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INTERNATIONAL AGRICULTURAL PRODUCTIVITY PATTERNS

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Abstract

In this paper we present measures of land and labor productivity for a group of 98 developed and developing countries using an entirely new data set with annual observations spanning the past three decades. The substantial cross-country and intertemporal variation in productivity in our sample is linked to both natural and economic factors. We extend previous work by dealing with multiple sources of measurement error in conventional agricultural inputs when accounting for observed differences in productivity. In addition to the mix of conventional inputs in agriculture, we find that indicators of quality change in these inputs and the amount of publicly provided infrastructure are significant in explaining cross-sectional differences in productivity patterns.

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To understand the process of development, analysts have often relied on measures of productivity to describe economic growth or explain its sources. International comparisons of productivity in general and agriculture in particular are usually based on partial productivity indices such as output per worker or output per hectare. Such partial measures cannot by themselves explain growth since they do not attempt to account for the role played by other inputs such as energy, chemicals, capital, or infrastructure, but they do convey useful information about the evolution of patterns of resource use. Because there are important data constraints when using any large-country sample, partial productivity measures appear the only option in comparing development over a broad set of countries or time periods.

The seminal work of Clark (1940) laid the foundations for the long and growing literature on international comparisons of agricultural growth and productivity on which we build.[1] To gain a global understanding of the nature and sources of agricultural productivity developments we have compiled an entirely new international data set. In contrast with much of the earlier work, we use annual observations over a thirty year period, and we significantly expand the country coverage to include a total of 98

[1]See, among others, Bhattacharjee (1955) Hayami and Inagi (1969); Hayami and Ruttan (1971 and 1985); Yudelman, Butler, and Banerji (1976); Nguyen (1979); Yamada and Ruttan (1980); Scandizzo (1984); Kawagoe and Hayami (1985); Kawagoe, Hayami, and Ruttan (1985); APO (1987); Capalbo and Antle (1988); Peterson (1988); Lau and Yotopolous (1989); and Craig, Pardey, and Roseboom (1991). A survey of some of this literature is provided by Trueblood (1991).

countries. Of particular contemporary interest is our addition of the former USSR, Eastern Europe, and China.

In this paper we develop land and labor productivity measures for 13 geopolitical regions. In addition, we incorporate new information on the distribution of arable land types within a smaller set of developing countries. The resulting productivity measures suggest that the process of agricultural development is affected by both the natural and economic environment of the region.

In our statistical analysis of the partial productivity measures, we extend the work of Binswanger et al. (1987) and Lau and Yotopolous (1989) by taking explicit account of various types of measurement errors likely to be present in our data. In addition, and of particular interest to policymakers, we find that publicly provided inputs -- represented here by agricultural research, road density, and life expectancy -- are important in explaining cross-country differences in agricultural productivity.

In section I we begin with a brief discussion of the data and measurement techniques used to construct comparable partial productivity measures. Crop-related productivity measures for developing countries are grouped according to agroecological zones to contrast the variation of crop productivity patterns across climate zones with the variation of the same patterns across geopolitical regions. In section II, regression results provide a summary of some of the possible explanations of cross-sectional disparities in agricultural productivity levels. In the final section, conclusions and suggestions for further research are included.

I. Productivity Measures

Data and techniques

Obtaining comparable measures of real agricultural output for a wide range of countries and time periods requires considerable care. In the absence of a detailed data set on local prices and quantities for each country, one is forced to use published aggregates that must be recast in internationally comparable units. As Pardey, Roseboom, and Craig (1992) argued, the generally preferred method of handling such data involves two steps. First an index of real output can be constructed directly using national commodity values or indirectly by deflating the value of national output with a national price index to capture real changes over time in each country. The resulting time series on national real output can then be scaled in the base year so that each country's agricultural output basket is measured in comparable currency units.

For our study, measures of real national output were constructed using separate FAO agricultural production indices for crops and livestock for each country.[2] Each of these two national time series was scaled with the value of the appropriate output for 1980, the base year. Both the index and value figures net out feeds and seeds used in the production process, and, unlike agricultural GDP figures, they exclude the output of forestry and fisheries.

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[2] The FAO index of agricultural output is a Laspeyres quantity index whose base is a three-year average centered on 1980. This index has the advantage of being an explicit quantity index instead of an index derived by deflating the value of agricultural output with a potentially inappropriate price index. We would have preferred a chained (e.g., *Divisia)* quantity index since a fixed weight index like the Laspeyres is accurate only if relative output prices are unchanged. However, chained indices are simply unavailable for large international samples.

The value series for each country was then converted to a common currency using an "agricultural exchange rate" or purchasing power parity (PPP) developed by Rao (1993) specifically for agricultural production. This is justified, as has been argued extensively in the international comparisons literature, because official or market exchange rates need not reflect the agricultural purchasing power of any particular currency (Summers and Heston 1991). The resulting value series for the two types of agricultural production were then summed to get a comparable total agricultural output series for each country (see appendix I).[3]

The land measure is a stock of total hectares of land in agriculture, whether they be arable, permanently cropped, or permanently pastured lands taken from FAO (1991). The number of agricultural workers is represented by the economically active agricultural population also obtained from FAO (1991). Unavoidably these labor statistics include workers in agriculture, forestry, and fisheries and so are not entirely compatible with the agricultural output measure used in this study. But, in contrast with earlier studies, this labor figure includes both male and female workers using FAO's most recent data.[4]

[3]The output measure used in most of the international studies in this literature are total wheat equivalent units (following the work of Hayami and Inagi 1969) where the vector of relative prices employed are not specific to any country. While the method allows one to avoid the use of problematic exchange rates it introduces some unpredictable biases in the measure of total output. See Craig, Pardey, and Roseboom (1991), pages 133-137 for a discussion.

[4]Some researchers have left out the female component of agricultural labor reasoning that it was so poorly measured as to represent no improvement. It is important to get this figure right because the female portion of the workforce is undeniably important in many countries, but it is not uniformly so. Any cross-country study of agriculture makes the omission of the female workforce a serious problem. At FAO a substantial effort has been made to improve estimates of female participation rates in agriculture; consequently, we have chosen to use these revised data.

