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Agricultural Production and Technical Change Around the World, 1961-2010

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Disciplines
Agricultural and Resource Economics | Agricultural Economics | Growth and Development

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JEL Codes: Q16, O13

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Agricultural Production and Technical Change Around the World, 1961-2010

Agriculture provides a particularly useful industry to evaluate technical change, productivity growth, factor substitution, and input demands. The measures of outputs are common across countries and time, but there are many different technologies employed to produce that common output. Hayami and Ruttan's (1971, 1985) path-breaking work represented the first systematic evaluation of the factors inducing innovation across countries by exploiting that variation in agricultural inputs, outputs, and technology use. They concluded that the adoption of mechanization was driven by rising relative costs of labor while population pressures induced the development of fertility improving land management practices and improved genetics.

This study extends the Hayami-Ruttan research agenda by including 3 more decades and 129 more countries than they had available. The 50-year time span from 1960-2010 and inclusion of data from 173 countries allow us to make several useful additions to Hayami and Ruttan's analysis. First, we show that the data are well-described by the Cobb-Douglas form which allows us to graphically illustrate the changing shapes of isoquants over the 50-year period. In particular, we can demonstrate and measure the progress of agricultural productivity by the magnitude of the shift in isoquants toward the origin for each input pair in the production process. That strategy will allow us to test the implications of technical change on the productivity of labor, land, fertilizer, and capital.

The data also allow us to demonstrate how input use varies with agricultural wages. Like Hayami and Ruttan, we illustrate how labor costs influence mechanization in agriculture, but we are able to measure the long-run responses of other inputs to labor costs as well. Finally, we measure the pace of technical change in agriculture across countries and explore how trade protection of the agricultural sector and lack of political freedom slow the pace of a country's agricultural productivity growth.

Literature Review

Hayami and Ruttan viewed labor costs as a key driving force toward mechanization of agriculture. More recent work on changes in agricultural productivity over time has also focused on the role of labor in improving or hindering efficiency gains in the agricultural sector. Gollin, Lagakos, and Waugh (2014) report large differences in labor productivity between nonagricultural and agricultural sectors. The agricultural productivity disadvantage is particularly pronounced in developing countries, and thus gaps in labor productivity between developed and developing countries are larger in agricultural than in nonagricultural sectors. These large gaps in sectoral productivity suggest that there are substantial inefficiencies in labor allocation with too many workers allocated to agriculture in developing countries. Lagakos and Waugh (2013) argue that part of the inefficient labor allocation in developing countries is due to the necessity of producing sufficient food in the face of poor aggregate productivity. In effect, the large share of labor devoted to agricultural production in developing countries is a constrained choice dictated by the need to produce a subsistence level of food using relatively less productive agricultural production methods.

This discussion is reminiscent of an older discussion of whether peasant farmers are poor because they do not allocate resources efficiently or because they are not able to access modern technologies or superior inputs. Schultz (1964) argued that farmers using traditional methods are maximizing output. Without altering production technologies, there would be negligible returns to further investments in land, education, or hours of work. Varied evidence supports the conclusion that schooling has little reward in traditional agriculture compared to off-farm labor opportunities including Yang (1997) in China, Jolliffe (1998) in Ghana and Fafchamps and Quisumbing (1999) in Pakistan.

Not all research has supported Schultz's (1964) view that peasant farmers are "poor but efficient". Market failures such as incomplete commodity or labor markets, poor transportation, or asymmetric information may prevent farmers from equating input prices and marginal revenue products (Ball and Pounder 1996; Barrett, Shirland and Adesina 2008). Poor access to credit or incomplete insurance markets may cause farmers to underinvest in capital or critical inputs such as fertilizer (Duflo 2006). New technologies may be complementary with education or farm size, meaning that the least educated farmers and those on small plots may not adopt modern techniques (Welch 1970; Feder, Just and Zilberman 1985). Poverty itself may lead to poor decisions because malnutrition may alter behavior (Mullainathan and Shafir 2013). However, there are several reasons to suspect that the plight of agricultural production advance is not as dire as suggested by available information at the time Schultz wrote. Ball and Pounder (1996) argued that virtually all countries were no longer mired in the long-term low productivity equilibrium which Schultz characterized as traditional agriculture. Moreover, farmers can be taught to improve their resource allocations such as adopting high yielding seeds and fertilizers (Duflo 2006). Our own work below will show that agriculture has been able to sustain productivity advances across all technologies, both labor and capital intensive.

Data

Hayami and Ruttan (1971, 1985) pioneered empirical research on induced innovation in agriculture using data on 44 countries over the 20 year period from 1960 through 1980. Their work was based on data compiled by the Food and Agriculture Organization (FAO) and FAO yearbooks. Since then, the data sets have been greatly expanded, including many more countries with more consistent reporting of input levels. In addition, this study adds data spanning an additional 30 years from 1980 – 2010, a period when the percentage of the world population that was undernourished fell from 25% to 15% (FAO, 2009).

The main sources of data for this study are the Food and Agriculture Organization Statistics, Year Book of Labour Statistics, and the World Census of Agriculture. The countries included in the data set varies from 79 in 1961 to 144 in 2010, depending on the availability of data on inputs and outputs.

Following Hayami and Ruttan (1971, 1985), total agricultural output is represented in thousands of wheat equivalent units (i.e. the value of total agricultural production, evaluated at international prices, divided by the international price of wheat). The conversion to wheat equivalent units is innocuous as we could have left the output in constant international dollars, but the conversion to wheat makes our results consistent with the earlier studies.

We include 5 inputs in the production function. *Land (H)* is hectares of arable land. *Labor (L)* is measured in thousands of male and female agricultural workers. *Mechanical Capital* (K_M) is measured in thousands of tractors. *Fertilizer* (F) is the sum of metric tons of nitrogen, phosphate, and potash.

In contrast to Hayami and Ruttan (1971, 1985), we add an additional capital measure to account for the use of draft animals in agricultural production. *Animal Capital (K_A)* is a weighted average of the stock of draft animals in the country including horses, oxen, mules, donkeys, camel, and buffalo. We use two different sets of weights, one based on horsepower per animal and the other based on horsepower times the fraction of a 10 hour day the animal can produce.[2] We then compute the weighted sum across the 6 draft animal species using $K_A = \sum_{i=1}^{6} \omega_i * N_i$, where ω_i is the horsepower weight and N_i is the number of draft animals of type *i* in the country. In practice, the two sets of horsepower-weighted draft animals were highly correlated and results were very similar using either measure. The results reported in this article use the workday * horsepower weights.

Wages (W) are monthly equivalent earnings paid per agricultural worker, in U.S. dollars. We use the Hayami-Ruttan (1985) estimated agricultural wages for the period 1961-1980, supplemented by the wages reported in Elisiana, Fulginiti, and Perrin (1993) and the International Labor Organization Labor Statistics series. Where there was disagreement among the various series, we used the wage that most closely represented the unskilled wage to provide some consistency across countries. For wages after 1980,

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[2] Hicks (1997) provides estimates of average horsepower and the effective work day by draft animal which were used to compute the weights presented below. A horse can provide 0.67 horsepower over a 10 hour day, while a camel can produce more horsepower per hour but only for 6 hours.

Animal	**Horsepower (HP)**	**HP*(hours per day/10)**
Draft horse	0.67	0.67
Ox	0.60	0.36
Mule	0.54	0.32
Donkey	0.27	0.11
Camel	0.87	0.52
Buffalo	0.70	0.35

we relied on Oostendorp's (2012) harmonized wage series based on household data across countries.

The number of countries included in the data set depends on the availability of information. Table 1 reports the number of countries included in the production function estimation and the lower-bound of the number of countries included in the derived demand regressions.[3] We are able to greatly expand the number of countries included in the production function estimation compared to the 44 in Hayami-Ruttan. We also greatly expand the number of countries for which we have wage information compared to the 20-28 available in Hayami-Ruttan. As a result, we have more degrees of freedom to support our statistical tests than was available to Hayami and Ruttan.

Table 2 provides descriptive statistics for the output measure and all inputs by year. While the means reflect changes in the composition of countries with the required data over time, some trends are apparent. There has been an increase in agricultural output, with the largest increase being between 1990 and 2000. As agricultural land in production has fallen, yields have risen nearly four-fold. The pace of productivity gains appears to have leveled off in the last 20 years, but this may be due to the inclusion of more small developing countries in the more recent periods. Our data analysis will address those composition changes by using country fixed effects.

The Estimated Agricultural Production Function

Agricultural productivity has steadily increased over time. As shown in Table 2, output per hectare doubled between 1960 and 1970 and doubled again by 1990. Agricultural

[3] Because information on the various inputs was not universally reported, we have more countries included in each of the input demand equations but the numbers reported in Table 1 are for the countries that have all inputs and wage information.

productivity leveled off thereafter. The gains could reflect increased input application per hectare, rising productivity of the inputs, or some combination of the two[4].

We examine that issue following the original Cobb-Douglas (1928) strategy. Let the *i*th country's agricultural output in year *t*, Q_{it}, be of the Cobb-Douglas functional form

$$Q_{it} = A_{it}\, H_{it}^{\alpha_H} L_{it}^{\alpha_L} K_{Mit}^{\alpha_M} K_{Ait}^{\alpha_A} F_{it}^{\alpha_F} \tag{1}$$

where *Land* (H_{it}), *Labor* (L_{it}), *Mechanical Capital* (K_{Mit}), *Animal Capital* (K_{Ait}), and *Fertilizer* (F_{it}) are the inputs into the production of wheat equivalent units of agricultural output. The Hicksian aggregate technology term A_{it} has both time and country-specific components such that $\ln(A_{it}) = \ln(A) + \alpha_i + \alpha_T t + \varepsilon_{it}$. The country-specific fixed effect α_i reflects factors permanently affecting the country's agricultural productivity including its land quality and agro-climatic region. To the extent that the country does not vary its policies regulating agriculture, the fixed effect also captures time-invariant agricultural policies specific to the country. The time effect $\alpha_T t$ captures changes in technology that raise productivity across countries. The coefficient α_T measures the annual increase in world agricultural productivity. The last term ε_{it} is a transitory shock to the country's agricultural production from factors such as weather or unanticipated commodity price fluctuations that alter the translation from other commodities to wheat equivalent units.

The logarithmic form of Equation (1) represents the first-order Taylor approximation to an unknown production function. The log form of the Cobb-Douglas specification can be tested against the second-order approximation given by the translog specification:

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[4] Ball et al (2016) estimate that 90 percent of growth in U.S. agricultural output between 1948 and 2013 was due to productivity growth as opposed to increased inputs.

