Genetically modified crops, factor endowments, biased technological change, wages and poverty reduction

Jenifer Piesse*

Department of Management,
King's College London,
150 Stamford Street,
London SE1 9HN, UK
E-mail: jenifer.piesse@kcl.ac.uk

University of Stellenbosch, RSA
*Corresponding author

Colin Thirtle

Centre for Environmental Policy,
Imperial College London,
Exhibition Road,
London SW7 2BP, UK
E-mail: c.thirtle@ic.ac.uk

University of Pretoria, RSA

Abstract: Genetically Modified (GM), Herbicide Tolerant (HT) white maize, developed in the USA to save labour, is being grown by smallholders in KwaZulu Natal, South Africa. This paper uses panel data for Africa, Asia and Latin America to investigate the effects of factor endowments and biased technological change on productivity growth, labour incomes and poverty reduction. Preliminary results show that lack of population pressure on the land slows yield growth, which itself largely explains labour productivity growth in agriculture. Labour productivity growth is the key determinant of wages, growth in GDP per capita and poverty reduction. Africa seems to have fared poorly in poverty reduction because many countries have abundant poor quality land. There has been yield growth, but it has not led to growth in labour productivity, as it did during the Asian green revolution. Thus, a GM technology that raises labour productivity could be beneficial, so long as employment is maintained.

Keywords: factor endowments; biased technological change; biotechnology; genetically modified crops; Sub-Saharan Africa; SSA.

Reference to this paper should be made as follows: Piesse, J. and Thirtle, C. (XXXX) 'Genetically modified crops, factor endowments, biased technological change, wages and poverty reduction', *Int. J. Biotechnology*, Vol. X, No. Y, pp.XXX–XXX.

Biographical notes: Jenifer Piesse is the Professor of International Business in the School of Social Science and Public Policy at King's College London and Visiting Professor at the University of Stellenbosch. She received her BA and MA from Columbia University, an MSc from the LSE and a PhD from

Birkbeck College, University of London. She has published in the area of productivity and efficiency measurement, with a major focus on developing and transitional economies. More recently, she has worked on cooperatives as an organisational form, and emerging financial markets including Sub-Saharan Africa and India. She has been involved in a number of projects with the Department for International Development (UK) related to privatisation and competition policy and the impact of public sector R&D on poverty reduction.

Colin Thirtle studied Economics at LSE, Southern Illinois and Columbia and has taught at Columbia, San Francisco, Manchester and Reading. He is now Professor of Development Economics at Imperial College London and Extraordinary Professor at the Universities of Pretoria and Stellenbosch. He has published extensively on agricultural technology and productivity, including genetically modified crops and impacts on poverty reduction in LDCs. He has been awarded the South African Agricultural Economics Association prize for the best journal article in 1994, 2002 and 2005 and is on the Editorial board of Agrekon, which is the society's journal. He is currently the Principal Investigator on an ESRC/DfID project investigating the impact of GM maize on poverty in SSA.

1 Introduction

Export opinion from International Food Policy Research Institute (IFPRI) and International Fund for Agricultural Development (IFAD) regards Genetically Modified (GM) crop varieties as a key to increasing food production in Sub-Saharan Africa (SSA). But can GM produce a Green Revolution (GR) in Africa and if it did, would it be poverty reducing, as in Asia? The distributional impact of biased technological change depends both on the factor-saving (or -using) biases and the factor endowments in the economy. If a labour-saving technology is introduced in a land scarce/labour abundant economy labour incomes will fall and poverty will increase. GM white maize, developed in the USA, is now being used by Zulu smallholders in South Africa. In Asia, importing labour-saving machinery increased unemployment and interviews with the few early adopters in SA suggest that GM can reduce planting labour (per unit of output) by over 50%. But the ultimate impact depends on the change in output as well as the bias, and labour for planting is the constraint in much of SSA. If land is poor but plentiful, planting area and output could double and labour demand for all other tasks increase substantially. Thus, a labour-saving technology need not displace labour: it depends on the factor endowments. Also, high levels of HIV/AIDS now exacerbate labour scarcity in many communities, including KwaZulu Natal.

This paper uses panel data for Africa, Asia and Latin America to investigate the effects of factor endowments and biased technological change on productivity growth, labour incomes and poverty reduction. The long-term aim is to discover the countries or regions in SSA where GM would cause output expansion and those where it should be avoided as labour displacement would be the dominant effect. This will facilitate predicting the expected poverty impact of GM maize in SSA.

2 GM maize in South Africa

In SSA, GM varieties are in commercial use only in South Africa, where both Herbicide Tolerant (HT) and insect resistant *Bacillus thuringiensis* (Bt) maize and cotton are grown. Bt cotton, which is resistant to bollworm, was released in 1997 and by 2003 was used in over 80% of the area planted. Bt yellow maize (resistant to stem borers) followed in 1998, Bt white maize in 2001 and HT white maize, which is the main food crop of Southern and Eastern Africa, in 2004. In KwaZulu Natal, both Bt and HT white maize is grown by resource-poor smallholders, under farm conditions that are typical of many countries in SSA, although some South African farm families have off-farm income (such as pensions) and employment opportunities that are lacking north of the Limpopo.

Bt maize has the potential to address Africa's disadvantages, with insect resistance displacing dangerous pesticides that are expensive due to distance and poor infrastructure. It is neutral with respect to employment as the reduction in spraying labour is matched by increases in harvest labour, given yields are higher. Bt reduces risk, an important issue in SSA, and in South Africa has been adopted as insurance by commercial farmers. Smallholders are less impressed, as most years are too dry for stem borers to be a problem and yield gains are therefore small. However, its effects are of interest in the rest of South and East Africa where there is significantly more rain.

HT varieties were developed in the US to save weeding labour. This seems unsuitable for much of SSA, but in South Africa the great success is HT combined with minimum tillage, called Planting Without Ploughing (PWP). Rather than deep ploughing, herbicide is used to kill the weeds, reducing preparation and planting labour by over 50%. HT complements PWP, providing a very effective alternative to ploughing by reducing erosion, maintaining the structure of soil and vegetation and minimising runoff, which improves rainwater retention. Together, HT and PWP result in yield increases of approximately 10%.

Stacked gene maize combining Bt and HT traits in a single variety was submitted for regulatory approval in September 2004. This is likely to be the dominant variety for SSA and we need to disentangle the effects of HT, Bt and PWP now, before they are bundled together.

