	11.561	11.831	1.64e+07	7775373	5.050	4.781	1	1	1
Guinea	-0.586	12.431	11.845	1.27e+07	7886640	3.924	4.510	1	0	1
Guinea-Bissau	-0.141	10.359	10.217	1837629	1549393	4.065	4.206	1	0	0
Guyana	0.141	12.242	12.383	739448.6	1.35e+07	1.271	1.130	1	0	1
Haiti	0.834	10.152	10.986	1.03e+07	3342694	5.993	5.159	1	1	1
Honduras	0.310	11.610	11.920	7923566	8506588	4.275	3.965	1	1	1
Hong Kong	2.081	6.637	8.718	6188948	345846.3	9.002	6.920	0	0	1
Hungary	1.631	11.400	13.031	9557496	2.58e+07	4.673	3.041	1	1	0
Iceland	-0.647	11.315	10.667	292202.8	2429452	1.271	1.918	0	0	
India	0.237	14.951	15.188	1.31e+09	2.23e+08	6.043	5.806	1	1	0
Indonesia	-0.155	14.329	14.175	2.30e+08	8.10e+07	4.925	5.080	1	1	0
Iran	-1.027	14.294	13.268	7.83e+07	3.27e+07	3.882	4.909	1	1	0
Iraq	-0.905	12.998	12.093	3.65e+07	1.01e+07	4.416	5.321	1	1	0
Ireland	1.648	11.136	12.783	4699620	2.02e+07	4.227	2.580	1	0	0
Israel	0.813	9.967	10.781	8582651	2721072	5.998	5.185	1	0	1
Italy	1.497	12.503	14.000	5.44e+07	6.81e+07	5.310	3.812	1	1	0
Ivory Coast	-0.252	12.683	12.431	2.28e+07	1.42e+07	4.257	4.509	1	0	1
Japan	0.466	12.788	13.254	1.24e+08	3.23e+07	5.847	5.381	1	1	0
Jordan	-0.901	11.366	10.465	7542924	1984993	4.470	5.371	1	1	1
Kazakhstan	-1.512	14.780	13.269	1.75e+07	3.28e+07	1.897	3.409	1	0	1
Kenya	-0.663	13.262	12.599	4.55e+07	1.68e+07	4.372	5.035	1	0	1
Kuwait	-1.295	9.789	8.493	3891785	276276.9	5.386	6.681	1	0	1
Kyrgyzstan	-2.747	12.149	9.402	6449465	685347.2	3.531	6.278	1	0	0
Laos	0.116	12.347	12.463	7232625	1.46e+07	3.447	3.331	1	1	0
Latvia	1.062	11.055	12.117	1986918	1.04e+07	3.447	2.385	1	0	1
Lebanon	0.903	9.286	10.189	6012262	1505748	6.324	5.420	1	1	1
Lesotho	-0.268	10.318	10.050	1836294	1310418	4.105	4.373	1	0	0
Liberia	-0.271	11.472	11.202	4555475	4145476	3.860	4.130	1	0	0
Libya	-1.176	14.298	13.122	6258891	2.83e+07	1.351	2.527	1	1	0
Liechtenstein	-2.883	6.267	3.384	81507.48	1669.133	5.042	7.924	0	0	
Lithuania	1.103	11.043	12.146	2885031	1.07e+07	3.832	2.729	1	0	0
Luxembourg	1.482	7.822	9.304	407045.9	621517.1	5.094	3.613	1	0	0
Macedonia	0.601	10.056	10.657	2022966	2403850	4.464	3.863	1	0	0
Madagascar	0.692	13.287	13.978	2.41e+07	6.66e+07	3.712	3.020	1	1	0
Malawi	0.174	11.437	11.610	1.61e+07	6238022	5.156	4.983	1	0	0
Malaysia	-0.073	12.697	12.624	3.02e+07	1.72e+07	4.527	4.600	1	1	1
Mali	-2.507	14.043	11.536	1.75e+07	5789425	2.636	5.144	1	0	0
Mauritania	-2.769	13.858	11.089	4308521	3705473	1.418	4.187	1	0	0

