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The role of land in temperate and tropical agriculture

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ONLINE APPENDIX ——————————————————————————————————

Robustness checks and alternative assumptions for empirical work from the main paper are contained here. Also included are definitions of countries included in regions used in paper, as well as additional theoretical work related to the model.

Contents

A.1 General version of empirical setup

This is to demonstrate that the elasticity of agricultural productivity with respect to the density of agricultural labor is equal to the elasticity of agricultural output with respect to land given any constant returns to scale production function. Let agricultural production be

$$Y_{Ai} = A_{Ai}F(X_i, K_{Ai}, L_{Ai}) \tag{A.1}$$

for district i in province I, where $F()$ is a constant returns to scale function with respect to the three inputs: land, capital, and labor. As in the main paper, we make the same mobility assumptions for labor and capital across districts, which again implies that K_{Ai}/L_{Ai} is identical for all districts.

Dividing the production function through by L_{Ai} we have that

$$Y_{Ai}/L_{Ai} = A_{Ai}F(X_i/L_{Ai}, K_{Ai}/L_{Ai}, 1). \tag{A.2}$$

Define $x_i = X_i/L_{Ai}$ and $k_{Ai} = K_{Ai}/L_{Ai}$ as the per-worker amounts of land and capital, and define

$$f(x_i, k_{Ai}) = F(X_i/L_{Ai}, K_{Ai}/L_{Ai}, 1) \tag{A.3}$$

as the intensive form of the aggregate production function. By the mobility assumption, we know that $\phi_L Y_i/L_{Ai} = w$, where ϕ_L is the elasticity with respect to labor, and the wage is common across districts. This allows us to write that

$$w = \phi_L A_{Ai}f(x_i, k_{Ai}). \tag{A.4}$$

Holding this wage constant as it is given by state-level factors, and noting that k_{Ai} is also given by state-level factors, use the implicit function theorem to solve for

$$\frac{\partial A_{Ai}}{\partial x_i}\frac{x_i}{A_{Ai}} = -\frac{\phi_L A_{Ai}f_1(x_i, k_{Ai})}{\phi_L f(x_i, k_{Ai})}\frac{x_i}{A_{Ai}} = -\frac{f_1(x_i, k_{Ai})x_i}{f(x_i, k_{Ai})}. \tag{A.5}$$

The elasticity of productivity, A_i, with respect to land per worker, x_i, is equal to the elasticity of $f()$ with respect to land per worker. This simply implies that the relationship of land per worker to productivity depends on how sensitive output per worker is to land per worker.

It is straightforward to show, given the constant returns to scale production function, that

$$\frac{f_1(x_i, k_{Ai})x_i}{f(x_i, k_{Ai})} = \frac{F_1(X_i, K_{Ai}, L_{Ai})X_i}{F(X_i, K_{Ai}, L_{Ai})} \tag{A.6}$$

or that the elasticity of the intensive production function with respect to land per worker is equal to the elasticity of the aggregate production function with respect to land. Thus it follows that

$$\frac{\partial A_{Ai}}{\partial x_i}\frac{x_i}{A_{Ai}} = -\frac{F_1(X_i, K_{Ai}, L_{Ai})X_i}{F(X_i, K_{Ai}, L_{Ai})} \tag{A.7}$$

or that the elasticity of productivity with respect to land per worker, x_i, is equal to the negative of the elasticity of aggregate output with respect to land. It is then trivial that the elasticity of productivity with respect to density, $1/x_i$, is equal to the elasticity of aggregate output with respect to land. The Cobb-Douglas assumption used in the main paper is not necessary to derive the main estimating equation used in the paper.

A.2 Specification with capital immobile between sectors

In our main derivation, we assume that capital can move freely between agriculture and non-agriculture. If that were not true, then equation (8) in the main paper would be

$$w_{As} = (1 - \phi)(1 - \beta)(1 + \tau_{As})p_{As}A_{Ais}\left(\frac{X_{is}}{L_{Ais}}\right)^{\beta}\left(\frac{K_{Ais}}{L_{Ais}}\right)^{\phi(1-\beta)}, \tag{A.8}$$

and our estimation would be based on

$$\ln A_{Ais} = \beta \ln L_{Ais}/X_{is} - \phi(1-\beta)\ln K_{Ais}/L_{Ais} - \ln w_{As}/p_{As} - \ln(1+\tau_{As}) + \ln(1-\phi)(1-\beta). \tag{A.9}$$

Here it becomes obvious that we need to control for *agricultural capital per worker*, rather than aggregate capital per worker. The controls we use - nighttime lights, urban share, and total population - may not be as useful in controlling for this. However, in the robustness checks using DHS data on assets, we do have controls that are explicitly measuring rural assets (livestock, etc..). As these results conform to our baseline, it does not appear that this assumption about mobile capital is driving our results.

A.3 Multiple labor types

Our empirical setting is not dependent on the assumption that all labor is homogenous. Allow the production function to have two kinds of labor, unskilled (U) and skilled (S). Agricultural production is then

$$Y_{Ais} = A_{Ais}X_{is}^{\beta}\left(K_{Ais}^{\phi}(U_{Ais}^{\theta}S_{Ais}^{1-\theta})^{1-\phi}\right)^{1-\beta} \tag{A.10}$$

where θ indicates their relative importance to production. Let producers profit maximize taking the relative price as given, as well as a separate wage for unskilled, w_{Uis}, and skilled w_{Sis} workers. Taking first order conditions, the district will employ a ratio of skilled to unskilled workers of

$$\frac{S_{Ais}}{U_{Ais}} = \frac{1 - \theta}{\theta} \frac{w_{Uis}}{w_{Sis}}. \tag{A.11}$$

Given the mobility assumptions, all districts will use the same ratio of skilled to unskilled workers. Call that ratio ω_{SU}. The total raw number of agricultural workers will be $L_{Ais} = S_{Ais} + U_{Ais}$. With this identity and the ratio of skilled to unskilled workers, production can be written

$$Y_{Ais} = A_{Ais} X_{is}^{\beta} \left(K_{Ais}^{\phi} (L_{Ais} \Omega_{As})^{1-\phi} \right)^{1-\beta} \tag{A.12}$$

where

$$\Omega_{As} = \left(\frac{1}{1 + \omega_{SU}} \right)^{\theta} \left(\frac{\omega_{SU}}{1 + \omega_{SU}} \right)^{1-\theta} \tag{A.13}$$

is a fixed term common to all districts in a state. Given that it is common to all districts, the Ω_{Ais} term drops out of our regressions. The production function can thus be examined just in terms of L_{Ais}, the raw number of agricultural workers.