Figure 1 Labour-saving biases of the alternative technologies

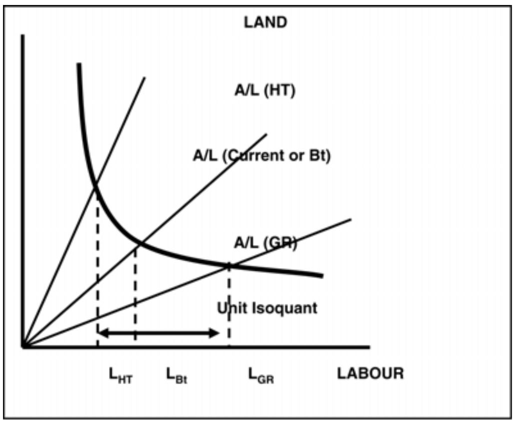


Figure 1 shows the labour impact of these four technologies: Bt is neutral, retaining the factor proportions of conventional seed, the GR technology is labour-using and HT is labour-saving. Adoption of HT is proceeding rapidly, which must mean that farmers are convinced they get benefits, but what does the labour-saving bias mean for wages and subsistence labour incomes and poverty reduction, if GM spreads across South and East Africa?

3 Poverty and the GR

3.1 World poverty

Almost half the world's 6 billion people live on less than \$2 per day and 1.2 billion on less than \$1 per day. More than 90% of these live in Asia and SSA and between two-thirds and three-quarters live in rural areas. SSA is the only region of the developing world expected to have more poor people in 2015 than in 1990. A 6.2% annual reduction in poverty is needed to halve hunger by 2015. The rural poor in SSA get over 66% of their incomes from farming (25% for Asia) and spend 72% of these incomes on agricultural products (40% in Asia).

3.2 Poverty reduction and the GR

Agricultural productivity growth increases the incomes of semi-subsistence farmers and lowers food prices, benefiting both the rural population and the urban poor who spend much of their incomes on food. The poorest farm households are in food deficit, so they gain both from moving closer to self-sufficiency and by cheaper purchased food. Those with little or no land gain disproportionately from employment generated by agricultural growth as real wages rise. This happened in Asia, but the failure of the GR in Africa has resulted in high levels of poverty.

3.3 Factor scarcities in Asia and Africa

David Ricardo considered extending both the intensive and extensive margins to increase output. The FAO statistics show that although output growth in SSA is faster than in Asia, per capita output growth is positive in Asia and negative in SSA, due to faster population growth in SSA. Asian growth is almost all from yield increases, whereas growth in SSA is mostly due to area expansion, with little change in yields. This is especially true of maize-based farming systems in South and East Africa. Generalisations are always dangerous, but they can help our understanding, and some simplified perceptions of Asian and African agriculture are in Table 1.

3.4 Induced innovation

Biological/chemical GR technologies use more labour than conventional crops, as more fertiliser means more weeding and more harvest labour. Under Asian conditions, the induced innovation case for land-saving intensification based on high yielding varieties and fertiliser is compelling and it has been highly successful. Similarly, mechanisation was appropriate for the land-abundant US. Yet neither has been effective in SSA (Binswanger, 1986; Pingali et al., 1997; Ruttan and Thirtle, 1989). Rusting tractors are

SSA's memorial to the supposition that the area is simply labour-scarce. In much of SSA, land is not particularly scarce but it is marginal (Hansen, 1979). Thus, Binswanger (1986) suggested that for land-abundant areas of SSA, technological change had to be labour-saving or it would not be adopted. Labour is scarce at peak periods such as ploughing and planting (exacerbated by HIV/AIDS) and modern inputs are always in short supply, often due to lack of credit.

Table 1 Stylised generalisations of African agriculture relative to Asian conditions

	Asia	*SSA*
Land	Scarce, fertile, irrigated land, reliable rain	Often abundant, rain-fed marginal land and frequent droughts
Labour	Abundant labour	Relatively scarce labour (often inhibited by poor health) especially at planting time
Modern inputs	Modern chemical inputs available and economical	Unreliable supplies of uneconomical modern inputs
Capital	Fixed and working capital available, labour gets its marginal product	Credit unavailable, markets incomplete: no landlord, labour gets its average product
Transport costs	Transportion and other infrastructures and institutions are good	Distance are huge, transportation infrastructure and institutions are poor
Crop diversity	Small range of staples (wheat and rice account for 60%)	Diversity of staples (maize, banana, wheat, millet, rice, cassava) and soils and climate

Mosley (2002) argues in favour of the GR as 'a pro-poor policy instrument' in SSA. Empirical evidence alongside the decline in public funding suggests the impact of the GR will remain limited. On the other hand, GM could give 70–80% output growth but it is not clear whether this will be poverty reducing and farmers will be offered US technology, appropriate or not. Historically, technologies developed in high wage economies have increased poverty when they have been imported into developing countries. In the 1970s, each tractor imported by Pakistan put 10 beggars on the streets of Karachi and each combine harvester a further 100.

3.5 Institutional innovation and other factors

IFPRI's Pretoria Statement listed new technology and good governance as the two underlying factors in all past successes in Africa agriculture. Our work has shown that Bt cotton collapsed in KwaZulu Natal due to weak institutions, despite being a very effective technology. Factors such as education, health, institutions and governance do matter and must be taken into account. The differences in institutional efficiency, noted in Table 1, can also be tested, but the World Bank governance measures do not fit agriculture well. The limited success of the GR in SSA indicates an element of political will with respect to agriculture. This too can be tested, with perhaps the best proxy being agriculture's share of government expenditures.

4 Explaining the impact of the GR on employment, wages and poverty

Lipton (2005) stresses the importance of factor-saving biases. In comparing GM with the GR technologies, he argues the GR was pro-poor because it increased yields (output per unit of land – *Q/A*) more than labour productivity (output per unit of labour – *Q/L*). Lipton claims that as the rural labour supply in LDCs is still expected to increase at over 1% per annum, despite HIV/AIDS, *Q/A* must increase at least 1.5% per annum faster than *Q/L* for employment and wages to increase, and reduce poverty. In proportional terms, with the changes expressed as time derivatives, this is

Demand for Agricultural Labour Supply of Agricultural Labour

$$\frac{\mathrm{dIn}W_a}{\mathrm{d}t} > 0 \quad \text{iff} \frac{\mathrm{d}\left[\mathrm{In}\left(Q/A\right)\right]}{\mathrm{d}t} - \frac{d\left[\mathrm{In}\left(Q/L\right)\right]}{\mathrm{d}t} > \frac{\mathrm{d}\left[\mathrm{In}La\right]}{\mathrm{d}t} = \frac{\mathrm{d}\left[\mathrm{In}Lt\right]}{\mathrm{d}t} - \frac{\mathrm{d}\left[\mathrm{In}Lna\right]}{\mathrm{d}t} \tag{1}$$

where W_a is the agricultural wage, or the return to labour, $d[\ln La]/\mathrm{d}t$ is the proportional growth over time of the agricultural labour force, $d[\ln Lt]/\mathrm{d}t$ is growth in the total labour force and $d[\ln Lna]/\mathrm{d}t$ is growth in the non-agricultural labour force. This condition for poverty reduction may fit well for Asia, but may not for SSA. The fact that extensification seems to have mattered more than yield increases suggests that labour-saving technology may be appropriate and/or better for some countries or regions than others. If the reverse is true, then the poverty impact of the dominant stacked gene technology will be negative. Note too that this condition can only apply until the turning point in the structural transformation, at which the total labour force in agriculture begins to decline. After that point labour productivity has to rise, as Figures 2 and 3 illustrate for Brazil and Egypt.

