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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 is 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

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

and our estimation would be based on

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

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 Specification with a wage/rent wedge included

In our main setting, we allowed for a "revenue" wedge on agriculture and non-agricultural production, but not a separate wage or rental rate wedge. If we go back to the profit function for agriculture and add a state-level wage wedge

$$\pi_{Ai} = (1-\tau_{Asi})p_{As}Y_{Ais} - (1+\tau_{sw})w_{Ais}L_{Ais} - r_{Ais}K_{Ais}, \tag{A.10}$$

we can re-solve the problem with this in place. Note that we do not need a separate capital wedge, as this will be redundant in creating a gap in the factor costs to the agricultural producers.

First order conditions for the producers are now

$$\begin{aligned} w_{Ais} &= (1-\phi)(1-\beta)\frac{(1-\tau_{Asi})}{(1+\tau_{sw})}p_{As}\frac{Y_{Ais}}{L_{Ais}} \qquad \text{(A.11)} \\ r_{Ais} &= \phi(1-\beta)(1-\tau_{Asi})p_{As}\frac{Y_{Ais}}{K_{Ais}}. \end{aligned}$$

which results in a capital/labor ratio of

$$\frac{K_{Ais}}{L_{Ais}} = (1+\tau_{sw})\frac{\phi}{1-\phi}\frac{w_{Ais}}{r_{Ais}}. \tag{A.12}$$

τ_{sw} scales up wages (or lowers them if negative) and in response producers choose a higher capital/labor ratio, no different than if the wage were higher.

If the non-agricultural sector faces the same τ_{sw} wage wedge, then from this point forward nothing changes in our model. Both sectors choose the same capital/labor ratio, and that capital/labor ratio is equal to the district aggregate capital/labor ratio, K_{is}/L_{is}, which we then have to control for in our regressions.

If the non-agricultural sector faces a different τ_{sw} wedge, then this complicates the model slightly. The capital/labor ratios in the two sectors would be

$$\frac{K_{Ais}}{L_{Ais}} = (1+\tau_{Asw})\frac{\phi}{1-\phi}\frac{w_{Ais}}{r_{Ais}} \tag{A.13}$$

$$\frac{K_{Nis}}{L_{Nis}} = (1+\tau_{Nsw})\frac{\phi}{1-\phi}\frac{w_{Nis}}{r_{Nis}}. \tag{A.14}$$

They remain proportional, with

$$\frac{K_{Ais}}{L_{Ais}} = \frac{(1+\tau_{Asw})}{(1+\tau_{Nsw})}\frac{K_{Nis}}{L_{Nis}}. \tag{A.15}$$

Without being identical, we cannot replace K_{Ais}/L_{Ais} with the aggregate capital/labor ratio, and the equilibrium condition underlying our empirical specification (equation 8 in the main paper) is

$$w_{As} = (1-\phi_A)(1-\beta)(1-\tau_{Asi})p_{As}A_{Ais}\left(\frac{X_{is}}{L_{Ais}}\right)^{\beta}\left(\frac{K_{Ais}}{L_{Ais}}\right)^{\phi_A(1-\beta)}. \tag{A.16}$$

This means our specification equation for the empirics can be written as

$$\ln A_{Ais} = \beta \ln L_{Ais}/X_{is} - \phi_A(1-\beta)\ln K_{Ais}/L_{Ais} - \ln(1-\tau_{Asi}) - \ln w_{As}/p_{As} + \ln(1-\phi_A)(1-\beta), \tag{A.17}$$

and shows that we need some control for agricultural capital/labor ratios. This is identical to the issue raised by having different ϕ values by sector, discussed in the following section.

Our results using DHS controls (Table 6 in the main paper) include specific measures of agricultural capital, and our results are consistent (if not indicating a larger spread between temperate and tropical). In addition, even if one believes that our night lights, road density, total population, and urban share controls are measures of the non-agricultural capital/labor ratio, they still provide a control for agricultural capital/labor ratios given that the two ratios are proportional. That is, the variation across districts in non-agricultural capital/labor ratios is still informative about agricultural capital/labor ratios even if the level of the two ratios is not identical.

