May 18, 2019

Differences in the role of land in temperate and tropical agriculture and the consequences for development

Abstract

We document that the elasticity of agricultural output with respect to land differs across temperate and tropical regions of the world. We show how to estimate this elasticity using the relationship of rural density and agro-climatic constraints. Using global district-level data we find the elasticity in temperate areas (0.24) is higher than the tropics (0.12), and this is not an artifact of the level of development. A two-sector model shows the larger the land elasticity, the more sensitive living standards are to shocks in population or technology. Evidence from the post-war mortality transition supports this prediction.

JEL Codes: O1, O13, O44, Q10

Keywords: land constraints, land elasticity, agricultural productivity, agro-climatic, temperate, tropical

1 Introduction

Agricultural production relies on the use of a finite (or inelastically supplied) resource, land. But that reliance on land need not be identical in different locations. To be specific, the elasticity of agricultural output with respect to land may differ by climate or the type of crops suitable for production. This land elasticity is relevant to any study of growth and development that includes an agricultural sector, as with the mild assumption of constant returns to scale, one minus the land elasticity tells us how sensitive agricultural output is to the use of non-land inputs like capital and labor. This in turn determines how many non-land inputs move out of (or into) agriculture in response to shocks to productivity and population. Differences in the land elasticity by crop or climate thus imply differences in the reaction of economies to such shocks, with implications for studies of comparative development, structural change, Malthusian stagnation, the take-off to sustained growth, and long-run growth prospects with finite resources.[1]

In this paper, we estimate the land elasticity, and show that it varies across different agricultural regions and climate types. Estimating the parameter(s) of an agricultural production function is not straightforward, for the standard reasons that total factor productivity is unobserved and inputs may be mis-measured. To address these issues, 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. 2nd-level 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 use agro-climatic yield data to give us a source of exogenous variation in productivity, and combine that with measures of district-level development (e.g. night lights and urbanization) to control for other unobservable elements of agricultural productivity. In addition, our estimates are made using only within-province variation across districts, meaning that unobservable variation in productivity across provinces, as well as across countries, is excluded from the estimates. Finally, our framework is robust to arbitrary distortions (e.g. taxes, subsidies) in agricultural output and factor prices at the province level.[2]

[1] Agriculture and land 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 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). On the relevance of resources for long-run growth, see Peretto and Valente (2015).

[2] There are two main 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.

We assemble data at the district level for rural population density in the year 2000, 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.

In the end, we have a dataset of 35,444 districts, coming from 2,553 provinces in 154 countries. Using this data, we divide districts into "temperate" and "tropical" regions based on their agro-climatic characteristics. In our baseline, we make this division based on the types of crops that can be grown within a district. The temperate region includes districts that can grow crops such as wheat, barley, and rye, while the tropical region includes districts that can grow crops such as paddy rice, cassava, and pearl millet. We also divide districts based on their frost-free days (e.g. tropical areas are frost-free all year round, while temperate areas are not), or by their Köppen-Geiger climate classification (Kottek et al., 2006), and our results are similar. Regardless of the definition, our assignment of districts allows us to separate temperate and tropical areas within countries, so that we do not have to assume that agriculture has a homogenous land elasticity within a country, or even within a given province/state.

Our baseline estimate is that the land elasticity is 0.238 in temperate districts. In contrast, our baseline estimate of the land elasticity is only 0.119 for tropical districts. The difference is statistically significant, and is robust to the exclusion of districts that contain large urban areas or of districts from any developed country. 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. In all cases, the aggregate land elasticity in temperate districts remains approximately 0.10-0.12 higher than in tropical districts, and the difference remains statistically significant.[3] As the measure of agro-climatic yield we use is based on staple crops, these results should be interpreted as differences in the land elasticity in staple crop production, and may not be relevant for areas that rely heavily on livestock or cash crop production.[4]

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

[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.

[4]We show as part of our robustness checks that our results hold if districts that are large livestock or cash crop producers are included or excluded from the regressions.

functions, with a common set of coefficients across countries for each input, including land. Issues 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). Compared to this, our district-level data allows us to control for unobserved country and province-level effects, and the use of agro-climatic yield data gives us an explicit measure of productivity.

As may be apparent, 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 techniques available to farmers (Hayami and Ruttan, 1970).[5] The aggregate land elasticity is a useful parameter for studying the role of the agricultural sector and its interaction with other sectors at the macro level, as we discuss below, while farm-level elasticities would be useful for studying farm-level policies or outcomes within the agricultural sector itself. This distinction explains one of the limitations of our study, which is that we cannot use our results to identify why the aggregate land elasticity differs between temperate and tropical regions. An explanation would require details on the interaction of farmers with biological production functions for specific crops that are beyond the scope of this paper.

With that caveat in mind, we show in the second half of the paper that the aggregate land elasticity is central to any study that looks at the relationship of agriculture to non-agriculture, and the variation we have identified between temperate and tropical regions has implications for development. To show this we first describe 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 sensitivity of both real income per capita and the share of labor in agriculture with respect to shocks in either population or TFP depend on the size of the land elasticity. The larger is the land elasticity, the more sensitive are real income per capita and the share of labor in agriculture to population and TFP. This is a benefit to temperate areas when shocks are positive (e.g. higher TFP or lower population growth), but a burden 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. The shock to mortality had a negative impact on GDP per capita, and per

[5]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-level production functions may well take on different forms (i.e. Leontief verus Cobb-Dougals) than the aggregate function.

worker, across all developing countries. But we find that the size of that negative effect was three times larger for countries with high land elasticities compared to countries with low land elasticities, consistent with our theoretical predictions. The difference in effect size is statistically significant, and holds whether we measure the population shock in terms of mortality, life 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 growth), areas with temperate land elasticities will experience more urbanization and faster growth in living standards, whatever the fundamental driver of those shocks: institutions, geography, or culture.[6] This may help explain why it was that western Europe, with a high aggregate land elasticity, diverged from even the more advanced areas of Asia, with a low aggregate land elasticity, even if western Europe did not have an advantage in technological or institutional improvements.[7] 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.[8]

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 then discuss how to implement this empirically.

[6] 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).

[7] The divergence of China, and the lower Yangtze region in particular, from north-western Europe is the subject of a large literature. Pomeranz (2000) is the standard starting point, while Allen et al. (2011); Huang (2002); Ma (2013); Lee, Campbell and Feng (2002); Broadberry and Gupta (2006) are a brief selection of relevant papers.

[8] 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.