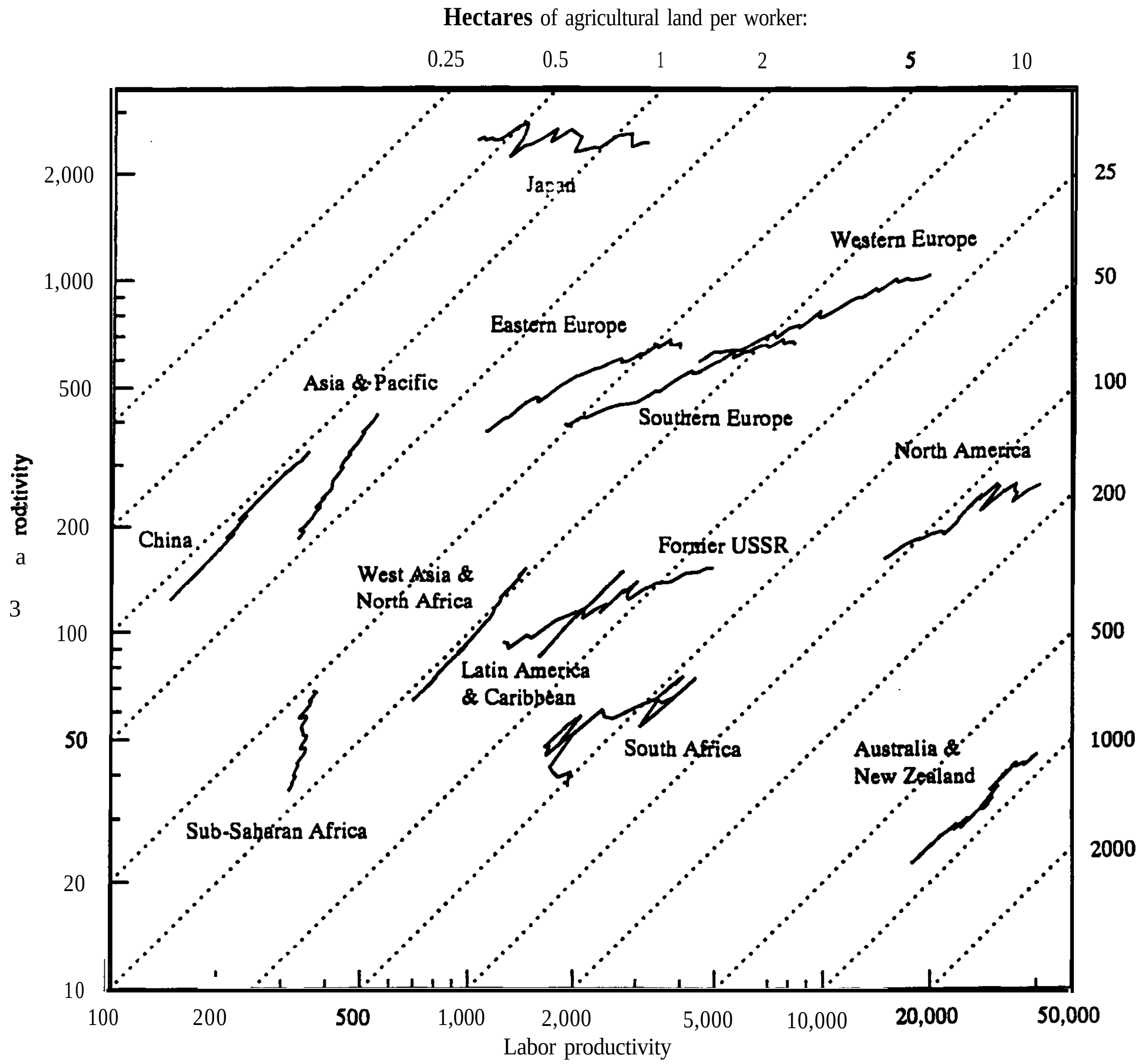
Agricultural productivity

To summarize global trends in land and labor productivity, we adopted the graphical techniques used by Hayami and Ruttan (1971 and 1985). The figures present the measures of real output per hectare and real output per worker each measured in natural logs. The vectors indicate the path of these two productivity measures as they move over time in a broadly northeasterly direction. The diagonals indicate constant land-labor ratios. A productivity path that crosses a diagonal from left to right indicates an increase in the number of hectares per worker. Given the double log scale, longer paths reflect greater percentage changes in productivity.

In figure 1, productivity measures are grouped into 10 regions and three countries for the years 1961 to 1990. The regional productivity measures are a weighted average of the inidividual productivity measures of each country in the region with the weights being defined by each country's share of total land and labor in the region. The regional groupings of countries are given in appendix I.

As is evident from figure 1, there are considerable differences across regions both in the levels of these partial-productivity measures and their paths over time. The highest measured output per hectare occurs in Japan and Europe, and the lowest in Australasia. Among developing countries, output per hectare is highest in China and Asia & Pacific. Output per worker is highest in more-developed countries and is lowest in Asia and sub-Saharan Africa.

Figure la: ***International comparison** of **agricultural** land and **labor productivities** by region, **1961** to **1990***



The paths of these partial-productivity measures over the past three decades display informative differences. In Europe, the former USSR, North America, and especially Japan, increases in output per worker have largely exceeded increases in output per hectare. The average annual gain in labor productivity in agriculture ranged from a low of 3.1% in North America to a high of 5.4% in Southern Europe. The countries in these regions generally recorded slightly smaller annual average increases in land productivity than the others in the sample. Consequently, in these regions, there has been increased output with fewer total workers and fewer workers per hectare of land.

In Asia & Pacific increases in land productivity have been dominant; and the ratio of land per worker has fallen over the sample period. In China, rates of growth in labor and land productivity have been relatively high and there has been little change in land-labor ratios.

In Latin America & Caribbean as well as West Asia & North Africa, productivity increases in both factors have been roughly equal; consequently their land-labor ratios have remained fairly constant. Although sub-Saharan Africa experienced some moderate increase in land productivity over the past 30 years, labor productivity has been stagnant and there has been a dramatic decrease in the land-labor ratio.

The productivity measures for the former eastern block countries place them in an intermediate position in terms of both labor and land productivity. The former USSR uses far more land per worker with far less output per hectare than its neighbors in all parts of Europe. Both the levels and the rates of change in labor productivity are quite similar in the former USSR and Eastern Europe, but attained levels of output per worker lag well behind those in Australasia, North America, and the rest of Europe.

The annual productivity changes in individual countries are typically more erratic than the regional aggregates. Local weather fluctuations, policy changes, or political instability can substantially affect real agricultural output although they are unlikely to have much of an impact, at least in the short run, on the labor and land input measures we have at our disposal.

Crop productivity in developing countries

For the less-developed countries in our sample we have more specific information on the distribution of arable land across nine agroecological zones (AEZs). One longstanding question in agriculture is the relative importance of the natural and economic environment in accounting for productivity differentials. Because the AEZs are defined by "major climate" and "length of growing period" instead of geopolitical boundaries (table 1), they can be used to regroup the data in ways that may shed some light on this question.

Kassam (1991) reports a classification scheme that groups cropland in 122 less-developed countries into nine AEZs and prorates 33 of the larger countries across multiple zones.[5] This classification scheme fails to account explicitly for variations in soil and terrain attributes but does capture important climatic characteristics.

[5] Of the countries which span more than one of the AEZs in our study, 9 are in sub-Saharan Africa, 14 in Latin America & Caribbean, and 6 in Asia.

Table 1: ***Agroecological Zones***

Zone/ region	Name	Length of growing period	Temperature	5% of LDC arable land	5% of total arable land
Developing Countries					
AEZ1	Warm, Semi-Arid Tropics	**75-180** days	> 20°C all year round	21.4	11.3
AEZ2	Warm, **Subhumid** Tropics	180-270 days	> 20°C all year round	14.1	7.4
AEZ3	Warm Humid Tropics	**270-365** days	> 20°C all year round	14.1	7.4
AEZ4	Cool Tropics	**75-365** days	**5-20°C** during growing period	4.9	2.6
AEZ5	Warm, Semi-Arid Subtropics (Summer Rainfall)	75-180 days	> 20°C during growing period	11.8	6.2
AEZ6	Warm, **Subhumid** Subtropics (Summer Rainfall)	180-270 days	> 20°C during growing period	**3.7**	**2.0**
AEZ7	Warm/Cool Humid Subtropics (Summer Rainfall)	**270-365** days	> 20°C during one part of the growing period and **15-20°C during the other**	**9.8**	5.1
AEZ8	Cool Subtropics (Summer Rainfall)	75-365 days	**5-20°C during growing period**	**8.3**	**4.4**
AEZ9	Cool Subtropics (Winter Rainfall)	75-365 days	**5-20°C during growing period**	**11.9**	**6.3**
Developed Countries					**47.5**

Note: Zones that have a mean monthly temperature, corrected to sea level, above 18°C for all months have been classified *tropical*. Zones with one or more **months below 18°C but above 5°C are** *subtropical* **and zones with one or more months below 5°C are *temperate*. Length of growing period has been defined as the period (in days) during the year when rainfed available soil moisture is greater than the half potential evapotranspiration (PET) rate. It includes the period required to evapotranspire up to 100m of available soil moisture stored in the soil profile. It excluder any time interval when mean daily temperature is less than 5°C. Zones with mean daily temperature greater than 20°C during the growing period have been classified as *warm*. Zoner with mean daily temperature between 5-20°C are cool, below 5°C are cold, and if one part of the growing period has temperatures greater than 20°C and the other is between 5-20°C they are classified as *warm/cool*. Zones** *have* **been classified as *arid* if the length of growing period is leer than 75 days, as semi-arid if the range is between 75-180 days, as *subhumid* if the range is between 180-270 days, and • 8 *humid* if the range is greater than 270 days.**

In order to calculate partial productivity measures for different cropland types, we need to have data on the spatial distribution of agricultural output and labor within any country with multiple **AEZs.** That information is simply unavailable, so we have used Kassam's data on cropland types to prorate national totals of labor and output to each zone according to the level of labor and output per hectare in the country as a whole. Since the zonal characteristics of land apply only to cropland, our output measure in this instance includes only crop production. Labor could not be so simply divided into crop or livestock production, so the fraction of the total workforce allocated to crops corresponds to the value share of crop production in each country's total **output.**[6] This procedure cannot provide any new information on productivity across AEZs within one country, but aggregating productivity measures across AEZs in different countries will provide an indication of the impact of climate variation on cropland productivity.

Figures 2a through 2c present land and labor productivity patterns for 72 less-developed countries aggregated into five regions, reaggregated into nine AEZs, and then aggregated by AEZs within four regions, **respectively.**[7] Our sample set of less-developed countries account for 95% of the total arable land area in the developing world. See appendix II for the distribution across AEZs for the countries in our sample.

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[6]Our procedure for dividing the total workforce into crop and livestock production would be quite accurate if the *average* productivity of workers is equal in both types of agricultural production within the same country. Even if there are barriers to labor mobility across countries and sectors, mobility of labor within agriculture should put pressure for convergence on the returns to labor used in crop and livestock production and hence productivity of labor in both types of agricultural output.

[7]Because of data limitations, particularly for small countries, only 72 of the 122 less-developed countries included in Kassam's classification scheme can be included in our productivity graphs.