A.4 Explicit two-sector model

In Section 2 of the paper we derived our estimation equation for β, and this was done using an aggregate agricultural production function, but without reference to any specific preferences. 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 state as a whole. We 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.

A.4.1 State-level agricultural and non-agricultural production

The agricultural sector operates as described in Section 2 of the main paper. We also continue with the assumptions made in the main paper, namely that $p_{Ais} = p_{As}$, $w_{Ais} = w_{Nis} = w_s$, and $r_{Ais} = r_{Nis}$. To that we add the assumption that $r_{Ais} = r_{Nis} = r_s$, or that capital is mobile across districts within a state.

These assumptions imply that $K_{Ais}/L_{Ais} = K_{Nis}/L_{Nis} = K_{is}/L_{is} = K_s/L_s$, or that the capital output ratio in each sector, in each district, is identical. This can be seen by examining equations (4) and (7) in the main paper, which show the capital output ratio of a sector in a district as proportion to the wage/rental ratio, which is identical across districts.

In equation (8) of the main paper, we derive the following expression relating the agricultural wage, district agricultural productivity, the district labor/land ratio, and the district capital/labor ratio. With the assumptions here on mobility of labor and capital, this can be re-written slightly as

$$w_s = (1 - \phi)(1 - \beta) p_{As} A_{Ais} \left(\frac{X_{is}}{L_{Ais}} \right)^{\beta} \left(\frac{K_s}{L_s} \right)^{\phi(1-\beta)}. \tag{A.14}$$

This equation holds for any two districts i and j. Hence we can find that

$$A_{Ais}\left(\frac{X_{is}}{L_{Ais}}\right)^{\beta} = A_{Ajs}\left(\frac{X_{js}}{L_{Ajs}}\right)^{\beta} \tag{A.15}$$

for any two districts. In addition, we know that $\sum_i L_{Ais} = L_{As}$. Combining the expression above with this summation, one can solve for

$$\frac{L_{Ajs}}{L_{As}} = \frac{A_{Ajs}^{1/\beta}X_{js}}{\sum_i A_{Ais}^{1/\beta}X_{is}} \tag{A.16}$$

which simply says that the fraction of the states agricultural workers that work in district j depends on the size of productivity and land in district j relative to the aggregate productivity and land in the state. As the capital/labor ratios are identical across all districts, the same expression describes the share of total agricultural capital that is employed in district j.

Based on the district-level production functions from (1) in the main paper, total agricultural supply in state s can be written as

$$Y_{As} = \sum_i A_{Ais}X_{is}^{\beta}\left(K_{Ais}^{\alpha}L_{Ais}^{1-\alpha}\right)^{1-\beta}. \tag{A.17}$$

Combine (A.16) and the equivalent expression for capital with (A.17) and we can solve for

$$Y_{As} = A_{As}\left(\frac{K_{As}}{L_{As}}\right)^{\alpha(1-\beta)}L_{As}^{1-\beta} \tag{A.18}$$

where

$$A_{As} = \left(\sum_j A_{js}^{1/\beta}X_{js}\right)^{\beta}$$

is the measure of aggregate agricultural total factor productivity for the province.

A similar process can be performed for non-agriculture. The aggregate production function for the state is given by

$$Y_{Ns} = A_{Ns}\left(\frac{K_{Ns}}{L_{Ns}}\right)^{\phi}L_{Ns}. \tag{A.19}$$

Note that because capital and labor are perfectly mobile, it will be the case that $A_{Ns} = max(A_{N1s},...,A_{NJs})$, where J is the number of districts in the state. That is, all non-agricultural activity will concentrate in the single district with the highest non-agricultural productivity. Given the data we presented on districts, this is not a terrible description of reality, in that many states in our data have mainly rural districts along with one or two significant urban (and hence heavily non-agricultural) districts. If we wanted to allow for more subtlety, we could introduce a fixed factor into non-agriculture, and this would generate a distribution of non-agricultural activity across districts.

A.4.2 Preferences and optimization

For preferences over those consumption goods, we follow **?**, who specifies a functional form for the indirect utility function that allows for analysis of structural change involving income effects.[1] This function results in non-linear Engel curves while still allowing for aggregation across individuals.

Let the amount of agricultural consumption done per person be c_A, the non-agricultural consumption be c_N, and M be the nominal income M. The nominal price of agricultural goods facing the consumer is P_A, and the nominal price of non-agricultural goods is P_N (and hence $p_A = P_A/P_N$). The budget constraint is $M = P_A c_A + P_N c_N$. The demand function for agricultural consumption by individuals with the Boppart preferences is

$$\ln c_A = \ln \theta_A + (1-\epsilon)\ln M + (\gamma - 1)\ln P_A + (\epsilon - \gamma)\ln P_N \qquad (A.20)$$

where θ_A is a preference parameter, and with $\gamma < 1$ implying a standard inverse relationship of price and quantity demanded. With $0 < \epsilon < 1$, these preferences imply that the income elasticity of agricultural demand is less than one, capturing Engel's Law. The specific indirect utility function for our model would be $V(P_A, P_N, M) = 1/\epsilon\,(M/P_N)^\epsilon - \theta_A/\gamma\,(P_A/P_N)^\gamma - 1/\epsilon + \theta_A/\gamma$.

