The Role of Crop Type in Cross-Country Income Differences*

Markus Eberhardt[a,b,c] Dietrich Vollrath[d†]

[a] *School of Economics, University of Nottingham, U.K.*
[b] *Centre for the Study of African Economies, University of Oxford, U.K.*
[c] *Centre for Economic Policy Research, U.K.*
[d] *Department of Economics, University of Houston, Texas, U.S.A.*

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Abstract: Labor productivity and labor share in the agricultural sector are key determinants of living standards across countries. We show that differences in agricultural *technology* – the coefficients on factor inputs in the production function – account for a substantial portion of cross-country differences in agricultural labor productivity, agricultural labor share, and per capita income. In a panel of 100 countries we document differences in technology estimates associated with major crops, and then illustrate the quantitative implications for development. Counterfactually eliminating crop-type technology heterogeneity reduces variance in log income per capita by 25%, and raises the median by 60%.

Keywords: agricultural development, crop type, structural change, technology heterogeneity

JEL classification: O47, O11, Q16, F63, C23

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†Correspondence: University of Houston, Department of Economics, 201C McElhinney Hall, Houston, TX 77204, U.S.A. Email: devollrath@uh.edu

1. INTRODUCTION

Developing countries employ a relatively large share of their workers in agriculture, and the labor productivity of these agricultural workers is only a fraction of that found in advanced economies. Together, these two facts account for a significant portion of the gap in *aggregate* output per worker between the developing and developed world (Caselli, 2005; Restuccia, Yang & Zhu, 2008). Explanations for these patterns have focused on either agricultural total factor productivity (TFP) (Gollin, Parente & Rogerson, 2007) or aggregate TFP (Restuccia, Yang & Zhu, 2008; Lagakos & Waugh, 2013), typically combined with non-homothetic preferences that incorporate the idea of a 'food problem' (Schultz, 1953).[1] Similarly, the literature on long-run growth has often explicitly linked variation in the take-off to sustained growth with agricultural productivity.[2] While aggregate or agricultural TFP in these theories is allowed to vary across countries, the agricultural sector's *technology*, the elasticity of agricultural output with respect to factor inputs, is assumed to be identical.[3]

At the same time, the agricultural economics literature has long emphasized heterogeneity in agricultural technology across countries, over and above differences in agricultural productivity. Hayami & Ruttan (1985) remark that simply allowing for differences in the level of TFP between countries is insufficient to capture underlying variation in agricultural *technology* (p. 142). Agricultural technology is viewed as location-specific, such that disparate agro-climatic conditions and endowments hamper the transfer of technology from advanced to developing nations (Ruttan, 2002). Ruthenberg (1976) finds that lowland rice farming and upland dry cereal farming differ distinctly in the shape of their production functions, noting that when compared to rice farming the marginal returns to labor in upland farming "decrease more rapidly with greater employment of labor" (p. 189) – equivalent to saying that the elasticity of output with respect to labor is lower for upland than for rice farming. Ruthenberg (p. 158) further discusses how temperate rain-fed agriculture has marginal returns to labor that decline very quickly with the addition of more labor, in contrast to tropical systems of agriculture that depend on more irregular (seasonal) rainfall. Rice production, in particular, "seems to have

[1] This concept has long been taken as a given in work on agriculture and development (see Johnston & Mellor, 1961; Johnston & Kilby, 1975; Mellor, 1995). Gollin (2010) provides an overview of this line of thinking. Echevarria (1997) and Kongasmut, Rebelo & Xie (2001) use it to explain structural change, while Alvarez-Cuadrado & Poschke (2011) and Duarte & Restuccia (2010) use this concept to account for the importance of productivity growth across different sectors in aggregate growth.

[2] Examples include Kogel & Prskawetz (2001); Hansen & Prescott (2002); Hayashi & Prescott (2008) and Vollrath (2009*a*). Galor (2011) provides an overview of the long-run growth literature.

[3] We use 'technology' synonymously with 'elasticities with respect to factor inputs' or 'curvature of the production function', and 'productivity' synonymously with TFP.

almost constant marginal returns from extra labour" (p. 167). Similarly, Grigg (1974, p. 81) states that tropical wet-rice farming is more labor-intense than temperate dry-cereal cultivation, referring specifically to the nature of the production function and not to land/labor ratios. In short, agricultural *technology* differs with the type of crop grown and prevailing agro-climatic conditions.

In this paper we take the concept of heterogeneity in agricultural technology seriously, and find that it can explain a substantial portion of cross-country variation in agricultural output per worker, the labor share of agriculture, and per capita GDP. We first document that agricultural technology – the coefficients on factor inputs in a Cobb-Douglas production function – varies widely in a panel of 100 countries from 1960–2002. We use recent panel econometric methods (Pesaran, 2006; Chudik, Pesaran & Tosetti, 2011) to identify heterogenous technology coefficients by country. We then show that the country-specific technology coefficients are closely related to the major crops grown. Countries that have wheat as a main staple crop have an average elasticity of output with respect to labor of between 0.10 and 0.20, depending on exactly how we group countries. In comparison, the same coefficient is between 0.45 and 0.60 for countries that primarily grow rice. As we find strong evidence of constant returns to scale, these estimates imply that the coefficients on non-labor inputs (e.g. fertilizer and land) are relatively high in wheat-growing places, and relatively low in rice-growing places. These patterns are robust to the exact method we use to group countries by crop types, which includes both *ad hoc* groupings and formal clustering methods based on observed production of over 160 crops.

It is not the case that the agricultural technology coefficients are a proxy for the level of development. Our analysis shows 'wheat' countries that are relatively poor (e.g. Pakistan), and 'rice' countries that are relatively rich (e.g. South Korea). Further, the distinctions across crop types are robust to including controls for output per capita in our original estimation, and the technology coefficient estimates are insignificantly correlated with measures of development. We find no evidence of time trends in the technology coefficients, either.

The second part of the paper establishes the quantitative importance of this crop-type technology heterogeneity. First, we ask by what scale TFP, or TFP and input use, would have to increase in order for a country to reach U.S. levels of agricultural output per capita and labor share in agriculture. Among the poorest countries in our sample, those that use wheat technology would require TFP to scale up by less than 10, or both TFP and inputs by a factor less than 5, to reach the U.S. targets. In contrast, countries that have similar initial levels of per capita GDP, but use rice or maize technologies, would need TFP to scale up by a factor of 10-30, and

TFP and inputs by a factor of 10-20, to reach the same U.S. targets.

Second, we ask whether the variation in technology coefficients across crops has a material impact on the current distribution and level of agricultural output per worker, the agricultural labor share, and GDP per capita. To do this, we undertake standard accounting exercises (Caselli, 2005) where we eliminate variation in technology coefficients and see how much variation in outcomes remains. This takes the form of two different counterfactual exercises. In the first we hold TFP, input use, and the labor share in agriculture constant in each country, and ask what agricultural output would be if all countries used the wheat technology coefficients. We find that variation in agricultural output per worker falls; the variance (in logs) falls by 11% across countries, and the 90/10 ratio by 17%. Moreover, the median level of agricultural output per worker rises by nearly 42%. The variance of log GDP per capita falls by 8%, and the 90/10 ratio by 13% when we eliminate agricultural technology heterogeneity. Median log GDP per capita rises by nearly 34%.

We find even stronger results in our second counterfactual exercise. Here we hold TFP, input use, and agricultural output constant in each country, and ask what the labor allocation to agriculture would be if all countries used the wheat technology. We find little change in cross-country variation in agricultural output per worker, but the variation in agricultural labor shares drops dramatically; the 90/10 difference drops by 18 percentage points, and the median labor share falls from 34% to 16%. For log GDP per capita the variance in our counterfactual falls by 23%, and the 90/10 ratio by 45%. Furthermore, median log GDP per capita rises by 60% when all countries use wheat technology.

The counterfactuals show that crop types, acting through technology heterogeneity, play a significant role in cross-country development. The importance of technology heterogeneity here contrasts with Gollin (2002), who finds technology differences the 'least appealing' explanation for cross-country income differences. And while Gollin finds no systematic relationship between labor's share of aggregate output and income per capita, he does find substantial variation in the labor share. Furthermore, there is no systematic relationship of agricultural technology coefficients and income per capita, so our results are consistent with Gollin's findings.

In addition to explaining a meaningful part of the variation across countries, our counterfactuals show that using the wheat technology coefficients provides a significant boost to development; median agricultural output per worker is higher, median GDP per capita is higher, and the median agricultural labor share is lower. This is not due to any assumed advantage for wheat in the level of TFP. In our counterfactuals the level of TFP remains unchanged. The reasoning behind the advantage of the wheat technology coefficients is straightforward. The agricultural production function forms a 'budget constraint' that dictates the trade-off between increased output and decreased labor inputs to agriculture. This trade-off depends directly on the labor coefficient in the agricultural technology. As mentioned above, the labor coefficient in wheat-growing economies is much smaller than for regions dominated by other crop types. Thus the cost of releasing labor from agriculture is quite low in terms of foregone output for 'wheat economies'. When we counterfactually compute outcomes adopting the wheat coefficients, many countries become capable of supporting similar output levels with fewer workers, or higher output levels with the same number of workers. Either ultimately translates into higher levels of per capita GDP.[4]

As part of our counterfactuals, we purposely did not attempt to model the demand side of the economy. As we discuss below, our two counterfactual exercises capture particular special cases for preferences. When we hold the labor allocation constant and let output vary (our first counterfactual), we are effectively looking at a case with Cobb-Douglas preferences for agriculture and non-agriculture. When we hold output constant and let the labor share vary (our second counterfactual), this is consistent with models that have fixed demand for agricultural output (Gollin, Parente & Rogerson, 2007). Models with non-homothetic preferences (i.e. Stone-Geary) for agricultural goods fall between these two extremes (Duarte & Restuccia, 2010; Alvarez-Cuadrado & Poschke, 2011; Herrendorf, Rogerson & Valentinyi, 2014). As the results show, the importance of agricultural technology differences is not dependent on any particular choice regarding demand.

It should be made clear that our counterfactuals show that technology heterogeneity by crop type can *account* for a large portion of the variation in agricultural outcomes and GDP per capita across countries. This does not imply any kind of policy recommendation. Technology coefficients may be crop-specific, but this does not mean a developing country can – or would be biologically able to – switch to a new type of crop. But our results indicate that the natural variation in these technology coefficients across crop types is an important source of cross-country variation in economic outcomes, over and above any variation induced by differences in TFP or factor intensities.

[4]The logic works in reverse if we assume that all countries use the rice technology with a large labor coefficient in agricultural production. In this case, median labor produtivity and GDP per capita fall, and the median labor share in agriculture rises. The variance of agricultural output per worker and GDP per capita fall, but this is due to declines in countries at the top of the distribution rather than increases in those at the bottom.

Because wheat technology has such a low coefficient on labor, the transition out of agriculture can occur more rapidly and with smaller improvements to TFP than in otherwise identical rice- or maize-growing economies. Thus an explanation for the relative wealth of temperate areas of the world may be their ability to use these low-labor coefficient technologies. More speculatively, the differences in crop technologies may also offer part of the explanation why wheat-growing areas of the world (e.g. Europe) were able to take off to sustained growth before others (e.g. Asia).[5] This advantage of wheat production would exist regardless of whether wheat had a higher level or growth rate of TFP than other crops.

The remainder of the paper proceeds as follows. We introduce the empirical model, data, implementation and results for our cross-country agricultural production functions in the following section. Having established the variation in the technology coefficients from the estimation, we then present our counterfactual quantitative exercises. The final section concludes.

2. DATA, EMPIRICAL STRATEGY AND RESULTS

We estimate agricultural production functions using techniques that explicitly allow for technology heterogeneity across countries. These methods also allow for cross-sectional dependence and flexible unobserved TFP, alleviating biases that we explain in more detail below. Once we have estimates of the technology coefficients for each country, we show that these tend to be similar for countries with the same dominant crop type.

Our techniques are not intended to recover 'farm-level' production functions, but rather the 'meta-production' function that captures the trade-offs available to the agricultural sector as a whole (Hayami & Ruttan, 1985). This meta-production function need not match any specific farm-level technology.[6] For studying structural change and development, however, the meta-production is relevant, as it informs us of the degree to which output responds as labor and other inputs are moved into and out of the agricultural sector as a whole.

[5] The literature on 'why Europe and not China?' is too vast to survey here, (*inter alia*, see Pomeranz, 2000; Allen, 2005; Galor, 2011). Vollrath (2011) uses differences in the labor intensity of crop types to explain differences in living standards between Europe and Asia prior to the Industrial Revolution.

[6] Jones (2005), extending Houthakker (1955), shows how individual firm-level production technologies aggregate up to Cobb-Douglas forms under mild assumptions.

2.1 Empirical Model

We employ a common factor framework to model agricultural production in country i at time t adopting a (log-linearised) Cobb-Douglas form:

$$y_{it} = \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + u_{it}, \tag{1}$$

where $\boldsymbol{x}$ is a vector of observed inputs (labor, capital, livestock, fertilizer and land) and y is observed output (all in logarithms). Agricultural *technology* ($\boldsymbol{\beta}_i$) is allowed to differ across countries but is constant over time.[7]

Simply allowing for heterogeneous technology by estimating the production function in (1) separately for each country fails to deal with the primary issue in cross-country production function estimation, unobserved TFP, u_{it}. We ultimately adopt the flexible structure of the common factor framework, which leverages information from the entire panel, to deal with this issue. But it is worth detailing how the common factor approach compares to the existing literature (see Eberhardt & Teal, 2011, for a detailed review). In the simplest case we could follow Mankiw, Romer & Weil (1992) and assume that all countries have identical TFP levels and evolution over time; then we would specify TFP as $u_{it} = \alpha + \gamma t + \varepsilon_{it}$ (a linear trend in TFP) or $u_{it} = \alpha + \gamma_t + \varepsilon_{it}$ (time-specific TFP).[8] If we thought that TFP levels differed across countries in a non-random fashion, but still agreed with identical TFP growth across all countries (perhaps arguing for knowledge as a public good), we could adopt the Islam (1995) specification $u_{it} = \alpha_i + \gamma_t + \varepsilon_{it}$. A more flexible approach would be to assume differential TFP growth across countries in addition to differential TFP levels. This is captured by the specifications in Martin & Mitra (2001) and Pedroni (2007) $u_{it} = \alpha_i + \gamma_i^a t + \gamma_t^b + \varepsilon_{it}$, which allow for a common "frontier" TFP growth term γ_t^b.

Ultimately, though, we want to allow for the possibility that TFP growth differs not only across countries, but also within countries over time; we would like to model TFP as $u_{it} = \alpha_i + \gamma_{it} + \varepsilon_{it}$. The issue here is how to separate the country-time specific productivity shock, γ_{it}, from random noise, ε_{it}. We cannot include country-specific sets of year dummies to capture γ_{it} since we

[7]Our empirical setup can be motivated from the theoretical model developed in Mundlak, Butzer & Larson (2012) – see Eberhardt & Teal (2013*b*) for detailed discussion. Conceptually, $\boldsymbol{\beta}$ may well vary within countries *over time*. We have estimated equation (1) using various strategies (different start dates, different end dates) but found no systematic variation in $\boldsymbol{\beta}$ over time (see Appendix). Additionally, there is no tendency for $\boldsymbol{\beta}$ to be correlated with output per worker. Hence we focus on the results that hold $\boldsymbol{\beta}$ constant over time.

[8]Mankiw, Romer & Weil (1992) of course did not exploit the *panel* element of the data in their specification of TFP levels and growth but still assumed common TFP levels and a constant common TFP growth rate.

would encounter a dimensionality problem; there are not enough observations in our dataset to estimate this equation. We can however model such idiosyncratic TFP evolution with a minimum of reasonable assumptions by adopting a 'common factor' framework. Let

$$u_{it} = \alpha_i + \gamma_i' \boldsymbol{f}_t + \varepsilon_{it} = \alpha_i + \gamma_{Si}' \boldsymbol{f}_t^S + \gamma_{Wi}' \boldsymbol{f}_t^W + \varepsilon_{it}, \tag{2}$$

where ε_{it} is white noise. The α_i term represents country fixed effects which capture country-specific TFP levels. Next we include a set of common factors $\boldsymbol{f}$, with country-specific parameters (factor loadings) γ_i.

These factors, which are orthogonal to each other, come in two flavours, as can be illustrated by the nature of their factor loadings: one type, 'strong' factors ($\boldsymbol{f}^S$), are assumed to affect *all* countries.[9] These factors can be thought of as structural elements of technical progress (e.g. the process and evolution of agricultural innovation) and/or global shocks which affect all economies in the world, but to a different extent (e.g. the recent global financial crisis or, with reference to agriculture, the 2007/8 global food price crisis). There is assumed to be a fixed number of these 'strong' factors, in line with findings in the macro literature (Stock & Watson, 2002). A second type, 'weak' factors ($\boldsymbol{f}^W$), only affect a subsample of countries.[10] These represent localized effects, such as spillovers between economies in a geographic region, or productivity shocks to a small group of economies, possibly those sharing the same types of main crops. Following the insights of Chudik, Pesaran & Tosetti (2011) our implementation can accommodate an arbitrary number of these weak factors. The presence of the strong and weak factors in the model induces correlation across countries, which is econometrically referred to as 'cross-section dependence' (Andrews, 2005), and which we thus need to account for in our estimation.