Figure 2a: Comparison of land and labor pductivities for crop production by region, 1961 to 1990

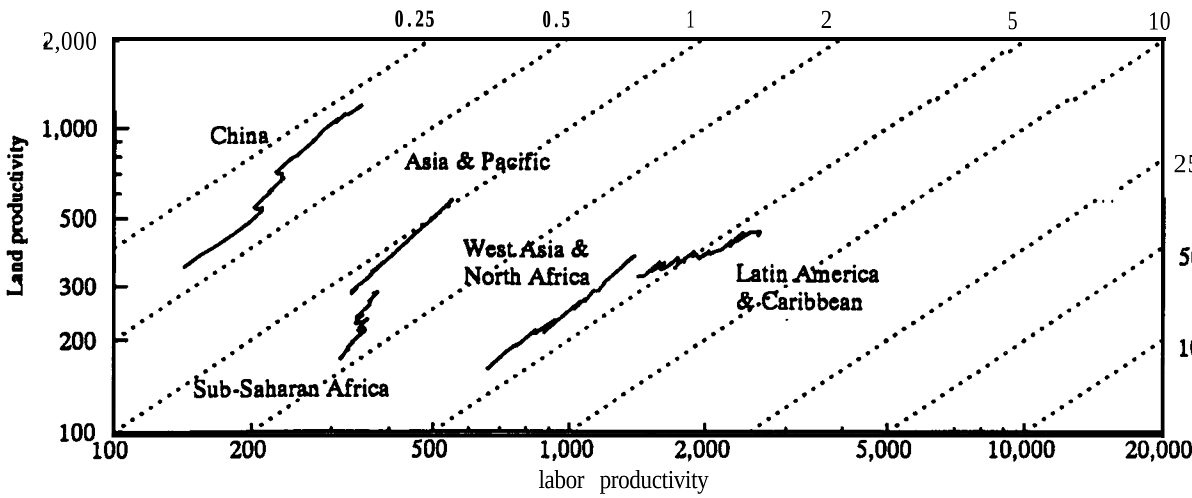


Figure *2b: Comparison of **land** and **labor productivities** for crop production by **agroecological zone,** 1961 to 1990*

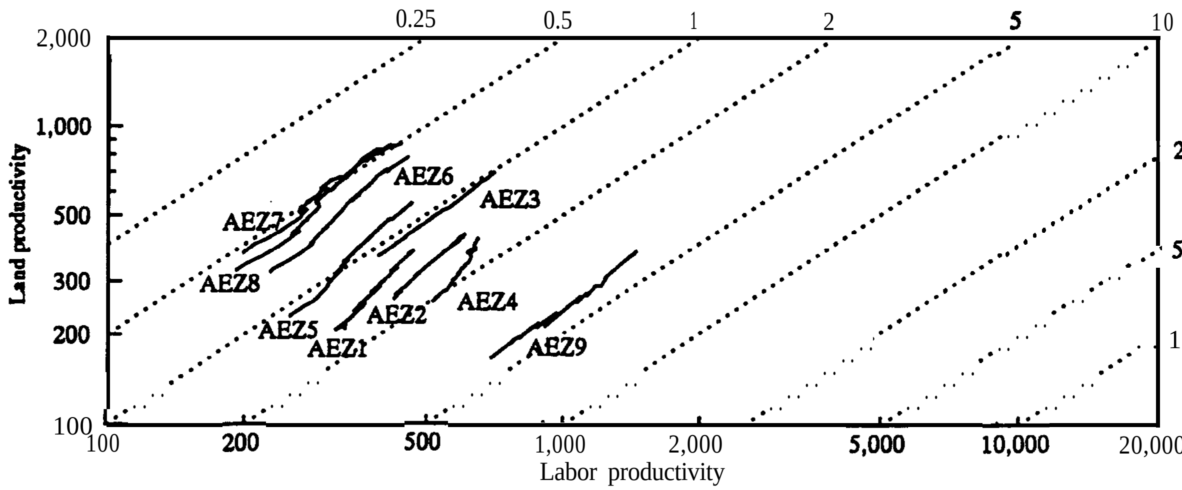
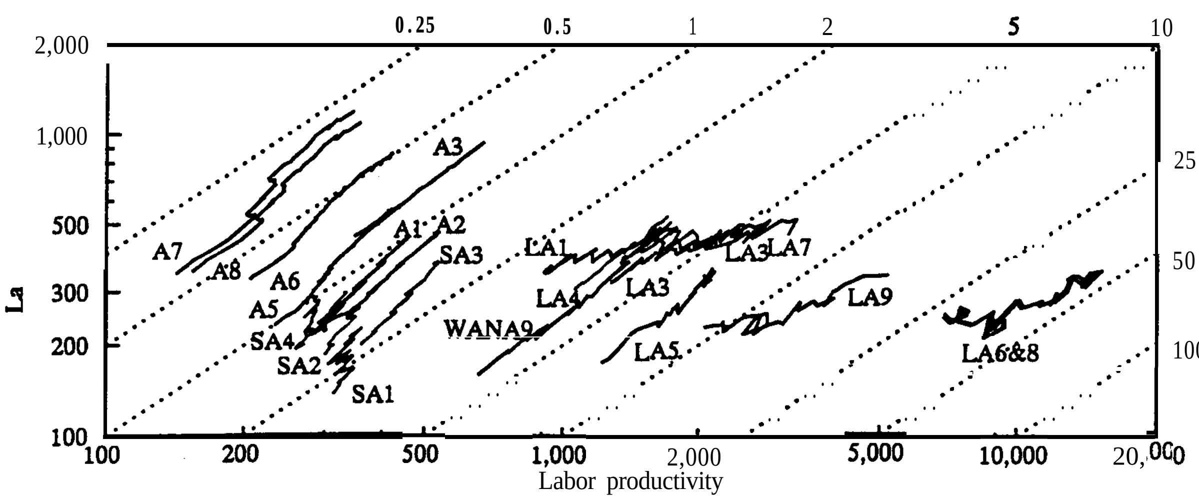


*Figure **2c:** Comparison of **land** and **labor** productivities for crop production by **agroecological zones** within regions, 1961 to 1990*



When one considers only crop production (figure 2a), the level of land productivity is higher than the corresponding level of land productivity when using total agricultural output and total land in agriculture (figure 1). The cross-country productivity differentials are also reduced across these five regions when only crop production is considered. For most developing regions, particularly China and sub-Saharan Africa, the productivity of land used for crops is significantly higher than that used for livestock. Consequently, some of the spatial variation in land productivity reflects differences across countries in the relative share of crops in total agricultural output.

The reaggregation of inputs and outputs by AEZs for these regions indicates that land productivity differentials across AEZs in developing countries are smaller than regional differentials (figure 2b). The highest levels of output per hectare of cropland are found in the wetter subtropics which experience summer rainfall (AEZs 6, 7, and 8). The highest cropland productivities in both the tropics and subtropics occur in zones with long enough growing periods to allow multiple cropping. It is not surprising that those regions where many countries can grow more than one crop per year will have higher measured land productivities since in our sample land is measured in stock rather than flow terms.

Over time, the level of cropland productivities have become more similar in the zones where temperature and length of growing period are less favorable (AEZs 1, 2, 4, and 9). It is noteworthy that the zones with the smallest proportionate increase in cropland productivity (AEZs 1, 2, and 4) account for over 40% of the total arable land in developing countries.

In figure 2c the productivity measures are grouped again by region, maintaining separate measures for each AEZ represented in each of four **regions.**[8] The differences between levels and rates of change in zonal cropland productivity within a region are smaller than the cross-region differences in cropland productivity for a particular AEZ. The apparent similarities of cropland productivity in the subtropics (particularly AEZs 6, 7, and 8) in figure 2b are not preserved when we look at AEZs at the regional level as in figure 2c. The productivity paths for **AEZs** 1, **2** and **4** in sub-Saharan Africa (i.e., SAl, 2 and 4) are more erratic and relatively shorter than the path in SA3, a warm-humid tropical zone that is characterized by a year-round growing season. Differences in zonal patterns of development seem to be strongly conditioned by regional factors; climate conditions alone do not account for the substantial cross-country differences in cropland productivity patterns.

II. Accounting for productivity differences

The relative position of the productivity vectors in figures 1 and 2 provide an indication of the relative productivity of labor and land in different locations, but the quantitative significance of observed disparities must be interpreted carefully. Obviously there are unmeasured inputs of production that may account for the cross-sectional differences in partial productivity measures. In table 2 we report regional differences in output and input variables for the most recent period in our sample.

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[8]In this graph, Asia includes China along with the countries from the region Asia & Pacific.