2.1 Theoretical setting

Consider a district i located in province (or state) s. Let the aggregate agricultural production function for that district be given by

$$Y_{Ais} = A_{Ais} X_{is}^{\beta} \left(K_{Ais}^{\phi} L_{Ais}^{1-\phi} \right)^{1-\beta} \tag{1}$$

where A_{Ais} is total factor productivity, X_{is} is land, K_{Ais} is capital (or any other inputs aside from land and labor), and L_{Ais} is the number of agricultural workers. The land elasticity we are interested in is β.[9]

We assume that operators in this district are cost-minimizers, and take the real wage of agricultural workers and real rental rate of agricultural capital as given. The real wage is denoted by $(1+\tau_{is}^{w})w_{As}$, where w_{As} is the province average wage, and $(1+\tau_{is}^{w})$ is a district-specific wedge relative to that average wage, similar to the structure used in Hsieh and Klenow (2009). For capital, the real rental rate is $(1+\tau_{is}^{r})r_{As}$, where r_{As} is the province average rental rate, and $(1+\tau_{is}^{r})$ is a district-specific wedge on that rental rate. These wedges capture any arbitrary distortion, and not just explicit taxes or subsidies set by governments.

Given the real wage and rental rate, the first-order conditions governing the choice of labor and capital to employ are

$$\begin{aligned} (1+\tau_{is}^{w})w_{As} &= (1-\phi)(1-\beta)\frac{Y_{Ais}}{L_{Ais}} \\ (1+\tau_{is}^{r})r_{As} &= \phi(1-\beta)\frac{Y_{Ais}}{K_{Ais}}. \end{aligned} \tag{2}$$

Given these two conditions, the capital/labor ratio used in the district will be

$$\frac{K_{Ais}}{L_{Ais}} = \frac{\phi}{1-\phi}\frac{(1+\tau_{is}^{w})}{(1+\tau_{is}^{r})}\frac{w_{As}}{r_{As}}.$$

Using this capital/labor ratio together with the first-order condition for labor from (2) and the production function from (1), the cost-minimizing labor/land ratio will satisfy

$$\left(\frac{L_{Ais}}{X_{is}}\right)^{\beta} = (1-\beta)A_{Ais}\left(\frac{\phi}{(1+\tau_{is}^{r})r_{As}}\right)^{\phi(1-\beta)}\left(\frac{(1-\phi)}{(1+\tau_{is}^{w})w_{As}}\right)^{1-\phi(1-\beta)}. \tag{3}$$

As would be expected, this ratio depends positively on productivity, A_{Ais}, such that for given output and factor prices, the district will employ more labor per unit of land if they are more productive. Similarly, for a given productivity level and output price, higher real wages and/or

[9] 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.

rental rates for capital will be associated with a lower labor/land ratio.

This relationship forms the basis for our estimation of β. To make this more clear, take logs of both sides of (3), and re-arrange to the following

$$\ln A_{Ais} = \alpha + \beta \ln L_{Ais}/X_{is} + \tau_{is} + \omega_s, \tag{4}$$

where α is a collection of fixed parameters.[10]. The last two terms are defined as:

$$\tau_{is} = \phi(1-\beta)\ln(1+\tau^r_{is}) + [1-\phi(1-\beta)]\ln(1+\tau^w_{is}) \tag{5}$$

$$\omega_s = \phi(1-\beta)\ln r_{As} + [1-\phi(1-\beta)]\ln w_{As}. \tag{6}$$

The first term, τ_{is}, is a combined wedge term representing how district i real wages and rental rates deviate from the province averages. The second term, ω_s, captures that province average level of real wages and rental rates. No assumption is necessary about how those province-level rates are set. They may be arbitrarily distorted relative to competitive market equilibrium rates due to taxes, subsidies, barriers to movement of labor and/or capital between provinces, or other frictions. The wedge term τ_{is} reflects specific policies or distortions (e.g. taxes or subsidies) at the district level.

The non-agricultural sector is not explicit, but is embedded in the terms involving wages and rental rates. Non-agricultural productivity, taxes, subsidies, or other distortions would, in equilibrium, be reflected in the real rental and wages rates in agriculture. Province-level effects of the non-agricultural sector common to all districts are captured by ω_s. District-specific effects of non-agriculture that create deviations from the province wages or rental rates are picked up by the wedge term τ_{is}.

2.2 Empirical approach

Equation (4) shows, in principle, that we could use variation in A_{Ais} and L_{Ais}/X_{is} to estimate the value of β using district level data. The province level of average wages and rental rates, ω_s, can be accounted for by fixed effects. Given those province fixed effects, we can identify β by looking at the relationship of $\ln A_{Ais}$ to L_{Ais}/X_{is} across districts *within* a given province. This means that the overall *level* of agricultural productivity or rural density at the province level is not used. Therefore distortions to the price of agricultural goods at the province level, wedges between provinces in the real wage or rental rate, or differences in non-agricultural productivity between provinces may all be present in reality, but do not affect our estimation of β. In particular, differences across provinces (and countries) in the overall level of development (and hence the level of real wages or the real return to capital) do not influence our estimates.

[10] Formally, $\alpha = -\phi(1-\beta)\ln\phi/(1-\phi) - \ln(1-\phi) - \ln(1-\beta)$

However, the district-specific wedge, τ_{is}, is unobservable. Thus if there is meaningful variation in the real wage or real rental rate of capital across districts *within* a given province, our estimates of β may be biased. We cannot measure these wedges directly, and instead use a set of proxy variables to capture their variation. In practice, we replace the wedge terms in equation (4) with $\delta'_\tau \mathbf{Z}_{is}$, so that we have

$$\ln A_{Ais} = \alpha + \beta \ln L_{Ais}/X_{is} + \delta'_\tau \mathbf{Z}_{is} + \omega_s, \tag{7}$$

where δ'_τ is the vector of coefficients on the controls contained in $\mathbf{Z}_{is}$. We discuss the specific controls included at the end of this section.

Prior to that, a second issue with using equation (7) to estimate β is the measurement of A_{Ais}. We address this by using an agro-climatic measure of inherent productivity. In particular, let overall agricultural productivity be defined by

$$\ln A_{Ais} = \ln A^{Agro}_{Ais} + \rho_s + \delta'_A \mathbf{Z}_{is}. \tag{8}$$

The first factor is potential agro-climatic productivity, $\ln A^{Agro}_{Ais}$, which captures productivity coming from things such as temperature, rainfall, and soil conditions. This agro-climatic productivity measure is specific to a district. Second, ρ_s captures technological (or institutional or cultural) factors that affect agricultural productivity, common to all districts within a given province s. Finally, $\mathbf{Z}_{is}$ captures district-specific observable characteristics that may also influence productivity in agriculture. The term δ'_A is a vector of the effect these characteristics have on productivity, which is distinct from the effect they may have on the wedge term through δ'_τ.

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,

$$\ln A^{GAEZ}_{Ais} = \ln A^{Agro}_{Ais} + \epsilon_{is}. \tag{9}$$

Here ϵ_{is} is a 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. Assessing that will be part of our robustness checks.

