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The role of land in agricultural production across climates

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Abstract

We document that the importance of land for agriculture differs significantly between temperate and tropical areas. Using sub-national data, we estimate the aggregate elasticity of agricultural output with respect to land by examining the relationship of rural density and inherent agricultural productivity. The elasticity in temperate districts (0.23) is significantly higher than in tropical districts (0.13), and is not a proxy for development level. A two-sector model shows that the high elasticity in temperate areas makes their living standards more sensitive to shocks in population growth and technology. We confirm these predictions using evidence from the post-war mortality transition.

JEL Codes: O1, O13, O44, Q10

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1 Introduction

Agricultural production depends, to some degree, on the use of the finite (or inelastically supplied) resource, land. Yet the importance of land to production need not be identical across countries or climates. The raw data shows large differences in the amount of land used around the world, with places like Argentina, Canada, and the United States averaging hundreds of hectares per farmer, while in much of south-east and east Asia the average is often below two hectares per farmer, and at times below one. While these differences are stark, they are not informative about the sensitivity of any given economies agricultural output to the amount of land. For that we need to know the parameters of the aggregate agricultural production function, and in particular, the elasticity of agricultural output with respect to land.

That land elasticity is useful in the broader study of development. If one is willing to make the mild assumption that agriculture has constant returns to scale in the aggregate, then one minus the land elasticity tells us how sensitive aggregate agricultural output is to the use of all *other* inputs (e.g. capital and labor). Thus the land elasticity is a relevant parameter for any research that involves the aggregate agricultural sector, including work on structural change in the process of development, Malthusian stagnation and the take-off to sustained growth, and the prospects for long-run growth in a world of finite resources.[1]

In this paper, we estimate the aggregate land elasticity, and examine how it varies across different agricultural and climate types. Estimating the parameter(s) of a production function is not straightforward, for the standard reasons that total factor productivity is unobserved and inputs may be mis-measured. To address this, we first develop a method for estimating the aggregate land elasticity using the relationship between the density of agricultural workers and the potential agro-climatic yield across small geographic units (e.g. districts within provinces/states). Our method allows for inputs other than land and labor in the production function, but does not require us to identify exactly what those other inputs are, avoiding mis-measurement issues. We do not have a direct measure of total factor productivity at the district level. But the agro-climatic yield data we use, the additional controls we include, and the fact that we are only using within-province variation to estimate the elasticity, should ensure that any remaining unobservable within-province variation in total factor productivity does not bias our estimates. Because we are using within-province variation only, the clear variation in capital and technologies across countries (or even across provinces/states within countries) is not driving any of our estimates.

[1]On structural change, see Gollin, Parente and Rogerson (2007); Restuccia, Yang and Zhu (2008); Weil and Wilde (2009); Gollin (2010); Eberhardt and Vollrath (2018). For Malthusian stagnation, see Ashraf and Galor (2011) for a baseline model, and Galor (2011) for a review of major contributions to the literature on the take-off to growth (Galor and Weil, 2000; Galor and Moav, 2002; Hansen and Prescott, 2002; Doepke, 2004; Cervellati and Sunde, 2005; Lagerlöf, 2006; Crafts and Mills, 2009; Strulik and Weisdorf, 2008). Agriculture and land also feature in stories of divergence across global regions (Kogel and Prskawetz, 2001; Galor and Mountford, 2008; Vollrath, 2011; Voigtländer and Voth, 2013*b*,*a*; Cervellati and Sunde, 2015). On the relevance of resources for long-run growth, see Peretto and Valente (2015).

We assemble data at the district level for rural population density in the year 2000 from the HYDE database (Goldewijk et al., 2011), and combine that with a measure of potential agro-climatic yield in districts built from the data of Galor and Özak (2016). As in their work, our measure is built on constraints plausibly unaffected by human activity (e.g. soil quality and length of growing season) from the Global Agro-Ecological Zone (GAEZ) project (Food and Agriculture Organization, 2012), combined with information on the calorie content of various crops. Grid cell potential caloric yields are aggregated to the district level to serve as our measure of agro-climatic yield.[2]

In the end, we have a dataset of 35,451 districts, coming from 2,554 provinces in 154 countries. Using this data, we provide estimates of the land elasticity for different regions defined by the types of crops they are capable of growing. "Temperate" areas (i.e. those that can grow crops such as wheat, barley, and rye) are distinguished from "tropical" areas (i.e. those that can grow crops such as rice, cassava, and pearl millet). We estimate a land elasticity of 0.228 in temperate districts in our baseline specification. In contrast, we estimate an elasticity of only 0.132 for tropical districts. Our baseline definition of temperate and tropical are based on suitability for growing specific crops, and not on direct temperature or precipitation regimes. Nevertheless, the approximate 0.10 difference in the land elasticity holds up across alternate definitions of what constitutes temperate and tropical regions.

Our results are robust to the exclusion of districts that contain large urban areas, the exclusion of districts from any developed country, or the exclusion of districts that appear to depend more on pastoralism than crop production. Further, the results are consistent if we use alternative measures of rural population density, alternative measures of the potential agro-climatic yield, or alternative measures of the area of agricultural land used within a district. All of our estimates are made using night light data and the urban percent to control for district-level variation in development. In all cases, the aggregate land elasticity in temperate districts remains approximately 0.10 higher than in tropical districts, and the difference remains statistically significant.[3]

Relative to the existing literature, our approach to estimating the aggregate land elasticity has several advantages. The standard approach has been to use country-level panel data (Hayami and Ruttan, 1970, 1985; Craig, Pardey and Roseboom, 1997; Martin and Mitra, 2001; Mundlak, 2000; Mundlak, Butzer and Larson, 2012; Eberhardt and Teal, 2013) to estimate agricultural production functions, with a common set of coefficients across countries for each input, including land. Issues

[2]There are two studies that focus on the spatial distribution of labor (in general) and economic activity. The first is Motamed, Florax and Masters (2014). Those authors examine the growth of urbanization at the grid-cell level over the last two-thousand years. The second is Henderson et al. (2016), who examine the spatial distribution of economic activity (associated with urbanization) at the grid-cell level using night lights, relating it to geographic characteristics associated with either agriculture or trade.

[3]These results are consistent with the work of Ruthenberg (1976) and Bray (1994), who discuss the inherent differences in the response of tropical crops (rice, in particular) to the application of labor. They both cite the relatively *high* elasticity of output with respect to labor in tropical agriculture, which is consistent with a low elasticity of output with respect to land.

arise with unobserved productivity, the measurement of non-land inputs, and the assumption that coefficients are common to all countries. Some have examined heterogeneity in these coefficients (Gutierrez and Gutierrez, 2003; Wiebe et al., 2003) by continent, while others have attempted to estimate country-level coefficients using factor analysis to address unobserved productivity (Eberhardt and Teal, 2013; Eberhardt and Vollrath, 2018). Relative to this work, our district-level data allows us to control for unobserved country and province-level effects.

As may be clear, we are not estimating the elasticity of a *farm*-level production function, but rather for an aggregate production function. Farm-level estimates of the land elasticity would not necessarily be informative about the aggregate production function, given that those estimates would refer to farmers using a given technique, while the aggregate function can be thought of as an envelope across available the techniques available to farmers (Hayami and Ruttan, 1970).[4] The aggregate land elasticity itself is a useful parameter for studying the role of the agricultural sectors role in development, as we discuss below, while farm-level elasticities would be useful in studying farm-level policies or outcomes within the agricultural sector.

We show in the second half of the paper that the aggregate land elasticity is in fact central to any study that looks at the relationship of agriculture to non-agriculture. The variation we have identified between temperate and tropical regions has implications for development. To show this we first elaborate a model that incorporates both an agricultural as well as a non-agricultural sector, allows for the movement of labor and capital between those sectors, and incorporates preferences that lead to Engel's Law holding for the demand for agricultural output.

The model shows that the elasticities of real income per capita and the share of labor in agriculture with respect to either population or total factor productivity TFP depend on the size of the land elasticity itself. In particular, the larger is the land elasticity, the larger are the elasticities of real income per capita and the share of labor in agriculture with respect to population and TFP. This implies that temperate areas have living standards and labor allocations that are more sensitive to shocks than in tropical areas. This is a benefit to temperate areas when shocks are positive (e.g. higher TFP or lower population growth), but negative in the face of negative shocks (e.g. lower TFP or higher population growth).

In the last part of the paper we confirm these predictions by using data from Acemoglu and Johnson (2007) to examine the effect of population shocks arising from the epidemiological transition after World War II on GDP per capita and GDP per worker. The shock to mortality had a negative impact on living standards across all developing countries. But we find that the size of that negative effect was three times larger for countries with high, temperate, land elasticities compared to countries with low, tropical, land elasticities. The difference in effect size is statistically significant, and holds whether we measure the population shock in terms of mortality, life

[4] More general treatments of this idea can be found in Houthakker (1955) and Jones (2005). In short, the farm-level land elasticities may not be informative on the aggregate land elasticity, and farm-;eve; production functions may well take on different forms (i.e. Leontief verus Cobb-Dougals) than the aggregate function.

expectancy, or population size.

At a broader level, variation in the land elasticity may be relevant for the study of historical and contemporary development. For any given positive shock to productivity (or negative shock to population), areas with high temperate land elasticities will experience more urbanization and more rapid growth in living standards, whatever the fundamental driver of those shocks: institutions, geography, or culture.[5] This may help explain why it was that Europe, with a high aggregate land, developed faster than other regions even if it did not experience "better" productivity or population shocks than others. It may also help explain why the tropical areas of Central America and Sub-Saharan Africa, with relatively low land elasticities, lagged behind other areas following decolonization.[6]

To proceed, Section 2 presents our method for recovering estimates of the aggregate land elasticity from cross-sectional information on agricultural worker density and a measure of inherent agro-climatic productivity. Section 3 contains the exact empirical specification for estimating the land elasticity, describes the data sources, and presents the main results. Section 4 presents the model of the importance of the land elasticity in development, and provides supportive evidence from the mortality transition. Section 5 concludes.

2 Rural density, productivity, and the aggregate land elasticity

Our method of estimating the aggregate land elasticity rests on making comparisons across small geographic areas (e.g. districts within states/provinces). We show here how the relationship between agricultural worker density and a measure of inherent agricultural total factor productivity (TFP) can be used to recover an estimate of the aggregate land elasticity, and how this method eliminates the need to identify or measure other inputs (e.g. capital) as part of the estimation.

2.1 Agricultural production and allocations across districts

An economy (e.g. province or state) I is divided into districts denoted by i. The aggregate agricultural production function for district i is given by

$$Y_i = A_i X_i^{\beta} \left(K_{Ai}^{\alpha} L_{Ai}^{1-\alpha} \right)^{1-\beta} \tag{1}$$

[5]It would be hopeless to summarize or cite all the research on comparative development. Several useful reviews of this literature can be found in Acemoglu, Johnson and Robinson (2005); Nunn (2009); Galor (2011); Spolaore and Wacziarg (2013); Vries (2013).

[6]Our work is related to several recent studies on the the role of geography and/or inherent agricultural productivity in development (Olsson and Hibbs, 2005; Ashraf and Galor, 2011; Nunn and Qian, 2011; Nunn and Puga, 2012; Michalopoulos, 2012; Alesina, Giuliano and Nunn, 2013; Cook, 2014*a*,*b*; Fenske, 2014; Alsan, 2015; Ashraf and Michalopoulos, 2015; Dalgaard, Knudsen and Selaya, 2015; Galor and Özak, 2016; Litina, 2016; Andersen, Dalgaard and Selaya, 2016; Frankema and Papaioannou, 2017). Unlike those papers, ours does not propose a direct causal relationship between geography and development, but rather suggests that *any* proposed causal impact has differential effects based on the size of the land elasticity.

where A_i is total factor productivity, X_i is land, K_{Ai} is capital (or any other inputs aside from land and labor), and L_{Ai} is the number of agricultural workers. The aggregate land elasticity is β. Note that we presume β is not specific to the district i, but rather common to the province I in which this district lies. Also note that equation (1) does not denote a farm-specific production function, but an aggregate production function at the level of the district i. While we have written the function here as Cobb-Douglas, this is solely for ease of exposition. The analysis does not require this. In the Appendix we show that one could use a general constant returns to scale function to derive a similar estimation equation.

The amount of labor employed in district i will depend on its productivity relative to other districts in the same province. We assume that both labor and capital are mobile across districts within province I, and hence the real wage, w, and return on capital, r, are the same for each district i. In each district those wages and returns are determined by

$$\begin{aligned} w &= \phi_L \frac{Y_i}{L_i} \\ r &= \phi_K \frac{Y_i}{K_i} \end{aligned} \tag{2}$$

where ϕ_L and ϕ_K are the fraction of output paid to labor and capital, respectively. These fractions may or may not be equal to the respective elasticities in the production function of these inputs, meaning that the wage and rate of return may or may not be equal to the marginal product of these factors. We set the model up this way to make two things clear. First, we are not going to identify the value of β by using information on shares of output, and second that our empirical work only depends on these factors being mobile across districts, not on them being paid their marginal product.

