A Joint Livestock-Crop Multi-factor Relative Productivity Approach

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Selected paper prepared for presentation at the Southern Agricultural Economics Association Annual Meeting, Mobile, Alabama, February 1-5, 2003

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Abstract

An output distance function conditional on the expansion of a second output is presented. These distance functions are used to calculate distinct relative Total Factor Productivity (TFP) scores for two jointly produced products—livestock and crops for 27 countries. From these, TFP growth and direction of growth are calculated.

Key Words: conditional distance functions, data envelopment analysis, directional output distance function, joint production, total factor productivity

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Introduction

Several studies have been conducted that measures both domestic and international total factor productivity (TFP) for the agriculture sector Ball et al. (1997, 2001), Capalbo et. al. (1990), Arnade (1998), Fernandez-Cornejo and Shumway (1997), Fulginiti and Perrin (1997), Jorgenson and Gallup (1992), Lambert and Ussif (1997), Lusigi and Thirtle (1997), Trueblood (1996). Since TFP measures are related to the rate of cost diminution (Ball and Chambers (1985), Chambers (1988)), international TFP comparisons can provide some insights into a country's relative agricultural performance. However, aggregate TFP measures for agriculture can only serve a limited role in economic trade models since trade theory is built on the concept of comparative advantage, which is related to the issue of relative productivity. What prevents the measurement of distinct TFP indices for agricultural sub-sectors, such as crops and livestock, is that most agricultural products are jointly produced, and, it is difficult to allocate agricultural input use among various agricultural sub-sectors (Huffman and Everson 1992).

This paper shows how to calculate separate relative TFP indices for crops and livestock even when these products are jointly produced[1]. To do this, conditional distance functions are defined for each output. A variation of the standard Data Envelopment Analysis (DEA) program is introduced which makes it possible to calculate separate conditional distance functions, and thus allows for calculation of separate Malmquist TFP indices for crops and livestock.

Calculating separate relative TFP measures has validity at both the micro and the macro levels. At the micro level, a multi-output farmer may be interested in knowing how to improve the overall of operation through his choice of crops and/or livestock. At the macro level, countries face similar choices of how

[1] Our paper shows a physical, rather than an economic, allocation. As such, if production is joint, a dual cost function **can not** be calculated form these distance functions.

they can raise productivity through their allocation of agricultural support, such as research and extension, to crops and livestock. Our study focuses on the macro level, but it is also portable to other situations.

Methodological Framework

This paper is related to the concept of directional distance functions (see Chambers, et al.1998), Färe and Grosskopf (2000)). Generally, the concept of directional distance functions allows for the joint calculation of output and input distance functions for a single technology. In contrast, we use Data Envelopment Analysis to calculate two output-specific distance functions. Rather than measure the distance from an observation to a Production Possibilities Frontier (PPF) in a predetermined direction (i.e. towards output "*a*," or output "*b*"), a DEA programming model is formulated which calculates both the distance from, and direction of movement to, the PPF.

Conditional Efficiency

The first step in calculating total factor productivity for two jointly produced products is to introduce the following conditional distance function. Suppose X^t defines a vector of inputs, and y_1 represents output "*a*" and y_2 represents output "*b*". Now consider the conditional distance function:

(1) $$D_0^{t,a:dr}(X^t, y_1^{\,t}, y_2^t | DR) = \inf\{\theta_a, \{\ X^t, y_1/\theta_a, y_2/\theta_b\ \} \in S^t\ |\theta_b\}$$

where S^t is a technology set in time period t, θ_a and θ_b are efficiency scores for time period output "*a*" and output "*b*", respectively, and DR is the direction of the distance function $D_o^{t,a:dr}$.

For a given level of inputs and technology, the above distance function calculates the maximum amount output "*a*" can expand conditional on a predetermined level of expansion for output "*b*". Superscript *dr* is included to indicate that conditioning the expansion of output "*a"* on a predetermined level of expansion for output "*b*", also determines the direction of expansion.