Combining (9) with (8), (7), and (4) we arrive at a final specification

$$\ln A^{GAEZ}_{Ais} = \alpha + \beta \ln L_{Ais}/X_{is} + \gamma_s + \delta' \mathbf{Z}_{is} + \epsilon_{is}. \tag{10}$$

Here, $\gamma_s = \omega_s + \rho_s$ is a province-specific fixed effect which absorbs the province-level differences in real factor prices and the level of agricultural productivity. The vector $\delta' = \delta'_\tau + \delta'_A$ is the combined effect of the controls in $\mathbf{Z}_{is}$ on factor prices and productivity.

The specification in (10) will deliver unbiased estimates of β so long as our controls and fixed effects ensure that within-province variation in rural density is not related to ϵ_{is}. To the extent that ϵ_{is} captures simple GAEZ measurement error in inherent productivity, this should not be problematic. However, more worrisome is the possibility of some systematic district-level variation in wedges or agricultural productivity that is related to rural density. We do not have a natural experiment to leverage for random or quasi-random variation in productivity or rural density that would rule this out. We argue instead that the province fixed effects and controls contained in $\mathbf{Z}_{is}$ capture all the relevant variation in district real factor price wedges and unobserved productivity.

A reason to believe that the district-specific wedges are not very relevant (even if province- or country- level ones may be) is that each district tends to be quite small relative to its province. The median province has 28 disticts, and the median district contains only 6.7% of total province population and 7.7% of total province rural population. In absolute terms, the median district contains only about 26,000 total people, and about 12,500 rural residents. The districts in our dataset are not large relative to the wider economy around them, and as such the province-level fixed effects should capture almost all of the relevant variation in real wages, rental rates, and productivity. As part of our robustness checks, we also exclude particular districts from our sample that *are* large in population, or contain urban areas with more than 25,000 residents, as these may be more likely to have significant district-level wedges to factor prices. We also examine only provinces with more than 50 districts, to ensure we are looking at districts that are relatively small with respect to their province.

Beyond that, we have the sets of controls contained in $\mathbf{Z}_{is}$. To summarize, we include measures of district (log) night light density, the district share of population in urban areas, and the (log) total district population. Among many possible relationships in the data, high night light density and large urban share (relative to the province as a whole) can indicate that real wages or rental rates are higher than in surrounding districts, suggesting positive wedges on those two factor prices. A large population (relative to province as a whole) could imply either a positive or negative wedge on factor prices, depending on if agglomeration or congestion effects prevail. We also include polynomials of all three control variables in a robustness check to allow for non-linear relationships between them, wedges, and unmeasured productivity. For a sub-sample of our main data, we also include controls for demographics and household asset data from the Demographic and Health Surveys to provide more proxies for real wages and rental rates. As we show below, the patterns we find for the elasticity β are consistent regardless of the controls we include.

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 (10). We rewrite that here while adding one additional subscript to make clear the structure of the data we will be using,

$$\ln A^{GAEZ}_{Aisg} = \alpha_g + \beta_g \ln L_{Aisg}/X_{isg} + \gamma_s + \delta'_g \mathbf{Z}_{isg} + \epsilon_{isg} \tag{11}$$

where i denotes a district (e.g. Saoguan) in province 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. temperate climate), 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.

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 (10) 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

$$\begin{aligned} \ln A^{GAEZ}_{isg} &= \alpha_g + \beta_g \ln L_{Aisg}/X_{isg} + (\beta_{Ref} - \beta_g) \ln L_{Aisg}/X_{isg} \times I(Ref) + \gamma_s \\ &\quad + \delta'_g \mathbf{Z}_{isg} + (\delta'_{Ref} - \delta'_g)\mathbf{Z}_{isg} \times I(Ref) + \epsilon_{isg}. \end{aligned} \tag{12}$$

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.

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.[11]

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 (10) 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 use data on the urbanization rate within provinces and districts, as well as (log) total population. 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 35,444 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

[11]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.

to the nutritional needs of humans. We address the use of calories to compare crops below in the robustness section, and this is not driving our results.

For our purposes, we use 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.[12] We used a subset of the crops in the original Galor and Özak (2016) dataset, so that we focus on crops that are primary staples.[13] Those authors provide details of the construction of this data, but we can provide a summary. For each grid-cell, we 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, we 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}.

After we calculate A_{isg}^{GAEZ} for each district, we discard values above the 99th and below the 1st percentile from that total 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 a 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 actualproductivity, 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 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.

[12] 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.

[13] 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.

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 Defining temperate and tropical regions

Our primary distinction of a region g is as either temperate or tropical. There is no definitive way of assigning districts to either temperate or tropical regions, so we pursue several possibilities. Regardless of the assignment rule, it is worth reiterating that it is applied at the district level, and countries (and provinces) are not assumed to be homogenous.

By crop suitability: The first way of denoting temperate and tropical is through the types of crops capable of being grown, as this depends on the overall agro-climatic characteristics of a region. Here we define **temperate** districts as those that have positive GAEZ suitability for any of barley, buckwheat, rye, oats, wheat, or white potatoes, but have precisely *zero* suitability for all of cassava, cowpeas, paddy rice, pearl millet, sweet potato, and yams. The **tropical** districts are those that have positive GAEZ suitability for any of cassava, cowpeas, paddy rice, pearl millet, sweet potato, or yams, but precisely *zero* suitability for barley, buckwheat, rye, oats, wheat, and white potatoes.[14] In total, we have 10,661 districts classified as temperate using crop suitability,

[14]We have experimented with alternative sets of crops to define the regions, without any material change to our results.

and 9,088 classified as tropical. There are 15,692 districts that are suitable for *both* types of crops, and these are excluded from the analysis when we use this definition.

By frost-free days: Rather than crop suitability, which combines several climate characteristics, we can narrow the assignment down to a single characteristic, frost-free days. Frost plays a role in agriculture through culling various micro-organisms related to plant disease and the mineralization of organic matter (Masters and McMillan, 2001), and its presence or absence can be a useful indicator. We define **temperate** districts as those which have fewer than 365 frost-free days, meaning that they experience at least one frost day during the year, on average. We define **tropical** districts as those with 365 frost-free days, meaning they do not experience any frost, on average. This gives us 17,750 temperate districts, and 17,701 tropical districts, for total coverage of our sample.[15] Data on frost-free days is from the GAEZ.

By Köppen-Geiger climate zones: A final classification is to use direct climate characteristics. We use the Köppen-Geiger scheme to assign 11,618 districts as **temperate** and another 12,292 as **tropical**.[16] This broad classification also does not result in exclusive assignment, and there are 446 districts that qualify as *both* temperate and tropical, as their land area is split across both definitions. Excluding or including those districts with an overlap has no effect on our results.

