THE IMPACT OF RESEARCH LED AGRICULTURAL PRODUCTIVITY GROWTH ON POVERTY REDUCTION IN AFRICA, ASIA AND LATIN AMERICA

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Abstract: *Twenty percent of the world population, or 1.2 billion live on less than $1 per day; 70% of these are rural and 90% in Asia and Sub-Saharan Africa. Research led technological change in agriculture generates sufficient productivity growth to give high rates of return in Africa and Asia and has a substantial impact on poverty, currently reducing this number by 27 million per annum, whereas productivity growth in industry and services has no impact. The per capita "cost" of poverty reduction by means of agricultural research expenditures in Africa is $144 and in Asia $180, or 50 cents per day, but this is covered by output growth. By contrast, the per capita cost for the richer countries of Latin America is over $11,000.*

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Abstract: *Twenty percent of the world population, or 1.2 billion live on less than \$1 per day; 70% of these are rural and 90% in Asia and Sub-Saharan Africa. Research led technological change in agriculture generates sufficient productivity growth to give high rates of return in Africa and Asia and has a substantial impact on poverty, currently reducing this number by 27 million per annum, whereas productivity growth in industry and services has no impact. The per capita "cost" of poverty reduction by means of agricultural research expenditures in Africa is \$144 and in Asia \$180, or 50 cents per day, but this is covered by output growth. By contrast, the per capita cost for the richer countries of Latin America is over \$11,000.*

1 Introduction

The World Development Report (World Bank, 2001) summarises the poverty surveys that the Bank has conducted, showing that almost half of the world's six billion people live on less than \$2 per day, and a fifth, or 1.2 billion on less than \$1 per day. Poverty alleviation targets have become central to the policies of governments and aid agencies. For example, the White Paper on International Development (UK Government, 2000) states that the Department for International Development (DFID) it is committed to halving the number of people living on less than \$1 per day, by 2015.

More than 90% of these 1.2 billion live in South Asia, East Asia and Sub-Saharan Africa (SSA) and Chen and Ravallion (2000) show that although poverty has declined from 1987-98, especially in Asia, it has increased substantially in Sub-Saharan Africa. Between two thirds and three quarters live in rural areas (estimates vary from 62%, CGIAR, 2000, to 75%, IFAD, 2001). The poorest have little or no land and they gain disproportionately from the employment generated by agricultural growth and from lower food prices, as do the urban poor, who spend much of their incomes on food. Thus, agricultural growth has a powerful impact on poverty, because it helps all poor people, whereas growth in the manufacturing and service sectors does not. This conventional wisdom applies far less to Latin America, where inequality in the distribution of income and especially of land means that the rural poor gain little from agricultural growth (de Janvry and Sadoulet, 2000).

The literature provides theoretical reasoning and piecemeal empirical evidence on the impact of agricultural growth on poverty reduction, mostly for single countries. However, the World Bank \$1 per day poverty survey and inequality data, used in the World Bank growth studies, has not been used in investigating the impact of agricultural productivity growth. There is now a panel of over 120 observations, which in combination with many other variables, especially on agricultural R&D expenditures, allows estimation of the global poverty impact of agricultural R&D, on which there is no empirical evidence. A four-equation model that incorporates causal chains, allows inclusion of as many of the relevant variables as is possible. The causal chains cover all the relationships from agricultural R&D, to agricultural productivity growth, to GDP per capita, to inequality and poverty reduction.

Section two describes the data, before progressing to simple regression models, which show that agricultural productivity growth has a substantial impact on poverty reduction. Section three introduces the causal chain model and presents the results. Section four reports the reductions in $1 per day poverty that result from agricultural R&D expenditures and the per capita cost of poverty reduction.

2. DATA AND PRELIMINARY RESULTS

The first limiting factor is the poverty indicator, which is the percentage of the population living on less than $1 per day. These data are from the limited number of World Bank surveys are used in Ravallion (1997) and Hanmer and Naschold (2000). The initial pooled sample of 121 observations covers Africa, Asia, Latin America and the Caribbean and 13 observations for ten transitional economies. The second limiting factor is data on agricultural R&D expenditures, which were not available for the transitional economies. Thus, the sample used for the causal chain model has 108 observations for 48 developing countries. For Africa, there are 44 observations on 22 countries (including Mauritius); for Asia 29, observations on 11 counties (including Jordan); for the Americas, 35 observations on 15 counties (including Jamaica). All the other data for the independent variables are from World Development Indicators (World Bank, 2000), which provides definitions.