Table 2: *Average per Unit Labor and Hectare Values of Agricultural Output and Input Variables, 1986-90*

Region	output		Land	Labor	Fertilizer use		Tractor use		Animal traction		Livestock	
	/labor	/land	/labor	/land	/labor	/land	/labor	/land	/labor	/land	/labor	/land
	$/L	*$/ha*	*ha/l*	*L/1000ha*	*kg/L*	*kg/ha*	*HP/1000L*	*HP/1000ha*	*HP/1000L*	*HP/1000ha*	*#/1000L*	*#/1000ha*
Sub-saharan Africa (24) [a]												
Mean	412	123	7.4	354	9	2	65	14	175	18	1629	312
Standard deviation	208	111	8.1	398	13	5	99	29	444	31	1301	192
Low	164	12	0.5	30	0	0	2	0	0	0	225	31
High	1122	469	33.2	1872	64	21	449	146	2201	103	5079	840
China												
Mean	324	300	1.1	925	51	48	191	177	76	70	403	373
Asia *& Pacific* (13)												
Mean	817	955	1.0	1289	73	80	167	173	237	230	781	983
Standard deviation	568	677	0.5	640	86	98	173	165	215	173	355	609
Low	238	363	0.4	460	0	0	10	10	1	2	340	260
High	2579	2479	2.2	2567	326	394	581	502	753	494	1463	2486
Latin America & Caribbean (19)												
Mean	3260	239	24.6	179	228	21	2601	121	805	71	12160	591
Standard deviation	3409	165	33.3	286	233	25	3768	164	694	84	18109	279
Low	418	38	0.8	7	2	0	8	10	107	15	1048	209
High	14347	536	138.6	1284	790	103	13860	780	2837	403	76802	1346
West Asia & North Africa (11)												
Mean	2608	534	15.9	292	288	63	3457	519	303	116	2439	385
Standard deviation	3615	864	14.6	616	331	110	5465	775	112	289	1323	453
Low	546	13	0.4	18	24	2	13	1	136	4	754	19
High	13832	2771	56.0	2223	1300	379	20203	2683	466	1030	5595	1675
Australasia (2)												
Mean	38580	216	613.7	5	2708	13	40808	188	754	4	109282	616
Standard deviation	1926	183	512.3	4	269	11	6962	146	55	3	6533	525
Low	36654	33	101.5	1	2439	3	33846	42	699	1	102749	91
High	40505	399	1126.0	10	2977	24	47770	333	808	7	115815	1141

Table 2: *Average per Unit Labor and Hectare Values of Agricultural Output and Input Variables, 1986-90*

Region	output		Land	Labor	Fertilizer use		Tractor use		Animal traction		Livestock	
	/labor	/land	/labor	/land	/labor	/land	/labor	/land	/labor	/land	/labor	/land
	$/L	*$/ha*	*ha/l*	*L/1000ha*	*kg/L*	*kg/ha*	*HP/1000L*	*HP/1000ha*	*HP/1000L*	*HP/1000ha*	*#/1000L*	*#/1000ha*
Western Europe (12)												
Mean	18088	1231	17.0	70	2917	186	5949 1	4222	254	17	23804	1563
Standard deviation	9191	908	7.0	30	1182	73	13027	2032	62	8	12836	1012
Low	6898	525	8.1	33	1192	87	40467	1584	140	9	8054	670
High	38128	3867	30.3	124	4900	314	82500	8656	333	32	54872	4186
Southern Europe (4)												
Mean	6662	652	10.4	118	827	82	19752	1955	198	23	5154	538
Standard deviation	3336	288	4.8	53	343	22	13676	1413	20	8	2018	181
Low	2158	438	4.9	55	342	66	5168	1049	175	12	2950	317
High	10627	1148	18.1	203	1194	119	40719	4399	218	35	7371	751
Eastern Europe (7)												
Mean	5324	703	7.4	147	1316	171	10068	1632	218	32	6295	856
Standard deviation	2254	200	2.1	44	691	71	6361	1333	131	19	2665	302
Low	2503	446	4.4	96	387	69	3606	442	54	7	3106	553
High	8052	1057	10.4	227	2107	276	22926	4082	464	57	11371	1492
USSR (former)												
Mean	4432	150	29.6	34	1278	43	8107	274	318	11	7745	262
North America (2)												
Mean	32948	224	148.9	7	5236	35	93535	629	1286	9	34456	233
Standard deviation	4696	44	8.0	0	659	6	2003	20	424	3	3305	35
Low	28252	180	140.9	6	4577	29	91533	609	862	5	31151	198
High	37644	267	157.0	7	5895	42	95538	650	1710	12	37761	268
Japan												
Mean	3103	2589	1.2	834	448	373	15696	13095	5	4	1718	1434
South Africa												
Mean	3812	72	53.2	19	437	8	5668	107	176	3	9411	177

Table 2: *Average per Unit Labor and Hectare Values of Agricultural Output and Input Variables, 1986-90*

	Research expenditures		Researchers		Life expectancy	Literacy	Road length	Rainfall	% cropland	% irrigated
	/labor	/land	/labor	/land						
	$/L	$/ha	#/millionL	#/millionha	years	%	km/100ha	inches	%	%
Sub-saharan Africa (24)										
Mean	3.01	0.85	**40**	11	50	**44**	0.26	**44**	28	4
Standard deviation	2.67	0.75	30	9	5	17	0.25	la	22	6
Low	0.19	0.01	5	1	43	17	**0.02**	14	2	0
High	11.56	2.71	121	32	62	75	1.11	91	79	29
China										
Mean	2.07	1.91	71	66	70	72	0.19	39	20	47
Asia ***& Pacific*** (13)										
Mean	8.28	9.61	121	151	**60**	64	1.47	76	a3	**28**
Standard deviation	12.52	11.98	101	154	7	24	1.79	26	15	21
Low	1.08	0.85	22	17	49	26	0.10	13	53	0
High	49.14	43.00	359	613	70	**96**	6.53	107	99	**78**
Latin America ***& Caribbean*** (19)										
Mean	17.03	1.18	257	22	66	a2	0.43	57	29	13
Standard deviation	15.03	0.88	208	22	6	13	0.29	24	la	9
Low	0.92	0.08	la	4	53	47	0.05	26	a	3
High	50.43	4.03	**868**	97	76	**96**	1.24	112	64	33
West Asia ***& North Africa*** (11)										
Mean	66.63	9.80	**868**	250	63	58	0.54	16	**46**	31
Standard deviation	164.90	22.08	1983	515	a	17	0.58	7	28	27
LOW	1.55	0.11	31	2	41	27	**0.06**	3	3	5
High	587.33	**78.00**	**7106**	1647	75	**96**	**2.06**	25	**100**	loo
Australasia (2)										
Mean	557.52	2.96	lo231	52	76	99	0.42	37	7	33
Standard deviation	8.61	2.45	750	42	1	0	0.24	14	4	29
Low	548.90	0.50	9481	10	75	99	0.18	24	3	4
High	566.13	5.41	**10980**	93	76	99	0.66	51	10	62

Table 2: *Average per Unit Labor and Hectare Values of Agricultural Output and Input Variables, 1986-90*

	Research expenditures		Researchers		Life expectancy	Literacy	Road length	Rainfall	% cropland	5% irrigated
	/labor	/land	/labor	/land						
	$/L	$/ha	#/millionL	#/millionha	years	%	km/100ha	inches	%	%
Western *Europe* **(12)**										
Mean	310.91	24.09	3711	275	76	99	3.61	35	59	9
Standard deviation	212.41	25.48	2141	245	1	0	2.05	9	26	16
Low	81.17	4.37	1263	71	74	99	1.24	21	17	0
High	783.06	94.37	6729	811	77	99	8.87	50	95	61
Southern Europe (4)										
Mean	51.01	5.46	758	85	76	93	0.99	32	65	23
Standard deviation	29.79	3.23	314	41	1	5	0.58	4	13	5
Low	25.38	2.72	467	41	74	85	0.38	27	43	16
High	99.17	10.71	1273	138	77	97	1.78	37	79	30
Eastern Europe (7)										
Mean					71	98	1.07	27	72	11
Standard deviation					1	2	0.51	7	9	13
Low					70	92	0.49	24	55	1
High					73	99	2.01	43	81	31
USSR (former)										
Mean					70	98	0.27	19	38	9
North America *(2)*										
Mean	677.81	4.49	5239	35	76	99	1.29	29	53	6
Standard deviation	212.67	1.19	546	2	1	0	0.15	6	9	4
Low	465.13	3.30	4693	33	75	99	1.14	23	44	2
High	890.48	5.67	5784	37	77	99	1.44	36	62	10
Japan										
Mean	230.71	192.49	3338	2785	78	99	20.81	67	88	62
South Africa										
Mean					61	79	0.19	21	14	9

Note: Smce the data relates to the penod before the unification of Germany, the East German data has been included in Eastern Europe. The data for Czechsolovakia, USSR, and Yugoslavia relate to the pm-1990 boundaries.
[a] Number in brackets denotes the number of countries in each region sample.

Data on the consumption of chemical fertilizers measured in equivalent nutrient units of nitrogen, phosphorous, and potash are published by FAO (1991). These figures indicate Asia and Europe, the regions with the highest output per hectare, are among the heaviest users of fertilizer. The regions with the lowest output per hectare, Australasia and sub-Saharan Africa, use far less fertilizer per hectare than the other regions in this sample. This is so even though commercial fertilizer use has increased more than fivefold in sub-Saharan Africa since 1961.

The use of capital services in agriculture over the past two decades is much more difficult to document. The spotty information on agricultural capital stock we do have indicates substantial cross-sectional differences. The total tractors in use in agriculture are available from FAO (1991) for a wide range of countries. These provide, at best, a crude indicator of total services from capital because they omit many types of harvesting and forage equipment, all buildings, and even two-wheeled tractors -- a particularly important omission for Asian agriculture. Moreover, tractor counts do not indicate the range of quality and intensity of use of tractors -- much less other capital equipment -- either over time or across countries.

