The Agricultural Exit Problem; an Empirical Assessment[1]

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Summary

As suggested by Engel's Law, this paper finds a strong and robust negative correlation between GDP per capita and the share of the labour force employed in agriculture. We exploit this relationship to project rates of exit from agriculture by 2015 for different regions of the world plus China and India. The results show that Asian countries have or soon will reach a tipping point in their agricultural transformation when the absolute size of the agricultural workforce will begin to decline and large numbers of agricultural workers can be expected to leave agriculture by 2015. China alone may have to accommodate an exit of between 50 and 70 million workers between 2000 and 2015, equivalent to 5-7 million per year. India is still adding to the size of its agricultural workforce, but this will change if the country continues to grow at the GDP growth rates attained in the 1990s. In that case India is projected to pass its tipping point and lose 6 million agricultural by 2015. This is equivalent to 386,000 workers per year.

These levels of exit will far exceed anything that has been experienced in the region in the past, and will pose serious challenges for employment creation in the non-agricultural economy. If Asia is to significantly reduce its levels of rural-urban income inequality, then the exit from agriculture will need to be even larger. The greatest danger for Asia is that exits will fall well below the levels required to maintain (let alone reduce) rural-urban income inequalities.

The situation in Africa is more sanguine. If African countries continue to grow slowly if at all, then their agricultural work forces will continue to increase to 2015, even though agriculture's employment share will fall slightly. We do not find any evidence that recent globalization has increased the exit elasticity for agriculture, so the threat to small farmers and agricultural employment in Africa may not be as serious as some experts fear. We do not see much change in LAC, MENA or EE&CA.

Introduction

History shows that most small farmers and agricultural workers leave agriculture over the course of the economic transformation of a country, leading to a sharp decline in the share of the labour force engaged in agriculture as average per capita incomes rise. This exit pattern is not new, but part of the global challenge we are seeing today arises because this transformation is happening on an unprecedented scale. For example, the rapid growth of Asian countries like China and India is leading to enormous pressure for many millions of small farms to adapt and/or find exit strategies, and this at a time when rural populations are still growing in many countries. Europe is still struggling to solve the remnants of its own small farm problem after several decades of highly expensive interventions. Yet the scale of the problem Europe faced after World War II was tiny compared to what Asia faces today.

But this is only part of the change that we are seeing today. New driving forces, particularly globalization, seismic shifts in development policy paradigms, and HIV/AIDS, are fundamentally changing the economic landscape within which the agricultural transformation must take place in developing countries. We are now seeing a situation in which small farms in all kinds of countries are threatened, even in countries where the normal economic transformation is not very advanced. Today we face the prospect of a mass exodus of workers from agriculture in all kinds of countries. But just how serious is this problem likely to be? This paper analyses historical data to develop quantitative projections to 2015 of the size of the exit problem for different continents and selected countries.

Approach

Exits from agriculture are defined to occur when a full time worker in agriculture leaves the sector. This is consistent with the usual census definition of the labour force. The exit may involve actual relocation from say a farm to an urban area, or it may involve remaining in rural areas (perhaps as a part time farmer) and diversifying into nonagricultural employment. Although this definition ignores part time exits by workers whose primary occupation remains in farming -- and hence may overestimate the amount of employment remaining in agriculture -- comparative cross country data do not exist to enable a broader definition to be used. We calculate expected exits from agriculture based on a) observed relationships between the growth and distribution of per capita national income and agriculture’s share in total employment, and b) projections of the per capita income growth rate and its distribution.

For policy purposes, our exit projections provide a direct measure of the number of full time workers that are expected to leave agriculture each year. These projections can be compared with projected growth in nonagricultural employment for a given country or region to see if an absorption problem is likely to arise or not. We expect the outlook to be very different in fast growing Asian countries like China and slow growing or stagnant countries such as found in much of Africa or the Middle East.

Conceptual Framework

The basic conceptual framework for our approach is that as countries get richer in terms of average per capita income, then consumption patterns change in accordance with Engel's Law leading to more rapid growth in demand for nonfoods than foods. In a closed economy this inevitably leads to declining shares of agriculture in national GDP and total employment. That is, growth in per capita income leads to changing consumption patterns, which in turn leads to an outflow of labour from agriculture and a diminishing agricultural employment share.

There are a number of factors that may modify this pattern to some extent for individual countries. International trade is one, especially for countries that are strongly competitive in world agricultural markets. In this case agriculture may continue as a relatively large sector because of its access to outside markets. Income inequality is another important factor. GDP growth that is less equitable will have different impacts on aggregate expenditure patterns and hence economic diversification than countries with similar but more equitable growth. But the cross-country empirical evidence for the basic inverse relationship between per capita income and the agricultural employment share is compelling (Figures 1 and 2).