A.4 Specification with different capital elasticities

One assumption in our main model is that there is a common ϕ parameter governing the elasticity of output to capital (and labor) in both agriculture and non-agriculture. If there were in fact different parameters, our model would still lead to a similar empirical specification. To see this, let agricultural production be

$$Y_{Ais} = A_{Ais} X_{is}^{\beta} \left(K_{Ais}^{\phi_A} L_{Ais}^{1-\phi_A} \right)^{1-\beta} \tag{A.18}$$

and non-agricultural production be

$$Y_{Nis} = A_{Nis} K_{Nis}^{\phi_N} L_{Nis}^{1-\phi_N}. \tag{A.19}$$

With the same profit-maximization problem taken by each sector as in our baseline model, we would arrive at the following capital/labor ratios in the two sectors,

$$\frac{K_{Ais}}{L_{Ais}} = \frac{\phi_A}{1-\phi_A} \frac{w_{Ais}}{r_{Ais}} \tag{A.20}$$

$$\frac{K_{Nis}}{L_{Nis}} = \frac{\phi_N}{1-\phi_N} \frac{w_{Nis}}{r_{Nis}}. \tag{A.21}$$

Now, even with the assumption that $w_{Ais} = w_{Nis}$ and $r_{Ais} = r_{Nis}$ the capital/labor ratios will not be identical across the two sectors. We have that

$$\frac{K_{Ais}}{L_{Ais}} = \frac{\phi_A}{1-\phi_A} \frac{1-\phi_N}{\phi_N} \frac{K_{Nis}}{L_{Nis}}. \tag{A.22}$$

They are proportional, but not identical.

Without being identical, we cannot replace K_{Ais}/L_{Ais} with the aggregate capital/labor ratio, and the equilibrium condition underlying our empirical specification (equation 8 in the main paper) is

$$w_{As} = (1-\phi_A)(1-\beta)(1-\tau_{Asi}) p_{As} A_{Ais} \left(\frac{X_{is}}{L_{Ais}} \right)^{\beta} \left(\frac{K_{Ais}}{L_{Ais}} \right)^{\phi_A(1-\beta)}. \tag{A.23}$$

This means our specification equation for the empirics can be written as

$$\ln A_{Ais} = \beta \ln L_{Ais}/X_{is} - \phi_A(1-\beta) \ln K_{Ais}/L_{Ais} - \ln(1-\tau_{Asi}) - \ln w_{As}/p_{As} + \ln(1-\phi_A)(1-\beta), \tag{A.24}$$

and shows that we need some control for agricultural capital/labor ratios. This is the identical problem to assuming different wage/rental wedges in agriculture and non-agriculture, discussed in the prior section.

Our results using DHS controls (Table 6 in the main paper) include specific measures of agricultural capital, and our results are consistent (if not indicating a larger spread between temperate and tropical). In addition, even if one believes that our night lights, road density, total population, and urban share controls are measures of the non-agricultural capital/labor ratio, they still provide a control for agricultural capital/labor ratios given that the two ratios are proportional. That is, the variation across districts in non-agricultural capital/labor ratios is still informative about agricultural capital/labor ratios even if the level of the two ratios is not identical.

A.5 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

$$Y_{Ais} = A_{Ais} X_{is}^{\beta} \left(K_{Ais}^{\phi} (U_{Ais}^{\theta} S_{Ais}^{1-\theta})^{1-\phi} \right)^{1-\beta} \tag{A.25}$$

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

$$\frac{S_{Ais}}{U_{Ais}} = \frac{1-\theta}{\theta} \frac{w_{Uis}}{w_{Sis}}. \tag{A.26}$$

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

$$Y_{Ais} = A_{Ais} X_{is}^{\beta} \left(K_{Ais}^{\phi} (L_{Ais} \Omega_{As})^{1-\phi} \right)^{1-\beta} \tag{A.27}$$

where

$$\Omega_{As} = \left(\frac{1}{1+\omega_{SU}} \right)^{\theta} \left(\frac{\omega_{SU}}{1+\omega_{SU}} \right)^{1-\theta} \tag{A.28}$$