Using the common factor framework also allows us to address possible endogeneity, as unobserved TFP directly influences input use. Our vector of inputs $\boldsymbol{x}$ is specified as

$$\boldsymbol{x}_{it} = \boldsymbol{\eta}_i + \boldsymbol{\Phi}_{Si}' \boldsymbol{f}_t^S + \boldsymbol{\Phi}_{Wi}' \boldsymbol{f}_t^W + \boldsymbol{\Upsilon}_i' y_{it-1} + \epsilon_{it}, \tag{3}$$

where the ϵ_{it} are white noise processes. The input equations can be seen to be functions of (some of) *the same strong and weak factors* which are contained in the output equation, albeit

[9]Thus formally $\gamma_{Si} \neq 0 \, \forall \, i$ and as we let the number of cross-sections go to infinity the *average* of the absolute γ_{Si} converges to a positive constant.

[10]Thus $\gamma_{Wi} = 0 \, \forall \, i = 1, \ldots, M$, where $M/N \to 0$ as $N \to \infty$, and as we let the number of cross-sections go to infinity the *sum* of the absolute γ_{Wi} converges to a positive constant.

with different factor loadings.[11] This accounts for the endogeneity of production inputs, driven (in part) by unobserved TFP, leading to 'transmission bias' (Marschak & Andrews, 1944). With $\boldsymbol{\Upsilon}_i' \neq 0$ the above system also incorporates direct feedback from output to inputs as well.

Finally, we specify the properties of the common factors themselves, and we allow for a general evolution of these:

$$\boldsymbol{f}_t = \boldsymbol{\Pi} + \boldsymbol{\Lambda}' \boldsymbol{f}_{t-1} + \boldsymbol{E}_t. \tag{4}$$

The setup allows factors to be stationary $|\boldsymbol{\Lambda}_i| < 1$ or nonstationary $\boldsymbol{\Lambda}_i = 1$, thus potentially yielding random walk processes with drifts which are frequently adopted in the empirical literature to represent the evolution of macroeconomic variables.

By allowing for both global global common factors ($\boldsymbol{f}_t^S$) and more localized common factors ($\boldsymbol{f}_t^W$), our specification for u_{it} in (2) and inputs in (3) accounts for country-time variation in unobservable TFP and endogenous input choices. In their impact on inputs and output these global or local factors are not constrained to have an identical effect in all countries. Taking an international food price spike as an example of a global shock, this setup allows for a differential impact of the shock between net food exporters and net food importers. A more localized shock, for instance a drought in parts of Sub-Saharan Africa, is allowed to impact some countries in the region more severely than others, while not affecting other regions at all.

To estimate the production function in (1) given the common factor framework for TFP and inputs we focus on recent panel time series estimators that allow for cross-sectional dependence (which the common factors imply) *and* parameter heterogeneity (which is ultimately what we are interested in). The presence of the unobserved common factors creates difficulties for the identification of the technology parameters $\boldsymbol{\beta}_i$ since internal instruments such as lags and instruments external to this system are all functions of these factors as well (Andrews, 2005; Coakley, Fuertes & Smith, 2006). The panel time series literature provides two avenues for identification: firstly, using methods developed by Jushan Bai and co-authors (Bai, Kao & Ng, 2009; Bai, 2009), the common factors and respective factor loadings can be estimated using principal component analysis and then included in the production function equation.[12] This approach crucially depends on the pre-estimation choice of the number of 'relevant' factors for the data at hand, which is difficult in the presence of both strong and weak factors (Bailey, Kapetanios & Pesaran, 2015).

[11] For ease of exposition and without any bearing on the empirical setup we abstract from any additional factors which only enter the input equations.

[12] In practice these estimators employ iterations of these steps since the inclusion of estimated factors introduces finite sample bias into the second stage estimates.

The alternative approach of Pesaran (2006) that we rely on instead has been shown to provide consistent results in the presence of nonstationary common factors, structural breaks, and cointegration or noncointegration of the model variables (Chudik, Pesaran & Tosetti, 2011; Kapetanios, Pesaran & Yamagata, 2011; Pesaran & Tosetti, 2011). It is also easy to implement, even in unbalanced panels with missing observations. The Common Correlated Effects Mean Group (CMG) estimator augments the regression equation with cross-section averages of the dependent ($\overline{y}_t$) and independent variables ($\overline{\boldsymbol{x}}_t$) to account for the presence of the unobserved common factors. A regression with k independent variables specified as

$$y_{it} = a_i + \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + c_{0i}\overline{y}_t + \sum_{m=1}^{k} \boldsymbol{c}_{mi}\overline{x}_{mt} + e_{it}, \tag{5}$$

is estimated separately for each country by Ordinary Least Squares. The parameter estimates $\hat{\boldsymbol{\beta}}_i$ are then averaged across countries following the Pesaran & Smith (1995) Mean Group approach.[13] In our specific implementation, having estimated the equation separately for each country, we can average the $\hat{\boldsymbol{\beta}}_i$ for sub-sets of countries sharing similar crop types. The composition of those sub-sets is a decision made outside of the estimation itself, and we discuss below in detail the various methods we use to choose those sub-sets.

In (5) the cross-section averages of input x and output y proxy for the unobserved common factors, while the country-specific coefficient on these averages, c_{0i} and $\boldsymbol{c}_{mi}$, capture the heterogeneous factor loadings γ_i in our common factor framework. In the Appendix we give a simple example of how using these cross-section averages of inputs and output substitute for the unobserved common factors, allowing us to get consistent estimates of $\boldsymbol{\beta}_i$.

The final point regarding the estimation strategy regards the construction of the cross-sectional averages $\overline{y}_t$ and $\overline{\boldsymbol{x}}_t$ in (5). We implement three methods for calculating these averages:

- **Simple unweighted averaging**. Here we calculate $\overline{y}_t = \sum_{i=1}^{N}(1/N)y_{it}$, where N is the number of countries i, and there is a similar expression for each input – this is the standard approach in Pesaran (2006). The resulting values of $\overline{y}_t$ and $\overline{\boldsymbol{x}}_t$ are identical for all countries but vary by year.
- **Weighting by crop similarity**. We first construct an index of the similarity of crop types between all bilateral pairs of countries indexed by i and j, for each period t. The index – in essence a multivariate correlation coefficient of cropped land area between countries – is

[13] Although $\overline{y}_t$ and e_{it} are not independent their correlation goes to zero as N becomes large. Inference is established using a nonparametric variance estimator (Pesaran & Smith, 1995).

calculated as in Jaffe (1986), using FAOSTAT data on the shares of total harvested land area by crop m in country i at time t (h_{imt}). For country-pair i and j in an individual year t let

$$\omega_{ijt} = \omega_{jit} = \frac{\sum_m h_{imt} h_{jmt}}{\left(\sum_m h_{imt}^2\right)^{1/2} \left(\sum_m h_{jmt}^2\right)^{1/2}}.$$

The cross-sectional average of output for country i is then given by[14] $\overline{y}_{it} = \sum_{j=1}^{N} \omega_{ijt} y_{jt}$, with a similar expression for each input in $\overline{\boldsymbol{x}}_{it}$. Thus the cross-sectional averages for output and input are unique to each country and year. The motivation for this approach is the importance of similar production technology for knowledge spillovers (Ruttan, 2002).

- **Weighting by average crop similarity**. The similarity index may be quite noisy over time due to idiosyncratic (weather) shocks, so our last approach is to construct a time-averaged value of the index, as in $\overline{\omega}_{ij} = \sum_{t=1}^{T} (1/T) \omega_{ijt}$. We then use this averaged weight to construct $\overline{y}_{it} = \sum_{j=1}^{N-1} \overline{\omega}_{ij} y_{jt}$, and similarly for each input. The cross-sectional average still varies across countries and across time.

We discuss below that weighting by crop similarity results in better diagnostics for our regressions. In particular, we can more confidently reject any remaining cross-sectional dependence in our panels if we weight $\overline{y}_t$ and $\overline{\boldsymbol{x}}_t$ using crop similarity.

It is important not to overstate the power of our empirical approach: using less than 50 annual observations per country our *country*-specific estimates will be subject to small-sample bias. The panel time series estimator pursued here relies upon construction of *averages* of technology coefficients across countries – see Eberhardt & Teal (2013*a*) for a discussion of the sources of bias in individual estimates and the elimination of this bias through averaging. However, given the large size of our sample, we are able to construct fairly precise technology estimates for various sub-samples – by dominant crop types – in our data.

2.2 Data

The data for agricultural inputs and output are taken from the U.N. Food and Agriculture Organization's FAOSTAT database. This contains annual data for net agricultural output (in thousands of real International \$), labor (economically active population in agriculture), capital

[14]Note that following convention in the spatial econometric literature $\omega_{ijt} = 0$ for $i = j$. Subsequently the weights for each country i are row-normalized, such that $\sum_i \omega_{ijt} = 1$.

stock (we follow convention using tractors as a proxy), livestock (in cattle-equivalents following Hayami & Ruttan, 1970), fertilizer (aggregated across various types, expressed in volume terms) and arable and permanent crop land (in hectare) for 100 countries over the 1961–2002 period. Our sample is constrained by the availability of data on land area harvested by crop (henceforth 'crop area'), also from FAOSTAT. More details and descriptive statistics can be found in the Appendix.[15]

2.3 Empirical Results and Discussion

We present our production function estimates in Table 1. In each column (except [1]), the reported coefficients for each factor input are the averages across all countries. However, recall that we do have unique estimates of each coefficient for each country in the sample. Here we note some important properties of the 'global' results, while in the next section we discuss the heterogeneity in parameter estimates in detail.

We estimate a transformation of the empirical production function in equation (1) where all observed inputs and output are expressed in per worker terms. The coefficient on (log) labor as a separate input indicates the *deviation* from constant returns (increasing or decreasing returns), while excluding it entirely imposes constant returns to scale (CRS). The results in Table 1 report in the first row the estimated value of $\hat{\beta}_L + \hat{\beta}_K + \hat{\beta}_{Live} + \hat{\beta}_F + \hat{\beta}_N - 1$, where the subscripts refer to labor, capital, livestock, fertilizer, and land, respectively. The second panel of the table shows the 'implied $\hat{\beta}_L$' in each specification.[16] The results are not contingent on using per-worker values, but presenting the results this way allows us to highlight the implied returns to scale in each estimation.

Columns [1] and [2] report results from a simple OLS with country and year fixed effects (2FE) and outlier-robust means from the Pesaran and Smith (1995) Mean Group (MG) estimators.[17] As the literature review in Eberhardt & Teal (2013*a*) suggests, the 2FE is by far the most popular empirical estimator used in the existing literature on inter-country agricultural production

[15] As a robustness check to ensure that differences in $\hat{\beta}_L$ are not driven by variation in the prevalence of livestock we employ total net output and livestock in *value* terms from a more recent version of FAOSTAT. Countries where livestock takes up on average more than 60% of total agricultural output value were then excluded, resulting in a sample of 87 countries. The empirical model in this case has total net output less livestock value (in logs) as dependent variable and excludes the livestock variable. See Appendix for details. The results are unchanged.

[16] This implied $\hat{\beta}_L$ is the average of the individual country level values.

[17] We adopt robust regression methods (Hamilton, 1992) to compute weighted means where more weight is given to observations close to the mass of the distribution than to outliers.

functions. The performance of the MG estimator provides important insights regarding the importance of accounting for both technology heterogeneity *and* cross-section correlation, thus meriting its inclusion. Alongside these we report robust mean estimates for three CMG estimators in columns [3] to [5]. These implementations vary in the weighting used in constructing the cross-sectional averages. In column [3] $\overline{y}_t$ and $\overline{x}_t$ are simple averages of all variables across the entire sample, while in columns [4] and [5] they are weighted averages, where we use the crop similarity measures introduced above as weights: in [4] we adopt the time-averaged weights for every period, in the [5] we use the annual weights.

Looking across the results, it is notable that the 2FE and MG estimates imply large and statistically significant *decreasing* returns to scale (DRS) at the global level, as can be inferred from the negative coefficient on labor in the first row. In constrast, the three CMG estimates cannot reject constant returns (CRS), and so we have reported the results of these specifications with CRS imposed. In the 2FE and MG models evidence of DRS translates into almost negligible labor coefficients, $\hat{\beta}_L$, while diagnostic tests reveal nonstationary and cross-sectionally dependent residuals in the former and cross-sectionally dependent residuals in the latter – evidence of serious misspecification. The versions of the CMG estimator, in contrast, yield stationary and cross-sectionally independent residuals. In the Appendix we provide evidence that our crop area-weighted CMG specifications in [4] and [5] can be interpreted as production functions and do not suffer from bias due to reverse causality, using the weak exogeneity test of Canning & Pedroni (2008). These results strongly support the notion that we are estimating production functions; that is, our parameters capture the elasticity of output with respect to a given input.[18] The average technology in our CMG specifications in [4] and [5] provides for substantially larger labor coefficients than the 2FE or MG models, as well as smaller fertilizer and larger capital (tractor) coefficients. Recall that we are only interested in these *average* technology results to compare them with specifications assuming common technology (2FE) and/or cross-sectional independence (2FE, MG), and to confirm that the residual diagnostics are sound. Our data reject basic assumptions for the consistency of both our 2FE and MG estimates, while the CMG estimators pass the fundamental diagnostics by incorporating both heterogenous technology coefficients and endogenous factor inputs.

These preferred CMG models are argued to identify the technology parameters by successfully accounting for unobserved productivity. As one of a number of robustness checks we added

[18]In contrast, for the 2FE, MG and standard CMG specifications there is less evidence of weak exogeneity and hence these estimates may be biased. Diagnostic testing by crop-cluster (see below on clustering) further indicate residual cross-section dependence in two of the four clusters for the standard CMG results (available on request).

per capita income (in logarithms, taken from the Penn World Tables: Heston, Summers & Aten, 2009) as an additional covariate in our production function.[19] Adopting income per capita as a proxy for productivity in country i, this specification addresses the concern that estimates of the technology coefficients would be systematically biased if our CMG approach failed to capture unobserved productivity adequately.[20] Results from this exercise are qualitatively unchanged from those in Table 1 and if we compare estimated labor elasticities between our preferred CMG models in [4] and [5] with and without per capita income we obtain correlation coefficients in excess of 0.9. These results can further be taken to argue that our technology estimates are not systematically biased due to the omission of human capital, since average years of schooling in the population are highly correlated with per capita income.[21]

2.4 Technology Heterogeneity Across Crop Types

Table 1 presented *average* estimated technology coefficients across all countries, but our primary interest is in the *heterogeneity* in the estimated technology parameters across countries related to their major crop type. We work with the individual country coefficients underlying column [5] of Table 1, our preferred set of estimates, which uses annual crop data to form the cross-sectional averages included in the estimation.

No country exclusively produces only one crop, but since our agricultural technology is estimated at the country-level the choice of how we map countries into crop types will be relevant, and our findings potentially sensitive to this choice. We adopted a range of approaches to investigate this, but find consistently that the output elasticity with respect to labor tends to be large in countries dominated by rice production and small in those dominated by wheat production.[22]

[19] We also carried out further analysis to find that there is limited correlation between estimated coefficients and averages of input in the preferred CMG models, which implies that there is no systematic relationship between the size of the estimated coefficient on an input and the amount of that input used. This corroborates our suggestion that technology coefficients do not vary systematically with higher or lower factor intensities. While examining specifications that use different start or end dates for the data, we found no evidence that the value of $\hat{\beta}_L$ varied systematically over time for any crop type group. Results related to these exercises are contained in the Appendix.

[20] We include y^{PWT} (in logs) but not its cross-section average in the CMG models given that income is interpreted as a proxy for (heterogeneous) TFP.

[21] We employed measures for rural human capital reported in Timmer (2002) and economy-wide average schooling attainment from Barro & Lee (2013). Quinquennial schooling measures for a reduced sample of 94 countries on the one hand and real aggregate per capita income on the other have a correlation coefficient of 0.82 (rural measure 0.64, Barro-Lee measure 0.85).

[22] Using the country-level coefficients from either of the other CMG estimates in columns [3] or [4] does not substantially change this result regarding rice and wheat, but the coefficients drawn from column [5] most strongly

We begin by focusing on two dominant crops (wheat and rice), each of which on average accounts for more than 10% of the crop area within countries (see Appendix Table). In Panel A of Table 2 we compare the average technology coefficients between the quartiles of the crop area distribution for each of wheat and rice: countries in the bottom quartile of the crop area distribution are grouped together and their average technology coefficients reported in the column marked '1st', those in the second quartile are averaged and reported in '2nd', and so on.[23] This avoids double-counting of country estimates and assures equally-sized groups, but suffers from the caveat of summarizing the crop mix of 161 commodities by the distributions of a mere two. Focusing on the estimated labor coefficient, we can see that this is large in countries where rice is the dominant crop (3rd and 4th quartiles for rice), and small in wheat-dominant countries (3rd and 4th quartile for wheat). Further, countries that do *not* grow wheat (1st and 2nd quartiles for wheat) have relatively large labor coefficients, while countries that do *not* grow rice (1st and 2nd quartiles for rice) have relatively small labor coefficients. This shows that there are distinct technologies based around the representative crops wheat and rice.

