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How Tight are Malthusian Constraints?

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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

$$Y_i = A_i F(X_i, K_i, L_{Ai}) \tag{A.1}$$

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_i/L_{Ai} is identical for all districts.

Dividing the production function through by L_i, and multiplying by ϕ_L (the share of output paid to labor), we have that

$$\phi_L Y_i/L_{Ai} = \phi_L A_i F(X_i/L_i, K_i/L_i, 1). \tag{A.2}$$

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

$$f(x_i, k_i) = F(X_i/L_i, K_i/L_i, 1) \tag{A.3}$$

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

$$w = \phi_L A_i f(x_i, k_i). \tag{A.4}$$

Holding this wage constant as it is given by province-level factors, and noting that k_i is also given by province-level factors, we use the implicit function theorem to solve for

$$\frac{\partial A_i}{\partial x_i}\frac{x_i}{A_i} = -\frac{\phi_L A_i f_1(x_i, k_i)}{\phi_L f(x_i, k_i)}\frac{x_i}{A_i} = -\frac{f_1(x_i, k_i) x_i}{f(x_i, k_i)}. \tag{A.5}$$

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

$$\frac{f_1(x_i,k_i)x_i}{f(x_i,k_i)} = \frac{F_1(X_i,K_i,L_i)X_i}{F(X_i,K_i,L_i)} \tag{A.6}$$

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

$$\frac{\partial A_i}{\partial x_i}\frac{x_i}{A_i} = -\frac{F_1(X_i,K_i,L_i)X_i}{F(X_i,K_i,L_i)} \tag{A.7}$$

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 Solving for Labor Share and Real Income

In section 2 we solved for L_A/L and y, the agricultural labor share and real income, respectively. The algebra leading to equations (12) and (13) in the main paper is as follows. From here forward, any equation references without a prefix, (e.g. (2)), refer to the main paper, while references with a prefix (e.g. (A.2)) refer to this Appendix.

Based on the district-level production functions from (1), total agricultural supply in province I can be written as

$$Y_A = \sum_{i\in I} A_i X_i^{\beta}\left(K_{Ai}^{\alpha}L_{Ai}^{1-\alpha}\right)^{1-\beta}. \tag{A.8}$$

We know each L_{Ai} from (4). By a similar logic used for labor we can establish that the allocation of capital to any individual location i is

$$K_{Ai} = A_i^{1/\beta}X_i\frac{K_A}{\sum_{j\in I}A_j^{1/\beta}X_j} \tag{A.9}$$

where K_A is the aggregate allocation of capital to agriculture. Combine (11) from the main paper and (A.9) with the expression in (A.8) and we can solve for

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

where

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

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

With the assumption that land earns no return, and the share earned by capital is ϕ_K is both sectors, and for labor the share is ϕ_L in both sectors, it follows that the capital/labor ratio in both sectors is equal to the aggregate capital labor ratio,

$$\frac{K_A}{L_A} = \frac{K_N}{L_N} = \frac{K}{L} = \frac{w}{r}\frac{\phi_K}{\phi_L}.$$

Using the equilibrium condition on wages across sectors from (9), we can solve for

$$\frac{p_A}{p_N} = \frac{Y_N}{L_N}\frac{L_A}{Y_A}. \tag{A.10}$$

Noting that $Y_N = c_N L$ and $Y_A = c_A L$, we can rearrange this be

$$\frac{p_A c_A}{p_N c_N} = \frac{L_A}{L_N}, \tag{A.11}$$

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 $L_A + L_N = L$ and $p_A c_A + p_N c_N = M$, it follows that in log terms

$$\ln L_A/L = \ln p_A c_A/M. \tag{A.12}$$

Turning to the demand function from (8), 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.10) and (A.12), as well as the fact that $c_A = (Y_A/L_A)(L_A/L)$, we can substitute here to find

$$(1-\epsilon)\ln L_A/L = \ln\theta_A + (\epsilon-\gamma)\left(\ln Y_N/L_N - \ln Y_A/L_A\right) - \epsilon\left(\ln Y_A/L_A + \ln L_A/L\right).$$

Collecting terms we have

$$\ln L_A/L = \ln\theta_A + (\epsilon-\gamma)\ln Y_N/L_N - \gamma\ln Y_A/L_A.$$

Using the production functions in (7) and (A.8), we can write this as

$$\ln L_A/L = \ln\theta_A + (\epsilon-\gamma)\ln\left(A_N(K/L)^{\alpha}\right) - \gamma\ln\left(A_A(K/L)^{\alpha(1-\beta)}L_A^{-\beta}\right) - \gamma\beta\ln L + \gamma\beta\ln L,$$

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

$$\ln L_A/L = \ln\theta_A + \frac{\beta\gamma}{1-\beta\gamma}\ln L - \frac{\gamma}{1-\beta\gamma}\ln A_A + \frac{\gamma-\epsilon}{1-\beta\gamma}\ln A_N + \frac{\alpha(\beta\gamma-\epsilon)}{1-\beta\gamma}\ln K/L.$$

Exponentiating this, we arrive at (10) from the main text.