Figure 2 Brazil

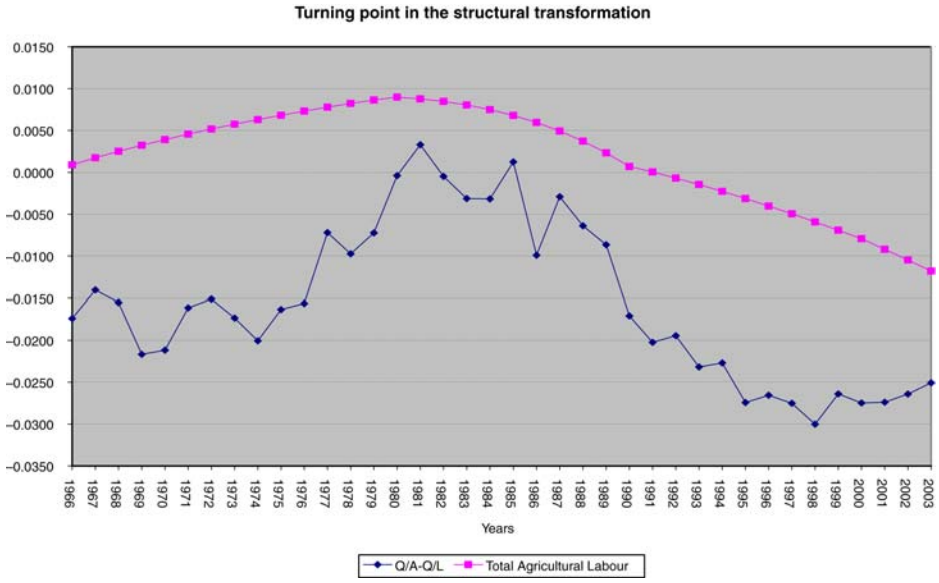
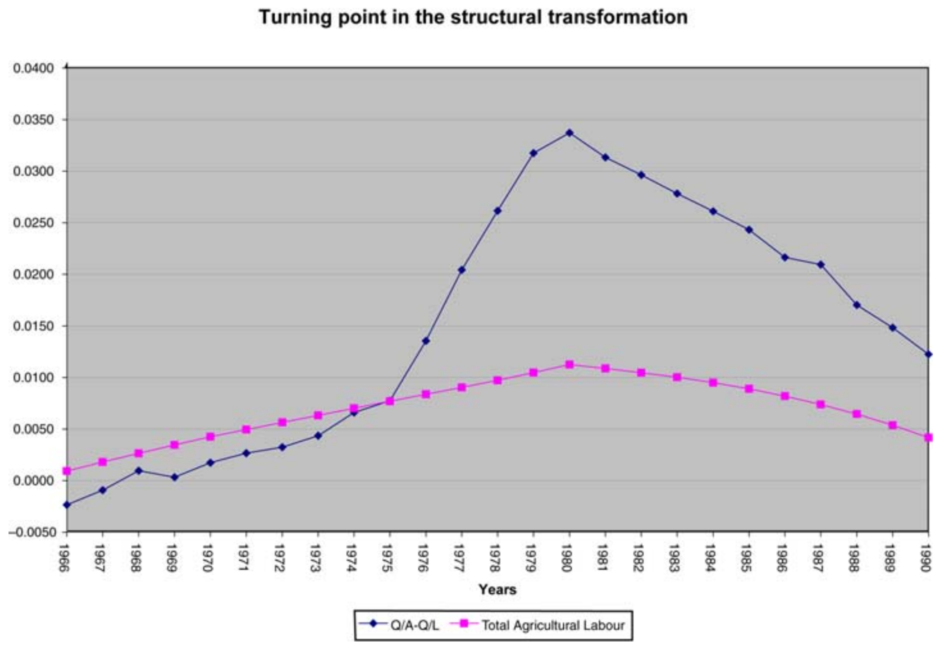


Figure 3 Egypt



5 Questions

5.1 Shortcomings in current knowledge

Despite substantial work on the GR in SSA, there has been little work on factor endowments and biases since Hayami and Ruttan (1985). There are no empirical papers on the effects of these biases on wages and labour incomes, or on poverty reduction. For instance, Thirtle et al. (2003) considered only yields and had no wage data. Now there is significantly more and better data that will allow us to tackle the important questions outlined below.

5.2 Research questions

1. How different were the rates of agricultural productivity growth in Africa, Asia and Latin America and how different were the factor-saving biases?
2. Do factor proportions play a major role in explaining the *rate and biases* of technological change, across space and time, during the GR? Do the biases of the GR technologies fit the factor proportions in Asia and Latin America better than in SSA? Are these differences between Asia and Africa important in accounting for Asian success and comparative failure in Africa, or do markets, institutions and infrastructure dominate?
3. Do the biases of the GR technology really explain its impact on wages and non-wage labour incomes in Asia and SSA? How much do lower food output prices account for rises in real wages and poverty reduction?

4 What is the poverty reducing elasticity of GR-driven agricultural output growth across time and space? Is it the same in SSA and Asia?

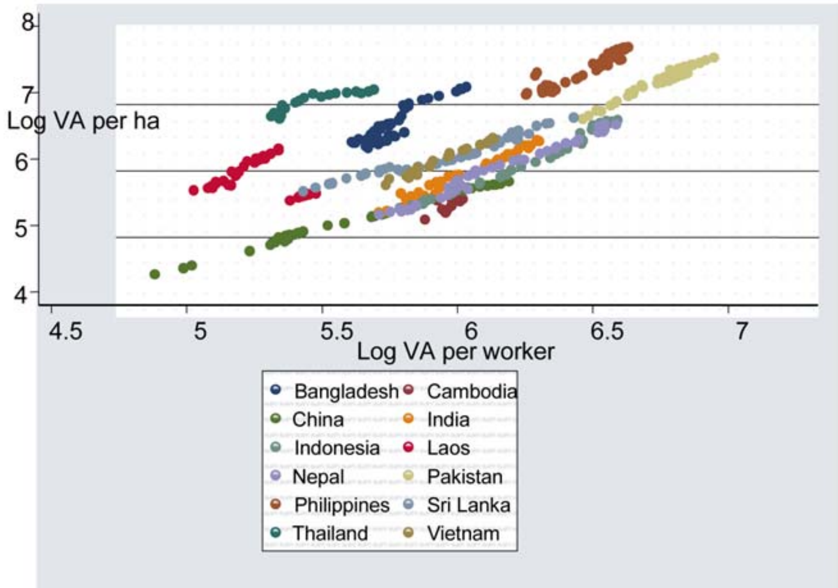
5 Do the partial productivities of land and labour have different poverty impacts, especially in SSA?