Our results are not contingent of the choice of definition for temperate/tropical, as will be shown below. For much of the paper, we will focus on the first definition, based on crop suitability. Using that definition of temperate and tropical, Figure 1 shows the density plots of (log) rural density for the two regions. One can see that rural density tends to be higher in 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

[15] There are reasons to believe that frost may raise the productivity *level* of agriculture by killing off pests and organisms that mineralize organic matter, but this difference in productivity does *not* have anything to do with our results. Our estimates of β_g are made within-province for districts that have the *same* frost characteristics, and are not based on any comparison of frost versus frost-free districts.

[16] The Köppen-Geiger scheme has several levels. For temperate, we use districts that have any land in their climate class "C" (warm temperate) or "D" (snow), and also having any land in their temperature class "b" (warm summer) or "c" (cool summer). For tropical, we use districts that have any land in their climate class "A" (Equatorial). There are no temperature sub-divisions within the Equatorial class. There are also precipitation classifications, but we do not use those for either temperate or tropical assignment. Pixel-level data on Köppen-Geiger classification is from Kottek et al. (2006).

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. cassava, wet rice, etc.) are much higher than the calories per tonne defining temperate districts (e.g. barley and wheat). We discuss below that the calories per tonne values for each crop cannot explain our results.

These two plots capture the raw information about rural density and calories per hectare, but note that the distinction in medians and modes between temperate and tropical districts are immaterial to our estimation. We will only be using the district-level variation in rural density and caloric yield *within* provinces, 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.

3.3 Estimates for temperate and tropical regions

Table 2 shows the estimates of β_g for both our temperate and tropical regions. In column (1) of Panel A, one can see the estimate of β_g for temperate districts is 0.238, while in column (2) the estimate of β_g for tropical districts is 0.119, a difference of approximately 0.12. 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, log population, 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.[17] 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 2, the remainder of the table shows variations on our baseline result using different definitions of temperate and tropical districts. In columns (3) and (4), we use the definition of temperate and tropical based on the number of frost-free days. The results are similar to our

[17] 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.

baseline, with an estimated β_g of 0.223 for temperate districts, but only 0.107 for tropical ones. The gap here is about the same as our baseline results from columns (1) and (2), and is significant at less than 0.1%. Columns (5) and (6) use the Köppen-Geiger definition of temperate and tropical regions. Here, the results are similar to those using the crop suitability definition. β_g is estimated to be 0.235 in temperate districts, and only 0.093 in tropical ones, for a difference of about 0.14, again statistically significant at less than 0.1%. Our results are not sensitive to the exact definition of temperate/tropical, and if anything would be stronger using the frost-free days or Köppen-Geiger definitions.

Panel B of Table 2 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 crop suitability as in 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 affected by this. As can be seen from the table, however, the distinction in β_g remains, 0.286 for temperate districts and 0.122 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 districts where the urban share of population is above 50 percent, to again eliminate districts that are mainly urban areas. The results conform to those in the rest of the table, with a temperate estiamte of β_g equal to 0.302, and a tropical estimate of 0.134, a difference that is statistically significant at less than 0.1%. Finally, columns (5) and (6) 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.[18] The finding that districts suitable for tropical crops have a lower land elasticity still holds, with an estimated β_g of 0.119 compared to 0.264 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.

3.4 Robustness checks

Rural density data: Panel A of Table 3 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

[18] 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.

would have held prior to the heavy mechanization of agriculture in the 20th century.

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 0.121 for tropical) are similar to our baseline results.[19]

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 the Global Rural-Urban Mapping Project (CIESIN, 2011). 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 (0.236 for temperate and 0.123 for tropical) with our baseline.

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.[20] Nevertheless, in columns (5) and (6) the results are consistent with our baseline. The temperate elasticity is estimated to be 0.189, while the tropical elasticity is only 0.016.

The second use for 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 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.

[19] 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.

[20] 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.

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 3, columns (1) and (2), we present results using cultivated land to measure rural density. Again, the results are consistent with our baseline (0.226 for temperate areas and 0.122 for tropical).

Cash crops and livestock: Our measure of A_{isg}^{GAEZ} is based on staple crops, as opposed to cash crops (e.g. cocoa) or livestock production. If some districts within a state produce mainly cash crops or livestock, A_{isg}^{GAEZ} may be a poor proxy for the actual agricultural total factor productivity in that district. A particular problem would be if some districts within a province focus on cash crops or livestock, while other districts focus on staple crops. The differences in density between these districts would not be related to our measure of staple crop productivity, A_{isg}^{GAEZ}, and thus our estimate of β_g could be biased.

To address this, we draw in additional data on land use to eliminate districts that are heavy cash crop or livestock producers. In columns (3) and (4) of Panel B in Table 3 we drop any district that has more than 5% of its harvested area coming from cash crops. Data on the harvested area is from Monfreda, Ramankutty and Foley (2008).[21] The estimated β_g in temperate areas, 0.216, remains about twice as large as the estimate for tropical areas, 0.104, and that difference remains significant. Columns (5) and (6) drop any districts that have more than 5% of their area devoted to pasture, using data from Ramankutty et al. (2008). Again, the temperate estimate is around our prior estimates, 0.219. The tropical estimate, 0.130, is slightly higher than found in wider samples, but remains significantly different from the temperate estimate. Neither cash cropping or livestock explain the difference in β_g between temperate and tropical areas.

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

[21] The cash crops we consider are bananas, cocoa, coffee, cotton, jute, palm oil, rubber, sunflower, tea, tobacco, sugarbeets, and sugarcane.

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 4, 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 (0.200 for temperate and 0.111 for tropical) compared to our baseline estimate. But the gap remains 0.09, 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 (0.233 for temperate and 0.126 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 (0.197 for temperate and 0.110 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, similar to our baseline results.

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 be that the calorie counts used by Galor and Özak (2016), that we adopt, are incorrect. Or perhaps 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, rather than calories) 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 crop-specific raw potential yields shows that 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.

3.5 Demographic and asset controls

The province fixed effects and controls for night lights, urban share, and total population may not control fully for district-level variation in wedges or technology, in particular due to differences in the characteristics of the population in a district (e.g. education) and the availability of capital (e.g. livestock or the presence of electrical service). To assess if this is biasing our results, we run the same regressions for a limited sub-sample of districts for which we can assemble detailed data on demographics and assets.

We use the Demographic and Health Surveys (DHS), which provide individual and household level data in a consistent manner across a wide range of developing countries. Many of these surveys contain GIS information on the latitude and longitude of the surveyed clusters (e.g. a village), which allows us to identify which clusters are located within which districts. For those surveys with GIS data, we create district-level aggregate demographic and asset measures.[22] With the DHS data, this gives us a sample of 2,106 districts, of which 331 are part of our temperate region, and 1775 part of our tropical region. Details on the countries from which these districts are drawn are available in the appendix.