Mexico	0.476	14.480	14.956	1.26e+08	1.77e+08	4.169	3.693	1	1	1
Moldova	1.631	10.490	12.121	4114565	1.04e+07	4.740	3.110	1	0	1
Mongolia	-2.619	14.254	11.635	2908918	6391901	0.629	3.249	1	1	0
Montenegro	0.235	9.499	9.735	626093.2	955999.9	3.848	3.613	0	0	
Morocco	0.416	13.437	13.853	3.49e+07	5.88e+07	3.932	3.516	1	1	0
Mozambique	0.298	13.565	13.863	2.79e+07	5.94e+07	3.580	3.282	1	1	0
Myanmar	0.340	13.401	13.741	5.33e+07	5.26e+07	4.391	4.050	1	1	0
Namibia	-0.274	13.617	13.344	2205659	3.53e+07	0.989	1.263	1	0	1
Nepal	-0.416	11.842	11.425	2.89e+07	5184456	5.337	5.753	1	1	0
Netherlands	2.818	10.413	13.232	1.64e+07	3.16e+07	6.197	3.378	1	1	0
New Zealand	1.638	12.478	14.116	4520006	7.64e+07	2.846	1.208	1	1	1
Nicaragua	0.181	11.677	11.858	5929566	7993133	3.919	3.737	1	1	1
Niger	-3.153	13.989	10.836	2.07e+07	2875711	2.857	6.011	1	0	1
Nigeria	-0.719	13.710	12.991	1.81e+08	2.48e+07	5.301	6.020	1	0	0
North Korea	0.172	11.725	11.897	2.44e+07	8310306	5.283	5.111	0	0	0
Norway	-1.323	12.622	11.299	5044548	4568920	2.812	4.135	1	1	0
Oman	-0.867	12.646	11.779	4574933	7385212	2.690	3.557	1	1	1
Pakistan	-0.857	13.660	12.803	1.88e+08	2.06e+07	5.392	6.249	1	1	0
Palestine	0.649	8.655	9.303	4032173	620959.1	6.555	5.907	0	0	
Panama	0.091	11.221	11.313	3877890	4631913	3.949	3.858	1	0	1
Papua New Guinea	-0.531	12.897	12.365	6430413	1.33e+07	2.780	3.311	1	0	0
Paraguay	0.469	12.890	13.359	6710950	3.59e+07	2.829	2.360	1	1	1
Peru	-0.321	14.063	13.743	3.13e+07	5.26e+07	3.196	3.517	1	1	1
Philippines	0.451	12.446	12.896	9.27e+07	2.26e+07	5.900	5.449	1	1	0
Poland	1.761	12.628	14.389	3.83e+07	1.00e+08	4.832	3.071	1	1	0
Portugal	2.166	11.383	13.549	9736527	4.33e+07	4.709	2.543	1	1	0
Qatar	-0.816	9.404	8.589	2224458	303890.7	5.211	6.026	1	0	1
Republic of Congo	-0.218	12.742	12.524	4023043	1.56e+07	2.466	2.684	1	0	0
Romania	1.559	12.377	13.936	1.99e+07	6.39e+07	4.431	2.872	1	1	0
Russia	-1.357	16.591	15.234	1.43e+08	2.34e+08	2.187	3.544	1	0	0
Rwanda	-0.353	10.082	9.730	1.15e+07	951529	6.174	6.526	1	0	0
Saudi Arabia	-1.742	14.469	12.727	3.14e+07	1.91e+07	2.794	4.536	1	1	0
Senegal	-1.250	12.170	10.920	1.48e+07	3128165	4.343	5.592	1	0	0
Serbia	1.272	11.415	12.687	8957588	1.83e+07	4.593	3.321	0	0	
Sierra Leone	-0.585	11.186	10.600	5978825	2271808	4.418	5.004	1	0	1
Singapore	1.481	6.358	7.840	5186609	143725.7	9.103	7.622	0	0	1
Slovakia	0.899	10.827	11.726	5500804	7005527	4.693	3.794	1	0	0
Slovenia	0.688	9.893	10.581	2053164	2228016	4.642	3.954	1	0	0
Somalia	-1.710	13.368	11.658	1.11e+07	6544565	2.853	4.563	0	0	0
South Africa	0.585	14.017	14.602	5.49e+07	1.24e+08	3.805	3.220	1	1	1
South Korea	0.763	11.456	12.220	4.95e+07	1.15e+07	6.261	5.498	1	1	0
Spain	1.338	13.109	14.446	4.28e+07	1.06e+08	4.464	3.127	1	1	0
Sri Lanka	0.593	11.077	11.671	2.05e+07	6625879	5.758	5.165	1	1	0
Sudan	-2.465	14.735	12.269	5.27e+07	1.21e+07	3.046	5.512	1	0	0
Suriname	0.209	11.888	12.097	581462	1.02e+07	1.385	1.176	0	0	
Swaziland	0.908	9.757	10.665	1292376	2424693	4.315	3.407	1	0	1
Sweden	0.414	12.927	13.341	9615212	3.52e+07	3.151	2.738	1	1	0
Switzerland	-0.405	10.554	10.148	7398703	1446054	5.263	5.668	1	1	0
Syria	-0.307	12.134	11.827	1.83e+07	7750438	4.591	4.897	0	0	0