6 Results

6.1 Biases

The work on biases by Hayami and Ruttan (1985) presents pictures of the relative land and labour saving biases over time for many countries, supported by regression results. Figure 4 updates their work for Asia, and is a scatter diagram with the natural logarithm of output per unit of land (value added per hectare) on the vertical axis and the natural logarithm of output per unit of labour (value added per person) on the horizontal axis. There are clear upward trends for all the countries (although the series need not be monotonically increasing) and it is easy to calculate the average slope coefficient.

Figure 4 Biases of partial productivity measures for Asian countries



The cross section and time series data needs to be taken into account, so the obvious choices are Swamy's random coefficients (the average of the individual country OLS regressions) or fixed or random effects. The results are similar for all three so the random coefficients results are reported because they give more information. In Table 2 the countries are ranked according to the coefficient on the *X* variable, which averages 1.7, indicating that there appears to be a land-saving bias. Note that the *t* statistics show that the relationship is very strong for all the countries and that the average R^2 is almost 0.9. Only Cambodia, with just 11 observations has a relatively low R^2.

Table 2 Swamy random coefficients for biases: Asia

Country	*Coefficient*	*t stat.*	R^2
Average	1.690734	12.14	0.8935
Bangladesh	2.268378	14.46	0.8366
Cambodia	1.77336	7.07	0.4804
China	1.076929	84.64	0.9951
India	1.89149	34.14	0.9698
Indonesia	1.762166	41.46	0.9795
Laos	1.700942	26.42	0.9767
Nepal	2.327443	19.46	0.9153
Pakistan	1.614033	46.93	0.9840
Philippines	1.902307	34.82	0.9707
Sri Lanka	1.843809	17.12	0.8781
Thailand	1.082674	27.83	0.9553
Vietnam	1.045272	8.31	0.7801
12 countries: 433 observations, min = 11, max = 43			
Wald χ^2 (1) = 147.44, Prob > χ^2 = 0.000			

Figure 5 shows the same results for Africa, where there is again a clear upward trend for all countries, but perhaps more dispersion. The average slope coefficient is almost exactly unity, which could be called neutral with respect to the factor-saving biases. However, as given in Table 3, while Uganda has as strong a land-saving bias as Bangladesh, there are 19 countries with a labour-saving bias and three for which the relationship between land and labour productivity is negative.

Figure 5 Biases of partial productivity measures for African countries

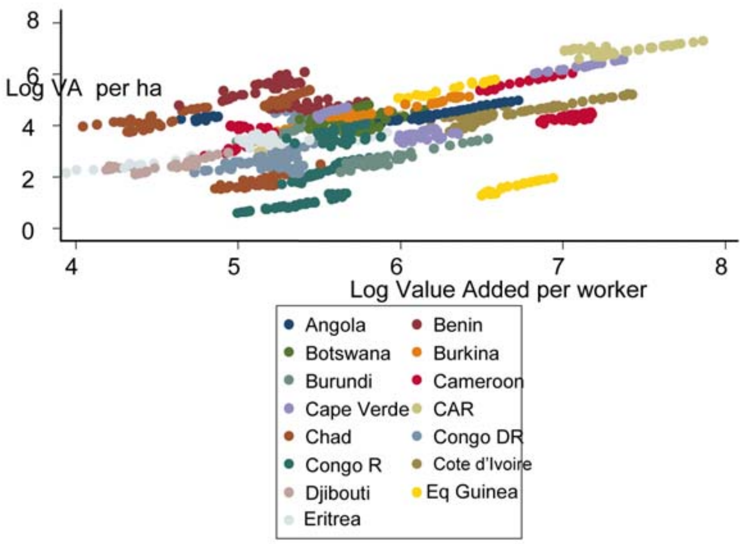


Table 3 Swamy random coefficients for biases: Africa

Country	*Coefficient*	*t stat.*	R^2
Average	1.034943	8.52	0.615
Uganda	2.215398	12.26	0.877
Congo R	2.169051	27.17	0.948
Tanzania	2.155573	10.11	0.883
Burkina Faso	2.117418	17.68	0.907
Guinea	1.855679	15.65	0.936
Togo	1.729102	23.44	0.937
Mali	1.717906	23.25	0.94
Rwanda	1.623187	11.16	0.767
Namibia	1.609816	19.95	0.947
CAR	1.597958	16.82	0.884
Chad	1.464841	8.46	0.654
Mozambique	1.444915	11.82	0.88
Cote d'Ivoire	1.415843	5.03	0.313
Cameroon	1.36774	30.02	0.961
Equatorial Guinea	1.365722	20.7	0.961
Sudan	1.325995	14.74	0.858
Malawi	1.180824	6.59	0.531
Mauritania	1.136422	22.24	0.924
Botswana	1.10894	31.92	0.962
Nigeria	1.104174	40.74	0.976
Morocco	1.058373	57.55	0.989
Cape Verde	1.048251	56.3	0.995
Sierra Leone	1.000525	20.11	0.915
Burundi	0.977002	5.58	0.432
Kenya	0.955295	2.59	0.0441
Angola	0.835746	11.99	0.897
Benin	0.827789	25.34	0.953
Eritrea	0.822321	11.54	0.931
Swaziland	0.793848	5.01	0.406
Le Soto	0.790549	3.48	0.212
Seychelles	0.759153	15.66	0.909

Table 3 Swamy random coefficients for biases: Africa (continued)

Country	*Coefficient*	*t stat.*	R^2
Guinea Bissau	0.752373	3.48	0.214
Ethiopia	0.730646	2.65	0.277
Zimbabwe	0.598273	2.17	0.052
Djibouti	0.436053	1.81	0.03
Zambia	0.290587	0.93	−0.026
Niger	0.286412	4.76	0.342
Gambia	0.157362	0.88	−0.185
Congo DR	0.01929	0.05	−0.0111
Ghana	−0.19241	−1.34	0.043
Senegal	−0.3599	−1.83	0.088
Madagascar	−0.82645	−2.83	0.259

6.2 *Rates of change*

The biases shown in the figures are somewhat misleading as this section will show. By simply regressing the logarithm of value added per hectare on time, the growth rate over the period can be estimated and the same can be done for value added per worker. Table 4 indicates that Lao has the highest yield growth rate in Asia, at 3.7% and even Nepal, with the lowest rate has 1.6% pa growth. The Asian average of 2.6% is well above the average for Africa, which is reported in Table 5 as 2.0%, but this is far higher than most would expect, given that African agriculture is regarded as failing. Over half the sample (22 of the 42 countries) had yield growth of over 2% and only 8 had less than 1%.