Table 5 shows the results of estimating β_g for temperate and tropical regions. Columns (1) and (2) are limited to those districts that have DHS data, but this data is not included as controls in these regressions. The results here, with a land elasticity of 0.277 for temperate districts and 0.117 for tropical districts, conform in size to the estimates we received in our larger samples. In columns (3) and (4), we repeat these regressions, but now include the DHS demographic data. The results are nearly identical, with a small drop in the temperate estimate to 0.274, while the tropical estimate remains similar at 0.116. Columns (5) and (6) include both the DHS demograhpic and asset data, and again the results are nearly identical.

The results using the DHS data provide some reassurance that the main findings are not due to unobserved district-level variation in the composition of the labor force or availability of capital. These DHS controls should also alleviate some concern about unmeasured differences in agricultural productivity across districts within a province, to the extent that they proxy for the level of

[22]On the demographic side we have the median, 10th, and 90th percentile of household head's age, years of education, and typical number of household residents. On the asset side we have the fraction of households with the following: toilet, electricity, television, refrigerator, improved flooring, any agricultural land, a bank account, any cattle, any draft animals, and any sheep. Some surveys contain measures of the amount of agricultural land, as well as counts of livestock, but there are too few of these to do a comparison across temperate and tropical regions.

technology used within a district.

3.6 Production function specification

For expositional purposes, we specified a Cobb-Douglas production function in equation (1), which implies that the land elasticity does not vary with the endowment of land, labor, or other inputs. This need not be the case, of course, and the different results on β_g for temperate and tropical areas may not reflect a fundamental difference in the production function, but rather a difference in those endowments. In particular, we know from Figure 1 that tropical areas have higher rural densities than temperate areas. If the elasticity of substitution between land and labor were more than one, then higher rural density would be associated with a lower land elasticity (and a higher labor elasticity).[23]

There are several reasons, though, that we do not believe this can explain our results. First, if it were the case that labor and land were substitutes in production, then holding constant the climate type, we should find higher estimate values of β_g in less densely populated areas. In the Appendix, we show results for sub-regions of the world (e.g. South-east Asia, tropical Africa), and find that the values of β_g are similar for tropical areas of southeast Asia, with high density, and for tropical areas of Africa, with low densities. Temperate sub-regions (e.g. western Europe or North America) also do not show systematic relationships of estimated β_g values and rural density.

Second, we can examine how estimated values of β_g vary with density at the province level. We have estimated a separate β_g for each province in our dataset that contains 10 or more districts within it. In each case, we run the same regression as in (10), excluding the province fixed effect but including the normal controls (e.g. night lights). This gives us a total of 1,018 estimates of β_g. In Figure 4 we plot the value of all these β_g estimates against the rural density of the province.[24] The dark dashed line shows a simple linear fit for this data. As can be seen there is a slight tendency of the estimated β_g values to get larger as a province gets more dense, although the effect is small. Doubling rural density only increase the estimated β_g by around 0.004.

This positive relationship of the land elasticity and rural density is consistent with land and labor being complements, not substitutes. If anything, the higher rural density of tropical areas would push up our estimated value of β_g for that region. The gap in β_g between tropical and temperate areas we find in our main results therefore does not appear to be driven by differences in rural density.

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

[24]These estimates are quite noisy, given that the average number of districts within a province is only 26. That does not represent an issue for our baseline resutls. Our baseline regressions with province fixed effects are effectively finding an efficient combination of these separate province-level estimates.

3.7 Comparison to factor shares

A 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 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. Furthermore, the factor share data is an aggregation from a snapshot of *farm*-level payments to land, but as noted before the farm-level production function may not be equivalent to the aggregate production function we are estimating. 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 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 present a two-sector model 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 model 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 in the data. 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, with the assumption that all district-specific wedges (e.g. τ_{is}^{w}) are equal to zero. Summing agricultural production over all districts in a province, we can write aggregate agricultural output for the province as

$$Y_A = A_A \left(\frac{K_A}{L_A}\right)^{\phi(1-\beta)} L_A^{1-\beta}, \tag{13}$$

where

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

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

$$Y_N = A_N \left(\frac{K_N}{L_N}\right)^{\phi} L_N. \tag{14}$$

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 (14).

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.[25] 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

$$\ln c_A = \ln \theta_A + (1-\epsilon)\ln M + (\gamma - 1)\ln p_A + (\epsilon - \gamma)\ln p_N \tag{15}$$

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.[26]

To go further, the most important assumptions we make are that the share of output paid to labor in both non-agriculture and agriculture is equal to s_L, while the share paid to capital in both sectors is s_K. We also assume $s_L + s_K = 1$, which 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.

Mobility between sectors ensures that the payments to labor are equalized,

$$p_A s_L \frac{Y_A}{L_A} = p_N s_L \frac{Y_N}{L_N}. \tag{16}$$

Combining the production functions in (13) and (14), the demand function in (15), and the mobility condition in (16) we can solve for the share of labor employed in agriculture and a measure of real

[25] 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.

[26] 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.

income in terms of agricultural goods (M/p_A). The labor share is

$$\frac{L_A}{L} = \theta_A \left(\frac{L^{\beta\gamma}}{A_A^{\gamma} A_N^{\epsilon-\gamma} \hat{k}^{\phi(\epsilon-\beta\gamma)}} \right)^{\frac{1}{1-\beta\gamma}} \tag{17}$$

while real income is

$$y = \left(\frac{A_A A_N^{\beta(\epsilon-\gamma)} \hat{k}^{\Omega}}{L^{\beta}} \right)^{\frac{1}{1-\beta\gamma}} \tag{18}$$

where $\hat{k} = (s_K K / s_L L)$, and $\Omega = \phi(1-\beta) + \phi\beta(\epsilon - \gamma)$. 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 (17) and (18). ■

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. In response to a shock to productivity or population, in economies with larger β it 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.[27]

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 (10), 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 land elasticity) or above the median (high land elasticity).[28]

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

$$y_{it} = \alpha + \theta x_{it} + \gamma_i + \delta_t + \epsilon_{it} \tag{19}$$

where y_{it} is one of three different dependent variables (log GDP per capita, log GDP per worker,

[27]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.

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

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 low land elasticities or high land elasticities. 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.[29]

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 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

[29] 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.

and GDP per worker.[30] 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 agriculture and development. We estimated the elasticity of aggregate agricultural production with respect to land, and found that it differed 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. This also avoids comparing countries - or even provinces - at different levels of development. Our baseline finding, that the land elasticity in temperate areas is about 0.24 while it is only 0.12 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

[30] 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).

and temperate areas, and whether that is due to biological requirements of certain crops, or the constraints imposed by aspects of the climate itself.