A.4.3 Equilibrium

To go further, the most important assumption we make is that the share of output paid to agricultural land is zero. This simplifies the analysis, and ensures that the solutions are not driven by any connection of β to the share of output paid to land.

Total supply must equal total demand, so $Y_{As} = c_A L_s$ and $Y_{Ns} = c_N L_s$, where c_A and c_N are per-capita consumption of agricultural and non-agricultural goods, respectively, and L_s is the total population, with $L_s = L_{As} + L_{Ns}$.

Mobility between sectors ensures that, in nominal terms,

$$P_A \frac{Y_{As}}{L_{As}} = p_N \frac{Y_{Ns}}{L_{Ns}}. \qquad (A.21)$$

We can rearrange this to be

$$\frac{P_A c_A}{P_N c_N} = \frac{L_{As}}{L_{Ns}}, \qquad (A.22)$$

which shows that the relative amount of labor employed in agriculture and non-agriculture is equal to the relative expenditures on those goods. With the adding up conditions on state labor and the budget constraint for consumers, it follows that in log terms

$$\ln L_{As}/L_s = \ln P_A c_A / M. \qquad (A.23)$$

Turning to the demand function from (A.20), we can re-arrange that to

$$(1-\epsilon)\ln P_A c_A / M = \ln \theta_A + (\epsilon - \gamma)(\ln P_N - \ln P_A) - \epsilon \ln c_A.$$

Using the relationships in (A.22) and (A.23), we can find

$$(1-\epsilon)\ln L_{As}/L_s = \ln \theta_A + (\epsilon - \gamma)\left(\ln Y_{Ns}/L_{Ns} - \ln Y_{As}/L_{As}\right) - \epsilon\left(\ln Y_{As}/L_{As} + \ln L_{As}/L_s\right).$$

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[1] 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.

Collecting terms we have

$$\ln L_{As}/L_s = \ln \theta_A + (\epsilon - \gamma)\ln Y_{Ns}/L_{Ns} - \gamma \ln Y_{As}/L_{As}.$$

Using the production functions in (A.18) and (A.19), we can write this as

$$\ln L_{As}/L_s = \ln \theta_A + (\epsilon - \gamma)\ln\left(A_{Ns}(K_s/L_s)^\alpha\right) - \gamma \ln\left(A_{As}(K_s/L_s)^{\alpha(1-\beta)}L_{As}^{-\beta}\right) - \gamma\beta \ln L_s + \gamma\beta \ln L_s,$$

where we've added and subtracted the term involving L_s. At this point, what remains is to separate the productivity and capital terms using the logs, and then straightforward algebra to arrive at

$$\ln L_{As}/L_s = \ln \theta_A + \frac{\beta\gamma}{1-\beta\gamma}\ln L_s - \frac{\gamma}{1-\beta\gamma}\ln A_{As} + \frac{\gamma-\epsilon}{1-\beta\gamma}\ln A_{Ns} + \frac{\alpha(\beta\gamma-\epsilon)}{1-\beta\gamma}\ln K_s/L_s. \quad \text{(A.24)}$$

As we'll ultimately be interested in elasticities of the agricultural labor share with respect to other terms, we leave the expression in logs and the elasticities are easy to read off of the right-hand side.

For real income, in agricultural terms we have

$$y_s = \frac{M}{P_A} = c_A + \frac{P_N}{P_A}c_N.$$

Using (A.22) we can write this as

$$y_s = c_A + \frac{P_N c_N}{P_A c_A}c_A = c_A\left(1 + \frac{L_{Ns}}{L_{As}}\right) = c_A\frac{L_s}{L_{As}}.$$

Noting that $c_A = Y_{As}/L_s$, we have that

$$y_s = \frac{Y_{As}}{L_{As}} = A_{As}(K_s/L_s)^{\alpha(1-\beta)}(L_{As}/L_s)^{-\beta}L^{-\beta}.$$

At this point, we can use (A.24) to plug in for L_{As}/L_s, and solve for

$$\ln y_s = \frac{1}{1-\beta\gamma}\ln A_{As} - \frac{\beta}{1-\beta\gamma}\ln L_s + \frac{\beta(\epsilon-\gamma)}{1-\beta\gamma}\ln A_{Ns} + \frac{\alpha(1-\beta)+\alpha\beta(\epsilon-\gamma)}{1-\beta\gamma}\ln K_s/L_s. \quad \text{(A.25)}$$

Again, we leave this in log form to read off the elasticities.

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_{As}):* $\frac{\partial \ln L_{As}/L_s}{\partial \ln A_{As}} = -\frac{\gamma}{1-\beta\gamma}$ *and* $\frac{\partial \ln y_s}{\partial \ln A_{As}} = \frac{1}{1-\beta\gamma}$

(b) *Population (L_s):* $\frac{\partial \ln L_{As}/L_s}{\partial \ln L_s} = \frac{\beta\gamma}{1-\beta\gamma}$ *and* $\frac{\partial \ln y_s}{\partial \ln L_s} = -\frac{\beta}{1-\beta\gamma}$

(c) *Non-agricultural productivity (A_{Ns}):* $\frac{\partial \ln L_{As}/L_s}{\partial \ln A_{Ns}} = -\frac{\epsilon-\gamma}{1-\beta\gamma}$ *and* $\frac{\partial \ln y_s}{\partial \ln A_{Ns}} = \frac{\beta(\epsilon-\gamma)}{1-\beta\gamma}$

(d) *Capital/labor (K_s/L_s):* $\frac{\partial \ln L_A/L}{\partial \ln K_s/L_s} = -\frac{\alpha(\epsilon-\beta\gamma)}{1-\beta\gamma}$ *and* $\frac{\partial \ln y_s}{\partial \ln K_s/L_s} = \frac{\alpha\beta(\epsilon-\gamma)}{1-\beta\gamma}$

are both increasing in absolute value with β.