To better proxy capital services in agriculture, data from a wide variety of published sources were used to generate a new machinery series that includes two- and four-wheel tractors. Available tractor horsepower data were used to derive average horsepower of tractors over time for each region. These regional averages were then used to scale country-specific tractor counts to get a measure of total tractor horsepower that reflects quality differences across countries in the tractor stock.

The regions with the lowest tractor horsepower stock per hectare in this sample were sub-Saharan Africa and Australasia. These regions also have the lowest levels of land productivity. Not surprisingly, those regions with the largest amount of tractor horsepower per worker -- North America, Western Europe, and Australasia -- are the regions with the highest levels of output per worker.

Livestock serve many different purposes in agriculture, and so care must be taken in measuring and interpreting stocks of animals as inputs in agriculture. Animals on farms provide traction, fertilizer, breeding, recreation, and ".banking" services (as stores of wealth) as well as representing part of output. We have no reliable information on agricultural use of animal manure, but we have partitioned animals into those used primarily for traction and those that provide breeding services.[9] Any livestock which serve neither function are properly treated as part of output but not inputs.

[9]Hayami and Ruttan (1971 and 1985) do not make the traction/breeding stock distinction and so lump all animals into a single livestock input. The animals they used were camels, buffaloes, horses, mules, cattle, asses, pigs, sheep, goats, and chickens. Since it is inappropriate to try and explain output (part of which is livestock) using livestock output, we have excluded all animals with short lives as breeder stock and unlikely use as traction animals, e.g., chickens and turkeys. The animals used primarily for traction were translated into horsepower equivalents using Campbell's (1990) estimates of the horsepower ratings of a horse (l.0), buffalo (0.75), mule (0.7), camel (0.67), and donkey (0.35). The total count of traction animals--particularly horses--probably overstates animals used for traction in many of the countries in our sample. In the industrialized countries, a high percentage of the horses on farms do not represent work stock, but the information needed to discount horse totals for the entire sample is simply not available. The total count of non-traction animals (pigs, goats, sheep, and cattle) is a weighted sum of individual animal counts using the weights reported by Hayami and Ruttan (1985). These weights can be interpreted as relative prices that allow us to form a cattle-equivalent livestock aggregate. This total nevertheless is an exaggeration of the breeding stock. Unfortunately, we have no information on the share of breeders of each type of animal in the total animal stock and are forced to work with the assumption that breeders represent a similar fraction of the total stock of animals in different countries and at different points in time.

Animal traction as a percentage of total horsepower on farms does differ quite dramatically across countries in our sample in ways that appear systematically related to both land and labor productivity. Animal traction currently represents almost 70 percent of total traction horsepower in sub-Saharan Africa where land and labor productivity are both relatively low. Less than two percent of total traction is animal traction in Europe, Australasia, Japan, and North America where productivity levels are relatively high.

A less conventional factor that may well influence productivity in agriculture is publicly provided infrastructure. Better roads and transportation, as well as more reliable communications and irrigation services may improve the timing of agricultural operations and make productivity gains from specialization possible. Local research and extension may reduce the cost of disseminating information on better crop varieties and farming techniques. Recent studies by Antle (1983), Binswanger et al. (1987), and Lau and Yotopoulos (1989) indicate that public investments in such things as transportation, communication, irrigation, agricultural research, education, and health care do influence agricultural production. Hence, cross-sectional differences in public spending patterns may well explain part of the variability of land and labor productivity in our sample.

For our sample we have a single observation for each country on road density. It is calculated as the total length of roads per square kilometer of agricultural land. Data on road length were obtained from World Bank (1992b) and Europa Publications (1991), but no adjustment for road quality was possible. For each country the most recent observation was taken, most of them refer to the mid-1980s.

Literacy rates for the population over 15 years of age and life expectancy at birth were taken from World Bank (1980, 1989, 1992a, and 1992c). These series may reflect public spending on education and health care but may also be thought of as human capital characteristics as discussed below.

Annual data series on real public resources devoted to agricultural research (measured in 1980 PPP dollars) were taken from the 154-country sample developed by Pardey, Roseboom, and Anderson (1992). Again, there are multiple interpretations that can be given to this variable. Research may contribute to a stock of knowledge relevant to agricultural production as assumed by Kislev and Evenson (1975) and Antle (1983). Alternatively, research spending may simply be interpreted as a proxy for total public resources targeted at the rural population since, as Roe and Pardey (1992) show, there is little difference in the average share of research in total public spending on agriculture in rich and poor countries.[10]

The use of other inputs in agriculture will undoubtedly help explain cross-sectional partial productivity differences in land and labor. But it is also possible that mismeasurement of the inputs of land and labor themselves may account for much of the observed productivity disparities across regions.

The agricultural land total for each country or region includes heterogeneous land types. The mix of land types varies across regions as may the average quality of any

[10]Agricultural research expenditure series were used in preference to published IMF data on agricultural spending, because the former cover more sources of spending and spending that is more likely to represent infrastructure. The only comparable series on total spending for large international cross-sections cover only national government spending and often fail to account for spending by ministries other than agriculture. In addition, they include much spending that relates to explicit and implicit income transfers.

particular type of land. Cross-sectional differences in land productivity measures will tend to be exaggerated when output is not scaled by hectares of constant quality.[11] For instance, if a hectare of irrigated cropland is effectively more than one hectare of nonirrigated cropland, one overstates the output per hectare of cropland by failing to weight nonirrigated and irrigated land differently in the cropland total. For Asian countries with relatively large shares of total agricultural land under irrigation, measures of output per unadjusted land totals will be higher than a measure of output per hectare of constant quality. For countries such as Australia with large shares of poor-quality pastureland, the reverse will be true.

The cross-sectional quality differentials in the average worker may not be as great as those in land, but there are similar problems in obtaining comparable measures of the labor input in agriculture. We have used data on the numbers of economically active population in agriculture, but we cannot convert these head counts to hours actually worked in agriculture for more than a handful of countries. In addition, differences in average educational attainment and health status of the general population do suggest that there have been smaller per capita investments in human capital in less-developed countries. Consequently, cross-sectional differences in labor productivity will be exaggerated when output is not scaled by comparable measures of effective labor units.

[11]Peterson (1988) used an international land quality index to scale total hectares of land. It was an interesting attempt to get at the problem of heterogeneity, but the index has some problems that lead us to think it would be inadequate in our cross-sectional study. The index was built on a hedonic price approach using only U.S. land values whose relative prices may not be representative of values in other parts of the world. Peterson's index was constructed by netting out population pressures on prices which we think inappropriate, and the resulting index provides a once-and-for-all scaling factor that may not reflect changes in the land mix within any country over a period as long as thirty years.

Broadly speaking, quality adjustment would reduce the measured difference in levels of output per worker between more- and less-developed regions to the extent that workers in more-developed regions embody more labor services. It is important to keep in mind that accounting for changes over time in human capital characteristics would also be likely to reduce the implied rates of increase in labor productivity. If one worker is replaced by another with more experience or education, the likely increase in output per worker would be discounted to reflect the fact that some of the output change is properly attributed to the increased quality of labor.

Statistical evidence

One way to draw statistical inferences about the sources of productivity differentials is to impose some structure on the data through the use of a meta-production function. If all countries share the same production function but are on different points of the production surface because a different mix of inputs is being employed, this would lead to differences in observed output per worker or output per unit of land. Because detailed data on quantities and qualities of all inputs are simply unavailable, there will be unavoidable problems in the interpretation of some coefficients. Omission of relevant variables will bias the estimated coefficients on variables correlated with the omitted information. In addition, we have good reasons to believe that observed and effective inputs are not the same thing. However, there is still hope of getting some indications of the sources of the observed cross-country productivity differentials.