Similarly, a second conditional distance function also exists:

$$(2) \quad D_0^{t,b:dr}(X^{t,}Y_1^t, Y_2^t \,|DR) = \inf\{\theta_b, \{\ X^t, Y_1/\theta_a, Y_2/\theta_b\ \} \in S^t\ \ |\theta_a\ \}$$

where the distance function in Equation 2 represents the maximum expansion of output *b*, conditional on a predetermined level of expansion for output *a.*

Directional technical change

The idea of conditional expansion can also be applied to determine the direction or bias of technical change since a technical change index measures how far one period's observation lies from another period's PPF. In devising a DEA problem that allows for the possible expansion of both outputs towards the frontier where the program implicitly chooses the direction of the expansion, the angle of the expansion represents the technical change.

For example, if this angle were 45° then there would be equal expansion of both outputs indicating that the change in the technology favors neither output. The angle or direction of the technical change is measured by developing a programming problem that jointly calculates, $\theta_{a\,,}$ and, θ_b that respectively represent the distance or the amount by which output can expand.

The Malmquist Index

The Malmquist TFP indices for both outputs are determined. In the most general form, the Malmquist TFP index as described by Färe and Grosskopf (1992), Balk (1993) and Färe et. al. (1994) represents the product of an efficiency index and a technical change index and can be written as:

$$(3) \quad M_i(y^0, y^1, x^0, x^1) = E_i(y^1, y^0, x^1, x^0) * T_i(y^1, y^o, x^1, x^0)$$

The first subindex, the function E(.), represents productivity changes arising from changes in technical efficiency. It is measured by the ratio of two distance functions at two different points in time, or as:

$$(4) \qquad E(y^t, y^{t+i}, x^t, x^{t+i}) = \left[\frac{D^{t+i}(y^{t+i}, x^{t+i})}{D^t(y^t, x^t)} \right]$$

The second component of the Malmquist index, the function T(.), represents changes in productivity due to technical change. The function T(.) is composed of distance functions which mix technology from one time period with observations from another time period. This technology index captures the shift in technology between the two time periods by evaluating technology at two different data points (y^t, x^t and y^{t+i}, x^{t+i}). This index is expressed as a geometric mean of these two shifts and is defined as:

$$(5) \qquad T(y^0, y^1, x^0, x^1) = \left[\frac{D^0(y^1, x^1)\, D^0(y^0, x^0)}{D^1(y^1, x^1)\, D^1(y^0, x^0)} \right]^{1/2}$$

Malmquist indices can be composed of either output or input distance functions. The output distance function measures the largest possible radial expansion of the output vector consistent with the feasible technology. If no further expansion is possible, then production is efficient. A directional output distance function measures the radial expansion of the output vector from itself to the technology frontier in a pre-assigned direction. This would make possible expansion in the direction of more than one frontier.

Computation of Two-Output Malmquist Indices

Charnes et al., (1978) introduced Data Envelopment Analysis (DEA) to compute production efficiency without imposing restrictions on production technology. The distance from a frontier calculated by a DEA programming problem and a particular observation provides a measure of technical efficiency. Färe et al. (1994) showed that efficiency scores, which represent the solution to a DEA programming problem, are related to distance functions. Furthermore, the authors showed that DEA could be used to calculate each distance function in the Malmquist index.

Färe's paper in 1994 lead to a wide number of studies that applied DEA Programming models to calculate Malmquist TFP indices for international agriculture (Arnade (1998,) Bureau et al., (1995), Fuliginiti and Perrin (1997), Lusigi and Thirtle (1997), Trueblood (1996). Despite the numerous applications and refinements in Färe's technique, a programming problem has not been formulated which calculates distinct Malmquist TFP indices for different outputs. The following DEA programming problem does this for two outputs:

$$
\begin{aligned}
&(F^t(y^t_{k'}, x^t_{k'})) = \max\, (\theta_a \theta_b)^{1/2} \\
&\quad s.t. \sum_{k=1}^{K} z_k\, y^t_{k1} \ge \theta_a\, y^t_{k'm} \\
&\quad \sum_{k=1}^{K} z_k\, y^t_{k2} \ge \theta_b\, y^t_{k'm} \\
&\sum_{k=1}^{K} z_k\, x^t_{kn} \le x^t_{k'n} \qquad n = 1..,N \\
&\quad z_k \ge 0, \qquad k = 1..,K
\end{aligned} \tag{6}
$$

where superscripts on the variable represent the time-period of the data. Superscripts on functions represent the time period of the reference technology, which is represented by a *z*-weighted frontier of observations from *K* cross-sections. The final constraint ensures that the *z*-weights cannot be negative.