Proof. This follows from inspection of (A.24) and (A.25). ∎

This conforms to the intuition explained in the text. One note is that the *sign* of the elasticities with respect to agricultural productivity and population are unambiguous. Agricultural productivity lowers the agricultural labor share and raises real income per capita. To see this, note that $\gamma < 1$ so that the demand function is downward sloping, and so $1 - \beta\gamma > 0$. For population, an increase will raise the agricultural labor share, but decrease real income per capita.

The *sign* of the elasticities with respect to non-agricultural productivity and the capital/labor ratio are ambiguous, and depend on the relative size of γ and ϵ. If $\epsilon > \gamma$, then the cross-price elasticity of demand for agriculture is positive with respect to non-agriculture prices. In that case non-agricultural productivity will lower the agricultural labor share (as this productivity lowers the price of non-agricultural goods and people substitute towards them) while also raising real income per capita. For the capital/labor ratio, a similar logic holds. Regardless of the exact values, it is the case that the absolute size of the elasticities is increasing in β.

A.5 Adding Malthusian fertility responses

Our main model is static, taking the size of population (and capital) as given. By adding in a simple Malthusian fertility response, one can establish several results related to population density and the land elasticity.

Without specifying a particular utility function, let population growth from t to $t + 1$ be a function of income per capita in t

$$n_{t+1} = y_t^\theta$$

where $0 < \theta < 1$ so that population growth is a concave function of income per capita. The dynamics of population are thus

$$L_{t+1} = n_{t+1}L_t = \left(A_A A_N^{\beta(\epsilon-\gamma)} \hat{k}^\Omega \right)^{\frac{\theta}{1-\beta\gamma}} L_t^{\frac{1-\beta(\theta+\gamma)}{1-\beta\gamma}}.$$

Examining the exponent on L_t, it is clear that this is less than one, making L_{t+1} a concave function of L_t, and thus we have a stable steady state for population. Solving for that steady state by setting $L_{t+1} = L_t$ we have

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

From this, one can see the influence of agricultural productivity on population, and hence on population density. Note that the elasticity of steady state population with respect to A_A depends inversely on β. As the land elasticity gets larger, the effect of agricultural productivity on population size decreases. The positive Malthusian relationship of population size and (agricultural) productivity remains, but because the Malthusian constraint is much tighter when β is large, the relationship is not as strong as when β is small.

A.6 Demographic and Health Survey Data

In the main text, we used Demographic and Health Survey (DHS) data to create controls for demographics and assets at the district level. To do this, we started with all available DHS surveys for which latitude/longitude data was provided for the location of each cluster of surveyed individuals.

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For each survey, we overlaid these points on the map of 2nd-level political units (districts), creating a concordance of clusters to districts.

One note here is that for privacy reasons, the DHS perturbs the actual latitude/longitude point of a cluster by 10km in an arbitrary direction. Thus, for clusters very close to district borders, we may assign them to the incorrect district. Given the large number of clusters within any given district, and the fact that this is done randomly, we do not believe it creates any systematic errors in our ultimate district-level aggregates.

Having linked clusters to districts, we can then link all households in a survey to a district. For each district, we construct several measures of demographics and assets using this household data.

- **Demographics** We calculate the 10th, 50th, and 90th percentile values of the following household variables: years of education of household head (hv107-01), age of household head (hv220), and number of regular household members (hv012).

- **Assets** We calculate the mean value of the following dummy variables for household possession of the following assets: flush toilet (hv205), electricity (hv206), television (hv208), refrigerator (hv209), improved flooring (hv213), agricultural land (hv244), a bank account (hv247), any cattle (hv246a), any draft animals (hv246c), and any sheep (hv246e).

Detailed data on the number of agricultural hectares held, or counts of livestock held, are only available for a small number of recent surveys, so were not used. The mean values of the asset dummies thus indicate the percentage of households in a district that report having these assets. For the demographic data, the percentiles allow us a crude control for the distribution of education, age, and household size.

Given that there are countries which have been surveyed multiple time, we use the latest available survey from any given country. This is done because later surveys have more variables available, allowing us to control for more characteristics.

The specific country surveys that we draw from, and which have districts that fall into our temperate/tropical distinction, are: Albania (2008), Angola (2015), Benin (2012), Bolivia (2008), Burundi (2016), Democratic Republic of the Congo (2013), Cte d'Ivoire (2012), Cameroon (2011), Colombia (2010), Dominican Republic (2013), Ethiopia (2016), Gabon (2012), Guinea (2012), Guatemala (2015), Guyana (2009), Honduras (2011), Haiti (2012), India (2014), Jordan (2012), Cambodia (2014), Kyrgyzstan (2012), Myanmar (2015), Mozambique (2015), Nigeria (2015), Peru (2009), Philippines (2008), Rwanda (2014), Senegal (2015), Chad (2014), Togo (2013), Tajikistan (2012), Timor-Leste (2016), Tanzania (2015), Uganda (2016)

A.7 Alternative Population Data

As mentioned in the main text, we use alternative data sources for population beyond GRUMP.

A.7.1 HYDE Data

A secondary source is HYDE, which uses larger pixels (5 arc-minutes versus 30 arc-seconds for GRUMP). The district definitions are from GADM, identical to those used with the HYDE data, so we can compare the counts directly.