For real income, in agricultural terms we have

$$y = \frac{M}{p_A} = c_A + \frac{p_N}{p_A}c_N.$$

Using (A.11) we can write this as

$$y = c_A + \frac{p_N c_N}{p_A c_A} c_A = c_A \left(1 + \frac{L_N}{L_A}\right) = c_A \frac{L}{L_A}.$$

Noting that $c_A = Y_A/L$, we have that

$$y = \frac{Y_A}{L_A} = A_A (K/L)^{\alpha(1-\beta)} (L_A/L)^{-\beta} L^{-\beta},$$

where the second equality follows from (A.8). At this point, we can use (10) to plug in for L_A/L in the above equation, and solve for

$$\ln y = \frac{1}{1-\beta\gamma} \ln A_A - \frac{\beta}{1-\beta\gamma} \ln L + \frac{\beta(\epsilon-\gamma)}{1-\beta\gamma} \ln A_N + \frac{\alpha(1-\beta)+\alpha\beta(\epsilon-\gamma)}{1-\beta\gamma} \ln K/L.$$

Exponentiating, we arrive at (11) in the main text.

A.3 Alternative Mobility Assumptions

Our baseline specifications are built off of a model that assumes agricultural output, as well as labor and capital, are freely mobile across districts within a given province (although we do not require them to be mobile across provinces). However, even within a given province, there may be frictions or limits on the mobility of either output or inputs, or both. If these frictions exist, then our regressions may not be delivering unbiased estimates of β. We outline two alternative assumptions about mobility here, and how our results relate to those.

A.3.1 Immobile Factors

The baseline model assumes capital and labor are free to move between districts within a region. If we make factors immobile, but allow both agricultural and non-agricultural output to move between districts, this changes the specification of the relationship between agricultural productivity and rural density.

The agricultural production function for a district is the same as in (1), and we also need to specify a production function for non-agriculture. We do so as $Y_{Ni} = A_{Ni} K_{Ni}^{\alpha} L_{Ni}^{1-\alpha}$. Capital and labor are assumed to be mobile *within* the district between the two sectors, implying that the return to capital and the return to labor are equalized across different uses. Because of this, the capital/labor ratio in both sectors will be identical, with $K_{Ai}/L_{Ai} = K_{Ni}/L_{Ni} = K_i/L_i$, where K_i/L_i is the district's aggregate capital/labor ratio.

Equality of the return to labor across different sectors implies that

$$p_A (1-\alpha)(1-\beta) \frac{Y_{Ai}}{L_{Ai}} = p_N (1-\alpha) \frac{Y_{Ni}}{L_{Ni}}.$$

Using the condition that the capital/labor ratio will be identical across the two sectors, and rearranging this relationship, we have that

$$p_A (1-\beta) A_{Ai} \left(\frac{K_i}{L_i}\right)^{\alpha(1-\beta)} \left(\frac{X_i}{L_{Ai}}\right)^{\beta} = p_N A_{Ni} \left(\frac{K_i}{L_i}\right)^{\alpha}$$

Taking logs, are again re-arranging terms, we arrive at

$$\ln A_{Ai} = \beta \ln L_{Ai}/X_i + \ln A_{Ni} + \alpha\beta \ln K_i/L_i + \ln p_N/p_A.$$

This equation shows that the relationship between agricultural productivity, A_{Ai}, and rural density, L_{Ai}/X_i, can still be used to recover an estimate of β. To do this, we must control for the district-specific levels of non-agricultural productivity, A_{Ni}, and capital/labor, K_i/L_i. While we do not have direct measures of those, we believe that our control for night lights will act as a decent proxy for these terms. Finally, the price ratio, p_N/p_A, is the province relative price, as goods are traded freely, so this will be captured by the province level fixed effects.

If our night lights control is not capturing the variation in A_{Ni} or K_i/L_i, then our estimates may be biased if there is a relationship between those variables and rural density. In particular, if rural density is negatively related to A_{Ni} and/or K_i/L_i then we could be under-stating the value of β. It is not clear why this negative relationship would hold only in tropical areas (with small estimate β values), but not in other areas.

A.3.2 Autarkic Districts

If districts are entirely closed, in that neither factors of production nor output can move between districts, then this again changes the specification of our regressions. Here, the crucial remaining assumption is that the value of β is the same across all districts within a given province.