With respect to the elasticities on the other inputs, there is relatively little variation in the capital, livestock, and fertilizer coefficients across the quartiles for either of the crops. The capital coefficient is generally around 0.05, the livestock coefficient around 0.33, and the fertilizer coefficient around 0.03. Variation in the labor coefficient by crop type is almost entirely mirrored by variation in the coefficient on land. Hence countries where wheat dominates (3rd and 4th quartiles) have land coefficients over 0.30. In contrast, countries where rice dominates (3rd and 4th quartiles) have land coefficients of only between 0.04 and 0.10. The main variation in the agricultural technologies we uncover is in the relative intensity of labor and land use.

The quartile analysis is rather crude, since it ignores 159 other crops widely cultivated across the world. In an alternative approach, results for which are reported in Panel B of Table 2, we employed cluster analysis to create four groups of countries based on their similarity of crop area (i) across all 161 crops, or (ii) across the three dominant crops of maize, wheat and rice.[24] While the algorithmic selection into groups is now based on a much larger number of crops and not determined by quartile cut-offs, the downside of this approach is that the resulting clusters are no longer of equal size. But again the labor coefficient in the clusters dominated by wheat cultivation (columns marked 'I': 0.089 and 0.127) is significantly lower than those in the clus-

reject cross-sectional dependence within the subgroups we form by crop type.

[23]The cut-offs are as follows: for wheat 1st 0.0%, 2nd 0.0%≤ x<2.7%, 3rd 2.7%≤ x<25.5%, and 4th >25.5%; for rice 1st <0.2%, 2nd 0.2%≤ x<1.7%, 3rd 1.7%≤ x<10.5%, and 4th >10.5%. In this Table we again present outlier-robust means obtained from robust regressions (Hamilton, 1992).

[24]Details on the clustering algorithm and the country makeup of each cluster are reported in the Appendix.

ters dominated by rice cultivation ('III': 0.474 and 0.314), whether we create clusters using all or just the three dominant crops. Both the maize cluster (columns marked 'II') and the 'other' cluster (columns marked 'IV') show distinct differences with wheat. The crop cluster based around maize has technology coefficients similar to rice, while the 'other' category, which includes many countries in Sub-Saharan Africa, tends to have the highest labor coefficients of any cluster.

The conclusion from Table 2 is that there is a systematic pattern relating agricultural technology coefficients to the dominance of specific crops in countries' agricultural sectors. Wheat technology appears to be systematically linked with comparatively low labor technology coefficients and comparatively high coefficients for land. The reverse is the case for rice technology, with maize forming an intermediate-level technology. These technology differences do not indicate that countries centered around wheat production necessarily have higher *productivity* – TFP – than countries based around other crops. They do indicate that the response of output to changes in an input – particularly labor and land – is different depending on the major type of crop grown.

3. IMPLICATIONS OF TECHNOLOGY HETEROGENEITY

An implication of agricultural technology heterogeneity is that countries with different values of $\boldsymbol{\beta}_i$ face different constraints in transitioning away from agriculture and to other economic activities. To see this, first write output *per worker* as

$$z_{it} = y_{it} - l_{it} \tag{6}$$

where l_{it} is the (log) labor input to agriculture. Using the production function in (1) we can then write

$$z_{it} = \boldsymbol{\beta}_i' \boldsymbol{x_{it}} + (\beta_i^L - 1) l_{it} + u_{it} \tag{7}$$

where we have explicitly separated the labor input, l_{it}, from the other inputs, $\boldsymbol{x}_{it}$, as the labor coefficient β_i^L is going to be the crucial term in our analysis. The term u_{it} is again TFP.

Denote log output *per capita* as c_{it}, and the log population size as n_{it}, which implies that

$$c_{it} = \boldsymbol{\beta}_i'(\boldsymbol{x_{it}} - \boldsymbol{n_{it}}) + \beta_i^L (l_{it} - n_{it}) + u_{it}. \tag{8}$$

Equation (8) effectively forms a budget constraint for the economy.[25] Given a positive shock to inputs per capita $(\boldsymbol{x_{it}} - \boldsymbol{n_{it}})$ and/or TFP (u_{it}), the economy can 'spend' this on either (i) increased output per capita c_{it}, or (ii) a lower agricultural labor share, $(l_{it} - n_{it})$.

Since we are ultimately concerned with outcomes in per worker or per capita terms, the labor coefficient β_i^L is crucial for how much the budget constraint shifts in response to TFP or inputs. A low β_i^L value means the cost of lowering the labor share, in terms of foregone output, falls. As β_i^L goes to zero output is unaffected by the amount of labor in the agricultural sector and moving workers out of agriculture is costless. Thus the labor share in agriculture can quickly fall to zero while maintaining output per capita. In response to a TFP shock or increased non-labor input use, a low β_i^L means a county can either shed more labor while maintaining the existing level of output, or raise output more given their existing labor allocation.

3.1 The Potential for Agriculture-Led Growth

To illustrate the quantitative importance of variation in β_i^L, using (8) we first ask for each country what it would take to achieve a specific set of targets for output per capita, c_{it}, and agricultural labor share, $(l_{it} - n_{it})$. These targets are the U.S. level of agricultural output per capita in 2002 (992 international dollars, compared to a sample mean of 530), and the U.S. labor share in agriculture in 2002 (0.02, compared to a sample mean of 0.40). Hitting the U.S. level of output per capita, while also reducing labor share to the U.S. level, requires an increase in either TFP (u_{it}), input use ($\boldsymbol{x_{it}}$), or both. As per the above discussion, the scale of the necessary increase in these items depends on the size of the β_i^L.[26]

Figure 1 presents the results of two different evaluations. In panel (a), we calculated how much TFP would have to be scaled up in order to reach the U.S. targets, and plot this against countries' 2002 per capita GDP. Each country was evaluated using the technology coefficients associated with their quartile of crop area devoted to wheat, taken from Table 2, but the results are similar if we use the cluster breakdowns in panel B of that table instead. In the Figure we distinguish countries with high labor coefficients (those in the lower two quartiles of wheat crop area) and low labor coefficients (those in the upper two quartiles).

As can be seen, the scale of TFP necessary to reach the U.S. targets is very large for the poorest

[25] Note that we are not assuming that c_{it} is *consumption* per capita, despite the notation. It is output per capita, and whether that is the amount consumed or not depends on whether the economy is open or closed.

[26] Practically, we solve $c_{US,2002} = \beta_i'(\boldsymbol{x_{i,2002}} - \boldsymbol{n_{i,2002}}) + \beta_i^L(l_{US,2002} - n_{US,2002}) + u_{it} + \ln\phi_i$ for the value ϕ_i, which captures how much TFP must be scaled up to reach the US targets.

countries, implying a factor of between 10 and 60 is necessary for many of them. But notice that the low labor coefficient economies have a much smaller mountain to climb. The relative TFP required is at the most around 10, and typically between 5-8. Compare this to the high labor coefficient economies, where the scale does fall below 10 in a few cases, but for the majority of poor countries is close to 20, and rises as high as 60. Countries that use agricultural technologies with high values of β_i^L, associated with rice production, have to experience higher TFP growth to reach the same targets. Their agricultural technology limits their ability to develop quickly.

Panel (b) of Figure 1 shows a similar exercise, but now we ask how much both TFP and all non-labor inputs would have to increase in order to reach the same U.S. targets.[27] The absolute scale required is now smaller, as both inputs and TFP are allowed to expand, but the distinction by crop type remains. Low β_i^L countries need only to scale up productivity by roughly a factor of 5 to reach the U.S. targets, while high β_i^L countries require scaling of between 5 and 20. Again, technology heterogeneity by crop type implies that some countries have more work to do than others to reach rich country levels.

A final thing to note in Figure 1 is that low labor coefficients are not simply a proxy for high per capita GDP. Our sample includes some very poor countries that have low labor coefficients, as well as a few very rich countries that have high labor coefficients. Technology coefficients do not dictate the level of productivity, they dictate how a country responds to changes in productivity.

3.2 Accounting for Development Levels

The prior section shows that differences in crop technologies create differences in the potential for agricultural growth. But how much of currently observed variation in agricultural production and GDP per capita is due to variation in these technology coefficients? To answer this question we adopt counterfactual exercises from the development accounting literature. We shut down variation in the object of interest – agricultural technology coefficients – and examine how the distribution of output per worker or the agricultural labor share changes in response. Practically, we will do this by setting the technology coefficients in each country to be equal to those from a 'wheat' country, and observe what this implies for output per worker and the agricultural labor share given their observed growth in inputs and TFP.[28]

[27] This includes land as an input. If we exclude land the results are qualitatively identical.
[28] We discuss our choice of adopting average wheat technology in section 3.3 below.

3.2.1 Counterfactual Scenarios

Our two main objects of interest are agricultural output per worker and the agricultural labor share. They are linked through the production function, and how each of them changes when we remove technology heterogeneity in turn depends on the other.

Start by writing equation (8) in terms of growth rates, where 'hats' denote the average growth rate of a variable country i from time 0 to time t,

$$\hat{c}_{it} = \beta_i'(\hat{\boldsymbol{x}}_{\boldsymbol{it}} - \hat{\boldsymbol{n}}_{\boldsymbol{it}}) + \beta_i^L(\hat{l}_{it} - \hat{n}_{it}) + \hat{u}_{it}. \tag{9}$$

Note that the term $\hat{\boldsymbol{n}}_{\boldsymbol{it}}$ is the change in population multiplied by a column vector of ones, so that $(\hat{\boldsymbol{x}}_{\boldsymbol{it}} - \hat{\boldsymbol{n}}_{\boldsymbol{it}})$ is a vector of the growth of inputs per capita. The $(\hat{l}_{it} - \hat{n}_{it})$ term is the growth rate in the agricultural labor share.

In our counterfactual exercises we remove the variation across countries in $\boldsymbol{\beta}_i$ and β_i^L by setting them to $\boldsymbol{\beta}_{wheat}$ and β_{wheat}^L for each country, respectively.[29] By changing the technology coefficients, we are both shifting and changing the slope of the budget constraint for each economy i. Figure 2 gives a visual example for the case of Thailand. Here we have plotted the growth rate of agricultural output per capita, $\hat{c}_{it}$, from 1962–2002, against the growth rate of agricultural labor share, $(\hat{l}_{it} - \hat{n}_{it})$. The point marked 'Actual' is what we observe in the data for Thailand, and the dashed line denotes the implied budget constraint from (9) using Thailand's own technology coefficients (Thailand is a 'rice' economy according to our classification).

When we replace Thailand's technology coefficients with the wheat coefficients, this shifts the budget constraint to the solid line. The intercept of this budget constraint has shifted up because Thailand had positive growth in non-labor inputs per capita, $(\hat{\boldsymbol{x}}_{\boldsymbol{it}} - \hat{\boldsymbol{n}}_{\boldsymbol{it}}) > 0$, and the wheat coefficients on these inputs are larger than the rice coefficients. The slope of the budget constraint has become flatter because the labor coefficient, β_i^L, for wheat is smaller than the labor coefficient for rice. Thus Thailand's observed input per capita and TFP growth would have allowed for more growth in output per capita and/or a more rapid decline in agricultural labor share if they had taken place in a wheat technology economy. We are not implying that Thailand could, or should, try to adopt wheat as a crop. We are simply performing a counterfactual calculation. The best way to interpret this exercise is to ask what a wheat-growing economy could have done with Thailand's observed non-labor input and TFP growth.

[29] The values for $\boldsymbol{\beta}_{wheat}$ and β_{wheat}^L are taken directly from our estimated values. We use the technology coefficients associated with the 4th quartile of wheat producers in panel A of Table 2. The results are similar if we use other estimates of the wheat coefficients from panel B.

We have the counterfactual budget constraint, but what point along that alternative budget constraint would a country choose? Without specifying preferences, we cannot say. Rather than to take a stand on a given set of preferences, we look at several possibilities that effectively nest preferences frequently adopted in the literature. In simple closed-economy models of non-homothetic preferences with a fixed demand for food, any increase in non-labor inputs or TFP is spent on reducing the agricultural labor share, such that $\hat{c}_{it} = 0$. In a closed economy model with homothetic preferences, such as with Cobb-Douglas utility, all the adjustment takes place through increased output per capita, and thus $\hat{l}_{it} - \hat{n}_{it} = 0$. We typically observe countries with both increasing output per capita and falling labor shares (e.g. Thailand in Figure 2), so neither of these cases is precisely correct, but they provide useful benchmarks. Furthermore, with free trade there is no reason that output per capita could not shrink, $\hat{c}_{it} < 0$, in the counterfactual, or that the agricultural labor share could not increase, due to comparative advantage.[30] Regardless of whether the economy is open or closed, equation (9) constrains the response of these variables to changes in output per worker coming from either input growth or TFP improvements.

For our counterfactuals we examine two responses to changes in the budget constraint:

- **Counterfactual 1:** This scenario assumes that the economy is closed, and that the price elasticity for agricultural output is -1, consistent with a model of demand for agricultural output where people have Cobb-Douglas preferences. This counterfactual point is noted by 'CF1' in Figure 2.

  We set the change in the agricultural labor share, $(\hat{l}_{it} - \hat{n}_{it})$, to the observed change for country i and then calculate the counterfactual change in agricultural output per capita for country i, $\hat{c}_{it}^{CF1}$, using the wheat technology coefficients,

  $$\hat{c}_{it}^{CF1} = \boldsymbol{\beta}'_{wheat}(\hat{\boldsymbol{x}}_{\boldsymbol{it}} - \hat{\boldsymbol{n}}_{\boldsymbol{it}}) + \beta^{L}_{wheat}(\hat{l}_{it} - \hat{n}_{it}) + \hat{u}_{it}. \tag{10}$$

  The counterfactual change in output per worker is now easily recovered, given $\hat{c}_{it}^{CF1}$ and the observed value for the growth in agricultural labor share, $(\hat{l}_{it} - \hat{n}_{it})$:

  $$\hat{z}_{it}^{CF1} = \hat{c}_{it}^{CF1} - (\hat{l}_{it} - \hat{n}_{it}). \tag{11}$$

[30] Tombe (2015) analyzes a model of development that explicitly allows for trade, finding that it exaggerates the effect of agricultural productivity differences on cross-country income per capita differences. This suggests that the results we present may be understating the effect of technology heterogeneity on economic development.

- **Counterfactual 2:** Here, the economy is again closed, but the price elasticity of agricultural demand is zero, consistent with a model of fixed demand for agricultural output. This counterfactual point is noted by 'CF2' for the example of Thailand in Figure 2.

  In this case we set the change in output per capita, $\hat{c}_{it}$, to the observed change for country i. We then calculate the counterfactual change in the agricultural labor input for country i, $\hat{l}_{it}^{CF2}$, using the observed population growth, $\hat{n}_{it}$, and the wheat technology coefficients to fit the following equation:

$$\hat{c}_{it} = \boldsymbol{\beta}'_{wheat}(\hat{\boldsymbol{x}}_{it} - \hat{\boldsymbol{n}}_{it}) + \beta^{L}_{wheat}(\hat{l}_{it}^{CF2} - \hat{n}_{it}) + \hat{u}_{it}. \tag{12}$$

  The counterfactual growth in output per worker is then simply

$$\hat{z}_{it}^{CF2} = \hat{c}_{it} - (\hat{l}_{it}^{CF2} - \hat{n}_{it}). \tag{13}$$

Conceptually, we could do alternative exercises by placing each country at any given point along their counterfactual budget constraint. Points between CF1 and CF2 in Figure 2 vary in the price elasticity with respect to agricultural output. Varying the income elasticity would move both CF1 and CF2 up (higher elasticity) or down (lower elasticity) the budget line.

3.2.2 From Growth to Levels

The two counterfactuals in the previous section are written in terms of growth rates, but ultimately we are interested in understanding level differences across countries in their agricultural output per worker and labor allocations. We cannot directly calculate counterfactual levels of agricultural output per worker or the labor share in agriculture because we have an 'apples and oranges' problem (Bernard & Jones, 1996; Martin & Mitra, 2001): the units of measurement for TFP levels vary with the technology coefficients $\boldsymbol{\beta}$. Hence we cannot hold TFP constant for any given country while changing its technology coefficients $\boldsymbol{\beta}$. There is no issue with computing counterfactual *growth rates*, as these are unaffected by differences in the units of measurement of TFP.

To find counterfactual *levels* in 2002 we therefore fix agricultural output per worker, output per capita (both in logs) and the labor share (difference of log l and log n) at observed levels in a base year, 1962, and apply our counterfactual growth rates to those initial levels. Mechanically, for scenario 1 we have

$$\begin{aligned} c^{CF1}_{i,2002} &= c_{i,1962} + 40 \times \ln(1 + \hat{c}^{CF1}_{i,40}) \\ z^{CF1}_{i,2002} &= z_{i,1962} + 40 \times \ln(1 + \hat{z}^{CF1}_{i,40}), \end{aligned} \tag{14}$$

where the counterfactual growth rates on the right-hand side are calculated for the 40-year period running from 1963–2002. A similar set of equations governs the counterfactual levels in scenario 2,

$$\begin{aligned} z^{CF2}_{i,2002} &= z_{i,1962} + 40 \times \ln(1 + \hat{z}^{CF2}_{i,40}) \\ l^{CF2}_{i,2002} - n_{i,2002} &= (l_{i,1962} - n_{i,1962}) + 40 \times \ln(1 + \hat{l}^{CF2}_{i,40} - \hat{n}_{i,40}). \end{aligned} \tag{15}$$

For each country we find what they would look like in 2002 if starting in 1962 they had grown with the wheat technology over the next 40 years.