A.7.2 IPUMS Data

We use 39 countries that have both geographic identifier data (the GEOLEV2 variable from IPUMS) as well as information on individual industry of employment. We create a 0/1 variable indicating whether an individual is an agricultural worker (meaning they are reported as in the workforce). We then aggregate this variable (weighted by their IPUMS provided sampling weight) across individuals within a geographic area to get a count of the total agricultural workers. Using a similar method, we are also able to count the number of urban residents, which allows us to measure the percent urban within a geographic area. We end up with a total of 8,393 geographic areas.

Before we run regressions, the IPUMS data is useful in assessing how good of an approximation rural population (including workers and non-workers) is for the number of agricultural workers. The correlation of (log) rural residents and (log) agricultural workers across the areas is 0.91, significant at less than 1%. There are a few outliers where the number of agricultural workers is high relative to rural residents, which likely represents agricultural processing work in urban areas, or urban farmers with small plots. Our results are not affected by excluding these outliers.

The geographic areas provided by IPUMS in the GEOLEV2 variable are in many cases agglomerations of the districts we use from GADM. This is because IPUMS aggregates districts with fewer than 25000 observations (to protect anonymity) or districts whose boundaries have changed over time (so that the agglomerations are comparable over time for a given country). This means the IPUMS geographic areas are not directly comparable to our districts. Because the IPUMS agglomerations are much larger than districts, it is not practical to use province/state fixed effects, as most of these have only one or two IPUMS areas within them. Hence we run our regressions only with country fixed effects. Because the GEOLEV2 areas are different than the districts in our baseline specifications, we create new GEOLEV2 level versions of our caloric suitability index, night lights data, and other crop suitability measures.

The 39 countries included from IPUMS are, with the census date listed: Argentina (2001), Austria (2001), Bolivia (2001), Brazil (2000), Cambodia (1998), Cameroon (2005), Chile (2002), Colombia (2005), Costa Rica (2000), Ecuador (2001), El Salvador (2007), Fiji (1996), Ghana (2000), Greece (2001), Haiti (2003), India (1999), Iran (2006), Iraq (1997), Jordan (2004), Kyrghzstan (1999), Malawi (1998), Mexico (2000), Morocco (2004), Mozambique (1997), Panama (2000), Peru (2007), Sierra Leone (2004), South Africa (2001), Spain (2001), South Sudan (2008), Sudan (2008), Turkey (2000), Uganda (2002), Egypt (1996), Tanzania (2002), United States (2000), Burkina Faso (1996), Venezuela (2001), Zambia (2000)

A.8   Labor/land and β_g

We can examine how estimated values of β_g vary with labor/land ratios at the state level. We have estimated a separate β_g for each state in our dataset that contains 10 or more districts within it. In each case, we run the same regression as in (10) of the main paper, excluding the state 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 1 we plot the value of all these β_g estimates against the rural labor/land ratio of the state. These estimates are quite noisy, given that the average number of districts within a state is only 26. That does not represent an issue for our baseline resutls. Our baseline regressions with state fixed effects are effectively finding an efficient combination of these separate state-level estimates.

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 state gets more dense, although the effect is small. Doubling rural labor/land ratios only increase the estimated β_g by around 0.004. This positive relationship of the land elasticity and rural labor/land is consistent with land and labor being complements, not substitutes. If anything, the higher rural labor/land ratios 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 labor/land ratios.

A.9   Alternative measure of A_{isg}

The CSI index used as the baseline measure of A_{isg} combines the raw potential tonnage of production of specific crops with information on their calorie content so that one can compare the *caloric* yield of each crop within a given grid-cell. Then the maximum value of that caloric yield is selected across crops, and those maximums are aggregated across grid-cells in a district to arrive at the A_{isg} measure. This follows Galor and Ozak's (2016) methodology, but there may be an issue with using these calorie counts to compare crops. The calorie count of each crop may not be an accurate measure of the available calories from those crops, given storage and preparation techniques. A worry is that we may have created variation in A_{isg} because of variation in the calorie counts of crops, and that this is driving the results. For example, given paddy rice's very high caloric yield in the Galor and Ozak methodology, it is possible that we are overstating the productivity of districts that are in fact very un-productive from the perspective of farmers, but because they are capable of growing rice, Galor and Ozak have coded them as having very high productivity. This would bias our estimates of β down for these areas.

To see that this is not driving our results, we have performed separate regressions estiamting β where we use a single crop-specific raw yield from GAEZ as the measure of productivity (e.g. wheat or rice). In this case, there is no caloric information employed at all, as we are not trying to combine data across crops. Each district is thus measured on a comparable basis. Table A.5 shows these results. Panel A is for the temperate districts identified in the main paper as those capable of growing the temperate crops, while Panel B is for the tropical districts capable of growing tropical crops. In both panels, the first column replicates our baseline results from Table 2 of the main paper.

For temperate crops, the baseline estimate of β is 0.228. The next six columns show the estimated value of β if in place of the CSI yield from Galor and Ozak as the A_{isg} variable, we use the raw yield of the specified crop. For example, using just the raw yield of barley to measure A_{isg} in temperate districts, we find an estimated β of 0.225. Given that this is nearly identical to the baseline estimate, this indicates that the baseline is not driven simply by the caloric values assigned to barley versus other temperate crops. The rest of the columns show the same kind of result. In each case, the estimate of β is very close to 0.228, indicating that the CSI index is not driven by caloric information, but by common variation in the raw productivity of these crops across districts. In Panel B, a similar story is shown. The baseline estimate for the tropical districts is 0.132, while each of the separate columns delivers a result nearly identical, save pearl millet (although still at 0.145). Again, the baseline estimate using the CSI index is not driven simply by the use of calories to weight the different crops.