Given that all districts face the same wage and rate of return, in each district the capital/labor ratio will be the same at

$$\frac{K_i}{L_{Ai}} = \frac{w}{r}\frac{\phi_K}{\phi_L}.$$

Using this ratio, we can write production in each district i as

$$Y_i = A_i X_i^{\beta} \left(\frac{w}{r}\frac{\phi_K}{\phi_L}\right)^{\alpha(1-\beta)} L_{Ai}^{1-\beta} \tag{3}$$

which relates production in district i to district level productivity, A_i, land, X_i, and labor, L_{Ai}, but also the *province*-specific w/r ratio.

Combine the wage definition from (3) and the production function in (3) with an adding-up condition for agricultural labor

$$\sum_{i \in I} L_{Ai} = L_A,$$

where L_A is the total amount of agricultural labor in province I. These can be solved for the density of agricultural workers in sub-unit i,

$$\frac{L_{Ai}}{X_i} = A_i^{1/\beta} \frac{L_A}{\sum_{j \in I} A_j^{1/\beta} X_j}. \tag{4}$$

A district that is more productive should have a greater share of the agricultural labor force employed in it. In addition, the larger is the province-wide agricultural labor force, L_A, the more dense is agricultural labor in all districts.[7]

Take logs of (4) and re-arrange to

$$\ln A_i = \beta \ln L_{Ai}/X_i + \Omega, \tag{5}$$

where $\Omega = \beta \ln \sum_{j \in I} A_j^{1/\beta} X_j - \beta \ln L_A$ is a term common to any district within a given province. The intuition of the empirical work to come is apparent in equation (5). Given the assumption of mobile labor between districts, we can identify the value of β by using data on productivity, A_i, and agricultural labor density, L_{Ai}/X_i. To be clear, the assumption of mobile labor (meaning each district faces a horizontal labor supply curve) is crucial. Without that, the reduced form relationship of productivity and agricultural density would involve both β and the slope of the labor supply curve within a district. We discuss in the Appendix how specific violations of that assumption would change our empirical work, and whether these appear to be significant issues.

3 Estimates of the aggregate land elasticity

Given the structure set up in the prior section, we can now turn to the actual estimation. The basis of our estimations is equation (5). We rewrite that here while adding some additional subscripts to make clear the structure of the data we will be using,

$$\ln A_{isg} = \beta_g \ln L_{Aisg}/X_{isg} + \Omega_s \tag{6}$$

where i denotes a district/prefecture/county (e.g. Saoguan) in province state s (e.g. Guangdong in China), which is part of a geographic region g. As can be seen, the coefficient β_g is unique to a geographic region. We will assign districts to a geographic region based on some physical characteristic (e.g. suitability for paddy rice), and all districts within that geographic region will be assumed to have an identical value for β_g. Our hypothesis is that the values of β_g vary with geographic characteristics, and over the course of the empirical work we will document that there are differences in β_g between geographic regions.

[7] We use a Cobb-Douglas specification for clarity. We show in the Appendix that a relationship like (4) holds for any constant returns to scale function.

Equation (6) can be used to identify β_g using variation in A_{isg} and L_{Aisg}/X_{isg}. But productivity, A_{isg}, is unobserved, so to implement this in a regression we build a proxy for it using data on agro-climatic suitability for agriculture. To be clear on the assumptions necessary for this to work, we present a structure for productivity that has three separate factors,

$$\ln A_{isg} = \ln A_{isg}^{Agro} + \ln A_s^{Tech} + \delta_g' \mathbf{Z}_{isg}. \tag{7}$$

The first factor is potential agro-climatic productivity, $\ln A_{isg}^{Agro}$, which captures agricultural productivity coming from things such as temperature, rainfall, and soil conditions. This agro-climatic productivity measure is specific to a district. Second is $\ln A_s^{Tech}$, which captures technological (or institutional or cultural) factors that affect agricultural productivity, and is assumed to be common to all districts within a given province s. Finally, $\mathbf{Z}_{isg}$ captures district-specific observable characteristics that may also influence productivity in agriculture, in particular characteristics capturing the overall level of development in a district. The term δ_g is a vector of effect these characteristics have on productivity.

We will measure the agro-climatic productivity term within a district using the work of Galor and Özak (2016), which is itself built on the Global Agro-ecological Zone project from the Food and Agriculture Organization (2012). We describe the details of the GAEZ data below, but consider it to be a noisy measure of true agro-climatic productivity,

$$\ln A_{isg}^{GAEZ} = \ln A_{isg}^{Agro} + \epsilon_{isg}. \tag{8}$$

Here ϵ_{isg} is the noise term and is assumed to be uncorrelated with true agro-climatic productivity. In short, we assume that the GAEZ did not make systematic errors in measuring agro-climatic productivity. We will return to that assumption below in our robustness checks.

If we put together equations (6), (7), and (8), we arrive at the following estimation specification

$$\ln A_{isg}^{GAEZ} = \beta_g \ln L_{Aisg}/X_{isg} + \gamma_s + \delta_g' \mathbf{Z}_{isg} + \epsilon_{isg}, \tag{9}$$

where $\gamma_s = \Omega_s - \ln A_s^{Tech}$ is a province fixed-effect term. Regressing (log) agro-climatic productivity on (log) agricultural density will provide an estimate of the value of β_g for a given geographic region. This estimate is driven entirely by within-province variation in density and productivity, as we are using the province fixed effect, γ_s, to capture the province-specific level of agricultural employment and productivity common to all districts. The additional control variables included in $\mathbf{Z}_{isg}$ (e.g. urbanization and night light intensity) will capture district-level variation in development level that may also proxy for productivity at the district level. As ϵ_{isg} is noise in the measurement of agro-climatic productivity, it is uncorrelated with the level of agricultural density, giving us unbiased estimates of β_g.

The threat to this empirical strategy is unobservable variation in agricultural productivity that varies across districts *within* provinces, but is not captured by the observable characteristics in $\mathbf{Z}_{isg}$. While we cannot say with certainty that such an omitted variable does not exist, we believe that our province fixed effects and district-level controls capture all the material variation in productivity not associated with agro-climatic conditions. The significant differences in agricultural technologies and institutions across countries - or even across provinces within countries - that most readers will be familiar with are *not* sufficient to create bias in this setting, given our set of controls. In the robustness section, we consider several alternative ways of measuring A_{isg}^{GAEZ} that also may alleviate concerns that we are missing relevant district-level variation in productivity.

Standard errors: ϵ_{isg} is a noise term, and we allow that it may be spatially auto-correlated. To account for this in our standard errors, we use Conley standard errors. For any given district i, the error term of any other district that has a centroid (lat/lon) within 500km of the centroid (lat/lon) of district i is allowed to have a non-zero covariance with ϵ_{isg}. The covariance of all other districts outside that 500km window is presumed to be zero. Allowing the weight on the covariance to decay with distance from the centroid of i does not change the results in a material way. We also experimented with other windows (1000km, 2000km), but we obtain the largest standard errors using 500km and hence report those.

Hypothesis testing: We will be estimating (9) for geographic regions, g. The typical significance test of estimated coefficients, with a null hypothesis that $\beta_g = 0$, is a test of whether the land elasticity is zero in region g. As will be seen in the results, we can reject this null hypothesis in all sub-samples.

What is more relevant is whether the β_g we estimate for one geographic region is statistically different from the β_g we estimate using a different region. We choose one region to be a reference region, and then test the estimated $\hat{\beta}_g$ values for all *other* regions against the $\hat{\beta}_{Ref}$. In practice, this is implemented as a simple interaction regression, where $I(Ref)$ is an indicator variable for inclusion in the reference region. The specification is

$$\begin{aligned} \ln A_{isg}^{GAEZ} \quad &= \quad \beta_g \ln L_{Aisg}/X_{isg} + (\beta_{Ref} - \beta_g) \ln L_{Aisg}/X_{isg} \times I(Ref) + \gamma_s \\ &\quad\quad +\delta_g' \mathbf{Z}_{isg} + (\delta_{Ref}' - \delta_g') \mathbf{Z}_{isg} \times I(Ref) + \epsilon_{isg}. \end{aligned} \tag{10}$$

We then perform a statistical test with the null of $H_0 : (\beta_{Ref} - \beta_g) = 0$ using the results of this interaction regression. Rejecting this null indicates that β_{Ref} and β_g are statistically different, and for our purposes this is the hypothesis of interest.[8]

[8]The individual tests we run this way are identical to what we would obtain if we included all observations in a single regression, and interacted rural population density with a series of dummies indicating the sample.

3.1 District Population and Productivity Data

Population: The underlying population data comes from HYDE 3.1 (Goldewijk et al., 2011), and is provided at a 5 degree grid-cell resolution. The authors provide counts of total population as well as urban and rural population for each cell. These counts are derived from political administrative data at varying levels (e.g. districts, states) which are then used to assign counts to the grid-cells within the given political unit.[9]

Because of the nature of their estimates, the grid-cell level counts are inappropriate for our purposes. The authors explain in the associated paper that they use several algorithms to smooth the population counts across grid cells based on land productivity and assumptions about the gradient of population density with respect to distance from urban centers. If we use their grid-cell population data, we will be estimating their algorithm, and not the relationship of density and productivity. Therefore, we only use their data at the level of districts (or provinces). We overlay 2nd-level political boundary data from the Global Administrative Areas project (GADM) on top of the HYDE grid-cell data, and use this to rebuild the population count data for each district.

The estimation in (9) requires data on *agricultural* population, and HYDE provides a measure of *rural* population. There is not a perfect overlap of these two sets, but in the absence of any way of measuring the spatial distribution of agricultural workers, we use the rural data as a proxy. After the main results, we discuss several alternative sources of data to control for agricultural workers. We also require data on the urbanization rate within provinces and districts. This can be recovered from HYDE using their counts of total population (rural plus urban) and urban population.

Using the data from HYDE from 2000CE, we calculate the rural density for each district. We then discard all observations above the 99th percentile and below the 1st from that overall sample, to avoid outliers that may drive results. We also excluded all districts with fewer than 100 total rural residents, again to avoid outliers. Regressions including these observations do not appear to change the results. Summary statistics for the remaining data on rural density can be round in Table 1. For our entire sample, which covers 35,451 districts for the year 2000CE, there are 0.57 rural residents per hectare. The percentile distribution of this is shown as well, ranging from only 0.03 per hectare at the 10th percentile to 1.53 at the 90th.

Inherent agricultural productivity: We rely on the work of Galor and Özak (2016) to provide our measure of agricultural productivity, A_{isg}^{GAEZ}. The authors form a measure of the potential caloric yield at a grid-cell level, combining crop yield information from the GAEZ with nutritional information on those crops. As argued by Galor and Özak (2016), the caloric suitability index is more informative for analysis of agricultural productivity than raw tonnes of output, as it relates to the nutritional needs of humans. We address the use of calories to compare crops below in the

[9] Links to the raw files for population, and all other data used in this paper, along with code to build our datasets, and replicate all regressions, can be found at https://github.com/dvollrath/Crops.

robustness section, and this is not driving our results.

For our purposes, we use have accessed the crop-specific data underlying the Galor and Özak (2016) index, so that we can measure both the total potential calories produced within a given district, as well as identifying *which* crops are assumed to provide those calories.[10] We have also used a subset of the crops in the original Galor and Özak (2016) dataset, so that we focus on crops that are primary staples.[11] Those authors provide details of the construction of this data, but we can provide a summary. For each grid-cell, they calculate the total potential calories each crop will provide, given the potential production from the GAEZ project (Food and Agriculture Organization, 2012) combined with information on calories per tonne for each crop. Within each cell, they then identify the maximum amount of calories possible across the different crops. Finally, for a given district one can sum up those maximum calories to arrive at A_{isg}^{GAEZ}. In addition to this total, we also know which specific crops are responsible for providing the maximum's, and will use that below as one means of distinguishing regions.

After we calculate A_{isg}^{GAEZ} for each district, we discard values above the 99th and below the 1st percentile from that total available sample to avoid outliers. Our results are not sensitive to this trimming. Summary statistics for A_{isg}^{GAEZ} in the remaining districts can be found in Table 1 in the second row, reported in millions of calories per hectare. The mean is 10.57 million calories per hectare. At the 10th percentile of the trimmed distribution, the caloric yield is only 4.84 million calories per hectare, while it is four times higher at the 90th percentile, around 16.54 million calories per hectare. The maximum caloric yield in our sample is 32.64 millions calories, while the lowest is only 0.48 million calories.