FIGURES 1 AND 2

These figures show the share of agricultural employment in total employment[4] against the log of GDP per capita. They show scatter around univariate regression lines. The regional aggregates are unweighted regional averages based on a sample of countries for which data were available (see later). Thus, they may not correspond to true region-wide values. In Figure 2 we show movements in the period 1980-2000 for our regional averages.

The country data in Figure 1 show a strong negative relationship, but with considerable country variation due to factors like differences in comparative advantage and income inequality. As should be expected, the regional averages follow the regression line more tightly. Over time, Asia, China and LAC followed the expected pattern of falling agricultural employment shares as their per capita incomes rose. Sub-Saharan Africa and the Middle East experienced falling per capita incomes while agriculture's employment shares also shrank. This may be a sign of the general neglect of agriculture in Africa's growth strategy, but the MENA result is harder to explain. Transition countries in East Europe and Central Asia saw falling incomes with rising agricultural employment shares, primarily because the rest of the economy did so badly in the last days of socialism during the 1980s and again during the economic transition in the 1990s. This effect is mainly relevant to Central Asian countries, which are included in the 2000 figures but not in the 1990 figure.

The regression line can be interpreted as a long-term global equilibrium relation. From this perspective, regions under (above) the line have too few (too many) workers in agriculture. Sub-

[4] We prefer this to using the share of the agricultural *labour force* in the total labour force. The difference is the number of unemployed. Employment shares give a better measure of the number of people actually active in agriculture relative to those actually active in non-agricultural sectors. Thus, we avoid variations in the agricultural labour share purely due to statistical redefinitions of the labour force (e.g. based on job search registrations). We also capture the falling relative importance of agricultural employment if unemployment in nonagricultural sectors falls relative to unemployment in agriculture. Such a development would not be measured when using labour force shares.

Saharan Africa moved from having too many to too few workers relative to its (worsening) per capita income, another indication that it has been neglecting agriculture since 1980. China moved from below the regression line in 1980 (it was still below in 1990) to above the line in 2000, while experiencing rapid growth in per capita GDP. This suggests a growing backlog of workers is building up who will need to exit agriculture in the near future. A similar backlog may be emerging in the rest of Asia. The LAC region, in contrast, has been experiencing larger outflows of labour from agriculture than is commensurate with its income growth.

Although our primary interest is in how GDP growth affects the agricultural labour share, we recognize that these two variables are likely to be jointly determined as part of the growth process, particularly during the early stages of development when agriculture dominates GDP and its growth. To avoid endogeneity problems, we hypothesise the following structural relationships between the agricultural employment share (AESHARE), average per capita income (GDPpc) and factors determining economic growth:

(1) $\ln(AESHARE)_{ij} = C_{i1} + b*\ln(GDPpc)_{ij} + e_{i1}$

(2) $\ln(GDPpc)_{ij} = C_{i2} + [a_1*\ln(AESHARE) + a_2*(RUPID) + a_3*(LIT) + a_3*\ln(FIXCAP) + a_4*\ln(POP) + a_5*(YEAR)]_{ij} + e_{i2}$

Where j denotes country j (j=1,2,,…54) and i denotes year i (i= 1980, 1981, …, 2001).

To estimate this model we use an Instrumental Variables (IV) approach. Equation (2) is first estimated to obtain predicted values of GDPpc which are then used in the estimation of equation (1). As instruments in equation (2), we selected the literacy rate (LIT), annual gross fixed capital formation (FIXCAP), population size (POP), a measure of income inequality (RUPID), and a time trend (YEAR) which captures the overall development level not attributable to the other factors. To measure income inequality we use the ratio of rural to urban incomes, so that larger RUPID values indicate smaller rural-urban income inequality. We expect that inequality is growth reducing, and hence reduces the impact of GDP growth on AESHARE.

In order to assess differences by region and time period we disaggregated the data by five global regions plus China and India, and by the 1980s and 1990s. This reduced our sample size and hence scope for introducing additional growth controls in equation (2). We experimented with additional variables, such as ROADS (the length of the road network) and GDPpc1980s (the average GDPpc level 1980-1989) but both proved to be near linear combinations of the above variables. Thus, the growth model appears reasonably well specified, at least for the predictive purposes of IS. We also obtained very satisfactory R squares between 70 and 80 %.

Using equation (1), the exit elasticity for agricultural workers with respect to income growth is equal to the estimate of coefficient b. This is the relative decline in AESHARE for a 1% increase in GDPpc. By including AESHARE as an independent variable in the growth equation (2), the estimate for b in equation (1) can be interpreted causally as the elasticity of AESHARE with respect to growth. We expect to find different exit elasticities for different types of regions and countries. To gain a sense of how globalization may have led to shifts in the elasticity, each of the regional and global regressions were estimated separately for the 1980s and 1990s.

