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Abstract

Drawing upon panel data estimations, we have analysed the relationships among agricultural productivity, employment, technology, openness of the economy, inequality in land distribution and poverty. First, we have identified a number of important factors affecting agricultural productivity, such as agricultural R&D expenditure, irrigation, fertilizer use, agricultural tractor/machinery use, reduction in inequality of land distributions, or reduction in gender inequality. Second, while agricultural wage rate is negatively associated with agricultural productivity and food price in levels, the growth in agricultural wage rate is positively correlated with the growth in agricultural land or labour productivity as well as with the growth in food price, particularly after 2000. Contrary to the ILO's (2012) claim that the gap has widened recently, this suggests the narrowing gap between wage and labour productivity once we focus on the conditional relationship between the two. Third, agricultural employment per hectare tends to increase agricultural productivity after taking account of the endogeneity of the former, while the growth in agricultural employment per hectare tends to increase the growth in non-agricultural employment over time with adjustment for endogeneity of the former. In this context, we have reviewed the recent literature and emphasised the importance of enhancing agricultural productivity and employment. Fourth, both agricultural growth and non-agricultural growth tend to lead to reduction in overall inequality. Finally, increase in agricultural productivity which is treated as endogenous will reduce poverty significantly through the overall economic growth. Overall, policies to increase agricultural productivity and agricultural employment are likely to increase non-agricultural growth, overall growth and reduce poverty, where guaranteeing gender inequality is likely to be one of the key factors.

JEL Codes: C20, I15, I39, O13

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Agricultural Employment, Wages and Poverty in Developing Countries

I. Introduction

The purpose of this paper is to re-examine the relationships among agricultural productivity, employment, wage rates and poverty, based on econometric analysis of cross-country panel data. We propose to extend our study (Gaiha and Imai, 2008) by (i) updating the datasets, (ii) adding a few additional variables, such as, gender indices[1], and (iii) estimating poverty by a system of equations where agricultural productivity is treated as an endogenous variable.

Although agricultural growth is central to economic growth and poverty reduction in developing countries, there have been relatively few studies to analyse the determinants of agricultural growth and to link poverty reduction to growth of employment in agriculture using cross-country datasets, with Gaiha and Imai (2008) as one of the few notable exceptions. As we discussed recently in a series of studies (Imai and Gaiha, 2014; Imai, Gaiha, and Garbero, 2014; Imai, Abekah-Nkrumah, and Purohit, 2014), contrary to the recent study by Collier and Dercon (2013) questioning the role of smallholders in development process, we have shown that agricultural growth has played a key role in the overall economic growth and poverty reduction. In this context, the present study uses cross-country panel data and investigates the relationships among agricultural productivity, employment, wage rates and poverty, using state-of-art econometric methods.

The rest of the paper is organised as follows. The next section discusses the background issue to motivate our econometric study. Section III outlines the data sources and variables. Section IV presents the econometric models we will use, followed by discussions of econometric results in

[1] The gender equality index (discrete variable taking values from 1 to 5) assesses the extent to which the country has installed institutions and programs to enforce laws and policies that promote equal access for men and women in education, health, the economy, and protection under law. See p.8 for the definition and discussions of the gender equality index.

Section V. Section VI reviews the recent literature on agricultural youth employment. Section VII offers concluding observations.

II. Background - Employment, Wages, Productivity and Poverty[2]

In 2013, global economic growth slowed down to 2.9 per cent, its lowest rate since 2009 and more than 1 percentage point below the average annual growth rate over the pre-crisis decade[3]. The only two regions worldwide in which growth did not slow between 2012 and 2013 were South Asia and East Asia, which saw accelerations from 3.6 to 3.9 per cent and from 6.6 to 6.7 per cent, respectively. All other regions lost momentum in growth, with Central and South-Eastern Europe growing at a rate of 2.5 per cent, Latin America and the Caribbean at 2.7 per cent and Sub-Saharan Africa at 4.8 per cent in 2013. A more pronounced deceleration took place in South-East Asia and the Pacific, where the growth rate dropped from 5.7 per cent in 2012 to 4.9 per cent in 2013. The largest growth decelerations took place in the Middle East and North Africa, mainly due to political events (ILO, 2014)

Responding to this slowdown of overall economic growth, employment growth also slowed down in 2013 across most regions, leading to a further upward revision of unemployment rates. Global employment grew by a mere 1.4 per cent in 2013 - broadly unchanged from 2012, but lower than in any year of the pre-crisis decade. Employment growth deteriorated in every geographic region except South Asia and North Africa. The largest slowdowns occurred in Central and South-Eastern Europe and CIS, Latin America and the Caribbean and South-East Asia and the Pacific. As a consequence, the crisis-related global jobs gap, measuring the number of jobs lost in comparison to pre-crisis trends, widened further to 62 million workers in 2013. As

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[2]This section draws upon Section 6 of Gaiha (2014a).
[3]Much of this review is based on ILO (2012, 2014).

unemployment continues to persist, by 2018 the global gap is projected to rise to 81 million; this includes some 30 million discouraged workers who might never come back to the labour market (ILO, 2014).

The labour market outlook for young people worsened in nearly every region of the world. The global youth unemployment rate rose to 13.1 per cent in 2013, from 12.9 per cent in 2012 and 11.6 per cent in 2007. The largest increase occurred in the Middle East region. This region has one of the highest youth unemployment rates in the world, with 27.2 per cent of young people in the labour force without work in 2013, versus 26.6 per cent in 2012. Central and South-Eastern Europe and CIS, East Asia, South-East Asia and the Pacific and North Africa all saw a substantial increase in youth unemployment rates (ILO, 2014).

By sector, services accounted for more than half of total global employment growth in 2013, while agricultural employment accounted for around one quarter. Overall, just below 32 per cent of the world's workforce was employed in the agricultural sector in 2013, a decline of 11.7 percentage points over the previous two decades. The services sector employed 45.1 per cent of the world's workers in 2013 and the share of services workers increased by 10.1 percentage points over the same period. Industrial employment now accounts for around 23 per cent of all global employment, an increase of only 1.6 percentage points over the past two decades.

Monthly average wages adjusted for inflation - known as real average wages - grew globally by 1.2 per cent in 2011, down from 2.1 per cent in 2010 and 3 per cent in 2007. Because of its size and strong economic performance, China weighs heavily in this global calculation. Omitting China, global real average wages grew at only 0.2 per cent in 2011, down from 1.3 per cent in 2010 and 2.3 per cent in 2007 (ILO, 2012).

The global trend (productivity rising faster than wages) has resulted in a change in the distribution of national income, with the workers' share decreasing while capital income shares increased in a majority of countries. Even in China, a country where wages roughly tripled over the last decade, GDP increased at a faster rate than the total wage bill - and hence the labour share went down. The drop in the labour share is due to technological progress, trade globalization, the expansion of financial markets, and decreasing union density, which have eroded the bargaining power of labour. Financial globalization, in particular, may have played a bigger role than previously thought. One of the key findings is the growing inequality in income, in terms of *functional* and *personal* income distribution.

There is a long run trend towards a falling share of wages and a rising share of profits in many countries. The personal distribution of wages has also become more unequal, with a growing gap between the top 10 per cent and the bottom 10 per cent of wage earners. These internal "imbalances" have tended to create or exacerbate external imbalances, even before the Great Recession, with countries trying to compensate the adverse effects of lower wage shares on consumption demands through easy credit or export surpluses (ILO, 2012).

ILO (2012, pp 47-53) argued that the gap between labour productivity and wages has been expanding due to the declining share of labour in comparison with the share of profits in many countries. However, it is unclear whether the gap between labour productivity and wages has actually narrowed for developing countries - for which the wage data are limited. Also, even if the share of labour has declined, it may not necessarily imply a narrowing gap between labour productivity and wages. The present study will partly address the issue by estimating the conditional relationship between the growth rate of nominal and real wage rates and the growth rate of labour productivity. The results imply that the gap between the two has been narrowing after 2000.

In Latin America and the Caribbean, job quality continued to improve. In particular, working poverty or the share of workers living in households with consumption levels of less than US$2 per day and per person showed a clear and consistent improvement in the past decade, falling from 15 per cent of total employment in 2003 to an expected 6.7 per cent in 2013. The share of East Asia's workers living on less than US$1.25 per day fell to 4.5 per cent in 2013 and the comparable share under the US$2-poverty line declined to 11.2 per cent. Since 1991, the region has successfully moved 464.5 million workers out of poverty, an astounding and unprecedented pace of improving household incomes and living standards**.** In South East Asia and the Pacific, the share of workers earning less than US$2 a day is estimated to have declined notably, from 62.3 per cent in 2000 to 30.5 per cent in 2013[4]. In this study, we propose to build on our earlier work (Gaiha and Imai, 2008) to re-examine the relationships among agricultural productivity, employment, wage rates and poverty.

III. Data

Following Gaiha and Imai (2008), we have construct the panel data from various data sources, such as, World Development Indicators or WDI 2014 (World Bank, 2014), FAOSTAT (FAO, 2014), and LABORSTA (ILO, 2014). The data on agricultural R&D (government expenditure) are sourced from FAOSTAT. Gender index is based on WDI 2014. We still face a constraint that agricultural wage series and R&D data are available only for a limited number of developing countries. Appendix provides the descriptive statistics of variables.

[4]Estimates of working poor in South Asia are not given in ILO (2014).

IV. Econometric Models

Econometric specifications follow Gaiha and Imai (2008) and we extend them to examine the effcts of agricultural productivity based on Imai and Gaiha (2014). The following models are estimated. Model 1 aims at analysing the relationship among agricultural productivity, employment, new technologies, and wage rates. In Model 2, the focus shifts to growth rates of farm and non-farm employment, and the relationship between them.

Model 1: Model for the relationships among agricultural productivity, employment, technology, openness of the economy, inequality in land distribution

Model 1 is formulated to assess the determinants (e.g. technology, R&D, agricultural employment, inequality in land distribution, openness) of agricultural production per hectare of arable land (hereafter referred to as agricultural productivity). Agricultural wage is included as an additional endogenous variable, determined by food price and agricultural productivity.

$$\log Y_{a,it} = \alpha + \beta_1 \, logAm_{it} + \beta_2 logIrr_{it} + \beta_3 logFert_{it} + \beta_4 logL_{it} + \beta_5 logAgriR\&D_{it} + \beta_6 logGINI(Land)_i + \beta_7 Open_i + \beta_8 Gender_{it} + \gamma_t + \pi_i + \varepsilon_{it} \qquad (1)$$

where $\log Y_{a,it}$ is log of value added per hectare of arable land (in constant 2005 US

dollars, taken from WDI2014) i denotes country, and t denotes year. $\log Y_{a,it}$ measures a country's agricultural productivity. The explanatory variables include technology comprising log of agricultural machinery/ tractors per hectare of arable land ($logAm_{it}$)[5], log of share of irrigated

[5] $logAm_{it}$ captures the total value of powered agricultural machinery and tractors (in use) as an aggregate category and as such these are labour saving equipment in nature. We realise the importance of

land in total arable land ($logIrr_{it}$), and log of fertiliser consumption per hectare of arable land ($logFert_{it}$); $logL_{it}$ refers to log of total employment in agricultural sector per hectare of arable land (based on WDI2014); $logAgriR\&A_{it}$ is log of agricultural R&D expenditure her hectare (in constant 2005 US dollars, taken from FAOSTAT2014)[6] $\beta_6 logGINI(Land)_i$ is log of Gini coefficient of land distribution to capture the inequality in land distribution. Lower inequality in land distribution is likely to be associated with better incentives as well as higher efficiency of small farmers or labourers in agricultural production or activities. This raises total agricultural productivity and production.