Taiwan	0.723	10.489	11.212	2.32e+07	4190626	6.470	5.747	0	0	
Tajikistan	-1.689	11.809	10.120	8145079	1405379	4.104	5.793	1	0	0
Tanzania	-0.016	13.684	13.668	5.08e+07	4.88e+07	4.059	4.074	1	0	0
Thailand	0.189	13.140	13.329	6.80e+07	3.48e+07	4.894	4.705	1	1	0
Timor-Leste	0.614	9.643	10.257	1296552	1611555	4.432	3.818	1	0	0
Togo	-0.568	10.996	10.427	5731419	1911436	4.566	5.134	1	0	1
Trinidad and Tobago	1.153	8.488	9.640	1290954	869977.4	5.583	4.431	1	1	1
Tunisia	0.650	11.957	12.607	1.11e+07	1.69e+07	4.262	3.612	1	1	0
Turkey	0.477	13.551	14.028	7.70e+07	7.00e+07	4.608	4.131	1	1	0
Turkmenistan	-1.000	13.041	12.042	5457316	9601121	2.471	3.471	1	0	0
Uganda	-0.792	12.207	11.415	3.76e+07	5131515	5.235	6.026	1	0	0
Ukraine	1.455	13.277	14.732	4.46e+07	1.41e+08	4.336	2.881	1	0	0
United Arab Emirates	-1.404	11.182	9.778	9004571	998612.3	4.831	6.235	1	0	0
United Kingdom	1.992	12.362	14.355	6.46e+07	9.70e+07	5.621	3.628	1	0	0
United States	0.449	16.013	16.462	3.19e+08	7.98e+08	3.568	3.119	1	1	1
Uruguay	2.476	12.073	14.549	3531141	1.18e+08	3.004	0.528	1	1	1
Uzbekistan	-1.235	12.947	11.713	2.94e+07	6910822	4.248	5.483	1	0	0
Venezuela	0.125	13.712	13.837	3.08e+07	5.78e+07	3.530	3.405	1	1	1
Vietnam	0.596	12.692	13.288	9.30e+07	3.34e+07	5.657	5.061	1	1	0
Yemen	-1.047	13.021	11.973	2.68e+07	8969197	4.083	5.131	1	1	0
Zambia	-0.431	13.518	13.087	1.71e+07	2.73e+07	3.139	3.569	1	0	1
Zimbabwe	-0.027	12.869	12.842	1.55e+07	2.14e+07	3.688	3.715	1	0	0