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, we 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.

Allen, Robert C., Jean-Pascal Bassino, Debin Ma, Christine Moll-Murata, and Jan Luiten Van Zanden. 2011. "Wages, prices, and living standards in China, 1738-1925: in comparison with Europe, Japan, and India." *Economic History Review*, 64(s1): 8–38.

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.

Broadberry, Stephen, and Bishnupriya Gupta. 2006. "The early modern great divergence: wages, prices and economic development in Europe and Asia, 1500-1800." *Economic History Review*, 59(1): 2–31.

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.

Hsieh, Chang-Tai, and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *Quarterly Journal of Economics*, 124(4): 1403–1448.

Huang, Philip C. C. 2002. "Development or Involution in Eighteenth-Century Britain and China? A Review of Kenneth Pomeranz's The Great Divergence: China, Europe, and the Making of the Modern World Economy." *The Journal of Asian Studies*, 61(2): 501–538.

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.

Kottek, Markus, Jürgen Grieser, Christoph Beck, Bruno Rudolf, and Franz Rubel. 2006. "World Map of the Köppen-Geiger climate classification updated." *Meteorologische Zeitschrift*, 15(3): 259–263.

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

Lee, James, Cameron Campbell, and Wang Feng. 2002. "Positive Check or Chinese Checks?" *The Journal of Asian Studies*, 61(2): 591–607.

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

Ma, Debin. 2013. "State capacity and great divergence, the case of Qing China (1644–1911)." *Eurasian Geography and Economics*, 54(5-6): 484–499.

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

Masters, William A., and Margaret S. McMillan. 2001. "Climate and Scale in Economic Growth." *Journal of Economic Growth*, 6(3): 167–186.

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.

Monfreda, Chad, Navin Ramankutty, and Jonathan A. Foley. 2008. "Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000." *Global Biogeochemical Cycles*, 22(1).

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.

Pomeranz, Kenneth. 2000. *The Great Divergence.* Princeton University Press.

Ramankutty, Navin, Amato T. Evan, Chad Monfreda, and Jonathan A. Foley. 2008. "Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000." *Global Biogeochemical Cycles*, 22(1).

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.

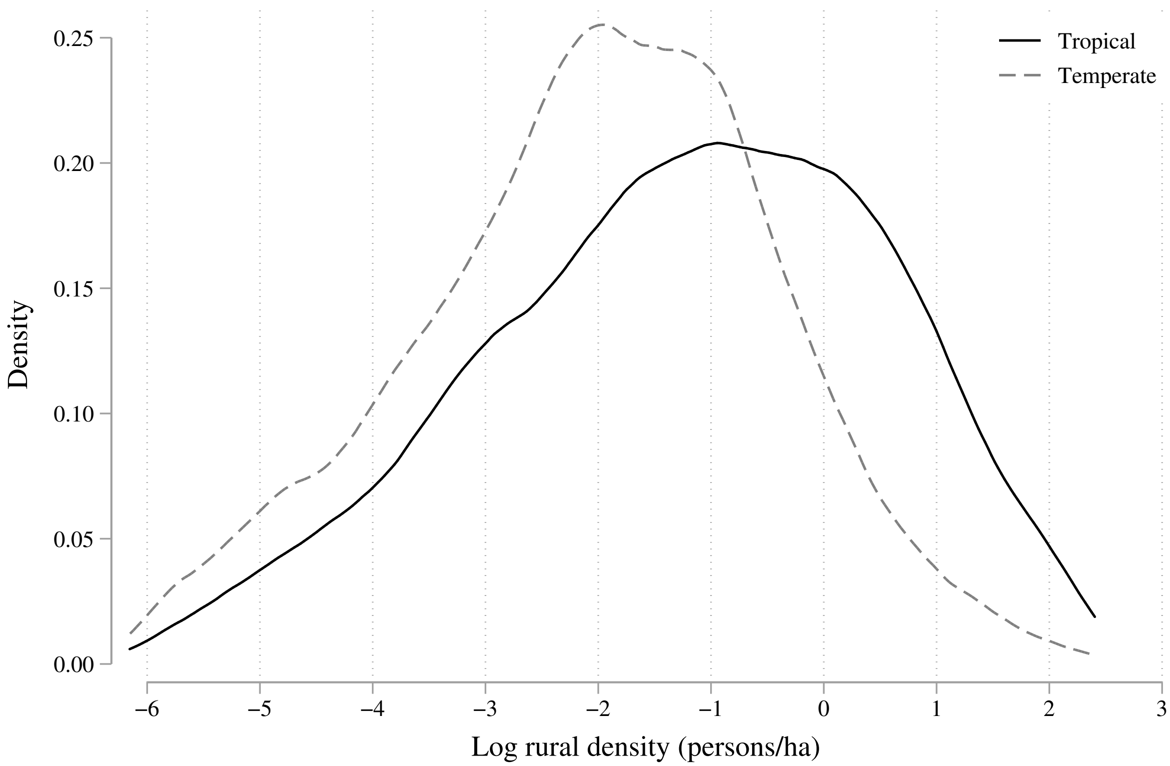
Vries, Peer. 2013. *Escaping Poverty: The Origins of Modern Economic Growth.* Vienna University Press.

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.