(2) $\ln(Q_{it}) = \sum_{k=1}^{5} \beta_k \ln(X_{itk}) + \frac{1}{2}\sum_{k=1}^{5}\sum_{j=1}^{5} \beta_{jk} \ln(X_{itk}) \ln\left(X_{itj}\right) + \ln(A') + \gamma_i +$

$\gamma_T t + \epsilon_{it}; \beta_{jk} = \beta_{kj}$

where the X_{itk} represent the inputs in Equation (1). The translog form has 15 more coefficients than the Cobb-Douglas form. All specifications of the translog form resulted in estimates of β_{jk} that were not significantly different from zero for all *j* and *k*. The joint test that the $\beta_{jk} = 0\ \forall j, k$ could not be rejected in the fixed-effect regressions and the addition of the 15 parameters only increased the explained variation of log output by 0.0012 versus the R^2 of 0.972 obtained with the fixed-effects regression using the Cobb-Douglas form. Therefore, we proceed under the assumption that the Cobb-Douglas form adequately approximates the unknown world agricultural production function.[5]

The Cobb-Douglas form provides a direct link between the theoretical propositions derived from neoclassical economics and the observed data (Orazem 1998). The coefficients $\alpha_H, \alpha_L, \alpha_M, \alpha_A,$ and α_F in Equation (1) are output elasticities. The form for the k^{th} input is

(3) $$\alpha_k = \frac{\partial Q_{it}}{\partial X_{kt}} \cdot \frac{X_{kt}}{Q_{it}} = \frac{MP_k}{AP_k}$$

Profit maximization requires that all inputs be in the range $0 < MP_k < AP_k$ and so all the α_k must fall in the range [0, 1) for agricultural production to fall in stage II of production. If $\alpha_H + \alpha_L + \alpha_M + \alpha_A + \alpha_F = 1$, then agricultural production is characterized by constant returns to scale. The Cobb-Douglas estimation is reported in Table 3.

[5] Note that if our production function is fully specified so that $Q_{it} - A_{it}\, H_{it}^{\alpha_H} L_{it}^{\alpha_L} K_{Mit}^{\alpha_M} K_{Ait}^{\alpha_A} F_{it}^{\alpha_F} = 0$, the implicit function rule allows us to specify an equation where any one of the variables is a function of the rest of the variables. That serves as justification for our regression where output is regressed against all the inputs.

All the estimated output elasticities lie between 0 and 1, and so agricultural production lies in Stage 2 of production where marginal products are positive but less than average products and derived factor demand curves are downward sloping in input prices.[6] The sum of the output elasticities is 0.91 which is consistent with diminishing returns to scale. However, we cannot reject the null hypothesis that the coefficients sum to 1. Consequently, world agricultural production is not significantly different from a constant returns to scale Cobb-Douglas form.

The trend coefficient suggests that agricultural total factor productivity is increasing at 3.7% per year[7]. The world population has increased at 1.4% per year over the 1960-2010 period according to data provided by the U.S. Census Bureau's International Database. As a result, agricultural productivity increases have outpaced world population growth over the 50-year period, leading to the slow but steady reduction in world malnutrition over time reported by the FAO (2009).

Our assumption that the error term ε_{it} is an *iid* random shock may be incorrect. If instead, it is a missing input that interacts with the observed inputs, then it will be correlated with the regressors in equation (1) so that the estimated coefficients will be biased[8]. However, if ε_{it} also enters the production in the Cobb Douglas form, it will not

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[6] This condition is consistent with but not sufficient for concluding that agricultural inputs are efficiently allocated.

[7] The implied increase in output due to productivity over the 49 years period is a 5.93 fold increase, holding inputs at their 1961 levels. The actual increase in world production over the time period was 3.26. This implies that 55 percent fewer inputs were required to produce 3.26 times the output in 2010 relative to 1961.

[8] It is widely acknowledged that fixed effects estimation of production functions has not generally succeeded in solving the problem of endogenous input choice (Ackerberg, Benkard, Berry and Pakes 2005). The method relies on the strong assumption that the fixed effect does not change over time. In addition, when there is measurement error in inputs, fixed effects can generate higher biases in the estimators than ordinary least squares. Lastly, fixed effects estimations tends to provide estimates of capital coefficients that are much lower than capital's cost share or which imply very low returns to scale. However, Ackerberg, et al (2005) note, "…whether or not one takes the fixed effects estimates as serious

bias the nonparametric analysis that follows because the Cobb-Douglas specification implies that the relationship between any two of the observed inputs will be unaffected by the addition of an additional unobserved input.

Empirical Isoquants

The Cobb-Douglas form allows us to trace out isoquants for each of the ten possible pairs of inputs included in the production function. The changes in the height of these isoquants illustrate how the technology advances found in the last section show up in rising input productivities. The pace of productivity gains is not the same across all inputs and so the changing slopes of these isoquants demonstrate the direction of technology bias in advancing productivity.

The Cobb-Douglas form imposes the condition that the marginal and average products differ only by a constant of proportionality. Using equation (3), the marginal products of labor and machinery capital are

$$MP_L = \frac{\partial Q_{it}}{\partial L_{it}} = \alpha_L \frac{Q_{it}}{L_{it}}\,;\, MP_{K_M} = \frac{\partial Q_{it}}{\partial K_{Mit}} = \alpha_M \frac{Q_{it}}{K_{Mit}} \tag{4}$$

The slope of an isoquant is the ratio of the marginal products of the two inputs. In this case, the slope will be $-\frac{MP_M}{MP_L} = -\frac{\alpha_M}{\alpha_L}\frac{L_{it}}{K_{Mit}} = -\frac{\alpha_M}{\alpha_L}\frac{AP_M}{AP_L}$. Importantly, when Cobb-Douglas holds, the marginal products of any two inputs will be independent of the other input values. That means that a scatter plot of any pair of inputs per unit output will be interpretable as an isoquant. In this case, the scatter plot of $\frac{L_{it}}{Q_{it}}$ against $\frac{K_{Mit}}{Q_{it}}$ is the isoquant representing the trade-off between labor and mechanical capital in world agriculture. The result is shown in Figure 1. Developed countries, such as Canada, United States, and

estimates of structural production function parameters, the fixed effects decomposition of variation into within and between components often provides a useful reduced form look at a dataset" (p. 46).

Germany use capital-intensive production methods to produce wheat equivalent agricultural output, while developing countries such as India, Zambia, and Indonesia use more labor intensive methods.

We can show how technology involving the use of machinery and labor has evolved by comparing the scatter plots in 1961 and 2010. In both years the inputs are normalized per unit of output, and so each represents the amount of labor and mechanical capital necessary to produce one unit of output, other inputs held fixed. The movement of the isoquant toward the origin indicates rising input productivity, as shown in Figure 2[9].

This same strategy can be used to demonstrate the trade-offs between all 10 input pairs (see Appendix A). Each isoquant is time-specific, reflecting the available technologies in use around the world at that point in time. As input productivity increases over time, the scatter plots should shift toward the origin. The magnitude of the movement toward the origin will indicate the pace of productivity advances for the input pair. Parallel shifts in the isoquant will indicate that the productivity advances are equal, across the two inputs, while changes in the slope of the isoquant will indicate that the productivity advances are biased toward one input[10].

We devised two mechanisms to measure the relative magnitudes of the input-pair specific productivity advances over time. One uses the fitted isoquants for the starting

[9] This shift in a given isoquant toward the origin over time is what Chambers (1994) refers to as progressive technical change, that is change that "expands the input requirement set and allows input bundles formerly incapable of producing output y to produce y." (p. 206).

[10] Hicks described technical change as neutral if the optimal factor proportions are unaffected. If the technological change results in a cost-minimizing allocation that lowers the amount of an input relative to another, is it referred to as input-saving, whereas if it increases the relative amount of the input, it is input-using. (Antle and Capalbo 1988). Note however, that we are only able to examine the relative changes in input use pairwise; therefore it is not necessarily clear whether technical change is using or saving in each input overall. Antle and Capalbo propose an overall bias measure for each factor; however it's estimation requires data on all the input prices, which are not available in our dataset.

and ending period, and the other uses the average productivity advance for each country from the starting to the ending period. We derive each strategy in turn.

The first strategy uses the two fitted isoquants as illustrated in Figure 3. Let an arbitrary ray from the origin be defined by the equation $x_2 = \alpha_1 * x_1$. The differential of x_2 is $dx_2 = \alpha_1 * dx_1$. Converting this into percentages to make the relative changes in input use comparable across inputs yields $\frac{dx_2}{x_2} = \frac{\alpha_1 * dx_1}{x_2} = \frac{\alpha_1 * dx_1}{\alpha_1 * x_1} = \frac{dx_1}{x_1}$. This implies that the percentage change in either input along a ray from the origin will give the percentage productivity improvement from the base period. In Figure 3, the measure of input productivity gain will be

(5) $\mathrm{T}_1^2 = \frac{(x_{11} - x_{12})}{x_{11}} = \frac{\alpha_1 (x_{11} - x_{12})}{\alpha_1 x_{11}} = \frac{(x_{21} - x_{22})}{x_{21}} = T_2^1$

And so the measure of input productivity growth is specific to the input pair, and the productivity gain will be the same for both inputs in the pair. Nevertheless, we may find that the gains differ in magnitude if we start in 1961 with a relatively high x_1 intensity or a high x_2 intensity. For that reason, we compute measures of productivity gains for any 2 inputs *j* and *k* at 3 different rays from the origin:

(6)

63.4^o line: $x_2 = 2x_1$

45^o line: $x_2 = x_1$

26.6^o line: $x_2 = 0.5 * x_1$

If the change is greatest along the 63.4^o line, it suggests the isoquant became relatively flatter and is an indication that the productivity advance was input-saving for the input on the vertical axis. If the magnitude is greater along the 26.6^o line, the isoquants became relatively steeper, suggesting productivity improved faster in the input on the horizontal axis. The results are reported in the first three columns of Table 4. Noting that all five inputs increased in productivity, meaning that less of each input was required to produce a unit of wheat in 2010 compared to 1961, the smallest relative efficiency gains were for labor. Labor use decreased less relative to all other inputs per unit of output. Fertilizer use per unit of output decreased only in comparison to labor and had equal efficiency gains in comparison to land. The largest decline in use per acre was for draft animals whose utilization fell more than all its paired inputs although only modestly so compared to land. Land use fell compared to mechanical capital and labor. The overall pattern of results implies that technical change led to the greatest reduction in use of animal capital and land and the least reduction in the use of labor and fertilizers.

Because the FAO data base gradually added more developing countries to its panel data sets, the previous measure may overweight observations from developing countries in 2010 and overweight observations from developed countries in 1961. To mitigate that concern, we developed an alternative measure of input productivity growth that relies on the countries that have input-pair observations in both 1961 and 2010. For the country *i* pairs, $x_2^i = \alpha_{0i} + \alpha_{1i} * x_1^i$, where $\alpha_{0i} = x_{21}^i - \frac{x_{22}^i - x_{21}^i}{x_{12}^i - x_{11}^i} * x_{11}^i$ and $\alpha_{1i} = \frac{x_{22}^i - x_{21}^i}{x_{12}^i - x_{11}^i}$. From this information, we can derive an estimate of $\mathrm{T}_{1i}^{2i} = \frac{\alpha_{1i} dx_1^i}{\alpha_{0i} + \alpha_{1i} x_1^i}$ where dx_1^i will be approximated by the change in the input levels from 1961 to 2010 in country *i*. Since it is arbitrary which input we assign as x_1^i, we can compute this measure for each input in the pair. We report the absolute value of the median of all these country specific measures for every input pair in the last two columns of Table 4.[11]

These results provide much clearer evidence of relative reductions in input use per unit of output. The first four rows report the input pair productivity changes over time for land and each of the other inputs. These measures demonstrate that the biggest gains in productivity occurred for land. Labor use fell relative to all inputs except land. Use of draft animals fell more than mechanical capital and fertilizer. Fertilizer use fell least among the five inputs and mechanical capital use fell less than all the other inputs except for fertilizer. To summarize, all inputs gained in productivity over the 50-year period, but input use per unit output fell most for land and then labor and fell least for fertilizer and mechanical capital.

Derived Demand for Factors

Hayami and Ruttan placed a great weight on labor costs in their explanation for technical change in agriculture. The Cobb-Douglas approximation to the production function generates own- and cross-price relationships between wages and the five inputs. These relationships show which inputs are complementary with or substitutes for labor.