Taking the production function for the *ith* country at time t to be a Cobb-Douglas production function with k conventional inputs, $X_{ij}^*(t)$; m infrastructure inputs, $P_{ij}(t)$; and a country-invariant temporal shift variable, A(t), yields:

$$Y_i(t) = A(t)\prod_{j=1}^{k} X_{ij} * (t)^{\beta_j} \prod_{j=1}^{m} P_{ij}(t)^{\gamma_j} \tag{1}$$

If the conventional inputs are measured with error, there is a difference between observed and effective inputs. In this instance, the production function depends on measured inputs as well as the sources of errors in those inputs. Drawing from Binswanger et al. (1987) we define some of those errors to be quality shifters in inputj, $Z_{ij}(t)$, which may vary over time in ways that are specific to country i. And, as in Lau and Yotopolous (1989), we also allow for a country-specific but time-invariant measurement error α_{ij} in inputj. Thus the relationship between observed input $X_{ij}(t)$ and effective input $X_{ij}^*(t)$ is given by

$$X_{ij}^*(t) = \alpha_{ij}\, Z_{ij}(t)\, X_{ij}(t) \tag{2}$$

To understand the sources of differences in output per worker, equations (1) and (2) were combined and both output and conventional inputs were divided by the number of workers, $X_{i1}(t)$, to yield

$$\frac{Y_i(t)}{X_{i1}(t)} = A(t)\, X_{i1}(t)^{\delta} \prod_{j=2}^{k} \left[\frac{X_{ij}(t)}{X_{i1}(t)}\right]^{\beta_j} \prod_{j=1}^{k} \left[\alpha_{ij}\, Z_{ij}(t)\right]^{\beta_j} \prod_{j=1}^{m} P_{ij}(t)^{\gamma_j} \tag{3}$$

$$\text{where} \quad \delta = \sum_{j=1}^{k} \beta_j - 1$$

It is important to note that labor still appears on the right hand side of the equation unless constant returns to scale in the scaled inputs is imposed on the production **function.**[12]

The logarithmic form of equation (3) estimated in this study is given by

$$y_i(t) = \sum_{i=1}^{n} \mu_i CD_i + \sum_{s=2}^{5} a_s TD(s) + \sum_{j=2}^{k} \beta_j \, x_{ij}(t) + \delta x_{i1}(t) + \sum_{j=1}^{k} \lambda_j \, z_{ij}(t) + \sum_{j=1}^{m} \gamma_j \, p_{ij}(t) + \epsilon_{ij}(t) \qquad (4)$$

where the lower case letters indicate logs; output and the conventional inputs are scaled by the total agricultural workforce; and $\epsilon_{ij}(t)$ represents random shocks to output that are uncorrelated with the other variables.

In addition to land, we use fertilizer, tractor horsepower, horsepower of animals used primarily for traction, and breeding livestock to measure conventional agricultural inputs that might influence labor productivity. Two variables that are commonly classified as public infrastructure were included as well. One is one-period lagged real public expenditures on agricultural research per agricultural worker and the other is road **density.**[13]

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[12]**Cross-section** production function estimates reported in the literature are usually based on an aggregate production function while the empirical model involves some scaling of the output and input variables (e.g., by number of farms or hectares). Failure to include the scaling variable then as an explanatory variable amounts to either an assumption that there is constant returns to scale among all scaled inputs or that the "aggregate" production function is appropriately defined in the scaled units.

[13]**Regressions** were run with an alternative measure of real resources devoted to agricultural research. When researchers, measured in full-time equivalents, were used in the place of real expenditures, there were no substantive changes in any other coefficents or their levels of significance.

To account for quality differences in the land aggregate for each region, we used three indicators. The first was the percentage of total agricultural land in each region that was classified as either arable land or permanently cropped land. The second measure was the percentage of arable and permanent cropland that was not irrigated. In addition, we included long-term average rainfall for the country as a whole; the rainfall data were taken from Wernstedt (1972).

Indicators of the quality of labor in agriculture are hard to come by, so we used two variables that apply to the total population, namely life expectancy at birth and literacy rates. While there may be significant differences within a country between the health and educational status of rural and urban workers, the cross-country differences in workforce characteristics appear to be much larger. Hence, these measures should suit our purpose of trying to explain some of the systematic differences in agricultural labor productivity.

It is important to realize that broad human capital variables do not just reflect the likely effectiveness of labor, they can also be interpreted as measures of public infrastructure in that health and education of the total population are rarely the result of only private decisions. A similar argument could be made regarding the variable measuring the percentage of land under irrigation. These variables cannot enter the regression directly as both a quality shifter, $z_{ij}(t)$, and an infrastructure variable, $p_{ij}(t)$, even if they enter the production function in both ways. Consequently, the estimated coefficients on these variables, i.e., the λ's, will be the sum of the relevant β and γ coefficients from the production **function.**[14] In the absence of properly measured inputs, we may simply be unable to identify the separate effects of infrastructure.

Dummy variables for five time periods, $TD(t)$, appear in the empirical specification to allow for temporal shifts in the production function that are common to all countries. Dummy variables for each of the countries, CD_i, $i = 1,\ldots,n$, were also included to account for the time-invariant measurement errors. This country dummy is a composite measurement error and as such conveys no information about which inputs are actually **mismeasured.**[15]

The individual observations for each country are five-year averages leaving us with six observations per country for a sample of 98 **countries.**[16] Data on lagged agricultural research expenditures were only available for a smaller subset of 88 countries and five, five-year periods. Regression results for samples with and without agricultural research are reported in table 3.[17]

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[14]**If** the variable carries no information about infrastructure or the true coefficient on infrastructure is exactly zero, then the λ is an estimate of β.

[15]**Instead** of including 98 country dummies, we could have taken first differences of the data as did Lau and Yotopolous (1989). However, we have two quality and infrastructure variables -- mean rainfall and road density -- which do not vary over time within a country; they would also be removed from the regression along with the dummies if the data were differenced.

[16]**We** would have prefered to use annual data in the regressions, but this was not feasible given the incomplete coverage for a number of the inputs besides labor and land in our sample. Nevertheless, this represents a substantial improvement in coverage over the studies that have relied on the three-period, 43-country data set of Hayami and Ruttan (1985) in which two-thirds of the countries are currently classified as high and upper-middle income countries by the World Bank.

[17]**Parallel** regressions for land productivity are not reported since the set of variables on the right-hand side would not change with two exceptions. In the labor productivity equation, unscaled labor and land per worker are explanatory variables, and in the land productivity equation, unscaled land and labor per hectare would be used instead. All other

Table 3: *Labor Productivity Regressions*

Variable	Model 1 with country dummies	Model2 without country dummies	Model3 with country dummies	Model 4 without country dummies
constant	-7.226	-6.992	-5.735	-5.772
	(-8.518)	(-9.669)	(-5.174)	(-6.217)
Labor	-0.069	-0.074	-0.058	-0.071
	(-4.956)	(6.031)	(-3.476)	(4.912)
Land	0.398	0.357	0.356	0.307
	(13.196)	(13.846)	(8.770)	(9.467)
Fertilizer	0.038	0.043	0.022	0.025
	(2.862)	(3.561)	(1.129)	(1.460)
Tractor HP	0.048	0.060	0.028	0.054
	(3.045)	(4.467)	(1.377)	(3.294)
Animal Traction HP	-0.060	-0.056	-0.045	-0.039
	(-7.079)	(-7.416)	(-4.364)	(-4.227)
Livestock	0.348	0.356	0.337	0.325
	(13.863)	(15.992)	(11.035)	(12.428)
Road Density	0.142	0.128	0.107	0.090
	(5.763)	(6.161)	(3.342)	(3.437)
Mean Rainfall	0.272	0.266	0.263	0.267
	(7.536)	(8.495)	(5.702)	(6.963)
% Arable & Penn. Cropped	0.352	0.336	0.331	0.305
	(12.298)	(13.179)	(9.469)	(10.392)
% Not Irrigated	-0.415	-0.395	-0.394	-0.368
	(-10.261)	(-10.897)	(-7.768)	(-8.402)
Life Expectancy	1.759	1.678	1.488	1.502
	(7.823)	(8.746)	(5.119)	(6.142)
Adult Literacy	-0.132	-0.134	-0.065	-0.097
	(-2.864)	(-3.267)	(-1.002)	(-1.769)
Research Expenditures			0.104	0.102
			(3.854)	(4.43 1)
R squared	0.953	0.946	0.957	0.950
# observations	588	588	440	440
# countries	98	98	88	88

Note: The figurer in brackets are t-values. All models repotted were eatimated without time dummies.

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variables will have identical coefficients in the two regressions. The relationship between estimated parameters in the two regressions make it possible to derive one set from the other. If, β_j indicates coefficients on the k independent variables that are scaled by the total agricultural workforce, and δ is the coefficient on unscaled labor in the labor productivity equation, then the coefficient on labor in the land productivity equation will be δ plus one minus the sum of the k β's. A similar correspondence can be drawn between the productivity estimates and the underlying production function. No variables would be scaled by labor in the production function. The coefficient on labor in the production function would simply be δ plus one minus the sum of the β's on all conventional inputs other than labor.

As results in table 3 indicate, a substantial proportion of the cross-country variation in output per worker can be accounted for by differences in the use of conventional inputs. The greater the inputs of land and livestock, the greater the productivity of labor. The coefficients on these variables are statistically significant and are fairly insensitive to both the sample and the specification.

Animal livestock used in production is associated with higher labor productivity, but greater animal horsepower used for traction is associated with lower output per worker. [18] To make sense of this negative effect of animal traction it is worth noting that this variable may be acting as a proxy for unmeasured or mismeasured variables such as the actual rural infrastructure or average size of farms. For example, the road density variable we have tells us nothing about the quality or rural/urban distribution of roads within a country, and the land in agriculture figure tells us nothing of average farm size. So if the quality of roads or the size of farms enhance labor productivity but are negatively correlated with animal traction, we would expect to find that relatively high use of animal traction is associated with relatively low labor productivity.