The implication of these results is that *any* scheme used to weight raw yields across crops is

going to deliver similar results regarding β. Prices, or alternative means of measuring nutritional quality, if used to construct A_{isg} would still show that temperate areas have larger land elasticities than tropical areas.

A.10 Climate zone results

For this, we use the Köppen-Geiger scheme, which classifies each grid cell on the planet on three dimensions. First are the *main climate* zones: equatorial (denoted with an "A"), arid (B), warm temperate (C), and snow (D).[2] Second, each grid-cell has a *precipitation* classification: fully humid (f), dry summers (s), dry winters (w), monsoonal (m), desert (D), and steppe (S). Finally, there is the *temperature* dimension: hot summers (a), warm summers (b), cool summers (c), hot arid (h), and dry arid (k).[3] Each grid cell thus receives either a three or two-part code. The area around Paris, for example, is "Cfb", meaning it is a warm temperate area, fully humid (rain throughout the year), with warm summers. The area near Saigon is "Aw", meaning it is equatorial, with dry winters. There is no separate temperature dimension assigned to equatorial zones, as it tends to be redundant.

What we do in Table A.2 is divide districts into regions based on their Köppen-Geiger classifications, as opposed to crop suitability or production data. We do this along each individual dimension (climate, precipitation, and temperature), including a district in a region if more than 66% of its land area falls in the given zone. For example, for the equatorial region, we include all districts in which 66% (or more) of their land area is classified as being in "A" in the Köppen-Geiger system, regardless of their precipitation or temperature codes. Narrowing down to very specific classifications ("Cfb", for example) is impractical because the number of districts becomes very small. Similar to the temperate/tropical regressions, the climate zone regions do not force heterogeneous districts to be lumped into single regions based on their nation.

A.11 Figures

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[2]There is another classification of climate, polar (E), but that covers only areas that are uninhabited for all intents and purposes.

[3]There are three other temperature classifications - extreme continental, polar frost, and polar tundra - that also cover only uninhabited areas.

Figure 1: Relationship of state-level β_g and Rural Labor/land Ratio
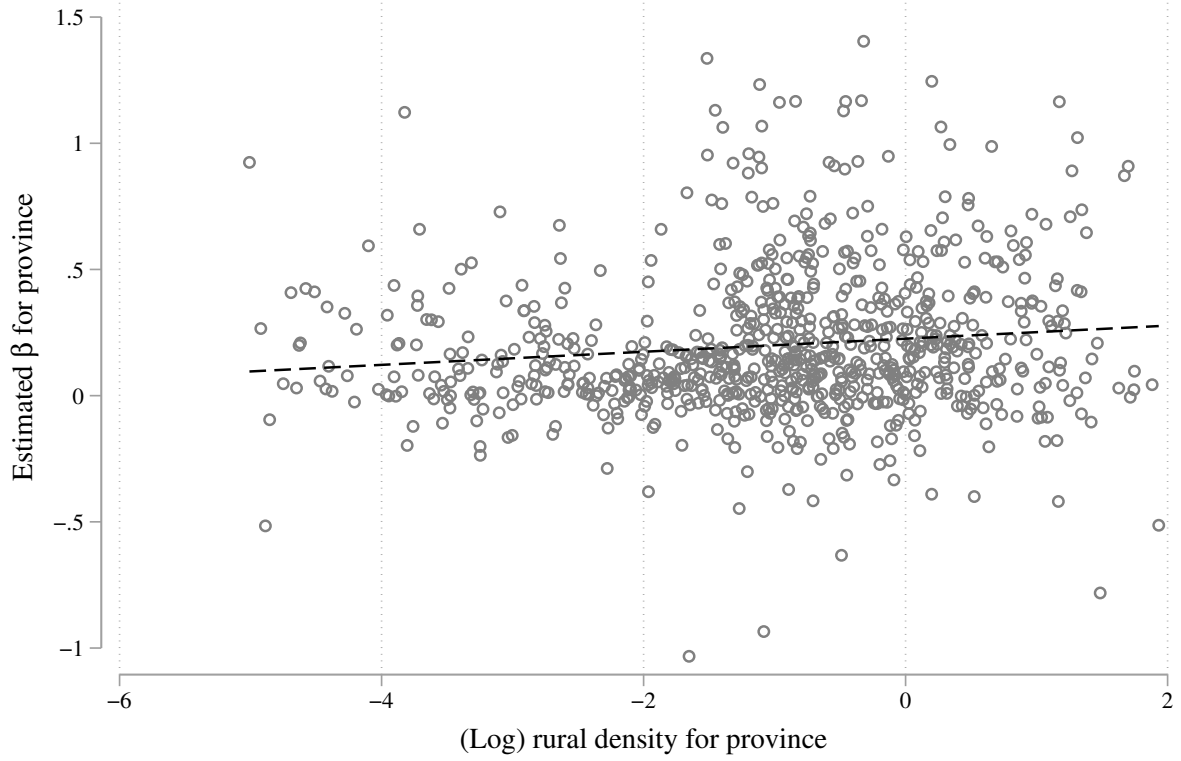
Notes: Plotted are the values of β_g estimated for each individual state in our dataset that contains 10 or more districts. The specification for these regressions is equation (**??**), and includes the controls for (log) night lights, (log) total population, and the percent urban. The value of rural labor/land for a state is total rural population of the state divided by total land area of the state.