The derived demand for labor is the marginal revenue product of labor which, using Equation (3), is proportional to the observed average product: $MRP_L = p \cdot MP_L = p \cdot \alpha_L \cdot \frac{Q_{it}}{L_{it}}$. Because wages equal marginal revenue products in equilibrium, we would expect an upward sloping relationship between agricultural wages and $\alpha_L \cdot \frac{Q_{it}}{L_{it}}$. To get a traditional labor demand curve, we plot the logarithm of the agricultural wage, $\ln(W_{it})$

[11] The median changes for all input pairs are negative, indicating a reduction in the amount of input per unit of output. We report the absolute value to be consistent with the measures derived from the fitted isoquants, T_1^2.

against $\ln(\frac{L_{it}}{Q_{it}})$ or the logarithm of agricultural labor per unit output. We illustrate the relationship in Figure 4 along with the regression that describes the best linear fit through the scatterplots.

Because the labor input is measured per unit of output, Figure 4 can be interpreted as tracing out the response of labor demand to wages along an isoquant. The inverse of the slope, which equals -1.72, is a measure of the substitution effect of a wage change. Following Hamermesh (1993, pp. 24-35), the substitution effect is $S_L\sigma = -1.72$, where S_L is labor's share in production, and σ is the elasticity of substitution. The fundamental law of factor demand defines the long-run labor demand elasticity according as $\theta_{LL} = S_L(\eta + \sigma)$, with η being the elasticity of demand for agricultural output. Our estimate of labor's share in production, from table 2 is 0.23. Roberts and Schklenker (2010) estimate that the world elasticity of demand for agricultural commodities is -0.06, and so the scale effect, $S_L\eta = (-0.06)(0.23) = -0.014$, is very small. As a result, the long-run labor demand elasticity is -1.73 with the primary response being the substitution effect away from labor as wages rise.

The small scale effects enter the other input demand elasticities as well. We illustrate the derivation of the long-run own- and cross-price elasticities with respect to the agricultural wage in Figures 5-8. The small scale elasticities are swamped by the large substitution effects, and so the long-run cross-price or own-price relationships have the same signs and approximate magnitudes as the output-constant effects. Consequently, the slopes indicate if labor and the other inputs are substitutes or complements. The plots of agricultural wages against the inputs show that mechanical capital and fertilizer have positive slopes, implying that mechanical capital and fertilizer use are substitutes with agricultural labor. Draft animals and agricultural land have negative slopes, and so they are complements with agricultural labor.

These findings are consistent with our conclusions from Table 4 that input use has declined most for land, labor and animal capital and declined least for mechanical capital and fertilizer. It appears that rising agricultural wages are indeed shaping the relative input use and technological change in agriculture as posited by Hayami and Ruttan.

Unit Labor Cost and Allocative Efficiency

A remaining puzzle is why countries seem to lag in agricultural productivity as found by Lagakos, and Waugh (2013) and Gollin, Lagakos, and Waugh (2014). While gains in agricultural productivity have been impressive over the past 50 years, the gains are not universal. Some countries are not sharing in benefits of productivity advances across all five inputs considered. We explore two possible reasons: agricultural trade policy and protection of property rights.

As reviewed by Ball and Pounder (1996), market failures attributable to poor government policies are one of the reasons why farmers may not make efficient resource allocation decisions. We explore two such policies: trade restrictions and protection of property rights. Openness to trade may expose domestic producers to economic pressure that induces greater effort to improve yields or lower cost. It may also expose domestic producers to new varieties, new technologies and new agronomic practices. Agricultural productivity may also be affected by private property protection. There is little incentive to invest in new technologies or raise yields if the farmer fears that the government cannot protect his rights to reap the reward from the investment or if the government itself takes the return either directly or through extortionary taxes.

It is easier to capture the effects of agricultural trade protection and polity by looking at input costs relative to productivity. In our context, more protectionist policies may allow farmers to use technologies or to select output levels that are inefficient when compared to prevailing input or output prices. Similarly, governments that do not protect property rights may cause farmers to hold back on investments that would be profitable if their returns were not subject to expropriation.[12] These inefficiencies will not show up in the production function but in the resource allocation decisions.

Efficient resource allocation implies that $W_{it} = MRP_L = p \cdot MP_L \ = p \cdot \alpha_L \cdot \frac{Q_{it}}{L_{it}}$, where all variables are defined as before. Rearranging, we have an observable form of real unit labor cost that is consistent with optimal input allocation:

$$ULC_{it} = \frac{W_{it} \cdot L_{it}}{\alpha_L \cdot Q_{it}} = p \tag{7}$$

In this formulation, unit labor cost is identical to the marginal cost of agricultural production. With perfect competition and zero transport costs across countries, the marginal cost should be identical across countries and equal to the world price of wheat. If countries are allocating resources optimally, there should be no relationship between unit labor cost and the wage rate. High wage countries should have high labor productivity so that their unit labor costs are competitive with low wage countries. Consistent with our earlier results, high wage countries will invest more heavily in capital per worker in order to conserve on their more expensive labor input while boosting output per worker. Low wage countries will use labor-intensive technologies, which lower output per worker on the margin. However, trade protection and poor government

[12] To illustrate this point, Frank Orazem undertook a USAID trip to assess whether soybeans could be grown profitably in Uganda during the Idi Amin era. He reported that, "you could put a stick in the ground and it will grow in Uganda. The only problem is that someone will shoot you and take the stick away."

institutions may increase unit labor cost by distorting the technology adoption and resource allocation decisions.

We test these hypotheses using the equation

(8) $$\ln(ULC_{it}) = \varphi_0 + \varphi_W \ln(W_{it}) + \varphi_{TP} TP_{it} + \varphi_D D_{it} + \zeta_{it}$$

Our measure of agricultural trade protection, TP_{it}, was developed by Anderson et al. (2009) and Lloyd, Croser and Anderson (2009). Their trade protection index varies between 0 (no price distortions from trade protection) to 1 (completely restrictive trade protection). The data base has been made available on line at Anderson and Croser (2009). As shown in Table 2, agricultural trade protection has remained almost constant over the past 50 years, but it varies substantially across countries.

Our measure of protection of personal property is based on D_{it}, the extent of democratic political institutions in the country. Our use of the democracy measure as an indicator of property rights protection reflects the availability of data over the 50-year period required. The longest available continuous measure of political freedom is the Polity IV Project available on line at Marshall and Jaggers (2007). Higher values of polity should be correlated with stronger enforcement of the rule of law and protection of property rights. The polity index varies from -10 (absolute dictatorship) to +10 (approaching pure democracy). Our assessment that the polity measure will reflect economic and political freedoms more generally is supported by its strong positive correlation with the Freedom House index of Political Freedom and the Heritage Foundation's Economic Freedom Index for years where the series overlapped. As shown in Table 2, the Polity IV measure demonstrates a steady movement toward more democratic political institutions over time.

In equation (8), we would expect that $\varphi_W = 0$ if resources are allocated efficiently. However, political or economic institutions may cause farmers to allocate resources inefficiently. If the latter two measures cause inefficient allocations as we hypothesized, we would expect that $\varphi_{TP} > 0$ and $\varphi_D < 0$.

The limited temporal variation in trade policy and democratic institutions make it difficult to distinguish the effects of the economic and political institutions from the country-specific fixed effects. In addition, as we illustrate in table 1, the sample size is greatly constrained by the requirement that we have information on wages and the institutional measures. The number of observations falls by 73% and the number of countries by 63%. Imposing fixed effects further limits the degrees of freedom because we have relatively few countries with at least two observations with the required data. For all these reasons, we only report the results without fixed effects imposed. The results are suggestive, but not definitive.

The results are reported in Table 5. In the first column, we cannot reject the null hypothesis that unit labor cost is invariant to wages, consistent with efficient allocation of agricultural labor across countries. Unit labor cost is falling by 3% each year, consistent with the 3% - 3.7% increase in productivity from the production function estimated in table 3. When we add information on trade protection and democratic institutions, the coefficient on wages becomes statistically significant. A 10% increase in wages raises the unit labor cost by approximately 2%. As trade protection increases, unit labor cost increases, either by lowering agricultural productivity or raising input costs for farmers insulated from competition. Polity lowers unit labor cost, presumably increasing incentives to raise productivity through increased protection of property rights. The unit labor cost increase from a one standard deviation change in the wage rate would be counteracted by a 0.55 standard deviation in polity or a 1.7 standard deviation decrease in trade protection or about 5.2 years of trend productivity growth.

Conclusions

This article expands on the Hayami-Ruttan tradition by increasing the number of countries included from 44 to 173 and the time frame from 20 years to 50 years. The longer time series and the availability of data from many more countries allow us to make several useful additions to previous work. First, we show that the data are well-described by the Cobb-Douglas form. This enables us to illustrate the changing shape of isoquants over the 50-year period. In particular, we can demonstrate and measure the progress of agricultural productivity by the magnitude of the shift in isoquants toward the origin for each input pair in the production process. We show that, holding fixed other inputs, the biggest productivity gains in the agricultural sector have occurred through reductions in the amount and land and labor used per unit of output produced.

The expanded time series includes the period between 1980-2010 that had dramatic reductions in the incidence of malnutrition in the world, from 25% to 15%. Over the past 50 years, agricultural productivity has increased at 3.7% per year while the world population has increased at 1.4% per year. This means agricultural productivity increases have outpaced world population growth, leading to slow but steady reductions in world malnutrition over time.

The data also allow us to demonstrate how input use varies with agriculture wages. Our estimates show that the substitution effects of a wage change are large, while the scale effects are very small. This implies that the slope of the isoquants reveal whether the other inputs are substitutes or complements with labor. We find that mechanical capital and fertilizer use are substitutes with agricultural labor, while draft animals and agricultural land are complements.

Lastly, we explore why some countries seem to lag in agricultural productivity by examining the impacts of trade protection and polity (democracy) on unit labor costs. We find some suggestive evidence that trade protection raises unit labor cost either by lowing agricultural productivity or raising wages for farmers who do not have to compete. Polity lowers unit labor cost, presumably increasing incentives to raise productivity.

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Table 1: Summary of the Number of Countries for which Complete Information is Available, by Year

Number of Countries with Complete Information		
Year	Production Function	Production Function Plus Wage Information
1961	78	25
1970	84	31
1980	143	35
1990	140	47
2000	160	39
2010	145	28
Total	750	205

Table 2. Average Output and Inputs per Year

Year	Output	Labor	Land	Fertilizer	Mechanical Capital	Animal Capital	Real Wage	Output/ Hectare	Trade Protection	Polity
1961	9,809.5	4,405.4	8,411.2	209,853.4	77,725.8	4,511,446.7	421.8	4.0	0.2	1.5
	(26,924.0)	(18,244.9)	(28,414.3)	(763,300.8)	(415,312.5)	(14,212,839.6)	(411.4)	(9.4)	(0.3)	(7.8)
1970	22,366.3	4,328.6	8,712.0	465,025.5	106,282.4	5,174,618.0	691.3	8.5	0.3	0.8
	(60,562.1)	(17,984.2)	(28,615.8)	(1,671,406.1)	(487,829.7)	(15,553,114.2)	(652.4)	(19.2)	(0.3)	(7.5)
1980	20,050.9	6,325.4	8,853.6	784,677.5	144,919.0	5,782,430.5	768.0	9.6	0.4	0.6
	(54,043.6)	(34,310.5)	(28,676.3)	(2,757,953.5)	(501,223.8)	(17,288,083.2)	(918.8)	(38.5)	(0.5)	(7.7)
1990	47,869.0	7,465.4	9,194.7	926,406.6	173,468.4	6,199,268.9	918.3	17.8	0.3	2.7
	(139,345.3)	(42,817.3)	(29,169.7)	(3,387,451.6)	(534,845.5)	(19,271,777.8)	(1,109.9)	(63.9)	(0.5)	(7.3)
2000	86,291.4	7,178.1	8,011.1	801,843.3	149,445.5	5,680,634.8	853.0	24.0	0.2	5.8
	(299,285.0)	(42,654.6)	(23,278.2)	(3,315,150.8)	(473,233.4)	(18,418,032.9)	(1,184.9)	(42.2)	(0.4)	(5.2)
2010	63,794.3	7,547.0	7,999.6	1,212,701.5	157,428.5	6,200,377.2	1,359.5	16.4	0.1	6.4
	(235,805.3)	(43,328.3)	(22,208.8)	(5,536,666.1)	(496,390.6)	(20,338,907.8)	(1,549.6)	(26.1)	(0.3)	(4.5)

Note: Standard deviations in parentheses.