Data Considerations

Our analysis uses the Groningen Growth and Development (GGDC) database, which is based on national census data (for more details on the data, see Appendix A and http://www.ggdc.net**)**. We chose this data set over the more usual World Development Indicator data because serious anomalies and gaps were found in the latter data. In particular, the number of observations on agricultural employment is smaller, so that there are too few (or only a single) obervations per decade for a number of countries. This precludes estimation work by decade and increases the dependence of the results on a few observations. This was especially problematic since in the WDI data, our central variable, agricultural employment, had values which were in many cases far too small to be credible. This was sufficiently common to give us unreliable estimation and projection results when we first used this data set. For instance, Argentina, Peru, Colombia, Paraquay, Bolivia, El Salvador and Honduras are all recorded as having agricultural employment shares of less than 2% at some point in the 1990s; Djibouti has 2.2 % (1991), Nigeria 2.9 % (1995), Puerto Rico 3.4 % (1994), Surinam 3.7 % (1990), Turkey 4.8 % (1983), Morocco 6.3 % (1995), Ecuador 6.6 % 1998, Kenya 8.6 % (1986), and so on. It appears that these numbers are based on *urban* labour surveys, which were then erroneously extrapolated to country levels.

A common method of calculating rural-urban income differences is to use the ratio between agriculture's share in GDP and its share in the labour force. This is identical to the ratio between agricultural GDP per worker and total GDP per worker. Since this is the ratio between agricultural and total labour productivity, we called this ratio Relative Agricultural Labour Productivity, or RALP. We assume that it is a proxy for the gap between agricultural and other incomes. But RALP is a rather crude proxy for the income gap. A more sophisticated measurement was developed at the Centre for Efficiency and Productivity Analysis of the University of Queensland, Australia.

We briefly describe the methodology used to construct this measure for 'rural-urban primary income disparities' (RUPID); full details are in Heady (2006). GDP shares from the WDI were multiplied by aggregate GDP in 1996 international dollars from the Penn World Tables Version 6.1 (Summers and Heston 2002). Since the interest is not in labour productivity but in income measures, the population measures in the denominator must include workers and their dependents, which were taken from FAO estimates of agricultural and non-agricultural populations. The FAO uses a relatively consistent approach, compared to the rural and urban populations used in WDI, which have no common definitions of 'rural' and 'urban' across countries, and where there is no guarantee that most rural (urban) people are primarily engaged in agriculture (non-agriculture). Therefore defined 'rural' people were defined as households who obtain the majority of their income from agriculture, and conversely for 'urban' and non-agricultural income. These definitions were applied to FAO data. Agricultural value added in international dollars was then divided by the agricultural population, and non-agricultural output divided by the non-agricultural population, resulting in what might be termed rural and urban GDP per capita (although definitions of rural and urban are rather loose). The ratio of urban to rural GDP per capita is then adjusted by correcting for rural-urban price differentials. This purchasing power correction is useful since international dollars are calculated with national purchasing power parities (PPPs), supposedly weighted averages of agricultural and non-agricultural price levels. A literature review (see Heady, 2006) suggests that in developing countries, rural price levels are around 15-20% lower than urban price levels, depending on the basket of goods being compared. Applying this estimate to all implies the assumption that they have equal rural-urban price differentials; an examination of actual urban-rural price differentials within different countries suggests that this assumption approximately holds). The effect on urban-rural income differentials is different because it depends on the share size of the rural population. Thus, the ratio of urban to rural GDP per capita, using an appropriate definition of urban and rural populations and adjusting for rural-urban price differences gives the 'rural-urban primary income disparities' (RUPID). The term 'primary' refers to the fact that the household's primary, but not sole, source of income is agriculture or non-agriculture. For full details we refer to Heady (2006).

Estimation

Equation (2) was first estimated to provide predicted values for use in equation (1). Several methods for estimating equation (2) were tried, taking account of the nature of the data set used. Since many of the country-level time series of income and employment could be serially correlated leading to autocorrelation in the error terms, we introduced an autoregressive term of the first order. Given considerable heterogeneity in our data set, we also choose to allow this AR(1) term to vary over countries, so that a unique autoregressive term was computed for each panel. Second, given variation in the distribution of errors over time, we introduced a correction for heteroskedasticity.