Table 4 Swamy random coefficients – growth in *Q/A*: Asia

Country	*Coefficient*	*t stat.*	R^2
Average	0.026	12.7	0.92061
Lao PDR	0.037092	31.07	0.9807
Indonesia	0.034405	40.82	0.9754
Pakistan	0.033879	59.58	0.9883
Cambodia	0.031068	8.21	0.869
China	0.028772	28.24	0.9499
India	0.02671	39.61	0.9739
Vietnam	0.024493	14.54	0.9212
Thailand	0.023284	37.08	0.9703
Bangladesh	0.02059	17.62	0.8805
Sri Lanka	0.017974	14.44	0.8317
Philippines	0.017343	17.25	0.8759
Nepal	0.01628	13.68	0.8305

Table 5 Swamy random coefficients – growth in *Q/A*: Africa

Country	*Coefficient*	*t stat.*	R^2
Average	0.020002	12.44	0.659329
Guinea	0.040688	33.06	0.9847
Equatorial Guinea	0.0394	8.14	0.7666
Mozambique	0.038016	10.24	0.8454
Tanzania	0.033391	32.39	0.9877
Namibia	0.032395	16.79	0.9243
Cameroon	0.032325	29.08	0.9569
Uganda	0.031863	16.97	0.9318
Togo	0.029595	28.34	0.9548
Kenya	0.029426	21.05	0.9189
Mali	0.02912	20.18	0.9186
Botswana	0.026582	7.21	0.5482
Sudan	0.026569	11.27	0.7729
Cape Verde	0.026211	3.92	0.4586
Rwanda	0.025785	12.61	0.8062
Benin	0.025336	16.56	0.8922
Congo R	0.025129	32.91	0.9626
Malawi	0.024029	11.77	0.7925
Burkina Faso	0.023315	17.82	0.9056
Cote d’Ivoire	0.021719	22.83	0.9253
Zambia	0.020786	15.56	0.8639
Zimbabwe	0.020454	10.74	0.7761
Chad	0.020095	8.70	0.6746
Guinea Bissau	0.017899	6.72	0.572
CAR	0.017235	19.93	0.9125
Congo DR	0.016831	14.97	0.8678
Morocco	0.016112	6.50	0.5207
Nigeria	0.016099	9.50	0.6801
Ethiopia	0.015998	2.37	0.3156
Madagascar	0.015517	18.05	0.9078
Burundi	0.015471	8.88	0.6721
Mauritania	0.014156	7.67	0.5793
Senegal	0.013425	11.73	0.7648
Lesotho	0.012918	7.70	0.6383

Table 5 Swamy random coefficients – growth in *Q/A*: Africa (continued)

Country	*Coefficient*	*t stat.*	R^2
Gambia	0.01235	6.58	0.5337
Ghana	0.009999	8.39	0.6464
Eritrea	0.00907	1.46	–0.0088
Djibouti	0.00743	1.90	0.0979
Swaziland	0.006076	3.39	0.2463
Seychelles	0.005101	1.22	0.0126
Angola	0.004188	0.60	–0.0134
Niger	–0.00116	–0.63	–0.0146
Sierra Leone	–0.00686	–2.64	0.1923

Table 6 shows that labour productivity in Asia grew at an average of 1.5% in Asia, but that five of the twelve countries had less than 1% growth. Note that this means that on average, the bias could be expressed as 2.6/1.5 = 1.7, so there is a land-saving bias, just as Figure 4 suggested. For Africa, Table 7 indicates that labour productivity grew at only 0.4% per annum and although the top few countries are in the same league as Asia, almost half the sample (18 countries) actually have negative growth. This has serious connotations for poverty reduction, as this paper will show that there is a strong negative correlation between labour productivity growth and poverty. The bias calculated as before is 2.0/0.4 = 5, which is hugely in the land productivity direction and very different from the impression given by Figure 5. This can of course be reconciled by the simple fact that there was substantial regression in labour productivity for Africa, so Figure 5 is misleading.

Table 6 Swamy random coefficients – growth in *Q/L*: Asia

Country	*Coefficient*	*t stat.*	R^2
Average	0.0150049	6.79	0.795017
China	0.0264611	24.65	0.9353
Vietnam	0.0220453	16.14	0.9352
Lao PDR	0.0210582	16.50	0.9346
Thailand	0.0210216	32.93	0.9627
Pakistan	0.020465	29.74	0.9546
Indonesia	0.0190638	28.11	0.9495
India	0.0133148	18.73	0.8929
Sri Lanka	0.0092573	16.20	0.8616
Philippines	0.0085732	13.10	0.8025
Bangladesh	0.0064339	7.24	0.551
Nepal	0.0058187	8.36	0.6449
Cambodia	0.0053564	1.51	0.1154

Table 7 Swamy random coefficients – growth in *Q/L*: Africa

Country	*Coefficient*	*t stat.*	R^2
Average	0.0040328	2.04	0.418031
Benin	0.0307099	23.10752	0.9417
Equatorial Guinea	0.0270407	5.101056	0.5816
Cape Verde	0.0237493	3.577241	0.4097
Cameroon	0.0220523	15.61004	0.8646
Mozambique	0.0217116	5.15519	0.5738
Botswana	0.0210698	5.781101	0.4356
Guinea	0.0199209	11.08935	0.8777
Namibia	0.0182347	10.04777	0.8129
Togo	0.0155431	14.2297	0.8413
Mali	0.0148307	10.35663	0.747
Morocco	0.0138564	5.464742	0.4317
Sudan	0.0138447	5.272364	0.42
Nigeria	0.0134171	7.781187	0.5464
Tanzania	0.01278	7.511461	0.81
Uganda	0.0111871	6.615671	0.6707
Congo R	0.0105195	15.02356	0.8425
Mauritania	0.0103312	5.64886	0.4239
Rwanda	0.0094988	4.85326	0.3725
Burkina Faso	0.0089534	8.254264	0.6704
CAR	0.0085264	8.311141	0.6418
Malawi	0.0061623	2.413087	0.1181
Chad	0.0046711	2.206993	0.0971
Burundi	0.0035392	1.783422	0.0543
Cote d'Ivoire	0.0032037	2.606753	0.1213
Kenya	–0.000129	–0.09217	–0.0261
Le Soto	–0.001158	–0.65651	–0.0175
Zimbabwe	–0.002092	–0.96148	–0.0023
Swaziland	–0.002121	–1.25998	0.018
Seychelles	–0.002145	–0.52933	–0.0188
Guinea Bissau	–0.002914	–1.06788	0.0042
Zambia	–0.003011	–1.99847	0.073
Congo DR	–0.003051	–3.12774	0.2053