In the above problem, there are two outputs (y_1 and y_2), *N* inputs, and *K* cross-sectional observations. In a traditional DEA program, output based efficiency scores are calculated by maximizing a single θ even when there is more than one output. In contrast, the objective of the above problem is to maximize the geometric mean of two distinct theta's (θ_a and θ_b). The solution to the above problem θ_a^* and θ_b^*

represent distinct inefficiency scores for each output. The inefficiency score (for output *a*) measures the largest possible radial expansion in the direction of output *a*, given the technology, the level of inputs, and a predetermined level of expansion for output *b*. It is equivalent to the conditional distance function $D_a^{t,b:dr}(X^t, Y^t)$ of Equation 1 evaluated at the solution level θ_b^*. Similarly, the same is true for the second measure of inefficiency for output *b* since the program, as designed, jointly calculates the expansion of output *a* and output *b,* and in doing so implicitly calculates a direction.

The calculation of distinct efficiency scores for two jointly produced outputs provides a critical step towards calculating distinct Malmquist productivity for two jointly produced outputs. The unique feature of this problem is that these distinct efficiency measures are calculated from one set of data in a single optimization problem.

Mixed Distance Functions

The standard method for using DEA to calculate technical change is to mix data from one period with calculation of the frontiers from another period (see Färe et al. 1994). The solution to this problem is a mixed period distance function. Mixed period distance functions can be similarly calculated for the above two-output problem. For example to calculate $D_a^{t+1,b:dr}(X^t, Y^t)$ and $D_b^{t+1,a:dr}(X^t, Y^t)$ substitute data from time t+1 (i.e. X^{t+} and Y^{t+1}) into the left-hand side of the inequalities in the above programming problem. This calculates the distance from observations in time t with frontiers in time t+1. To calculate $D_a^{t,b:dr}(X^{t+1}, Y^{t+1})$ and $D_b^{t,a:dr}(X^{t+1}, Y^{t+1})$ substitute data from time t+1 into the right hand side of the programming problem.

This method of calculating mixed distance functions and the relationship between mixed distance functions and technical change has been well established and has been applied to numerous industries (Arnade (1998), Lusigi and Thirtle (1997), Färe et. al. (1994)). Again, what is unique about this paper's DEA problem is that the technical change index is comprised of mixed "conditional" distance functions, which are calculated from two jointly produced outputs. Note that once the "same period" and "mixed period" efficiency scores are calculated for crops and livestock, efficiency change, technical change, and Malmquist TFP indices can be calculated for the two distinct, although generalized, outputs.

Data

Data for 27 countries are used to calculate distinct same-period and mixed-period efficiency scores for crops and livestock. From these scores, efficiency change, technical change, and TFP indices for two distinct sub-sectors of agriculture, crops and livestock, are calculated. These scores are then combined to determine the direction of technical change, i.e. whether it favors crops or livestock.

We applied the above technique to calculate distinct crop and livestock Malmquist TFP indices for 27 countries using FAO data from 1961 to 1999. A two-output programming problem was set up as in Equation 1. Livestock output was represented as a price weighted sum of beef, pork, poultry, mutton, output, milk, eggs, and wool. Price weights consist of a 3-year average of U.S. prices from 1983-1985. Crop outputs represented the price-weighted sum of cereals, fiber crops, oilseeds, pulses, root and tubers, tree-nuts, and vegetables. FOA inputs included data from fertilizers, livestock, cropland, pasture land, labor, and tractors and are similar to the data used by Arnade (1998) and Trueblood (1996).

The programming problem was repeatedly run using same year and mixed year data to obtain efficiency change, technical change, and productivity indices for years 1961 to 1999 for the 27 countries. From these indices, we calculated TFP growth for crops, and again for livestock, in each of the 27 countries.