Within each district, let the amount of agricultural output consumed be c_{Ai}, and hence market clearing within the district requires $c_{Ai}L_i = Y_i$ for agricultural output. Using the same production function as in the main section, and again assuming that capital and labor move freely between sectors (non-agriculture and agriculture) so that the capital/labor ratios are equal to the aggregate ratio, we have

$$c_{Ai}L_i = A_i X_i^{\beta} \left(K_i/L_i\right)^{\alpha(1-\beta)} L_{Ai}^{1-\beta}.$$

Taking logs and re-arranging, we have the following

$$\ln A_i = \beta \ln L_{Ai}/X_i - \ln L_{A_i}/L_i - \alpha(1-\beta) \ln K_i/L_i + \ln c_{Ai}.$$

We can recover an estimate of β from the relationship of productivity and rural density, but now must control for the agricultural share of labor, L_{Ai}/L_i, the capital/labor ratio, and the consumption of agricultural goods per capita. For L_{Ai}/L_i, we have this data, and can include it directly in a regression (it is implicitly included in our baseline regression when we use the percent urban). For the capital/labor ratio and consumption of agricultural goods, we believe that the night lights data are a decent proxy for these terms.

Including the log of L_{Ai}/L_i explicitly as a control is possible, and the results of this are shown in Table A.11 at the end of this Appendix.

The results in Table A.11 may still be biased, however, if the night lights proxy does not pick up the variation in consumption or the capital/labor ratio. If the capital/labor ratio is positively related to the rural density, then we would be under-estimating the true value of β. The small estimated values of β in tropical areas may be because of this relationship, although it is not clear why rural density would be positively related to capital/labor ratios only in tropical areas. Alternatively, if consumption of agricultural goods is negatively related to rural density, and we are not controlling for it with night lights, then we may be under-estimating β. This could possibly be true only in tropical areas if they are relatively poor, whereas this relationship no longer holds in richer, temperate areas. This is clearly a possibility, although recall that this would only be a problem if we believe that districts are *autarkic*, which may be an extreme assumption.

A.4 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

$$n_{t+1} = y_t^{\theta} \tag{A.13}$$

where $0 < \theta < 1$ so that population growth is a concave function of income per capita. This delivers, using equation (11) from the main text,

$$L_{t+1} = n_{t+1} L_t = \left(A_A A_N^{\beta(\epsilon-\gamma)} \hat{k}^{\Omega} \right)^{\frac{\theta}{1-\beta\gamma}} L_t^{\frac{1-\beta(\theta+\gamma)}{1-\beta\gamma}}. \tag{A.14}$$

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

$$L^* = \left(A_A A_N^{\beta(\epsilon-\gamma)} \hat{k}^{\Omega} \right)^{\frac{1}{\beta}}. \tag{A.15}$$

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.5 Definitions of regions

Regions: Countries are included as follows:.

- **Central and West Asia**: Afghanistan, Azerbaijan, Bhutan, Georgia, Iran, Iraq, Jordan, Kazakhstan, Kyrgyzstan, Lebanon, Oman, Pakistan, Palestina, Russia (Asia), Syria, Tajikistan, Turkey, Uzbekistan
- **Eastern Europe**: Belarus, Bulgaria, Czech Republic, Hungary, Poland, Romania, Russia (Europe), Slovakia, Ukraine
- **North Africa**: Algeria, Egypt, Morocco, Sudan, Tunisia
- **Northwest Europe**: Austria, Belgium, Denmark, Estonia, Finland, France, Germany, Isle of Man, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Sweden, Switzerland, United Kingdom
- **South Africa**: Botswana, Namibia, South Africa, Swaziland

- **South and Southeast Asia**: Bangladesh, Brunei, Cambodia, India, Indonesia, Laos, Malaysia, Myanmar, Philippines, Sri Lanka, Thailand, Timor-Leste, Vietnam
- **Southern Europe**: Albania, Bosnia and Herzegovina, Croatia, Greece, Italy, Portugal, Serbia, Slovenia, Spain
- **Temperate Americas**: Argentina, Canada, Chile, United States, Uruguay
- **Tropical Africa**: Angola, Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Cte d'Ivoire, Democratic Republic of the Congo, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Niger, Nigeria, Republic of Congo, Reunion, Rwanda, Senegal, Sierra Leone, Somalia, South Sudan, So Tom and Prncipe, Tanzania, Togo, Uganda, Zambia, Zimbabwe
- **Tropical Americas**: Bolivia, Brazil, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, French Guiana, Guadeloupe, Guatemala, Guyana, Haiti, Honduras, Martinique, Mexico, Nicaragua, Panama, Paraguay, Peru, Suriname, Venezuela

For China-only regressions: We exclude Tibet, Xinjiang, Gansu, and Qinghai entirely, given that their climates do not fit well into the temperate versus sub-tropical distinction we make in the regressions.