Table 3. Cobb Douglas Regression

Variable	1	2
ln(labor)	0.215	0.235
	(6.14)	(4.81)
ln(fertilizer)	0.249	0.063
	(9.10)	(3.28)
ln(mechanical capital)	0.090	0.062
	(4.52)	(3.85)
ln(animal capital)	0.100	0.242
	(2.98)	(3.54)
ln(land)	0.222	0.309
	(5.69)	(3.77)
Year	0.030	0.037
	(25.0)	(35.5)
Constant	-57.66	-
	(24.01)	
N, *n*	750, 173	750, 173
R^2	0.91	0.97
Fixed Effect	No	Yes
Returns to Scale	0.87	0.91
Test of Constant Returns *F(1,172)*	43.1	0.85

Note: t-statistics in parentheses. Standard errors corrected for clustering at the country level.

N is the number of observations and *n* is the number of countries

Table 4. Measures of Input-Pair Specific Productivity Advances Over Time

	T_1^2			Median Value of T_{1i}^{2i}	
Input per Unit Output	63.4°	45°	26.6°	Input 1	Input 2
Mechanical Capital vs. Land	0.818	0.859	0.896	0.444	0.841
Labor vs. Land	0.817	0.828	0.835	0.855	0.827
Fertilizer vs. Land	0.719	0.723	0.718	0.129	0.827
Animal Capital vs. Land	0.669	0.668	0.668	0.768	0.806
Mechanical Capital vs. Labor	0.524	0.511	0.501	0.274	0.857
Fertilizer vs. Labor	0.262	0.135	-0.003	0.198	0.862
Animal Capital vs. Labor	0.518	0.515	0.512	0.797	0.850
Fertilization vs. Mechanical Capital	0.480	0.492	0.500	0.154	0.367
Mechanical Capital vs. Animal Capital	0.212	0.225	0.240	0.274	0.769
Animal Capital vs. Fertilizer	0.635	0.598	0.546	0.794	0.129

Table 5. Unit Labor Cost Regression

ln(unit labor cost)	coefficient	coefficient
ln(wage)	0.089	0.188
	(1.39)	(2.19)
polity		-0.052
		(2.94)
trade protection		0.293
		(1.97)
year	-0.03	-0.029
	(7.96)	(7.56)
constant	63.4	59.80
	(8.47)	(8.01)
N, *n*	222,65	205,64
R^2	0.22	0.31

Note: t-statistics in parentheses. Standard errors corrected for clustering at the country level.

N is the number of observations and *n* is the number of countries

Figure 1. Empirical Isoquant

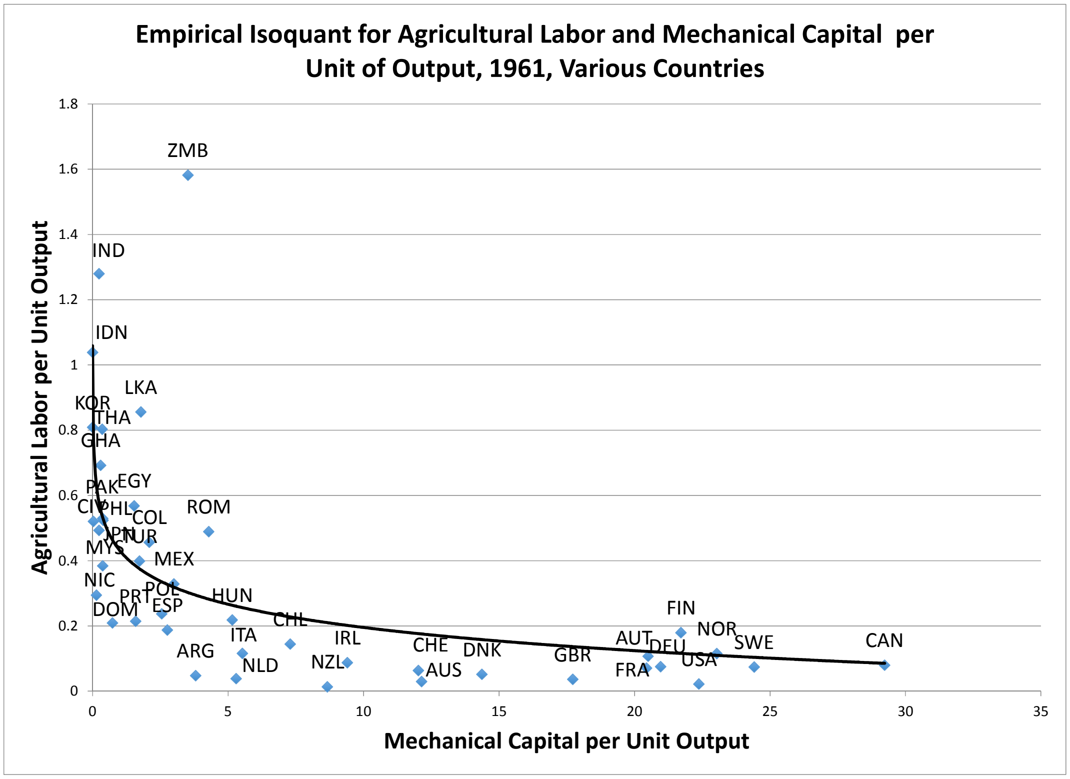


Figure 2. Empirical Isoquants for 1961 and 2010

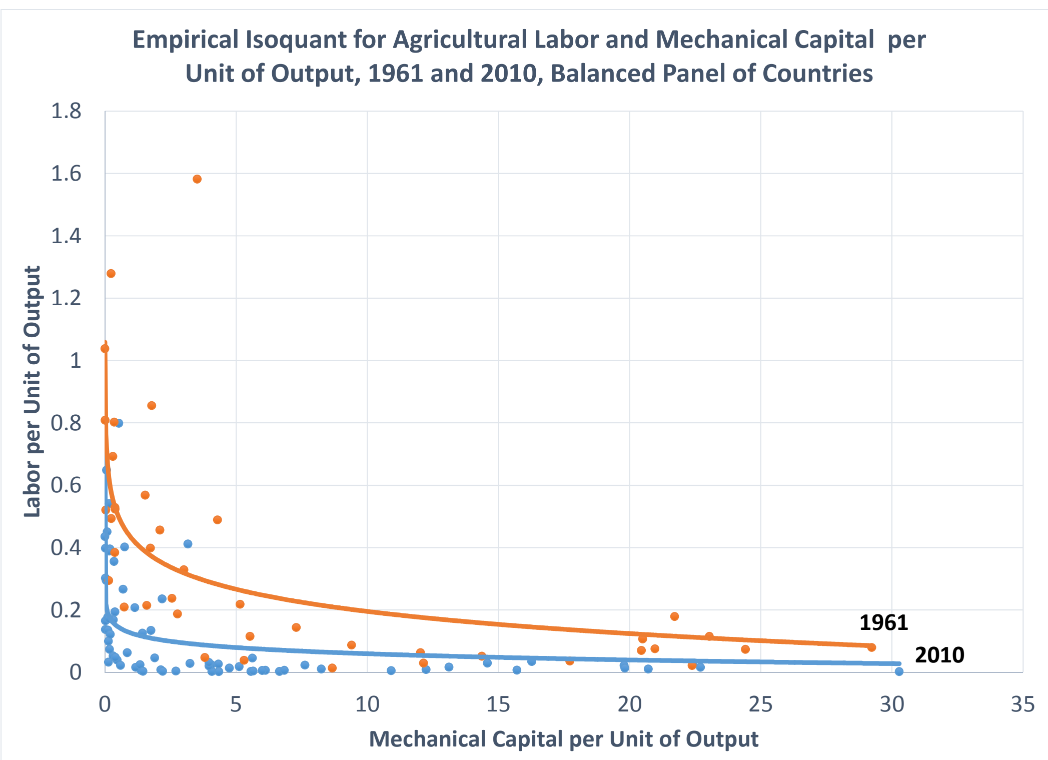


Figure 3. Illustration of Input-Pair Specific Productivity Advances Over Time

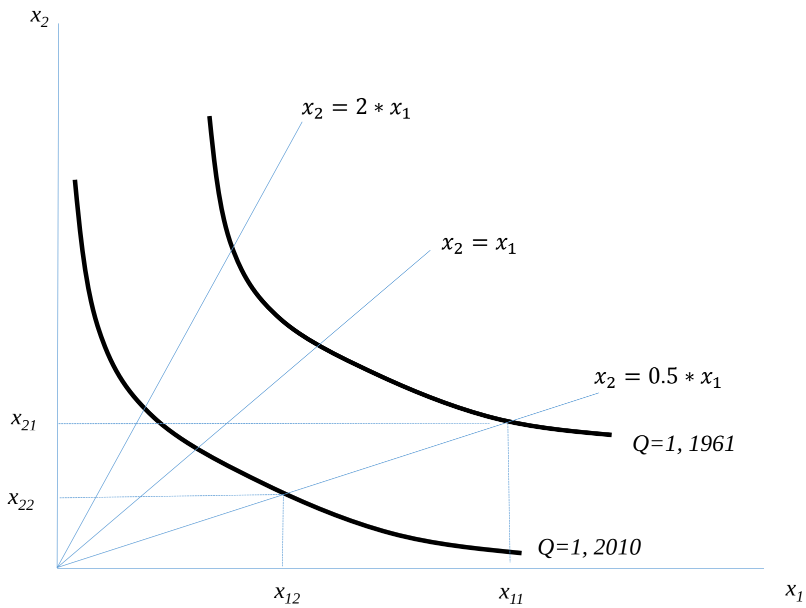


Figure 4. Own-Price Effects of Agricultural Wages on Agricultural Labor, Holding Output Fixed