Panel A in Table 3 presents the results of our experiments. We report summary statistics from the sample of 100 countries for the observed data (column 1) and the two counterfactual scenarios (columns 2 and 3). In panel A one can see that there is a large gulf between the most and least productive economies, with the observed 90/10 ratio for agricultural output *per worker* almost 90. The observed 90/10 ratio for agricultural output *per capita* in panel B of 5.2 is not nearly as severe. Finally, in panel C labor shares in agriculture average about 40% in our sample, and the 90/10 *difference* in these ratios is 76.3 percentage points.

In column [2], we show how these distributions change when we eliminate variation in agricultural technology across countries, but hold constant the labor allocation to agriculture (counterfactual 1). In panel A regarding output per worker, the variation across countries declines slightly, with the variance dropping from 2.75 to 2.47 (roughly 11%), and the 90/10 ratio dropping from 89 to 74 (about 17%). Moreover, note that the mean and median output per worker are higher when we set all countries to have wheat technology. The median is roughly 42% higher with the wheat (1.7) than with the actual technology coefficients (1.2). In panel B, agricultural output per capita also increases, with the median rising by 18% (from 0.39 to 0.46). Its variance decreases only slightly, while the 90/10 ratio actually increases from 5.2 to 5.5. These changes in the distribution of agricultural output in per worker and per capita terms are easiest to see in the density plots in the top row of Figure 3. Panel (a) displays the distribution of agricultural output *per worker*, and one can see how the entire distribution has essentially shifted to the right, matching the increase in median and mean in Table 3. Panel (b) shows the distribution of agricultural output *per capita*, and again there is a distinct shift to the right.

Our second counterfactual exercise, in column [3] of Table 3, finds somewhat different results. Here we hold agricultural output constant, but allow the labor allocation to vary when we remove variation in agricultural technology coefficients. For agricultural output per worker the counterfactual variance is essentially identical to the observed variance, as is the 90/10 ratio. However, the mean and median levels of output per worker are more than double their observed levels. This shift is reflected in the dramatic decrease in labor shares in agriculture. In panel C the mean labor share falls from 0.40 to 0.26 (a drop of about one-third), and the median falls from 0.34 to 0.16 (a drop of over one-half). The 90/10 difference in labor allocations drops from 0.76 to 0.59.

The bottom row of Figure 3 shows these counterfactual effects in density plots. Panel (c) again shows agricultural output per worker, where the shift in the distribution is far more pronounced than in the first counterfactual. There remain very few countries with output per worker in the lower tail, while the large mass are able to shift to the right. The tail to the right accounts for the fact that the variance and 90/10 ratios did not change much. What is occurring here is that almost all countries across the observed distribution using non-wheat technologies benefit from using the wheat technology in the counterfactual scenario. Those that were already highly productive become even more so, and hence the distribution remains stretched out.

Panel (d) plots the agricultural labor share, and again there is a dramatic shift in the counterfactual distribution. The mass of countries with labor shares above 0.50 declines sharply, and there is a distinct cluster in the counterfactual around 0.10. Thus the average level of the agricultural labor share falls, and the variance of its distribution decreases.

The distinct changes we see in our counterfactuals not only occur because we removed *variation* in the agricultural technology coefficients, but also because we specifically used the *wheat coefficients* in our computations.[31]

[31] To be clear, our findings are that *on average* outcomes are better in the counterfactual scenarios. But it is not universally the case that applying the wheat coefficients results in higher calculated output per worker or a lower labor share. For countries that experienced declining inputs per capita over this period, using the wheat technology coefficients is particularly bad, as we are putting more weight on those input terms. In terms of our exposition above, this would be equivalent to the budget constraint shifting *down*, even as the slope became flatter. It so happens that most countries experienced increasing inputs per capita over this period, and hence using wheat coefficients results in increased output per worker and/or lower labor shares.

3.2.3 Per Capita GDP

With distinct changes in agricultural output per worker and/or labor shares in our counterfactuals, it is very likely that this will translate into noticeable changes in average living standards and their variance across countries. To illustrate this, we generate counterfactual levels of GDP per capita for both of our counterfactual scenarios.

For counterfactual 1, GDP per capita in 2002 is calculated by taking non-agricultural output per capita in 2002 as given, and adding to that counterfactual agricultural output per capita.

$$GDPpc^{CF1}_{i,2002} = \frac{Y^{ag}_{i,1962}}{N_{i,1962}} \times (1 + \hat{c}^{CF1}_{i,40})^{40} + \frac{Y^{non}_{i,2002}}{N_{i,2002}}. \tag{16}$$

The 1962 level of agricultural output per capita, $Y^{ag}_{i,1962}/N_{i,1962}$, and the 2002 level of non-agricultural output per capita, $Y^{non}_{i,2002}/N_{i,2002}$, are taken from the World Bank World Development Indicators (WDI).

In counterfactual 2, per capita GDP is calculated using observed agricultural output per capita from 2002, and adding to that counterfactual non-agricultural output per capita. The latter is found by holding constant observed non-agricultural output *per worker* in 2002, but using our counterfactual share of labor in agriculture to determine the per capita value.

$$GDPpc^{CF2}_{i,2002} = \frac{Y^{ag}_{i,2002}}{N_{i,2002}} + \frac{Y^{non}_{i,2002}}{L^{non}_{i,2002}} \left(1 - s^{CF2}_{i,2002}\right), \tag{17}$$

where $s^{CF2}_{i,2002} = exp(l^{CF2}_{i,2002} - n_{i,2002})$ is the counterfactual share of agricultural labor, calculated using equation (15). The values of agricultural and non-agricultural output per worker are again taken from the WDI.

The WDI do not provide PPP-adjusted levels of agricultural and non-agricultural output and ideally, we would use such measures for our calculations. It is common in the literature (Caselli, 2005; Vollrath, 2009*b*; Lagakos & Waugh, 2013) to use data from Rao (1993) for this purpose, however, Rao's numbers date back to 1985, and we prefer to base our development accounting exercise on more recent data. Vollrath (2009*b*) shows that using the WDI data delivers similar development accounting results to using PPP-adjusted data, such as the Penn World Tables, even though the absolute variation of per capita GDP is wider in the former than in the latter.

In panel D of Table 3 we report the summary statistics for the observed data, as well as for the two counterfactuals. As noted, the absolute variation in per capita GDP is much higher than would be expected if we used the Penn World Tables. The variance is 2.74, and the 90/10 ratio is 115. Mean GDP per capita for our sample is $7,752, with a median of $1,735.

For counterfactual 1, where we hold the labor allocation constant and allow agricultural output to respond, the variance of GDP per capita falls by about 8%, from 2.74 to 2.53, and the 90/10 ratio falls by about 14%, from 115 to 100. Similar to what we saw with the agricultural data, aggregate per capita income increases as well; the mean increases by about 4% and the median by about 34%, thus the left tail of the distribution moves to the right rather significantly. This can be seen in panel (a) of Figure 4, which plots the densities of per capita GDP for the observed and counterfactual data.

Counterfactual 2 shows more sizable results still, as is illustrated in panel (b) of Figure 4. The large mass of countries at 6.0 log points shifts to 8.0 log points, an increase in per capita GDP by a factor of 7. Returning to Panel B of Table 3, this can be seen in column [3]. The mean level of GDP per capita rises by about 10%, from $7,752 to $8,500, while the median rises by 59%, from $1,735 to $2,763. There is also a distinct compression of the distribution, as the variance falls by 23% to 2.11, and the 90/10 ratio falls by 45% from 115 to 63.

Eliminating the variation in agricultural technology across countries lowers the variation in per capita GDP across countries. This effect is strongest when we force all the adjustment to occur by moving labor out of agriculture, since workers move into the more productive non-agriculture sector. Further, this compression occurs because it is the very poorest economies that see a sizeable increase in per capita income when we eliminate technology heterogeneity in agriculture.

3.3 The Importance of Crop Types

In Table 3 we established that eliminating variation in agricultural technology by applying the wheat coefficients to all countries results in outcomes that are distinctly positive for global per capita GDP. Agricultural output per worker increases in either counterfactual, and, depending on the scenario, the agricultural labor share declines or output per capita increases. The positive effects we see when using the wheat coefficients as the counterfactual technology are unique to that crop. If we used coefficients from the rice-intense economies, we would see average output per worker *fall* and labor shares in agriculture *increase* in our sample.

What makes the wheat technology so conducive to development? It is the relatively small value for the labor coefficient, β^L, and the relatively high values for the other inputs. Recall from Table 2 that the wheat technologies, however we define them, have labor coefficients of roughly 0.10-0.20, compared to rice technologies that have values in the range 0.45-0.60.

In either levels, equation (8), or growth rates, equation (9), the value of β^L governs the trade-off between a lower agricultural labor share and higher agricultural output. The low value of β^L in wheat-growing countries allows them to shift labor out of agriculture easily in response to TFP improvements without sacrificing much agricultural output per capita. In contrast, countries with high β^L crops – like rice – must sacrifice more output to shift labor out of agriculture. Thus in response to an increase in TFP or non-labor inputs they cannot shed as much labor while keeping output constant, or alternatively they cannot raise output as much while maintaining their existing labor allocation.

Note that the effect of β^L works through this trade-off, and not through the level of productivity. β^L dictates the consequences of any given TFP or input growth. Our findings are not that wheat is inherently more productivty (i.e. has a higher TFP), but rather that the trade-off between labor and output in wheat is less severe (i.e. the coefficient on labor is lower). Wheat technology by itself does not make countries rich, but it does make it easier to become rich in response to productivity improvements.

4. CONCLUSION

Agricultural technology varies widely across countries. In particular, the labor elasticity of agricultural production tends to differ with crop type. We exploit new techniques in macro panel estimation to control for unobserved productivity to establish that there is systematic heterogeneity in the technology parameters across countries. Specifically, we find that the elasticity of output with respect to labor is much lower in countries growing primarily wheat (0.10-0.20) than in countries growing maize or rice (0.40-0.60).

We examine the effect of this technology heterogeneity using counterfactual exercises adapted from the development accounting literature and embedded in standard theory models of structural change and development. The implication of our findings is that economies where wheat crops dominate have the potential to develop more swiftly than economies dominated by rice cultivation, in the sense that a smaller shock to total factor productivity or a smaller increase in factor inputs is necessary for them to transition to a low agricultural labor share. We provide counterfactual exercises to evaluate the effect of eliminating technology heterogeneity by examining how countries would have grown if they had been able to use the wheat technology. These counterfactuals provide stark implications for the distribution of aggregate income per capita and concomitantly for the welfare of populations in poor countries; depending on the counterfactual scenario, median per capita GDP rises by 34 to 59%, while its variance in either case contracts substantially.

Our work implies that there are significant effects of crop type on development. However, we must be very clear on what precisely those effects are. Our findings are not an example of 'geographic determinism,' the idea that tropical countries dominated by rice or maize crops are somehow doomed to be poor. The fact that agricultural *technology* varies by crop type does not imply anything about levels of TFP or factor inputs. This is consistent with our finding that the estimated labor elasticities are only weakly correlated with output per worker in our sample. Crop type does not necessarily predict which countries will be rich and which will be poor. But these elasticities do have quantitative implications for the response of countries to changes in TFP or factor inputs.

It is worth repeating that we are making counterfactual calculations, not policy recommendations. It may be biologically impossible for a tropical country to either adopt crops such as wheat in their agricultural sector or to grow their own crops using a production function that has a lower labor coefficient. Nonetheless, it can still be true that the variation in technology coefficients across countries accounts for a significant portion of the variation in agricultural output per worker, agricultural labor share, and ultimately per capita GDP. Different agricultural technologies, associated with different crop types, can explain a significant portion of cross-country variation in living standards.

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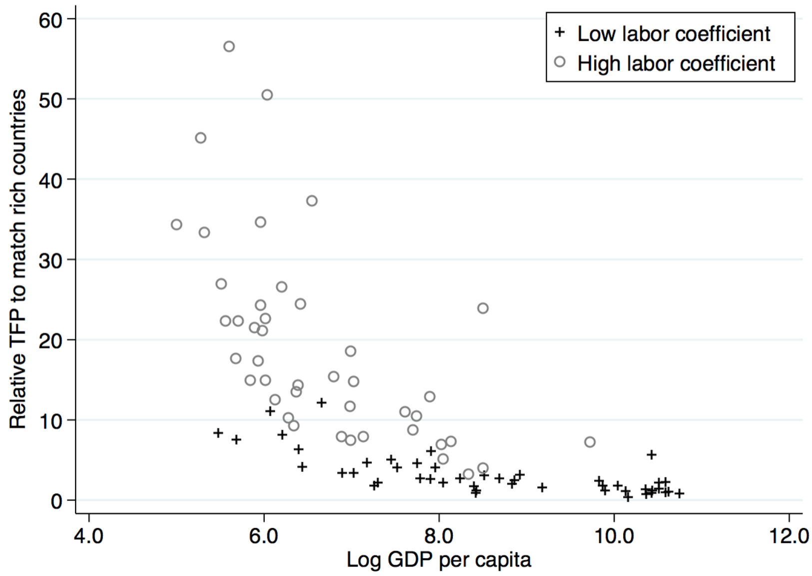
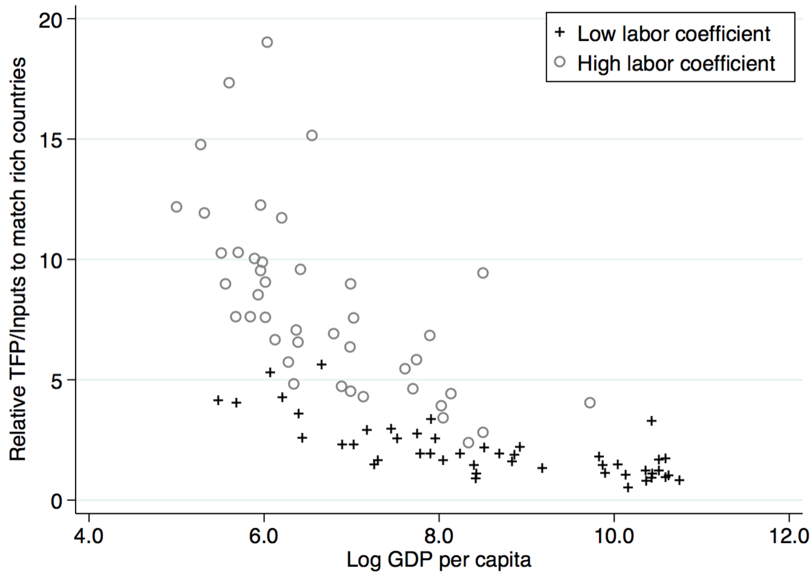


(a) Scale TFP only



(b) Scale both TFP and inputs

Figure 1: Scale of productivity improvements to reach rich country target

Notes: The figures show the relative scale of (a) TFP, and (b) TFP and input use necessary to reach an output per worker and a labor share equivalent to the U.S. in 2002. High labor coefficient countries are those in the lower two quartiles of cropped area of wheat, while low labor coefficient countries are those in the upper two quartiles. Each country is evaluated using the technology coefficients for their specific quartile based on cropped area of wheat.