Commercial fertilizer use and tractor horsepower were the only conventional inputs whose coefficients were not consistently significant. Interestingly, they are uniformly significant when research expenditures are dropped from the regression and the country

[18] We tried combining animal and tractor horsepower to measure total traction reasoning that they represented similar services in spite of the fact that some are derived from mechanical and others from biological inputs. However, total traction was insignificant as an explanatory variable. Separately, both are significant and of opposite sign. Evidently, they display very different and informative cross-sectional differences; therefore, we decided to treat animal traction as distinct from mechanical horsepower.

coverage expands to include South Africa and the former Soviet Bloc countries. This is understandable since, in our sample, both fertilizer use and tractor horsepower are highly correlated with real research expenditures. Our results are consistent with the findings of Lau and Yotopolous (1989) who also report that the size and significance of fertilizer and machinery coefficients are sensitive to the specification and sample.

Land quality indicators have the expected sign and are significant. Higher mean rainfall and greater percentages of arable and permanently cropped land are associated with higher output per worker. The higher the percentage of nonirrigated cropland in use, the lower is labor productivity. These results contrast with the findings of Kawago ,Hayami, and Ruttan (1985) who used similar measures of quality but got implausible or insignificant coefficients.

Labor quality indicators are a bit more problematic. Regardless of the specification, longer life expectancy is significant and associated with higher labor productivity. The low explanatory power of literacy rates is probably a consequence of the small amount of cross-country variation in this measure of human capital. Its unexpected sign in models 1 and 2 -- from which research expenditures are excluded and the sample composition changes -- indicates that this variable may simply be picking up an Eastern bloc anomaly. In Eastern Europe and the Soviet Union, in contrast to the rest of the sample, literacy rates are near the maximium and yet labor productivity in agriculture lags well behind that of other regions with similar human capital characteristics.

As we discussed above in reference to our empirical specification (equation 4), interpretation of the coefficients on land and labor quality shifters is difficult when they also carry aspects of public sector infrastructure. The coefficient on the mismeasured variable and its quality shifters should be identical if the shifters are accurate reflections of only quality change. In our estimates, the coefficients on land and its suggested quality shifters (rainfall, percent arable and permanently cropped land, percent nonirrigated) are quite similar in magnitude. This is not true for the labor quality indicators which we know to be much less direct measures of the human capital characteristics of the agricultural workforce. It may be more appropriate to think of these broad human capital measures as capturing both quality adjustment and the effects of public sector investments in health and education.

The variables more clearly identified as measures of infrastructure -- road density and real agricultural research expenditures -- have uniformly positive and, significant effects on labor productivity. This may indicate direct effects of research and transportation on productivity or these variables may simply be proxies for a broader set of public resources targeted at the rural population.

The regression results reported in table 3 are for models without time-period dummies. In no specification tried were time dummies individually or jointly significant (table 4). The models estimated with country dummies excluded the country dummy for Egypt. Hence, the coefficient on a country dummy is interpreted as the difference in mean labor productivity between that country and Egypt which is not explained by the other included variables. The country dummies taken as a group are jointly insignificant. All significant dummies were negative, but in no specification were more than 14 individual coefficients significant. There is no obvious pattern to the significant country dummy

Table 4: *Joint Significance Tests*

H_0 the group of coefficients are jointly insignificant	F statistic	Critical value for 1% test	Numerator end Denominator degrees of freedom
98 country sample			
country effects	0.734	1.32	97/478
time effects	0.020	3.02	5/473
nonconventional effects (no country or time dummies)	72.76	2.80	6/575
88 country sample			
country effects	0.634	1.32	87/339
time effects	0.000	3.32	4/335
nonconventional effects (no country or time dummies)	42.60	2.64	7/426
67 ***country*** *sample*			
country effects			
(with AEZs)	0.633	1.47	661247
(without AEZs)	0.620	1.47	66/255
time effects	0.047	3.32	4/243
nonconventional effects (no country or time dummies)	39.51	2.64	7/321
AEZ effects			
(with country dummies)	0.018	2.51	8/247
(without country dummies)	5.185	2.51	8/313

coefficients.[19] It seems that the group of explanatory variables included in our analysis does a reasonable job of accounting for cross-sectional differences in labor productivity. This suggests that either the time-invariant measurement errors in variables cancel out or that systematic measurement errors across countries are not time-invariant.

For 67 less-developed countries, we had additional information on climate in the form of cropland shares in each of nine AEZs Additional variables representing eight of the nine AEZs were used to reestimate the labor productivity equation with results reported in table 5.

When the sample is restricted to developing countries, the results are not significantly altered. Qualitative results (signs and statistical significance) are quite robust across specifications, but there are some differences. The coefficients on tractor horsepower are.. uniformly significant in the developing country sample. In contrast, the animal traction and road density variables are no longer significant. This suggests that these last two variables contain more information about differences between developing and developed countries than they do about differences among developing countries.

The quantitative changes in coefficients estimated are slight. Time dummies are jointly insignificant in this sample as well, so the reported results exclude them. Once again, Egypt is the country taken to be the norm, and the group of country dummies is jointly insignificant. Even fewer individual country dummies gain significance; there are only two in model 5 and one in model 7.

[19]For example, Argentina, Norway and Papua New Guinea all had significant coefficents of -0.37 in model 1. There is no obvious explanation for this outcome.

Table 5: ***Labor Productivity Regressions for Developing Countries***

Variable	Model 5 with country dummies	Model 6 without country dummies	Model 7 with country dummies	Model 8 without country dummies
Constant	-4.554	-4.983	-6.700	-6.298
	(-3.807)	(-5.265)	(-6.205)	(-6.914)
Labor	-0.115	-0.118	-0.093	-0.101
	(-5.999)	(-7.211)	(-5.023)	(-6.386)
Land	0.294	0.273	0.360	0.332
	(5.867)	(6.719)	(7.624)	(8.693)
Fertilizer	-0.017	-0.016	-0.009	-0.013
	(-0.898)	(-0.924)	(-0.447)	(-0.752)
Tractor HP	0.077	0.086	0.048	0.061
	(3.508)	(5.079)	(2.387)	(3.757)
Animal Traction HP	-0.020	-0.012	-0.024	-0.017
	(-1.798)	(-1.309)	(-2.296)	(-1.955)
Livestock	0.241	0.229	0.214	0.206
	(6.438)	(6.992)	(6.686)	(7.391)
Road Density	0.012	0.034	0.023	0.048
	(0.311)	(1.199)	(0.628)	(1.679)
Mean Rainfall	0.179	0.143	0.281	0.266
	0.423)	(2.465)	(5.676)	(6.843)
% Arable & Perm. Cropped	0.352	0.327	0.387	0.351
	(7.984)	(8.690)	(9.455)	(10.257)
% Irrigated	-0.293	-0.282	-0.385	-0.374
	(-5.055)	(-5.863)	(-7.024)	(-8.239)
Life Expectancy	1.228	1.415	1.681	1.640
	(4.021)	(5.809)	(5.935)	(6.957)
Adult Literacy	-0.023	-0.090	-0.045	-0.053
	(-0.352)	(-1.610)	(-0.721)	(-1.007)
Research Expenditures	0.091	0.086	0.093	0.092
	(3.242)	(3.638)	(3.331)	(3.866)
AEZ1	0.001	-0.001		
	(-1.013)	(-0.949)		
AEZ2	-0.0004	0.0004		
	(-0.330)	(0.336)		
AEZ3	0.002	0.003		
	(1.902)	(2.992)		
AEz4	-0.0004	0.001		
	(-0.305)	(0.844)		
AEZ5	0.002	0.002		
	(1.409)	(1.304)		
AEZ6	0.007	0.007		
	(2.781)	(3.337)		
AEz7	0.001	0.002		
	(0.538)	(1.488)		
AEZ8	0.002	0.002		
	(1.487)	(1.334)		
R squared	0.929	0.917	0.919	0.906
# observations	335	335	335	335
# countries	67	67	67	67

***Note*:** The figures in brackets are t-valuer.

AEZ dummies added to the developing country regressions are insignificant taken as a group if country dummies are included in the model. They do attain joint significance when country dummies are excluded. Since these agroecologial zones are broadly defined, most of our countries lie entirely within one zone, so the country and AEZ dummies are performing essentially the same role in the regression.

Only AEZs covering warm subhumid tropics and subtropics (AEZ3 and AEZ6) had significant dummy coefficients; they were positive although quite small. As these zones have relatively favorable growing conditions -- especially, as compared with the numeraire zone (AEZ9) -- the sign of these coefficients is not surprising.

Given the general lack of significance and small size of the AEZ coefficients, it is obvious that these measures of the distribution of land types appear to add little information on productivity differences beyond what is already captured in input mix, mean rainfall, and broader land quality variables (e.g., the percentage of agricultural land that is arable or permanently cropped and the percentage of such land that is irrigated).