Three simple regressions establish that there is relationship between agricultural productivity and poverty. The poverty index is regressed on labour productivity in agriculture, industry and services, with all variables in logarithms, showing that labour productivity has no explanatory power in the industry and services regressions. However, labour productivity in agriculture alone explains

31% of the variance and the poverty elasticity of –0.63 is significant at the 1% confidence level. The yield contribution to labour productivity can be separated from the relative scarcity of land since value added per unit of labour is identically equal to value added per unit of land multiplied by the ratio of land to labour. These two variables, with the Gini coefficient, explain 50% of the variance in poverty and all are statistically significant at the 1% level.

3. CAUSAL CHAIN MODELS AND RESULTS

3.1. A Causal Chain Model

Further variables can be added to expand the single equation model, but if GDP per capita is included, the poverty elasticity of yields falls to -0.25, the elasticity of the land-labour ratio also falls to about half its previous size and GDP per capita has a high poverty elasticity of -0.47. This happens because higher yields and higher land labour ratios are an important cause of higher GDP per capita, which suggests that the way to include more of the relevant variables is to explicitly model the causal chain. The result of this approach is a system of equations in which agricultural R&D results in agricultural productivity growth, which in turn contributes to growth in GDP per capita and finally has an impact on poverty reduction. Thus, the equations incorporate a *causal chain*, to use the term introduced by Wold (1954), who was largely responsible for developing such models.[1]

These relationships, all in logarithms, are stated in equations 1 to 4, which are estimated for the full sample and the three continents. In the first equation, yields (value added per unit of land), are explained by R&D, fertiliser, labour and machinery per hectare, a land quality index and illiteracy. In 2, GDP per capita is explained by the yield, the land labour ratio, exports, gross fixed investment, government expenditures and illiteracy. In 3, the Gini coefficient is explained by value added per unit of land, or per unit of labour, the land/labour ratio, GDP per capita, the growth rate of GDP per capita, government expenditures, the share of the population that is rural, exports or trade (exports plus imports) and a dummy variable for the Americas. Finally, in 4, the poverty index is explained by the Gini, GDP per capita, exports or trade, government expenditures, gross fixed investment and rural population.

[1] Wold's model is a recursive causal chain, which requires a diagonal covariance matrix and a triangular coefficient matrix. In this case, the model is a causal chain, but is not recursive, since the off-diagonal elements of the covariance matrix are numerous.

Thus, the causal chain model has the advantage of imposing a structure that accommodates eighteen variables, four of which are treated as endogenous. The equations are as follows.

$$\begin{aligned}\ln[Value\ Added / Land]_t &= \alpha_0 + \alpha_1 \ln[R\&D / Land]_{t-5} + \alpha_2 \ln[Fertiliser / Land]_t + \alpha_3 [\ln[Fertiliser / Land]_t]^2 \\ &+ \alpha_4 \ln[Labour / Land]_t + \alpha_5 \ln[Machinery / Land]_t + \alpha_6 [Land\ Quality\ Index]_t + \alpha_7 \ln[Illiteracy]_t + \varepsilon_1\end{aligned} \quad \textbf{(1)}$$

$$\begin{aligned}\ln[GDP\ per\ capita]_t &= \beta_0 + \beta_1 \ln[Value\ Added / Land]_{t-1} + \beta_2 \ln[Land / Labour]_t + \beta_3 \ln[Exports]_t \\ &+ \beta_4 \ln[Fixed\ Investment]_t + \beta_5 \ln[Gov\ Expenditure]_t + \beta_6 \ln[Illiteracy]_t + \varepsilon_2\end{aligned} \quad \textbf{(2)}$$

$$\begin{aligned}\ln[Gini]_t &= \phi_0 + \phi_1 \ln[VA / Land]_{t-1} + \phi_2 \ln[VA / Labour]_t + \phi_3 \ln[Land / Labour]_t \\ &+ \phi_4 \ln[GDP\ per\ cap]_{t-1} + \phi_5 \ln[\Delta GDP\ per\ cap]_t + \phi_6 \ln[Gov\ Exp]_t + \phi_7 [Rural\ Pop] \\ &+ \phi_8 Ln[Exports]_t + \phi_9 Ln[Trade]_t + \phi_{10} Ln[Americas\ dummy]_t + \varepsilon_3\end{aligned} \quad \textbf{(3)}$$