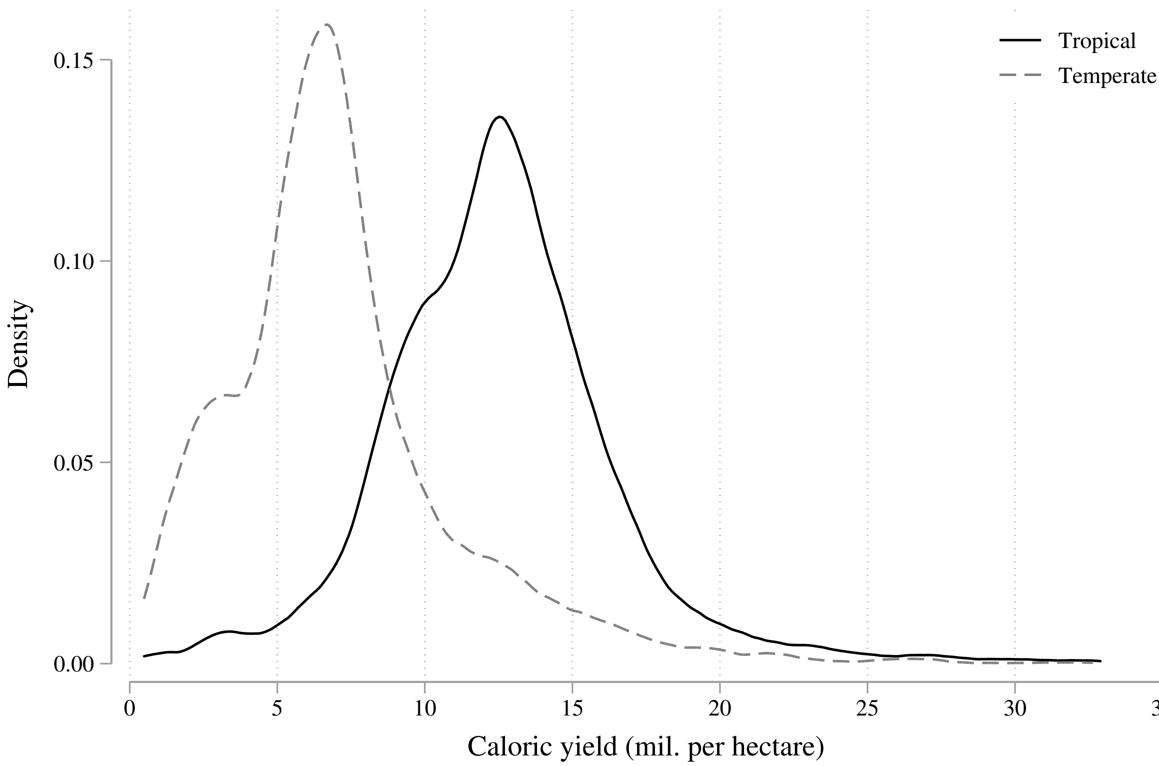
Wilde, Joshua. 2012. "How substitutable are fixed factors in production? evidence from pre-industrial England." University Library of Munich, Germany MPRA Paper 39278.

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



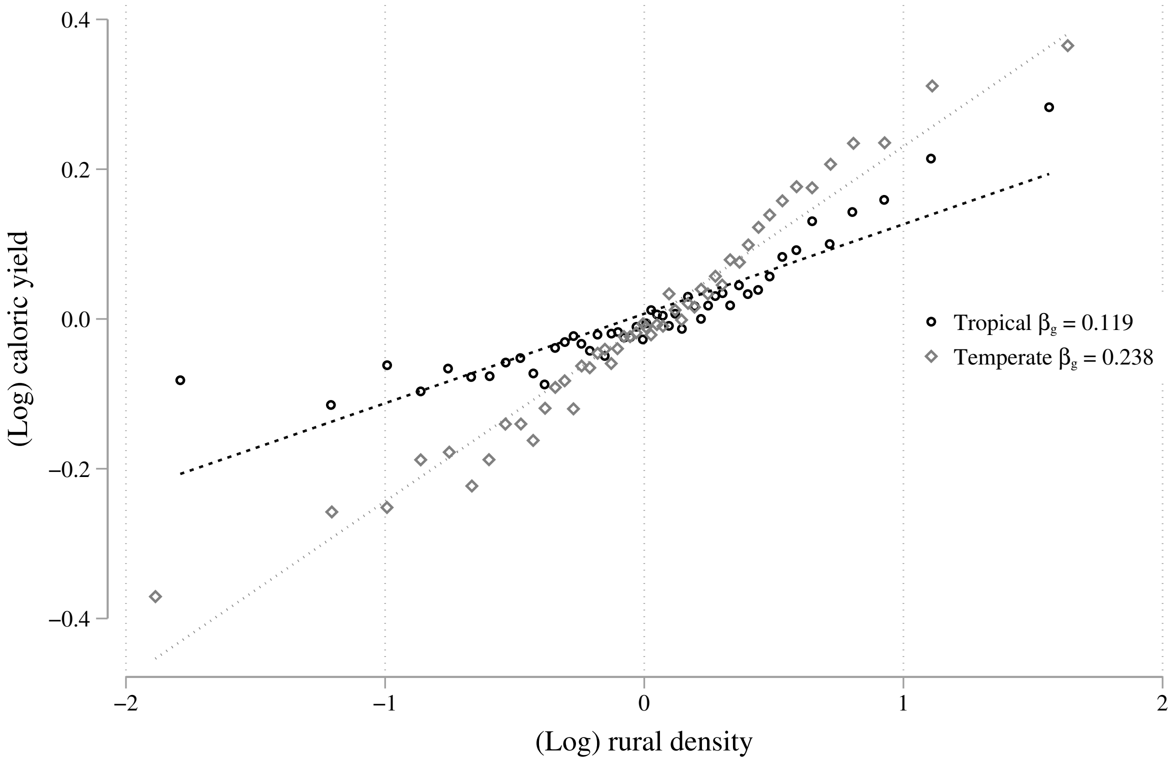
Notes: Kernel density plot, Epanechnikov kernel, of the (log) rural density, L_{Aisc}/X_{isc}, at the district level, calculated by the authors using data from Goldewijk et al. (2011) for rural population. "Temperate" includes districts that are suitable for growing barley, buckwheat, oats, rye, wheat, 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



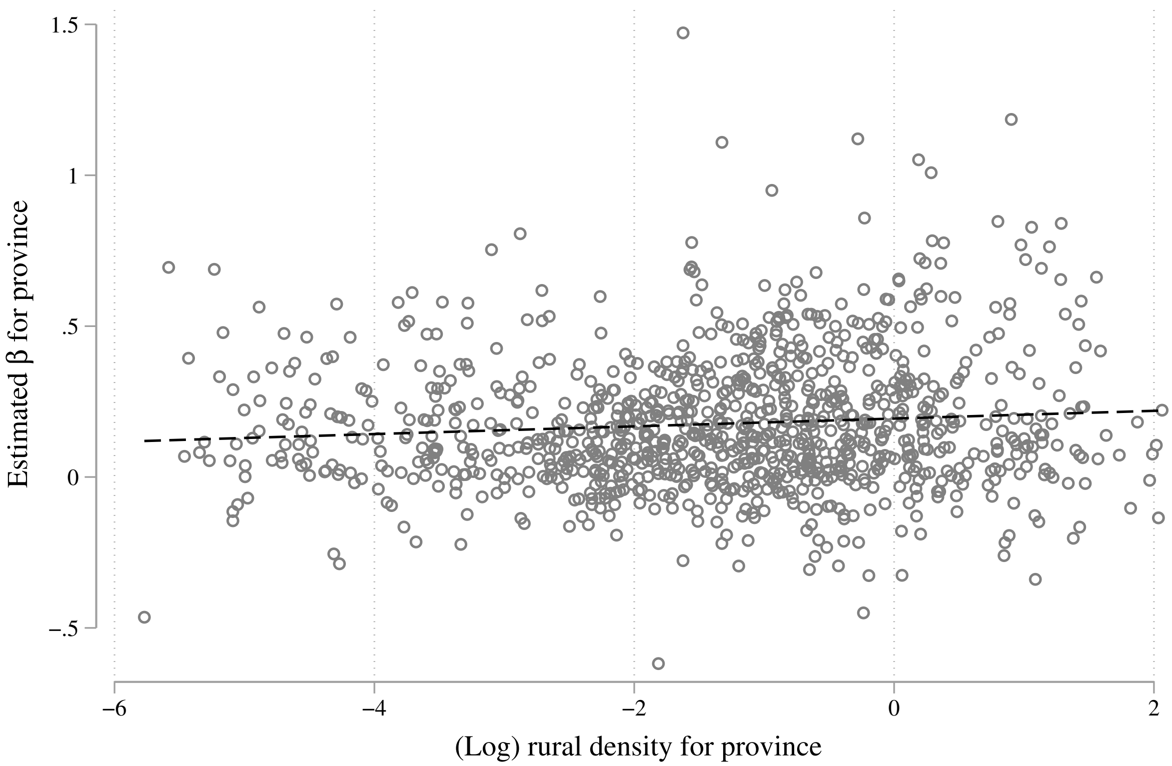
Notes: Kernel density plot, Epanechnikov kernel, of the caloric yield, A_{isc}, at the district level, calculated by the authors using data from Galor and Özak (2016). See text for details. This measure sums the maximum calories available per grid cell within a district, then divides by total area of 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: Residual Relationship of Caloric Yield (A_{isc}^{GAEZ}) and Rural Density