$Open_i$ refers to openness of an economy to the rest of the world or to degree of integration with global markets. We have used trade share (the share of sum of exports and imports in GDP), Frankel-Romer measure and Sachs-Warner measure. The Frankel-Romer index is the aggregated fitted values of trade share, derived from a bilateral trade equation with geographical variables (e.g., area, population) (Frankel and Romer, 1999) On the other hand, the Sachs and Warner measure is a binary variable based on a series of trade related indicators- tariffs, quotas, black market premium, social organisation and the existence of export marketing boards (Sachs and Warner, 1995).

$Gender_{it}$ is the gender equality index (discrete variable taking values from 1 to 5) which assesses the extent to which the country has installed institutions and programs to enforce laws and policies that promote equal access for men and women in education, health, the economy,

distinguish the type of implements by e.g. the requirement for labour use, but FAOATAT does not allow us to do so for the sample countries.

[6] Gaiha and Imai (2008) used Thirtle, Lin and Piesse (2003), but we use FAOSTAT2014 because the latter covers more countries.

and protection under law.[7] γ_t is a time effect constant for all countries for a particular year, π_i is an unobservable individual (country) effect, and ε_{it} is an *i.i.d.* error term. The coverage of countries and the period considerably varies according to the specifications (Table 1)

Equations (2) and (3) specify the determinants of agricultural employment and wage rates, respectively.

$$logL_{it} = \chi + \delta_1 logYa_{it} + \delta_2 logWage_{it_{it}} + \delta_3 logNon - Cereal_{it} + \delta_4 Gender_{it} + \upsilon_i + \mu_i + \omega_{it} \qquad (2)$$

where $logL_{it}$, log of agricultural employment per hectare, is estimated by $logYa_{it}$, log of agricultural value added, and log of monthly agricultural wage, $logWage_{it}$. Monthly agricultural wages have been taken from LABORSTAT, the ILO data set. We use both nominal agricultural wage rate - which has been derived as "average agricultural monthly wage rate in local currency adjusted only by exchange rates" (Table 2a) - and real agricultural wage rate, "average agricultural monthly wage rate in local currency adjusted only by both annual average Consumer Price Index and exchange rates" (Table 2b). $logNon - Cereal_{it}$ is the share of land used for crops other than cereal crops in total arable land. This is a proxy for agricultural diversification towards high value commodities, e.g. fruits and vegetables. $Gender_{it}$ is the gender index. χ is a constant term, υ_i is a time effect, μ_i is an individual (country) effect, and ω_{it} is an error term.

Log of Agricultural wages is estimated by equation (3):

$$logWage_{it} = \phi + \varphi_1 logYa_{it} + \varphi_2 logFoodPrice_{it} + \varphi_3 \log \mathrm{Schooling}\, Yeas(primry) + \varphi_4 logPopulation\ Growth_{it} + \varphi_5 logInflation + \zeta_t + \pi_i + \epsilon_{it} \qquad (3)$$

[7] It is noted that employment and wage data disaggregated by gender and aggregated at country levels are unavailable for most of the sample countries. Gender Index has thus been used to address the gender issue of employment and wage.

where $logWage_{it}$ refers to either log of *nominal* agricultural wage rate (the results of which are presented in Table 3a) or log of *real* agricultural wage rate (Table 3b). $logYa_{it}$, our proxy for the agricultural productivity, has been inserted to examine how agricultural productivity has been translated into wage rates. $logFoodPrice_{it}$ is log of consumer food price index, which will negatively affect real wage rates, or negatively or positively affects nominal wage rates depending on the general-equilibrium effect of food price on wage rates, which could be positive or negative. Log Schooling $Yeas(primry)$ is log of average years of schooling years at the level of primary education. The expected sign is positive as the quality of labour force tends to be improved by education. $logPopulation\ Growth_{it}$ is log of population growth that captures the increase in labour supply of younger generations. $logInflation$ is log of the rate of inflation, which captures the inflationary pressure of the economy (e.g. excessive money supply) or the degree of uncertainty of the economy. The inflation is supposed to reduce real wage rate, while nominal wages are slow to adjust to the change in prices. ϕ is a constant, ζ_t is a time effect, π_i is an individual (country) effect, and ϵ_{it} is an error term.

As an extension, we will examine the effect of agricultural and non-agricultural employment on wage rate by adding $logL$ and $logLN$ as explanatory variables, as in Equation (3)'.

$$logWage_{it} = \phi + \varphi_1 logYa_{it} + \varphi_2 logFoodPrice_{it} + \varphi_3 \log \text{Schooling}\, Yeas(primry) + \varphi_4 logPopulation\ Growth_{it} + \varphi_5 logInflation + \varphi_6 logL + \varphi_7 logLN + \zeta_t + \pi_i + \epsilon_{it} \quad (3)'$$

In order to examine the dynamic relationship between agricultural wage rate and agricultural productivity over time and how the relationship between the two variables has changed over time, it would be necessary to examine the change in agricultural wage rates and the change in the agricultural wage rate. As a variant of (3), we will estimate the equation (3)".

$$DlogWage_{it} = \phi' + \varphi'_1 DlogYa_{it} + \varphi'_2 DlogFoodPrice_{it} + \varphi'_3 D \log \text{Schooling}\, Yeas(primry) + \varphi'_4 DlogPopulation\ Growth_{it} + \varphi'_5 DlogInflation + \zeta'_t + \pi'_i + \epsilon'_{it} \qquad (3)”$$

As an extension, $DlogYa_{it}$ has been replaced by the first difference of log Agricultural Value Added per Worker to examine the relationship between the growth rate of labour productivity and that of wage rate (Table 3c).

We cannot apply simultaneous system equations estimation because of the small overlap between samples for different variables. For efficient use of these samples, a compromise is made. First, equations (1)-(3) are estimated separately as fixed-effects or random-effects specifications.[8] Second, we estimate real agricultural wages using fixed or random effects specifications of equation (3) Using the predicted values, we use IV (instrumental variable) specifications for equations (1) and (2) simultaneously.

Model 2: Model for agricultural and non-agricultural employment growth

Following Gaiha and Imai (2008), we estimate an alternative model for agricultural employment growth and non-agricultural employment growth. While Gaiha and Imai used the Arellano-Bond GMM estimator (Arellano and Bond, 1991) to estimate the dynamic panel model, the present study applies Blundell and Bond (1998)'s System GMM (SGMM) estimator[9] which builds upon the Arellano-Bond GMM model and is implemented with the finite sample correction of the two-step standard errors proposed by Windmeijer (2005). First, agricultural employment growth is estimated as a function of lagged growth rates of agricultural employment growth, lagged

[8] The issue of endogeneity will be addressed later.

[9] Blundell and Bond's System GMM uses additional moment conditions as the Arellano and Bond estimator may perform poorly if the autoregressive parameters are too large or the ratio of the variance of the panel-level effect to the variance of idiosyncratic error is too large.

changes in agricultural wage rates – which are treated as endogenous in SGMM - and lagged changes in share of area devoted to non-cereal crops in the total arable area. Here growth rates can be expressed as the first differences of logarithmic transformation of a variable. Second, the growth in non-agricultural employment is estimated by its own lags and the agricultural employment growth which is treated as endogenous , and it is instrumented by its own lagged values in the SGMM model.

$$DlogL_{it} = \beta_1 logL_{it-1} + \beta_2 logL_{it-2} + \beta_3 DlogYa_{it-1} + \beta_4 DlogYa_{it-2} + \beta_5 DlogWage_{it-1} + \beta_6 DlogNon - Cereal_{it-1} + \varepsilon_{it} \quad (4)$$

$$DlogLN_{it} = \pi_1 DlogLN_{it-1} + \pi_2 DlogLN_{it-2} + \pi_3 DlogL_{it-1} + \pi_4 DlogL_{it-2} + e_{it} \quad (5)$$

where LN_{it} denotes non-agricultural employment (defined as the total number of people employed in sectors other than agriculture). The growth rate of non-agricultural employment, $DlogLN_{it}$, is estimated by its own lags and the growth rates of agricultural employment ($DlogL_{it-1}$ and $DlogL_{it-2}$) where they are treated as endogenous and instrumented by their own lags in SGMM, in order to examine the effects of growth of agricultural employment on that of non- agricultural employment over time.

Model 3: Model for the effect of agricultural value added per capita growth and non-agricultural per capita growth on the change in inequality

To see the overall relation between agricultural and non-agricultural growth on inequality changes, in one of our recent papers, we have applied various models (e.g. static and dynamic panel models) in Imai and Gaiha (2014). As an extension of this study, in equation (6), we have estimated $DInequality_{it}$, the first difference in inequality, by $log\ \widehat{Agri\,VA}\ pc_{it}$, the predicted value of the first difference in agricultural value added per capita, and $log\ Non\widehat{Agri}\ VA\ pc_{it}$, the predicted value of the first difference in non-agricultural value added per capita.

$$DInequality_{it} = \vartheta'_0 + \vartheta'_1 DInequality_{it-1} + \vartheta'_2 Dlog\ \widehat{Agri}\ VA\ pc_{it} + \vartheta'_3 Dlog\ Non\widehat{Agri}\ VA\ pc_{it} + \vartheta'_4 D\widehat{log\ L}_{it} + \vartheta'_5 D\widehat{log\ L}N_{it} + \sigma'_t + \mu'_i + \varepsilon'_{it} \qquad (6)$$

Here we have added the first difference in log of agricultural employment per hectare and the first difference in log of non-agricultural employment per hectare as explanatory variables - which have been predicted by Model 2 - to examine the effects of changes in agricultural or non-agricultural employment on the change in inequality. In equation (6), the dynamic panel model, based on the Blundell and Bond's SGMM estimator, has been applied to incorporate the effect of the lagged inequality changes on the current inequality change.

$$DInequality_{it} = \vartheta"_0 + \vartheta"_2 Dlog\ \widehat{Agri}\ VA\ pc_{it} + \vartheta"_3 Dlog\ Non\widehat{Agri}\ VA\ pc_{it} + \vartheta"_4 D\widehat{log\ L}_{it-1} + \vartheta"_5 D\widehat{log\ L}N_{it-1} + \sigma"_t + \mu"_i + \varepsilon"_{it} \qquad (6)'$$

As an alternative specification, the static panel model has been estimated, as in equation (6)'. In this specification, the growth terms in agricultural and non-agricultural employment have been lagged.

Model 4: Model for agricultural productivity and Poverty

As an extension of Model 1, we apply 3SLS (three stage least squares) to the following system equations (1)', (7) and (8) for (lagged) $\log Y_{a,it}$ (log of value added per hectare of arable land), our proxy for agricultural productivity, $logGDPpc_{it}$ (log of GDP per capita) and $Poverty_{it}$

(*either* poverty gap *or* poverty headcount ratio based on the international poverty line (US$1.25 or US$2.00)) as an extension of Imai and Gaiha (2014).