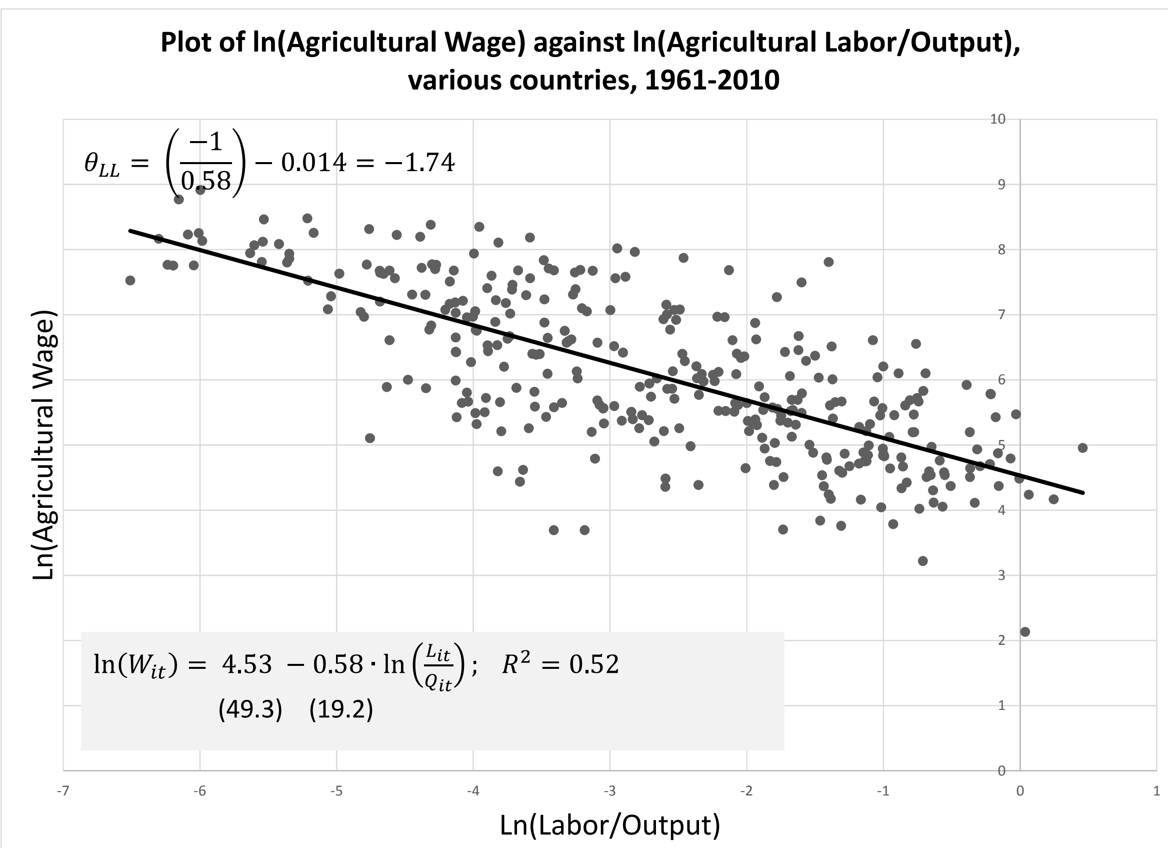


Figure 5. Cross-Price Effect of Agricultural Wage on Animal Capital, Holding Output Fixed

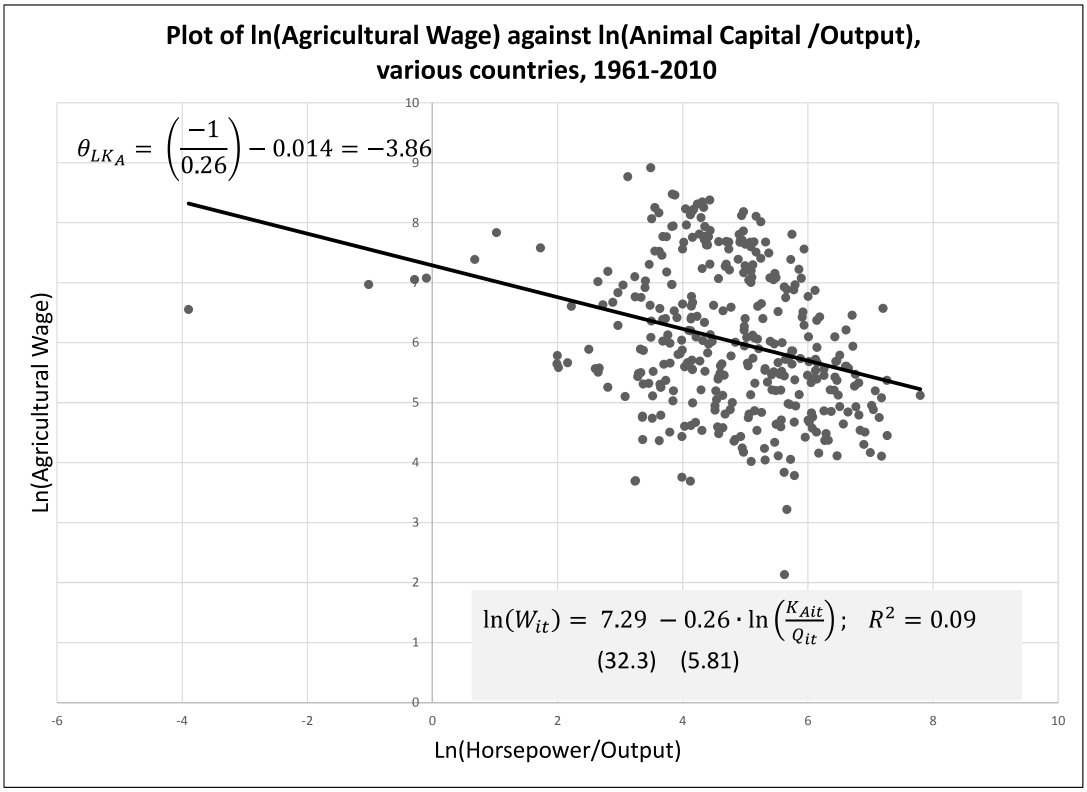


Figure 6. Cross-Price Effect of Agricultural Wage on Agricultural Land, Holding Output Fixed

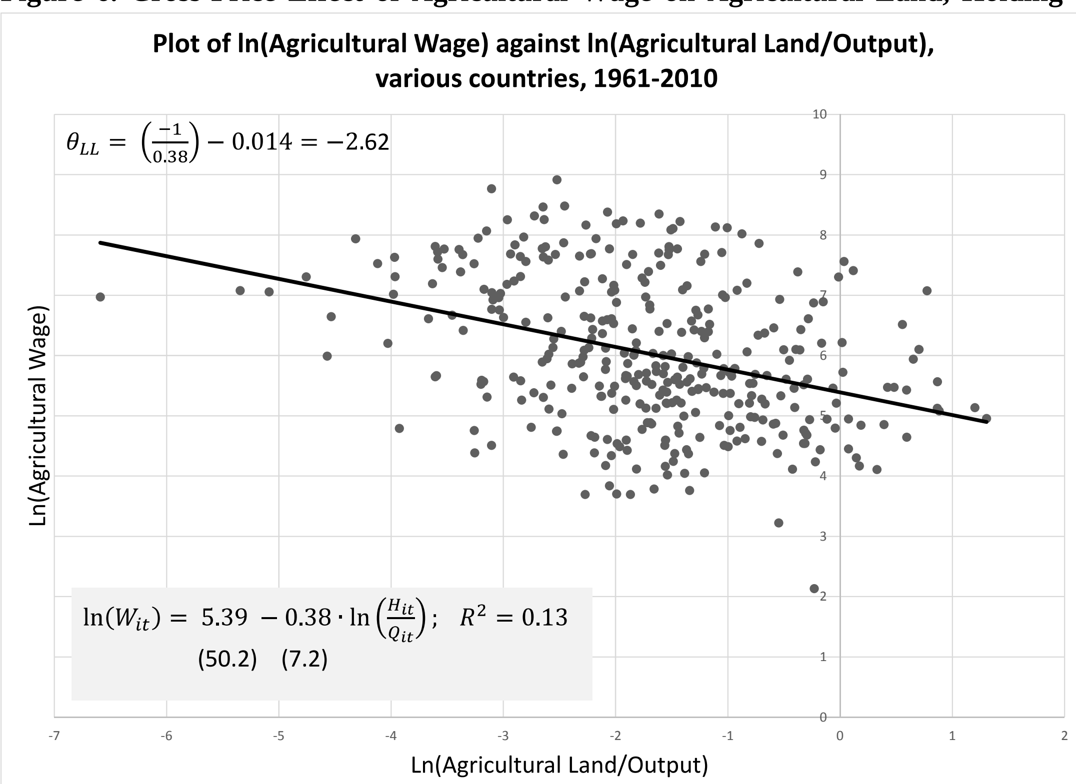


Figure 7. Cross-Price Effect of Agricultural Wage on Mechanical Capital, Holding Output Fixed