Crop suitability: As an alternative way of creating geographic regions of districts based on crop types, we use "crop suitability indices", which are also from the Global Agro-ecological Zones (GAEZ) project (Food and Agriculture Organization, 2012), and are provided for each grid-cell on a scale of 0 to 100. Using this to identify which districts are suitable for wheat or rice (for example) avoids errors we may have introduced by introducing calorie counts to our measure of A_{isg}^{GAEZ}, and serves as a validation check. The GAEZ crop suitability indices are used to divide districts based on the types of crops they produce, but we continue to use our A_{isg}^{GAEZ} to measure productivity, as the suitability indices are not a measure of potential output.

The GAEZ suitability index depends on climate conditions (precipitation, temperature, evapotranspiration), soil (acidity, nutrient availability), and terrain (slope). For districts of a country, we construct an overall suitability index as a weighted (by area) sum of the grid-cell suitability

[10] We use the low-input, rain-fed indices of caloric yield provided by Galor and Özak (2016) in our baseline specification. Our results are robust to using different assumptions on inputs and water use, shown below.

[11] The specific crops included in our calculation are: alfalfa, banana, barley, buckwheat, cassava, chickpea, cowpea, drypea, flax, foxtail millet, greengram, groundnut, indica rice, maize, oat, pearl millet, phaselous bean, pigeon pea, rye, sorghum, soybean, spring wheat, sweetpotato, rape, wet/paddy rice, wheat, winter wheat, white potato, and yams.

indices. Given that the grid-cell suitability measures run from 0 to 100, our aggregated index for each district also runs from 0 to 100.

Land area: Our measure of land area, X_{isg}, is the total land area of a district, without adjusting for cultivated area. We will thus be estimating the elasticity of output with respect to the *possible* stock of land. Choosing to not crop certain plots is akin to choosing to apply zero labor or capital to those plots. We discuss after the main results that our estimates do not differ if we use information on cultivated area in place of total land.

Nighttime lights: We follow Henderson et al. (2016) and use the Global Radiance Calibrated Nightime Lights data provided by NOAA/NGDC, described in Elvidge et al. (1999), and reported at 1/120 degree resolution. This dataset contains more detail on low levels of light emissions (thus capturing detail for undeveloped areas), and avoids most top-coding of areas saturated by light (thus capturing more detail in developed areas). To match the data we use on population, we use the dataset from 2000, and create district-level measures of nighttime light density by averaging across the pixels contained within each district.

We adjust for the fact that the lights data are reported with zero values, which is part of an adjustment from NOAA/NGDC to account for possible noise in pixels that report very small amounts of light. Similar to Henderson et al. (2016), for any district that has a raw value of zero for night lights, we replace that with the minimum positive value found in the rest of the sample of districts. This prevents us from understating light density in those districts. Once this adjustment is made, we take logs of the average lights in a district. Summary statistics for the final night lights data can be found in Table 1.

3.2 Results for Temperate versus Tropical Agriculture

Our primary defintion of region g is by agricultural type, either temperate or tropical. There is no definitive way of deciding which districts practice temperate or tropical agriculture, and so we will explore several possible definitions. Our baseline definition uses the GAEZ measures of crop suitability discussed above, as these incorporate both geographic characteristics (e.g. rainfall and soil type) as well as the biological needs of crops (e.g. wheat or rice). The **temperate** region includes any district that has positive GAEZ suitability for barley, buckwheat, rye, oats, wheat, or white potatoes, but has exactly *zero* suitability for cassava, cowpeas, paddy rice, pearl millet, sweet potatoes, or yams. The **tropical** region is defined in opposite terms. It includes any district that has positive GAEZ suitability cassava, cowpeas, paddy rice, pearl millet, sweet potatoes, or yams, but has exactly *zero* suitability for barley, buckwheat, rye, oats, wheat, or white potatoes.[12]

[12]We have experimented with alternative sets of crops to define the regions, without any material change to our results. A further note is that our definitions of tropical and temperate are not all-encompassing, and thus there are

An important advantage of our data is that we are not forced to treat all districts within a *nation* as having the same agriculture type. Inclusion of a district in a given geographic region is based on that district's data alone, allowing us to distinguish temperate areas and tropical areas of countries like Brazil, China, and the United States that are very heterogeneous in agricultural types.

Our terms "tropical" and "temperate" for our samples are useful labels, and capture the rough correlation of the specific crops with certain climate zones. But they are not hard and fast geographic definitions. Table 2 shows how the total 35,451 districts in our sample are distributed across these two groups. Row 2 (Tropical) and 3 (Temperate) are our baseline groups that we use to estimate β_g, and include 9,088 and 10,661 districts respectively. Row 1 shows that there are 10 districts that are suitable for neither the tropical nor the temperate crops we noted above. Row 4 shows that there are a large number, 15,692, districts that have some suitability for *both* sets of crops. For example, many areas of Japan are capable of growing both wheat and rice. These are excluded from our baseline analysis because we want to make a stark distinction between the values of β_g associated with different types of agriculture. In the appendix are shown results that incorporate these districts.

Figure 1 shows the density plots of (log) rural density for both the tropical and temperate groups, as just defined. One can see that rural density tends to be higher in our tropical districts, with a peak around 0.33 rural residents per hectare (i.e. log value of -1), or roughly 3 hectares per rural person. However, there are districts that have densities of 1 rural person per hectare (i.e. log of 0), or higher. In comparison, while there are a few districts in the temperate group with densities this high, the peak is closer to 0.05 rural residents per hectare (i.e. log of -3), and more districts with even lower densities of rural workers per hectare.

There is a similar distinction in the density plots of caloric yield, A_{isg}^{GAEZ}, for districts in the tropical and temperate groups. Figure 2 shows these plots, and the tropical districts have a strong peak around 12-15 million calories per hectare, while the peak for temperate districts is closer to 5 million calories, although the tail of the temperate distribution runs as high as for tropical districts. This reflects both inherent agro-climatic productivity differences, and the fact that the calories per tonne of the crops defining the tropical districts (e.g. cassave, wet rice, etc.) is much higher than the calories per tonne defining temperate districts (e.g. barley and wheat).

These two plots capture the raw information about rural density and calories per hectare, but the distinction between temperate and tropical districts found in both are immaterial to our estimation. Recall that we will only be using the district-level variation in rural density and caloric yield *within* a given province, and only for districts that share a common definition of temperate or tropical. Hence the shifts in the distributions seen in Figures 1 and 2 are not driving our results.

To get to those results, Table 3 shows the estimates of β_g for both our temperate and tropical

districts that are classified as neither, because they have agro-climatic conditions amenable to both temperate and tropical crops. There are also districts that are classified as both, as they can grow crops from both groups.

regions, as just defined. In column (1) of Panel A, one can see the estimate of β_g for temperate districts is 0.228, while in column (2) the estimate of β_g for tropical districts is 0.132, a difference of approximately 0.10. Below these estimates are two hypothesis tests. The first row tests the hypothesis that the true β_g is equal to zero, and in both samples we reject this at below 0.1% significance. The second row tests the hypothesis that the β_g from the tropical region is equal to the β_g from the temperate. We can reject that null hypothesis at 0.1%.

Figure 3 plots the residual relationship of log caloric yield and log rural density found from columns (1) and (2) of the Table, controlling for province fixed-effects, log light density, and the urban percentage in a district. Given the large number of observations, we plot the average values of the residuals for 50 different quantiles of our data to make the figure more legible, and as these are residuals the values of rural density and caloric yield are all centered around zero.[13] The difference in the slopes of the lines for tropical and temperate districts imply a difference in the value of the land elasticity, β_g, and as the Table indicates that difference is statistically significant. The additional value of the Figure is that it allows us to assess our linearity assumption, and judge if there are outliers perhaps driving the results. Overall, the linearity assumption appears solid, and there are no obvious outliers. At very high levels of rural density among tropical districts (above -1) the quantile averages appear to diverge from the estimated relationship. These represent only 6% of the total data points, and if we exclude them from our regressions we obtain similar results.

Returning to Table 3, the remainder of the table shows variations on our baseline result. In columns (3) and (4), we use a different definition to allocate districts to temperate and tropical agriculture, based on the information underlying the A_{isg} measure of productivity. In column (3), the temperate region is defined as those where more than one-third of their maximum calories come from the six temperate crops (barley, buckwheat, rye, oats, wheat, and white potatoes), and fewer than one-third of the maximum calories come from the six main tropical crops (cassava, cowpeas, paddy rice, pearl millet, sweet potatoes, or yams). In column (4), the definition is reversed to define districts with tropical agriculture. The estimated value of β_g is lower in both sample than in columns (1) and (2), but the tropical districts again have a smaller estimated land elasticity, at 0.112, compared to districts with temperate agriculture, at 0.191. The difference in these is statistically significant at 0.1%.[14]

Completing Panel A, columns (5) and (6) define temperate and tropical regions based on the observed harvested area of crops, using data from GAEZ. In column (5) are districts with more than half of their harvested area accounted for by the six temperate crops, and in column (6) are districts with more than half of their harvested area coming from the six tropical crops. The pattern repeats, with the temperate region having a larger estimated β_g value of 0.205, compared

[13] Using the quantiles still gives an accurate indication of the relationships in the data. See Chetty, Friedman and Saez (2013) for an explanation and example of this kind of figure.

[14] While it is possible for a district to be in both categories, receiving more than one-third of its maximum calories from both the temperate and tropical crops, in practice they are so distinct that only 9 districts have this feature.

to the tropical region at 0.133. The difference is significant at less than 0.1%.

Panel B provides a set of robustness checks on the results from Panel A. In all regressions in Panel B, the definition of temperate versus tropical region is based on the GAEZ suitability measures used the first two columns of Panel A. In Panel B, columns (1) and (2) exclude any district with a reported urban population greater than 25,000 people. The worry is that highly urbanized districts may operate a different type of agricultural technology and/or may skew the density of rural population near them (perhaps due to definitions of urban areas), and that our original results were skewed by this. As can be seen from the table, however, the distinction in β_g remains, 0.261 for temperate districts and 0.143 for tropical districts, which is an absolute difference larger than in Panel A. This difference is again significant.

Columns (3) and (4) of Panel B exclude both Europe (including Russia west of the Urals) and North America from the samples, to address the worry that these areas may use different types of agricultural technologies than other places at lower development levels.[15] The finding that districts suitable for tropical crops have a lower land elasticity still holds, with an estimated β_g of 0.133 compared to 0.242 for temperate districts. The difference is significant at 0.3%, with the higher p-value a result of the smaller sample size (824) of temperate districts in this restricted sample.

Finally, columns (5) and (6) exclude districts below the 25th percentile of rural density in the whole sample. The estimated values of β_g are based on variation in rural densities within provinces, and the worry is that districts with very low densities may represent a different type of agricultural technology (i.e. pastoralism) than crop-based agriculture. Provinces in the tropical region could include both pastoral districts and crop-growing districts, and this would lead us to estimate a very low value of β_g, even though it may not represent the technology used in either kind of district. By eliminating low-density districts, we are making it more difficult to find low β_g estimates. However, as we see in columns (5) and (6) the pattern of lower land elasticities in tropical districts holds up. Both the temperate and tropical estimates are larger (0.281 and 0.185, respectively), but the difference remains similar to prior results, and significant at 1.5%.

3.3 Robustness checks

Rural density data: Panel A of Table 4 shows results using different sources for the rural population data, L_{Ai}. First, there may be a concern that by using rural population data from 2000 to perform the estimation, we are relying on an era where agricultural employment is very small in many countries, and where rapid technological progress in that sector has changed the nature of the production function. In particular, one may worry that the high elasticities estimated for temperate areas (which tend to be more developed) do not represent the same constraints that would have held prior to the heavy mechanization of agriculture in the 20th century.

[15] Advanced economies with modern farming like Japan and South Korea are already excluded from our regressions by how we defined tropical and temperate areas, given that they are capable of growing both kinds of crops.

In columns (1) and (2) of Panel A we re-estimate the values of β_g for temperate and tropical regions using population data from Goldewijk et al. (2011) for 1950, when most developing countries were still engaged in traditional agriculture, and most developed countries were still in the process of mechanization. As can be seen, the results (0.240 for temperate areas and 0.133 for tropical) are similar to our baseline results. In the Appendix, we also show further results using the HYDE 1950 rural population data, including estimates where we exclude the nations of Western Europe and North America, similar to what we did in Table 3. The results are consistent, and again are not dependent on comparing developed to developing nations. Also in the Appendix are results using the HYDE data from 1900, and again the results are consistent.[16]

A broader issue is that the HYDE data on rural population may be mis-measured or incorrect in some way. To address this, we use a different source of gridded population data from (Center for International Earth Science Information Network (CIESIN), Columbia University et al., 2011), the Global Rural-Urban Mapping Project (GRUMP). GRUMP has a finer resolution than the HYDE data, and maps urban extents to divide population into urban versus rural (rather than relying on census reporting). In columns (3) and (4) of Panel A we use this GRUMP data to measure rural density, and the results are again consistent (0.207 for temperate and 0.115 for tropical) with our baseline, although the absolute size of both estimates is slightly lower than what we find using the HYDE data. Nevertheless, the distinct, and statistically significant, gap between the temperate and tropical elasticities remains.