Results

Table 1 presents the TFP growth rates for the crops and livestock sectors in the selected countries. The indices are presented so that positive numbers represents growth in TFP. Table 1 indicates that there has been positive TFP growth in both sectors for most countries. However, the growth rates for crops and livestock are quite different. For example, Australia has consistently high rates of TFP growth in its crops sector throughout the whole sample period but only has had a strong rate of TFP growth in the livestock sector since 1980. In contrast, in the 1990's Thailand's TFP fell for crops, but rose for livestock. Throughout the entire sample period, Costa Rica appears to have the highest TFP growth rate for both sectors, followed by the United States.

Table 2 presents the average rate of growth of efficiency and technical change for both crops and livestock. Note that many countries indicate zero growth in efficiency because they were efficient over the entire sample and thus could not improve. This implies there was no wastage of inputs in these countries. Most notably, the primary source of TFP growth in Costa Rica was an improvement in efficiency rather than technical change. This occurred despite the fact that Costa Rica also belongs to the group of countries, as do China, Kenya, Japan, and Zimbabwe, where technical change is regressive in the crops sector but progressive in the livestock sector.

Table 2 also shows that several developing countries have a negative rate of technical change. These results are similar to that found for agriculture as whole by Arnade (1998), Fulginiti and Perrin (1997), Trueblood (1996), and others. These authors have argued that output growth in these countries may be advancing due to high rates of input growth rather than due to productivity growth.

Table 3 reports the calculations of the angle, λ, for each country, which, as described earlier, provides a measure of the direction of technical change. If technical change favors neither crops nor livestock, then λ is equal to 45 degrees. As measured, when λ is greater than 45 degrees, technical change favors crops. When λ is less than 45 degrees, technical change favors livestock.

The results in Table 3 reveal that technical change in the larger, more developed agricultural economies tended to favor crops. The PPF for Australia, Argentina, Canada, Denmark, France, New Zealand, and Uruguay moved strongly in the direction of crop production, while the U.K. and the U.S move somewhat in that direction. Countries that moved strongly in the direction of livestock production, tended to be developing or rapidly growing, such as China, Costa Rica, Mexico, Kenya, Spain, and Zimbabwe. Interestingly, technical change has also favored livestock production in Japan.

A Formal Comparison Using the Wilcoxon Test

To further test the robustness of the productivity scores, the two-sample Wilcoxon test was done. This test evaluates statistical changes in productivity between crops and livestock in each country and among different countries. The two-sample Wilcoxon sum rank test was used to compare the United States' productivity growth pattern with each of the other countries in the study. Comparisons were made for both livestock and crop productivity growth. Following this, a third set of tests was conducted to compare crop and livestock productivity in each country.

In an attempt to address the question of heterogeneity across samples, we tested the hypothesis that the productivity ranking from two countries came from populations that have the same distributions and similarly, the productivity ranking of crop and livestock for each country came from populations with the same distributions. In the first set of tests each country's productivity ranking was referenced against the United States' using the Wilcoxon rank-sum test.

The two-sample Wilcoxon rank-sum test statistic (Wilcoxon, 1945) assumes that given two random samples, $Y_i,....,Y_m$ and $Z_i,....,Z_n$ from two populations with unknown cumulative distribution functions, F and, G , respectively, the hypothesis of homogeneity of the two samples $H_O: F(a) = G(a)$ against the one-sided alternative hypothesis of heterogeneity of the two samples

$H_A : F(a) \geq G(a)$ and $F(a) \neq G(a)$ for some a. Since the two populations are assumed to be identical under the null hypothesis, independent random samples from the two populations should be similar with similar location parameters. Jointly ranking the measurements from both samples, from lowest to highest and then examining the sum of the ranks for sample Y or equivalently for sample Z can then measure a comparison between the two samples. The Wilcoxon rank sum test statistic is expressed as:

$$\sum_{i=1}^{m} r_i$$

where $r_i, \ldots, r_m$ are the Y ranks in the *combined* sample. The Z ranks are similarly derived. The Wilcoxon test also assumes continuous population distributions so that there is zero probability that any two observations are identical. In practice, however, two or more observations may have the same value. For example, it is logical for a country to have the same productivity level for two different years. As such, if two observations are tied the ordinal rank score of both observations will be equal to the average value of the tied ranks (Jacobson, 1963).