$\log Y_{a,it-1} = \gamma_0 + \gamma_1\, logAm_{it-1} + \gamma_2 logIrr_{it-1} + \gamma_3 logFert_{it-1} + \gamma_4 TradeOpen_{it-1} + \vartheta_t + Region + \varepsilon_{it-1}$ (1)’

$logGDPpc_{it} = \beta_0 + \beta_1 Conflict\ Intensity_{it} + \beta_2 logYa_{it-1} + \beta_3 TotNonofg_{it} + \beta_4 Inequality_{it-1} + \tau_t + Region + \omega_{it}$ (7)

$Poverty_{it} = \alpha_0 + \alpha_1 Conflict\ Intensity_{it} + \alpha_2 TotNonofg_{it} + \alpha_3 logGDPpc_{it} + \kappa_t + Region + e_{it}$ (8)

The specification for $\log Y_{a,it}$ (equation (1)’) is similar to equation (1), but we adopt a simplified version to make the estimation feasible given the limited sample availability of explanatory variables for equation (1) Here we take the first period lag in estimating equation (1)’ considering the fact that the agricultural productivity, $logYa_{it}$, is endogenous to $logGDPpc_{it}$, log of GDP per capita. The lagged value of $\log Y_{a,it}$ is estimated by the lagged value of $logAm_{it}$ (log of agricultural machinery/ tractors per hectare of arable land), the lag of log share of irrigated land in total arable land ($logIrr_{it-1}$), and the lag of log fertiliser consumption per hectare of arable land ($logFert_{it-1}$) as well as the lagged value of trade openness ($TradeOpen_{it-1}$) To capture the effect of time as well as the regional fixed effects, we have inserted, time effects, ϑ_t, and $Region$, or a set of regional dummy variables for six regions (namely, South Asia; East or South East Asia and the Pacific; Sub-Saharan Africa; Middle East & North Africa; Latin America & the Caribbean; Central Asia & East Europe – where Middle East & North Africa is the reference case) ε_{it} is the error term, supposed to be independent and identically distributed (i.i.d.).

Following Imai and Gaiha (2014), $logGDPpc_{it}$ in equation (7) is estimated by $Conflict\ Intensity_{it}$, capturing the intensity of conflict obtained from CSCW and Uppsala Conflict Data Program (UCDP) at the Department of Peace and Conflict Research, Uppsala University (available at http://www.pcr.uu.se/research/UCDP/). This covers armed conflicts, both internal and external, in the period 1946 to the present. To take account of the endogeneity of agricultural productivity, the lagged value of $logYa_{it}$ (estimated simultaneously by equation (1)') is used to capture the effect of agricultural productivity on the overall economic growth over time. Other explanatory variables include $TotNonofg_{it}$ as a measure of the uncertainty in the export price (excluding oil, food and gold) at the country level estimated by GARCH (1, 1) (Imai and Gaiha, 2014). Lagged value of the inequality has been inserted to capture the effect of inequality on growth (ibid., 2014). Regional dummies and time effects have also been inserted in equation (7).

To capture the effect of economic growth on poverty after taking account of the effect of agricultural growth on the former, poverty gap or headcount ratio is estimated in equation (8) by $Conflict\ Intensity_{it}, TotNonofg_{it}$ (uncertainty in export price), and $logGDPpc_{it}$, which are simultaneously estimated by equation (7). Time effect, κ_t, regional dummies and the error term, e_{it} have also been used to estimate equation (8).

V. Econometric Results

This section summarises the econometric results for Models 1, 2, 3 and 4 outlined in the last section to derive a few useful insights into the relationships among agricultural productivity, employment, wage rates and poverty. As the results are voluminous, we will provide explanations selectively.

Model 1: Model for the relationships among agricultural productivity, employment, technology, openness of the economy, and inequality in land distribution

Tables 1a and 1b report the results for equation (1) where log Ya, agricultural value added per hectare, is estimated. Depending on the inclusion of time effects, the choice of explanatory variables (varying due to the limited country coverage of a few explanatory variables) and the choice of the model (whether fixed-effects (FE) model or random-effects (RE) model is selected). We have indicated the coefficient estimates favoured by Hausman specification tests in bold. Below our explanations are mainly based on the models which are selected by Hausman specification test. Coefficient estimates of year dummies are not included to save the space.

Table 1a: Elasticity estimates of agricultural value added per hectare (Model1, Single Equation (1)): Dependent Variable: log Ya = Agricultural value added per hectare; Fixed Effects (FE) or Random Effects (RE) Model

Column No.	(1)	**(2)**	**(3)**	(4)	**(5)**	(6)	(7)	**(8)**	(9)	**(10)**
EXP. VARIABLES	FE	**RE**	**FE with time effects**	RE with time effects	**FE**	RE	FE	**RE**	FE with time effects	**RE with time effects**
logAm	0.232***	**0.215*****	**0.067**	0.376***	**-0.024**	-1.068	0.122***	**0.0960*****	0.146***	**0.115*****
	(0.0277)	**(0.0263)**	**(0.0423)**	(0.0240)	**(0.731)**	(0.827)	(0.0369)	**(0.0353)**	(0.0240)	**(0.0246)**
logTrade	0.104	**0.149****	**-0.133*****	-0.269***	**-2.823**	-0.445	0.362***	**0.363*****	0.124***	**0.131*****
	(0.0680)	**(0.0651)**	**(0.0414)**	(0.0902)	**(1.784)**	(1.512)	(0.0413)	**(0.0410)**	(0.0330)	**(0.0357)**
logAg R&D			**-0.02**	0.0834***			0.102***	**0.108*****	0.0430*	**0.0458***
			(0.0421)	(0.0319)			(0.0363)	**(0.0349)**	(0.0246)	**(0.0253)**
logIrr	-0.613*	**0.032**		-0.234***	**0.241**	0.598	0.014	**0.149****	-0.069	**0.164*****
	(0.357)	**(0.109)**		(0.0365)	**(0.552)**	(0.568)	(0.111)	**(0.0714)**	(0.0796)	**(0.0469)**
logFert	1.398***	**0.602*****		0.772***	**-0.237**	0.743***	0.267***	**0.213*****	0.044	**0.120****
	(0.374)	**(0.167)**		(0.0505)	**(0.366)**	(0.107)	(0.0971)	**(0.0771)**	(0.0725)	**(0.0538)**
logLandGini		**-4.017*****		-7.061***						
		(0.951)		(0.410)						
Gender					**-0.385**	0.875**				
					(0.368)	(0.368)				
Year Dummies	**No**	**No**	✓ **1982 -2006**	✓ **1982 -2006**	**No**	**No**	**No**	**No**	✓ **1982-2008**	✓ **1982-2008**
Constant	4.333	**22.71**	**10.50**	35.42	**24.05**	10.39	6.384	**6.77**	8.006	**7.826**
	(1.494)	**(3.888)**	**(0.208)**	(1.780)	**(9.577)**	(3.655)	(0.371)	**(0.35)**	(0.320)	**(0.264)**

Observations	152	**152**	**64**	64	**12**	12	327	**327**	327	**327**
R-squared	0.581		**0.962**		**0.647**		0.313		0.751	
Number of code1	7	**7**	**6**	6	**5**	5	21	21	21	**21**
Hausman Test: Test: Ho: difference in coefficients not systematic	$Chi^2(4)=5.86$ $Prob>Chi^2$ =0.2099 Favours RE model		$Chi^2(28)=1257.66$** $Prob>Chi^2$ =0.000 Favours FE model		$Chi^2(5)=37.30$** $Prob>Chi^2$ =0.0000 Favours FE model		$Chi^2(5)=9.21$ $Prob>Chi^2$ =0.1012 Favours RE model		$Chi^2(32)=27.56$ $Prob>Chi^2$ =0.6910 Favours RE model	

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; The results based on the model chosen based on Hausman test statistic are shown in bold.

Table 1b: Elasticity estimates of agricultural value added per hectare (Model1, Single Equation (1)); Dependent Variable: log Ya = Agricultural value added per hectare; Fixed Effects (FE) or Random Effects (RE) Model

Column No. EXP.VARIABLES	**(11)** **FE**	(12) RE	(13) FE with time effects	**(14)** **RE with time effects**	**(15)** **FE**	(16) RE	(17) FE with time effects	**(18)** **RE with time effects**
logAm	**0.0657***	0.052	0.141***	**0.134*****	**0.0657***	0.049	0.141***	**0.123*****
	(0.0398)	(0.0386)	(0.0240)	**(0.0244)**	**(0.0398)**	(0.0385)	(0.0240)	**(0.0250)**
logAg R&D	**0.192*****	0.190***	0.0942***	**0.0837*****	**0.192*****	0.189***	0.0942***	**0.0800*****
	(0.0421)	(0.0407)	(0.0276)	**(0.0277)**	**(0.0421)**	(0.0418)	(0.0276)	**(0.0294)**
logIrr	**0.001**	0.089	-0.129	**0.075**	**0.001**	0.09	-0.129	**0.125****
	(0.120)	(0.0834)	(0.0829)	**(0.0591)**	**(0.120)**	(0.0840)	(0.0829)	**(0.0530)**
logFert	**0.455*****	0.360***	-0.079	**0.055**	**0.455*****	0.358***	-0.079	**0.076**
	(0.107)	(0.0910)	(0.0898)	**(0.0718)**	**(0.107)**	(0.0929)	(0.0898)	**(0.0685)**
Sachs and Warner (SW)		-0.321		**-0.266**				
		(0.454)		**(0.350)**				
Frankel						-0.005		**-0.005**
						(0.0155)		**(0.00937)**
Year Dummies	**No**	**No**	✓ **1982 -2006**	✓ **1982 -2006**	**No**	**No**	✓ **1982 -2006**	✓ **1982 -2006**
Constant	**6.908**	7.812	8.971	**8.774**	**6.908**	7.683	8.971	**8.570**
	(0.428)	(0.475)	(0.375)	**(0.378)**	**(0.428)**	(0.441)	(0.375)	**(0.295)**
Observations	**276**	276	276	**276**	**276**	276	276	**276**
R-squared	**0.198**		0.747		**0.198**		0.747	
Number of countries	**18**	18	18	**18**	**18**	18	18	**18**
Hausman Test: Test: Ho: difference in coefficients not systematic	$Chi^2(4)=9.23$* $Prob>Chi^2$ =0.0556 Favours FE model		$Chi^2(29)=4.46$ $Prob>Chi^2$ =1.0000 Favours RE model		$Chi^2(3)=10.00$** $Prob>Chi^2$ =0.0404 Favours FE model		$Chi^2(29)=2.46$ $Prob>Chi^2$ =1.0000 Favours RE model	

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; The results based on the model chosen based on Hausman test statistic are shown in bold. *Sachs & Warner Indicator or Frankel-Romer indicator has been dropped since there is no time variance.