A.12 Robustness Tables

List of Tables

Table A.1: Estimates of β using individual crop productivity terms

Panel A: Using only temperate districts defined by crop suitability

Dependent variable is A_{isg} measured by:

	CSI (1)	Barley (2)	Buckwheat (3)	Oats (4)	Rye (5)	W. Pot. (6)	Wheat (7)
Log labor/land ratio (β_g)	0.245 (0.043)	0.234 (0.042)	0.228 (0.048)	0.239 (0.052)	0.223 (0.045)	0.247 (0.052)	0.236 (0.042)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Countries	84	84	63	62	62	84	84
Observations	9404	9382	8459	8524	8503	9362	9383
R-square (ex. FE)	0.25	0.22	0.21	0.24	0.23	0.23	0.23

Panel B: Using only tropical districts defined by crop suitability

Dependent variable is A_{isg} measured by:

	CSI (1)	Cassava (2)	Cowpea (3)	P. Millet (4)	Sw. Pot. (5)	Wet Rice (6)	Yams (7)
Log labor/land ratio (β_g)	0.093 (0.019)	0.113 (0.026)	0.089 (0.022)	0.066 (0.031)	0.101 (0.020)	0.149 (0.047)	0.113 (0.024)
p-value $\beta = 0$	0.000	0.000	0.000	0.034	0.000	0.002	0.000
Countries	76	71	75	71	75	70	74
Observations	7229	7061	7223	6802	7219	6731	7183
R-square (ex. FE)	0.13	0.13	0.11	0.04	0.13	0.10	0.14

The panels differ in the districts included in each regression. In Panel A, only districts that are suitable for temperate agriculture are included (based on the criteria we outline in the paper based on GAEZ suitability measures). In Panel B, on tropical districts are included. The columns differ by the variable used to measure A_{isg}, inherent agricultural productivity. Column (1) uses the CSI index from Galor and Ozak (2016), as in our baseline results. Columns (2)-(7) use the raw potential yield (in tonnes) of the crop, from the GAEZ, for the crop specified. Additional controls are as in our basline results, and include province fixed effects. Conley standard errors, adjusted for spatial auto-correlation, are shown in parentheses.

Table A.2: Estimates of Land Elasticity, β, by Köppen-Geiger Zone, 2000CE

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

Panel A: Climate Zones

	Equatorial (1)	Arid (2)	Temperate (3)	Snow (4)
Log labor/land ratio (β_g)	0.090 (0.017)	0.142 (0.034)	0.153 (0.025)	0.252 (0.063)
p-value $\beta = 0$	0.000	0.000	0.000	0.000
p-value $\beta = \beta_{Equa}$		0.172	0.017	0.012
Countries	76	53	90	39
Observations	9345	2237	12291	5373
R-square (ex. FE)	0.13	0.11	0.17	0.19

Panel B: Precipitation Zones

	Fully Humid (1)	Dry Summer (2)	Dry Winter (3)	Monsoon (4)	Desert (5)	Steppe (6)
Log labor/land ratio (β_g)	0.186 (0.040)	0.167 (0.045)	0.091 (0.020)	0.069 (0.029)	0.106 (0.062)	0.153 (0.034)
p-value $\beta = 0$	0.000	0.000	0.000	0.019	0.088	0.000
p-value $\beta = \beta_{Humid}$		0.760	0.048	0.016	0.286	0.518
Countries	89	39	70	35	28	51
Observations	14862	2690	8141	1360	206	1961
R-square (ex. FE)	0.22	0.22	0.19	0.21	0.22	0.21

Panel C: Temperature Zones

	Hot Summer (1)	Warm Summer (2)	Cool Summer (3)	Hot Arid (4)	Cold Arid (5)
Log labor/land ratio (β_g)	0.142 (0.021)	0.226 (0.053)	0.207 (0.076)	0.140 (0.035)	0.190 (0.046)
p-value $\beta = 0$	0.000	0.000	0.007	0.000	0.000
p-value $\beta = \beta_{Humid}$		0.065	0.405	0.969	0.254
Countries	57	82	18	42	25
Observations	8101	9003	340	1230	956
R-square (ex. FE)	0.20	0.23	0.20	0.17	0.21

Notes: Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include province fixed effects, a constant, and controls for the district urbanization rate and log density of district nighttime lights. The coefficient estimate on rural population density indicates the value of β_g. Inclusion of districts is based on whether they have more than 50% of their land area in the given Köppen-Geiger zone. See text for details.

Table A.3: Country-level aggregate land elasticity estimates, from grid-cell level