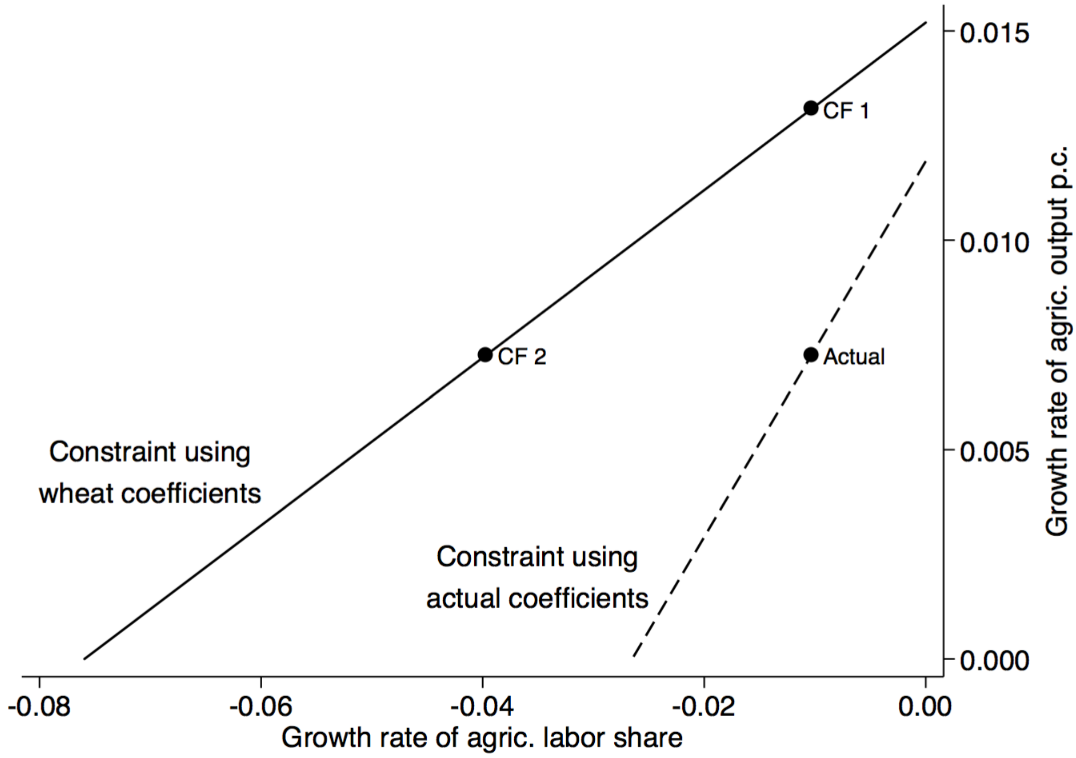
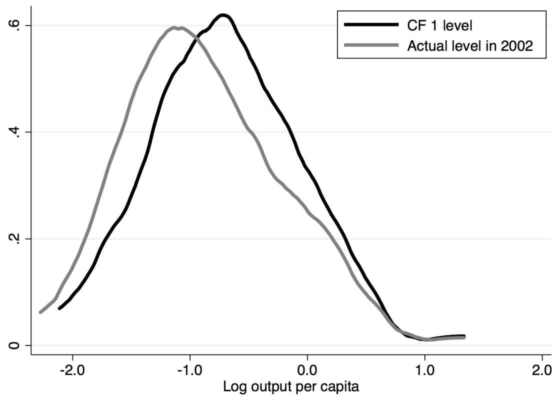


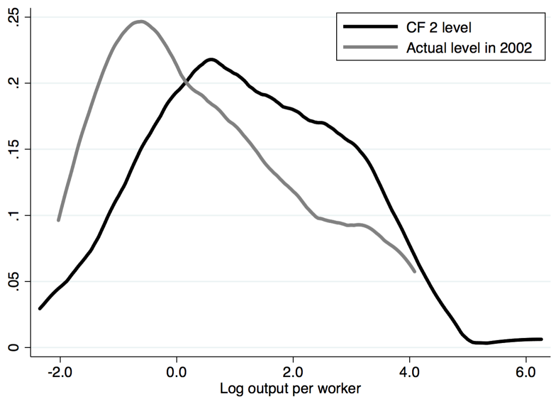
Figure 2: Example of Counterfactual Budget Constraint, Thailand

Notes: The figure illustrates our counterfactual scenarios for the case of Thailand. The dashed line shows the trade-offs faced between output per capita growth and growth in the agricultural labor share, with the actual choice marked by 'Actual'. The solid line shows their counterfactual budget constraint when we apply wheat technology coefficients, but hold TFP growth and input growth constant at their observed levels. 'CF1' is our first counterfactual, holding constant the labor allocation growth rate but allowing output growth to vary, and 'CF2' is our second counterfactual, holding constant output growth, but allowing labor allocation growth to vary.

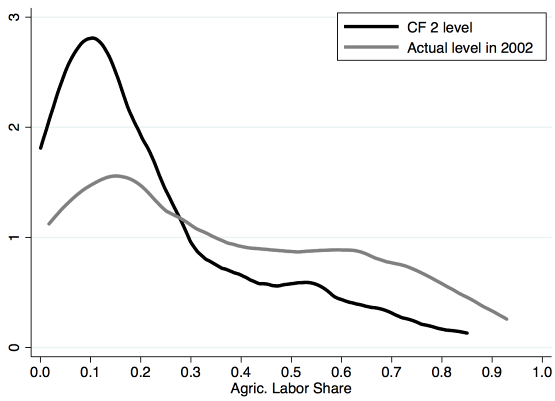
(a) Agricultural output per worker



(b) Agricultural output per capita



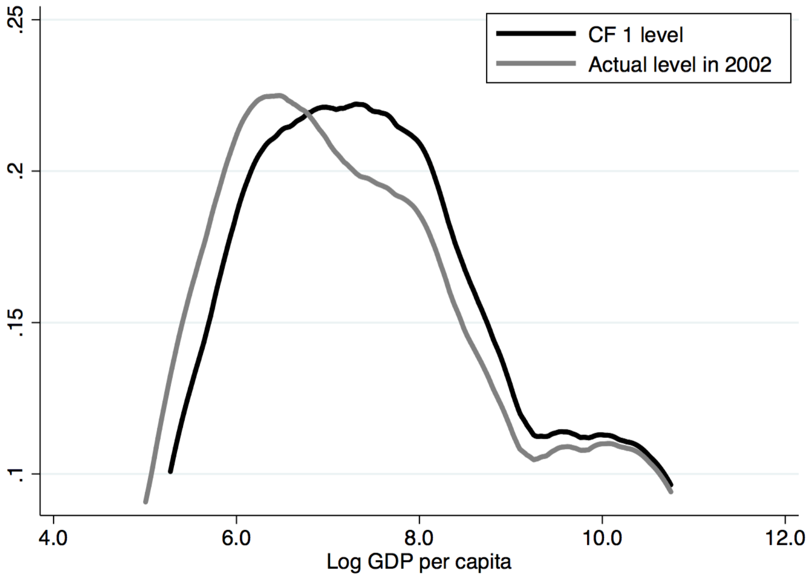
(c) Agricultural output per worker



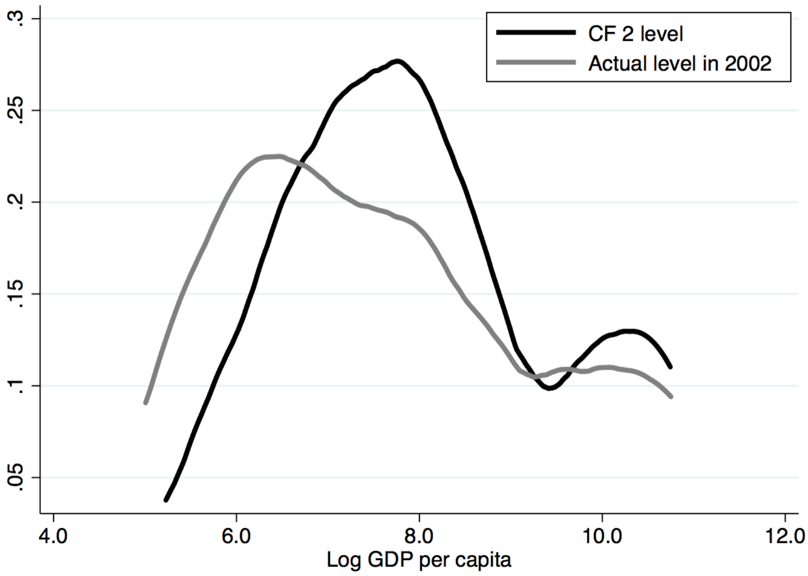
(d) Labor share in agriculture

Figure 3: Country-level Distributions in 2002 under
Counterfactuals 1 (a,b) and 2 (c,d)

Notes: The figures show the actual and counterfactual distributions for the two counterfactual exercises. Scenario 1, which holds constant the allocation of labor to agriculture (labor share), but assigns the wheat technology coefficients to each country, is presented in the first row and plots actual and counterfactual levels of agricultural (a) output per worker and (b) agricultural output per capita. Scenario 2, which holds constant the total output of agriculture, but assigns the wheat technology coefficients to each country, is presented in the second row and plots actual and counterfactual levels of agricultural (c) output per worker and (d) labor share. The levels of both measures in the two scenarios are calculated as described in the text, using the counterfactual growth rate from 1962-2002 applied to the observed level in 1962.



(a) Counterfactual 1



(b) Counterfactual 2

Figure 4: Country-level Distributions in 2002 of GDP per capita

Notes: The figures show the actual and counterfactual distributions of per capita GDP in the two counterfactual scenarios describe in the text. Counterfactual 1 holds constant the labor allocation to agriculture and calculates GDP using the counterfactual level of agricultural output per worker. Counterfactual 2 holds constant agricultural output and calculates GDP using the counterfactual allocation of labor to agriculture.

Weight matrix ♯	[1] 2FE	[2] MG	[3] CMG standard	[4] CMG crop-area	[5] CMG crop-area pa
Labor	-0.291	-0.323			
(deviation from CRS)	[0.020]***	[0.194]*			
Tractors per worker	0.046	0.066	0.095	0.089	0.061
$\hat{\beta}_K$	[0.004]***	[0.025]***	[0.025]***	[0.024]***	[0.026]**
Livestock per worker	0.325	0.231	0.298	0.310	0.318
$\hat{\beta}_{Live}$	[0.014]***	[0.034]***	[0.038]***	[0.038]***	[0.037]***
Fertilizer per worker	0.063	0.031	0.037	0.035	0.036
$\hat{\beta}_F$	[0.004]***	[0.007]***	[0.008]***	[0.008]***	[0.007]***
Land per worker	0.209	0.251	0.214	0.210	0.210
$\hat{\beta}_N$	[0.025]***	[0.090]***	[0.052]***	[0.057]***	[0.057]***
Wald Test for CRS (p)	14.53 (.00)	1.66 (.09)	1.49 (.14)	0.29 (.77)	0.33 (.74)
Returns to Scale ♭	DRS	DRS	CRS	CRS	CRS
Implied $\hat{\beta}_L$	0.066	0.169	0.260	0.243	0.325
	[0.011]***	[0.141]	[0.056]***	[0.063]***	[0.064]***
$\hat{\varepsilon}$ Stationarity †	I(1)	I(0)	I(0)	I(0)	I(0)
$\hat{\varepsilon}$ CD Test (p) ‡	11.00 (.00)	7.09 (.00)	-0.79 (0.43)	-0.95 (0.34)	-0.16 (0.87)
RMSE	0.133	0.060	0.055	0.056	0.054

Table 1: Production Function Estimates

Notes: Results for $n = 4,118$ observations from $N = 100$ countries. *, ** and *** indicate statistical significance at the 10,%, 5% and 1% level respectively. Estimators: 2FE – 2-way fixed effects, MG – Pesaran and Smith (1995) Mean Group, CMG – Pesaran (2006) Common Correlated Effects Mean Group. We present robust sample means for model parameters in [2]-[5]; [1] is a pooled model. Terms in square brackets are absolute standard errors based on standard heteroskedasticity-robust standard errors in [1] and based on the variance estimator following Pesaran and Smith (1995) in [2]-[5]. Dependent variable – log output per worker, [1] in 2FE transformation (Coakley, et al., 2006). Independent variables – all variables are in log per worker terms with the exception of 'Labor,' for which the coefficient estimate indicates deviation from constant returns (formally: $\hat{\beta}_L + \hat{\beta}_K + \hat{\beta}_{Live} + \hat{\beta}_F + \hat{\beta}_N - 1$). This is not the technology coefficient on labor, which is reported under 'Implied $\hat{\beta}_L$' in a lower panel.

♭ The implied returns to scale are labeled decreasing (DRS) if the coefficient on Labor is negative significant, and constant (CRS) if this coefficient is insignificant. We present models with CRS imposed if the unrestricted model cannot reject this specification. For heterogeneous models we present the implied labor coefficient as *constructed at the country level and then averaged* – the sum of all factor input coefficients sums to unity in each country, but this is not necessarily the case for the robust averages reported above.

♯ We apply time-averaged (in [4]) or annual (in [5]) $N \times N$ weight matrices for cross-country similarity in area harvested by crop to construct the cross-section averages (see main text). In model [3] we apply equal weights $1/N$ for each country. † Pesaran (2007) CIPS test results for residual nonstationarity: I(0) – stationary, I(1) – nonstationary. Full results available on request. ‡ Pesaran (2015) test for cross-section dependence (CD) in the residuals, H_0: no strong CD. RMSE reports the root mean squared error.

Panel A		**Creating equally-sized groups based on land-share of wheat or rice**							
		Groupings based on wheat				Groupings based on rice			
Quartile	All	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Labor $\hat{\beta}_L$	0.325	0.449	0.501	0.183	0.200	0.144	0.176	0.540	0.450
	[0.0638]***	[0.156]***	[0.121]***	[0.118]	[0.115]*	[0.083]*	[0.157]	[0.143]***	[0.125]***
Tractors $\hat{\beta}_K$	0.061	0.055	0.034	0.052	0.113	0.143	0.054	0.008	0.050
	[0.0262]**	[0.039]	[0.045]	[0.044]	[0.076]	[0.071]*	[0.047]	[0.053]	[0.028]*
Livestock $\hat{\beta}_{Live}$	0.318	0.231	0.366	0.360	0.317	0.290	0.361	0.358	0.230
	[0.0369]***	[0.066]***	[0.079]***	[0.072]***	[0.081]***	[0.078]***	[0.077]***	[0.073]***	[0.056]***
Fertilizer $\hat{\beta}_F$	0.036	0.045	0.014	0.032	0.058	0.039	0.022	0.025	0.064
	[0.0068]***	[0.011]***	[0.008]	[0.017]*	[0.019]***	[0.021]*	[0.012]*	[0.011]**	[0.015]***
Land $\hat{\beta}_N$	0.210	0.141	0.049	0.307	0.321	0.429	0.279	0.039	0.107
	[0.0574]***	[0.125]	[0.113]	[0.120]**	[0.105]***	[0.106]***	[0.130]**	[0.122]	[0.095]
Countries	100	25	25	25	25	25	25	25	25

Panel B		**Creating groups of unequal size using Cluster Analysis (CLA) of crop patterns**							
		(i) Using 161 crops for CLA				(ii) Using only maize, wheat and rice for CLA			
Mean Cluster Share: wheat		33%	4%	2%	1%	35%	5%	2%	3%
Mean Cluster Share: maize		7%	29%	6%	7%	7%	40%	5%	11%
Mean Cluster Share: rice		1%	5%	45%	3%	1%	2%	57%	7%
Cluster(s)	All	I	II	III	IV	I	II	III	IV
Labor $\hat{\beta}_L$	0.325	0.089	0.357	0.474	0.607	0.127	0.423	0.314	0.614
	[0.064]***	[0.102]	[0.106]***	[0.126]***	[0.194]***	[0.108]	[0.111]***	[0.116]**	[0.160]***
Tractors $\hat{\beta}_K$	0.061	0.136	-0.013	0.081	0.049	0.139	0.029	0.028	0.057
	[0.026]**	[0.061]**	[0.042]	[0.028]**	[0.043]	[0.064]**	[0.038]	[0.075]	[0.034]
Livestock $\hat{\beta}_{Live}$	0.318	0.340	0.323	0.218	0.396	0.357	0.362	0.243	0.160
	[0.037]***	[0.065]***	[0.063]***	[0.066]***	[0.109]***	[0.071]***	[0.059]***	[0.085]**	[0.068]**
Fertilizer $\hat{\beta}_F$	0.036	0.042	0.036	0.055	0.013	0.037	0.025	0.043	0.057
	[0.007]***	[0.015]***	[0.013]***	[0.017]***	[0.010]	[0.020]*	[0.007]***	[0.022]*	[0.020]**
Land $\hat{\beta}_N$	0.210	0.418	0.171	0.140	-0.042	0.370	0.111	0.249	0.011
	[0.057]***	[0.100]***	[0.069]**	[0.115]	[0.166]	[0.102]***	[0.099]	[0.077]***	[0.212]
	100	34	29	18	19	29	44	15	12

Table 2: Technology Heterogeneity

Notes: We present robust mean estimates for technology coefficients from the CMG specification (column [5], Table 1). In Panel A we group countries by quartiles of the land-share distribution of wheat and rice, respectively. In Panel B we use cluster analysis to form groups, which are now of *unequal* size: in section (i) we use land shares for all 161 crops (see Appendix) in the cluster analysis, in (ii) we only use land shares for maize, wheat and rice.

	[1] Actual Data	[2] Counterfactual 1	[3] Counterfactual 2
Panel A	**Agricultural output per worker**		
Variance (of logs)	2.75	2.47	2.73
90/10 Ratio	89.1	73.9	93.3
Mean	6.8	7.2	14.7
Median	1.2	1.7	3.0
Panel B	**Agricultural output per capita**		
Variance (of logs)	0.45	0.41	0.45
90/10 Ratio	5.2	5.5	5.2
Mean	0.53	0.61	0.53
Median	0.39	0.46	0.39
Panel C	**Agricultural labor share**		
90 - 10 Difference	0.763	0.763	0.585
Mean	0.397	0.397	0.256
Median	0.340	0.340	0.156
Panel D	**GDP per capita**		
Variance (of logs)	2.74	2.53	2.11
90/10 Ratio	115.0	100.0	63.2
Mean	7,752.6	8,098.3	8,499.2
Median	1,735.8	2,324.9	2,763.6

Table 3: Actual and Counterfactual Levels, 2002

Notes: Panels A through C show the counterfactual variation in the level of agricultural output per worker, agricultural output per capita, and the agricultural labor share in different scenarios. Column [1] shows summary statistics from the observed data 2002 for the 100 countries in our sample. In columns [2] and [3] we calculate the counterfactual levels of each variable by applying the counterfactual growth rates to the level of the variable in 1962 – see text and equations 15 and 15. Column [2] uses observed growth in agricultural labor, and removes variation in technology coefficients by using wheat coefficients for all countries. Column [3] uses observed growth in output per capita, and then removes variation in technology coefficients by using wheat coefficients for all countries. In all columns, the levels of non-labor inputs and total population are the observed values in 2002.