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.6 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.6.1 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

$$w_s = (1-\phi)(1-\beta)p_{As}A_{Ais}\left(\frac{X_{is}}{L_{Ais}}\right)^{\beta}\left(\frac{K_s}{L_s}\right)^{\phi(1-\beta)}. \tag{A.29}$$

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

$$A_{Ais}\left(\frac{X_{is}}{L_{Ais}}\right)^{\beta} = A_{Ajs}\left(\frac{X_{js}}{L_{Ajs}}\right)^{\beta} \tag{A.30}$$

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

$$\frac{L_{Ajs}}{L_{As}} = \frac{A_{Ajs}^{1/\beta}X_{js}}{\sum_i A_{Ais}^{1/\beta}X_{is}} \tag{A.31}$$

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

$$Y_{As} = \sum_i A_{Ais}X_{is}^{\beta}\left(K_{Ais}^{\alpha}L_{Ais}^{1-\alpha}\right)^{1-\beta}. \tag{A.32}$$

Combine (A.31) and the equivalent expression for capital with (A.32) and we can solve for

$$Y_{As} = A_{As}\left(\frac{K_{As}}{L_{As}}\right)^{\alpha(1-\beta)}L_{As}^{1-\beta} \tag{A.33}$$

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

$$Y_{Ns} = A_{Ns} \left(\frac{K_{Ns}}{L_{Ns}} \right)^{\phi} L_{Ns}. \tag{A.34}$$

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.6.2 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

$$\ln c_A = \ln \theta_A + (1 - \epsilon) \ln M + (\gamma - 1) \ln P_A + (\epsilon - \gamma) \ln P_N \tag{A.35}$$

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.6.3 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,

$$P_A \frac{Y_{As}}{L_{As}} = p_N \frac{Y_{Ns}}{L_{Ns}}. \tag{A.36}$$

We can rearrange this to be

$$\frac{P_A c_A}{P_N c_N} = \frac{L_{As}}{L_{Ns}}, \tag{A.37}$$

[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.

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

$$\ln L_{As}/L_s = \ln P_A c_A/M. \tag{A.38}$$

Turning to the demand function from (A.35), 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.37) and (A.38), we can find

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

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.33) and (A.34), 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

$$\ln L_{As}/L_s = \ln\theta_A + \frac{\beta\gamma}{1-\beta\gamma}\ln L_s - \frac{\gamma}{1-\beta\gamma}\ln A_{As} + \frac{\gamma-\epsilon}{1-\beta\gamma}\ln A_{Ns} + \frac{\alpha(\beta\gamma-\epsilon)}{1-\beta\gamma}\ln K_s/L_s. \tag{A.39}$$

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.37) 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.39) to plug in for L_{As}/L_s, and solve for

$$\ln y_s = \frac{1}{1-\beta\gamma}\ln A_{As} - \frac{\beta}{1-\beta\gamma}\ln L_s + \frac{\beta(\epsilon-\gamma)}{1-\beta\gamma}\ln A_{Ns} + \frac{\alpha(1-\beta)+\alpha\beta(\epsilon-\gamma)}{1-\beta\gamma}\ln K_s/L_s. \tag{A.40}$$

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.39) and (A.40). ■

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.7 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.8 GAEZ productivity measures and A_{Ais}

Our empirics rely on the specification that

$$\ln A_{Ais} = \ln A_{As} + \ln A_{Ais}^{GAEZ} + \epsilon_{is}, \tag{A.41}$$

which implies that A_{Ais}^{GAEZ} and A_{Ais} have an elasticity of exactly one with respect to one another. We justify this from the construction of the underlying GAEZ measures of agro-climatic yields which are used to calculate A_{Ais}^{GAEZ}.

First, note that A_{Ais}^{GAEZ} is measured as a yield (output per hectare), and most important, it is calculated holding input per hectare constant (low, medium, or high input use). Thus a one-percent variation in A_{Ais}^{GAEZ} is measuring a one-percent variation in yield for a given set of inputs per hectare. The theoretical object A_{Ais} is Hicks-neutral TFP. By definition, a one-percent variation in A_{Ais} is associated with a one-percent variation in yield, again holding input use constant. As the elasticity of both A_{Ais}^{GAEZ} and A_{Ais} with respect to yields is one, their elasticity with respect to one another must be equal to one as well.