First, on the variables on technology, log of agricultural machinery/ tractors per hectare of arable land ($logAm_{it}$) is mostly positive and significant (13 out of 18 cases). That is, more intensive use of labour-saving technology (i.e. agricultural machinery) tends to be associated with improved agricultural land productivity (proxied by agricultural value added per hectare). If we focus on the cases favoured by Hausman specification tests (i.e. the results shown in bold), the share of irrigated land in total arable land ($logIrr_{it}$) is also positive (significant in columns (8) and (10)), suggesting that irrigation is associated with higher agricultural productivity. Fertiliser consumption is positive and significant in most cases as expected. It is difficult to obtain a single conclusion about the relationship between openness and agricultural productivity because the sign of the coefficient estimate varies depending on the specifications. For instance, trade openness defined as the share of import and export in GDP is positive and significant in column (2), but it is negative and significant in column (3) once year dummies are included. Consistent with earlier research (e.g. Imai et al, 2010), Sachs & Warner index or Frankel index is statistically insignificant. Government R&D expenditure in agricultural is positive and significant in most cases to underscore the importance of governmental spending in the sector-specific R&D in raising agricultural productivity. As expected, more unequal land distribution tends to lead to lower agricultural productivity. Our coefficient estimate of land Gini is more intuitive than Gaiha and Imai's (2008).

We have added the gender index to differentiate our study from Gaiha and Imai (2008) and examine whether gender parity matters in explaining agricultural productivity. While Hausman test favours the fixed-effects model (column (5)), if we focus on the results of random-effects model, the gender index is found to be positive and significant in explaining agricultural productivity. That is, other things being equal, the country with the institutional framework allowing more equality between men and women tends to have a higher agricultural productivity.

Given the limitations in using the gender index as one of the explanatory variables[10], the results are consistent with the important role of women in promoting agricultural productivity in developing countries.

Tables 2a and 2b show the results of elasticity estimates for agricultural employment per hectare (logL) based on equation (2) - with nominal agricultural wage rates (Table 2a) and with real agricultural wage rate. In Table 2a, contrary to Gaiha and Imai (2008), the coefficient estimate for logYa - our proxy for agricultural productivity – is negative and significant in the first column (Case 1, FE) which may reflect the fact that agricultural productivity improvement may sometimes involve the introduction of labour-saving technologies or agricultural machinery. On the contrary, logYa is positive and significant in the fourth column, which is consistent with Gaiha and Imai (2008). Average nominal monthly wage has the same (negative) sign as in Gaiha and Imai, but it is statistically significant in the present study (Columns (1) and (4. The share of land devoted to non-cereal crop is statistically insignificant. Gender index is statistically insignificant (column (6)).

Table 2a: Elasticity estimates of agricultural employment per hectare (Equation (2)) Dependent Variable: log L = Agricultural employment per hectare; Fixed Effects (FE) or Random Effects (RE) Model, with nominal agricultural wage rate

Column No.	(1)	(2)	(3)	(4)	(5)	(6)
	Case 1	Case 1	Case 2	Case 2	Case 3	Case 3
	FE	RE	FE	RE	FE	RE
Exp. VARIABLES						
Log Ya	**-0.651*** **	-0.445**	**-0.334**	2.053***	**0.0493**	0.807
	(0.173)	(0.180)	**(0.322)**	(0.219)	**(0.351)**	(1.389)
Log Wage (nominal agricultural wage rate)	**-0.0473***	-0.0607**	**-0.0389**	-0.142***	**-0.0985**	2.313
	(0.0244)	(0.0262)	**(0.0284)**	(0.0486)	**(0.509)**	(1.568)
Log NonCereal	**-0.116**	0.0766	**-0.485**	6.117***	**-0.75**	-6.585
	(0.490)	(0.524)	**(0.572)**	(0.708)	**(2.368)**	(9.220)
Gender Index *						1.162
						(0.907)
Year Dummies	**No**	**No**	✓	✓	**No**	**No**

[10] We do not consider the endogeneity of gender index due to the limited availability of possible instruments. Because of its limited country coverages, the gender index cannot be instrumented, e.g., European's settlers mortality or population density in 1500 is used in the empirical literature estimating the relation between institution and growth (Imai et al., 2010).

			1984 -2008	**1984 -2008**		
Constant	**-1.477**	-4.142	**-4.849**	-25.98	**-6.845**	-34.63
	(1.710)	(1.793)	**(3.197)**	(2.454)	**(3.477)**	(6.954)
Observations	76	76	**76**	76	**8**	8
R-squared	0.293		**0.626**		**0.364**	
Number of countries	17	17	**17**	17	**3**	3
Hausman Test: Test: Ho: difference in coefficients not systematic	$Chi^2(3)=23.85$** Prob>Chi^2 =0.0000 Favours FE model		$Chi^2(27)=1122.76$** Prob>Chi^2 =0.0000 Favours FE model		$Chi^2(3)=51.84$** Prob>Chi^2 =0.0040 Favours FE model	

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; The results based on the model chosen based on Hausman test statistic are shown in bold.
*Gender Index has been dropped due to multicollineraity.

In Tables 2b, log of nominal average monthly agricultural wage rate is replaced by log of real average monthly agricultural wage rate. Because the number of observations has declined due to unavailability of the CPI data for a few countries, gender index cannot be added. The results in Table 2b are mostly consistent with those in Table 2a with a few changes. log Ya is negative and significant in column (1). Real agricultural wage rate is statistically insignificant, while nominal agricultural wage rate is negative and significant in column (1) of Table 2a. Log Non-Cereal is negative and statistically insignificant.

Table 2b: Elasticity estimates of agricultural employment per hectare (Equation (2)) Dependent Variable: log L = Agricultural employment per hectare; Fixed Effects (FE) or Random Effects (RE) Model, with real agricultural wage rate

Column No.	**(1)**	(2)	**(3)**	(4)
	Case 1	Case 1	**Case 2**	Case 2
	FE	RE	**FE**	RE
Exp. VARIABLES				
Log Ya	**-0.678*** **	-0.549***	**-0.617**	2.066***
	(0.186)	(0.188)	**(0.367)**	(0.367)
Log Wage (real agricultural wage rate)	**0.00112**	-0.00103	**-0.00125**	-0.0819**
	(0.0123)	(0.0129)	**(0.0149)**	(0.0410)
Log NonCereal	**-0.144**	-0.106	**-1.19**	5.776***
	(0.514)	(0.528)	**(0.751)**	(1.138)
Year Dummies	**No**	**No**	✓ **1984 -2008**	✓ **1984 -2008**
Constant	-2.301	-4.161**	**-3.283**	-26.63***
	(1.865).	(1.882).	**(3.576).**	(3.763).
Observations	62	62	**62**	62
R-squared	0.249		**0.708**	
Number of countries	15	15	**15**	15
Hausman Test: Test: Ho: difference in coefficients not systematic	$Chi^2(3)=9.96$* Prob>Chi^2 =0.018 Favours FE model		$Chi^2(27)=$ 136.05** Prob>Chi^2 =0.0000 Favours FE model	

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1; The results based on the model chosen based on Hausman test statistic are shown in bold.

Table 3a reports the estimates of log monthly nominal agricultural wage rate as a function of log agricultural land productivity (log Ya - log of value added per hectare of arable land), food prices, log of primary education years, population growth, and log inflation. The first six columns show the results of the level equations and the last six columns those of the first-difference equations to examine the relationship between the growth rate of land productivity and the growth rate of nominal agricultural wage rate before and after 2000. log farm employment (Log L) and log nonfarm employment (Log LN) have been added only to the level equations in one of the cases to see the effect of expansion on agricultural wages. In Table 3b we replace the dependent variable by log monthly real agricultural wage rate while using the exactly same specifications. Furthermore, in Table 3c, in order to investigate the relationship between the growth rate of *labour* productivity and the growth rate of agricultural wage rates - both nominal and real – before and after 2000, we have estimated the first difference equations by replacing log Ya by “log Agricultural Value Added per Worker”, our proxy for labour productivity.

Table 3a Estimates of log Nominal Agricultural Wage (Model1, Single Equation for (3)), Level and First Difference Equations; Dependent Variable: log Wage= log nominal agricultural monthly wage (or First Difference in log Wage); Fixed Effects (FE) or Random Effects (RE) Model

	Level Equation						Difference Equation					
Columns No.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Case 1 **Total Sample 1992-2008**		Case 2 **Total Sample 1992-2008**		Case 3 **Total Sample 1992-2008**		Case 4 **Total Sample 1992-2008**		Case 5 **Before 2000 (1992-1999)**		Case 6 **After 2000 (2000-2008)**	
Dep. Variable	log Agri Wage		log Agri Wage		log Agri Wage		D.log Agri Wage		D.log Agri Wage		D.log Agri Wage	
	FE	**RE**	**FE**	RE	**FE**	RE	FE	**RE**	FE	**RE**	FE	**RE**
Exp. VARIABLES												
logFoodPrice	-0.450*	-0.701***	0.0993	-1.085***	0.0494	-0.208						
	(0.242)	(0.218)	(0.401)	(0.347)	(0.0579)	(0.414)						
logYa	-1.116	-0.661	0.632	-0.39	0.669	-0.515						
	(1.980)	(0.571)	(2.769)	(0.360)	(0.612)	(0.883)						
Log primary ed years	13.97**	4.623	19.25**	2.136	-	-						
	(6.955)	(3.039)	(7.712)	(2.208)	-	-						
Population growth	-0.582	-0.45	-0.886	-0.837*	-0.13	-1.279***						
	(0.830)	(0.530)	(0.997)	(0.451)	(0.186)	(0.415)						
Log inflation	0.762***	0.732***	0.679***	1.203***	0.0165	1.543***						
	(0.216)	(0.204)	(0.254)	(0.295)	(0.0736)	(0.353)						
Log L					0.0164	-0.644						
(farm employment)					(0.279)	(0.608)						
Log LN (nonfarm employment)					-1.873*	-4.254						
					(1.037)	(3.992)						
D.logFoodPrice							2.888***	1.551***	0.257	-0.229	4.048***	3.137***
							(0.687)	(0.552)	(1.340)	(0.850)	(1.012)	(1.010)
D.logYa							4.285***	3.892***	-2.331	-0.859	5.324***	5.011***
							(1.502)	(1.500)	(4.222)	(3.277)	(1.699)	(1.764)
D.log primary edyears							8.234	9.019			7.86	8.663
							(6.257)	(5.733)			(6.123)	(5.826)
D.population growth							-0.0164	0.028	5.062*	4.039*	-0.29	-0.261
							(0.668)	(0.658)	(2.699)	(2.098)	(0.717)	(0.714)
D.log inflation							-0.398*	-0.102	-0.0985	-0.0118	-0.803	-0.456
							(0.215)	(0.168)	(0.276)	(0.169)	(0.519)	(0.502)
Year Dummies	No	No	✓ 1992-2008	✓ 1992-2008	No	No	✓ 1993-2008	✓ 1993-2008	✓ 1993-1999	✓ 1993-1999	✓ 2001-2008	✓ 2001-2008
Observations	110	110	110	110	29	29	84	84	34	34	50	50

R-squared	0.243		**0.401**		0.1822		0.502		0.592		0.545	
Number of countries	16	**16**	**16**	16	6	6	12	**12**	9	**9**	8	**8**
Hausman Test: Test: Ho: difference in coefficients not systematic	$Chi^2(5)=8.51$ Prob>Chi^2 =0.1305 Favours RE model		$Chi^2(22)=38.70$* Prob>Chi^2 =0.0153 Favours FE model		$Chi^2(6)=51.66$** Prob>Chi^2 =0.0000 Favours FE model		$Chi^2(21)=10.86$ Prob>Chi^2 =0.9654 Favours RE model		$Chi^2(11)=1.86$ Prob>Chi^2 =0.9989 Favours RE model		$Chi^2(12)=1.36$ Prob>Chi^2 =0.9999 Favours RE model	

Standard errors in parentheses. p<0.01, p<0.05, p<0.1; The results based on the model chosen based on Hausman test statistic are shown in bold.
Primary education has been dropped in columns (5) and (6) due to multicollinearity.