- **Temperate provinces**: Hebei, Heilongjiang, Jilin, Liaoning, Nei Mongol, Ningxia Hui, Shaanxi, Shanxi, Tianjin, Sichuan, Shandong, Yunnan
- **Sub-tropical provinces**: Guangxi, Guangdong, Fujian, Jiangxi, Hunan, Guizhou, Chongqing, Hubei, Anhui, Zhejiang, Henan, Jiangsu, Hainan

Russian provinces: We split Russia into separate Asian and European sections for inclusion in the regions. That breakdown takes place at the province level

- **Russia(Asia)**: Altay, Amur, Buryat, Chelyabinsk, Gorno-Altay, Irkutsk, Kemerovo, Khabarovsk, Khakass, Khanty-Mansiy, Krasnoyarsk, Kurgan, Novosibirsk, Omsk, Primor'ye, Sakhalin, Sverdlovsk, Tomsk, Tuva, Tyumen', Yevrey, Zabaykal'ye
- **Russia(Europe)**: Adygey, Arkhangel'sk, Astrakhan', Bashkortostan, Belgorod, Bryansk, Chechnya, Chuvash, City of St. Petersburg, Dagestan, Ingush, Ivanovo, Kabardin-Balkar, Kaliningrad, Kalmyk, Kaluga, Karachay-Cherkess, Karelia, Kirov, Komi, Kostroma, Krasnodar, Kursk, Leningrad, Lipetsk, Mariy-El, Mordovia, Moscow City, Moskva, Nizhegorod, North Ossetia, Novgorod, Orel, Orenburg, Penza, Perm', Pskov, Rostov, Ryazan', Samara, Saratov, Smolensk, Stavropol', Tambov, Tatarstan, Tula, Tver', Udmurt, Ul'yanovsk, Vladimir, Volgograd, Vologda, Voronezh, Yaroslavl'

A.6 Alternative Population Data

As mentioned in the main text, given possible issues with the HYDE data on population, we use two alternative sources of population data. These show that our results are not contingent on the particular data from HYDE.

A.6.1 GRUMP Data

We accessed both the gridded population map, and the urban extents grid. The GRUMP data is provided at 30 arc-second grids (rougly 1km squares), a higher resolution than the HYDE data (which has 5 arc-minute grids, or roughly 10km squares). We overlay the urban extents grid on the population map, and retrieve only the population count of grid cells that are not part of an urban extent. We then sum up the population count of grid cells within each district. The district definitions are from GADM, identical to those used with the HYDE data, so we can compare the counts directly.

Because GRUMP counts zero rural residents in an area that is part of an urban extent, and all population in non-urban locations as rural, the variation in rural residents across districts is more severe than with HYDE. Some districts in GRUMP are entirely covered by urban extents, and so have zero rural residents. Hence the GRUMP data leads to 28,471 districts with data on rural density, compared to 35,451 using HYDE. For those 28,471 districts, the correlation of (log) rural density across the two datasets is 0.81, significant at less than 1%.

Table A.2 shows the results using the GRUMP data. The results are consistent with our baseline findings. The elasticity for temperate suitable districts is about 0.20, while for tropical areas it is only 0.115, a difference of about 0.10 that is significant at less than 1%. Panel B shows that these results hold up if we restrict the sample due to urban size, country development, or the density of rural workers.

The only discrepancy with the baseline results is in Panel A, columns (5) and (6), which distinguish samples by their harvested area. In this case, the estimated β values are similar (statistically and practically). This appears to be due to a set of outliers in the GRUMP data that have very low reported rural density relative to the equivalent HYDE areas. We can identify these outliers by regressing the GRUMP (log) rural density on the HYDE (log) rural density, and looking for observations whose residuals from that regression are in the bottom 1% (meaning GRUMP's estimate is well below the HYDE estimate). If we eliminate those from the GRUMP data, then the results for columns (5) and (6) are much closer to the baseline results. The underlying issue here is that these districts have many cells coded as "urban" by GRUMP, but HYDE's data indicates large rural populations. Without better information, we do not know if this is an error of HYDE's or GRUMP's methodologies.

A.6.2 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.

Table A.3 shows the results using the IPUMS data. For the main results using the temperate and tropical areas, the results show a similar pattern to what we found in our baseline. The estimated β in temperate areas is 0.213, compared to 0.025 in tropical areas, and the difference is statistically significant.

In columns (3) and (4), the samples are selected on which crops we find deliver the maximum calories within an area. A slight modification is made here to the baseline selection criteria, because the IPUMS areas are so large. Column (3) includes areas that have any of their maximum calories derived from the temperate crops, and *none* from the tropical crops. Column (4) excludes areas where *none* of the maximum calories from the temperate crops, and includes areas with *any* maximum calories derived from the tropical crops. Here, we again see the temperate areas have an elasticity around 0.20, while the tropical elasticity is estimated to be zero, and the difference is statistically significant. In this case, we cannot reject the hypothesis that there is no land constraint in these tropical dominated areas. In columns (5) and (6), based on actual harvested area, we again get results similar to our baseline specification using HYDE data, and again the tropical coefficient is estimated to be very small.