Table 7 Swamy random coefficients – growth in *Q/L*: Africa (continued)

Country	*Coefficient*	*t stat.*	R^2
Ethiopia	–0.005208	–0.80347	–0.0367
Madagascar	–0.005396	–6.61007	0.564
Senegal	–0.008108	–7.0709	0.5385
Gambia	–0.008847	–4.39163	0.3308
Ghana	–0.010435	–7.43947	0.5885
Djibouti	–0.010507	–2.87635	0.398
Sierra Leone	–0.012923	–4.86855	0.4759
Niger	–0.021183	–9.97537	0.7011
Angola	–0.032271	–2.44647	0.2169
Eritrea	–0.044479	–1.86213	0.1979

6.3 Explaining land and labour productivities

Since *Q/A* (and *Q/L*) can be simply viewed as the intensive form of the agricultural production function, it should be straightforward to explain labour productivity with the other inputs similarly divided by *A* (or *L*). Tables 8 and 9 shows the results for both continents, using random effects to estimate the panels. In both cases, tractors and fertiliser improve yields, but with small elasticities. The big effect is that a country with 1% more land per unit of labour will have about 1% less growth in yields. This suggests that land-saving technologies, like the GR, are most effective in land scarce countries. Thus Africa should be expected to be disadvantaged when the available technologies are yield enhancing. Performing the same test for labour productivity shows that for both continents, tractors and fertiliser increase labour productivity and so did more land per unit of labour in Africa, but not in Asia. For Asia, the countries with more population pressure on the land also had higher growth in labour productivity, which is a little surprising.

Table 8 Panel regression – dependent variable *Q/A*

	Africa: countries = 40, obs = 1200		*Asia: countries = 12, obs = 415*	
	Coefficient	*t stat.*	*Coefficient*	*t stat.*
Tractors/land	0.0747	6.68	0.0405	3.21
Land/labour Ratio	–0.8886	–29.03	–1.0458	–15.37
Fertiliser/land	0.0202	2.83	0.1232	9.35
Constant	5.6017	43.55	5.1799	30.38
R^2: Within	0.4942		0.8605	
Between	0.8101		0.5721	
Overall	0.7647		0.5797	
Wald χ^2_3	1304.82		2484.2	

Table 9 Panel regression – dependent variable *Q/L*

	Africa: countries = 40, obs = 1200		*Asia: countries = 12, obs = 415*	
	Coefficient	*t stat.*	*Coefficient*	*t stat.*
Tractors/lab	0.0907	8.05	0.0405	3.17
Land/labour ratio	0.0642	2.26	–0.1988	–3.19
Fertiliser/lab	0.0202	2.88	0.1236	9.25
Constant	6.1640	41.75	5.4298	27.27
R^2: Within	0.0867		0.6642	
Between	0.1667		0.0605	
Overall	0.1953		0.2398	
Wald χ^2_3	119.31		792.92	

The next step investigates the relationship between land and labour productivities. Table 10 shows that the dominant force explaining labour productivity seems to be yields. In both continents, a 1% increase in yields gives rather more than 0.5% increase in labour productivity. Note that this result comes from the cross section, not the time series, so we next concentrate on Africa, using random coefficients again. The random coefficients regression shows that on an average almost 80% of the variance in labour productivity is explained by just yields, fertiliser and tractors. The dominant effect though is yields, with an average output elasticity of 0.64, which is only negative or insignificant for five countries. Although tractors contribute in the panel regression, the average elasticity is small and it is negative or insignificant for 22 countries. Fertiliser is not significant in any of the models, which suggests that it is made redundant by the inclusion of yields. The results of country level random coefficient models for Africa, by country, are reported in Table 11.

Table 10 Panel regression – dependent variable *Q/L*

	Africa: countries =40, obs =1200		*Asia: countries =12, obs =415*	
	Coefficient	*t stat.*	*Coefficient*	*t stat.*
Q/A	0.5093	33.25	0.6081	29.89
Tractors/lab	0.0242	2.89	0.0148	2.04
Fertiliser/lab	–0.0059	–1.16	–0.0090	–1.09
Constant	3.7651	27.39	2.2148	12.45
R^2: Within	0.5437		0.8929	
Between	0.1305		0.3358	
Overall	0.1170		0.5013	
Wald χ^2_3	1319.39		3342.19	

Table 11 Africa – random coefficients, dependent variable *Q/L*

Country	*Q/A*		*Tractors/lab*		*Fertiliser/lab*		*Constant*		*Adj. R^2*	*Obs*
	Coefficient	*t stat.*	*Coefficient*	*t stat.*	*Coefficient*	*t stat.*	*Coefficient*	*t stat.*		
Average	0.642	11.65	0.167	1.98	0.005	0.46	4.192	6.97	0.788	1220
Angola	1.001	116.02	1.003	171.15	0.000	0.37	8.68	233.58	1.000	16
Benin	1.005	8.12	0.214	1.78	0.000	−0.02	2.462	1.53	0.953	33
Botswana	0.972	27.16	−0.092	−3.57	−0.069	−3.75	4.433	24.79	0.977	42
Burkina Faso	0.582	8.79	−0.028	−2.05	−0.010	−1.91	2.336	5.92	0.924	33
Burundi	0.386	2.15	−0.035	−1.54	0.069	1.71	2.269	2.27	0.441	37
Cameroon	0.592	28.22	0.045	3.29	0.076	4.08	3.301	14.07	0.983	38
Cape Verde	0.841	7.66	−0.190	−0.51	0.013	1.00	0.074	0.03	0.993	8
CAR	0.649	16.34	0.107	3.37	0.009	1.05	4.068	13.91	0.913	38
Chad	0.421	6.50	−0.245	−3.46	−0.016	−0.61	2.019	2.99	0.732	35
Congo DR	0.073	0.87	−0.202	−2.45	0.025	1.43	3.324	3.40	0.121	34
Congo R	0.438	27.13	−0.041	−2.20	−0.003	−0.76	4.255	29.74	0.952	41
Cote d'Ivoire	0.128	1.60	−0.081	−2.64	0.141	3.19	4.625	9.71	0.428	42
Eritrea	1.210	15.54	−0.233	−1.81	0.007	0.19	−0.761	−0.60	0.970	10
Ethiopia	1.013	19.69	0.930	13.10	−0.019	−1.35	8.603	18.81	0.978	10
Gambia	0.947	17.91	0.689	22.94	0.014	1.45	6.950	39.52	0.956	37
Ghana	0.553	2.28	0.637	4.30	−0.096	−3.40	7.984	10.35	0.379	38
Guinea	0.660	22.43	−0.213	−6.46	−0.005	−0.69	0.792	2.08	0.984	17
Guinea Bissau	1.031	8.79	1.689	6.29	0.018	0.77	17.971	7.95	0.765	26
Kenya	−0.079	−0.93	−0.405	−2.06	0.133	1.51	2.062	1.65	0.145	39
Le Soto	0.604	6.09	−0.128	−1.55	−0.061	−1.63	3.502	5.80	0.567	33
Madagascar	0.138	1.25	1.021	3.56	−0.010	−0.27	12.239	6.48	0.457	33