Panel D shows the summary statistics for the counterfactual levels of per capita GDP in 2002 under different scenarios. Column [1] shows the observed data, which is drawn from the World Bank World Development Indicators. See text for explanation of why we use this source over the Penn World Tables. Column [2] uses observed agricultural labor, and removes variation in agricultural technology coefficients by giving each country the wheat coefficients, thus changing only agricultural output per (agricultural) worker – see text and equation (16). Column [3] uses observed agricultural output, and removes variation in agricultural technology coefficients by giving each country the wheat coefficients, thus changing the agricultural labor share – see text and equation (17) .

APPENDIX — NOT INTENDED FOR PUBLICATION

A. EMPIRICAL METHODOLOGY

We briefly illustrate the identification problem arising in the empirical model of equation (1) because of unobserved TFP, and how the common factor methodology we use alleviates this issue.

For simplicity we assume a single input production function with a single (strong) factor f which affects both y (output) and x (input) – the implications do not change if we extend this setup to multiple inputs and/or factors.

$$y_{it} = \beta_i x_{it} + \alpha_i + \gamma_i f_t + \varepsilon_{it} \tag{18}$$

$$x_{it} = \eta_i + \phi_i f_t + \epsilon_{it}. \tag{19}$$

Solving (19) for the common factor f and plugging into the production function in (18) yields

$$\begin{aligned} y_{it} &= \beta_i x_{it} + \alpha_i + \gamma_i \phi_i^{-1}(x_{it} - \eta_i - \epsilon_{it}) + \varepsilon_{it} = \underbrace{(\beta_i + \gamma_i \phi_i^{-1})}_{\varrho_i} x_{it} \\ &+ \underbrace{\alpha_i + \gamma_i \phi_i^{-1}\alpha_i - \gamma_i \phi_i^{-1}\eta_i}_{\varpi_i} + \underbrace{\varepsilon_{it} - \gamma_i \phi_i^{-1}\epsilon_{it}}_{\varsigma_{it}} = \varrho_i x_{it} + \varpi_i + \varsigma_{it}. \end{aligned} \tag{20}$$

Since typically $\varrho_i = \beta_i + \gamma_i \phi_i^{-1} \neq \beta_i$ the slope coefficient is not identified. While in the microeconometric case the standard solution to this ‘transmission bias’ (Marschak & Andrews, 1944) involves instrumental variables or control function estimators which require exclusion restrictions for identification, we assume that no instrumental variable exists which is correlated with the endogenous regressor but uncorrelated with the unobservables. This reflects the notion that unobserved factors are pervasive and represent the latent driving force behind *all* observable macroeconomic variables (Stock & Watson, 2002).

Following Pesaran (2006), we use cross-section averages to address the identification problem. The following lines of algebra show the intuition as to how this works. Returning to our simple production function in (18), we take the cross-section average and solve for f_t

$$\overline{y}_t = \bar{\beta}\,\overline{x}_t + \bar{\alpha} + \bar{\gamma} f_t \quad \Leftrightarrow \quad f_t = \bar{\gamma}^{-1}(\overline{y}_t - \bar{\beta}\overline{x}_t - \bar{\alpha}), \tag{21}$$

where the error term drops out by the standard assumption $\mathbb{E}[\varepsilon] = 0$. Plugging (21) back into the production function yields a specification similar to the CMG model in equation (5):

$$
\begin{aligned}
y_{it} &= \alpha_i - \gamma_i \bar{\gamma}^{-1}\bar{\alpha} + \beta_i x_{it} + \gamma_i \bar{\gamma}^{-1}\overline{y}_t - \gamma_i \bar{\gamma}^{-1}\bar{\beta}\overline{x}_t + \varepsilon_{it} \\
&= a_i + \beta_i x_{it} + c_{0i}\overline{y}_t + c_{1i}\overline{x}_t + e_{it}. \qquad (22)
\end{aligned}
$$

Thus we can allow for common factors such as f_t, and yet need not observe these factors in order to achieve identification. The common factors themselves allow for a substantial degree of flexibility in the process for unobserved TFP by country. Assume a simple setup with just two factors. The first factor is an upward-sloping integrated process (e.g. a random walk with drift), formally captured as $f_{1t} = \pi + f_{1,t-1} + e_{1t}$. The second is a U-shaped process, f_{2t}. For any country i, the factors loadings are $\gamma_{1i} f_{1t} + \gamma_{2i} f_{2t}$.

Now assume factor loadings are such that in country A the loadings are $\gamma_{1A} = \gamma_{2A} = 1$, while in country B they are $\gamma_{1B} = \gamma_{2B} = -1$. The combination of factors and loadings thus create very different paths for TFP in the two countries. For country A a U-shaped but non-stationary process would result, while for country B there is an inverse U-shaped non-stationary process. If the factor loadings were not precisely 1 or -1, the differences in the TFP processes for the two countries would already be more idiosyncratic. As we allow for more and more factors, the TFP paths of countries can become almost arbitrarily idiosyncratic (as in the case where we could allow for country-time dummies). The cost of our approach is assuming that there are a limited number of strong factors – those which affect each country (Stock & Watson, 2002).

B. DATA SOURCES AND CONSTRUCTION

The principal data source for our empirical analysis is the Food and Agriculture Organisation's *FAOSTAT* database (FAO, 2007), from which we obtain annual observations for agricultural net output, economically active labor force in agriculture, number of tractors used in agriculture, arable and permanent crop land and fertilizer use in 100 countries from 1961 to 2002. The total number of observations is 4,118 with an average T of 41.2. Real agricultural net output (in thousand International \$) is based on all crops and livestock products originating in each country. Intermediate primary inputs of agricultural origin are deducted, including fodder and seed. The quantities for each commodity are weighted by the respective 1999-2001 average international commodity prices and then summed for each year by country. The prices are in international dollars, derived using a Geary-Khamis formula for the agricultural sector.[32] The labor variable represents the annual time series for total economically active population in agriculture. For capital stock in agriculture we follow a common convention and use total number of agricultural tractors in use as a proxy. The livestock variable is constructed from the data for asses (donkeys), buffalos, camels, cattle, chickens, ducks, horses, mules, pigs, sheep & goats and turkeys. Following convention we use a formula detailed in Hayami and Ruttan (1970) to convert the numbers for individual animal species into cattle-equivalent livestock. The fertilizer variable represents agricultural fertilizer consumed in metric tons, which includes 'crude' and 'manufactured' fertilizers. Our land variable represents arable and permanent crop land (in hectare).

Analysing agricultural production for a large number of countries inevitably raises concerns over data reliability. In contrast to macro data provided in for instance the Penn World Table (GGDC Groningen) FAOSTAT does not offer a data quality grade for each country, but instead labels each observation. Most output data used in our analysis carries the note '[a]ggregates may include official, semi-official or estimates.' For inputs we obtain more details, which suggest that tractor data is least reliable, with around 45% of observations estimated.[33] Thus data is far from perfect for cross-country comparison, although estimating production functions country by country and accounting for unobserved common factors should go some way to ward against systematic over-/underreporting of variable magnitudes. We find that there is no statistically significant relationship between countries' share of tractor data estimated and the coefficients on tractor, livestock, fertilizer or land in our CMG models, which could be viewed as evidence to that end.

[32] Refer to the Technical Appendix to Restuccia, et al. (2008), available on Restuccia's website.

[33] We report PWT country quality grade and share of non-estimated tractor data in Table B-2.

Descriptive statistics are presented in Table B-1. The countries in our sample are listed in Table B-2. We further make use of FAOStat data on 'area harvested (in ha)' by crop, transformed into shares of total area harvested for the 161 commodities detailed in Table B-4 below (by commodity group, in alphabetical order). For all countries and time periods there are a total of 21 crops which have an average (mean) share of harvested land in excess of 1% (using data for all years and countries). These commodities alongside some descriptive statistics are presented in Table B-5. We use these crop-level data for two purposes: (a) to arrange countries into clusters based on the similarity of their cropping patterns, and (b) to create weights to be applied to the construction of cross-section averages for the Pesaran (2006) CCE estimator.

As suggested our technology parameter analysis builds on groups ('clusters') of countries, with 'cluster affiliation' presented in Table B-3. We create the underlying multivariate correlation coefficients (Jaffe measures) from the annual FAOStat crop share data for every country, resulting in annual correlation matrices of dimension 100×100, indicating in each row the weight assigned to country j in the cross-section average for country i (which itself has a zero weight). These Jaffe measures based on crop shares are time-variant, though additional analysis suggests that the Jaffe distance measure computed from these data does not vary very significantly over time.

For the cluster analysis we use the time-series average of the annual correlation matrices and apply 'partition-clustering,' which breaks the observations into a distinct number of non-overlapping groups: we adopt 'kmeans' clustering in Stata 11, where following the choice of number of groups to be created each observation is assigned to the group whose mean is closest. Based on this categorization the new group means are determined and the entire process is iterated until the group affiliation is stable (Stata 11 Multivariate Statistics Manual: 85ff). Note that we also provide a second set of clusters where instead of data from 161 crops we only use data for maize, wheat and rice.

For the second use of the crop-level data we take the (annual or time-averaged) weights and row-normalize them, in line with standard practice in the spatial econometric literature. These weights are then applied when computing the cross-section averages included in the CCE regressions.

Table B-1: Descriptive statistics

Variables in untransformed level terms					
Variable	*mean*	*median*	*std. dev.*	*min.*	*max.*
logs					
output	14.69	14.58	1.49	10.92	19.57
labor	14.50	14.51	1.53	10.34	20.05
tractors	9.34	9.27	2.82	0.69	15.51
livestock	15.36	15.30	1.39	11.62	19.51
fertilizer	11.25	11.47	2.63	2.71	17.49
land	15.20	15.07	1.41	11.73	19.07
annual growth rate					
output	2.2%	2.4%	8.1%	-60.6%	56.7%
labor	0.3%	0.9%	2.2%	-8.4%	10.9%
tractors	4.5%	2.0%	9.9%	-121.8%	138.6%
livestock	1.2%	1.5%	5.3%	-93.3%	27.2%
fertilizer	5.7%	3.6%	37.3%	-301.1%	393.2%
land	0.6%	0.1%	2.8%	-41.8%	40.0%

Variables in per worker terms					
Variable	**mean**	**median**	**std. dev.**	**min.**	**max.**
logs					
output	0.18	-0.16	1.46	-2.22	4.00
tractors	-5.17	-5.18	3.07	-13.67	0.68
livestock	0.86	0.66	1.36	-2.19	4.63
fertilizer	-3.25	-2.95	2.70	-11.56	1.95
land	0.70	0.66	1.19	-1.54	4.95
annual growth rate					
output	1.9%	2.0%	8.2%	-62.9%	55.2%
tractors	4.2%	2.1%	10.1%	-120.2%	136.5%
livestock	0.9%	1.1%	5.5%	-93.5%	28.7%
fertilizer	5.5%	4.3%	37.2%	-303.5%	390.8%
land	0.3%	-0.1%	3.3%	-43.0%	41.0%

Notes: We report the descriptive statistics for net output (in I$1,000), labor (headcount), tractors (number), livestock (cattle-equivalent numbers), fertilizer (in metric tonnes) and land (in hectare) for the full sample ($n = 4,118$; $N = 100$).

Table B-2: Sample of countries and number of observations

Country	Code	Obs	PWT-Q	FAO-Q	Country	Code	Obs	FAO-Q	FAO-Q
Afghanistan	AFG	40		5%	Japan	JPN	42	A	85%
Angola	AGO	40	D	45%	Kenya	KEN	42	C	60%
Albania	ALB	42	C	69%	Cambodia	KHM	33	D	25%
Argentina	ARG	42	B	50%	South Korea	KOR	42	B	95%
Australia	AUS	42	A	100%	Lao PDR	LAO	38	D	52%
Austria	AUT	42	A	76%	Sri Lanka	LKA	42	C	50%
Burundi	BDI	37	C	28%	Morocco	MAR	42	C	56%
Benin	BEN	42	C	13%	Madagascar	MDG	42	C	17%
Burkina Fasi	BFA	42	C	17%	Mexico	MEX	42	C	21%
Bangladesh	BGD	42	C	5%	Mali	MLI	42	C	12%
Bulgaria	BGR	42	C	79%	Myanmar	MMR	42	D	88%
Belgium-Luxemb.	BLX	39	A	85%	Mozambique	MOZ	42	D	20%
Bolivia	BOL	42	C	28%	Malawi	MWI	42	C	63%
Brazil	BRA	42	C	12%	Malaysia	MYS	42	C	51%
Botswana	BWA	42	C	33%	Niger	NER	34	D	63%
Central African Rep	CAF	42	D	22%	Nigeria	NGA	42	C	5%
Canada	CAN	42	A	62%	Nicaragua	NIC	42	C	16%
Chile	CHL	42	B	33%	Netherlands	NLD	42	A	29%
China	CHN	42	C	90%	Nepal	NPL	42	C	23%
Côte d'Ivoire	CIV	42	C	27%	New Zealand	NZL	42	B	62%
Cameroon	CMR	42	C	32%	Pakistan	PAK	42	C	43%
Colombia	COL	42	C	68%	Philippines	PHL	42	C	53%
Costa Rica	CRI	42	C	31%	Poland	POL	42	B	100%
Cuba	CUB	42	D	57%	Korea, PDR	PRK	42		50%
Cyprus	CYP	42	D	50%	Portugal	PRT	42	B	33%
Germany	DEU	42	B	93%	Paraguay	PRY	42	C	2%
Denmark	DNK	42	A	90%	Romania	ROM	42	C	100%
Dominican Republic	DOM	42	C	5%	Rwanda	RWA	34	C	24%
Algeria	DZA	42	D	48%	Sudan	SDN	42	D	21%
Ecuador	ECU	42	C	33%	Senegal	SEN	42	C	10%
Egypt	EGY	42	C	45%	El Salvador	SLV	42	C	9%
Spain	ESP	42	B	100%	Somalia	SOM	36	D	33%
France	FRA	42	A	79%	Sweden	SWE	42	A	52%
United Kingdom	GBR	42	A	76%	Swaziland	SWZ	42	C	74%
Ghana	GHA	42	C	5%	Syria	SYR	42	C	100%
Guinea	GIN	41	C	10%	Chad	TCD	41	D	100%
Gambia	GMB	39	C	22%	Togo	TGO	37	D	19%
Guinea-Bissau	GNB	26	D	14%	Thailand	THA	42	C	45%
Greece	GRC	42	B	100%	Tunisia	TUN	42	C	33%
Guatemala	GTM	42	C	30%	Turkey	TUR	42	C	100%
Honduras	HND	42	C	25%	Tanzania	TZA	42	C	10%
Haiti	HTI	42	D	8%	Uganda	UGA	39	D	59%
Hungary	HUN	42	C	79%	Uruguay	URY	42	B	17%
Indonesia	IDN	42	C	28%	United States	USA	42	A	40%
India	IND	42	C	83%	Venezuela	VEN	42	C	71%
Iran	IRN	42	C	33%	Vietnam	VNM	42	C	65%
Iraq	IRQ	42	D	45%	Yemen, Republic	YEM	37	D	15%
Israel	ISR	42	B	83%	South Africa	ZAF	42	C	60%
Italy	ITA	42	A	100%	Congo, DR	ZAR	41	D	18%
Jamaica	JAM	42	C	70%	Zimbabwe	ZWE	42	C	32%

Notes: The full sample contains $n = 4,118$ observations, from 1961 to 2002. PWT-Q reports a data quality rating for aggregate economy data from the Penn World Table project (Heston, et al., 2009), where A denotes the highest and D the lowest score (http://pwt.econ.upenn.edu/Documentation/append61.pdf, Table A, column 11). FAO-Q reports the share of observations for the tractor variable which are not estimated but taken from official publications or international organisations (FAO codes: I, W, Q).

Table B-3: Cluster country makeup

Panel A	**Cluster Analysis Based on 161 Crops**												Countries
I	Dominant crop-share of wheat												34
	AFG	ALB	ARG	AUS	AUT	BGR	BLX	CAN	CHL	CYP	DEU	DNK	
	DZA	ESP	FRA	GBR	GRC	HUN	IRN	IRQ	ISR	ITA	MAR	NLD	
	NZL	PAK	POL	PRT	ROM	SWE	SYR	TUN	TUR	URY			
II	Dominant crop-share of maize												29
	AGO	BEN	BOL	BRA	CHN	CMR	COL	CRI	ECU	EGY	GTM	HND	
	HTI	KEN	MEX	MOZ	MWI	NIC	PRK	PRY	SLV	SWZ	TGO	TZA	
	USA	VEN	ZAF	ZAR	ZWE								
III	Dominant crop-share of rice												18
	BGD	DOM	GIN	GNB	IDN	IND	JPN	KHM	KOR	LAO	LKA	MDG	
	MMR	MYS	NPL	PHL	THA	VNM							
IV	None of the top-3 crop dominates												19
	BDI	BFA	BWA	CAF	CIV	CUB	GHA	GMB	JAM	MLI	NER	NGA	
	RWA	SDN	SEN	SOM	TCD	UGA	YEM						

Panel B	**Cluster Analysis Based on Maize, Wheat and Rice**												
I	Dominant crop-share of wheat												29
	AFG	ALB	ARG	AUS	AUT	BGR	BLX	CAN	CHL	DEU	DZA	ESP	
	FRA	GBR	GRC	HUN	IRN	IRQ	ISR	ITA	MAR	NLD	NZL	PAK	
	SWE	SYR	TUN	TUR	URY								
II	Dominant crop-share of maize												15
	AGO	BEN	GTM	HND	KEN	MEX	MWI	NIC	ROM	SLV	SWZ	USA	
	VEN	ZAF	ZWE										
III	Dominant crop-share of rice												12
	BGD	IDN	JPN	KHM	KOR	LAO	LKA	MDG	MMR	NPL	THA	VNM	
IB	None of the top-3 crops dominates												44
	BDI	BFA	BOL	BRA	BWA	CAF	CHN	CIV	CMR	COL	CRI	CUB	
	CYP	DNK	DOM	ECU	EGY	GHA	GIN	GMB	GNB	HTI	IND	JAM	
	MLI	MOZ	MYS	NER	NGA	PHL	POL	PRK	PRT	PRY	RWA	SDN	
	SEN	SOM	TCD	TGO	TZA	UGA	YEM	ZAR					

Notes: We list the countries (isocodes, see Table B-2 for country names) in each of the four clusters estimated based on the time-averaged crop-share data for all 161 crops (Panel A) and that for maize, wheat and rice only (Panel B).