We cannot replicate the second panel of our baseline results, for several reasons. First, the areas from IPUMS are so large that they almost universally contain large cities, so there is no point in removing areas with large cities. Second, the 39 countries are dominated by poor countries, so eliminating "rich" countries does not change the results (it eliminates only the U.S., Spain, and Austria).

Finally, 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.7 Province Specific Estimates

In the main paper we create sub-samples first, and estimate β for each sub-sample, assuming that the β is identical for all provinces (and districts) within the sub-sample. As an alternative, we can first estimate β separately for each province, and then group those provinces into sub-samples based on agricultural type, climate, or region.

The one limitation we have is that we cannot estimate separate β values for provinces without sufficient districts within them. We include a province if it has at least 8 districts, and run our baseline regression, including controls for night lights and the urban percentage. This gives us a total of 1,183 provinces. From those, we trim value of β at the 1st and 99th percentiles, to eliminate severe outliers from the entire set.

Table A.13 shows the summary statistics of β values from different sub-samples. Row 1 shows the values from all the provinces, with a mean β of 0.21, and a median of 0.18. The next six rows replicate the sample selection criteria for our baseline results using crops. For provinces that are suitable for temperate agriculture (but not for tropical), the mean β is 0.23, with a median of 0.21. For tropical provinces (but not for temperate), the mean is 0.17, with a median of 0.15. As one reads down the rows, this patten is repeated, with temperate β values tending to be about 0.06 higher than tropical values.

The lower portion of the table shows the statistics for individual sub-regions. This replicates the general results of our regional analysis in the main paper. Focusing on the medians, the values for the European regions are in the range 0.22-0.25, and this drops to 0.16 in the Asian regions. The temperate Americas is one discrepancy, with a median of only 0.10, similar to the median value from Tropical Africa, 0.09. Tropical Americas shows a value of 0.17, similar to southern Africa. North Africa has a higher median, consistent with the original results, of 0.31.

A.8 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.14 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.9 Robustness Tables

Each table that follows is a replica of Table 2 from the main paper, which estimates β, the land elasticity, temperate and tropical districts. A list of tables is provided for convenience. The first table (A.1), replicates the baseline results for comparison purposes.

List of Tables

Table A.1: Baseline results

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

Panel A: Regions defined by:

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

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

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

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. Rural population is from HYDE database, and caloric yield is the author's calculations based on the data from Galor and Ozak (2016), see the main paper for an explanation of the construction of both.

Table A.2: Using GRUMP Population Data

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

Panel A: Regions defined by:

	Suitability:		Max calories:		Harvest area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.207	0.115	0.176	0.100	0.166	0.140
	(0.041)	(0.021)	(0.033)	(0.017)	(0.028)	(0.020)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.045		0.041		0.442
Countries	86	75	81	69	71	82
Observations	8734	6769	8585	6230	8922	5844
Adjusted R-square	0.19	0.16	0.15	0.13	0.14	0.13

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

	Urban Pop. $< 25K$:		Ex. Europe/N. Amer.:		Rural dens. $>$ 25th P'tile:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.264	0.129	0.195	0.115	0.298	0.191
	(0.047)	(0.024)	(0.019)	(0.022)	(0.048)	(0.031)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.010		0.002		0.056
Countries	81	71	23	67	80	68
Observations	6431	5050	777	6697	6078	5440
Adjusted R-square	0.24	0.20	0.13	0.11	0.24	0.21

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. Rural population is from the GRUMP database, and caloric yield is the author's calculations based on the data from Galor and Ozak (2016), see the main paper for an explanation of the construction of both.

Table A.3: Using IPUMS Population Data

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

Panel A: Samples defined by crop family (wheat vs. rice):

	By suitability:		By max calories:		By harvest area:	
	Wheat Only (1)	Rice Only (2)	Wheat/ No Rice (3)	Rice No Wheat (4)	Wheat $> 50\%$ (5)	Rice $> 50\%$ (6)
Log ag. worker density	0.213	0.025	0.200	0.000	0.223	0.034
	(0.067)	(0.016)	(0.056)	(0.017)	(0.030)	(0.014)
p-value $\beta = 0$	0.004	0.124	0.002	0.993	0.000	0.021
p-value $\beta = \beta^{Wheat}$		0.006		0.000		0.000
Countries	23	24	24	23	21	26
Observations	1104	2416	1595	2389	1207	1427
Adjusted R-square	0.50	0.54	0.39	0.56	0.37	0.51

Clustered standard errors at the country level are shown in parentheses. All regressions include country fixed effects, and controls for (log) night lights and urban percent. Agricultural worker density is from IPUMS, and caloric yield is the author's calculations based on the data from Galor and Ozak (2016), see the main paper for an explanation of the construction.