What does it mean that GAEZ holds inputs constant in their calculations? First, GAEZ calculates the maximum agro-climatic attainable yield for each crop, which is based on raw energy (sunlight) and available water (evapotranspiration). This represents an upper bound for each pixel, regardless of technologies employed or inputs applied. Second, GAEZ calculates a series of constraints for each pixel that keep yields from reaching those maximums. Examples are high slopes, unworkable soils, or a lack of soil nutrients. Each of these constraints applies some kind of multiplier less than one to the maximum yield. For example, very high slopes might mean a multiplier of 0.25, meaning the pixel can only reach 25% of the theoretical maximum.

Inputs in GAEZ are a way of alleviating constraints. Terraces, plows, and fertilizer are ways of making up for high slopes, unworkable soil, or a lack of soil nutrients, respectively. Each level of input use changes the constraint multiplier. Low input use might move the slope constraint from 0.25 to 0.5, while medium inputs move the slope constraint to 0.75, and high inputs move the slope constraint to 1.0, meaning that high inputs alleviate the entire constraint posed by high slopes.

Not all pixels, and therefore not all districts, have identical constraints. And thus the actual amount of input used within a district, even for the same input level (low, medium, and high) might differ. To ensure that this variation is not driving our results, we have looked at the robustness of our results once we control for the explicit constraints that GAEZ uses in their calculations. The specific constraints we identify from the GAEZ methodology as central are: dummies for soil nutrient availability, dummies for soil nutrient retention, dummies for soil workability, dummies for precipitation/evapotranspiration rates, dummies for the slope class, and dummies for the length of growing period.

In Table A.6 we show the results from including all of these constraints in our regressions as controls. The baseline results in columns (1) and (2) show a similar gap between temperate and tropical elasticities, 0.265 to 0.128. When we eliminate districts with urban population more than 50,000, or exclude North American and Europe, the results are nearly identical to our baseline results from the main paper. Variation in constraints across districts is not causing any distinct bias in our estimates.

A.9 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. 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.10 Alternative Population Data

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

A.10.1 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.10.2 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.11 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.12 Alternative measure of A_{isg}^{GAEZ}

The CSI index used as the baseline measure of A_{isg}^{GAEZ} 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}^{GAEZ} 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}^{GAEZ} 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.1 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}^{GAEZ} variable, we use the raw yield of the specified crop. For example, using just the raw yield of barley to measure A_{isg}^{GAEZ} 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}^{GAEZ} would still show that temperate areas have larger land elasticities than tropical areas.

A.13 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.