Our sample includes countries of vastly different size, ranging from Gabon with a 2001 population 1.3 million to China with a 2001 population 1.3 billion, so population weighing and separating out China and India are also important in our estimation procedure. Unexpectedly, weighted agricultural employment shares for Asia are larger than for Africa. Although many small African countries have high employment shares in agriculture (e.g., in 1990, Malawi, Mali, and Niger all had shares over 90 % and populations of 10 or 11 million people), these and other small countries (with average population of 12.7 million) are dwarfed by the 127 million population of Nigeria, with an official agricultural employment share of only 44 % (1990). Hence the figures do not represent a typical African country and may clash with stylised facts based on unweighed country statistics (as in graph 2). Still, they are accurate in terms of millions of people and so for our purposes, population weighting is conceptually preferable to using unweighted averages. Because of their vast size, we also consider China and India both as separate regions; both have roughly the same population as the rest of Asia, and because of population weighting they would hide the other-Asian relation between growth and labour flows if included.

Similar considerations hold for interpreting the results. Unweighted Asian coefficients do not reflect the larger impact that, say, Pakistan (2001 population 141 million) has on the Asian agricultural exit problem than, say, Afghanistan (2001 Population 20 million). Therefore we used a population-weighted GMM estimation method to estimate equation (1), and this implies that the elasticity estimate *b* does not reflect the average country experience, but the average region-wide experience in growth and agricultural labour flows.

Finally, we explored whether RALP or RUPID is the better estimate of rural-urban inequality.

In sum, equation (2) was estimated in different ways. We label them models A to E:

Method of Estimating Equation (2)

Model	*Estimation method*
A	Uncorrected panel estimation
B	GLS with heteroskedasticity correction
C	GLS autoregressive, with and common AR(1) term
D	GLS autoregressive, and panel-specific AR(1) terms
E	GLS autoregressive, with AR(1) term and population weights

We do not report all the results here but based on this exploration we opted for estimating equation (2) with model D (a GLS autoregressive model, with panel-specific AR(1) terms and heteroskedasticity weights). The population weights correction was applied in equation (1), which is estimated with a GMM estimator.

Table 1 shows the estimation results for equation 1, using predicted values for GDPpc based on estimation method D for equation (2). We note that the panels are highly unbalanced, mostly because of changes over time in data availability but also because of new states created after 1990, for instance in Eastern Europe and Central Asia. The specification is double logged for both GDPpc and AESHARE so that, for instance, in Sub-Saharan Africa in the 1980s model D results in an elasticity indicating that AESHARE falls by 1.3 % for a one per cent increase in GDPpc. We find that the elasticities of AESHARE with respect to growth are consistently negative, but as expected the magnitudes vary greatly over time and by regions and countries.

Table 1. Elasticities of the agricultural employment share with respect to GDPpc , by regions in the 1980s, 1990s and 1980-2001

Region	**1980s**	**1990s**	**1980-2001**
Sub Saharan Africa	-1.32 (8)	-1.25 (12)	-1.28 (12)
Asia w/o China & India	-0.37 (8)**	-0.56 (9)	-0.82 (9)
Middle East & North Africa	-1.36 (5)	-1.00 (6)	-1.74 (6)
Latin America & Caribbean	-0.53(4)	-1.45 (11)	-1.57 (11)
Eastern Europe & Central Asia	-	-1.52 (10)	-1.44 (10)
China	-1.48	-0.28	-0.35
India	-0.50*	-0.04*	-0.21*

Source: GGDC data and author's calculations.

Notes:

1. The number of countries include in the estimations is given in parentheses. Elasticities are population-weighted coefficients resulting from IV regressions of the agricultural employment share on instrumented GDPpc. All elasticities are statistically significant, $p < 0.1$ %.
2. The 1980s are 1980-1991. The 1990s are 1992-2001. These are so defined because of sparser data in the 1980s.
3. There are insufficient data to estimate the elasticity for Eastern Europe & Central Asia (Soviet Union and satellite states) in the 1980s.
4. Note that the estimation of equation (2) is based on fewer countries than the estimation of equation (1).

*Because of poor data availability, all elasticities for India are based on a restricted equation (2) estimation, omitting FIXCAP.

**For the 1980s Asia estimate we dropped FIXCAP otherwise the estimates did not converge.

Asia has smaller exit elasticities than Africa, and those for China and India are even smaller. This may reflect the fact that fast growing countries are building up a backlog of workers who have not had time to exit agriculture. It might also reflect the much stronger rural nonfarm economy in Asia which offers more opportunities for farm households to diversify their income sources without actually leaving the farm (e.g. more part time farming). Workers may also be leaving agriculture prematurely in Africa because of its stagnation during the time period covered.

There is no statistically significant evidence to suggest that exit elasticities were higher in the 1990s than the 1980s, hence we cannot infer that globalization is accelerating the exit from agriculture. If anything, the results suggest the opposite, at least in Africa, China and India. There may have been an increase in the exit elastcitiy for Latin America.