$$\begin{aligned}ln[Poverty\ Index]_t &= \gamma_0 + \gamma_1 ln[Gini]_{t-1} + \gamma_2 \ln[GDP\ per\ capita]_{t-1} + \gamma_3 ln[Exports]_t + \gamma_4 ln[Trade]_t + \gamma_5 ln[Gov\ Exp]_t \\ &+ \gamma_6 [ln[Gov\ Exp]_t]^2 + \gamma_7 ln[Fixed\ Investment]_t + \gamma_8 [ln[Fixed\ Investment]_t]^2 + \gamma_9 ln[Rural\ Pop]_t + \varepsilon_4\end{aligned} \quad \textbf{(4)}$$

Although exports, government expenditures and gross fixed investment appear in the GDP per capita equation, they remain significant in the poverty equation too, because they affect poverty directly, as well as through GDP per capita. Similarly, exports, government expenditures and rural population appear in the inequality equation and again in the poverty equation because not all their impacts are captured by way of their effects on the Gini coefficient and they remain significant. Last, land productivity and the land-labour ratio are in the GDP per capita equation and GDP per capita is in the Gini equation, but land productivity and the land-labour ratio also appear because they are still significant.

3.2. Testing for Endogeneity

Agricultural R&D is lagged five years in the productivity equation, so it is predetermined and may be regarded as weakly exogenous, so long as there is no serial correlation. For the model to be consistent, all the endogenous variables are lagged one year when they appear on the right hand side. This may also allow the effects to filter through and weak exogeneity again applies. The second causal chain incorporated in the model, running from the agricultural productivity to the poverty reduction equation, by way of the inequality equation is of lesser importance because it does not lead to poverty reduction calculations.

However, not all the variables can be endogenised, so all those that appear only on the right hand side were tested for endogeneity. Wu-Hausman tests show that for the full sample, the only problem was exports, in the poverty equation. This variable was replaced with an instrument, which was the fitted value when the variable was regressed on all the truly exogenous variables in the poverty equation and two instruments for itself, which were exports lagged one year and two years. For the regions, six variables were instrumented in this way. For Africa, they were illiteracy in the yield equation and trade in the poverty equation: for Asia, illiteracy in the GDP equation and government expenditure in the poverty equation: for the Americas, labour in the yield equation and illiteracy in the GDP equation.

3.3. Results

This system of equations was estimated using three stage least squares to take account of the interdependencies in the model and the results reported in Table 1.[2] In the first equation, which is basically an agricultural production function, 82% of the variance in land productivity is explained by R&D expenditures, inputs of fertiliser (the square indicates non-linearity) and labour (machinery was not significant), a land quality index and illiteracy. Literate farmers are more able to assimilate information and make effective use of the new technologies that become available.

Table 1

The next three columns report the results by continent, with similar results and explanatory power. Labour has large, highly significant elasticities for Africa and the Americas, but was insignificant for Asia, reflecting surplus labour, especially in South Asia. Machinery is significant only for Africa, where the land quality index is insignificant, whereas it has the highest elasticity of all the variables for both Asia and the Americas. Illiteracy was significant, with the expected sign, only for Asia. The positive result for Africa does not mean that illiteracy increases yields, but that there is an inverse relationship between fertility and development for enough countries to give this result.

In the GDP per capita equation, 84% of the variance is explained. Land productivity, the land labour ratio and exports increase per capita GDP, while illiteracy and government expenditures have a negative impact. Region differences are again pronounced: an increase in yields in Africa has 50% more impact than in the Americas. Exports had very different effects across the regions: for Africa,

[2] Seemingly unrelated estimation (SURE) would have been adequate if the model were truly recursive, but the non-zero off diagonal elements in the covariance matrix require an instrumental variable, or a two or three stage least squares approach.

the elasticity is large and positive, whereas for the Americas the impact was negative and for Asia there was no explanatory power, but gross fixed investment was positive and significant. The negative impact of government expenditures in the full sample is attributable to Africa, as this variable was not significant elsewhere.

In the inequality equation, only land productivity is inequality reducing. The richer countries have greater inequality, which suggests that many countries in the sample are sufficiently poor to be on the first (increasing inequality) segment of the Kuznet's curve. Government expenditures increase inequality and so does the percentage of the population that is rural, reflecting the fact that rural populations are generally poorer. The fit was improved by the dummy variable for the Americas, which was highly significant and positive, confirming the expectation that the Latin American countries have greater inequality. However, only 46% of the variance is explained, which suggests that non-economic variables are needed to model inequality better.