In the last columns of Panel A, we turn to the International Public-Use Microdata Series (IPUMS) database to extract individual level data for 39 countries that have geographic identifiers at the sub-national level. Using this, we can accomplish two things. We can extract direct information on the number of people living within a given geographic area, as opposed to relying on HYDE. Because of the limited country coverage of IPUMS, and because the "districts" IPUMS uses are larger than our baseline, we end up with only 3,520 observations.[17] Nevertheless, in columns (5) and (6) the results are consistent with our baseline. The temperate elasticity is estimated to be 0.213, while the tropical elasticity is only 0.032.

A second advantage of using IPUMS is that it has information on occupation and/or industry. This allows us to distinguish agricultural workers from rural residents. Hence the meaures of L_{Ai} in columns (5) and (6) is based on those who report agriculture as their industry of employment. An additional reassurance for our baseline results is that the IPUMS data show that the correlation of rural residents with the number of agricultural workers is 0.91, and significant at less than 1%. Thus our baseline HYDE data on rural residents is likely not making significant errors in measuring

[16]Our concerns about the construction of the HYDE data prevent us from going backwards in time even farther, as the distribution of rural labor in that dataset is extrapolated from the more recent data.

[17]Because district-level boundaries can change over time, IPUMS aggregates to the largest possible units that are stable over time, which means fewer districts. This also means that there are far fewer districts within any given province (and in some cases even provinces are aggregated), and so we use country-level fixed effects with the IPUMS regressions, rather than province-level.

agricultural worker density.

Land area: As noted above, our baseline results measure land, X_i, in a district as the total area, as this represents the stock of *possible* agricultural land. Choosing not to cultivate land is indicated by having no labor (or other inputs) used on that land, leading to a low rural density. As such, that density is still informative about the value of β.

However, we can restrict ourselves to looking at the density of agricultural workers on actual cultivated land. We use GAEZ to build a measure of the area of cultivated land in a given district as X_i^C. Our baseline rural density can thus be written as $\ln L_{Ai}/X_i = \ln L_{Ai}/X_i^C + \ln X_i^C/X_i$. The first term on the right is the (log) density of agricultural workers per cultivated land, while the second term is the (log) share of cultivated land in total land area. We can include both of the right-hand side terms as controls in our regressions, and recover the estimate of β_g from the coefficient on $\ln L_{Ai}/X_i^C$, density per unit of cultivated land.

In Panel B of Table 4, columns (1) and (2), we present results using cultivated land to measure rural density. Again, the results are consistent with our baseline (0.219 for temperate areas and 0.135 for tropical). In the Appendix, one can find further results using cultivated land as the measure of rural density for different samples.

Comparable provinces: All districts have a common *political* definition, as 2nd level administrative units, but this does not mean that districts are comparable in size or that provinces necessarily have comparable numbers of districts within them. A concern could be that tropical areas have provinces with few, but large, districts within them. A concentration of rural population in one of those large districts may be driving our low estimated β_g value, just because it is large. To allay that concern, in columns (3) and (4) of Panel B in Table 4 we drop any district that is above the 90th percentile of total district size across the whole sample. The results are similar to our baseline (0.231 for temperate and 0.149 for tropical). In the Appendix we also show results consistent with our baseline if we drop any province that has fewer than 10 districts within it.

Livestock and cash crop production: Our baseline estimates are made using a measure of productivity, A_{isg}^{GAEZ}, that is built up from information on the yields of specific staple crops. In addition, we are assuming that the value of α, dictating the elasticity of output with respect to capital, is the same throughout a province. There are two concerns regarding these assumptions. First, there is more to agriculture than staple crops, and districts may rely on livestock or cash crops (cotton, coffee, etc.) that our productivity measure does not capture. Second, the value of α may be different for livestock or cash crop producing districts, and hence our assumption that allowed us to sweep measures of capital (and other inputs) into the province fixed effect would no longer hold. To be clear, the problem here is if districts *within* a province vary in their reliance on livestock, cash crops, and staples. Variation in that reliance *across* provinces is not a problem, as the province fixed effect will absorb those differences.

We do not have matching data on numbers of livestock by district, so we cannot directly eliminate pastoral districts. However, we can take an indirect approach to this problem. In Panel B of Table 4, columns (5) and (6) omit all districts whose total production of staple crops (in tonnes) falls below the 25th percentile of production across all districts. This eliminates any district that produces zero staple crops, by definition, and districts that have only small amounts of staple crops. These districts may be pastoral, may rely heavily on *cash* crops, or may simply be uncultivated. Regardless, this restriction allows us to focus on districts that have meaningful staple crop production. The estimated elasticity for temperate areas is 0.220, and for tropical areas 0.131, again consistent with our baseline results.

Productivity data: Another possible concern with the existing results is that they are reliant on the specific caloric suitability index A_{isg}^{GAEZ} that we derived. In particular, we used the underlying data from the GAEZ for "low-input, rain-fed" agriculture to construct this index, matching Galor and Özak (2016). This could over-state the variation in "true" productivity (A_{isg} in our prior notation) across districts within provinces, because it ignores the possibility that inherently low-productivity districts can adopt the use of fertilizer and/or irrigation to bring their productivity up to match other districts in their province. If A_{isg}^{GAEZ} over-states the variation in productivity across districts, then we may be over-stating the size of β_g. If, for some reason, this problem is pronounced in temperate areas, this could explain our finding that temperate areas have high β_g values. Alternatively, A_{isg}^{GAEZ} may understate variation in A_{isg} if irrigation or modern inputs allow some districts to increase their total factor productivity relative to others. If this is true in tropical regions, we would be under-estimating β_g for tropical areas.

To address these concerns, in Table 5, Panel A, we show results where we reconstruct the index A_{isg}^{GAEZ} using different underlying data on productivity from the GAEZ. In columns (1) and (2), for example, we use their "medium-input, irrigated" estimates of productivity to derive A_{isg}^{GAEZ}, and then re-run our regressions. As can be seen, the gap between temperate and tropical β_g estimates narrows slightly (0.195 for temperate and 0.125 for tropical) compared to our baseline estimate. But the gap remains about 0.07, and is significant at conventional levels.

In columns (3) and (4) of the same panel, we do a similar exercise, but now use the "high-input, rain-fed" productivity data from GAEZ to construct A_{isg}^{GAEZ}. Here the results are nearly identical to our baseline (0.225 for temperate and 0.137 for tropical). Columns (5) and (6) use the "high-input, irrigated" productivity data to construct A_{isg}^{GAEZ}, and the results are similar to when we use the irrigated productivity measures from the first two columns. The estimated effects (0.192 for temperate and 0.124 for tropical) are again a little closer than in our baseline, but remain significantly different.

While everything we estimate is within-province, so that cross-country differences are not used directly, a further worry may be that within the provinces of rich countries, there is more scope for inputs and irrigation to reduce the gap in actual productivity between districts, and that we are doing a particularly bad job of capturing true productivity differences by using A_{isg}^{GAEZ}. Given that rich countries tend to be predominantly composed of temperate areas, we are perhaps over-estimating β_g in temperate zones. To address this, in Panel B we exclude North American and European countries from the sample, and re-estimate β_g under the different assumptions regarding inputs and water use. As can be seen, regardless of the choice of inputs and water use, the gap in β_g between temperate and tropical regions remains, and is in fact larger than estimated using the full sample in Panel A.

A final issue with the construction of A_{isg}^{GAEZ}, regardless of the choice of inputs and water use, is that it relies on the calorie content of different crops to make them comparable to one another. It could either be that the calorie counts used by Galor and Özak (2016), that we adopt, are incorrect. Or calories are an imperfect way of comparing crops, and we should be using something like relative prices. We address this by using the individual crop-level measures of raw productivity (in tonnes) from GAEZ as our measure of A_{isg}^{GAEZ}. For temperate regions, for example, we run separate regressions using the raw potential barley yield as our measure of A_{isg}^{GAEZ}, and then do so for buckwheat, then oats, etc. We do similar regressions for tropical areas with raw yields of the tropical crops. The full results are available in the Appendix.

In all cases, the estimated size of β_g using the individual crop raw potential yields give us nearly identical results to what we find in our baseline using the caloric suitability index. The consistency of the results using separate raw potential yields shows that the weighting crop yield by calorie counts to aggregate them together are not important to our results. Further, this consistency across crops also implies that *any* weighting scheme to compare the value of crops (e.g. prices) would also yield similar results for β_g as our baseline.

3.4 Production function specification

If the elasticity of substitution between land and labor is not one, then the level of rural density, L_{Ai}/X_i, would influence the estimated elasticity β_g. If the elasticity of substitution were *more* than one, then it would be the case that more densely populated areas would have lower estimated elasticities.[18] We do not feel this is driving our results on heterogeneity in β_g. We obtain similar results for β_g in tropical areas of southeast Asia, with high density, and in certain tropical areas of Africa with a very low density. If the elasticity of substitution were higher than one, then the tropical area of Africa should have a much higher estimated elasticity. A common production function with a high degree of substitution between land and labor does not appear to be consistent

[18]Work by Wilde (2012) indicates that the elasticity of substitution is *less* than one, using historical information from the United Kingdom.

with our results.

An alternative concern would be if the elasticity of substitution between capital and labor were not one, indicating that provinces with different capital/labor ratios may have a different elasticity with respect to capital or labor. For our purposes of estimating β_g, this should not pose a problem. With an elasticity of substitution not equal to one between capital and labor, this implies that the elasticity of output with respect to either of those inputs depends on the capital/labor ratio. Within our empirical setting, this is equivalent to assuming that α depends on the size of K/L in a province. The value of α, however, is contained within the province fixed effect in our estimations, so even if it *does* vary with capital/labor ratios, this introduces no bias into our estimation of β_g.

3.5 Comparison to Factor Shares

An possible point of comparison for our estimates of β_g is the factor share of land in agricultural output. With competitive markets for *all* inputs to agriculture, the factor share of land should be equal to the elasticity β_g. There is variation in these factor shares across countries, but they are not always consistent with our estimates. Fuglie (2010) reports factor share estimates for a set of countries, finding shares between 0.17 and 0.30 for land and structures. The inclusion of structures muddies the comparison with our estimate of β_g. Nevertheless, he reports land shares between 0.22 and 0.25 for India, Brazil, and Indonesia. There is substantial heterogeneity within each of these countries (save Indonesia) in climate and crop type, but our estimates would suggest values of β_g between 0.10 and 0.15, based on the prevalence of tropical agriculture. The factor share of land and structures for China is 0.22, which is difficult to compare to our results given the heterogeneity in climate zones within China.

Reported factor shares for land and structures in the US (0.19) and former Soviet Union (0.21 - 0.26) are in line with our β_g estimates for areas using temperate agriculture, although both of those countries also contain heterogeneity in climate zones. A study by Jorgenson and Gollop (1992) reported a land share of 0.21 for the U.S., close to our estimates for β_g areas. Fuglie reports a factor share of 0.17 for land and structures in the UK, lower than the value we get for temperate zones. However, Clark (2002) reports long-run factor shares of land for England, and that share is between 0.30-0.36 for several centuries, somewhat higher than our estimated β_g for temperate areas. Hayami, Ruttan and Southworth (1979) provide longer-run estimates of land shares for several east Asian economies, finding estimates between 0.3 and 0.5 for Taiwan, Japan, Korea, and the Philippines from the late 1800's until the middle of the 20th century. These numbers cannot be directly compared to our β_g estimates, as much of Japan and Korea, and all of Taiwan, are excluded from our analysis because they are suitable for *both* temperate and tropical crops, as we've defined them.

Comparing to land shares thus provides mixed results. Nevertheless, we think there is information our estimates. Our estimates are built using the assumption that non-land factors of production have returns that are equalized across districts within a province, but our technique is robust to the presence of distortions and frictions in the province-wide market for these factors (i.e. we do not require the share of output paid to a factor, ϕ_L for example, to be equal to the its elasticity). In contrast, for factor shares to be good estimates of the elasticities, it would have to be that returns are equalized across districts *and* there are no distortions or frictions in the province-wide factor markets, so that factor shares are in fact identical to elasticities. There is not an obvious reason to think that those assumptions about perfect factor markets conditions hold. It is not clear that the factor share data cited should be privileged in terms of its relevance for the question at hand.

4 Implications of variation in land elasticities

Having established that the aggregate elasticity of agricultural output with respect to land varies across climate types, we now want to show the relevance of this variation for development. We first extend the model from Section 2 and show that the elasticity β influences how sensitive real income and the share of labor in agriculture are to population and technological change. That extension shows that as β gets *higher*, the economy gets *more* sensitive to population and technological change. Second, we show using evidence from the epidemiological transition after World War II that this prediction holds. Developing countries that have high β values display larger drops in GDP per capita and GDP per worker following the population increase due to the decline in mortality.