Projections

To project AESHARE changes to 2015 we use the coefficients reported above together with projected values for total employment and GDPpc growth. We assume that:

- The total labour force will grow to 2015 at the rates published in ILO's (2004) Global Employment Trends. To convert these labour force projections to employed workers, we assume that growth in the labour force and growth in employment are identical, i.e. unemployment rates remains stable;
- Two scenarios for GDPpc growth rates for 2000-2015. One is that growth will continue at the average historical GDPpc growth rates for 1980-2001. The other is that GDPpc growth will continue at the rates of 1990-2001.
- That rural-urban inequality to 2015 will be mainly determined by development levels, with the relation between GDPpc growth and RUPID remaining the same as during 1980-2001. We note that RUPID has a 0.5031 bivariate correlation coefficient with GDPpc, and project a 2015 RUPID that starting from 2001 values, grows to 50.31 % of the GDPpc growth rate, (rather than applying 2000 RUPID values to 2015).

Expected Exits from Agriculture (EEA)

The resulting projections are shown in the tables below and compared to historical developments since 1980. We note that the numbers reported here differ from those in Graphs 1 and 2 because of different samples, and because here the regional averages are population weighted. We had to use a common sample for 1980, 1990 and 2000 which contained country-level data on the agricultural employment share, RUPID, and per capita income. This allowed us to use only 54 countries of the 69 countries plotted in Figure 1.

Table 2. GDP per capita, 1997 PPP adjusted Dollars

Region	1980	1990	2000	GDPpc growth rate 1980-2001	GDPpc growth rate 1990-2001
Sub Saharan Africa	1,476	1,289	1,309	-0.60	0.15
Asia w/o China & India	1,493	1,978	2,667	2.94	3.03
Middle East & North Africa	4,655	3,628	3,819	-0.99	0.51
Latin America & Caribbean	5,340	4,986	5,799	0.41	1.52
Eastern Europe & Central Asia	4,706	5,085	6,113	1.32	1.86
China	1,067	1,858	3,370	5.92	6.13
India	938	1,309	1,885	3.55	3.71

Source: GGDC data and author's calculations.
The 1980s are 1980-1991. The 1990s are 1992-2001. These are so defined because of sparser data in the 1980s.

Table 2 shows that based on 1980-2001 trends, Sub-Saharan African countries are projected to continue to experience negative growth in their GDPpc, while Asia, and especially China, will expand strongly. Weak growth will continue in LAC, MENA and the transition economies of East Europe and Central Asia. The projected growth rates based on 1990-2001 trends are marginally higher for most regions, and move from negative to positive for Africa.

Table 3. Projected rural-urban primary income ratios (RUPID), purchasing power adjusted

Region	1980	1990	2000	2015 projection
SSA	0 .26	0 .41	0 .49	0 .50
Asia w/o China, India	0 .29	0 .31	0 .33	0 .41
MENA	0 .34	0 .60	0 .47	0 .49
LAC	0 .32	0 .44	0 .49	0 .55
EE & CA	0 .66	0 .67	0 .69	0 .79
China	0 .17	0 .16	0 .11	0 .18
India	0 .41	0 .39	0 .34	0 .45

Source: GGDC data and author's calculations

Based on the projected 1980-2001 GDPpc growth rates and the rural-urban income ratios of 2000, we project in Table 3 that rural incomes in 2015 will remain at about half the level of urban incomes in LAC, Africa and MENA. China's growing inequality is expected to be reversed, with rural-to-urban income ratio's returning to their 1980s level of 17 % by 2015. India will also see an improvement in its rural-urban equality.

Table 4. Total employment, thousands

Region	1980	1990	2000	2015 projection (ILO)
SSA	11,741	15,601	20,350	29,472
Asia w/o China, India	28,488	39,170	47,078	58,858
MENA	6,017	8,682	12,271	18,034
LAC	23,281	32,731	38,130	49,100
EE & CA	13,988	14,989	15,455	15,455
China	425,102	647,490	720,850	800,363
India	241,534	315,152	366,021	406,395

Source: GGDC data and author's calculations.

Table 5. Agricultural employment to 2015, thousands

Region	1980	1990	2000	2015 projection (GDPpc growth rate 1980-2001)	2015 projection (GDPpc growth rate 1990-2001)
SSA	7,235	8,217	9,306	16,893	16,879
Asia w/o China, India	17,233	24,237	24,273	23,859	21,026
MENA	2,419	2,630	2,869	4,200	3,953
LAC	8,066	8,164	7,570	7,273	7,066
EE & CA	5,959	5,854	5,441	3,422	3,508
China	287,049	341,770	337,505	286,783	267,900
India	226,756	249,188	286,848	302,815	281,054

Source: GGDC data, ILO (2004) and author's calculations.