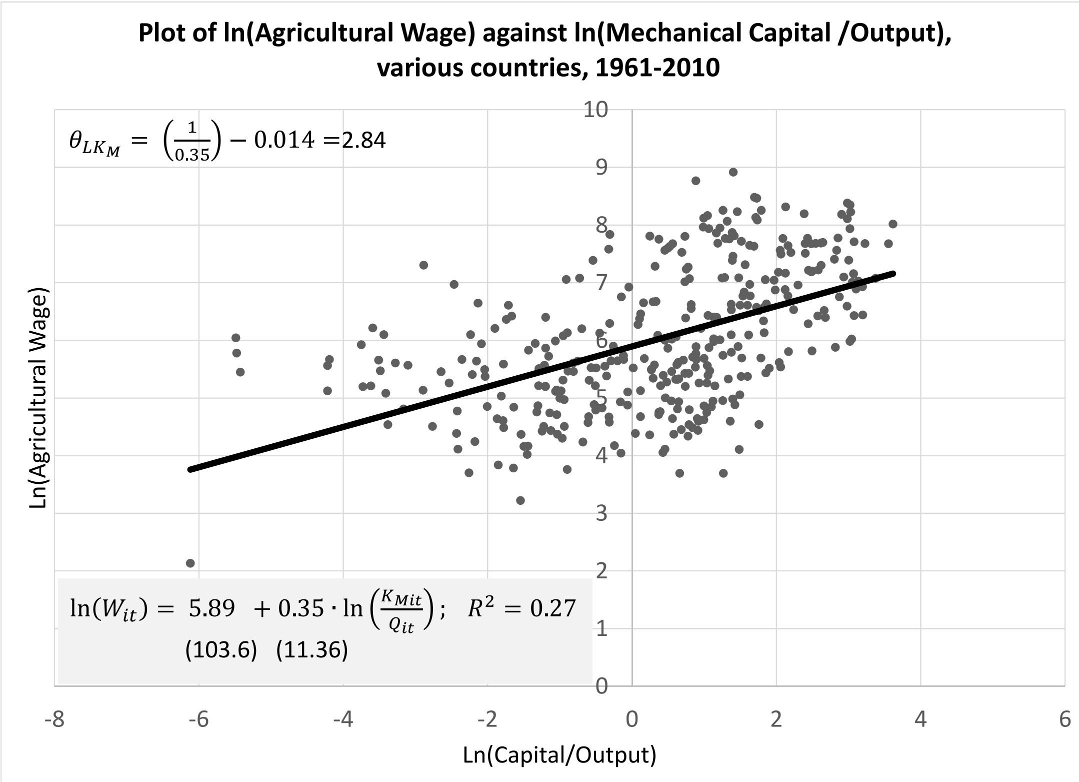
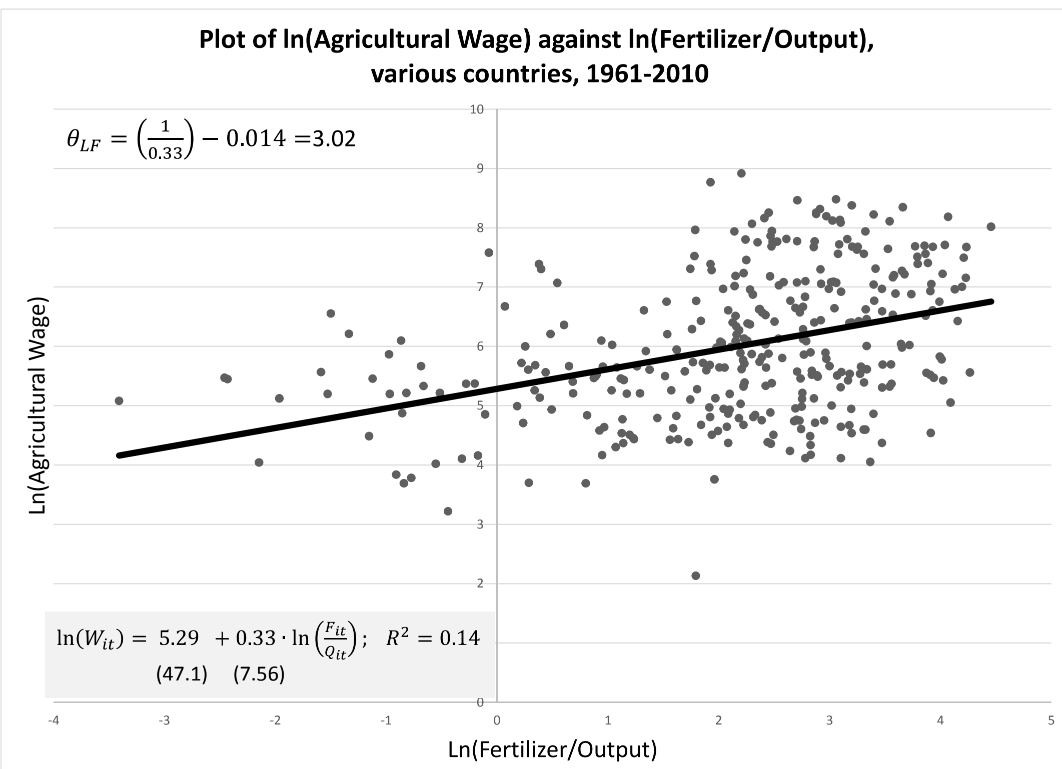
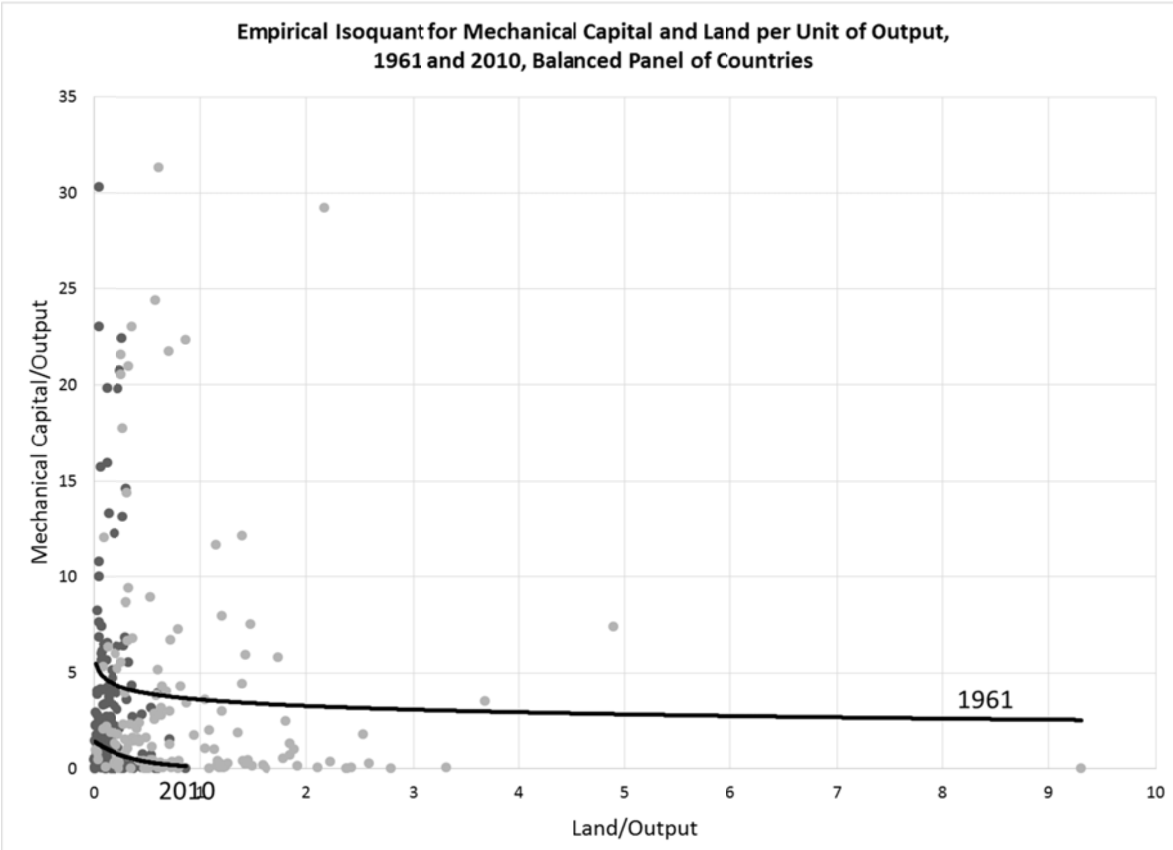
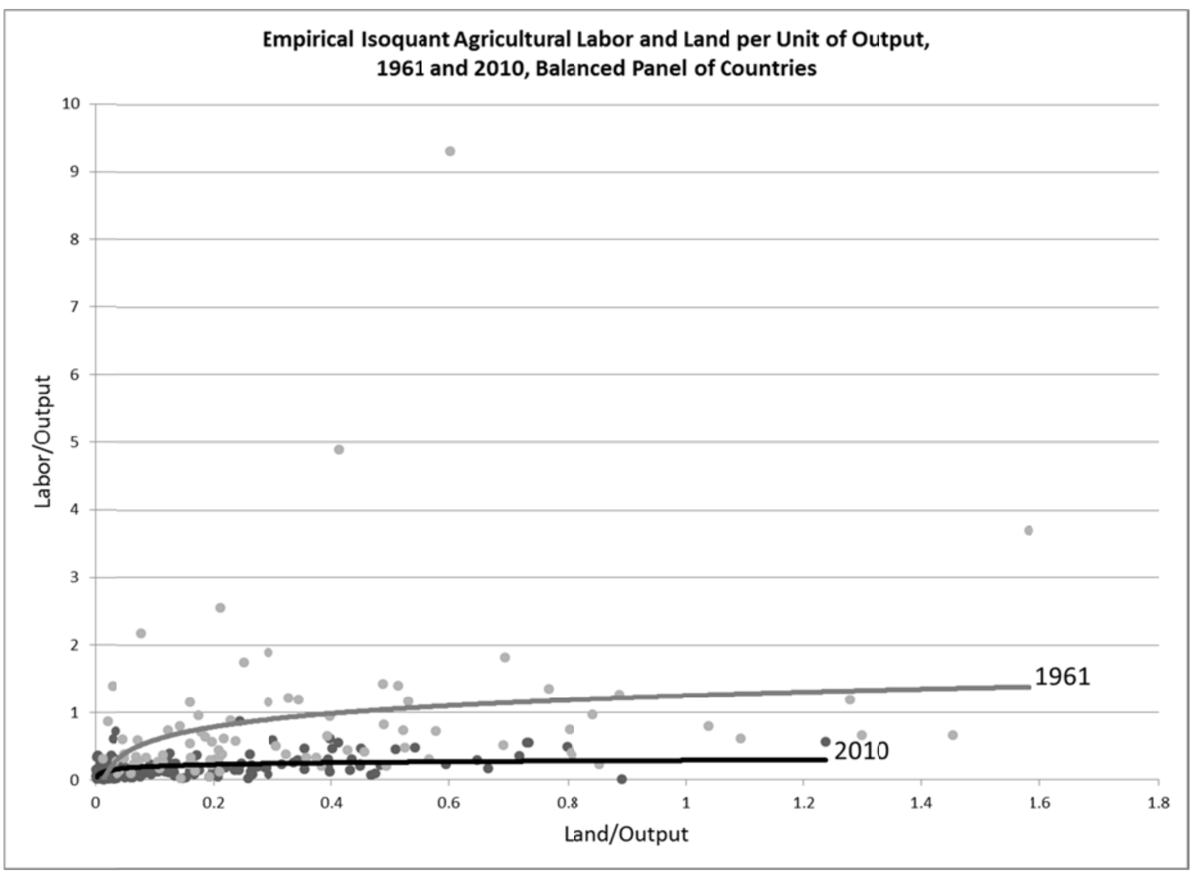


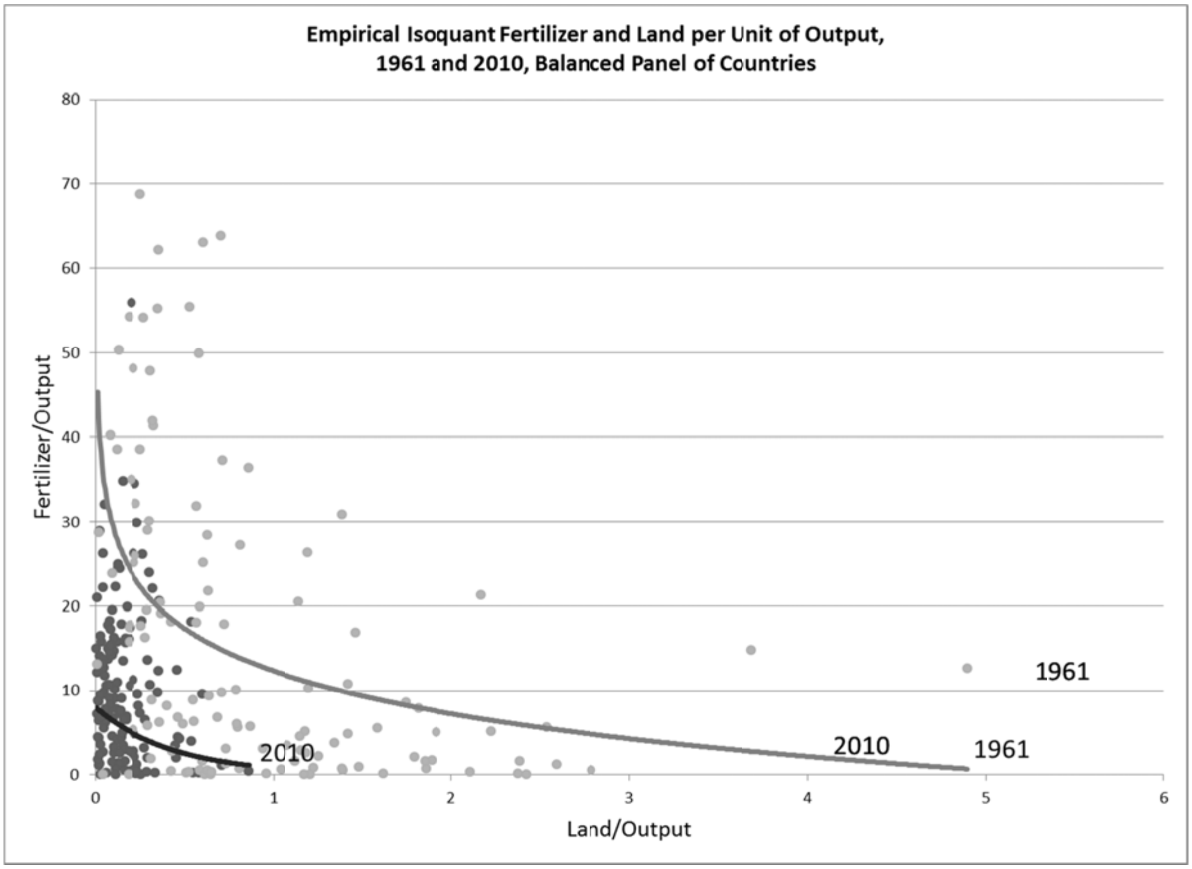
Figure 8. Cross-Price Effect of Agricultural Wage on Fertilizer Use, Holding Output Fixed