Table A.4: Conley SE cutoff of 1000km

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

Panel A: Regions defined by:

	Suitability:		Max calories:		Harvest area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.240	0.143	0.200	0.114	0.220	0.126
	(0.028)	(0.020)	(0.022)	(0.023)	(0.021)	(0.014)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.004		0.006		0.000
Countries	91	79	82	71	74	84
Observations	9922	8396	10142	7411	9929	6810
Adjusted R-square	0.24	0.20	0.21	0.17	0.20	0.17

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

	Urban Pop. $< 25K$:		Ex. Europe/N. Amer.:		Rural dens. $>$ 25th P'tile:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.279	0.156	0.253	0.143	0.289	0.188
	(0.027)	(0.023)	(0.041)	(0.021)	(0.039)	(0.024)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.001		0.018		0.028
Countries	83	74	24	69	89	74
Observations	7046	6117	785	8168	6807	6606
Adjusted R-square	0.29	0.24	0.18	0.14	0.26	0.22

Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 1000km, 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. Rural population is from HYDE database, and caloric yield is the author's calculations based on the data from Galor and Ozak (2016), see the main paper for an explanation of the construction of both.

Table A.5: Province-level data

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

Panel A: Regions defined by:

	Suitability:		Max calories:		Harvest area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.399	0.070	0.248	0.016	0.368	0.052
	(0.058)	(0.020)	(0.030)	(0.013)	(0.043)	(0.021)
p-value $\beta = 0$	0.000	0.000	0.000	0.199	0.000	0.014
p-value $\beta = \beta^{Wheat}$		0.000		0.000		0.000
Countries	60	65	70	63	69	73
Observations	417	587	768	617	797	721
Adjusted R-square	0.39	0.27	0.29	0.26	0.35	0.30

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

	Urban Pop. $< 25K$:		Ex. Europe/N. Amer.:		Rural dens. $>$ 25th P'tile:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.505	0.057	0.038	0.073	0.193	0.047
	(0.127)	(0.022)	(0.134)	(0.020)	(0.058)	(0.021)
p-value $\beta = 0$	0.000	0.012	0.780	0.000	0.001	0.023
p-value $\beta = \beta^{Wheat}$		0.001		0.797		0.019
Countries	13	28	6	59	49	61
Observations	28	89	11	557	234	470
Adjusted R-square	0.54	0.34	-0.09	0.05	0.13	0.06

Conley standard errors, adjusted for spatial auto-correlation with a cutoff distance of 500km, are shown in parentheses. All regressions include country fixed effects, a constant, and controls for the province-level urbanization rate and log density of district nighttime lights. Rural population is from HYDE database, and caloric yield is the author's calculations based on the data from Galor and Ozak (2016), see the main paper for an explanation of the construction of both.

Table A.6: Using cultivated area to measure density

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

Panel A: Regions defined by:

	Suitability:		Max calories:		Harvest area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.229	0.144	0.191	0.113	0.207	0.142
	(0.024)	(0.020)	(0.020)	(0.021)	(0.020)	(0.015)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.006		0.006		0.010
Countries	90	76	82	68	74	81
Observations	9871	8295	10100	7343	9911	6749
Adjusted R-square	0.20	0.17	0.17	0.15	0.16	0.15

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

	Urban Pop. $< 25K$:		Ex. Europe/N. Amer.:		Rural dens. $>$ 25th P'tile:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.277	0.161	0.248	0.146	0.262	0.170
	(0.021)	(0.024)	(0.038)	(0.021)	(0.032)	(0.023)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.000		0.014		0.019
Countries	82	72	23	67	90	75
Observations	7000	6025	778	8092	6263	7175
Adjusted R-square	0.26	0.22	0.17	0.14	0.21	0.18

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, the log density of district nighttime lights, and the percent of a district that is cultivated. Rural density is from HYDE database, and is measured as rural population per hectare of cultivated land (from the GAEZ). Caloric yield is the author's calculations based on the data from Galor and Ozak (2016), see the main paper for an explanation of the construction of both.

Table A.7: Using population from 1900CE

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

Panel A: Regions defined by:

	Suitability:		Max calories:		Harvest area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.294	0.170	0.239	0.149	0.258	0.182
	(0.032)	(0.025)	(0.023)	(0.025)	(0.026)	(0.017)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.002		0.007		0.014
Countries	91	81	83	71	74	84
Observations	10644	9081	10774	8213	10689	7561
Adjusted R-square	0.30	0.25	0.25	0.22	0.24	0.22

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

	Urban Pop. $< 25K$:		Ex. Europe/N. Amer.:		Rural dens. $>$ 25th P'tile:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.335	0.180	0.339	0.171	0.331	0.263
	(0.034)	(0.029)	(0.027)	(0.026)	(0.048)	(0.027)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.000		0.000		0.214
Countries	83	75	24	70	87	74
Observations	7636	6658	824	8822	8321	6536
Adjusted R-square	0.34	0.28	0.25	0.18	0.32	0.28

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. Rural population for 1900CE is from HYDE database, and caloric yield is the author's calculations based on the data from Galor and Ozak (2016), see the main paper for an explanation of the construction of both.