At the continent level, both land productivity and the land labour ratio were significant in all cases and for Asia and the Americas, were replaced by agricultural labour productivity, which combines the two, as this allowed other variables to be included. For Africa and Asia, agricultural labour productivity was inequality reducing, but for the Americas it has the opposite effect, corroborating the Latin America studies in the literature review. Conversely, for the Americas, which has the richest counties on average, GDP per capita was highly significant and inequality reducing, but for Asia and Africa it was inequality increasing. So, inequality increases with income growth at low income levels and then falls again, as the Kuznet's curve suggests, and for Africa, GDP per capita growth also appears to increase inequality. Government expenditures increased inequality in all three continents, while the most powerful inequality-reducing variable for the Americas sample was exports. This corroborates Ravallion (2001), who argues that openness reduces inequality in the richer countries.

The difference between the poor counties of Africa and Asia and the richer sample for Latin America emerges in these results. For the poorer regions, agricultural growth is clearly inequality reducing, but for the Americas it has the opposite effect. Instead, it is GDP per capita and exports that reduce inequality. This may be due to inequality, but the American countries are also more developed, so agriculture's share in GDP is far lower and industrialisation is now the driving force for these economies.

In the poverty equation, 53% of the variance is explained for the full sample. The Gini and rural population are poverty increasing, while GDP per capita, exports, government expenditures and gross fixed investment are all poverty reducing. These results are in general agreement with the literature and they quantify the effects. Gross fixed investments has a large impact because it includes land improvements and road building, which are labour intensive activities that provide jobs at the bottom end of the labour market, especially in rural areas.

For the continents, over 50% of the variance is explained in all three cases and the Gini has the largest elasticity. The poverty reducing effect of GDP per capita declines with income levels. Hence, GDP per capita gains in Africa have 38% more impact on poverty reduction than they do in Asia and three times as much as in the Americas. Exports and government expenditures were poverty reducing only for the Asia, but gross fixed investment reduced poverty in all cases.

3.4. Elasticities

In Table 2, the three elasticities from the causal chain from R&D to poverty reduction are followed by three compound elasticities, showing how these are calculated. The simple elasticities of yield with respect to agricultural R&D, shown in row (1), allow calculations of the rates of return (ROR) to agricultural research, which will follow in the next section. The elasticity of GDP per capita with respect to yield, in row (2) shows that the impact of yield increases on per capita incomes is substantial. The elasticity of poverty reduction (3) with respect to GDP per capita can be compared with estimates from other studies, such as Hanmer and Naschold (2000) and White and Anderson (2000). Thus, agricultural productivity has an impact on average incomes, as well as on poverty reduction.

Table 2

Since land productivity in the causal chain model is generated by R&D and affects poverty through its effect on GDP per capita, the poverty elasticity of R&D in row (6) is the product of all three elasticities. Similarly, the other two compound elasticities, in rows (4) and (5), are both products of two of the three terms. These elasticities are reported in Table 2, for the full sample and for the continents.

The cumulative elasticities are quite different for the three regions. The cumulative effect of the larger African elasticities results in a poverty elasticity of land productivity (row 5) that is 50% larger than for Asia and almost five times the size of the elasticity for the Americas. The poverty elasticity for R&D expenditures (row 6) for Africa is 58% greater than for Asia, whereas the Americas result is now less than one fifth of the Asian figure. The cumulative effect of another low elasticity for the Americas accentuates the pattern that runs throughout the results. Africa's potential for agriculture led poverty reduction is far greater than Latin America, where inequality in the distribution of incomes and land, are likely to prevent poverty reduction by means of agricultural productivity growth.

4. THE COST OF POVERTY REDUCTION

The elasticities of value added per unit of land with respect to agricultural R&D allow calculation of the rate of return (ROR) to agricultural R&D, at the country and continent levels. The conventional methodology, in which the output gains over time are set against the R&D costs, with appropriate discounting to allow for the time lag is well known and Thirtle et al. (1998) apply the method to yield increases. A similar approach is used here; for each country, the gain is the change in value added per hectare, from the first to the last observation (years t to t+m), divided by the number of years between the observations, to give the yield gain per annum. In all cases the time period is between five and ten years, usually five. The results show that the average rate of return for Africa is 22%, for Asia 31% and for Latin America, minus 6%. Thus, in the two poorest continents, agricultural research pays for itself and the any poverty reduction that also occurs can be viewed as a bonus.