Table 11 Africa – random coefficients, dependent variable *Q/L* (continued)

Country	*Q/A*		*Tractors/lab*		*Fertiliser/lab*		*Constant*		*Adj. R^2*	*Obs*
	Coefficient	*t stat.*	*Coefficient*	*t stat.*	*Coefficient*	*t stat.*	*Coefficient*	*t stat.*		
Malawi	0.719	7.85	0.559	3.45	–0.150	–3.62	6.430	5.63	0.650	36
Mali	0.869	26.27	–0.236	–9.22	–0.018	–2.30	0.815	2.77	0.984	36
Mauritania	0.865	21.34	–0.024	–1.15	0.010	0.90	4.210	21.54	0.943	33
Morocco	1.016	84.23	–0.049	–3.02	–0.010	–0.57	1.719	9.21	0.997	38
Mozambique	1.015	286.46	0.972	101.51	0.000	–0.14	8.784	150.82	1.000	19
Namibia	1.000	10.00	0.997	171.84	0.000	6.09	9.406	134.83	1.000	5
Niger	0.500	2.86	–0.213	–4.71	–0.090	–3.47	1.389	2.08	0.802	39
Nigeria	1.032	41.16	–0.071	–5.69	0.029	3.84	0.771	3.46	0.990	42
Rwanda	0.677	13.27	0.313	5.73	–0.015	–1.27	4.566	10.95	0.868	34
Senegal	0.064	0.53	–0.698	–4.02	0.140	3.34	–1.203	–0.62	0.369	42
Seychelles	0.916	18.22	1.113	5.33	0.018	6.87	4.741	2.81	0.994	6
Sierra Leone	0.703	15.26	0.136	5.70	0.011	1.14	3.661	8.95	0.963	39
Sudan	0.675	14.33	–0.100	–1.96	–0.027	–0.78	3.469	7.05	0.872	38
Swaziland	0.791	10.90	–0.239	–7.36	0.080	4.82	2.065	4.67	0.806	32
Tanzania	0.196	2.31	0.200	1.64	–0.042	–2.65	6.298	6.35	0.906	13
Togo	0.797	12.28	0.041	0.67	–0.058	–4.48	2.797	7.28	0.972	37
Uganda	0.336	10.35	–0.375	–3.88	–0.003	–0.51	0.793	1.21	0.969	19
Zambia	0.012	0.13	–0.076	–0.30	–0.033	–0.39	4.967	2.35	–0.020	38
Zimbabwe	0.472	10.12	0.640	8.75	0.256	5.28	5.512	9.90	0.831	34

7 Land and labour productivity, GDP per capita, wages and poverty reduction

There should be a close relationship between labour productivity and the wage. Indeed, in the Cobb Douglas production function, the wage or marginal product of labour is equal to the average product of labour multiplied by the output elasticity of labour. This becomes an identity with constant returns to scale since the real wage is:

$$\frac{W}{P} \equiv \alpha \frac{Q}{L} \equiv \frac{WL}{PQ}\frac{Q}{L} \equiv \frac{W}{P}\begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \tag{2}$$

Thus, it is not surprising that labour productivity is the key variable in explaining agricultural wages, results in Table 12. For Africa, it has an elasticity of 0.85 and is significant at the highest levels, whereas yields have little impact or significance. The land labour ratio is significant and the negative sign means that the more land abundant countries have lower wages. Again, if wages are important to explaining poverty the semi-arid countries of South and East Africa may be disadvantaged. Note that for both Asia and Latin America, the effect of labour productivity is weaker, which indicates that yields are important, and the land labour ratio has the opposite sign. It is the countries with lower population pressure that have higher wages. Note too that the wage data from the ILO gives only small samples for Asia and Latin America. For Africa there is also data from the World Bank.

Table 12 Explaining wages – dependent variable real agricultural wages

	Africa: obs =216		*Asia: obs =56*		*Latin America: obs =69*	
	Coefficient	*t stat.*	*Coefficient*	*t stat.*	*Coefficient*	*t stat.*
VA labour	0.847	9.06	0.589	4.27	0.424	3.90
VA land	0.054	1.53	0.223	2.45	0.418	4.30
Land/labour	−0.137	−2.79	0.241	7.11	0.084	2.05
Constant	1.044	0.95	−5.839	−5.47	−1.689	−1.25
Adj. R^2	0.496		0.592		0.343	

The next step examines whether agricultural wages and partial productivities explain GDP per capita. We start with this rather than poverty because the intersection of wage and poverty data will further reduce the sample (see Table 13). The agricultural wage does increase GDP per capita in all three regions, but more so where the average GDP per capita is lowest. Labour productivity has the same effect, but is weakest in Africa, which is odd, as Africa has a higher proportion of semi-subsistence farmers and a lower level of hired labour. Yields have most impact in Asia, less in Africa and none in Latin America. Tractors per labourer increase GDP per capita in Africa and Latin America, but not in Asia. Fertiliser per hectare works in Latin America, where yields did not. Note that high percentages of the variance were explained.

Poverty can be explained, with results in Table 14, but note the small size of the samples. For Africa, this falls to 43 observations and for Asia the sample is not viable.

For Africa, Latin America and the full sample, the wage reduces poverty, but its effect is less strong than that of labour productivity. Yields increase poverty in Latin America, but have a negative effect in the full sample. Greater rural population density is poverty reducing in Africa, which again suggests that the semi-arid countries may have a problem.