Table 4 presents the Wilcoxon rank, W and the Z statistics for three sets of tests. The statistics in the first Column 1 indicates that only in Costa, Rica, France, and UK were TFP indices not significantly different from that of the United States. Using a more rigorous 0.05 significance level Denmark and Germany were also not significantly different from the United States.

Livestock, however, presents a different story. Only Australia's, Germany's, and New Zealand's TFP growth are not significantly different that the U.S. at the 0.1 significance level. At the 0.05 significance level Denmark, Ireland, Romania, and Spain livestock TFP are not significantly different from the U.S.

Column 3, Table 4 compares TFP for livestock and crops for each country. At the 0.1 significance level in only a few counties (Brazil, Costa Rica, Hungary, Poland, South Africa, and Thailand) have TFP growth not significantly different between the crops and livestock sectors. At the 0.05 significance level, Ireland, Mexico and New Zealand can be added to the list countries where TFP growth was not significantly different from crops.

The results in column 4 underscore the pitfalls of relying on single measures of TFP growth for the entire agricultural sector. In the more develop countries, the crops sector and livestock sectors have diverged in their rate of TFP growth. This divergence may be a result of a more open agricultural trading system, which moves countries towards the sector where they have a comparative advantage. Supporting this argument is that in the six countries where TFP did not diverge between sectors, there were three countries (Hungary, Poland, and South Africa) that were isolated from the world trading system for much of the sample period. In two of the other non-divergent countries, Brazil and Costa Rica, (see Table 2) the differences in technical change between crops and livestock are offset by large and similar changes in efficiency. On the other hand, Romania also was isolated from world trade during much of the sample period, yet its crop and livestock TFP scores are significantly different.

Concluding Remarks

This paper introduces a programming method that can be used to calculate distinct measures of TFP for jointly produced products without requiring the allocation of inputs to either product. The program is applied to the agriculture sector for 27 countries in order to measure Malmquist TFP indices for both crop and livestock. We show how these distinct scores can be used to determine the direction of technical change. An empirical example shows that, generally, technical change has favored crops in the more developed countries but favored livestock in the developing countries.

The Wilcoxon test is used to determine if TFP growth rates for either crops or livestock are significantly different from TFP growth in the United States. Only three countries in our sample: Costa Rica, France and UK have similar TFP growth rates for crops as the U.S. Interestingly, however, three *different* countries have similar TFP growth rates for livestock: Australia, Germany, and New Zealand. This test was also used to demonstrate that for most countries TFP growth for crops was statistically different that TFP growth for livestock.

The method introduced in this paper can be extended to include more countries; or/and can be applied to domestic survey data. Doing so may provide some information on the direction of change in a country's (or a producer's) comparative advantage. Specific measures may also help to better understand the sources of growth of specific products. Follow up econometric studies on productivity or its components (technical change and efficiency) may also be used to explain what exogenous factors favor crops or livestock and/or investigate the comparative advantage issue. It may also be possible to broaden the method to calculate TFP indices for more than two jointly produced products, say crops, cattle, hogs and poultry if these are what make up the complete set of jointly produced goods.

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Table 1. Multi-factor Productivity Growth for Crops and Livestock.