4.1 The Agricultural Labor Share and Income per capita

In Section 2 we derived our estimation equation for β, and this was done using an aggregate agricultural production function, but without reference to any specific preferences or the nature of production in the non-agricultural sector. Here we add assumptions regarding preferences and non-agricultural production so that we can solve for the agricultural labor share and real income per capita in a province as a whole. In the interest of space, we have relegated much of the algebra to the Appendix, and outline the key assumptions and results here.

The agricultural sector operates as described in Section 2. Summing agricultural production over all districts in a province, we can write aggregate agricultural output for the province as

$$Y_A = A_A \left(\frac{K_A}{L_A}\right)^{\alpha(1-\beta)} L_A^{1-\beta}, \tag{11}$$

where

$$A_A = \left(\sum_{j \in I} A_j^{1/\beta} X_j\right)^{\beta}$$

is the measure of aggregate agricultural total factor productivity for province, consisting of districts denoted by j. K_A is the aggregate stock of capital in the agricultural sector in the province.

For non-agriculture, we write an aggregate production function for the province as

$$Y_N = A_N \left(\frac{K_N}{L_N}\right)^{\alpha} L_N. \tag{12}$$

We do not specify which specific district(s) the non-agricultural sector operates in, as our concern is not with the location of this activity. That said, if all districts had the same Cobb-Douglas form of the production function, and non-agricultural labor and capital are free to move across districts, then all non-agricultural activity would take place in the one district with the highest non-agricultural TFP. If we instead allowed for a fixed factor such as land in non-agricultural production then we'd get a distribution of non-agriculture across districts similar to agriculture. In either case, we could write an aggregate non-agricultural production function as in equation (12).

In both sectors, total supply must equal total demand, so $Y_A = c_A L$ and $Y_N = c_N L$, where c_A and c_N are per-capita consumption of agricultural and non-agricultural goods, respectively. For preferences over those consumption goods, we follow Boppart (2014), who specifies a functional form for the indirect utility function that allows for analysis of structural change involving income effects.[19] This function results in non-linear Engel curves while still allowing for aggregation across individuals, and results in a simple demand function for agricultural goods (c_A), in log form, of

$$\ln c_A = \ln \theta_A + (1-\epsilon)\ln M + (\gamma - 1)\ln p_A + (\epsilon - \gamma)\ln p_N \tag{13}$$

where θ_A is a preference parameter, M is nominal income, and p_A and p_N are the nominal prices of agricultural and non-agricultural goods, respectively. With $0 < \epsilon < 1$, these preferences imply that the income elasticity of agricultural demand is less than one, capturing Engel's Law. Further, assuming $\epsilon > \gamma$ means agricultural and non-agricultural goods are substitutes.[20]

To go further, the most important assumptions we make are that the share of non-agricultural output paid to labor is equal to the share in agriculture, ϕ_L, and also that capital is paid ϕ_K of output in both sectors. With $\phi_L + \phi_K = 1$, this implies that agricultural land earns no return, equivalent to assuming zero property rights. This simplifies the analysis, and ensures that the solutions are not driven by any connection of β to the share paid to land.

The combination of these assumptions ensures that the capital/labor ratio in both sectors is equal to the aggregate capital labor ratio, K/L. Mobility between sectors ensures that the payments

[19] The functional form is in the price independent generalized linearity (PIGL) preference family. It has a number of attractive properties that Boppart exploits, but which are not relevant for our analysis.

[20] The specific indirect utility function for our model would be $V(p_A, p_N, M) = 1/\epsilon\,(M/p_N)^{\epsilon} - \theta_A/\gamma\,(p_A/p_N)^{\gamma} - 1/\epsilon + \theta_A/\gamma$. The relative size of ϵ and γ is the opposite of what Boppart uses to describe the shift from manufacturing to services, where an increasing expenditure share on services is accompanied by *higher* prices in that sector, indicating complements. Here, the expenditure share of non-agriculture rises while also having *lower* prices.

to labor are equalized,

$$p_A \phi_L \frac{Y_A}{L_A} = p_N \phi_L \frac{Y_N}{L_N}. \tag{14}$$

Combining the production functions in (11) and (12), the demand function in (13), and the mobility condition in (14) we can solve for the share of labor employed in agriculture and a measure of real income in terms of agricultural goods (M/p_A). The labor share is

$$\frac{L_A}{L} = \theta_A \left(\frac{L^{\beta\gamma}}{A_A^{\gamma} A_N^{\epsilon-\gamma} \hat{k}^{\alpha(\epsilon-\beta\gamma)}} \right)^{\frac{1}{1-\beta\gamma}} \tag{15}$$

while the real income is

$$y = \left(\frac{A_A A_N^{\beta(\epsilon-\gamma)} \hat{k}^{\Omega}}{L^{\beta}} \right)^{\frac{1}{1-\beta\gamma}} \tag{16}$$

where $\hat{k} = (\phi_K K/\phi_L L)$, and $\Omega = \alpha(1-\beta) + \alpha\beta(\epsilon - \gamma)$. From these expressions it is straightforward to read off the elasticities of both L_A/L and y to shocks to technology or population, but for clarity we summarize those results in the following proposition.

Proposition 1 *The elasticities of the agricultural labor share (L_A/L) and real income (y) with respect to various shocks,*

(a) Agricultural productivity (A_A): $\frac{\partial \ln L_A/L}{\partial \ln A_A} = -\frac{\gamma}{1-\beta\gamma}$ *and* $\frac{\partial \ln y}{\partial \ln A_A} = \frac{1}{1-\beta\gamma}$

(b) Non-agricultural productivity (A_N): $\frac{\partial \ln L_A/L}{\partial \ln A_N} = -\frac{\epsilon-\gamma}{1-\beta\gamma}$ *and* $\frac{\partial \ln y}{\partial \ln A_N} = \frac{\beta(\epsilon-\gamma)}{1-\beta\gamma}$

(c) Population (L): $\frac{\partial \ln L_A/L}{\partial \ln L} = \frac{\beta\gamma}{1-\beta\gamma}$ *and* $\frac{\partial \ln y}{\partial \ln L} = -\frac{\beta}{1-\beta\gamma}$

are all increasing in absolute value with β.

Proof. This follows from inspection of (15) and (16). ■

The elasticities shown in the proposition are all consistent with standard models of structural change (Kogel and Prskawetz, 2001; Gollin, Parente and Rogerson, 2007; Restuccia, Yang and Zhu, 2008; Gollin, 2010; Vollrath, 2011; Alvarez-Cuadrado and Poschke, 2011; Herrendorf, Rogerson and Valentinyi, 2014; Duarte and Restuccia, 2010) in their *qualitative* predictions. The only difference in our model from these is that using the non-Gorman preference structure allows us to find simple analytical solutions as compared to using Stone-Geary preferences. What Proposition 1 shows is that the *quantitative* size of the elasticities depends on the size of the aggregate land elasticity, β.

This arises because as agricultural output gets more sensitive to land (β gets larger), it becomes *less* sensitive to labor and capital. This means it takes a larger shift of labor and capital into or out of agriculture to have a given effect on agricultural output. In response to a shock to productivity or population, in economies with larger β values it thus takes larger shifts of labor and capital into or out of agriculture to bring agricultural supply and demand into equilibrium.

Economies with a large β will experience larger increases in living standards and a larger drop in the agricultural labor share for any given percent increase in productivity (in either sector). They will also experience larger gains from any *drop* in population. Thus an economy with a large β is capable of developing faster than an economy with a low β, even if they experience similar shocks to technology and population. At the same time, a high value of β is not universally positive. If productivity declines, or population increases, then an economy with a high β will experience a larger *drop* in income per capita and a larger *increase* in the share of labor in agriculture, compared to an economy with a low β. A high β makes an economy more sensitive to shocks, which may be a positive or negative for development depending on the nature of the shocks it experiences.[21]

4.2 Evidence from the Epidemiological Transition

The epidemiological transition that occurred following World War II provides a useful context in which to test the effects of variation in β. Acemoglu and Johnson (2007) collect mortality rate data from the post-war period for a set of 15 infectious diseases (e.g. tuberculosis and malaria). They argue that the epidemiological transition formed an exogenous shock to population health, and therefore population size, in developing countries, and use it to identify the causal impact of health on living standards. We can use the same empirical setting to ask whether the impact of these plausibly exogenous health interventions *differed* based on whether countries had a high β value or a low β value. Based on our simple model, we would expect that living standards in places with the high βshould be more sensitive to these mortality shocks than places with low β values.

To implement this, we first estimate a separate β for each country. We use all districts within a country, and then estimate equation (9), including the province-level fixed effects. Given heterogeneity of climate types within countries, this is not ideal, as it assumes that all districts of the country have an identical value of β. However, the data from the Acemoglu and Johnson paper is at the country level, so in order to have a single observation for each country, we make the assumption that β is homogeneous within each.

We restrict ourselves to the low and middle income sample from Acemoglu and Johnson, which gives us 32 countries. We make this restriction because rich countries, regardless of their value of β, are not going to be affected by the decreasing returns in the agricultural sector to any meaningful degree given their low agricultural labor share to begin with. For the 32 low and middle income countries, we then split them into two groups based on whether their β is below the median of the 32 countries (low elasticity) or above the median (high elasticity).[22]

[21] This is completely static analysis, but these effects could have dynamic effects if one included endogenous demographic or savings effects. In the appendix we show a simple example of how this could affect the dynamics of population in a simple Malthusian model, and Vollrath (2011) offers a more thorough treatment.

[22] We can expand the data to include up to 45 countries in some regressions where we have sufficient mortality and

For each group, we use the original data from Acemoglu and Johnson to run panel regressions with the specification of

$$y_{it} = \alpha + \theta x_{it} + \gamma_i + \delta_t + \epsilon_{it} \tag{17}$$

where y_{it} is one of three different dependent variables (log GDP per capita, log GDP per worker, or log population), and x_{it} is one of three different independent variables (mortality rates, log life expectancy, or log population). θ captures the effect of the independent variable on y_{it}, and we will compare the value of θ across samples that differ based on whether they have loose land constraints or tight land constraints. γ_i and γ_t are country and decade fixed effects, while ϵ_{it} is the error term. Each country has up to eight decadal observations, running from 1930 to 2000, but the panel is not balanced.[23]

Table 6 presents the results. In Panel A, the explanatory x_{it} variable is the original mortality instrument from Acemoglu and Johnson, which measures the mortality rate from the 15 infectious diseases that were affected by the interventions following World War II. In columns (1) and (2), we show the effect of mortality rates on (log) GDP per capita. As can be see, the estimated coefficient for low-β countries (0.333) in column (1) is smaller than the estimate for high-β countries (0.723) in column (2). Below these estimates are two hypothesis tests. First, the test that the effect size is zero, $\theta = 0$. We cannot reject zero for low-β countries (p-value of 22.0%), but reject zero for high-β countries. The hypothesis that θ is identical for the two samples has a p-value of 19.9%, given the large standard error for the low-β sample, and we cannot reject equality at standard levels. Nevertheless, the pattern of results is consistent with our predictions.

Columns (3) and (4) of the same panel repeat this test, but now using (log) GDP per worker as the dependent variable. The effect of mortality is estimated to be almost three times larger when β is high than when it is small (0.776 vs. 0.284). This difference is significant at 10.2%, and shows that high-β countries are more sensitive to population shocks than low-β countries. These columns show that mortality shocks affected the average output of each *worker*, and the effect on per capita GDP did not arise because of short-run changes in the age structure of the economy.

The final columns, (5) and (6), show the effect of the mortality shocks on population size. In low-β countries, the effect of mortality on population was estimated to be smaller than in high-β countries (-0.361 versus -0.597), although we cannot reject that these effect sizes are the same (a p-value of 32.7%). Thus it may be that the high-β countries were hit by a larger shock to their population due to the epidemiological transition, perhaps acting as part of the explanation for their stronger response to the mortality changes, although the differences across samples are not

GDP data. To create comparable samples across all of our regressions, we limit ourselves to the 32 countries with full data. Our results are not affected in a material way by including all possible countries in each regression we run.

[23]Rather than separating countries into two groups based on β and comparing θ between them, an alternative specification would be to interact β_i with x_{it}, as in $y_{it} = \alpha + \theta_0 x_{it} + \theta_1 \beta_i \times x_{it} + \gamma_i + \delta_t + \epsilon_{it}$. In this case, the estimated value of θ_1 would indicate how the effect of x_{it} differs with the size of β. Doing this produces results consistent with those presented in Table 6.

statistically significant.