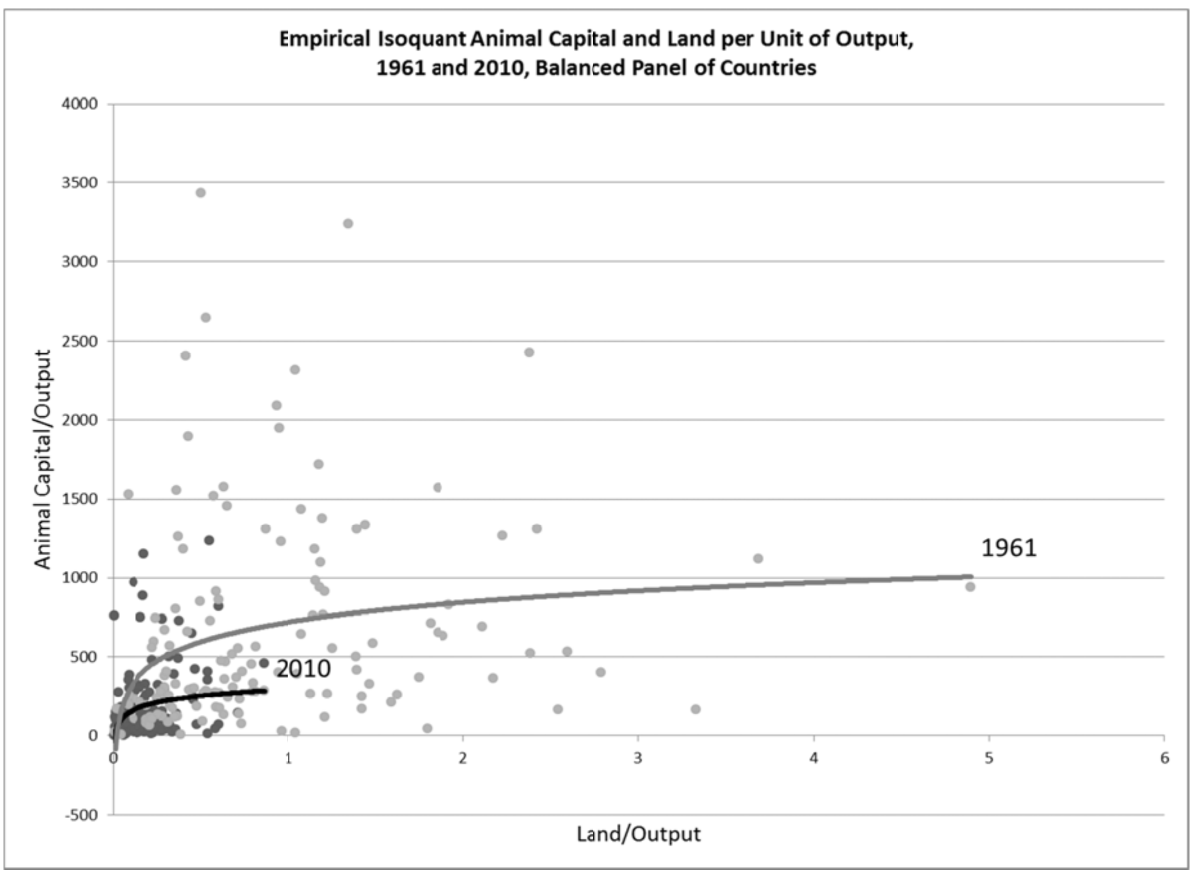


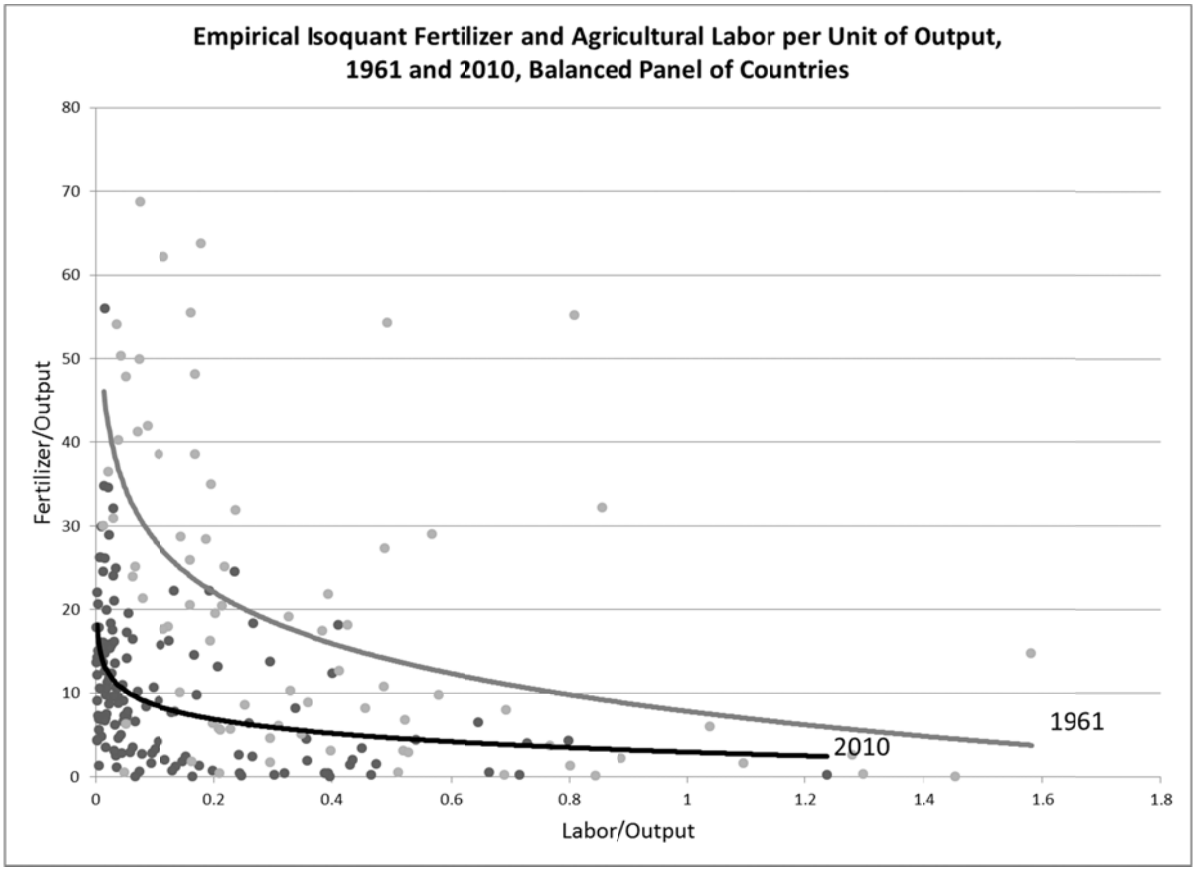
Appendix A. Empirical Isoquants for 1961 and 2010






Empirical Isoquant Fertilizer and Land per Unit of Output,
1961 and 2010, Balanced Panel of Countries
Fertilizer/Output
Land/Output
80
70
60
50
40
30
20
10
0
0
1
2
3
4
5
6
1961
2010
2010
1961


Empirical Isoquant Animal Capital and Land per Unit of Output,
1961 and 2010, Balanced Panel of Countries
Animal Capital/Output
Land/Output
4000
3500
3000
2500
2000
1500
1000
500
0
-500
0
1
2
3
4
5
6
1961
2010


Empirical Isoquant Fertilizer and Agricultural Labor per Unit of Output,
1961 and 2010, Balanced Panel of Countries
Fertilizer/Output
Labor/Output
1961
2010
0
10
20
30
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60
70
80
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0.4
0.6
0.8
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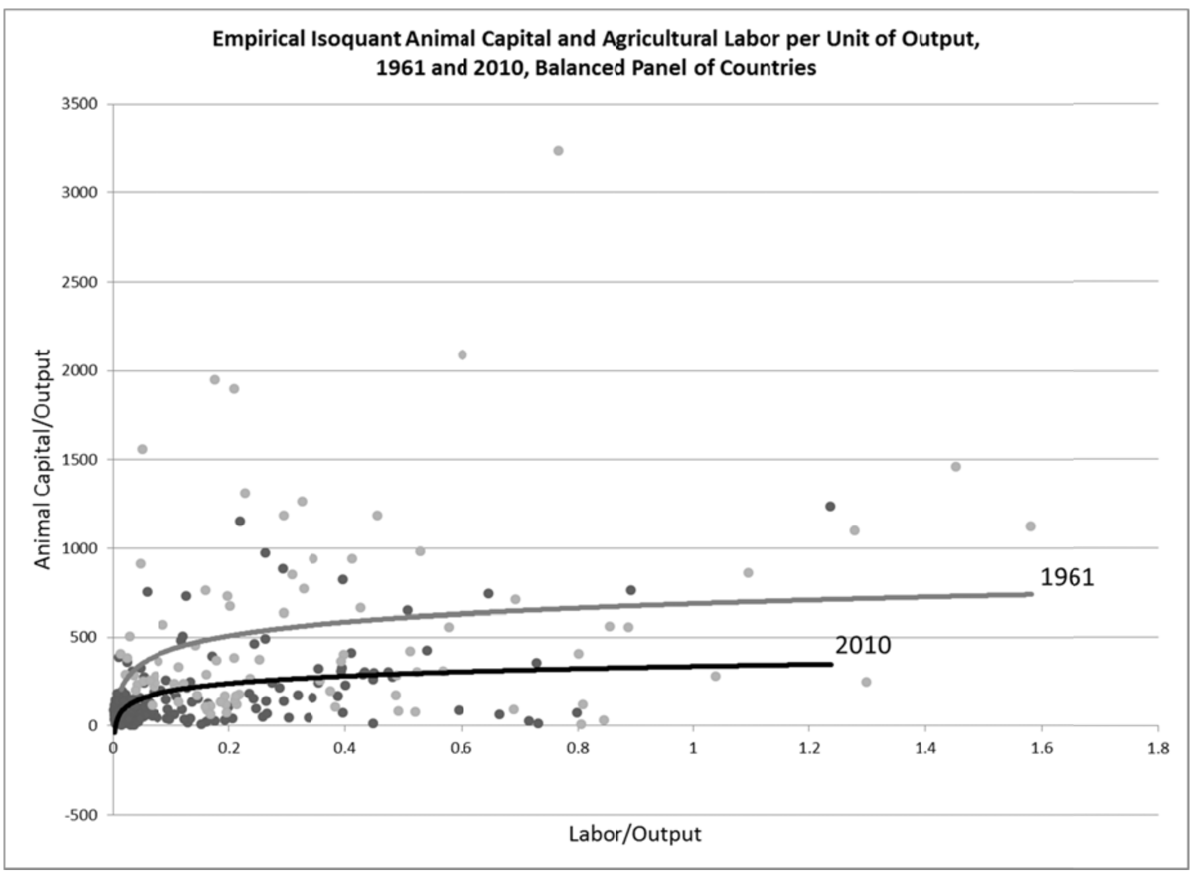
1.2
1.4
1.6
1.8