Table 3b Estimates of log Real Agricultural Wage (Model1, Single Equation for (3)), Level and First Difference Equations; Dependent Variable: log RWage= log real agricultural monthly wage (or First Difference in log RWage); Fixed Effects (FE) or Random Effects (RE) Model

	Level Equation						**Difference Equation**					
Columns No.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Case 1 **Total Sample 1992-2008**		Case 2 **Total Sample 1992-2008**		Case 3 **Total Sample 1992-2008**		Case 3 **Total Sample 1992-2008**		Case 4 **Before 2000 (1992-1999)**		Case 5 **After 2000 (2000-2008)**	
Dep. Variable	log Agri Wage		log Agri Wage		log Agri Wage		log Agri Wage		D.log Agri Wage		D.log Agri Wage	
	FE	**RE**	FE	**RE**	**FE**	RE	FE	**RE**	FE	**RE**	FE	**RE**
Exp. VARIABLES												
logFoodPrice	-1.512***	**-1.735*** **	-0.861**	**-2.044*** **	**-0.977*** **	-1.214***						
	(0.249)	**(0.225)**	(0.407)	**(0.351)**	**(0.0862)**	(0.394)						
logYa	-1.518	**-0.672**	0.492	**-0.336**	**1.133**	-0.378						
	(2.036)	**(0.610)**	(2.822)	**(0.364)**	**(0.911)**	(0.841)						
Log primary ed years	13.08*	**4.524**	19.41**	**2.072**	**-**	-						
	(7.151)	**(3.265)**	(7.846)	**(2.241)**	**-**	-						
Population growth	-0.524	**-0.425**	-1.003	**-0.905** **	**-0.368**	-1.404***						
	(0.853)	**(0.557)**	(1.012)	**(0.456)**	**(0.277)**	(0.395)						
Log inflation	0.838***	**0.818*** **	0.745***	**1.305*** **	**0.169**	1.616***						
	(0.223)	**(0.210)**	(0.258)	**(0.300)**	**(0.110)**	(0.336)						
Log L					**0.314**	-0.654						
(farm employment)					**(0.416)**	(0.579)						
Log LN (nonfarm employment)					**-3.424** **	-4.912						
					(1.543)	(3.801)						
D.logFoodPrice							2.420***	**0.876**	-0.362	**-1.057**	3.929***	**2.991*** **
							(0.692)	**(0.573)**	(1.339)	**(0.866)**	(1.014)	**(1.039)**
D.logYa							4.037**	**3.699** **	-2.575	**-0.802**	5.311***	**5.077*** **
							(1.515)	**(1.568)**	(4.218)	**(3.339)**	(1.702)	**(1.821)**
D.log primary							8.283	**9.205**			7.94	**8.777**

edyears												
							(6.311)	**(5.956)**			(6.133)	**(5.987)**
D.population growth							0.00984	**0.0207**	4.988*	**3.807***	-0.223	**-0.216**
							(0.673)	**(0.683)**	(2.697)	**(2.138)**	(0.718)	**(0.734)**
D.log inflation							-0.370*	**-0.0478**	-0.0718	**0.0535**	-0.783	**-0.472**
							(0.217)	**(0.176)**	(0.275)	**(0.172)**	(0.520)	**(0.533)**
Year Dummies	**No**	**No**	✓ **1992 -2008**	✓ **1992 -2008**	**No**	**No**	✓ **1993 -2008**	✓ **1993 -2008**	✓ **1993 -1999**	✓ **1993 -1999**	✓ **2001 -2008**	✓ **2001 -2008**
Observations	108	**108**	108	**108**	29	29	83	**83**	34	**34**	49	**49**
R-squared	0.495		0.612		0.1822		0.486		0.594		0.538	
Number of countries	15	**15**	15	**15**	6	6	11	**11**	9	**9**	7	**7**
Hausman Test: Test: Ho: difference in coefficients not systematic	$Chi^2(5)=6.43$ Prob>Chi^2 =0.2668 Favours RE model		$Chi^2(22)=22.78$ Prob>Chi^2 =0.4140 Favours RE model		$Chi^2(6)=244.55$** Prob>Chi^2 =0.0000 Favours FE model		$Chi^2(21)=15.20$ Prob>Chi^2 =0.8127 Favours RE model		$Chi^2(11)=.2.62$ Prob>Chi^2 =0.9949 Favours RE model		$Chi^2(12)=2.97$ Prob>Chi^2 =0.9958 Favours RE model	

Standard errors in parentheses. p<0.01, p<0.05, p<0.1; The results based on the model chosen based on Hausman test statistic are shown in bold.
Primary education has been dropped in columns (5) and (6) due to multicollinearity.

Table 3c Estimates of log Agricultural Real Wage (Model1, Single Equation for (3)), First Difference Equations; Dependent Variable: First Difference in Nominal or Real Average Agricultural Monthly Wage; Fixed Effects (FE) or Random Effects (RE) Model (Land Productivity is replaced by Labour productivity)

	Difference Equation (First Difference in log Nominal Agricultural Wage)						**Difference Equation (First Difference in log Real Agricultural Wage)**					
Columns No.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Case 1 **Total Sample 1992-2008**		Case 2 **Before 2000 (1992-1999)**		Case 3 **After 2000 (2000-2008)**		Case 4 **Total Sample 1992-2008**		Case 5 **Before 2000 (1992-1999)**		Case 6 **After 2000 (2000-2008)**	
Dep. Variable	log Agri Wage		D.log Agri Wage		D.log Agri Wage		log Agri Wage		D.log Agri Wage		D.log Agri Wage	
	FE	**RE**	FE	**RE**	FE	**RE**	FE	**RE**	FE	**RE**	**FE**	RE
Exp. VARIABLES												
D.logFoodPrice	2.908***	**1.318****	0.19	**-0.256**	3.957***	**2.698*****	2.442***	**0.649**	-0.407	**-1.095**	**3.835*****	2.520**
	(0.689)	**(0.550)**	(1.348)	**(0.781)**	(1.007)	**(1.020)**	(0.694)	**(0.571)**	(1.350)	**(0.795)**	**(1.010)**	(1.053)
D.log Agricultural Value Added per Worker	4.678***	**3.218****	-2.929	**-2.057**	5.839***	**4.281****	4.449***	**2.854***	-2.945	**-2.126**	**5.803*****	4.155**
	(1.649)	**(1.610)**	(4.499)	**(3.529)**	(1.879)	**(1.951)**	(1.660)	**(1.679)**	(4.506)	**(3.594)**	**(1.884)**	(2.012)
D.log primary edyears	7.218	**7.583**			6.717	**7.099**	7.318	**7.907**			**6.805**	7.309

	(6.271)	**(5.869)**			(6.146)	**(6.063)**	(6.315)	**(6.098)**			**(6.164)**	(6.261)
D.population growth	0.0545	**0.101**	5.208*	**4.369****	-0.191	**-0.171**	0.0758	**0.0948**	5.046*	**4.176****	**-0.124**	-0.121
	(0.666)	**(0.670)**	(2.679)	**(2.079)**	(0.720)	**(0.745)**	(0.671)	**(0.696)**	(2.682)	**(2.117)**	**(0.722)**	(0.769)
D.log inflation	-0.393*	**-0.0856**	-0.092	**-0.00823**	-0.709	**-0.303**	-0.366*	**-0.0304**	-0.0652	**0.0576**	**-0.69**	-0.294
	(0.215)	**(0.172)**	(0.275)	**(0.168)**	(0.521)	**(0.527)**	(0.217)	**(0.179)**	(0.275)	**(0.171)**	**(0.523)**	(0.562)
Year Dummies	✓ **1993 -2008**	✓ **1993 -2008**	✓ **1993 -1999**	✓ **1993 -1999**	✓ **2001 -2008**	✓ **2001 -2008**	✓ **1993 -2008**	✓ **1993 -2008**	✓ **1993 -1999**	✓ **1993 -1999**	✓ **2001 -2008**	✓ **2001 -2008**
Observations	84	84	34	34	50	50	83	83	34	34	49	49
R-squared	0.502		0.595		0.543		0.486		0.596		0.535	
Number of countries	12	12	9	9	8	8	11	11	9	9	7	7
Hausman Test: Test: Ho: difference in coefficients not systematic	Chi^2(21)=16.23 Prob>Chi^2 =0.7665 Favours RE model		Chi^2(11)=.1.81 Prob>Chi^2 =0.9991 Favours RE model		Chi^2(11)=.11.61 Prob>Chi^2 =0.4775 Favours RE model		Chi^2(21)=27.56 Prob>Chi^2 =0.1530 Favours RE model		Chi^2(11)=.2.47 Prob>Chi^2 =0.9960 Favours RE model		Chi^2(12)=85.42 Prob>Chi^2 =0.0000 Favours FE model	

Standard errors in parentheses. p<0.01, p<0.05, p<0.1; The results based on the model chosen based on Hausman test statistic are shown in bold.

In Table 3a (with nominal agricultural wage rates), we have found that food price is negative and significant (columns (1), (2) and (4)), that is, if food price is high, it is implied that real average monthly agricultural wage rate would be lower. This is consistent with Gaiha and Imai (2008). However, once log L and log LN are added and the number of observations reduces from 110 (for 16 countries) to 29 (only for 6 countries) in columns (5) and (6), food price becomes statistically insignificant reflecting the small number of observations. The coefficient estimate of log Ya is statistically insignificant in all the cases. As expected, primary education is positive and significant in columns (1) and (3) (based on fixed effects models). Population growth is negative and mostly statistically insignificant (except column (4) where it is significant at the 10% level). As expected, log inflation – capturing the annual price changes at aggregate levels - is positive and significant (except column (5)), reflecting the positive association between inflation and nominal monthly agricultural wage rate.

log L and log LN have been inserted in columns (5) and (6) to examine the effect of non-farm employment on agricultural wage rate where primary education is excluded due to multicollinearity. This is motivated by the idea that the expansion of non-farm employment may result in reduced farm labour supply, which will have an upward pressure for the agricultural wage. If we focus on the fixed effects model result in column (5) (which is favoured by the Hausman test), we find that the non-farm employment is negatively and significantly associated with nominal agricultural wage rate, while farm employment is not significant. This implies that the expansion of non-farm employment tends to have an upward pressure. The pattern of the results is unchanged if we estimate real agricultural wage rate (column (5) of Table 3b).