Panel B of Table 6 repeats the regressions, but now uses life expectancy itself as the explanatory variable x_{it}, matching Acemoglu and Johnson's original work. Whether looking at GDP per capita (columns 1 and 2) or GDP per worker (columns 3 and 4), we have large and statistically significant differences in the estimated effects of life expectancy in low and high-β samples. For low-β countries, the implied effect of rising life expectancy is close to zero (or positive) for both GDP per capita and GDP per worker.[24] In contrast, for high-β countries the estimated effect of life expectancy is negative and statistically significant for both GDP per capita and per worker. We can reject, at less than 0.1%, that the estimated effects in the two sets of countries are similar.

In contrast, in columns (5) and (6), the effect of life expectancy on population size is positive in both sets of countries, with a smaller estimated effect size in low-β countries, although the difference is significant at only 12.8%. Both low and high-β countries experienced significant population shocks from the rise in life expectancy, but this had more severe negative effects in high-β countries on living standards, consistent with the predictions in the prior section.

Finally, Panel C looks at the relationship of living standards and the size of population. This test is speculative, as population size is influenced by far more than the mortality shocks occassioned by the epidemiological transition. The pattern of are consistent, though, in that the correlation of population size and living standards (whether measured as GDP per capita or GDP per worker) is larger when β is high then when β is low. The scale of the difference is similar to the mortality results, with the coefficient size for high-β countries about twice that found for low-β countries. The statistical test for equality of the two coefficients has a p-value less than 1.0% in both cases.

The evidence in Table 6 shows that the variation in β we identified in the main part of the paper has effects consistent with those predicted by the model in this section. Given the differentials we estimated in the effect of the epidemiological transition, the variation in β appears to have non-trivial implications for development.

5 Conclusion

The role that land plays in agricultural production is relevant to any study of the role of agriculture in development. We have estimated the elasticity of aggregate agricultural production with respect to land, and found that it differs significantly between temperate and tropical regions of the world.

Our estimates are made by looking at the relationship between agricultural worker density and potential agro-climatic yield at the district level (e.g. 2nd level administrative units) from 154 countries. Our methodology lets us use the district variation within provinces to identify the land elasticity, and avoids the need to specify or measure other inputs directly, and avoids comparing

[24] Whether changes in health, as proxied by life expectancy, are in fact positive or negative in the long run for development is beyond the scope of this paper, and the original findings of Acemoglu and Johnson are debated (Bloom, Canning and Fink, 2014).

countries - or even provinces - at different levels of development. Our baseline finding, that the land elasticity in temperate areas is about 0.23 while it is only 0.13 in tropical areas, is robust to different ways of measuring rural density and potential yield, and robust to alternative definitions of what constitutes tropical versus temperate areas. What our estimation technique does not provide is a way of identifying *why* the aggregate elasticities vary so much between tropical and temperate areas, and whether that is due to biological requirements of certain crops, or the constraints imposed by aspects of the climate itself. However, our estimation technique, by looking only within provinces, does eliminate the explanation that this simply reflects differences in development levels.

These estimates are for the aggregate land elasticity, and as such are informative for research that studies the role of the aggregate agricultural sector in development, whether that is related to structural change in developing countries today, or related to historical development in standard Malthusian settings. We showed that this aggregate land elasticity, regardless of the setting, is a central parameter in determining the elasticity of income per capita and the share of labor in agriculture with respect to shocks in population growth or productivity. In short, the larger the land elasticity, the more sensitive an economy is to those shocks. We confirmed this prediction by showing that in response to the epidemiological transition following World War II, countries with larger land elasticities did see more severe changes in their GDP per worker and GDP per capita.

More generally, our contribute to the understanding of relative development levels in tropical and temperate areas of the world. By making temperate areas more sensitive to shocks, a high aggregate land elasticity allowed them to leverage positive shocks to productivity (e.g. technological improvements) and population growth (e.g. the demographic transition) to accelerate their growth relative to tropical areas. Slower development in tropical regions - either historically or in the current era - may reflect in part differences in the size of the aggregate land elasticity, rather than any deficiency in productivity or population growth.

References

Acemoglu, Daron, and Simon Johnson. 2007. "Disease and Development: The Effect of Life Expectancy on Economic Growth." *Journal of Political Economy*, 115(6): 925–985.

Acemoglu, Daron, Simon Johnson, and James A. Robinson. 2005. "Institutions and Fundamental Cause of Long-run Growth." In *Handbook of Economic Growth.* Vol. 1, , ed. Philippe Aghion and Steven Durlauf, 385–472. North-Holland.

Alesina, Alberto, Paola Giuliano, and Nathan Nunn. 2013. "On the Origins of Gender Roles: Women and the Plough." *The Quarterly Journal of Economics*, 128(2): 469–530.

Alsan, Marcella. 2015. "The Effect of the TseTse Fly on African Development." *American Economic Review*, 105(1): 382–410.

Alvarez-Cuadrado, Francisco, and Markus Poschke. 2011. "Structural Change Out of Agriculture: Labor Push versus Labor Pull." *American Economic Journal: Macroeconomics*, 3: 127–158.

Andersen, Thomas Barnebeck, Carl-Johan Dalgaard, and Pablo Selaya. 2016. "Climate and the Emergence of Global Income Differences." *Review of Economic Studies*, 83(4): 1334–1363.

Ashraf, Quamrul, and Oded Galor. 2011. "Dynamics and stagnation in the malthusian epoch." *American Economic Review*, 101(5): 2003–41.

Ashraf, Quamrul, and Stelios Michalopoulos. 2015. "Climatic Fluctuations and the Diffusion of Agriculture." *The Review of Economics and Statistics*, 97(3): 589–609.

Bloom, David E., David Canning, and Günther Fink. 2014. "Disease and Development Revisited." *Journal of Political Economy*, 122(6): 1355–1366.

Boppart, Timo. 2014. "Structural Change and the Kaldor Facts in a Growth Model With Relative Price Effects and Non Gorman Preferences." *Econometrica*, 82: 2167–2196.

Bray, Francesca. 1994. *The Rice Economies, Technology and Development in Asian Societies.* Berkeley, CA:University of California Press.

Center for International Earth Science Information Network (CIESIN), Columbia University, International Food Policy Research Institute (IFPRI), The World Bank, and Centro Internacional de Agricultura Tropical (CIAT). 2011. "Global Rural-Urban Mapping Project, Version 1 (GRUMPv1): Population Count Grid."

Cervellati, Matteo, and Uwe Sunde. 2005. "Human Capital Formation, Life Expectancy, and the Process of Development." *American Economic Review*, 95(5): 1653–1672.

Cervellati, Matteo, and Uwe Sunde. 2015. "The Economic and Demographic Transition, Mortality, and Comparative Development." *American Economic Journal: Macroeconomics*, 7(3): 189–225.

Chetty, Raj, John N. Friedman, and Emmanuel Saez. 2013. "Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings." *American Economic Review*, 103(7): 2683–2721.

Clark, Gregory. 2002. "The Agricultural Revolution and the Industrial Revolution." UC-Davis Working Paper.

Cook, C. Justin. 2014*a*. "Potatoes, milk, and the Old World population boom." *Journal of Development Economics*, 110(C): 123–138.

Cook, C. Justin. 2014*b*. "The role of lactase persistence in precolonial development." *Journal of Economic Growth*, 19(4): 369–406.

Crafts, Nicholas, and Terence C. Mills. 2009. "From Malthus to Solow: How did the Malthusian economy really evolve?" *Journal of Macroeconomics*, 31(1): 68–93.

Craig, Barbara J., Philip G. Pardey, and Johannes Roseboom. 1997. "International Productivity Patterns: Accounting for Input Quality, Infrastructure, and Research." *American Journal of Agricultural Economics*, 79(4): 1064–1076.

Dalgaard, Carl-Johan, Anne Sofie B. Knudsen, and Pablo Selaya. 2015. "The Bounty of the Sea and Long-Run Development." CESifo Group Munich CESifo Working Paper Series 5547.

Doepke, Matthias. 2004. "Accounting for fertility decline during the transition to growth." *Journal of Economic Growth*, 9(3): 347–383.

Duarte, Margarida, and Diego Restuccia. 2010. "The Role of the Structural Transformation in Aggregate Productivity." *Quarterly Journal of Economics*, 125(1): 129–173.

Eberhardt, Markus, and Dietrich Vollrath. 2018. "The Effect of Agricultural Technology on the Speed of Development." *World Development*, 109: 483–496.

Eberhardt, Markus, and Francis Teal. 2013. "No Mangos in the Tundra: Spatial Heterogeneity in Agricultural Productivity Analysis." *Oxford Bulletin of Economics and Statistics*, 75(6): 914–939.

Elvidge, Christopher D, Kimberly E Baugh, John B Dietz, Theodore Bland, Paul C Sutton, and Herbert W Kroehl. 1999. "Radiance Calibration of DMSP-OLS Low-Light Imaging Data of Human Settlements." *Remote Sensing of Environment*, 68(1): 77 – 88.

Fenske, James. 2014. "Ecology, Trade, And States In Pre-Colonial Africa." *Journal of the European Economic Association*, 12(3): 612–640.

Food and Agriculture Organization. 2012. "Global Agro-ecological Zones." United Nations. www.fao.org/nr/GAEZ.

Frankema, Ewout, and Kostadis Papaioannou. 2017. "Rainfall patterns and human settlement in tropical africa and asia compared. Did African farmers face greater insecurity?" C.E.P.R. Discussion Papers.

Fuglie, Keith. 2010. "Total factor productivity in the global agricultural economy: Evidence from FAO Data." 63–95. Ames, Iowa:Midwest Agribusiness Trade and Research Information Center.

Galor, Oded. 2011. *Unified Growth Theory.* Princeton, NJ:Princeton University Press.

Galor, Oded, and Andrew Mountford. 2008. "Trading population for productivity: theory and evidence." *Review of Economic Studies*, 75(4): 1143–1179.

Galor, Oded, and David N. Weil. 2000. "Population, technology, and growth: From Malthusian stagnation to the demographic transition and beyond." *The American Economic Review*, 90(4): 806–828.

Galor, Oded, and Omer Moav. 2002. "Natural Selection and the Origin of Economic Growth." *Quarterly Journal of Economics*, 117(4): 1133–1191.

Galor, Oded, and Ömer Özak. 2016. "The Agricultural Origins of Time Preference." *American Economic Review*, 106(10): 3064–3103.

Goldewijk, Klein Kees, Arthur Beusen, Gerard van Drecht, and Martine de Vos. 2011. "The HYDE 3.1 spatially explicit database of human-induced global land-use change over the past 12,000 years." *Global Ecology and Biogeography*, 20(1): 73–86.

Gollin, Douglas. 2010. "Agricultural Productivity and Economic Growth." In *Handbook of Agricultural Economics.* Vol. 4, , ed. Prabhu Pingali and Robert Evenson, 3825 – 3866. Elsevier.

Gollin, Douglas, Stephen Parente, and Richard Rogerson. 2007. "The Food Problem and the Evolution of International Income Levels." *Journal of Monetary Economics*, 54: 1230–1255.

Gutierrez, L., and M. M. Gutierrez. 2003. "International R&D spillovers and productivity growth in the agricultural sector. A panel cointegration approach." *European Review of Agricultural Economics*, 30(3): 281–303.

Hansen, Gary D., and Edward C. Prescott. 2002. "From Malthus to Solow." *American Economic Review*, 92(4): 1205–1217.

Hayami, Yujiro, and Vernon W. Ruttan. 1970. "Agricultural Productivity Differences among Countries." *American Economic Review*, 60(5): 895–911.

Hayami, Yujiro, and Vernon W. Ruttan. 1985. *Agricultural Development: An International Perspective.* Baltimore:Johns Hopkins University Press.

Hayami, Yujiro, Vernon W. Ruttan, and Herman M. Southworth. 1979. *Agricultural Growth in Japan, Taiwan, Korea, and the Philippines.* Honolulu, HI:East-West Center.

Henderson, J. Vernon, Tim L. Squires, Adam Storeygard, and David N. Weil. 2016. "The Global Spatial Distribution of Economic Activity: Nature, History, and the Role of Trade." National Bureau of Economic Research, Inc NBER Working Papers 22145.

Herrendorf, Berthold, Richard Rogerson, and Ákos Valentinyi. 2014. "Growth and Structural Transformation." In *Handbook of Economic Growth.* Vol. 2 of *Handbook of Economic Growth*, Chapter 6, 855–941. Elsevier.

Houthakker, H. S. 1955. "The Pareto Distribution and the Cobb-Douglas Production Function in Activity Analysis." *Review of Economic Studies*, 23(1): 27–31.

Jones, Charles I. 2005. "The Shape of the Production Function and the Direction of Technical Change." *Quarterly Journal of Economics*, 120(2): 517–549.

Jorgenson, Dale, and Frank Gollop. 1992. "Productivity Growth in U.S. Agriculture: A Postwar Perspective." *American Journal of Agricultural Economics*, 74(3): 745–50.

Kogel, Tomas, and Alexia Prskawetz. 2001. "Agricultural Productivity Growth and Escape from the Malthusian Trap." *Journal of Economic Growth*, 6(4): 337–57.