Table B-4: FAOSTAT Crops Data (Share of Harvested Land)

(i) Cereals
Barley, Buckwheat, Canary seed, Cereals nes, Fonio, Mixed Grain, Maize, Millet, Oats, Popcorn, Quinoa, Paddy Rice, Rye, Sorghum, Triticale, Wheat

(ii) Primary Fibres
Agave fibres nes, Other Bastfibres, Fibre crops nes, Flax fibre and tow, Hemp tow waste, Jute, Kapok fruit, Manila fibre (abaca), Ramie, Seed cotton, Sisal

(iii) Primary Fruit (excludes melons)
Apples, Apricots, Avocados, Bananas, Berries nes, Blueberries, Carobs, Cashewapple, Cherries, Sour Cherries, Cranberries, Currants, Dates, Figs, Citrus Fruit nes, Fresh Fruit nes, Pome Fruit nes, Stone Fruit nes, Tropical Fresh Fruit nes, Gooseberries, Grapefruit (inc. pomelos), Grapes, Kiwi Fruit, Lemons and limes, Mangoes-like fruit (mangos, mangosteens, guavas), Oranges, Papayas, Peaches and nectarines, Pears, Persimmons, Pineapples, Plantains, Plums and sloes, Quinces, Raspberries, Strawberries, Other citrus fruit (Tangerines, mandarins, clementines, satsumas).

(iv) Primary Oil crops
Castor oil seed, Coconuts, Groundnuts with shell, Hempseed, Jojoba seed, Kapok fruit, Karite nuts (sheanuts), Linseed, Melonseed, Mustard seed, Oil (palm fruit), Oilseeds nes, Olives, Poppy seed, Rapeseed, Safflower seed, Seed cotton, Sesame seed, Soybeans, Sunflower seed, Tallowtree seed, Tung nuts

(v) Pulses
Bambara beans, Dry Beans, Dry Broad and Horse Beans, Chick peas, Dry Cow Peas, Lentils, Lupins, Dry Peas, Pigeon peas, Pulses nes, Vetches

(vi) Roots and Tubers
Cassava, Potatoes, Roots and tubers nes, Sweet potatoes, Taro (cocoyam), Yams, Yautia (cocoyam)

(vii) Treenuts
Almonds with shell, Brazil nuts with shell, Cashew nuts with shell, Chestnut, Hazelnuts with shell, Nuts nes, Pistachios, Walnuts with shell

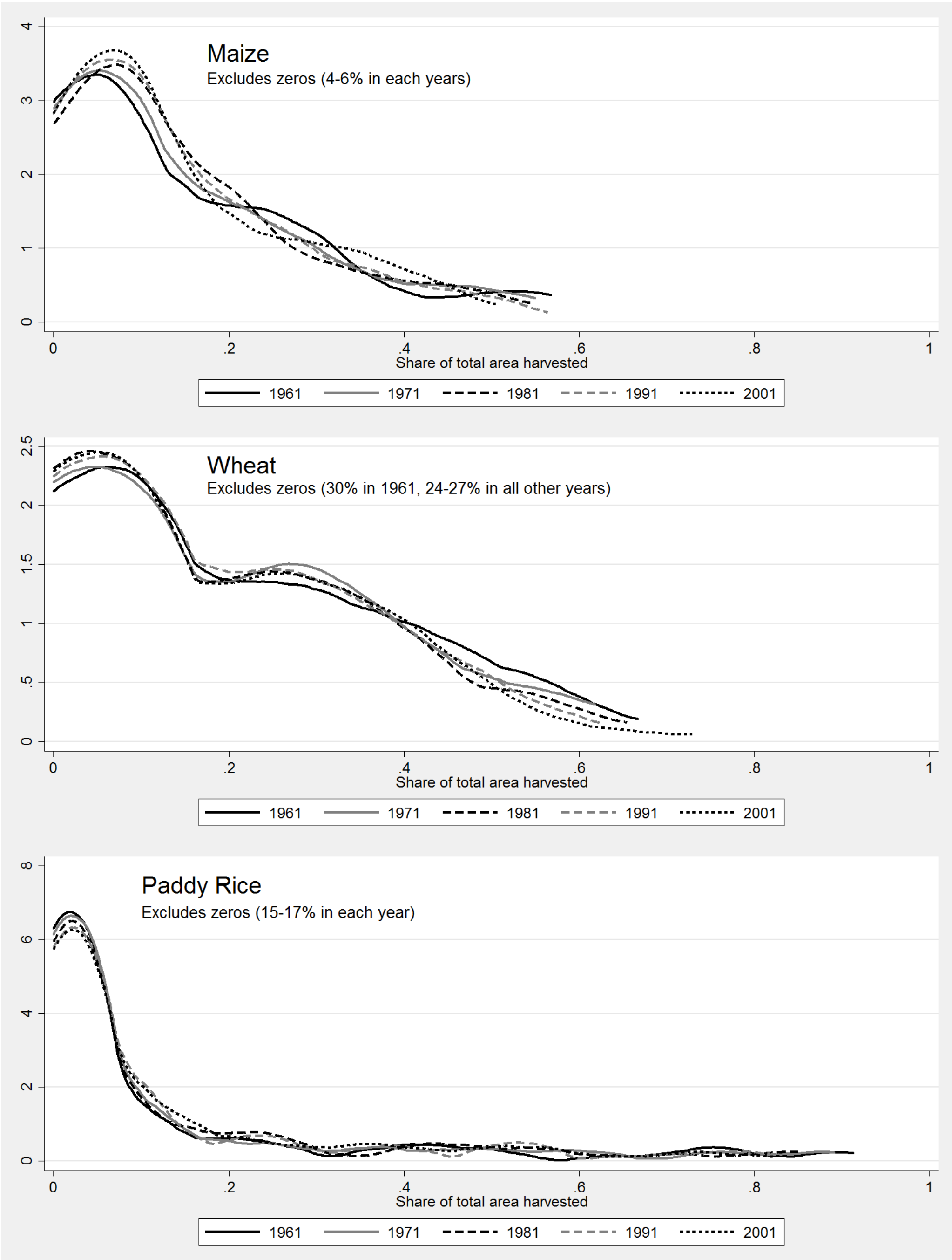
(viii) Vegetables
Artichokes, Asparagus, Beans green, Cabbages and other brassicas, Carrots and turnips, Cassava leaves, Cauliflowers and broccoli, Green Chillies and peppers, Cucumbers and gherkins, Eggplants (aubergines), Garlic, Leeks and other alliaceous vegetables, Lettuce and chicory, Green Maize, Other Melons (inc. cantaloupes), Mushrooms and truffles, Okra, Dry Onions, Green Onions and shallots, Green Peas, Pumpkins and squash and gourds, Spinach, String beans, Tomatoes, Vegetables fresh nes, Vegetables leguminous nes, Watermelons

Table B-5: Top Crops (share of harvested land)

Crop	mean	median	sd	max
Maize	13.4%	7.7%	14.2%	60.3%
Wheat	13.0%	2.6%	17.0%	73.9%
Rice Paddy	10.5%	1.5%	19.0%	92.9%
Barley	6.5%	0.2%	11.5%	79.5%
Sorghum	5.6%	0.6%	11.3%	82.1%
Millet	3.5%	0.0%	8.6%	60.9%
Beans, dry	3.0%	0.8%	4.7%	31.6%
Groundnuts	2.8%	0.4%	6.8%	59.7%
Coffee, green	2.8%	0.0%	5.8%	26.8%
Cassava	2.7%	0.1%	6.0%	39.1%
Seed Cotton	2.7%	0.8%	4.3%	27.2%
Sugar cane	2.4%	0.2%	7.0%	67.1%
Potatoes	1.8%	0.6%	3.6%	30.9%
Oats	1.5%	0.0%	3.6%	31.8%
Soybeans	1.4%	0.0%	4.8%	47.6%
Grapes	1.3%	0.0%	3.2%	26.9%
Cocoa beans	1.2%	0.0%	4.7%	58.7%
Plantains	1.2%	0.0%	3.6%	33.4%
Olives	1.2%	0.0%	4.9%	57.0%
Coconuts	1.2%	0.0%	4.2%	30.3%
Vegetables, fresh nes	1.0%	0.7%	1.1%	10.6%
All 161 crops	0.6%	0.0%	3.7%	92.9%

Notes: These are summary statistics for the observed share of harvested land by crop, focusing on those 21 crops where the full sample (panel) mean exceeds 1%. sd indicates the standard deviation, minimum values are omitted since they equate to zero for all crops.

Figure B-1: Individual crop share of total area harvested



Notes: We plot the density of three dominant crops (maize, wheat, paddy rice) in their share of total arable land harvested over time to illustrate the dynamics of this variable. Within each plot the kernels for the five different time periods are estimated using identical bandwidth. We *exclude zero crop-share* in each plot to aid illustration – the zero shares are indicated in each plot. Note that for the 4th-ranked crop (mean share), barley, more than 50% of countries have zero land share. These plots are for the sample of $N = 100$ countries. The crops are ordered by their mean share in all countries and time periods: Maize – 13.4%, Wheat – 13%, Rice – 10.5%.

C. SYSTEMATIC PATTERNS IN THE TECHNOLOGY ESTIMATES

We analyse the correlation between the country-specific means of log inputs and the country-specific estimated coefficient for that input. Our findings in Table C-1 indicate very limited correlation in the preferred standard and agro-climatic CMG models, which implies that there is no systematic relationship between the size of the estimated coefficient on an input and the amount of that input used.

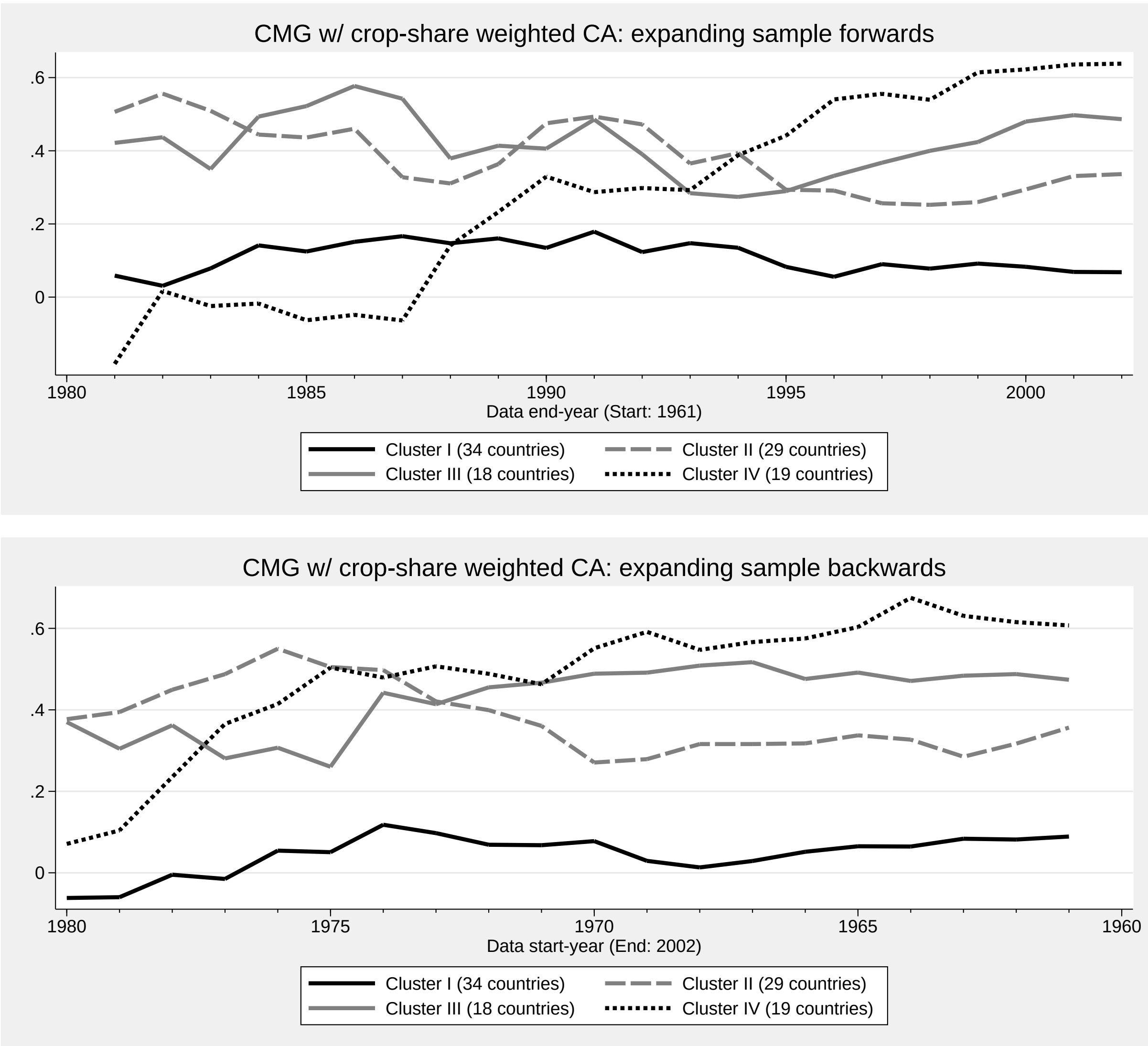
Table C-1: Correlation matrix – variable averages and CMG estimates

Variable averages	$\overline{\text{ly}}_i$	$\overline{\text{lL}}_i$	$\overline{\text{ltr}}_i$	$\overline{\text{llive}}_i$	$\overline{\text{lf}}_i$	$\overline{\text{ln}}_i$	$\hat{\beta}_i^{\text{L}}$	$\hat{\beta}_i^{\text{Tr}}$	$\hat{\beta}_i^{\text{Live}}$	$\hat{\beta}_i^{\text{F}}$	$\hat{\beta}_i^{\text{N}}$
Output pw $\overline{\text{ly}}_i$	1										
Labor $\overline{\text{ltr}}_i$	**-0.498**	1									
Tractors pw $\overline{\text{ltr}}_i$	**0.915**	**-0.401**	1								
Livestock pw $\overline{\text{llive}}_i$	**0.844**	**-0.535**	**0.770**	1							
Fertilizer pw $\overline{\text{lf}}_i$	**0.899**	**-0.343**	**0.919**	**0.699**	1						
Land pw $\overline{\text{ln}}_i$	**0.846**	**-0.474**	**0.745**	**0.801**	**0.706**	1					
CMG estimates	$\overline{\text{ly}}_i$	$\overline{\text{lL}}_i$	$\overline{\text{ltr}}_i$	$\overline{\text{llive}}_i$	$\overline{\text{lf}}_i$	$\overline{\text{ln}}_i$	$\hat{\beta}_i^{\text{L}}$	$\hat{\beta}_i^{\text{Tr}}$	$\hat{\beta}_i^{\text{Live}}$	$\hat{\beta}_i^{\text{F}}$	$\hat{\beta}_i^{\text{N}}$
$\hat{\beta}_i^{\text{L}}$	-0.144	0.081	**-0.484**	-0.071	**-0.214**	-0.055	1				
$\hat{\beta}_i^{\text{Tr}}$	0.120	-0.076	0.130	0.030	0.169	0.026	-0.168	1			
$\hat{\beta}_i^{\text{Live}}$	-0.025	0.030	0.012	0.044	-0.084	-0.048	**-0.364**	**-0.338**	1		
$\hat{\beta}_i^{\text{F}}$	0.013	0.161	0.030	-0.027	0.113	0.004	-0.016	-0.046	**-0.249**	1	
$\hat{\beta}_i^{\text{N}}$	0.112	-0.095	**0.197**	0.039	0.188	0.080	**-0.795**	-0.136	-0.034	0.052	1

Notes: We correlate the country-specific variable series (means) with the standard and agro-climatic CMG technology estimates. Significant coefficients (5% level) are in bold (except for the diagonals). We employ the CRS-based estimates for the crop-weighted CMG (Table 1, column [5]). Coefficient estimates are for 'lL' Labor, 'Tr' tractors, 'Live' livestock, 'F' fertilizer and 'N' land; 'pw' refers to variables in 'per worker' terms.