Table A.8: Using population from 1950CE

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

Panel A: Regions defined by:

	Suitability:		Max calories:		Harvest area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.255	0.141	0.208	0.119	0.222	0.153
	(0.027)	(0.021)	(0.019)	(0.021)	(0.021)	(0.015)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.001		0.001		0.008
Countries	91	81	83	71	74	84
Observations	10650	9082	10775	8215	10694	7562
Adjusted R-square	0.27	0.23	0.23	0.19	0.21	0.20

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

	Urban Pop. $< 25K$:		Ex. Europe/N. Amer.:		Rural dens. $>$ 25th P'tile:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.298	0.153	0.289	0.141	0.294	0.214
	(0.027)	(0.025)	(0.026)	(0.022)	(0.044)	(0.025)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.000		0.000		0.108
Countries	83	75	24	70	87	74
Observations	7642	6658	824	8823	7728	6814
Adjusted R-square	0.32	0.26	0.23	0.16	0.28	0.25

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. Rural population from 1950CE is from HYDE database, and caloric yield is the author's calculations based on the data from Galor and Ozak (2016), see the main paper for an explanation of the construction of both.

Table A.9: Dropping districts under 25th percentile in production

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

Panel A: Regions defined by:

	Suitability:		Max calories:		Harvest area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.226	0.140	0.186	0.111	0.213	0.125
	(0.025)	(0.020)	(0.017)	(0.021)	(0.018)	(0.013)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.008		0.005		0.000
Countries	82	65	77	58	70	72
Observations	7568	6092	7540	5374	8400	5704
Adjusted R-square	0.22	0.18	0.19	0.16	0.19	0.16

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

	Urban Pop. $< 25K$:		Ex. Europe/N. Amer.:		Rural dens. $>$ 25th P'tile:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.272	0.149	0.243	0.141	0.271	0.183
	(0.027)	(0.023)	(0.046)	(0.020)	(0.044)	(0.023)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.001		0.043		0.082
Countries	73	64	18	62	78	63
Observations	5093	4127	582	6036	5156	4982
Adjusted R-square	0.27	0.23	0.15	0.13	0.23	0.19

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. Rural population is from HYDE database, and caloric yield is the author's calculations based on the data from Galor and Ozak (2016), see the main paper for an explanation of the construction of both. All districts below the 25th percentile of total tonnes of staple crops produced across all districts are dropped. Raw tonnes are used, unadjusted for calorie content.

Table A.10: Using log rural percent of population as a control

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

Panel A: Regions defined by:

	Suitability:		Max calories:		Harvest area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.254	0.148	0.213	0.120	0.231	0.136
	(0.024)	(0.019)	(0.021)	(0.020)	(0.020)	(0.015)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.001		0.001		0.000
Countries	91	79	82	71	74	84
Observations	9922	8396	10142	7411	9929	6810
Adjusted R-square	0.25	0.21	0.22	0.18	0.21	0.18

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

	Urban Pop. $< 25K$:		Ex. Europe/N. Amer.:		Rural dens. $>$ 25th P'tile:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.286	0.159	0.288	0.149	0.299	0.194
	(0.025)	(0.022)	(0.041)	(0.020)	(0.036)	(0.020)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.000		0.002		0.012
Countries	83	74	24	69	89	74
Observations	7046	6117	785	8168	6807	6606
Adjusted R-square	0.30	0.25	0.21	0.15	0.27	0.22

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, the log density of district nighttime lights, and the log rural percent of the population. Rural population is from HYDE database, and caloric yield is the author's calculations based on the data from Galor and Ozak (2016), see the main paper for an explanation of the construction of both.

Table A.11: Dropping districts over 90th percentile in absolute size

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

Panel A: Regions defined by:

	Suitability:		Max calories:		Harvest area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.231	0.149	0.189	0.126	0.202	0.138
	(0.026)	(0.017)	(0.020)	(0.019)	(0.020)	(0.012)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.008		0.019		0.007
Countries	88	78	81	68	72	80
Observations	9440	8266	9564	7615	9350	6901
Adjusted R-square	0.24	0.21	0.20	0.18	0.19	0.17

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

	Urban Pop. $< 25K$:		Ex. Europe/N. Amer.:		Rural dens. > 25th P'tile:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.268	0.159	0.242	0.150	0.286	0.196
	(0.024)	(0.020)	(0.033)	(0.018)	(0.037)	(0.019)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta^{Wheat}$		0.001		0.012		0.031
Countries	80	74	23	67	85	76
Observations	6859	6213	818	8045	6689	6473
Adjusted R-square	0.29	0.24	0.19	0.16	0.27	0.23

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. Rural population is from HYDE database, and caloric yield is the author's calculations based on the data from Galor and Ozak (2016), see the main paper for an explanation of the construction of both. Districts over 493,000 hectares (the 90th percentile) are dropped.