	Crops				Livestock			
Country	1961-70	1971-80	1981-90	1991-99	1961-70	1971-80	1981-90	1991-99
Argentina	-1.33	-0.13	0.08	-1.16 :	-4.47	0.51	-3.28	-6.49
Australia	7.84	2.65	4.48	6.73 :	1.25	-0.38	2.51	3.04
Brazil	-1.56	-4.26	2.03	0.25 :	-2.65	-4.79	5.27	5.31
Canada	2.80	-0.40	3.25	2.22 :	0.93	-4.22	2.99	6.67
China	-3.00	-2.92	0.10	5.75 :	0.30	-4.23	4.38	10.82
Costa Rica	1.96	5.26	6.26	5.93 :	3.81	3.34	2.31	4.19
Denmark	3.05	2.94	6.62	0.12 :	-0.89	3.36	1.64	2.65
France	2.57	2.59	2.45	2.96 :	-3.23	1.42	2.23	11.94
Germany	3.56	0.29	2.85	3.17 :	1.18	1.70	0.65	0.01
Hungary	-2.15	3.63	2.03	0.98 :	-3.02	4.03	3.57	0.92
India	-8.89	0.93	-4.22	-2.42 :	-11.70	-2.00	-0.21	11.18
Ireland	-0.40	2.79	0.83	0.66 :	-0.13	2.25	2.08	0.67
Italy	1.67	0.26	3.42	2.76 :	-0.14	-0.09	2.58	3.59
Japan	-1.02	-4.53	0.43	1.74 :	-3.85	0.39	3.79	1.39
Kenya	2.90	-0.47	-4.93	-0.37 :	17.07	0.30	4.32	-0.03
Mexico	-2.29	3.65	-0.59	5.54 :	-1.57	2.93	-1.71	4.68
New Zealand	4.63	1.58	3.45	6.22 :	0.46	1.28	1.92	2.39
Paraguay	-8.32	5.58	7.31	-4.39 :	-9.03	1.48	-3.31	-2.35
Poland	-2.09	-3.37	1.46	-1.80 :	-2.29	-1.49	5.53	-2.45
Romania	-2.65	-0.60	0.87	5.36 :	4.48	0.58	0.52	6.84
Spain	0.82	4.76	0.14	8.10 :	-0.83	-0.43	-0.61	-2.73
South Africa	-1.55	2.43	4.41	4.24 :	-1.14	0.61	5.29	6.09
Thailand	-5.17	1.68	-6.35	-5.46 :	-1.76	-2.09	-0.02	4.54
UK	4.64	2.05	3.11	1.06 :	1.87	0.75	1.44	2.09
USA	1.80	0.50	3.43	4.17 :	0.10	1.75	2.26	5.36
Uruguay	-1.12	2.66	5.39	-1.40 :	-0.93	1.31	-0.20	1.11
Zimbabwe	-0.01	1.28	2.47	8.40 :	-0.60	0.39	1.47	-0.89

[a] Calculated from Malmquist indices

[b] For example between 1961 and 1970 TFP for Argentina's crops fell 1.33% a year while it grew 1.8% a years in the United States.

Table 2. Average Growth Rates of Efficiency and Technology.

	Crops		Livestock	
Country	Efficiency	Technology	Efficiency	Technology
Argentina	0.00	-0.919	0.00	-5.757
Australia	0.11	2.734	0.61	0.129
Brazil	-1.94	-0.018	-1.32	0.431
Canada	0.00	1.490	0.00	0.469
China	0.00	-0.599	0.00	0.714
Costa Rica	4.55	-0.710	1.68	0.420
Denmark	0.00	2.067	0.00	1.270
France	0.00	2.047	1.04	0.300
Germany	0.00	1.476	-0.41	1.167
Hungary	0.00	0.361	0.00	0.351
India	0.00	-3.915	0.00	-3.334
Ireland	0.71	0.233	0.17	0.786
Italy	0.91	0.385	0.66	0.506
Japan	0.00	-0.907	0.00	0.175
Kenya	0.59	-2.090	-0.64	0.716
Mexico	0.45	-0.029	0.08	0.350
New Zealand	0.00	2.496	0.00	0.937
Paraguay	0.00	-8.499	0.00	-8.079
Poland	-0.03	-1.327	-1.14	-0.078
Romania	0.99	-0.263	1.13	0.327
Spain	0.78	0.899	-3.28	1.287
South Africa	0.00	1.081	0.00	1.158
Thailand	0.00	-7.110	0.00	-3.828
UK	0.00	1.659	0.00	1.296
USA	0.00	1.937	0.00	1.327
Uruguay	-1.97	1.426	-0.23	0.027
Zimbabwe	0.25	-0.151	-2.19	0.637

[a] For example, in Australia crop efficiency growth average approximately one ten of one percent a year, which technical change was 2.7% a year. Calculation based on DEA scores.

Table 3. The Direction of Technical Change by Decade and Country.