Table C.2: ALQ and Conventional Population Density, Gapminder

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	all			exclude native< 80%		
Dependent Variable	log Population Density					
Year	2010	2010	1820	2010	2010	1820
log ALQ (Poisson GHS)	0.463***	0.434***	0.713***	0.498***	0.488***	0.854***
	(0.116)	(0.105)	(0.138)	(0.117)	(0.110)	(0.0984)
Native<80%	-0.668*	-0.633*	-1.667***			
	(0.263)	(0.286)	(0.270)			
Constant	4.311***	4.309***	2.174***	4.311***	4.308***	2.172***
	(0.109)	(0.109)	(0.135)	(0.109)	(0.111)	(0.135)
Observations	148	139	139	96	93	93
R-squared	0.254	0.236	0.485	0.313	0.294	0.551

Bootstrapped standard errors are reported in parentheses. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.3. Economic Development and Land Quality, Gapminder

A. ALQ and Takeoff Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	all				exclude native< 80%			
Dependent Variable	log 2010 GDP	Takeoff Year	log 2010 GDP	log 2010 GDP	log 2010 GDP	Takeoff Year	log 2010 GDP	log 2010 GDP
log ALQ (Poisson GHS)	0.430**	-16.83***		0.189	0.481***	-17.81***		0.161
	(0.158)	(3.646)		(0.142)	(0.133)	(3.079)		(0.147)
Takeoff year, Gapminder			-0.0164***	-0.0143***			-0.0203***	-0.0180***
			(0.00169)	(0.00293)			(0.00230)	(0.00424)
Native<80%	0.241	-20.18***	-0.0778	-0.0465				
	(0.162)	(3.472)	(0.103)	(0.0980)				
Constant	8.946***	1912.1***	40.38***	36.23***	8.947***	1912.1***	47.71***	43.35***
	(0.0878)	(2.874)	(3.187)	(5.602)	(0.0844)	(2.836)	(4.357)	(8.084)
Observations	148	148	148	148	96	96	96	96
R-squared	0.180	0.233	0.375	0.402	0.232	0.252	0.517	0.537

Standard errors are reported in parentheses. Standard errors in columns 1-2, 4-6, and 8 are bootstrapped. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B. ALQ and Historical GDP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	all				exclude native< 80%			
Dependent Variable	log 2010 GDP	log 1820 GDP	log 2010 GDP	log 2010 GDP	log 2010 GDP	log 1820 GDP	log 2010 GDP	log 2010 GDP
log ALQ (Poisson GHS)	0.426**	0.208***		0.0836	0.477***	0.238***		0.0244
	(0.158)	(0.0489)		(0.143)	(0.133)	(0.0489)		(0.119)
log 1820 GDP, Gapminder			1.744***	1.642***			1.938***	1.903***
			(0.201)	(0.266)			(0.0612)	(0.188)
Native<80%	0.250	-0.0158	0.283*	0.276*				
	(0.164)	(0.0658)	(0.134)	(0.128)				
Constant	8.938***	6.808***	-2.935*	-2.242	8.939***	6.808***	-4.255***	-4.016**
	(0.0859)	(0.0304)	(1.412)	(1.842)	(0.0828)	(0.0290)	(0.432)	(1.275)
Observations	147	147	147	147	95	95	95	95
R-squared	0.179	0.253	0.490	0.495	0.229	0.341	0.627	0.627

Standard errors are reported in parentheses. Standard errors in columns 1-2, 4-6, and 8 are bootstrapped. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.4. GDP per Capita, Population Density, and $QAPD$ in 1820, Gapminder

	(1)	(2)	(3)	(4)
Dependent Variable	log 1820 GDP per Capita, Gapminder			
log 1820 Population Density, Gapminder	0.0979*	0.173***		
	(0.0399)	(0.0235)		
log 1820 QAPD, Gapminder			-0.0582	-0.0144
			(0.0427)	(0.0788)
Native<80%	0.185**		-0.0711	
	(0.0595)		(0.0956)	
Constant	6.608***	6.444***	6.948***	6.853***
	(0.139)	(0.103)	(0.0953)	(0.135)
Observations	139	93	139	93
R-squared	0.0858	0.240	0.0222	0.000767

Columns (2) and (4) restrict the sample to countries where Native is greater than or equal to 80%. Standard errors in parentheses. Standard errors in columns 3 and 4 are bootstrapped. Details of the bootstrapping procedure are footnoted in Section 4.2.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.5: The Effects of Takeoff Year on Population Growth, Gapminder