Country	β	Country	β	Country	β	Country	β
Afghanistan	0.191	Denmark	0.239	Libya	0.136	Saint Vincent a	0.088
Akrotiri and Dh	0.239	Djibouti	0.088	Liechtenstein	0.239	Samoa	0.089
Albania	0.183	Dominica	0.088	Lithuania	0.239	San Marino	0.128
Algeria	0.155	Dominican Repub	0.103	Luxembourg	0.239	Saudi Arabia	0.123
American Samoa	0.088	Ecuador	0.127	Macao	0.128	Senegal	0.088
Andorra	0.239	Egypt	0.127	Macedonia	0.194	Serbia	0.194
Angola	0.126	El Salvador	0.089	Madagascar	0.115	Sierra Leone	0.088
Anguilla	0.088	Equatorial Guin	0.089	Malawi	0.124	Singapore	0.088
Antigua and Bar	0.088	Eritrea	0.101	Malaysia	0.088	Sint Maarten	0.088
Argentina	0.155	Estonia	0.239	Mali	0.091	Slovakia	0.236
Armenia	0.237	Ethiopia	0.121	Malta	0.128	Slovenia	0.234
Aruba	0.088	Fiji	0.091	Martinique	0.088	Solomon Islands	0.088
Australia	0.149	Finland	0.239	Mauritania	0.090	Somalia	0.090
Austria	0.239	France	0.221	Mauritius	0.111	South Africa	0.157
Azerbaijan	0.172	French Guiana	0.088	Mayotte	0.088	South Korea	0.168
Bahamas	0.096	Gabon	0.088	Mexico	0.137	South Sudan	0.088
Bahrain	0.128	Gambia	0.088	Moldova	0.217	Spain	0.182
Bangladesh	0.126	Georgia	0.189	Mongolia	0.239	Sri Lanka	0.090
Barbados	0.088	Germany	0.239	Montenegro	0.204	Sudan	0.091
Belarus	0.239	Ghana	0.088	Montserrat	0.088	Suriname	0.088
Belgium	0.239	Greece	0.176	Morocco	0.163	Swaziland	0.136
Belize	0.093	Grenada	0.088	Mozambique	0.109	Sweden	0.239
Benin	0.088	Guadeloupe	0.088	Myanmar	0.114	Switzerland	0.238
Bhutan	0.189	Guatemala	0.120	Namibia	0.137	Syria	0.210
Bolivia	0.113	Guernsey	0.239	Nepal	0.150	So Tom and	0.091
Bonaire, Sint E	0.088	Guinea	0.089	Netherlands	0.239	Taiwan	0.143
Bosnia and Herz	0.215	Guinea-Bissau	0.088	New Caledonia	0.115	Tajikistan	0.180
Botswana	0.112	Guyana	0.088	New Zealand	0.239	Tanzania	0.111
Brazil	0.096	Haiti	0.093	Nicaragua	0.089	Thailand	0.094
British Virgin	0.088	Honduras	0.099	Niger	0.088	Timor-Leste	0.091
Brunei	0.088	Hong Kong	0.128	Nigeria	0.088	Togo	0.088
Bulgaria	0.202	Hungary	0.201	North Korea	0.229	Tonga	0.088
Burkina Faso	0.088	India	0.112	Northern Cyprus	0.202	Trinidad and To	0.088
Burundi	0.145	Indonesia	0.091	Norway	0.239	Tunisia	0.132
Cambodia	0.088	Iran	0.205	Oman	0.090	Turkey	0.196
Cameroon	0.090	Iraq	0.168	Pakistan	0.147	Turkmenistan	0.227
Canada	0.238	Ireland	0.239	Palestina	0.181	Turks and Caico	0.088
Cape Verde	0.096	Isle of Man	0.239	Panama	0.091	Uganda	0.099
Caspian Sea	0.215	Israel	0.194	Papua New Guine	0.097	Ukraine	0.237
Cayman Islands	0.088	Italy	0.158	Paraguay	0.120	United Arab Emi	0.143
Central African	0.088	Jamaica	0.088	Peru	0.119	United Kingdom	0.239
Chad	0.088	Japan	0.162	Philippines	0.090	United States	0.182
Chile	0.233	Jersey	0.239	Poland	0.239	Uruguay	0.128
China	0.175	Jordan	0.220	Portugal	0.151	Uzbekistan	0.226
Colombia	0.102	Kazakhstan	0.238	Puerto Rico	0.090	Vanuatu	0.091
Comoros	0.094	Kenya	0.107	Qatar	0.128	Venezuela	0.092
Costa Rica	0.101	Kosovo	0.226	Republic of Con	0.088	Vietnam	0.110
Croatia	0.184	Kuwait	0.128	Reunion	0.153	Virgin Islands,	0.088
Cuba	0.088	Kyrgyzstan	0.238	Romania	0.205	Western Sahara	0.101
Curaao	0.088	Laos	0.115	Russia	0.237	Yemen	0.088
Cyprus	0.227	Latvia	0.239	Rwanda	0.200	Zambia	0.127
Czech Republic	0.239	Lebanon	0.191	Saint Kitts and	0.088	Zimbabwe	0.125
Cte d'Ivoire	0.088	Lesotho	0.225	Saint Lucia	0.088	land	0.239
Democratic Repu	0.095	Liberia	0.088	Saint Pierre an	0.239	.	

Notes: This table reports the aggregated value of the land elasticity, β, for each country. The aggregate value is a weighted average of the value for tropical pixels (0.088), temperate pixels (0.239), and "both" pixels (0.131) that can grow both tropical and temperate crops. The weights in the average are the maximum calories that can be produced in a pixel relative to the maximum calories that can be produced by all pixels in the country.

Table A.4: Estimates of β for cash crops

| | Dependent variable is A_{isg} measured for: | | | | | |
	Banana (1)	Coffee (2)	Cotton (3)	Sugarcane (4)	Tea (5)	Tobacco (6)
Log rural density	0.197 (0.046)	0.152 (0.034)	0.178 (0.032)	0.139 (0.028)	0.267 (0.064)	0.152 (0.038)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
Countries	26	24	35	26	38	54
Observations	598	643	1078	745	615	1088
Harv. perc. min	0.23	0.50	0.46	0.67	0.06	0.25

Each column is the result of a regression of the (log) productivity of the specified cash crop on the labor/land ratio. Districts included in each column are those where the percent of total harvested area in the specified crop is above the 99th percentile for the percent across all districts in our dataset. State fixed effects are included, as our our standard controls for (log) night lights, (log) total population, and the urban percent. Standard errors clustered at the state level are reported.

Table A.5: Estimates of β for terrain classes

	Dependent variable is A_{isg}^{GAEZ}:					
	Excluding districts with terrain index:					
	Below 1st ptile:		Below 5th ptile:		Below 25th ptile:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log labor/land ratio (β_g)	0.233	0.089	0.213	0.088	0.179	0.078
	(0.047)	(0.020)	(0.044)	(0.020)	(0.031)	(0.018)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.004		0.009		0.005
Countries	84	76	80	76	71	73
Observations	9284	7224	8822	7151	6977	6377
R-square (ex. FE)	0.24	0.20	0.23	0.19	0.23	0.18

Sets of regressions differ by exclusion of districts based on their terrain index (GAEZ). A lower terrain index indicates a more rugged terrain, so the regressions are exluding rugged areas, and including only flatter districts. State fixed effects are included, as our our standard controls for (log) night lights, (log) total population, and the urban percent. Standard errors clustered at the state level are reported.