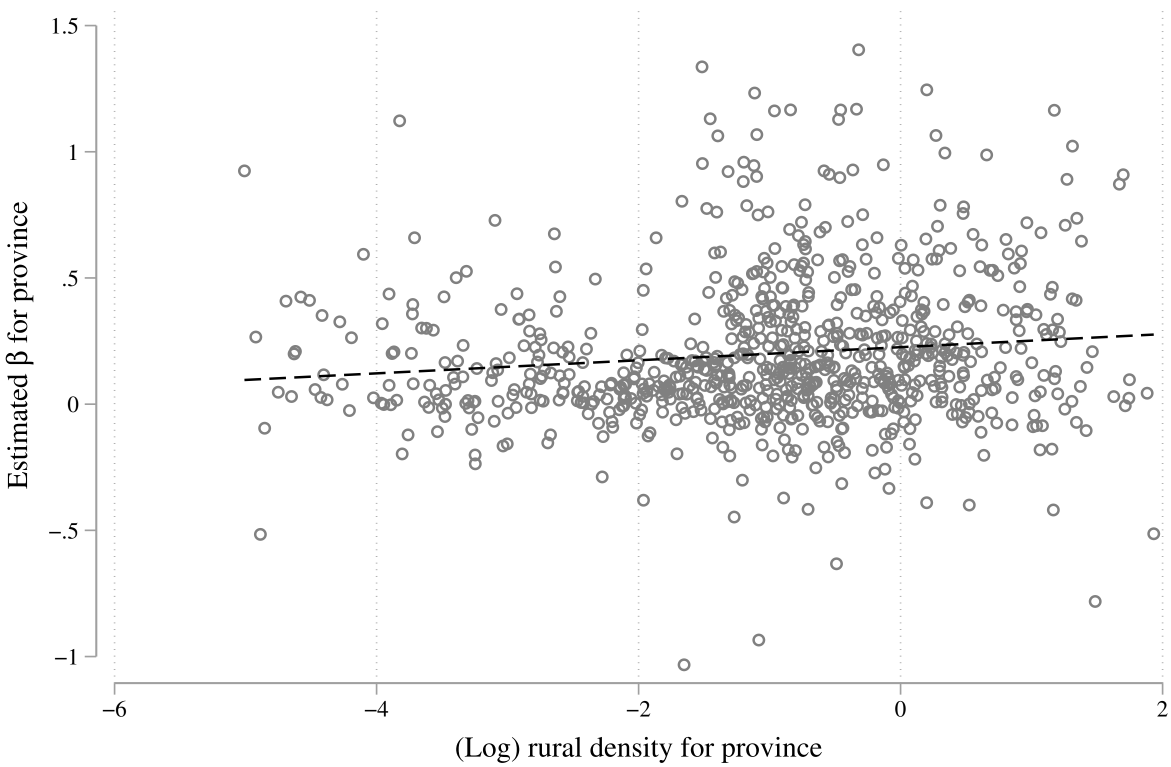
What we do in Table A.2 is divide districts into regions based on their Köppen-Geiger classifications, as opposed to crop suitability or production data. We do this along each individual dimension (climate, precipitation, and temperature), including a district in a region if more than 66% of its land 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.14 Figures

[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 (10), 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.15 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}^{GAEZ} 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}^{GAEZ} 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 inclueded (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. All regressions include state fixed effects, a constant, and controls for the district urbanization rate, log density of district nighttime lights, log total population, log road density, share of roads of different types, distance to nearest city of 100,000 people, and a log slope index. 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}^{GAEZ})

Panel A: Climate Zones

	Equatorial (1)	Arid (2)	Temperate (3)	Snow (4)
Log labor/land ratio (β_g)	0.123	0.115	0.212	0.287
	(0.020)	(0.033)	(0.029)	(0.057)
p-value $\beta = 0$	0.000	0.000	0.000	0.000
p-value $\beta = \beta_{Equa}$		0.829	0.006	0.007
Countries	69	51	86	34
Observations	8791	1977	11106	4921
R-square (ex. FE)	0.09	0.07	0.12	0.14

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)	0.240	0.215	0.124	0.125	0.130	0.147
	(0.044)	(0.063)	(0.022)	(0.039)	(0.072)	(0.029)
p-value $\beta = 0$	0.000	0.001	0.000	0.001	0.072	0.000
p-value $\beta = \beta_{Humid}$		0.739	0.020	0.043	0.190	0.072
Countries	78	37	67	32	20	49
Observations	13545	2373	7695	1267	146	1735
R-square (ex. FE)	0.17	0.17	0.15	0.17	0.17	0.16

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)	0.194	0.285	0.213	0.146	0.140
	(0.030)	(0.054)	(0.084)	(0.039)	(0.046)
p-value $\beta = 0$	0.000	0.000	0.011	0.000	0.002
p-value $\beta = \beta_{Humid}$		0.044	0.795	0.334	0.224
Countries	52	75	15	41	21
Observations	7343	8192	297	1114	815
R-square (ex. FE)	0.14	0.18	0.13	0.12	0.14