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	all				exclude native< 80%			
Dependent Variable	Pop. Growth	Takeoff	Pop. Growth	Pop. Growth	Pop. Growth	Takeoff	Pop. Growth	Pop. Growth
log ALQ (Poisson GHS)	-0.279***	-16.11***		-0.265***	-0.366***	-16.98***		-0.284***
	(0.0671)	(3.889)		(0.0637)	(0.0653)	(4.048)		(0.0648)
Takeoff year, Gapminder			0.00397**	0.000864			0.00859***	0.00478*
			(0.00123)	(0.00195)			(0.00163)	(0.00241)
Native<80%	1.033***	-25.17***	1.115***	1.055***				
	(0.140)	(5.437)	(0.140)	(0.174)				
Constant	2.135***	1911.5***	-5.456*	0.485	2.136***	1911.5***	-14.28***	-7.004
	(0.0483)	(3.709)	(2.336)	(3.714)	(0.0504)	(3.775)	(3.084)	(4.605)
Observations	139	139	139	139	93	93	93	93
R-squared	0.348	0.251	0.268	0.349	0.319	0.227	0.223	0.372

Standard errors are reported in parentheses. Standard errors in columns (1)-(2), (4)-(6), and (8) are bootstrapped. Details of the bootstrapping procedure are footnoted in Section 4.2.2. Pop. Growth refers to the log difference of the 2010 and 1820 populations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.6: Table C.6. The Effects of Life Expectancy Improvement on Population Growth, Gapminder

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	all				exclude native< 80%			
Dependent Variable	Pop. Growth	LE Imp. Time	Pop. Growth	Pop. Growth	Pop. Growth	LE Imp. Time	Pop. Growth	Pop. Growth
log ALQ (Poisson GHS)	-0.279***	16.21***		-0.150*	-0.366***	20.88***		-0.196
	(0.0671)	(1.168)		(0.0624)	(0.0653)	(1.452)		(0.102)
Life-expectancy Improvement Time			-0.00982***	-0.00793***			-0.0115***	-0.00812**
			(0.00143)	(0.00171)			(0.00179)	(0.00264)
Native<80%	1.033***	-16.20*	0.864***	0.905***				
	(0.140)	(6.358)	(0.0829)	(0.108)				
Constant	2.135***	55.17***	2.675***	2.573***	2.136***	55.12***	2.767***	2.583***
	(0.0483)	(4.011)	(0.106)	(0.125)	(0.0504)	(3.925)	(0.120)	(0.161)
Observations	139	139	139	139	93	93	93	93
R-squared	0.348	0.225	0.415	0.441	0.319	0.358	0.382	0.441

Standard errors are reported in parentheses. Standard errors in columns (1)-(2), (4)-(6), and (8) are bootstrapped. Details of the bootstrapping procedure are footnoted in Section 4.2.2. Pop. Growth refers to the log difference of the 2010 and 1820 populations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix D: Illustrative Model

We present a simple macro-demographic model that captures the main mechanisms that we think explain the data. Countries differ exogenously only in their levels of land quality. As in Lucas (2000), there is a lead country that takes off into growth, with trailing countries that take off at later dates. Unlike the Lucas model, where takeoff into growth is stochastic, we model takeoff dates as a deterministic function of land quality.

Productivity in the lead country grows at a constant rate, while trailing countries, once they experience takeoff themselves, benefit from a productivity spillover that leads to long-run convergence of productivity levels. In addition, as discussed in the text, we allow for a spillover of health technology from leaders to followers that is faster than the spillover of productive technology.

Population growth is just the difference between fertility and mortality rates, both of which are endogenous. Countries move from a Malthsuian equilibrium in which mortality and fertility are both high while income per capita and the size of the population are both constant, through a demographic transition in which fertility and mortality fall while population growth increases, into a post-transition equilibrium of constant population and constantly growing income.