4.1. Reduction in less than \$1 per day poverty from yield increasing agricultural R&D

The payoff to agricultural productivity growth, in terms of the number of people that it can shift out of the less than \$1 per day poverty bracket can also be calculated, using the elasticities reported in row (5) of Table 2. Table 3 first shows the percentages of the regional populations living on less than \$1 per day. SSA and South Asia have far higher proportions of their populations in this poverty bracket.

SSA has three times the Latin America and East Asian levels of poverty and South Asia two and one half times as much. This is followed by the number of people living on less than $1 per day. Of the total of 1,200 million, two thirds are in Asia, with 43% in South Asia alone and a further quarter in SSA, so that South Asia and SSA together account for almost three quarters of the total. These data are from the World Bank (2001), updated from the World Bank Poverty Monitor website (www.worldbank.org/research/povmonitor) and represent the current world situation.

Table 3

Then, the poverty elasticities of land productivity estimated in this study are applied to give the poverty reductions that can be expected. The next column shows the outcome of a 1% increase in yields. Applying the different elasticities for the three regions, which were reported in Table 2, the total is 6.24 million. The African elasticity was used for the Middle East and North Africa and the Asian elasticity for East Europe and Central Asia, but these regions are of less importance. The low elasticity for Latin America and the Caribbean gives the poor result shown for that region, but for Asia and Africa, where the poverty elasticities of agricultural productivity were high, the reduction is 5.94 million.

Thus, only this small proportion of the over 1, 200 million people living on less than $1 per day are removed from this category when value added per unit of land is increased by one percent. However, the data in this sample show that yields for Africa and Asia, measured in this way, were increasing by about 4.5% per annum, as Table 3 reported. All else being equal, this would give an annual reduction in $1 per day poverty in Africa and Asia of 26.7 million, which is 2.45% of the total number in this poverty range. To put these estimates in perspective, for Africa the poverty elasticity of agricultural value added was -0.72 and the poverty elasticity of GDP per capita was -0.99, so yield increases have 73% of the impact of increases in per capita incomes. For Asia the equivalent figures are -0.48 and -0.72 and the ratio is 67%. In both cases agricultural growth looks like a good policy for poverty reduction, in the sense that agricultural growth generated by R&D expenditures is relatively low cost.

4.3. Per Capita Cost of $1 a Day Poverty Reduction by R&D Led Agricultural Productivity Growth

The cost of poverty reduction can be calculated from the sample data as an extension of the approach used to generate the results in Table 3. For Africa, the number in poverty in the sample countries was 97 million, as of 1990. The reduction for a one percent yield increase is 0.69 million, using the same elasticity as in the last estimates. The total R&D cost was $144.29 million in 1990, measured in constant 1995 dollars. To get the cost of a one percent yield increase, this is divided by the yield growth of 4.7%, but it must also be divided by the elasticity of the yield with respect to R&D, which is 0.36, as only this proportion of the yield increase is attributable to R&D. This gives a cost of $ 84.74 million for a one percent yield increase attributable to R&D. Thus, the cost for each person taken out of $1 per day poverty is $119, but this is the 1990 figure expressed in 1995 Dollars. To update it to the current dollar cost per person taken out of poverty, this is converted to US $ for 2000. The adjustment scales up the result by a factor of 1.21 (calculated from the World Bank data on the US deflator) to give the current cost of $144 per person that is reported in the last column of Table 3.

Performing the same calculation for the Asian sample gives the reported figure of $179 per person. The shock result is the cumulative effect of high costs and low benefits for the Americas. The number in poverty in the sample is almost the same as for Africa, at 98 million and due to the low elasticity, a one percent yield increase reduces this by only 0.098 million. The total R&D cost of $639 million is divided by the lower yield change of 2.3%, but also by the very low yield/R&D elasticity of 0.20, with the result that a one percent yield increase attributable to R&D costs $9,418. When converted to current US$ the cost per capita is an amazing $11,397.