Country	1960s	1970s	1980's	1990s	Period Average
			Degrees		
Argentina	50	56	65	68	59.8
Australia	53	64	68	70	63.8
Brazil	44	46	44	41	43.8
Canada	55	60	64	59	59.5
China	40	44	42	26	38.0
Costa Rica	42	37	34	26	34.8
Denmark	50	53	58	58	54.8
France	55	61	63	65	61.0
Germany	49	47	48	49	48.3
Hungary	45	46	43	45	44.8
India	44	48	48	42	45.5
Ireland	46	44	43	38	42.8
Italy	44	46	48	43	45.3
Japan	49	46	36	30	40.3
Kenya	34	31	21	17	25.8
Mexico	48	42	49	39	44.5
New Zealand	50	57	57	60	56.0
Paraguay	49	56	64	58	56.8
Poland	43	47	43	37	42.5
Romania	37	39	36	37	37.3
Spain	36	38	29	35	34.5
South Africa	44	50	47	40	45.3
Thailand	47	50	51	39	46.8
United Kingdom	49	50	52	50	50.3
United States of America	51	53	55	50	52.3
Uruguay	48	54	52	58	53.0
Zimbabwe	42	47	51	34	43.5

[a] A 45-degree angle represents a technical change the neither favor crops nor livestock. It is equivalent to a homothetic shift in the PPF. Greater than 45 degrees represents a technical change favoring crops, while less than 45 degrees represents a technical change favoring livestock.

Table 4. Wilcoxon Scores and Z-statistic.

Country	[a]Crop Productivity Comparison		[a]Livestock Productivity Comparison		[b]Crop Versus Livestock Productivity Comparisons	
	Score	*Z-Statistic*	*Score*	*Z-Statistic*	*Score*	*Z-Statistic*
Argentina	826.5***	-7.13	823.5***	-7.16	2193.5***	6.52
Australia	1751.5**	2.11	1274***	-2.66	2193.5***	6.52
Brazil	781.5***	-7.58	812***	-7.27	1591.5	0.51
Canada	1364.5**	-1.75	950***	-5.89	2267.5***	7.26
China	780.5***	-7.59	1086***	-4.54	1169.5***	-3.71
Costa Rica	1520.5	-0.20	1908.5**	3.67	1554.5	0.14
Denmark	1698.5*	1.57	1655	1.14	1951***	4.10
France	1620.5	0.79	1024***	-5.16	2204.5***	6.63
Germany	1374.5*	-1.66	1726.5**	1.85	1875.5***	3.34
Hungary	924.5***	-6.15	1289***	-2.51	1581.5	0.41
India	780.5***	-7.59	792.5***	-7.47	2044.5***	5.03
Ireland	1275.5***	-2.64	1630.5	0.89	1692.5*	1.51
Italy	1118.5***	-4.21	1402*	-1.38	1901.5***	3.60
Japan	792.5***	-7.47	974.5***	-5.65	1213.5***	-3.26
Kenya	912.5***	-6.27	1520.5	-0.20	1224.5***	-3.15
Mexico	816.5***	-7.23	1089.5***	-4.50	1376.5*	-1.63
New Zealand	1727.5*	1.86	1557	0.16	2104.5***	5.63
Paraguay	810.5***	-7.29	792.5***	-7.47	1932.5***	3.91
Poland	780.5***	-7.59	800.5***	-7.39	1480.5	-0.59
Romania	826.5***	-7.13	1680.5*	1.39	876.5***	-6.63
Spain	1363.5**	-1.76	819.5***	-7.20	2274.5***	7.33
South Africa	999.5***	-5.40	1283.5***	-2.56	1661.5	1.20
Thailand	780.5***	-7.59	796***	-7.44	1625.5	0.84
United Kingdom	1586.5	0.45	1791.5***	2.50	2005.5***	4.64
United States of America	-	-	-	-	1974.5***	4.33
Uruguay	2132.5***	-5.91	2135.5***	-5.94	2008.5***	4.67
Zimbabwe	2102.5***	-5.61	2172.5***	-6.31	1968.5***	4.27

***Significant at the 99 percent level
**Significant at the 95 percent level
*Significant at the 90 percent level
[a/] All countries are compared to the U.S. in the two-sample test
[b/]Livestock is referenced to crops for all countries