Notes: Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include state fixed effects, a constant, and controls for the district urbanization rate, log density of district nighttime lights, log total population, log road density, share of roads of different types, distance to nearest city of 100,000 people, and a log slope index. 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	0.234	Denmark	0.285	Libya	0.176	Saint Vincent a	0.126
Akrotiri and Dh	0.285	Djibouti	0.126	Liechtenstein	0.285	Samoa	0.127
Albania	0.226	Dominica	0.126	Lithuania	0.285	San Marino	0.167
Algeria	0.196	Dominican Repub	0.142	Luxembourg	0.285	Saudi Arabia	0.162
American Samoa	0.126	Ecuador	0.167	Macao	0.167	Senegal	0.126
Andorra	0.285	Egypt	0.166	Macedonia	0.237	Serbia	0.237
Angola	0.165	El Salvador	0.127	Madagascar	0.154	Sierra Leone	0.126
Anguilla	0.126	Equatorial Guin	0.127	Malawi	0.163	Singapore	0.126
Antigua and Bar	0.126	Eritrea	0.139	Malaysia	0.126	Sint Maarten	0.126
Argentina	0.195	Estonia	0.285	Mali	0.129	Slovakia	0.282
Armenia	0.283	Ethiopia	0.160	Malta	0.167	Slovenia	0.280
Aruba	0.126	Fiji	0.129	Martinique	0.126	Solomon Islands	0.126
Australia	0.189	Finland	0.285	Mauritania	0.128	Somalia	0.128
Austria	0.285	France	0.266	Mauritius	0.149	South Africa	0.198
Azerbaijan	0.214	French Guiana	0.126	Mayotte	0.126	South Korea	0.209
Bahamas	0.134	Gabon	0.126	Mexico	0.177	South Sudan	0.126
Bahrain	0.167	Gambia	0.126	Moldova	0.262	Spain	0.224
Bangladesh	0.164	Georgia	0.232	Mongolia	0.285	Sri Lanka	0.128
Barbados	0.126	Germany	0.285	Montenegro	0.248	Sudan	0.129
Belarus	0.285	Ghana	0.126	Montserrat	0.126	Suriname	0.126
Belgium	0.285	Greece	0.218	Morocco	0.204	Swaziland	0.176
Belize	0.131	Grenada	0.126	Mozambique	0.148	Sweden	0.285
Benin	0.126	Guadeloupe	0.126	Myanmar	0.153	Switzerland	0.284
Bhutan	0.232	Guatemala	0.160	Namibia	0.177	Syria	0.255
Bolivia	0.152	Guernsey	0.285	Nepal	0.191	So Tom and	0.129
Bonaire, Sint E	0.126	Guinea	0.127	Netherlands	0.285	Taiwan	0.183
Bosnia and Herz	0.259	Guinea-Bissau	0.126	New Caledonia	0.153	Tajikistan	0.223
Botswana	0.150	Guyana	0.126	New Zealand	0.285	Tanzania	0.150
Brazil	0.135	Haiti	0.132	Nicaragua	0.128	Thailand	0.132
British Virgin	0.126	Honduras	0.138	Niger	0.126	Timor-Leste	0.129
Brunei	0.126	Hong Kong	0.167	Nigeria	0.126	Togo	0.126
Bulgaria	0.245	Hungary	0.244	North Korea	0.274	Tonga	0.126
Burkina Faso	0.126	India	0.151	Northern Cyprus	0.246	Trinidad and To	0.126
Burundi	0.186	Indonesia	0.129	Norway	0.285	Tunisia	0.171
Cambodia	0.126	Iran	0.248	Oman	0.128	Turkey	0.239
Cameroon	0.129	Iraq	0.210	Pakistan	0.188	Turkmenistan	0.273
Canada	0.284	Ireland	0.285	Palestina	0.224	Turks and Caico	0.126
Cape Verde	0.134	Isle of Man	0.285	Panama	0.129	Uganda	0.137
Caspian Sea	0.259	Israel	0.237	Papua New Guine	0.136	Ukraine	0.283
Cayman Islands	0.126	Italy	0.199	Paraguay	0.159	United Arab Emi	0.184
Central African	0.126	Jamaica	0.126	Peru	0.159	United Kingdom	0.285
Chad	0.126	Japan	0.203	Philippines	0.129	United States	0.225
Chile	0.279	Jersey	0.285	Poland	0.285	Uruguay	0.167
China	0.217	Jordan	0.264	Portugal	0.191	Uzbekistan	0.272
Colombia	0.141	Kazakhstan	0.284	Puerto Rico	0.128	Vanuatu	0.129
Comoros	0.132	Kenya	0.146	Qatar	0.167	Venezuela	0.130
Costa Rica	0.140	Kosovo	0.271	Republic of Con	0.126	Vietnam	0.149
Croatia	0.227	Kuwait	0.167	Reunion	0.193	Virgin Islands,	0.126
Cuba	0.126	Kyrgyzstan	0.283	Romania	0.249	Western Sahara	0.139
Curaao	0.126	Laos	0.153	Russia	0.283	Yemen	0.126
Cyprus	0.272	Latvia	0.285	Rwanda	0.244	Zambia	0.166
Czech Republic	0.285	Lebanon	0.234	Saint Kitts and	0.126	Zimbabwe	0.164
Cte d'Ivoire	0.126	Lesotho	0.270	Saint Lucia	0.126	land	0.285
Democratic Repu	0.133	Liberia	0.126	Saint Pierre an	0.285		.