D. ROBUSTNESS CHECK: PARAMETER STABILITY

Figure D-1: Technology Parameter Stability



Notes: We present average labour coefficients for each of the four clusters (161 crops) where the country-specific estimates of β_L are based on recursive estimates: in the upper panel we estimate the agricultural production function with a sample from 1961 to 1980, compute the robust mean β_L by cluster and then increase the end date of the sample by one year at a time until we reach 2002. Thus each line plot charts, from left to right, the evolution of the cluster-specific mean labor coefficient as the sample size is increased. In the lower panel we do the same beginning with a sample from 1981 to 2002, then shifting the start year of the sample one year at a time until we reach the full sample starting in 1961 – again sample size increases from left to right. In either plot we can see that mean coefficient estimates for each cluster stabilize once the time series reaches around 30 years.

E. WEAK EXOGENEITY TESTS

In Table E-1 we provide some evidence that our preferred CMG specifications can be interpreted as production functions and do not suffer from bias due to reverse causality. These results represent weak exogeneity tests following Canning and Pedroni (2008). An error correction specification incorporating the residuals from our empirical models in Table 1 of the maintext is estimated for output and each production input. For any causal relation to exist between x and y at least one of the coefficients on the residuals in these five equations has to be statistically significant. If this 'error correction' (EC) term is significant in the output but not the input equations, we can suggest that the inputs 'cause' output ($x \rightarrow y$). Note how the misspecified 2FE and MG models (but also the standard CMG specification) find multiple causal relationships between the variables.

Table E-1: Canning and Pedroni (2008) tests

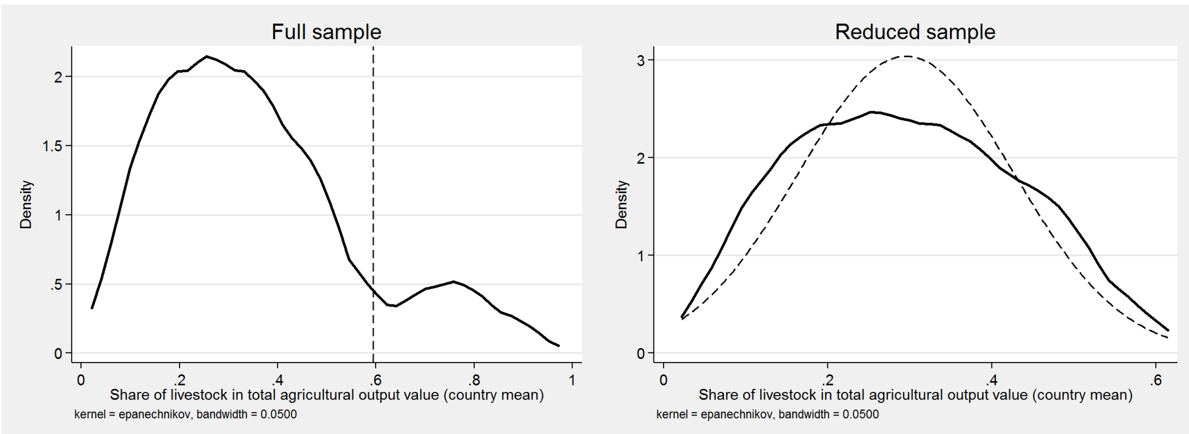
2FE	*GM*	(p)	*Fisher*	(p)	*mean* $\hat{\lambda}_i$	t*-ratio*	*Verdict*		
output equation	-1.06	0.30	388.7	0.00	-0.16	-7.96	x	$\rightarrow$	y
tractor equation	0.08	0.94	344.0	0.00	0.017	1.07	x_{-tr}, y	$\rightarrow$	x_{tr}
livestock equation	0.37	0.71	272.4	0.00	0.047	3.76	x_{-live}, y	$\rightarrow$	x_{live}
fertilizer equation	0.00	0.99	308.9	0.00	0.082	0.98	x_{-f}, y	$\rightarrow$	x_f
land equation	0.31	76.00	284.2	0.00	0.012	1.92	x_{-n}, y	$\rightarrow$	x_n
MG	*GM*	(p)	*Fisher*	(p)	*mean* $\hat{\lambda}_i$	t*-ratio*	*Verdict*		
output equation	-2.86	0.00	1187.6	0.00	-1.043	-21.53	x	$\rightarrow$	y
labor equation	0.17	0.87	238.9	0.03	0.001	0.40	x_{-tr}, y	$\rightarrow$	x_{tr}
tractor equation	-0.13	0.90	226.4	0.10	-0.066	-1.52	x_{-tr}, y	$\nrightarrow$	x_{tr}
livestock equation	0.17	0.87	228.0	0.09	0.062	1.95	x_{-live}, y	$\nrightarrow$	x_{live}
fertilizer equation	-0.09	0.93	202.6	0.44	-0.135	-0.80	x_{-f}, y	$\nrightarrow$	x_f
land equation	-0.02	0.99	198.2	0.52	-0.002	-0.12	x_{-n}, y	$\nrightarrow$	x_n
Standard CMG	*GM*	(p)	*Fisher*	(p)	*mean* $\hat{\lambda}_i$	t*-ratio*	*Verdict*		
output equation	-2.19	0.03	812.3	0.00	-0.938	-16.35	x, TFP	$\rightarrow$	y
tractor equation	-0.05	0.96	143.8	1.00	-0.057	-1.59	x_{-tr}, y, TFP	$\nrightarrow$	x_{tr}
livestock equation	0.07	0.95	238.5	0.03	0.025	0.62	x_{-live}, y, TFP	$\rightarrow$	x_{live}
fertilizer equation	-0.12	0.90	236.0	0.03	-0.330	-1.61	x_{-f}, y, TFP	$\rightarrow$	x_f
land equation	0.08	0.94	221.5	0.12	0.026	1.46	x_{-n}, y, TFP	$\nrightarrow$	x_n
CMG w/ avg crop-weights	*GM*	(p)	*Fisher*	(p)	*mean* $\hat{\lambda}_i$	t*-ratio*	*Verdict*		
output equation	-3.23	0.00	705.3	0.00	-0.985	-17.67	x, TFP	$\rightarrow$	y
tractor equation	-0.04	0.97	213.8	0.21	-0.008	-0.16	x_{-tr}, y, TFP	$\nrightarrow$	x_{tr}
livestock equation	0.20	0.85	196.4	0.52	0.052	1.47	x_{-live}, y, TFP	$\nrightarrow$	x_{live}
fertilizer equation	0.02	0.99	193.8	0.57	-0.180	-1.04	x_{-f}, y, TFP	$\nrightarrow$	x_f
land equation	0.03	0.98	202.4	0.40	0.013	0.83	x_{-n}, y, TFP	$\nrightarrow$	x_n
CMG w/ annual crop-weights	*GM*	(p)	*Fisher*	(p)	*mean* $\hat{\lambda}_i$	t*-ratio*	*Verdict*		
output equation	-2.03	0.04	748.0	0.00	-0.913	-15.20	x, TFP	$\rightarrow$	y
tractor equation	0.11	0.91	232.3	0.05	0.020	0.46	x_{-tr}, y, TFP	$\nrightarrow$	x_{tr}
livestock equation	0.08	0.93	217.6	0.16	0.067	1.69	x_{-live}, y, TFP	$\nrightarrow$	x_{live}
fertilizer equation	0.10	0.92	188.6	0.67	0.201	1.01	x_{-f}, y, TFP	$\nrightarrow$	x_f
land equation	-0.07	0.95	214.3	0.20	-0.002	-0.14	x_{-n}, y, TFP	$\nrightarrow$	x_n

Notes: We report various test statistics for the null of no long-run causal impact between sets of different variables. In each case '*variable* equation' refers to the ECM regression with 'variable' on the LHS. GM gives the group-mean average of country-specific t-ratios for the coefficient on the disequilibrium term ($\hat{\lambda}_i$) which is distributed $N(0,1)$. Fisher gives $-2\sum_i \log\pi_i$ where π_i is the probability value of the country-specific t-ratio on the disequilibrium term. The Fisher statistic is distributed $\chi^2(2N)$. The final two columns but one report the mean estimate for $\hat{\lambda}_i$ and the associated t-ratio. In the 'Verdict' column we summarise the analysis, using x_{-tr} for 'all inputs other than tractors' and $\rightarrow$ as short-hand for 'does cause' and $\nrightarrow$ for 'does not cause' — we employ a 5% significance level as the cut-off. TFP is included implicitly in the CMG models via cross-section averages. For comparability we impose constant returns on *all* models tested.

F. ROBUSTNESS CHECK: NON-LIVESTOCK SAMPLE

The dominance of livestock breeding in some economies may be seen to have a distorting impact on our agricultural production function estimation. As a robustness check we therefore exclude those economies from the sample where livestock rearing appears to account for a significant share of total agricultural output. In the left panel of Figure F-1 we plot the country-specific averages of livestock share in total agricultural output (in value terms) for our sample of $N = 100$ countries. The clear bi-modal nature of the distribution is driven by 13 economies with an average livestock share of more than 59.4% – with the exception of a small number of (at the time) low income countries (e.g. Botswana, Ghana, Somalia) these are predominantly developed economies, including Australia, Denmark, Germany, Netherlands and the New Zealand. If we exclude these economies, the distribution of livestock share is unimodal and normal, with a mean/median just under 30% and a standard deviation of 13% (right panel of Figure F-1).

Figure F-1: Distribution of Livestock Share in Total Agricultural Output



Notes: We plot the distribution of country-specific averages for the share of livestock in total agricultural output value (Data from FAOSTAT). Left panel: full sample of $N = 100$; right panel: we drop 13 countries for which this average share exceeds 59.4%.

Table F-1 provides agricultural production function estimates for a model of agricultural output net of livestock, where we have dropped the previous 'livestock' variable (the cattle-equivalent headcount). Patterns of returns to scale (with the exception of the standard CMG model) are very similar to those using the full sample data in Table 1 of the maintext, although all coefficient estimates appear somewhat elevated here, in particular the land coefficients. Taking diagnostics into account the crop-weighted versions of the CMG still emerges as the preferred specifications.

We replicate the technology heterogeneity analysis from the maintext for our sample of $N = 87$ countries in Table F-2, presenting robust averages by quartiles of wheat, rice and maize crop area in Panel A, and robust averages based on groupings arising from cluster analysis in Panel B. For the cluster analysis we selected only *three* clusters, since with four we obtain one very small cluster of only nine countries – note that qualitatively the patterns we describe here are identical in the four-cluster results. Like the results presented in our main text the sample excluding countries where livestock rearing dominates suggests a pattern whereby 'wheat technology' has a comparatively lower labor coefficient and thus comparatively higher non-labor inputs (in these specifications excluding livestock), while the reverse is the case for 'rice technology.'

	[1]	[2]	[3]	[4]	[5]
	2FE	MG	CMG	CMG	CMG
Weight matrix ♯			standard	crop-area	crop-area pa
Labor	-0.275	-0.546	-0.339		
(deviation from CRS)	[10.22]***	[2.58]***	[2.11]**		
Tractors per worker	0.066	0.063	0.054	0.116	0.080
$\hat{\beta}_K$	[12.69]***	[2.33]**	[2.29]**	[4.18]***	[2.87]***
Fertilizer per worker	0.082	0.044	0.043	0.052	0.050
$\hat{\beta}_F$	[17.11]***	[4.88]***	[4.80]***	[5.54]***	[5.34]***
Land per worker	0.399	0.329	0.317	0.354	0.332
$\hat{\beta}_N$	[12.21]***	[3.21]***	[3.37]***	[5.14]***	[4.46]***
Wald Test for CRS (p)	10.22 (.00)	2.58 (.01)	2.11 (.03)	1.49 (.14)	0.82 (.41)
Returns to Scale ♭	DRS	DRS	DRS	CRS	CRS
Implied $\hat{\beta}_L$	0.177	0.115	0.184	0.421	0.481
	[10.98]***	[0.66]	[1.78]	[5.68]***	[5.91]***
$\hat{\varepsilon}$ Stationarity †	I(1)	I(0)	I(0)	I(0)	I(0)
$\hat{\varepsilon}$ CD Test (p) ‡	3.36 (.00)	4.86 (.00)	-0.83 (0.41)	-0.74 (0.46)	0.15 (0.88)
RMSE	0.172	0.068	0.059	0.065	0.064

Table F-1: Production Function Estimates – excluding livestock

Notes: Results for $n = 3,581$ observations from $N = 87$ countries. *, ** and *** indicate statistical significance at the 10,%, 5% and 1% level respectively. Estimators: 2FE – 2-way fixed effects, MG – Pesaran and Smith (1995) Mean Group, CMG – Pesaran (2006) Common Correlated Effects Mean Group. We present robust sample means for model parameters in [2]-[5]; [1] is a pooled model. Terms in square brackets are absolute t-statistics based on standard heteroskedasticity-robust standard errors in [1] and based on the variance estimator following Pesaran and Smith (1995) in [2]-[5].

Dependent variable – log output per worker, [1] dto. in 2FE transformation (see Coakley, et al., 2006).

Independent variables – all variables are in log per worker terms with the exception of 'Labor,' for which the coefficient estimate indicates deviation from constant returns (formally: $\hat{\beta}_L + \hat{\beta}_K + \hat{\beta}_{Live} + \hat{\beta}_F + \hat{\beta}_N - 1$). This is not the technology coefficient on labor, which is reported under 'Implied $\hat{\beta}_L$' in a lower panel.

♭ The implied returns to scale are labeled decreasing (DRS) if the coefficient on Labor is negative significant, and constant (CRS) if this coefficient is insignificant. We present models with CRS imposed if the unrestricted model cannot reject this specification. For heterogeneous models we present the implied labor coefficient as *constructed at the country level and then averaged* – the sum of all factor input coefficients sums to unity in each country, but this is not necessarily the case for the robust averages reported above.

♯ We apply time-averaged (in [4]) or annual (in [5]) $N \times N$ weight matrices for cross-country similarity in area harvested by crop to construct the cross-section averages (see main text). In model [3] we apply the standard Pesaran (2006) approach using equal weights $1/N$ for each country. † Pesaran (2007) CIPS test results for residual nonstationarity: I(0) – stationary, I(1) – nonstationary. Full results available on request. ‡ Pesaran (2015) test for cross-section dependence (CD) in the residuals, H_0: no strong CD. RMSE reports the root mean squared error.

Panel A		**Creating similarly-sized groups based on land-share of wheat or rice**							
		Groupings based on wheat				Groupings based on rice			
Quartile	All	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Labor $\hat{\beta}_L$	0.481	0.631	0.673	0.454	0.201	0.094	0.456	0.610	0.695
	[0.081]***	[0.169]***	[0.185]***	[0.152]***	[0.125]	[0.162]	[0.159]***	[0.159]***	[0.142]***
Capital $\hat{\beta}_K$	0.080	0.122	0.049	0.039	0.157	0.089	0.093	0.107	0.048
	[0.028]***	[0.062]*	[0.047]	[0.039]	[0.071]**	[0.069]	[0.075]	[0.058]*	[0.027]*
Fertilizer $\hat{\beta}_F$	0.050	0.057	0.012	0.059	0.070	0.061	0.021	0.037	0.084
	[0.009]***	[0.013]***	[0.014]	[0.022]**	[0.026]**	[0.024]**	[0.013]	[0.018]*	[0.018]***
Land $\hat{\beta}_N$	0.332	0.211	0.179	0.417	0.489	0.756	0.297	0.235	0.197
	[0.074]***	[0.137]	[0.141]	[0.168]**	[0.142]***	[0.209]***	[0.126]**	[0.147]	[0.135]
Countries	87	24	18	24	21	21	24	23	19

Panel B		**Creating groups of unequal size using Cluster Analysis (CA) of crop patterns**					
		(i) Using 161 crops for CA			(ii) Using only 3 crops for CA		
Mean Cluster Share: maize		7%	30%	6%	7%	19%	5%
Mean Cluster Share: wheat		36%	5%	1%	38%	4%	2%
Mean Cluster Share: rice		1%	5%	25%	1%	6%	57%
Cluster(s)	All	I	II	III	I	II	III
Labor $\hat{\beta}_L$	0.481	0.074	0.482	0.752	0.158	0.533	0.776
	[0.081]***	[0.141]	[0.124]***	[0.123]***	[0.139]	[0.109]***	[0.175]***
Tractors $\hat{\beta}_K$	0.080	0.097	0.074	0.066	0.140	0.076	0.028
	[0.028]***	[0.068]	[0.046]	[0.030]**	[0.068]*	[0.038]*	[0.025]
Fertilizer $\hat{\beta}_F$	0.050	0.052	0.054	0.046	0.054	0.037	0.076
	[0.009]***	[0.022]**	[0.019]***	[0.012]***	[0.025]**	[0.011]***	[0.020]***
Land $\hat{\beta}_N$	0.332	0.745	0.258	0.145	0.581	0.259	0.123
	[0.074]***	[0.184]***	[0.082]***	[0.112]	[0.172]***	[0.095]***	[0.166]
Countries	87	22	29	35	20	54	12

Table F-2: Technology Heterogeneity

Notes: We present robust mean estimates for the technology coefficients from the CMG specification (column [5] of Table F-1). In Panel A we group countries by quartiles of the land-share distribution of maize, wheat and rice, respectively. In Panel B we use cluster analysis to form groups, which are now of *unequal* size: in section (i) of the Panel we use land shares for all 161 crops in the cluster analysis, in section (ii) we only use land shares for maize, wheat and rice.