The Africa figure of $144 and the Asia figure of $180 are convenient numbers: if the cost was per year, it amounts to 40 cents a day for Africa and 50 cents for Asia. Redistribution could achieve the same for less, but this would only be true if the R&D expenditures were recurrent, rather than one off payments. The marginal increment to R&D expenditures probably needs to continue for a perhaps three years in most applied research projects, to achieve the initial gain, which will be eroded over time due to physical, biological and economic changes that make existing technologies less suitable and effective. So, a brief increase in R&D does not buy improvements for perpetuity, but the effects do last for several years. However, the real point is that the R&D expenditures give a good ROR, by generating agriculture-led, broad-based economic growth. The poverty reduction effect is substantial and it is free, in the sense that R&D has already paid for itself, whereas redistribution can be counter-productive due to its negative effects on growth.

5. CONCLUSIONS

This paper quantifies the impact of agricultural productivity growth on the incidence of poverty in the LDCs, measured by the percentage of the population living on less than $1 per day. The literature shows that agricultural growth appears to be pro-poor, except in the Latin American countries, where extreme inequality in the distribution of incomes and especially land prevents the poor from gaining.

The empirical analysis begins with simple regressions, which show that agricultural productivity growth has a substantial impact on poverty reduction, whereas productivity growth in industry and services does not. Including other explanatory variables in the regressions shows that inequality increases poverty and that GDP per capita growth reduces it. The limitations of the single equation approach are overcome by developing a four equation, causal chain model, which incorporates many of the interactions between variables that affect poverty reduction. First, value added per unit of land, is explained by R&D, fertiliser, labour and machinery per hectare, a land quality index and illiteracy. In the second equation, GDP per capita is explained by yields, land labour ratios, exports as a percentage of GDP and the percentage of the population that is illiterate. In the third equation, the Gini coefficient is explained by value added per unit of land, GDP per capita, government expenditures as a percentage of GDP, the percentage of the population that is rural and a dummy variable for Latin America. In the last step, the poverty index is explained by the Gini, GDP per capita, exports, government expenditures and gross fixed investment.

The results show that investment in agricultural R&D raises agricultural value added sufficiently to give very satisfactory rates of return within the agricultural sector, in both Africa (22) and Asia (31), but not in Latin America (-6). Thus, agricultural productivity growth gives rise to sufficient broad-based growth to pay for the R&D investment needed to generate the technologies required and there is a substantial effect on poverty reduction. A one percent increase in yields reduces the numbers living in under $1 per day poverty by over six million, with 95% of these in

Africa and Asia. Finally, the per capita cost of poverty reduction in Africa is $144 and for Asia it is $180, but for Latin America it is $11,400.

If the poor tax base and negative growth effects of relieving poverty by redistribution are considered, it is difficult to avoid the conclusion that the results of this study corroborate the World Bank view that growth relieves poverty more effectively. But, the results also show that the sector does matter: the growth needs to be agriculture led, and it is effective only in the poorer continents, but that is where the poor are, and predominantly in the rural areas.

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Table 1: Recursive Model Estimates for the Full Sample, Africa, Asia and Latin America