Table 6. Share of agriculture in total employment

Region	1980	1990	2000	2015 projection (1980-2001 GDP growth rate assumed)	2015 projection (1990-2001 GDP growth rate assumed)
SSA	0.71	0.65	0.59	0.57	0.57
Asia w/o China, India	0.60	0.63	0.53	0.41	0.36
MENA	0.45	0.33	0.25	0.23	0.22
LAC	0.34	0.26	0.21	0.15	0.14
EE & CA	0.41	0.36	0.35	0.22	0.23
China	0.68	0.53	0.47	0.36	0.33
India	0.94	0.79	0.78	0.75	0.69

Source: GGDC data and author's calculations.
by 2015, averaging to zero labour force growth over 2001-2015. For China and India we take the East Asia figure.

Table 7. Changes in total and agricultural employment to 2015, thousands

Region	Total employment growth 2000-2015	Ag. Employment growth (1990-2000)	Ag. Employment growth (1980-2001 GDPpc growth rate assumed)	Ag. Employment growth (1990-2001 GDPpc growth rate assumed)
SSA	9,123	1,089	7,587	7,572
Asia w/o China, India	11,780	36	-414	-3,247
MENA	5,763	239	1,331	1,084
LAC	10,970	-594	-297	-504
EE & CA	0	-413	-2,019	-1,933
China	79,513	-4,265	-50,722	-69,606
India	40,374	37,660	15,967	-5,794

Source: GGDC data and author's calculations.

All regions except EE&CA (with no change) will continue to see increases in their total number of employed workers to 2015 (Tables 4 and 7). All regions will also see a decline in their agricultural employment shares (Table 6).

Africa and MENA will also continue to see increases in their total number of agricultural workers, with little difference between the two GDPpc growth rate scenarios (Table 7). All other regions have either already passed or will soon pass a tipping point and see a decline in their number of agriculturally employed workers. China, LAC and EE&CA already saw a decline in their agricultural employment during 1990-2000.

China will see a particularly large decline in its agricultural employment with an exit of about 50-70 million workers between 2000 and 2015 depending on whether GDPpc growth continues at its 1980-2000 or 1990-2000 rates. This is equivalent to between 3.3 and 4.7 million exits per year, up from a yearly average of 0.4 million during the 1990s. This huge increase poses a serious challenge for China's non-agricultural economy; not only must large numbers of additional non-agricultural jobs be created but many of them will need to be located in the Western region where many of the exits will occur.

India saw an increase in its agricultural employment in 2000-2015, and a further increase is predicted if the country's GDPpc continues to grow at its average 1980-2000 rate. But if growth continues at the higher rate achieved during the 1990s, then India will pass its tipping point and agricultural employment will fall during 2000-2015. The rate of exit will average 386,000 workers a year between 2000 and 2015, which will have to be absorbed into an economy that will also face an increase of 40 million additional workers over this period (Table 7).

Discussion and Conclusions

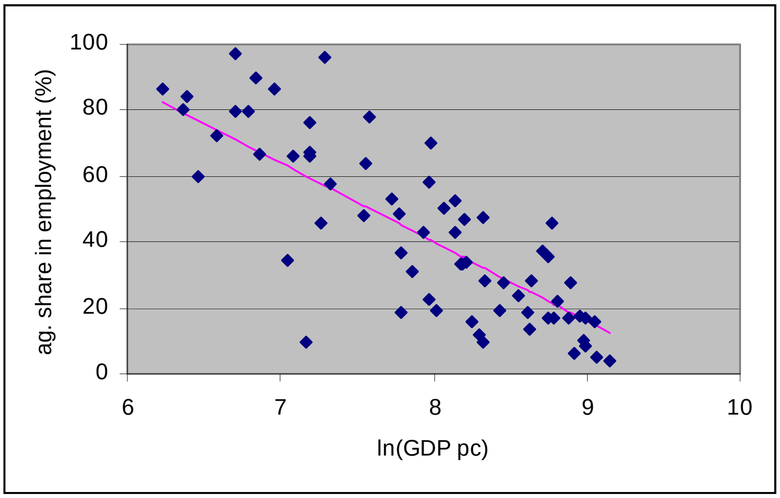
We have documented the development of agriculture's share in total employment in the developing world, and related this to developments in per capita income. As suggested by Engel's Law, we find a strong and robust negative correlation. We exploit this relation by estimating the relation between agriculture's share in total employment and the level and equality of incomes, and use these estimations to project development of agriculture's share in total employment for the five regions of the developing world plus China and India