Lagerlöf, Nils-Petter. 2006. "The Galor-Weil Model Revisited: A Quantitative Exercise." *Review of Economic Dynamics*, 9(1): 116–142.

Litina, Anastasia. 2016. "Natural land productivity, cooperation and comparative development." *Journal of Economic Growth*, 21(4): 351–408.

Martin, Will, and Devashish Mitra. 2001. "Productivity Growth and Convergence in Agriculture versus Manufacturing." *Economic Development and Cultural Change*, 49(2): 403–22.

Michalopoulos, Stelios. 2012. "The Origins of Ethnolinguistic Diversity." *American Economic Review*, 102(4): 1508–39.

Minnesota Population Center. 2017. "Integrated Public Use Microdata Series (IPUMS), International: Version 6.5." Minneapolis: University of Minnesota.

Motamed, Mesbah J., Raymond J.G.M. Florax, and William A. Masters. 2014. "Agriculture, transportation and the timing of urbanization: Global analysis at the grid cell level." *Journal of Economic Growth*, 19(3): 339–368.

Mundlak, Yair. 2000. *Agriculture and Economic Growth: Theory and Measurement.* Cambridge, MA:Harvard University Press.

Mundlak, Yair, Rita Butzer, and Donald F. Larson. 2012. "Heterogeneous technology and panel data: The case of the agricultural production function." *Journal of Development Economics*, 99(1): 139–149.

Nunn, Nathan. 2009. "The Importance of History for Economic Development." *Annual Review of Economics*, 1: 65–92.

Nunn, Nathan, and Diego Puga. 2012. "Ruggedness: The Blessing of Bad Geography in Africa." *The Review of Economics and Statistics*, 94(1): pp. 20–36.

Nunn, Nathan, and Nancy Qian. 2011. "The Potato's Contribution to Population and Urbanization: Evidence from a Historical Experiment." *The Quarterly Journal of Economics*, 126(2): pp. 593–650.

Olsson, Ola, and Douglas Jr. Hibbs. 2005. "Biogeography and long-run economic development." *European Economic Review*, 49(4): 909–938.

Peretto, Pietro, and Simone Valente. 2015. "Growth on a finite planet: resources, technology and population in the long run." *Journal of Economic Growth*, 20(3): 305–331.

Restuccia, Diego, Dennis Yang, and Xiaodong Zhu. 2008. "Agriculture and Aggregate Productivity." *Journal of Monetary Economics*, 55(2): 234–250.

Ruthenberg, H. 1976. *Farming Systems in the Tropics.* Oxford, UK:Clarendon Press.

Spolaore, Enrico, and Romain Wacziarg. 2013. "How Deep Are the Roots of Economic Development?" *Journal of Economic Literature*, 51(2): 325–369.

Strulik, Holger, and Jacob L. Weisdorf. 2008. "Population, food, and knowledge: A simple unified growth theory." *Journal of Economic Growth*, 13(3): 195–216.

Voigtländer, Nico, and Hans-Joachim Voth. 2013*a*. "How the West "Invented" Fertility Restriction." *American Economic Review*, 103(6): 2227–64.

Voigtländer, Nico, and Hans-Joachim Voth. 2013*b*. "The Three Horsemen of Riches: Plague, War, and Urbanization in Early Modern Europe." *Review of Economic Studies*, 80(2): 774–811.

Vollrath, Dietrich. 2011. "The agricultural basis of comparative development." *Journal of Economic Growth*, 16: 343–370.

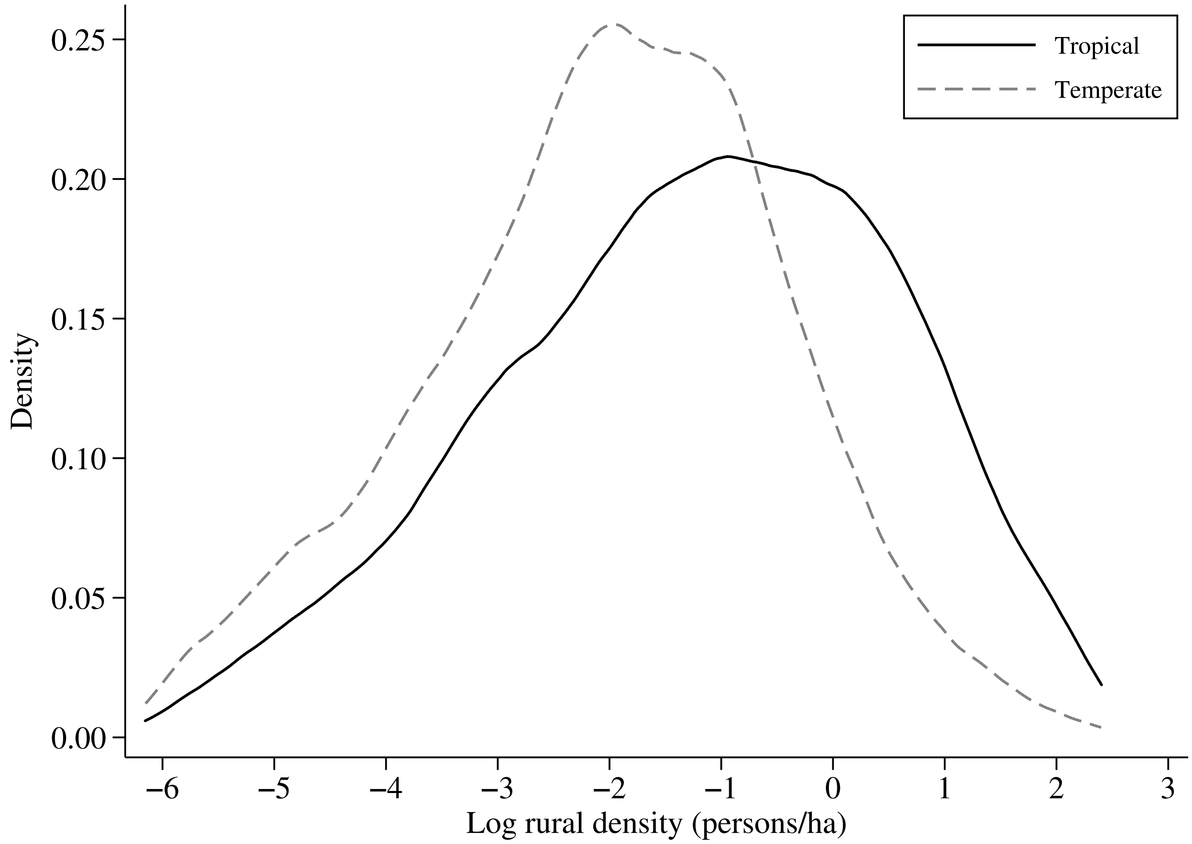
Vries, Peer. 2013. *Escaping Poverty: The Origins of Modern Economic Growth.* Vienna University Press.

Weil, David N., and Joshua Wilde. 2009. "How Relevant Is Malthus for Economic Development Today?" *American Economic Review Papers and Proceedings*, 99(2): 255–60.

Wiebe, Keith, Meredith J. Soule, Clare Narrod, and Vincent E. Breneman. 2003. "Resource Quality and Agricultural Productivity: A Multi-Country Comparison." In *Land Quality, Agricultural Productivity, and Food Security.* , ed. Keith Wiebe. Northhampton, MA:Edward Elgar Publishing.

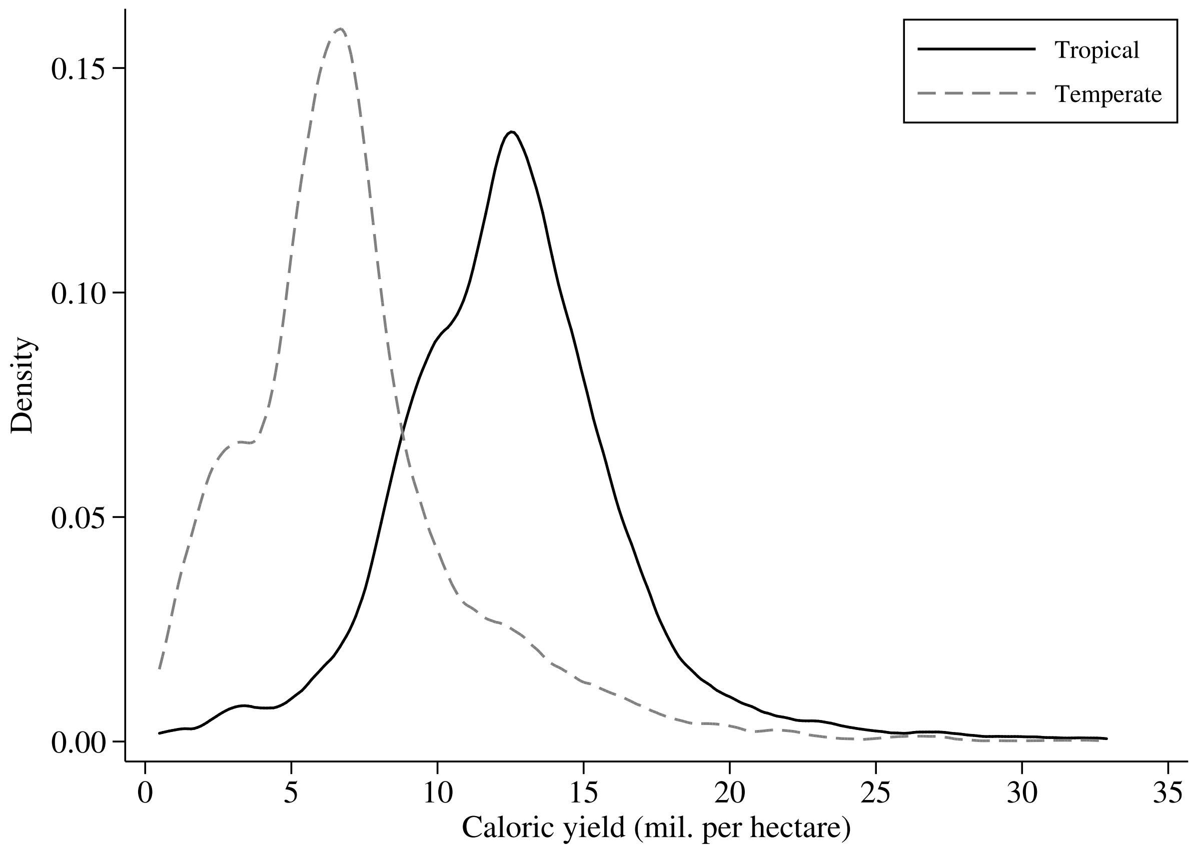
Wilde, Joshua. 2012. "How substitutable are fixed factors in production? evidence from pre-industrial England." University Library of Munich, Germany MPRA Paper 39278.

Figure 1: Density Plot of Log Rural Density (L_{Aisc}/X_{isc}), by Crop Type, 2000CE