Columns (7)-(12) of Table 3a report the results for the equation (3)" (wage equation) where the variables are first differenced. Both the growth in agricultural land productivity (DlogYa) and the growth in food price are positive and significant in explaining the growth in agricultural wage rate for the entire sample period, 1992-2008. For instance, 1% increase in the growth rate in agricultural productivity (value added per hectare of arable land) tends to lead to 3.9 % increase in the agricultural wage rate growth in column (8). 1% increase in the food price inflation tends to increase 1.6 % in the agricultural wage rate growth in the same case. These results are mainly driven by those after the year 2000. For instance, after 2000, 1% increase in the agricultural productivity growth tends to increase agricultural wage growth by 5.01%, while 1% increase in the growth rate in the food price tends to raise agricultural wage growth by 3.14%.[11] These results imply that in more recent years agricultural wage rates have become more sensitive to the changes in agricultural productivity or food inflation.

In Table 3b, the dependent variable has been replaced by log real monthly average agricultural wage rate. The pattern of the results is broadly similar with a few minor changes. The coefficient estimate of food price is negative and significant with the larger values in absolute terms. Contrary to normal expectations and somewhat surprisingly, the effect of inflation (after taking account of the effect of food prices) on real monthly average agricultural wage rate is *positive* and significant in most cases. A positive and significant association between log real average agricultural wage and log inflation is robust to the change in the specifications, for instance in the case where (only) food price is dropped from equation (3) or in the case where only log inflation is used as an explanatory variable – with or without year dummies. The reason is not clear, but the related factors influencing this relation include: (i) The inflation is negatively associated with CPI (with the correlation of coefficient -0.07 for sample countries); (ii) the former is calculated based on the annual change of spot prices and subject to the sudden price surges/shocks while the latter is calculated on the accumulated basis (using monthly prices of

[11] These elasticity estimates appear to be high because they are applied to the first difference, not levels.

multiple items); and (iii) the change in price levels is not necessarily positively correlated with the price levels in general. In columns (7)-(12) of Table 3b, the first difference equation is estimated for real average monthly agricultural wage rate.

In Table 3c we have examined the relationship between the growth rate of nominal or real agricultural wage and the growth rate of labour productivity. The pattern of the results is unchanged once land productivity is replaced by labour productivity. It has been found that 1% increase in labour productivity growth tends to lead to 3.22 % (2.85%) increase in the growth rate in nominal (real) agricultural wage, which is mostly explained by the relation of these variables after 2000. That is, the ILO's (2012) argument for the widening gap between agricultural wage and labour productivity in recent years - which was established by using the data of developed countries (Figure 36 on p.48 in ILO, 2012) - is unlikely to hold for developing countries. The results suggest that there has been a closer link between agricultural wage and labour productivity in more recent years for developing countries. This is related to the possible reasons for the relatively high growth rate of real wage for developing countries. For instance, annual average real wage growth in recent years (2006-2011) has been very low in developed countries ranging from -0.5% to 1%, while it has been high in developing countries (e.g. 0.5% to 6.2% for Africa, 3.9% to 6.8% for Asia, -3.5% to 14.4% for Eastern Europe and Central Asia, 0.8% to 3.5% for Latin America and the Caribbean) (ILO, 2012, pp.8-9). While it may be true to argue that the labour income share has been declining in developing countries as in developed countries, e.g., due to the negative effect of financialisation on the labour income share (ibid., 2012, pp.52-53), they should not use this as evidence for the widening gap between wages and productivity. It may be rather conjectured that both real wages and labour productivity have risen in recent years (e.g. after 2000) and this must continue to be supported by appropriate governmental policies.

In Table 4 we have estimated equations (1) and (2) simultaneously by 2SLS where in the first stage agricultural employment per hectare (log L) is estimated and in the second, after controlling for the first stage results, agricultural employment per hectare (log Ya) is estimated by log L predicted in the first stage together with other control variables.[12] It is found that the coefficient of log L is positive and significant in the second stage, that is, larger agricultural employment tends to lead to higher agricultural productivity. Here 1% increase in agricultural employment tends to raise agricultural productivity by 0.14% after taking into account the endogeneity of the former. Other results are mostly consistent with Gaiha and Imai (2008).

Table 4 Elasticity estimates for agricultural value added per hectare and agricultural employment per hectare (IV Model for equations (1) & (2)); Dep. Variable in the First Stage: log L = agricultural employment per hectare; Dep. Variable in the Second Stage: log Ya = agricultural value added per hectare

	First Stage	**Second Stage**
Dep. Variables	**log L**	**log Ya**
Exp. Variables		
logL	-	**0.141***
		(0.0730)
logAm	-5.026***	0.879***
	(0.005)	(0.132)
logIrr	-8.081***	1.963**
	(2.176)	(0.101)
logFert	2.541**	-0.903***
	(1.034)	(0.191)
logAg R&D	-2.470***	0.163
	(0.848)	(0.214)
logTrade	3.903***	-0.517*
	(0.744)	(0.280)
logYa	4.326***	-
	(1.357)	-
Log NonCereal	2.353**	-
	(1.146)	-
Predicted logWage	-0.285***	-
	(0.095)	-
Constant	-35.749	10.75

[12] The result of 2SLS should be interpreted with caution as Sargan statistic is statistically significant, that is, the null hypothesis that the over-identifying restrictions are valid is rejected. Moreover, the results of 2SLS based on the small sample should also be interpreted with caution (e.g. Hahn et al. 2004).

	(10.270)	(1.666)
Number of obs	15	
Joint Significant Tests	F(8, 6) = 194.89	

Sargan statistic (overidentification test of all instruments): 13.296: Chi-sq(2) P-val = 0.0013

Weak identification test: Ho: equation is weakly identified
Cragg-Donald Wald F-statistic 4.41

Weak-instrument-robust inference: Tests of joint significance of endogenous regressors B1 in main equation
Ho: B1=0 and overidentifying restrictions are valid
Anderson-Rubin Wald test F(3,6)= 4.3e+12 P-val=0.0000
Anderson-Rubin Wald test Chi-sq(3)=3.2e+13 P-val=0.0000
Stock-Wright LM S statistic Chi-sq(3)=15.00 P-val=0.0018

Model 2: Model for agricultural and non-agricultural employment growth

We have then estimated the model where agricultural employment growth and non-agricultural employment using the dynamic panel model (SGMM) for each variable in Table 5. The first column shows the result where D.logL is estimated. First, the lagged dependent variables are negative and significant, implying the adjustment process where the higher agricultural employment growth tends to be followed by the lower agricultural employment growth, or vice versa. The coefficient estimate for D.logYa(-1) (lagged agricultural land productivity growth) is positive and significant, implying that agricultural productivity growth leads to the larger agricultural employment (per hectare) over time.[13]

The result for D.logLN (non-agricultural employment growth) is reported in the second column. Here an important result is that the second lag of agricultural employment growth - which is treated as endogenous in SGMM - is positive and significant in explaining non-agricultural employment growth. That is, if agricultural employment growth increases by 1%, non-agricultural employment growth will increase by 0.0172%, other things being equal, and

[13] The estimation in Case 1 of Table 5 is based on only 44 observations for 9 countries and the results will have to be interpreted with caution due to the small number of observations as well as small *n*. As the number of observation is small, we have adopted SGMM with the finite sample correction of the two-step standard errors proposed by Windmeijer (2005). It should be noted that with the small sample the possible bias of the SGMM estimator is much smaller than that of the first differencing estimator as shown by a number of simulations carried out by Hayakawa (2007) for 50 observations. Hence SGMM with the finite sample correction by Windmeijer has been used in this analysis.

after adjusting for the endogeneity of agricultural employment growth. That is, agricultural employment growth tends to lead to non-agricultural employment growth over time with some lags. The Arellano-Bond test for zero autocorrelation in first-differenced errors as well as the Sargan test of overidentifying restrictions have been carried out for each case. On Arellano-Bond test, the null for zero autocorrelation is rejected for the order 1 (Cases 1 and 2) and for the order 2 (case 2) at the 10% significance level, broadly justifying our use of dynamic panel model. The Sargan test statistic is statistically insignificant at the 10% level in both Cases 1 and 2, which will broadly validate the instruments in SGMM.

Table 5 Estimates for log agricultural employment and non-agricultural employment growth (Blundell and Bond's (1998) System GMM model for the dynamic panel_ Dependent Variable: Case 1: D.log L (first difference of agricultural employment per hectare) Case 2: D.log LN (first difference of non-agricultural employment)

		Case 1	Case 2
	Dep. Variable	D.logL	D.logLN
Exp. Variables			
D.logL(-1)	Exogenous	-0.539***	
		(0.0935)	
D.logL(-2)	Exogenous	-0.595***	
		(0.171)	
D.logWage(-1)	Endogenous	0.00866	
		(0.0136)	
D.logYa(-1)	Exogenous	0.431**	
		(0.205)	
D.logNonCereal(-1)	Exogenous	0.264	
		(0.249)	
D.logLN(-1)	Exogenous		-0.0582***
			(0.0121)
D.logLN(-2)	Exogenous		-0.00941
			(0.0181)
D.logL(-1)	Endogenous		0.00152
			(0.00549)
D.logL(-2)	Endogenous		0.0172***
			(0.00520)
Constant		-0.0348	0.0144
		(0.0209)	(0.00295)

Observations		**44**	**656**
Number of Countries		**9**	**56**
Arellano-Bond test for	**Order**	**Prob>z**	**Prob>z**
zero autocorrelation in	**1**	**0.0908**	**0.0973**
first-differenced errors	**2**	**0.9005**	**0.0985**
H0: no autocorrelation			
Sargan test of overidentifying restrictions		**chi2(59) = 70.54**	**chi2(705) = 665.32**
H0: overidentifying restrictions are valid		Prob > chi2 = 0.1444	Prob > chi2 = 0.8553

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Model 3: Model for the effect of agricultural value added per capita growth non-agricultural per capita growth on the change in inequality

Table 6 extends the analysis in Imai and Gaiha (2014, Table 4). It has been found that both predicted agricultural growth and predicted non-agricultural growth tend to decrease the overall inequality over time (Case 1, taken from Imai and Gaiha, 2014). The result is robust to the choice of different estimation methods, such as, dynamic panel model, or CCEMG model (Imai and Gaiha, 2014).

Table 6: Effect of Predicted Agricultural/Non-Agricultural Growth on Inequality Change Dependent Variable: D.Inequality (Based on Annual panel (Fixed Effects Model (Robust Estimators)) (Cases 1, 3 and 4) and Blundell and Bond (1998) SGMM estimator (Case 2)

	Case 1	**Case 2**	**Case 3**	**Case 4**
Explanatory Variables	**FE**	**SGMM**	**FE**	**FE**
D.Log Agricultural Value Added per capita [Predicted]	-3.947**	-6.364	0.318	3.091
	(1.808)	(6.008)	(18.18)	(17.84)
D.Log Non-Agricultural Value Added per capita [Predicted]	-9.782***	4.813*	-16.99	-17.34*
	(3.133)	(2.481)	(10.58)	(10.25)
D.Inequality (-1)		0.867***		
		(0.0414)		
D.log L [First Difference of log Agricultural Employment Per Hectare] [Predicted]		-21.98*		
		(11.71)		
D.log LN [First Difference of log Non-Agricultural Employment] [Predicted]		-90.75		

		(70.96)		
D.log L (-1) [Lagged First Difference of log Agricultural Employment Per Hectare] [Predicted]			-13.95	-15.12
			(10.02)	(9.236)
D.log L (-1) [Lagged First Difference of log Agricultural Employment Per Hectare] [Predicted]			-82.28	-83.14*
			(48.02)	(50.03)
Constant	0.331	6.559	44.97	45.36
	(0.0791)	(2.098)	(0.565)	(1.169)
Observations	932	100	118	118
Number of countries	49	19	21	21
R-squared	0.014		0.047	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

Here we have carried out a few extensions. In Case 2 of Table 6, Blundell and Bond's (1998) SGMM model has been estimated to include the lagged dependent variable (or lagged inequality) and predicted values of the first difference of agricultural employment per hectare and the first difference of non-agricultural employment. Here we can confirm that change in agricultural employment per hectare is negatively associated with change in overall inequality. That is, if agricultural employment increases over time at a higher pace, inequality reduces over time at a higher pace, which is consistent with the role of agricultural employment in reducing overall inequality.