Table 13 Explaining GDP per capita

	Africa: obs =216		*Asia: obs =56*		*Latin America: obs =77*	
	Coefficient	*t stat.*	*Coefficient*	*t stat.*	*Coefficient*	*t stat.*
Agricultural wage	0.132	7.14	0.108	4.09	0.093	3.99
VA labour	0.227	2.69	0.745	18.73	0.546	5.51
VA land	0.078	1.66	0.175	6.43		
Tractors/lab	0.205	3.74			0.137	1.79
Fertiliser/land					0.059	2.21
Constant	5.373	7.91	–0.010	–0.06	3.156	3.58
R^2: Within	0.208		0.756		0.649	
Between	0.655		0.999		0.421	
Adj. R^2	0.711		0.983		0.637	

Table 14 Explaining $1 per day poverty reduction

	Africa: obs = 43		*Lat America: obs = 56*		*All countries: obs = 138*	
	Coefficient	*t stat.*	*Coefficient*	*t stat.*	*Coefficient*	*t stat.*
Wage	–0.209	–1.90	–0.354	–2.31	–0.235	–2.74
VA labour	–0.802	–4.99	–1.275	–4.63	–0.536	–4.37
VA land			0.603	2.44	–0.226	–2.59
Literacy					–0.327	–1.41
Rural pop density	–0.376	–1.68	–1.92		0.217	1.71
Constant	–0.376	–1.68	13.064	5.17	8.501	6.88
R^2: Within	0.011	6.64				
Between	0.660					
Adj. R^2	0.704		0.372		0.598	

It is not really possible to test Lipton's proposition of Equation (1) because it requires growth rates, which are hard to calculate with these incomplete series. If we apply the combination of cross section and time series to the variables Lipton suggests, we get the results reported in Table 15. Labour productivity seems to dominate yields in explaining poverty reduction and more land per labourer does not reduce poverty. In fact, the countries with more population pressure seem to do better. Thus, for SSA, it may not be yields growth faster than labour productivity that is required for poverty reduction, but simply adequate labour productivity growth, that is combined with maintaining employment levels. Clearly, this requires output expansion, which is quite possible in the regions where marginal land is abundant and these are the very areas where the GR technologies failed due to poor soil and lack of water management.

Table 15 Test of Lipton's hypothesis – dependent variable = $ day poverty

	Africa: obs =43		*Asia: obs =62*		*Latin America: obs =56*	
	Coefficient	*t stat*	*Coefficient*	*t stat*	*Coefficient*	*t stat*
VA labour	–0.844	–5.02	–0.557	–3.12	–0.878	–5.02
VA land	–0.205	–1.93	–0.196	–2.16	0.129	0.91
Land/labour	0.169	1.32	0.087	1.12	–0.016	–0.18
Constant	6.602	2.78	5.863	2.89	8.280	3.90
Adj. R^2	0.709		0.446		0.327	

8 Conclusion

This paper shows that yield growth in Asia averaged 2.6% per annum, but that Africa was not far behind at 2.0%. However, labour productivity in Asia grew at 1.5% per annum, whereas Africa managed only 0.4%. Lipton's observation that the GR reduced poverty in Asia because yields grew faster than labour productivity, so increasing employment, wages and labour incomes does not seem to hold for Africa. Yields in Asia grew at 1.1% faster than labour productivity and there was substantial progress in poverty alleviation. In Africa, yields grew 1.6% faster than labour productivity, but the impact on poverty has been less. This study finds that yield growth is in fact a main cause of labour productivity growth in both continents, but in Africa the impact is far weaker. Labour productivity growth in Asia has been 58% of yield growth, whereas in Africa it is only 20%. The most obvious cause is that both yields and labour productivity grow less where land/labour ratios are low. It is particularly in the countries of SSA with abundant marginal land that labour productivity growth has failed and this paper finds this to be the main force driving increasing wages, increasing GDP per capita and poverty reduction. Thus, the countries like South Africa and Zimbabwe, where the GR technologies fared least well due to poor soil and lack of water control, are among the countries with the greatest increases in poverty, as given in Table 16. For 9 of the 24 countries on which we have data, $1 per day poverty is increasing and the simple average rate is a 3.4% per annum increase in poverty.

This work is very much in progress, but the results to date have done little to disabuse us of the notion that it is labour productivity growth that reduces poverty. It may well be that in the heavily populated countries of Asia, yield growth was necessary to give growth in labour productivity and employment, but this may not be the case in the less heavily populated regions of Africa, where marginal land is abundant. A technology like HT white maize combined with minimum tillage may be poverty reducing, or it may increase poverty. This will depend on whether the technology is sufficiently output-increasing for employment to be maintained when labour productivity is enhanced.

This cannot be determined from the historical data because unemployment levels are not usually available. To find the answer to this question will require survey data on the users of HT maize in KwaZulu Natal, that can be generalised to provide estimates of the likely impact in other parts of SSA.

Table 16 $1 per day poverty in Africa

Country	*Change in $1 per day poverty, %*
Average	3.4
Algeria	0
Botswana	−1
Burkina Faso	−7
Burundi	3.4
Cameroon	−9.4
Cote d'Ivoire	−7.6
Ethiopia	−5.3
Ghana	10.6
Kenya	−6.4
Le Soto	−7.8
Madagascar	4.0
Mali	6.8
Mauritania	−2.4
Morocco	0
Niger	15
Nigeria	3.7
Rwanda	2.8
Senegal	−12.7
South Africa	14
Tunisia	0
Uganda	−0.5
Zambia	−6.2
Zimbabwe	13.7

Acknowledgements

This paper is derived from a presentation at the 26th Conference of the International Association of Agricultural Economists, Gold Coast, Queensland, August 2006. We thank the participants for their comments and the ESRC/DfID for funding under award number RES-167-25-0187.

References

Binswanger, H. (1986) 'Evaluating research system performance and targeting research in land-abundant areas of SSA', *World Development*, Vol. 14, pp.469–475.

Hansen, B. (1979) 'Colonial economic development with unlimited supply of land: a Ricardian case', *Economic Development and Cultural Change*, Vol. 27, pp.611–627.

Hayami, Y. and Ruttan, V. (1985) *Agricultural Development: An International Perspective*, (*Revised Edition*), Baltimore: Johns Hopkins University Press.

Lipton, M. (2005) 'From policy aims and small-farm characteristics to farm science needs', *Paper Presented at a Research Workshop on The Future of Small Farms*, Wye College, June.

Mosley, P. (2002) 'The African green revolution as a pro-poor policy instrument', *Journal of International Development*, Vol. 14, pp.695–724.

Pingali, P., Bigot, Y. and Binswanger, H. (1997) *Agricultural Mechanisation and the Evolution of Farming Systems in Sub-Saharan Africa*, Washington, DC: World Bank.

Ruttan, V.W. and Thirtle, C. (1989) 'Induced technical and institutional change in African agriculture', *Journal of International Development*, Vol. 1, pp.1–45.

Thirtle, C., Lin, L. and Piesse, J. (2003) 'The impact of research led agricultural productivity growth on poverty reduction in Africa, Asia and Latin America', *World Development*, Vol. 31, No. 12, pp.1959–1975.