	Total	***Africa***	***Asia***	***Americas***
Sample size	108	44	29	35
	Dependent Variable: Yield			
R&D/Land	0.4422 (7.994)	0.363 (4.43)	0.3435 (3.57)	0.1966 (3.843)
Fertiliser/Land			0.1585 (1.84)	0.3506 (7.384)
$(Fertiliser/Land)^2$	0.0101 (2.386)	0.019 (2.10)		
Labour/Land	0.3430 (5.720)	0.626 (6.31) **IV**		0.4785 (8.506) **IV**
Machinery/Land		0.169 (1.93)		
Land Quality Index	0.6524 (3.655)		1.0430 (5.01)	0.5322 (3.037)
Illiteracy	-0.2078 (-2.290)	0.955 (3.71)	-0.1807 (-2.11)	
Constant	3.8294 (4.454)	0.181 (0.13)	2.8563 (1.72)	-0.211 (-0.245)
Adjusted R^2	0.8217	0.7503	0.7136	0.9037
χ^2 test value	534.0714	155.681	75.33447	426.928
	Dependent Variable: GDP per capita			
VA/Land	0.6873 (12.941)	0.726 (9.00)	0.6724 (8.87)	0.4715 (4.527)
Land/Labour	0.8474 (16.623)	0.851 (9.38)	0.7080 (12.86)	0.4234 (3.102)
Exports	0.1259 (1.677)	0.467 (3.44)		-0.3846 (-2.704)
Gross Fixed Investment			0.6547 (3.30	
Government Expenditure	-0.2253 (-1.937)	-0.416 (-1.65)		
Illiteracy	-0.2195 (-3.278)	-0.375 (-2.60)	-0.1550 (-2.20) **IV**	-0.485 (-3.13) **IV**
Constant	8.6993 (17.101)	8.623 (7.30)	5.4557 (5.62)	9.6384 (15.075)
Adjusted R^2	0.8408	0.7996	0.9282	0.6666
χ^2 test value	644.9567	207.883	401.4241	80.6337
	Dependent Variable: Gini coefficient			
VA/Land	-0.0589 (-3.702)	-0.168 (-3.33)		
VA/AgriculturalLabour			-0.0738 (-2.07)	0.0916 (3.138)
Land/Labour		-0.158 (-2.66)		
GDP per capita	0.0935 (3.293)	0.125 (2.24)	0.2649 (6.82	-0.1009 (-2.844)
ΔGDP per capita		0.016 (2.90)		
Government Expenditure	0.1205 (2.418)	0.163 (1.62)	0.0755 (2.56)	0.0980 (2.189)
Rural Pop %	0.1013 (1.520)			
Exports				-0.1511 (-4.377)
Trade as %GDP			-0.0480 (-1.46)	
Americas dummy	0.2219 (4.448)			
Constant	2.6733 (6.392)	2.504 (4.59)	2.3453 (24.14	4.2592 (14.741)
Adjusted R^2	0.4597	0.4620	0.8207	0.3653
χ^2 test value	99.33189	33.984	161.1036	29.3485
	Dependent Variable: $1 a day poverty			
Gini coefficient	2.0892 (4.043)	2.645 (3.74)	3.7107 (2.56)	1.9973 (2.186)
GDP per capita	-0.3913 (-3.211)	-0.988 (-7.56)	-0.7147 (-2.29	-0.3249 (-2.116)
Exports	-0.2288 (-1.694) **IV**			-0.3471 (-1.583)
Trade as % GDP		0.548 (1.74) **IV**	-0.4871 (-1.879)	
Government Expenditure	-0.3702 (-1.885)			
$(Gov Expenditure)^2$			-0.1148 (-1.60) **IV**	
Gross Fixed Investment	-0.8422 (-5.145)	-1.069 (-4.30)		-0.9633 (-2.684)
$(Gross Fixed Invest)^2$			-0.1148 (-2.43)	
Rural Pop %	0.4486 (1.858)		0.8167 (1.32)	
Constant	0.1718 (0.075)	0.291 (0.13)	-6.344 (-1.37)	1.439 (0.336)
Adjusted R^2	0.5345	0.5371	0.5529	0.5273
χ^2 test: crit val	99.61028	91.203	39.8581	30.59497

Coefficients followed by t-statistics in parentheses. The significance levels for two-tailed tests for the smallest sample are; at 1%, 2.76, at 5%, 2.05, at 10%, 1.70. The seven elasticities marked **IV** indicates that an instrumental variable was used.

Table 2: Elasticities Linking R&D, Yields, GDP per Capita and Poverty

Elasticity of Y - with respect to X	*Full Sample*	*Africa*	*Asia*	*Americas*
1) Value added/Land - R&D	0.442	0.363	0.344	0.197
2) GDP per capita – Value added/Land	0.687	0.726	0.672	0.472
3) Poverty - GDP per capita	-0.391	-0.988	-0.715	-0.325
4) GDP per capita - R&D (1)(2)*	0.304	0.264	0.231	0.093
5) Poverty - Value added/Land[a] (2)(3)*	-0.269	-0.717	-0.480	-0.153
6) Poverty - R&D[4] (1)(2)*(3)*	-0.119	-0.260	-0.165	-0.030

Table 3: Reduction in the Numbers on Less than $1 per Day from a 1% Increase in Yield

Region	*Per cent in $1 poverty*	*Number in $1 poverty, millions*	*Reduction in $1 per day Poverty, millions*	*Cost per person*
East Asia	15.32	278.32	1.34	$179
South Asia	39.99	522.00	2.51	$179
Sub-Saharan Africa	46.30	290.87	2.09	$144
Middle East & North Africa	7.32	20.85	0.12	NA
Latin America	15.57	78.16	0.08	$11,397
East Europe and Central Asia	5.14	23.98	0.12	NA
Total	24.27	1214.18	6.24	NA

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