Model 4: Model for agricultural productivity and Poverty

Table 7 presents the results of the determinants of the long-term relation between agricultural productivity and poverty based on 3SLS, which has been carried out as an extension of Imai and Gaiha (2014). Four different definitions of poverty have been tried according to whether poverty is defined as poverty gap or poverty headcount ratio, based on US$1.25 or US$2 poverty threshold. An important finding is that agricultural productivity (log Ya) - which is treated as endogenous by including the equation for (lagged) log Ya – increases GDP per capita, which decreases poverty regardless of its definition.

For instance, in case where poverty gap based on US$2.00 is estimated (Case 1), 1% increase in agricultural productivity raises GDP per capita by 0.45%, which reduces poverty by 0.51%, over time, other things being equal. That is, 1% increase in agricultural productivity (treated as an endogenous variable in the system) will reduce poverty by 0.23% (0.45 * -0.51), other factors being equal. Similarly in Case 2, 1% increase in agricultural productivity tends to reduce poverty gap based on US$1.25 by 0.23% (0.45*-0.51). In Case 3, 1% increase in agricultural productivity will lead to the decline in poverty headcount by 0.25% (0.44*-0.56). In Case 4, log GDP per capita is not statistically significant in the poverty equation. Overall, the results are consistent with the significant role of raising agricultural productivity in reducing poverty among developing countries.

Table 7 Determinants of the Long-term relation between Agricultural Productivity and Poverty based on 3SLS

	Case 1 Poverty Gap US$2.00 With Equation: L.logYa			Case 2 Poverty Gap US$1.25 With Equation: L.logYa			Case 3 Poverty Headcount US$2.00 With Equation: L.logYa			Case 4 Poverty Headcount US$1.25 With Equation: L.logYa		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	poverty	loggdppc	L_logYa	poverty	loggdppc	L_logYa	Poverty	loggdppc	L_logYa	poverty	loggdppc	L_logYa
conflict_int	-0.053	0.0611		-0.387***	0.0624		0.176***	0.0248		0.223**	0.0203	
	(0.0863)	(0.0476)		(0.0907)	(0.0476)		(0.0680)	(0.0389)		(0.0949)	(0.0388)	
L.logYa		**0.449*****			**0.453*****			**0.440*****			**0.415*****	
		(0.0848)			**(0.0848)**			**(0.0799)**			**(0.0786)**	
tot_non_ofg	0.0057	0.00645**		0.0051	0.00617**		-9E-04	0.00402*		0.0118**	0.0036	
	(0.00479)	(0.00274)		(0.00503)	(0.00274)		(0.00393)	(0.00237)		(0.00549)	(0.00236)	
L.inequality_D		0.0121			0.0098			0.0141**			0.0130**	
		(0.00751)			(0.00750)			(0.00653)			(0.00634)	
Loggdppc	**-0.512****			**-0.512****			**-0.559*****			**-0.093**		
	(0.224)			**(0.235)**			**(0.207)**			**(0.285)**		
L.logAm			-0.0857***			-0.0857***			-0.0891***			-0.0872***
			(0.0247)			(0.0247)			(0.0194)			(0.0193)
L.logIrr			-0.273***			-0.272***			-0.299***			-0.301***
			(0.0400)			(0.0400)			(0.0402)			(0.0402)
L.logFert			0.280***			0.280***			0.269***			0.268***
			(0.0361)			(0.0362)			(0.0341)			(0.0341)
L.logTrade			0.736***			0.737***			0.707***			0.706***
			(0.0575)			(0.0575)			(0.0550)			(0.0549)
Regional Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓ **1980 -2009**	✓ **1980 -2009**	✓ **1980 -2009**	✓ **1980 -2009**	✓ **1980 -2009**	✓ **1980 -2009**	✓ **1980 -2009**	✓ **1980 -2009**	✓ **1980 -2009**	✓ **1980 -2009**	✓ **1980 -2009**	✓ **1980 -2009**
Observations	246	246	246	246	246	246	265	265	265	265	265	265
R-squared	0.913	0.932	0.846	0.921	0.932	0.846	0.888	0.941	0.876	0.862	0.941	0.876

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

VI. The Way Forward: Involving Young People in Agricultural Sector

The last part of econometric analyses in this paper has addressed how important it will be to increase agricultural productivity in reducing poverty (Table 7). In a separate estimation in Table 4, we have shown the importance of increasing agricultural employment in improving agricultural productivity. However, one of the limitations of these analyses is that we treat employment as an aggregate category, while disaggregated effect (e.g. age groups, gender) is likely to be important in analysing the link between agricultural productivity, employment and poverty. For instance, the young people are likely to play an important role in improving agriculture. While it is not feasible to carry out regressions to estimate the role of the youth (e.g. due to the absence of age-disaggregated agricultural employment), this section delineates a few useful policy implications regarding the role of young people in agriculture drawing upon recent works, such as, Proctor and Lucchesi (2012), and Paisley (2014) and Bi (2014).

First, labour is highly underutilised at younger generations across all the regions. As shown in Table 8, youth unemployment rates are much higher globally and across all the regions (Proctor and Lucchesi, 2012), implying that aggregate productivity could be improved by better utilisation of the labour force comprising younger generations.

Table 8.Youth and adult unemployment rate in key regions in 2010

	Youth unemployment rate (%)	Adult unemployment rate (%)
Asia and the Pacific	11.2	3.1
East Asia	8.4	3.3
South-East Asia and the Pacific	14.8	2.9
South Asia	10.3	3.2
Sub-Saharan Africa	23.8	6.5
Middle East and North Africa	23.8	6.4
Middle East	23.7	6.2
North Africa	23.8	6.5
Latin America and the Caribbean	15.8	5.9
Developed Economies and EU	19.1	7.4

World	13.1	4.8

Source: Table 1 of Proctor and Lucchesi (2012, based on ILO, 2010). Note: 'Youth unemployment rate' and 'adult unemployment rate' for 'Asia and Pacific' and for 'Middle East and North Africa' are calculated as average of the 'sub-regions'; South-East Asia and the Pacific are combined as reported in ILO (2011b).

The data on rural or agricultural employment or unemployment disaggregated by age- group are generally limited and thus it is difficult to use them in the cross-country regressions or to draw general conclusions. However, Table 9 below shows that for selected countries, youth unemployment rate is generally much higher than (aggregate) rural unemployment. Whether voluntary or involuntary unemployment dominates in the total rural unemployment rate has to be carefully examined with more detailed data, but Table 9 suggests that younger generations are underutilised in rural areas. Thus, given the importance of agricultural employment in improving agricultural productivity and reducing poverty, there is a need for making better use of rural youth in agricultural sector.

Table 9. Total rural employment and youth rural employment in selected countries

		Rural Unemployment Rate (%)	Rural Youth Unemployment Rate (%)
Zambia	1990	22	41
Benin	2002	0.3	0.4
Ghana	2000	9	12
Indonesia	2000	4	14
Lao	1995	1	2
Urguay	1996	4	8
Venezuela	1990	10	17

Source: Table 2 of Proctor and Lucchesi (2012, based on ILO Rural Labour Statistics Dataset, 2011).

Proctor and Lucchesi (2012, p.50) argues that given the important role of agriculture in employment and the sheer number of youth in rural areas, new models to enhance decent employment and livelihood in the agriculture sector must be developed, including support to employment opportunities along the entire agrifood market chain and the associated service sectors and calls for supportive policy and new investments, for instance, through public–private sector partnerships.

Paisley (2014, pp.1-2) points out that based on the study in Uganda the tendency for the rural youth to look for non-agricultural professions may have a negative effect on agricultural investment in rural areas. He points to the need for addressing mismatch between education and employment in the agricultural sector to ensure that young people can obtain the skills and competencies required for modern agriculture through education. For this, there is a need to work across different disciplines, in partnership with different stakeholders and understand the value chain and potential for profit and entrepreneurship at different stages, and to integrate this new way of thinking into educational institutions and agricultural curricula (ibid., 2014, p.2).

In terms of policy for more effective use of young people in agricultural sector, formalized and regular processes that bring together youth and decision makers are seen as more effective than informal and irregular consultations (ibid., 2014, p.2). These may include youth 'seats' in decision-making bodies and advisory groups. Youth representatives face similar challenges as those who represent other constituent groups, in that they represent the interests and concerns of all youth in agriculture, including those with different aims and interests in both urban and rural areas (ibid., 2014, p.2). Strategies for engaging the youth in agriculture recommended by Paisley (2014, p.4) include use of local media and social media to share the success stories/ideas experience and to reduces isolation.

A survey by YPARD of its network indicated that 93.5 per cent of its members were interested in joining a mentoring programme. It is thus something that many young people value, but few have access to. It is critical for young professionals for enhancing their skills and understanding of the sector, their confidence and the drive to excel. As the youth population rises and employment prospects become more limited, rural families will need to consider the farm as part of their children's future and this is thus how this critical legacy will be passed on (ibid., 2014, p.5).

Bi (2014) focuses on the role of the rural youth in China where with accelerating urbanization and industrialization, more and more of rural labour is migrating to urban areas. According to the annual statistics from the National Bureau of Statistics of China (2014), 268.9 million rural labourers, or 35.0 per cent of the total employed labour force, migrated to urban areas in 2013, and about 60 per cent of the migrants were less than 40 years old. A survey in 10 provinces of China revealed that the average age of farmers was 57 in 2010, while another survey asking “who will plant in the next 10 years in your family?” found that almost none of the parents interviewed expect their children to be engaged in farming (ibid., 2014, p.6).

Bi (2014, p.7) highlights the importance of considering market oriented production and industrialization because, driven by increasing labour, land and other input costs, together with increasing demand for safe and high quality food, both the government and private sector are accelerating the transition from traditional agriculture to market oriented agriculture integrated with domestic and international markets. Also, the food processing industry is growing very rapidly, food transportation is becoming quicker because of the development of better logistic systems, and food supply and value chains are becoming more efficient in China. Production, marketing, and distribution will be integrated and developed as part of a consolidated supply and value chain. Quality standards and branded production and processing will also attract more attention. The application of new information and communication technology has the potential to empower farmers and production cooperatives to access technical and market information. These features are making agriculture a more market-oriented, technology and capital-intensive, large scale, integrated, multifunctional and creative sector that is more attractive for innovative youth (ibid., p.7).