Land Quality and the Takeoff into Growth

Countries differ exogenously in their land quality, ALQ_i , which is constant over time. Land quality plays two roles in the model. First, it appears directly in the production function. As will be seen below, the determinants of population growth are such that prior to takeoff all countries are in Malthusian steady states with income per capita normalized to one. In this setting, conventionally defined population density will just be proportional to land quality.

The second role of land quality is in determining the date of takeoff. In the text, we show that there is a strong empirical relationship between these variables. Although we do not model it explicitly, we assume that the underlying mechanism here is through agglomeration and Marshallian externalities. Concretely, we set the relationship between ALQ and takeoff to be the one estimated in the text, with a one log unit decrease in ALQ leading to a takeoff that is 26 years later.

We normalize the time of takeoff of the country with highest ALQ to be date zero. In the figures below, we normalize the log of ALQ in the first country to take off to be zero, and consider values of log ALQ in trailing counties as low as -4.83 (consistent with land quality differing by a factor of 125. Recall that in our data, the log of ALQ ranges from a high of 2.82 (Netherlands) to a low of -3.15 (Niger).

Technology and Production

The model of technological progress is based on Lucas (2000) and Barro and Sala-i-Martin (1997). Prior to takeoff in the lead country, technology is stagnant and equal everywhere in the world. We normalize this level of technology as $B = 1$. In the lead country, technology grows at a constant rate of g_B following takeoff. Follower countries experience technological convergence after their own takeoff dates:

$$\frac{B_{i,t+1}}{B_{i,t}} = (1+g_B)\cdot\left(\frac{B_{l,t}}{B_{i,t}}\right)^{\rho} \qquad \text{for } \rho > 0 \tag{20}$$

where B_l is the level of technology in the leading country.

In every country, output is produced with labor and a fixed quantity of quality-adjusted land. From equations (3) and (5) in the main text, the level of GDP per capita in a country is given by

$$y_{i,t} = B_{i,t}^{1-\alpha} QAPD_{i,t}^{\alpha-1} \tag{21}$$

where $QAPD$ is quality-adjusted population density. Population growth is given by the difference between fertility and mortality rates. We do not explicitly consider the age structure of the population or the ages at which childbirth and mortality take place. Life expectancy (e_0) is just the inverse of the mortality rate (m). The growth of population is thus given by the equation

$$L_{t+1} = L_t(1+f-m) \tag{22}$$

Mortality

We model life expectancy in the lead country as a function of time since takeoff. Pre-takeoff life expectancy is set to 30 years. Oeppen and Vaupel (2002) show that in the period since 1840, life expectancy at birth in the country with the greatest longevity has increased at a constant linear pace of 3 months per year. We implement this in equation (23):

$$e_{0,l} = 30 + 0.25 \cdot \ln(B_l)/\ln(1+g_B) \tag{23}$$

Given the constant exponential growth of B, there will be corresponding linear growth of life expectancy. Over 200 years, life expectancy in the lead country rises from 30 to 80, which is quite close to historical experience.

For trailing countries, we model life expectancy as being based on a combination of life expectancy in the lead country and life expectancy that would be justified by productive technology in the country itself, where the latter relationship is the same as in the lead country:

$$e_{0,i} = \omega[30 + 0.25 \cdot \ln(B_i)/ln(1+g_B)] + (1-\omega)e_{0,l} \tag{24}$$

The parameter ω embodies the spillover of health technologies from the leader to the follower, and specifically, the extent to which this spillover of health technologies exceeds the spillover of productive technologies that is embodied in B_i.

Fertility

The fertility rate in the pre-takeoff period is set so that when income per capita is equal to 1, fertility is equal to mortality, which in turn was set so that life expectancy was 30 years. Specifically this implies $f = m = 0.03333$. Following Hansen and Prescott (2002), we model the relationship between income and population growth as being composed of three segments:

First, there is an upward sloping segment, in which higher income raises fertility. Then there is a downward sloping segment in which higher income lowers fertility. Finally, above a fixed level of income, fertility is set at the rate consistent with zero population growth. Hansen and Prescott model the transition from the first to the second regime as occurring when income is twice the level of the Malthusian steady state, and the transition from the second to the third regime as occurring when income is 18 times the Malthusian steady state, with all segments of the function being linear. They also model the peak population growth rate (when income is twice the Malthusian level) as being 2% per year (or a doubling every 35 years, which is the time period in their model).