Notes: Plotted are the quantile averages of both log caloric yield and log rural density for each sample, temperate and tropical. 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. 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.

Figure 4: Relationship of Province-level β_g and Rural Density



Notes: Plotted are the values of β_g estimated for each individual province in our dataset that contains 10 or more districts. The specification for these regressions is equation (10), and includes the controls for (log) night lights, (log) total population, and the percent urban. The value of rural density for a province is total rural population of the province divided by total land area of the province.

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
Population (000s)	142.27	568.96	3.59	8.72	26.09	77.17	208.80

Notes: A total of 35,444 observations for each variable (these come from 2,553 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: 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:

	Crop suitability:		Frost Days:		Koeppen-Geiger:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density (β_g)	0.238	0.119	0.223	0.107	0.235	0.093
	(0.026)	(0.019)	(0.022)	(0.012)	(0.028)	(0.015)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.000		0.000		0.000
Countries	91	81	94	107	88	83
Observations	10660	9086	17746	17698	11615	12289
R-square (ex. FE)	0.26	0.22	0.23	0.19	0.26	0.20

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

	Urban Pop. $< 25K$:		Urban Perc. < 50:		Ex. Europe/N. Amer.:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density (β_g)	0.286	0.122	0.302	0.134	0.264	0.119
	(0.029)	(0.022)	(0.036)	(0.023)	(0.046)	(0.019)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.000		0.000		0.003
Countries	83	75	84	76	24	70
Observations	7648	6661	6569	5851	824	8824
R-square (ex. FE)	0.29	0.24	0.31	0.25	0.18	0.15

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, log density of district nighttime lights, and log total population. The coefficient estimate on rural population density indicates the value of β_g, see equation (10). 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, either crop suitability, the number of frost-free days, or Köppen-Geiger climate zones. See text for details of how temperate and tropical regions are defined in each case. In Panel B, the columns either exclude districts with more than 25,000 urban residents, exclude districts from any country in Europe (incl. Russia east of the Urals) or North America, or with a percent of urban residents below 50 percent.

Table 3: 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 (β_g)	0.240	0.121	0.236	0.123	0.189	0.016
	(0.027)	(0.019)	(0.047)	(0.024)	(0.070)	(0.017)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.007	0.348
p-value $\beta_g = \beta_{Temp}$		0.000		0.031		0.010
Countries	91	81	86	75	23	24
Observations	10649	9080	8733	6767	1104	2416
R-square (ex. FE)	0.26	0.22	0.25	0.22	0.15	0.11

Panel B: Different land assumptions

	Cultivated Area:		Cash crops < 5% area:		Pasture < 5% area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density (β_g)	0.226	0.122	0.216	0.104	0.219	0.130
	(0.025)	(0.021)	(0.021)	(0.020)	(0.019)	(0.028)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.001		0.000		0.009
Countries	90	78	58	51	71	79
Observations	10599	8977	4893	1958	3127	4696
R-square (ex. FE)	0.27	0.22	0.25	0.21	0.26	0.21

Notes: Temperate and tropical samples are defined by the suitability measures described in Table 2. 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, log density of district nighttime lights, and log total population. The coefficient estimate on rural population density indicates the value of β_g, see equation (10). 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 with fewer than 50 thousand total population, and the third set drops districts from any province that has 50 or fewer districts total.

Table 4: 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 (β_g)	0.200	0.111	0.233	0.126	0.197	0.110
	(0.033)	(0.019)	(0.026)	(0.021)	(0.033)	(0.019)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.020		0.001		0.023
Countries	91	81	90	79	91	81
Observations	10660	9086	10627	9057	10660	9086
R-square (ex. FE)	0.21	0.19	0.23	0.19	0.20	0.18

Panel B: Excluding Europe and North America, 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 (β_g)	0.275	0.111	0.278	0.127	0.276	0.110
	(0.050)	(0.019)	(0.047)	(0.021)	(0.046)	(0.019)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.002		0.003		0.001
Countries	24	70	23	69	24	70
Observations	824	8824	816	8799	824	8824
R-square (ex. FE)	0.20	0.16	0.19	0.13	0.20	0.16

Notes: Temperate and tropical samples are defined by the suitability measures described in Table 2. 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, log density of district nighttime lights, and log total population. The coefficient estimate on rural population density indicates the value of β_g, see equation (10). 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 5: Estimates of Land Elasticity, β_g, with DHS district controls

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

	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density (β_g)	0.277	0.117	0.274	0.116	0.270	0.118
	(0.050)	(0.022)	(0.046)	(0.022)	(0.051)	(0.021)
Demog. controls	No	No	Yes	Yes	Yes	Yes
Asset controls	No	No	No	No	Yes	Yes
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.002		0.001		0.003
Countries	19	30	19	30	19	30
Observations	331	1775	331	1775	331	1775
R-square (ex. FE)	0.15	0.16	0.17	0.17	0.20	0.19

Notes: Temperate and tropical samples are defined by the suitability measures described in Table 2. 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 (10). The districts included in these regressions have villages/clusters that took part in a Demographic and Health Survey (DHS). Using the DHS data, the columns include district level means or medians of demograhpic variables (e.g. household head education and age) and asset variables (e.g. household ownership of cattle or use of electricity), see text for details of the precise controls.

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 (10) 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.