New patterns for youth participation in agriculture have emerged (Bi, 2014, pp.7-8): (i) In spite of the current rural-urban migration trends, more and more talented young people who are good at farming and who earn their first fortunes in the cities are shifting their focus to agriculture and going back to rural areas; (ii) Many well-educated graduates are similarly engaged in specialized businesses in the areas of agricultural production or related logistics fields; (iii) In the eyes of innovative youth, attractive opportunities are emerging (e.g organically grown fruits and vegetables or eco-friendly agriculture); and (iv) the unpolluted natural environment becomes an asset and a means of generating additional profit through tourism. These may be still specific to China, but these point to emergence of bright prospects for youth engagement in agriculture.

On the other hand, constraints hindering youth engagement in agriculture (Bi, 2014, p.8) include (i) farmers' lack of ability to resist risks (both natural and market risks) and shocks; (ii) limited application of technological innovation and low rate of technology transfer constrain the development of modern agriculture; (iii) lack of agribusiness management capacity and entrepreneurship; (iv) current land policy and lack of financial support as constraints for growth of modern, large scale agricultural production; (v) The generally low income levels in traditional small scale farming compared to other sectors and unfavourable notions about agriculture related careers resulting in lack of interest amongst youth in agricultural farming and research; and (iv) uncomfortable living conditions in rural areas tend to make youth prefer to live in cities.

Priorities and strategies for enhancing youth engagement in agriculture (ibid., p.8) include (i) national foresight and a vision for modern agriculture (as a "roadmap") with e.g. a five-year plan for youth to engage in agriculture; (ii) need for attaining a balance between urbanization and emergence of the 'new countryside', especially with respect to rural development and provision of a social safety net system; and (iii) a broad based advocacy network.

VII. Concluding Observations

This paper has extended our earlier study (Gaiha and Imai 2014) to re-examine the relationships among agricultural productivity, employment, wage rates and poverty, based on econometric analysis of cross-country panel data. We have updated the datasets, added a few additional variables, such as, gender indices, and estimated poverty by system equations where agricultural productivity is treated as an endogenous variable.

First, we have identified a number of important factors affecting agricultural productivity, such as agricultural R&D expenditure, irrigation, fertilizer use, agricultural tractor/machinery use, reduction in inequality of land distributions, or reduction in gender inequality. In policy terms, it is important for the government to allocate larger share of public expenditure to agricultural R&D, to implement policies enabling the landless or smallholders to have access to land in order to reduce inequality in land distributions, and to reduce gender inequality by installing institutions and programs to enforce laws and policies that promote equal access for men and women in education, health, economic/employment opportunities and property rights.

Second, while agricultural wage rate is negatively associated with agricultural productivity and food price in levels, the growth in agricultural wage rate is positively correlated with the growth in agricultural productivity and with the growth in food price, particularly after 2000. That is, agricultural wages have become more sensitive to, or more responsive to, change in food prices and agricultural land or labour productivity in recent years. Contrary to ILO's (2012) claim that the gap has widened recently, our results suggest narrowing of the gap between wage and labour productivity once we focus on the conditional relationship between the two. Third, agricultural employment per hectare tends to increase agricultural productivity after taking account of the endogeneity of the former. Also, the growth in agricultural employment per hectare tends to increase the growth in non-agricultural employment over time with the adjustment for the endogeneity of the former. We have also reviewed the recent literature and emphasised the importance of enhancing agricultural productivity and employment.[14]

Fourth, both agricultural growth and non-agricultural growth tend to lead to reduction in overall inequality. Finally, increase in agricultural productivity which is treated as endogenous will reduce poverty significantly through overall economic growth. Overall, a number of econometric results in the present study imply that policies to increase agricultural productivity and agricultural employment are likely to increase non-agricultural growth, overall growth and reduce poverty.

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[14] Future studies should investigate the differential effect of employment in different age groups or gender on agricultural productivity or poverty using the household datasets for selective developing countries given the lack of international data of employment or wages of rural youth.

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Appendix: Descriptive Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
logYa	overall	9.876515	1.349567	5.231017	13.8112	N = 3686
	between		1.318882	6.27102	13.37533	n = 114
	within		0.3094331	8.530314	11.04979	T = 32.3333
logAm	overall	3.184665	2.162559	-5.437993	8.794895	N = 3487
	between		2.186574	-2.898907	8.611008	n = 110
	within		0.6816546	-0.0740063	6.090359	T = 31.7
logIrr	overall	0.8930554	1.982855	-7.518917	4.330534	N = 2916
	between		1.993302	-7.23736	4.199683	n = 54
	within		0.1752255	-0.8995174	3.268996	T = 54
logFerr	overall	3.402485	1.896681	-4.327538	7.371776	N = 3480
	between		1.856429	-1.784782	6.890302	n = 100
	within		0.4257769	-2.497335	5.967347	T-bar = 34.8
logLan~i	overall	4.066477	0.2462856	3.637586	4.465908	N = 1026
	between		0.2529111	3.637586	4.465908	n = 19
	within		0	4.066477	4.066477	T = 54
logTrade	overall	4.104422	0.5826389	1.670378	5.636078	N = 4903
	between		0.4699554	2.869118	4.966186	n = 119
	within		0.3337833	2.123924	5.536276	T-bar = 41.2017
logAgRD	overall	2.317224	1.653559	-2.040221	6.494419	N = 1130
	between		1.611059	-1.513208	6.314017	n = 58
	within		0.3643778	-0.5520698	3.647747	T = 19.4828

GenderN	overall	3.402681	0.636812	2	5	N = 1007
	between		0.6099564	2.09375	4.71875	n = 64
	within		0.2028181	2.545538	4.045538	T-bar = 15.7344
sw	overall	0.4146341	0.4927661	0	1	N = 2296
	between		0.4956906	0	1	n = 82
	within		0	0.4146341	0.4146341	T = 28
frankel	overall	15.93779	12.54785	2.3	68.83	N = 2156
	between		12.6272	2.3	68.83	n = 77
	within		0	15.93779	15.93779	T = 28
logL	overall	-8.165094	2.333406	-16.43894	0.7190586	N = 995
	between		2.411109	-14.47385	0.6295472	n = 90
	within		0.5690946	-11.79891	-6.34625	T = 11.0556
logLN	overall	4.504785	0.3887504	2.415914	5.135798	N = 1296
	between		0.4457629	2.805248	5.048069	n = 97
	within		0.2317907	2.612994	5.399674	T-bar = 13.3608
logWage	overall	8.282192	3.899703	0.7377972	31.93626	N = 314
	between		4.693386	4.622152	31.93626	n = 64
	within		1.481767	1.210787	14.1857	T = 4.90625
logRWage	overall	5.001004	5.824899	-3.379543	56.4354	N = 287
	between		8.616522	0.2806707	56.4354	n = 58
	within		2.055797	-4.070332	17.58275	T = 4.94828
logNon~l	overall	-0.7521458	0.9635001	-9.173892	-1.55E-06	N = 6548
	between		0.6606344	-2.55807	-0.2144091	n = 120
	within		0.6890075	-7.367968	1.37128	T-bar = 54.5667
logFoo~e	overall	4.290067	1.032275	-4.60517	5.907702	N = 1038
	between		0.4131813	3.228835	4.975382	n = 52
	within		0.9499068	-4.13123	6.889	T = 19.9615
logAgr~w	overall	7.117318	1.145068	4.398173	11.63057	N = 3099
	between		1.16137	4.507414	10.77959	n = 114
	within		0.2524113	6.210769	8.122969	T-bar = 27.1842
logpri~s	overall	1.694504	0.204939	1.098612	2.079442	N = 4994

	between		0.1950136	1.13971	1.94591	n = 119
	within		0.0656541	1.293141	2.0517	T = 41.9664
popula~h	overall	1.974947	1.252397	-7.533252	11.18066	N = 6039
	between		0.9303525	-0.1853683	4.70327	n = 119
	within		0.853747	-8.252432	9.201019	T = 50.7479
loginf~n	overall	1.568645	2.312227	-13.43871	10.19474	N = 5019
	between		0.9850017	-0.3428978	4.270372	n = 119
	within		2.101953	-13.03498	10.18986	T-bar = 42.1765
lognoa~c	overall	6.412387	2.70524	-14.29116	9.782739	N = 4061
	between		2.338038	-13.85616	9.443203	n = 114
	within		0.4051493	4.05207	8.898143	T = 35.6228
logagr~c	overall	4.840795	2.281737	-14.3312	6.631798	N = 4088
	between		1.909991	-14.23328	6.256322	n = 115
	within		0.2044626	3.970452	5.824751	T = 35.5478
Inequa~l	overall	44.4115	5.896689	20.57831	59.95359	N = 2795
	between		4.292248	25.23815	51.37882	n = 119
	within		3.172033	31.43002	60.12818	T-bar = 23.4874
log~g200	overall	1.500566	2.074055	-4.60517	4.325985	N = 783
	between		1.935846	-3.606593	4.213312	n = 119
	within		0.8227494	-4.799615	4.6758	T = 6.57983
log~g125	overall	0.5347658	2.262646	-4.60517	4.148517	N = 783
	between		2.150242	-3.632215	3.965753	n = 119
	within		0.898589	-4.332395	3.861336	T = 6.57983
log~c200	overall	2.605432	1.924219	-4.60517	4.589549	N = 830
	between		1.789706	-3.392642	4.555455	n = 119
	within		0.8498869	-4.7545	5.615557	T = 6.97479
log~c200	overall	2.605432	1.924219	-4.60517	4.589549	N = 830
	between		1.789706	-3.392642	4.555455	n = 119
	within		0.8498869	-4.7545	5.615557	T = 6.97479
loggdppc	overall	6.797822	1.108446	4.056728	10.27328	N = 5135
	between		1.033475	4.871583	9.13772	n = 119
	within		0.3806555	4.981512	9.020123	T-bar = 43.1513

con~_int	overall	0.2005913	0.5074446	0	2	N = 6426
	between		0.3095017	0	1.407407	n = 119
	within		0.4031115	-1.206816	2.145036	T = 54
tot_no~g	overall	106.6506	32.13955	35.13227	532.8226	N = 4574
	between		17.95782	73.79354	166.2942	n = 109
	within		26.70446	11.786	473.1789	T = 41.9633
SSA	overall	0.3697479	0.4827739	0	1	N = 6426
	between		0.4847775	0	1	n = 119
	within		0	0.3697479	0.3697479	T = 54
LAC	overall	0.1932773	0.3948993	0	1	N = 6426
	between		0.3965382	0	1	n = 119
	within		0	0.1932773	0.1932773	T = 54
EAP	overall	0.092437	0.2896644	0	1	N = 6426
	between		0.2908665	0	1	n = 119
	within		0	0.092437	0.092437	T = 54
SA	overall	0.0504202	0.2188274	0	1	N = 6426
	between		0.2197356	0	1	n = 119
	within		0	0.0504202	0.0504202	T = 54
ECA	overall	0.1932773	0.3948993	0	1	N = 6426
	between		0.3965382	0	1	n = 119
	within		0	0.1932773	0.1932773	T = 54