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 (0.126), temperate pixels (0.287), and "both" pixels (0.168) 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}^{GAEZ} measured for:					
	Banana (1)	Coffee (2)	Cotton (3)	Sugarcane (4)	Tea (5)	Tobacco (6)
Log rural density	0.197	0.152	0.178	0.139	0.267	0.152
	(0.046)	(0.034)	(0.032)	(0.028)	(0.064)	(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. All regressions include state fixed effects, a constant, and controls for the district urbanization rate, log density of district nighttime lights, log total population, log road density, share of roads of different types, distance to nearest city of 100,000 people, and a log slope index. 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)	0.282	0.127	0.265	0.124	0.243	0.111
	(0.043)	(0.023)	(0.045)	(0.023)	(0.045)	(0.021)
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		0.005		0.008
Countries	72	67	69	67	55	65
Observations	8324	6726	7911	6666	6249	5958
R-square (ex. FE)	0.19	0.15	0.18	0.14	0.17	0.13

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. All regressions include state fixed effects, a constant, and controls for the district urbanization rate, log density of district nighttime lights, log total population, log road density, share of roads of different types, distance to nearest city of 100,000 people, and a log slope index. Conley standard errors are reported with a window of 500km.

Table A.6: Estimates of β with GAEZ constraint controls

	Dependent variable is A_{isg}^{GAEZ}:					
	Baseline:		Urban pop. $< 50K$:		Excl. N.A./Europe:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log labor/land ratio (β_g)	0.265	0.128	0.278	0.130	0.278	0.129
	(0.045)	(0.022)	(0.048)	(0.023)	(0.045)	(0.023)
p-value $\beta_g = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta_g = \beta_{Temp}$		0.006		0.005		0.003
Countries	72	67	68	66	17	62
Observations	8416	6731	7529	6192	813	6676
R-square (ex. FE)	0.17	0.14	0.18	0.14	0.15	0.11

Set of regressions with additional controls for GAEZ agro-climatic constraints included. These constraints are: dummies for soil nutrient availability, dummies for soil nutrient retention, dummies for soil workability, dummies for slope classes, dummies for annual precipitation/evapotranspiration, dummies for whether length of growing period is 365 days or less. All regressions include state fixed effects, a constant, and controls for the district urbanization rate, log density of district nighttime lights, log total population, log road density, share of roads of different types, distance to nearest city of 100,000 people, and a log slope index. Conley standard errors are reported with a window of 500km.

Table A.7: Estimates of β with Conley standard errors at different distances

	Dependent variable is A_{isg}^{GAEZ}:					
	Baseline (500km):		1000km		2000km	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log labor/land ratio (β_g)	0.285	0.126	0.285	0.126	0.285	0.126
	(0.043)	(0.023)	(0.049)	(0.027)	(0.047)	(0.031)
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		0.005		0.005
Countries	72	67	72	67	72	67
Observations	8416	6731	8416	6731	8416	6731
R-square (ex. FE)	0.19	0.15	0.19	0.15	0.19	0.15

Set of regressions where distance of spatial autocorrelation is set to different values. All regressions include state fixed effects, a constant, and controls for the district urbanization rate, log density of district nighttime lights, log total population, log road density, share of roads of different types, distance to nearest city of 100,000 people, and a log slope index. Conley standard errors are reported with a window of 500km.