Table A.12: Dropping provinces with fewer than 10 districts

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

Panel A: Regions defined by:

	Suitability:		Max calories:		Harvest area:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.230	0.146	0.196	0.123	0.207	0.145
	(0.022)	(0.021)	(0.017)	(0.020)	(0.016)	(0.013)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta_{Temp}$		0.005		0.005		0.002
Countries	68	44	58	45	54	47
Observations	9442	6798	9119	6491	9117	5665
Adjusted R-square	0.25	0.22	0.22	0.19	0.21	0.19

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

	Urban Pop. $< 25K$:		Ex. Europe/N. Amer.:		Rural dens. $>$ 25th P'tile:	
	Temperate (1)	Tropical (2)	Temperate (3)	Tropical (4)	Temperate (5)	Tropical (6)
Log rural density	0.259	0.156	0.244	0.147	0.284	0.202
	(0.023)	(0.024)	(0.036)	(0.021)	(0.037)	(0.020)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
p-value $\beta = \beta_{Temp}$		0.002		0.017		0.049
Countries	65	42	20	40	66	41
Observations	6999	5099	681	6635	6398	5310
Adjusted R-square	0.29	0.25	0.19	0.16	0.28	0.24

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. Rural population is from HYDE database, and caloric yield is the author's calculations based on the data from Galor and Ozak (2016), see the main paper for an explanation of the construction of both. Districts from provinces with fewer than 10 total districts are dropped.

Table A.13: Summary Statistics of Province-Specific β Estimates

				Percentiles				
Sub-sample	Provinces	Mean	SD	10th	25th	50th	75th	90th
All provinces	1,183	0.21	0.23	-0.02	0.05	0.18	0.33	0.49
Temperate Suitable	619	0.23	0.23	-0.00	0.08	0.21	0.36	0.50
Tropical Suitable	469	0.17	0.24	-0.04	0.03	0.15	0.28	0.43
Temperate cals over 33%	457	0.23	0.22	-0.00	0.08	0.21	0.36	0.50
Tropical cals over 33%	307	0.18	0.21	-0.04	0.03	0.15	0.29	0.41
Temperate area over 50%	485	0.22	0.23	-0.01	0.07	0.20	0.36	0.53
Tropical area over 50%	297	0.18	0.23	-0.04	0.03	0.14	0.29	0.47
Northwest Europe	79	0.26	0.31	0.00	0.08	0.22	0.46	0.62
Eastern Europe	173	0.24	0.20	0.01	0.09	0.23	0.38	0.50
Southern Europe	60	0.27	0.17	0.08	0.16	0.25	0.37	0.50
South and S. East Asia	248	0.20	0.23	-0.03	0.04	0.16	0.31	0.49
Central and West. Asia	163	0.20	0.20	-0.02	0.06	0.16	0.33	0.45
Temperate Americas	87	0.14	0.25	-0.13	0.02	0.10	0.26	0.40
Tropical Americas	195	0.18	0.26	-0.02	0.06	0.17	0.28	0.39
Tropical Africa	118	0.16	0.24	-0.09	-0.01	0.09	0.25	0.51
Southern Africa	11	0.15	0.21	-0.11	-0.05	0.17	0.33	0.34
Northern Africa	49	0.32	0.20	0.06	0.22	0.31	0.42	0.66

For each province with more than 7 districts, we estimated a separate β using our baseline specification. The table shows the summary statistics of those β values for the given sub-sample. Prior to any summary statistics, all values of β for the overall sample of provinces were trimmed at the 1st and 99th percentile to remove outliers.

Table A.14: 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 rural density	0.228 (0.021)	0.225 (0.019)	0.218 (0.023)	0.222 (0.027)	0.212 (0.021)	0.233 (0.029)	0.227 (0.019)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Countries	91	91	69	68	68	91	91
Observations	10661	10628	9699	9834	9804	10597	10631
Adjusted R-square	0.24	0.21	0.18	0.23	0.21	0.23	0.22

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 rural density	0.132 (0.018)	0.137 (0.022)	0.137 (0.019)	0.145 (0.018)	0.136 (0.019)	0.134 (0.028)	0.133 (0.020)
p-value $\beta = 0$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Countries	81	76	80	79	79	75	79
Observations	9088	8843	9074	8265	9066	8448	9020
Adjusted R-square	0.12	0.10	0.11	0.07	0.11	0.05	0.10

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. 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.