Empirical Isoquant Animal Capital and Agricultural Labor per Unit of Output,
1961 and 2010, Balanced Panel of Countries
Animal Capital/Output
Labor/Output
1961
2010
-500
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1500
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1.6
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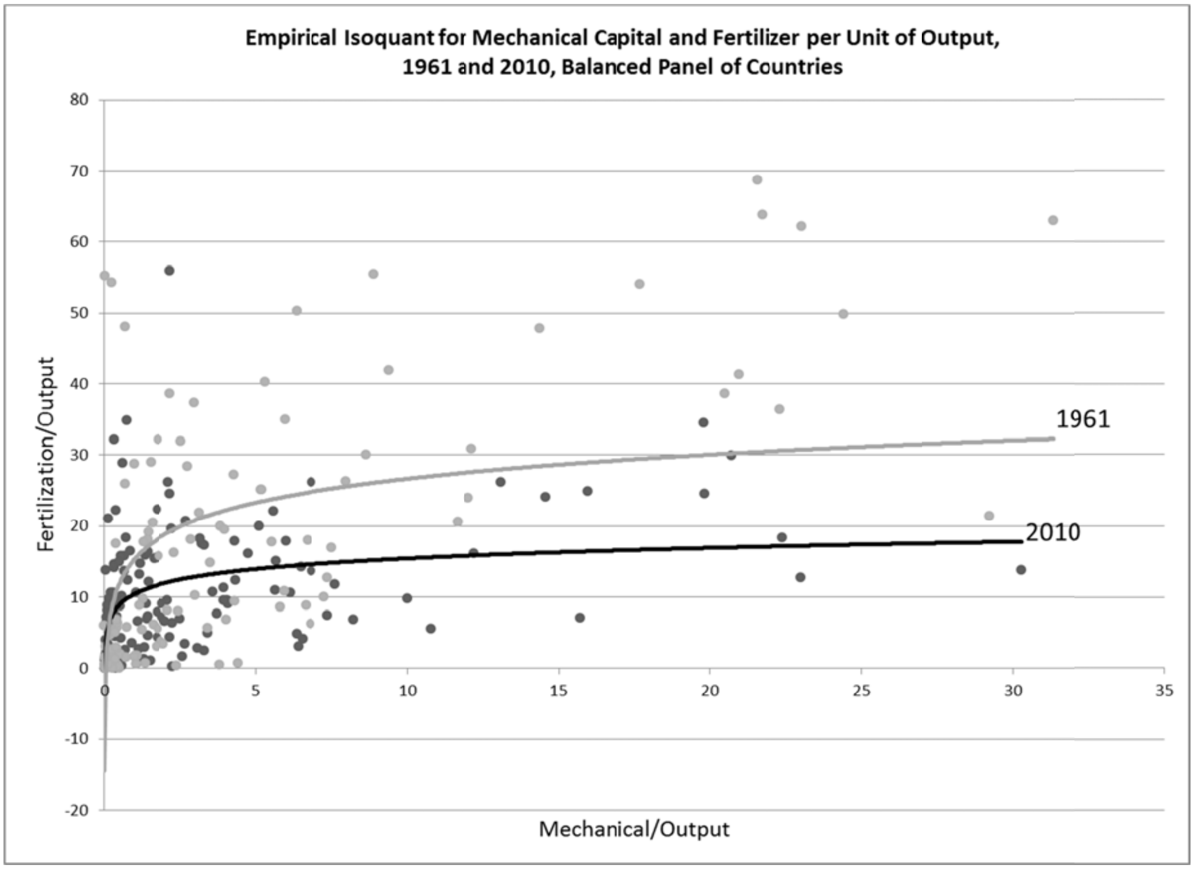
Empirical Isoquant for Mechanical Capital and Fertilizer per Unit of Output, 1961 and 2010, Balanced Panel of Countries
Fertilization/Output
Mechanical/Output
1961
2010
80
70
60
50
40
30
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10
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-10
-20
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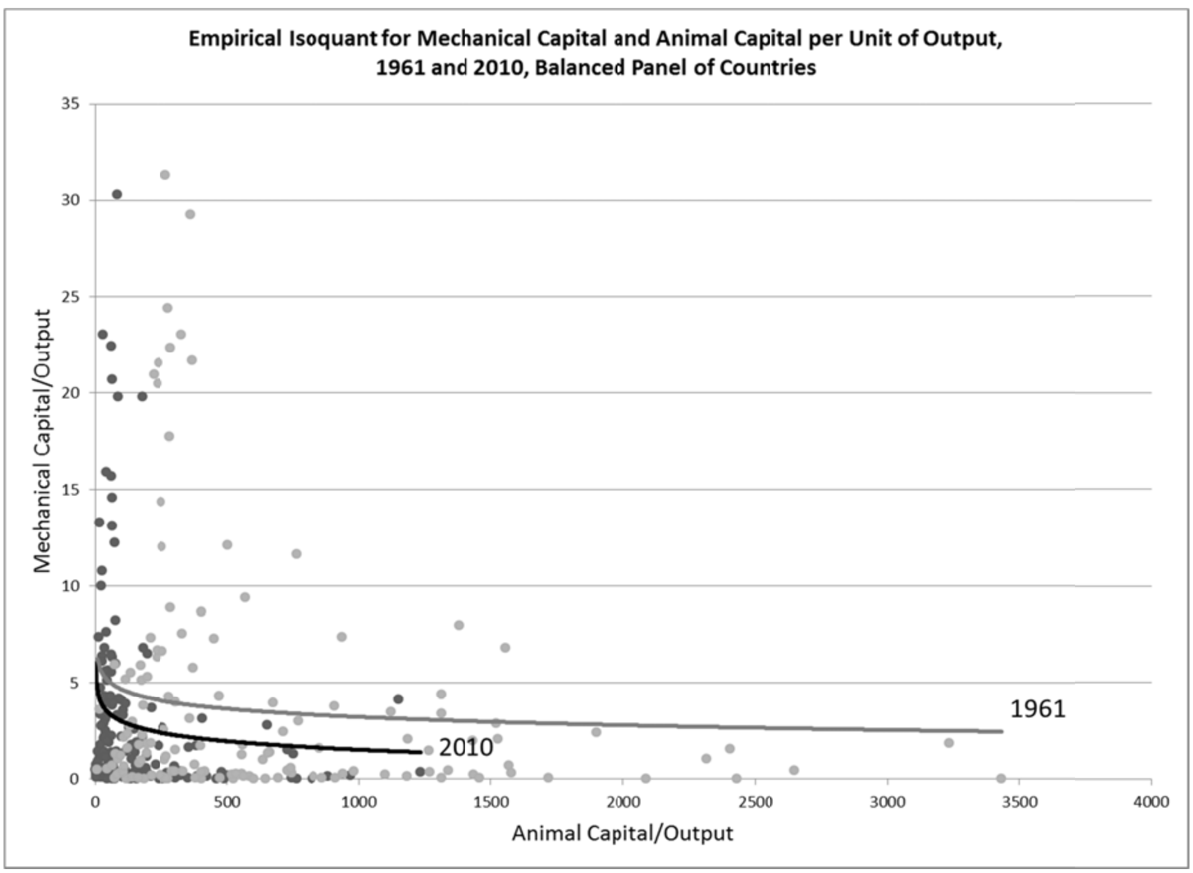
15
20
25
30
35


Empirical Isoquant for Mechanical Capital and Animal Capital per Unit of Output, 1961 and 2010, Balanced Panel of Countries
Mechanical Capital/Output
Animal Capital/Output
1961
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1500
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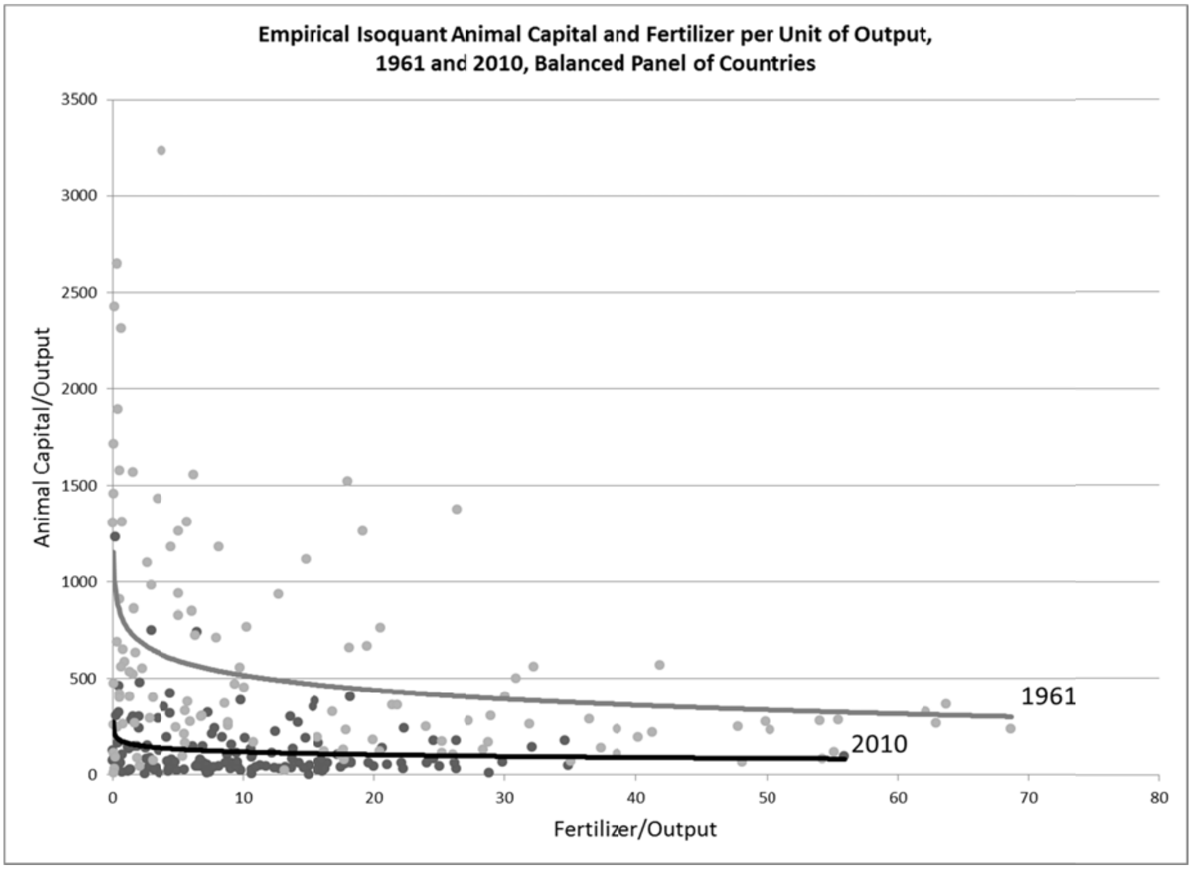
3500
4000


Empirical Isoquant Animal Capital and Fertilizer per Unit of Output,
1961 and 2010, Balanced Panel of Countries
Animal Capital/Output
Fertilizer/Output
1961
2010
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3500
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70
80