Our results confirm the widespread intuition that most Asian countries have reached or will very soon reach a tipping point in their agricultural transformation. Whereas the agricultural workforce has mostly been growing until now, the calculations presented in this paper suggest that it will start to decline in the next few years -- or has already started to decline as in China. Our results show that large numbers of agricultural workers in Asia can be expected to leave agriculture by 2015. China alone may have to accommodate an exit of 50-70 million workers between 2000 and 2015, equivalent to 5-7 million per year, depending on whether one assumes that per capita income will continue to grow at the average rate for 1980-2000 or at the higher rate of the 1990s. India saw further growth in its agricultural employment during the 1990s, and is projected to add another 16 million workers by 2015 if GDP per capita grows at the average rate achieved in 1980-2000. But if the higher growth rate of the 1990s is continues, then India will soon pass its tipping point and 6 million workers will exit agriculture by 2015. This is equivalent to 386,000 workers per year.

The size of the projected exits in Asia will be challenging, and especially as many of the exits will occur in backward regions, where it is difficult to create adequate non-agricultural jobs. Unless managed well, this could lead to massive inter-regional migration with all the social dislocations that this implies. The rapid exit from Asian agriculture will arise in part because there is already a backlog of workers who should have left agriculture given recent high per capita income growth in these countries. The problem will progressively worsen if these countries continue to grow at rapid rates. If Asia is to significantly reduce its levels of rural-urban income inequality, then the exit from agriculture will need to be even larger. The greatest danger for Asia is that exits will fall well below the levels required to maintain (let alone reduce) rural-urban income inequalities.

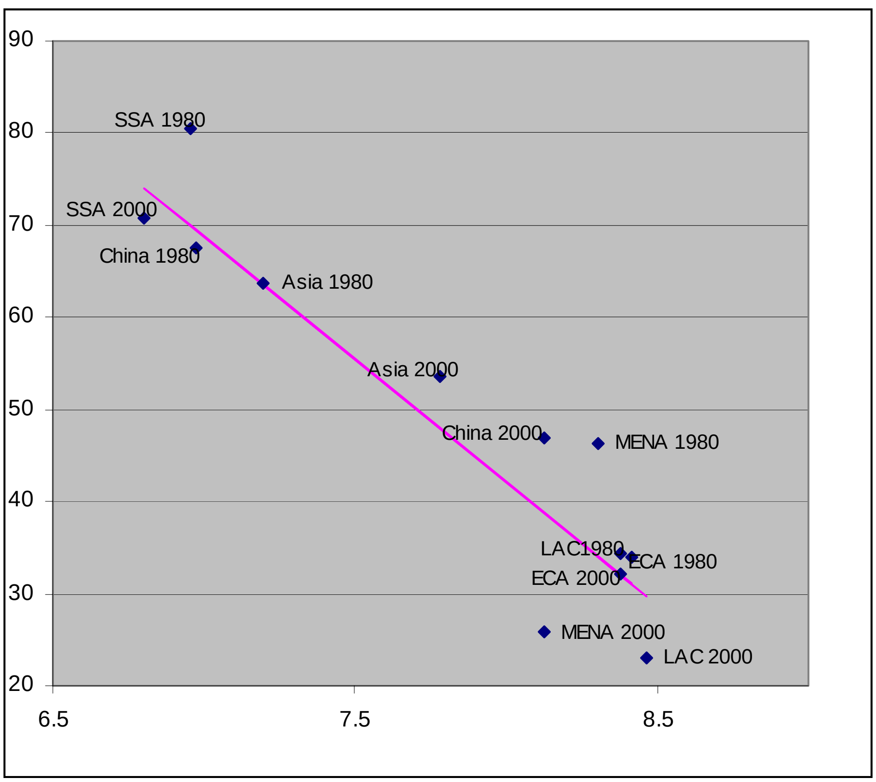
The situation in Africa is more sanguine. If African countries continue to grow slowly if at all, then their agricultural work forces will continue to increase to 2015, even though agriculture's employment share will fall slightly. We do not find any evidence that recent globalization has increased the exit elasticity for agriculture, so the threat to small farmers and agricultural employment in Africa may not be as serious as some experts fear. We do not see much change in LAC, MENA or EE&CA.

Graphs appendix



Note: Based on year 2001 data for 69 developing countries. The fitted line has an adjusted R-square of 0.63. Incomes are in constant, PPP adjusted dollars. Source: GGDC data base .

Figure 1. The inverse relationship between per capita income and the agricultural employment share



Notes: The regression line is fitted on 12 regional observation, with adjusted R-square of 0.70. The 1980 and 2000 figures for the share of employment in agriculture and for the log of GDP per capita are non-weighted averages of developing countries within a region. Developing countries include lower and middle-income countries. SSA denotes Sub-Saharan Africa; Asia denotes developing Asia without China; MENA denotes the Middle East and North Africa; LAC denotes Latin America and the Caribbean; ECA denotes Europe and Central Asia.