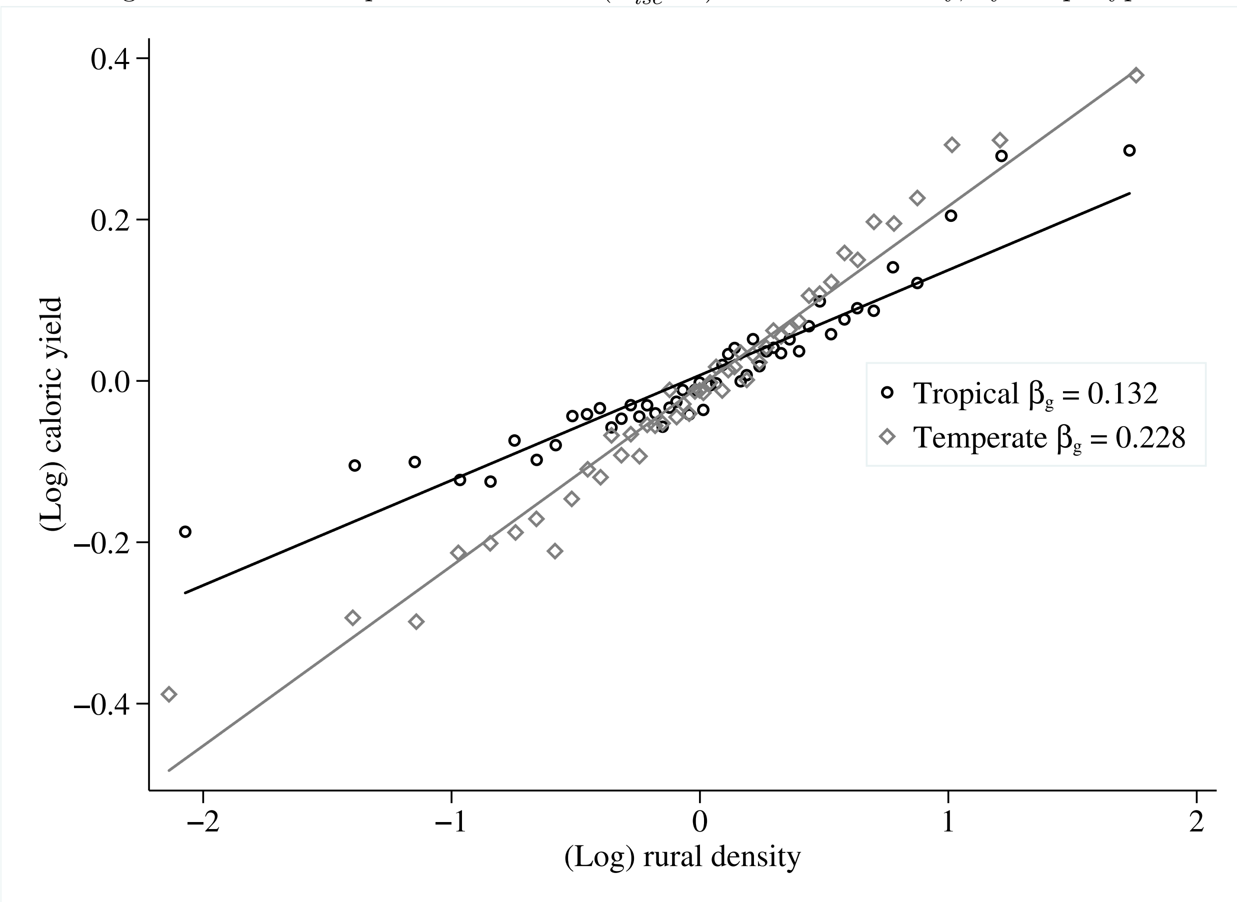
Notes: Kernel density plot, Epanechnikov kernel, of the (log) rural density, L_{Aisc}/X_{isc}, at the district level, calculated by the authors using data from Goldewijk et al. (2011) for rural population. "Temperate" includes districts that are suitable for growing barley, buckwheat, oats, rye, wheat, and white potatoes, but have zero suitability for cassava, cowpeas, pearl millet, sweet potato, wet rice, and yams. "Tropical" includes districts suitable for the latter set of crops, but zero suitability for the former.

Figure 2: Density Plot of Caloric Yield (A_{isc}^{GAEZ}), by Crop Type



Notes: Kernel density plot, Epanechnikov kernel, of the caloric yield, A_{isc}, at the district level, calculated by the authors using data from Galor and Özak (2016). See text for details. This measure sums the maximum calories available per grid cell within a district, then divides by total area of the district. "Temperate" includes districts that are suitable for growing barley, buckwheat, oats, rye, wheat, and white potatoes, but have zero suitability for cassava, cowpeas, pearl millet, sweet potato, wet rice, and yams. "Tropical" includes districts suitable for the latter set of crops, but zero suitability for the former.

Figure 3: Relationship of Caloric Yield (A_{isc}^{GAEZ}) and Rural Density, by Crop Type



Notes: Plotted are the quantile averages of both log caloric yield and log rural density for each sample. 50 quantiles are used in each sample. The quantiles are taken from the residuals of caloric yield and rural density after controlling for log light density, urban percentage in 2000, and province fixed effects. Average values of log caloric yield and log rural density are added back to all residual. Linear fits are shown, and the estimated slopes are in the legend. The `binscatter` command from Stata was used to prepare the figure. "Temperate" includes districts that are suitable for growing barley, buckwheat, oats, rye, wheat, and white potatoes, but have zero suitability for cassava, cowpeas, pearl millet, sweet potato, wet rice, and yams. "Tropical" includes districts suitable for the latter set of crops, but with zero suitability for the former.

Table 1: Summary Statistics for District Level Data, 2000CE

			Percentiles:				
	Mean	SD	10th	25th	50th	75th	90th
Rural density (persons/ha)	0.68	1.32	0.02	0.07	0.21	0.62	1.75
Caloric yield (mil cals/ha)	10.65	4.89	4.64	7.01	10.52	13.74	16.79
Urbanization rate	0.34	0.34	0.00	0.00	0.28	0.66	0.85
Log light density	-2.71	3.06	-6.42	-3.81	-2.33	-0.66	0.57

Notes: A total of 35,451 observations for each variable (these come from 2,554 provinces in 154 countries). Caloric yield, A_{isc} calculated by the authors using data from Galor and Özak (2016). Rural density, L_{Aisc}/X_{isc} calculated by the authors using data from Goldewijk et al. (2011) for rural population. Both caloric yield and rural density were trimmed at the 99th and 1st percentiles of their raw data prior to calculating the summary statistics in this table. Urbanization rate taken from Goldewijk et al. (2011). Log mean light density derived from the Global Radiance Calibrated Nightime Lights data provided by NOAA/NGDC, as in Henderson et al. (2016).

Table 2: Number of districts by Temperate/Tropical status

		Suitable for:		
	Sample	Tropical Crops	Temperate Crops	Number of Districts
1.	Excluded	No	No	10
2.	Tropical sample	Yes	No	9,088
3.	Temperate sample	No	Yes	10,661
4.	Excluded	Yes	Yes	15,692
	Total			35,451

Notes: The table shows the number of districts included in the two major sub-samples used in our analysis, the "temperate" and "tropical". These are defined by their suitability for specific crops. Tropical crops are cassava, cowpeas, pearl millet, sweet potatoes, wet rice, and yams. Temperate crops are barley, buckwheat, rye, oats, white potato, and wheat. "Excluded" groups are not used in the analysis.

Table 3: Estimates of Land Elasticity, β_g, by Agricultural Type, 2000CE

Dependent Variable in all panels: Log caloric yield (A_{isg}^{GAEZ})

Panel A: Regions defined by:

	Suitability:		Max calories:		Harvest area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.228	0.132	0.192	0.113	0.205	0.133
	(0.021)	(0.018)	(0.016)	(0.018)	(0.015)	(0.012)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta_{Temp}$		0.000		0.001		0.000
Countries	91	81	83	71	74	84
Observations	10661	9088	10768	8113	10708	7564
Adjusted R-square	0.24	0.20	0.21	0.18	0.20	0.18

Panel B: With other restrictions (using suitability to define temperate/tropical)

	Urban Pop. $< 25K$:		Ex. Europe/N. Amer.:		Rural dens. $>$ 25th P'tile:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.261	0.143	0.242	0.133	0.281	0.185
	(0.022)	(0.021)	(0.033)	(0.018)	(0.035)	(0.019)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta_{Temp}$		0.000		0.003		0.015
Countries	83	75	24	70	89	77
Observations	7648	6662	824	8826	7237	7082
Adjusted R-square	0.29	0.24	0.19	0.14	0.27	0.22

Notes: Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include province fixed effects, a constant, and controls for the district urbanization rate and log density of district nighttime lights. The coefficient estimate on rural population density indicates the value of β_g, see equation (9). Rural population is from HYDE database (Goldewijk et al., 2011), and caloric yield is the author's calculations based on the data from Galor and Özak (2016). Inclusion of districts in the regression is based on the listed criteria related to crop families. See text for details of how temperate and tropical regions are defined in each case.

Table 4: Estimates of Land Elasticity, β_g, Additional Robustness Checks

Dependent Variable in all panels: Log caloric yield (A_{isg}^{GAEZ})

Panel A: Different rural population density sources

	HYDE 1950:		GRUMP:		IPUMS:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.240	0.133	0.207	0.115	0.213	0.032
	(0.025)	(0.019)	(0.041)	(0.021)	(0.072)	(0.016)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.003	0.047
p-value $\beta = \beta_{Temp}$		0.001		0.045		0.007
Countries	91	81	86	75	23	24
Observations	10650	9082	8734	6769	1104	2416
Adjusted R-square	0.24	0.20	0.19	0.16	0.11	0.07

Panel B: Different land assumptions

	Cultivated Area:		Drop $>$ 90th Ptile district size:		Drop $<$ 25th Ptile Prod:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.219	0.135	0.231	0.149	0.220	0.131
	(0.020)	(0.020)	(0.026)	(0.017)	(0.021)	(0.020)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta_{Temp}$		0.003		0.008		0.002
Countries	90	78	88	78	82	66
Observations	10600	8979	9440	8266	8026	6537
Adjusted R-square	0.21	0.18	0.24	0.21	0.23	0.19

Notes: Temperate and tropical samples are defined by the suitability measures described in Table 3. Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include province fixed effects, a constant, and controls for the district urbanization rate and log density of district nighttime lights. The coefficient estimate on rural population density indicates the value of β_g, see equation (9). Caloric yield is the author's calculations based on the data from Galor and Özak (2016). In Panel A, the population data used to define rural density differs based on the heading in the table (see text for details). In Panel B, the first set of results use rural population (from HYDE) relative to cultivated land area (as opposed to actual land area) to measure density. The second set drops any district over the 90th percentile in aboslute size, and the third set drops districts with actual staple crop production (in tonnes) below the 25th percentile.

Table 5: Estimates of Land Elasticity, β_g, Alternative Productivity Measures

Dependent Variable in all panels: Log caloric yield (A_{isg}^{GAEZ})

Panel A: Caloric yield based on GAEZ input/water use:

	Medium/Irrigated:		High/Rain-fed:		High/Irrigated:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.195 (0.028)	0.125 (0.018)	0.225 (0.021)	0.137 (0.019)	0.192 (0.028)	0.124 (0.018)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta_{Temp}$		0.037		0.002		0.041
Countries	91	81	90	79	91	81
Observations	10661	9088	10628	9059	10661	9088
Adjusted R-square	0.19	0.17	0.22	0.18	0.19	0.17

Panel B: Excluding N.A. and Europe, caloric yield based on GAEZ input/water use:

	Medium/Irrigated:		High/Rain-fed:		High/Irrigated:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.254 (0.038)	0.126 (0.019)	0.252 (0.040)	0.138 (0.019)	0.254 (0.036)	0.125 (0.019)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta_{Temp}$		0.002		0.009		0.001
Countries	24	70	23	69	24	70
Observations	824	8826	816	8801	824	8826
Adjusted R-square	0.21	0.15	0.19	0.12	0.21	0.15

Notes: Temperate and tropical samples are defined by the suitability measures described in Table 3. Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include province fixed effects, a constant, and controls for the district urbanization rate and log density of district nighttime lights. The coefficient estimate on rural population density indicates the value of β_g, see equation (9). In Panel A, the construction of the A_{isg}^{GAEZ} caloric suitability yield differs across the columns. In (1) and (2), the yield is derived from the underlying GAEZ medium input, irrigated data, and the following columns use the high input, rain-fed data, or the high input, irrigated data, as noted. Panel B is identical, but excludes North American and European countries.

Table 6: Panel Estimates of Effect of Population Change, by Land Elasticity

	Dependent Variable:					
	Log GDP per capita		Log GDP per worker		Log population	
	β <Median (1)	β >Median (2)	β <Median (3)	β >Median (4)	β <Median (5)	β >Median (6)
	Panel A:					
Mortality rate	0.333	0.723	0.284	0.776	-0.361	-0.597
	(0.271)	(0.136)	(0.262)	(0.145)	(0.186)	(0.152)
p-value $\theta = 0$	0.220	0.000	0.281	0.000	0.054	0.000
p-value $\theta = \theta^{Below}$	.	0.199	.	0.102	.	0.327
Countries	16	16	16	16	16	16
Observations	128	128	128	128	128	128
	Panel B:					
Log life expectancy	0.067	-1.864	0.051	-1.876	1.520	2.008
	(0.419)	(0.226)	(0.399)	(0.236)	(0.228)	(0.223)
p-value $\theta = 0$	0.873	0.000	0.899	0.000	0.000	0.000
p-value $\theta = \theta^{Below}$	.	0.000	.	0.000	.	0.128
Countries	16	16	16	16	16	16
Observations	122	121	122	121	122	121
	Panel C:					
Log population	-0.380	-0.776	-0.383	-0.763		
	(0.125)	(0.067)	(0.121)	(0.062)		
p-value $\theta = 0$	0.003	0.000	0.002	0.000		
p-value $\theta = \theta^{Below}$	.	0.006	.	0.006		
Countries	16	16	16	16		
Observations	128	128	128	128		

Notes: Robust standard errors are reported in parentheses. All regressions include both year fixed effects and country fixed effects. The value of β for each country was found by estimating equation (9) separately for each, including province-level fixed effects. Countries are then included in a regression here based on how their β compares to the median from the 32 countries. The mortality rate used as an explanatory variable in Panel A is the mortality rate from 15 infectious diseases, as documented by Acemoglu and Johnson (2007). All data on GDP per capita, GDP per worker, population, and life expectancy is also taken from those author's dataset. The p-value of $\theta = \theta^{Below}$ is from a test that the estimated coefficient in a column for countries with elasticities above the median is equal to the estimated coefficient of countries below the median.