To assess the joint significance of the nonconventional variables used in models l-8, we dropped road density, rainfall, percent arable and permanently cropped and nonirrigated agricultural land, life expectancy, adult literacy, and research expenditures from the regression. Given the individual significance of the coefficients on these variables it is hardly surprising that we resoundingly reject the hypothesis that they do not belong in the models (table 4). Moreover, the coefficients on the conventional variables become implausible and much more sensitive to the sample of countries being used. This underscores the importance of accounting for quality differences, allowing for measurement errors, and making an effort to control for differences in the basic economic environment whenever attempting to draw empirical inferences from multi-country studies.

III. Conclusions

The considerable cross-section variability in land **and** labor productivity measures in agriculture can be attributed to both economic and climatic factors. Quality differences in land and labor inputs, as well as cross-sectional variation in other agricultural inputs, account for much of the observed productivity differentials. The significance of some individual country dummies indicates there is still room for improvement in data if one wants to account for all the observed cross-sectional variation in agricultural productivity.

The significance of such variables as road density, life expectancy, and agricultural research in explaining productivity differentials is especially interesting. This reinforces what others have found recently in estimating production functions and supply responses for agriculture. Unfortunately the interpretation of these variables in all such studies is problematic. These variables may be providing indirect information on the role played by conventional inputs -- particularly physical and human capital -- which have been mismeasured. Alternatively they may indeed measure direct effects of investments in public infrastructure.

Policy prescriptions for improving productivity in agriculture depend critically on disentangling the roles of private and public decisions. However, this depends in turn on resolving several remaining measurement problems. Investment in health care may well be more effective in increasing productivity in agriculture than subsidies designed to increase use of chemical fertilizer or tractors, but we cannot know for sure without better measures of human and physical capital inputs. The fact that omitting broad quality indicators changes empirical results in dramatic ways, but that more detailed information on land quality did not change estimates appreciably is an encouraging sign. Relatively modest improvements in the measures of labor and capital may generate more confidence in policy prescriptions based on multi-country empirical studies.

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Appendix I: *Value of Final* Agricultural Production for 1980

Country/region	Crop	Livestock	Total
	(millions PPP $)		
Angola	474	196	670
Burkina Faso	320	135	455
Burundi	525	44	569
Cameroon	1126	215	1340
Chad	304	216	521
Côte d'Ivoire	1997	130	2127
Ethiopia	2037	1281	3318
Ghana	1126	175	1301
Guinea	463	83	546
Kenya	1121	820	1941
Madagascar	1121	518	1639
Malawi	631	66	697
Mali	358	428	785
Mozambique	894	134	1027
Niger	380	273	653
Nigeria	5227	1296	6523
Rwanda	637	66	703
Senegal	340	118	458
Somalia	124	898	1022
Sudan	1463	1568	3031
Tanzania	1957	498	2455
Uganda	1617	369	1986
Zaire	2377	250	2627
Zimbabwe	721	239	960
Sub-Saharan Africa (24)[a]	27341	*10014*	3735s
China	80285	21264	*101550*
Bangladesh	5915	705	6620
Cambodia	470	60	531
India	50880	12712	63592
Indonesia	16004	1301	17305
Korea (North)	2170	357	2527
Korea (South)	2933	1055	3987
Laos	313	124	437
Malaysia.	3416	457	3872
Mongolia	47	592	639
Myanmar	3759	467	4226
Nepal	955	337	1292
Pakistan	5931	3749	9680
Papua New Guinea	871	60	931
Philippines	8319	1353	9672
Sri Lanka	1782	168	1950
Thailand	8401	1361	9762
Viet Nam	4342	841	5183
Asia & Pacific (17)	*116506*	25698	142204

Country/Region	Crop	Livestock	Total
	(millions PPP $)		
Argentina	7350	8733	16082
Bolivia	489	365	854
Brazil	22081	10051	32131
Chile	1134	905	2039
Colombia	3856	2224	6081
Costa Rica	532	271	804
Cuba	1981	744	2724
Dominican Republic	838	309	1147
Ecuador	1232	547	1779
El Salvador	646	197	843
Guatemala	1098	261	1358
Haiti	556	122	679
Honduras	533	227	760
Mexico	7652	5672	13324
Nicaragua	332	238	569
Paraguay	802	376	1179
Peru	1261	837	2098
Uruguay	311	1207	1518
Venezuela	956	1298	2255
Latin America & Caribbean (19)	53640	34584	88224
Afghanistan	968	726	1695
Algeria	880	538	1418
Egypt	4149	1158	5308
Iran	3318	1721	5039
Iraq	848	430	1278
Israel	574	421	995
Morocco	1468	699	2167
Saudi Arabii	158	161	320
Syria	1671	587	2258
Tunisia	835	262	1097
Turkey	9938	2796	12734
West Ma & North Africa (11)	*24809*	9499	*34308*
Australia	3911	8733	12643
New Zealand	306	4955	5261
Australasia (2)	4217	13688	*17905*
Austria	1012	1632	2644
Belgium-Luxembourg	716	2140	2856
Denmark	863	2276	3139
Finland	470	1045	1515
France	12461	14154	26615
Germany, FR	4819	11294	16113
Ireland	411	2383	2795
Netherlands	1420	5036	6457

Appendix I: *Value of Final Agricultural Production for 1980*

Country/region	Crop	Livestock	Total	country/Region	Crop	Livestock	Total
	(millions PPP $)				*(millions PPP $)*		
Norway	223	653	876	Poland	5184	6179	11363
Sweden	827	1396	2223	Romania	3937	3124	7061
Switzerland	393	1380	1773	Yugoslavia (former)	3353	2771	6124
UK	3901	8095	119%	*Eastern Europe (8)*	21618	22551	*44169*
Western Europe (12)	*27518*	51483	*79001*				
				USSR (former)	38498	*38039*	76538
Greece	3385	1329	4714				
Italy	12115	7328	19443	Canada	6290	5074	11364
Portugal	938	696	1634	USA	60414	47855	108268
Spain	8441	5215	13656	*North* America *(2)*	66703	52928	119632
Southern Europe (4)	24878	14568	*39446*				
				Japan	*6240*	6253	12493
Albania	277	218	495				
Bulgaria	1953	1491	3445	*South Africa*	*3515*	27'26	6241
Czechoslovakia (former)	1969	2962	4932				
Germany, NL	2240	3473	5712				
Hungary	2705	2333	5038				

Source: Rao (1993).

[a] Number in brackets indicatea number of countries in regional total.

Appendix **II**: ***Proportion of arable land by agroecological zones (AEZs)***

Country/region	AEZ 1	AEZ 2	AEZ 3	AEZ 4	AEZ 5	AEZ 6	AEZ 7	AEZ 8	AEZ 9
					(percentages)				
Sub-Saharan Africa									
Angola	14	56		30					
Burundi				100					
Cameroon			100						
Chad	**100**								
Côte d'Ivoire			100						
Ethiopia	11	10		79					
Ghana			100						
Kenya	35			65					
Madagascar	6	**15**	40	39					
Malawi	18	82							
Mali	100								
Mozambique	57	43							
Nigeria	31	41	28						
Senegal	100								
Somalia	100								
Sudan	100								
Tanzania	43	36		21					
Uganda	12	88							
Zaiie			100						
Zimbabwe	100								
China					15	10	40	**35**	
*Asia **& Pacific***									
Bangladesh			100						
Cambodia.			100						
India	52	15			**25**	7		1	
Indonesia			100						
Korea, **(North)[a]**						34		**66**	
Korea, (South)						74		26	
Laos			**100**						
Malaysia			100						
Mongolia'								100	
Myanmar		**100**							
Nepal								100	
Pakistan					100				
Papua New Guinea			**100**						
Phiippines			**100**						
Sri Lanka		51	49						
Thailand	6	54	40						

Appendix II: ***Proportion of arable land by agroecological zones (AEZs)***

Country/region	AEZ 1	AEZ 2	AEZ 3	AEZ 4	AEZ 5	AEZ 6	AEZ 7	AEZ 8	AEZ 9
					(percentages)				
Viet Nam[a]			100						
Latin America & Caribbean									
Argentina					8	16	5	69	2
Bolivia	18	14	19	49					
Brazil	7	29	20				45		
Chile									100
Colombia			32	68					
Costa Rica		7	10	82					
Cuba’	58	42							
Dominican Republic		100							
Ecuador	27	3	21	50					
El Salvador		41		59					
Guatemala			3	97					
Haiti	100								
Honduran			29	71					
Mexico	12	15	17	27	29				
Nicaragua			100						
Paraguay		2					98		
Peru			6	94					
Suriname			100						
Uruguay								100	
Venezuela	38	46	16						
West Asia & North Africa									
Afghanistan									100
Algeria									100
Egypt									100
Iran									loo
Iraq									100
Morocco									100
Saudi Arabia									100
Syria									100
Tunisia									100
Turkey									100

Source: **Kassam** (1991).

Note: For definitions of agroecological **zones** see table 1.

[a] Included in the productivity graphs but, for data reasons, not in the regression analysis.