Figure 2. Regional Shifts in per capita income and the agricultural employment share

Data appendix A

Observations used for Figures 1 and 2

SSA	ASIA	MENA	LAC	EE&CA, 1980	EE&CA, 2000
Congo, DR	Malaysia	Algeria	Argentina	Albania	Albania
Cote d'Ivoire	Thailand	Iran	Bolivia	Bulgaria	Belarus
Ghana	Philippines	Iraq	Brazil	Hungary	Bulgaria
Kenya	Indonesia	Jordan	Colombia	Poland	Czech Rep
Madagascar	Sri Lanka	Morocco	Costa Rica	Romania	Georgia
Malawi	Pakistan	Saudi Arabia	Cuba	Turkey	Hungary
Mali	India	Tunisia	Dom. Rep.		Kazakhstan
Mozambique	Cambodia	Yemen, Rep.	Ecuador		Kyrgyzistan
Niger	Myanmar		Guatemala		Latvia
Nigeria	Vietnam		Mexico		Lithuania
Senegal	Bangladesh		Peru		Poland
South Africa			Uruguay		Romania
Sudan					Russia
Tanzania					Slovakia
Uganda					Tajikistan
Zambia					Turkey
Zimbabwe					Turkmenistan
					Ukraine
					Uzbekistan

Observations used in description & projections in Tables 3-6: identical samples for 1980, 1990 and 2000

SSA	ASIA	MENA	LAC	EE&CA	CHINA
Congo, DR.	Bangladesh	Algeria	Argentina	Albania	China
Cote d'Ivoire	Cambodia	Iran	Bolivia	Bulgaria	
Ghana	India	Iraq	Brazil	Hungary	
Kenya	Indonesia	Jordan	Colombia	Poland	
Madagascar	Malaysia	Morocco	Costa Rica	Romania	
Malawi	Myanmar	Saudi Arabia	Cuba	Turkey	
Mali	Pakistan	Tunisia	Dom Rep		
Mozambique	Philippines	Yemen, Rep.	Ecuador		
Niger	Sri Lanka		Guatemala		
Nigeria	Thailand		Mexico		
Senegal	Vietnam		Peru		
South Africa			Uruguay		
Sudan					
Tanzania					
Uganda					
Zambia					
Zimbabwe					

Data appendix B: Groningen Growth and Development Centre databases contents used in this paper

GGDC Total economy database

GDP pc, in 1990 international Geary-Khamis dollars and Total Employment come from the The Conference Board and Groningen Growth and Development Centre, *Total Economy Database*, September 2006, http://www.ggdc.net. The Total Economy Database consists of series on Real Gross Domestic Product, Population , Employment ,Annual Working Hours, GDP per Capita, GDP per Person Engaged and GDP per Hour for at most 124 countries from 1950 onwards representing about 96,2 per cent of the world population and an even larger share of world GDP (99%). The website http://www.ggdc.nl/dseries/totecon.html gives all details about construction of this database. This database is contructed for the International Labour Organisation and is published in their Key Indicators of the Labour (KILM) (http://www.ilo.org/public/english/employment/strat/kilm/).

GGDC Agricultural Data Base

Total employment in agriculture is derived from the GGDC, Agricultural Data Base, 2006. This database contains information on GDP (in national and international prices) and employment in agriculture for 113 countries from 1960 onwards, representing 99.% % of world agricultural output. This database is contructed for the International Labour Organisation and is published in their Key Indicators of the Labour (KILM) (http://www.ilo.org/public/english/employment/strat/kilm/). It uses a multitude of national and international sources to compile consistent and comparable series of output and labour input over time and across countries. There is a variety of sources available for each of the countries. Based on our experience with other databases and reliability checks we have defined the following ranking of sources. The procedure to build up the database was to look at the availability of source 1, and proceed to lower ranked sources if there was no data available, and check the resulting time series for consistency and reliability.

1 GGDC 60 Industry database, see http://www.ggdc.nl/dseries/60-Industry.html
2 OECD STAN
3 OECD National Accounts
4 OECD National Accounts (Historical data)
5 OECD Labour Force Statistics
6 ILO, Laborstats database
7 Asian Development Bank, Key Indicators
8 EUROSTAT, SBS database.
9 Country specific sources
10 Worldbank, World Development Indicators
11 FAO, FAOSTAT database
12 UNECE, Statistical Division Database

For more details see Ypma (2006), The GGDC Agricultural database: sources and methods, forthcoming Groningen Growth and Development Centre.