We copy this structure, with minor modifications. In our model, population growth is a function of both fertility and mortality, with mortality changing following takeoff, as described above. We then model the fertility function as having the same three segments as in Hansen and Prescott, specifically choosing the slope parameters so that in the leading country population growth is 2% when income per capita is (approximately) twice the Malthusian level and 0% when income per capita is 18 times the Malthusian level.

$$f_t = \begin{cases} 0.03333 + \gamma_1(y_t - 1) & \text{if } y_t < y^* \\ 0.03333 + \gamma_1(y^* - 1) + \gamma_2(y_t - y^*) & \text{if } y^* \leq y \leq 18 \\ m_t & \text{if } y_t > 18 \end{cases} \tag{25}$$

The level of income at which fertility begins to decline, y^*, is not set to 2, as in Hansen and Prescott, because falling mortality leads population growth to continue to rise with income over a range even as fertility is falling. Rather, we choose y^*, along with the other parameters of the model, to hit a maximum population growth rate of 2% at an income level close to 2.

In carrying over the analysis to countries that are not the lead country, we maintain the effect of income on fertility calibrated in the lead country. Since these trailing countries have lower mortality (for a given level of income) than does the lead country, they will in turn experience faster population growth at any level of income than did the lead country. We think of this change as being particularly appropriate for looking at population growth in late-starting countries, which indeed experienced higher levels of peak population growth than those that took off first.

Parameterization

We set the weight on land in the production function to 0.25.[38]

The three parameters that describe fertility are chosen with the following values:

$$y^* = 1.5$$

[38] Kremer (1993) uses one third as an upper-end estimate of land's share for the economy as a whole, while Hansen and Prescott (2002) assume a value of the fixed factor share of 30% for preindustrial economies. Caselli and Coleman (2001) derive a value of 0.19 as land's share in agriculture in the United States in the twentieth century. All of these papers assume an elasticity of substitution between fixed factors and other inputs (either for the economy as a whole, or within agriculture) of one. Ashraf, Lester, and Weil (2009), using data from Caselli and Feyrer (2007), calculate resources shares in national income that are as high as 25% in many poor countries, and exceed 30% in a few.

$$\gamma_1 = 0.02$$

$$\gamma_2 = -0.0018$$

Together these yield a maximum population growth rate of 2% when income is equal to 3.5 times its Malthusian level in the lead country. This doesn't exactly match the Hansen and Prescott specification, but it is as close as we could manage to come. These parameters are also chosen so that there is no discontinuity in fertility in the lead country when income crosses the threshold of $y = 18$.[39]

The parameter ω, which gives the weight on a country's own technology vs. that of the world leader in determining the mortality rate, is set at 0.25. We had no firm basis for choosing this value, but did so in order to produce an increase in population in trailing countries that seemed reasonable.

The value of g_B, the growth rate of technology in the lead country, is chosen such that in the steady state, with constant population, GDP grows at 2% per year. The final parameter in our model is ρ in equation (20), which determines the speed of technological catch up (for both productivity and health) among trailing countries. In Lucas (2000), the analogous parameter has a value of 0.025. In our view, this value was too high, even for the setting that Lucas was trying to describe. It implies that a country that takes off 200 years after the leader will have an initial growth rate (of GDP per capita in his model; technology in ours) of 12% per year. Lucas seems to have been swayed by the experience of a few countries that had episodes of spectacular growth in the second half of the 20th century, but these are unusual. In any case, to fit our model to the data, we choose a much lower value of 0.005, implying slower catchup after takeoff.

The results of the model are presented in Figures 11 A and B.

[39]In trailing countries mortality rates are lower for any given level of income than in the leader, but we model the fertility process in these countries as being the same as in the leader. Thus there is a discrete downward jump in fertility in trailing countries when they cross the threshold of 18 times Malthusian income.