



Agricultural Employment, Wages and Poverty in Developing Countries*

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Abstract: Drawing upon panel data estimations, we have analyzed relationships between 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 distribution,

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Manuscript received 7.8.2014; revised 13.11.2014; accepted 13.11.2014.

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and reduction in gender inequality. Second, while agricultural wage rates are negatively associated with agricultural productivity and food price in terms of levels, rising agricultural wage rates are positively correlated with growth in agricultural land and/or labor productivity as well as with growth in food prices, particularly after 2000. Contrary to the International Labor Organization's 2012 claim of a widened gap between wage and labor productivity, this finding suggests a narrowing gap once the conditional relationship between the two is taken into account. Third, agricultural employment per hectare tends to increase agricultural productivity after taking account of the endogeneity of the former, while growth in agricultural employment per hectare tends to increase growth in non-agricultural employment over time with adjustment for the endogeneity of the former. Fourth, both agricultural growth and non-agricultural growth tend to lead to a reduction in overall inequality. Finally, increases in agricultural productivity (which is treated as endogenous) will reduce poverty significantly through contributing to overall economic growth. Overall, policies to increase agricultural productivity and agricultural employment are likely to increase non-agricultural growth, overall growth and reduce poverty. The presence of institutional frameworks to promote greater equality between men and women is likely to be one of the key factors, consistent with the important role of women in promoting agricultural productivity in developing countries.

Keywords: Agriculture, Poverty, Employment, Wage

This paper re-examines relationships between agricultural productivity, employment, wage rates and poverty, based on econometric analysis of cross-country panel data. While agricultural growth and rural development have been considered central to economic growth and poverty reduction in developing countries (e.g. Imai, Gaiha & Thapa 2010), recent studies by the World Bank and some others have given greater priority to urbanization, especially in small and secondary towns,

and have questioned the importance of smallholder agriculture as an important pathway out of poverty (e.g. World Bank 2013; Collier & Dercon 2014; Christiaensen & Todo 2014).

For instance, Collier and Dercon (2014) refute the World Development Report 2008's (World Bank 2007: xiii) arguments that stimulating agricultural growth is "vital for stimulating growth in other parts of the economy" and that smallholders are at the core of this strategy. Questioning the claim that production and demand linkages are stronger in agriculture than in any other sector, and therefore that promoting growth in agriculture has the highest multiplier effects, Collier and Dercon point out that the supporting evidence is far weaker than frequently suggested and causality of where growth is originating is far from fully established.

Contrary to Collier and Dercon (2014), we have shown in a series of recent studies that agricultural growth has played a key role in overall economic growth and poverty reduction (Imai & Gaiha 2014; Imai, Gaiha, & Garbero 2014; Imai, Abekah-Nkrumah, & Purohit 2014). Nevertheless, it remains important to re-examine the role of agricultural growth in overall economic growth and poverty reduction in developing countries with a focus on the determinants of agricultural growth. It is also necessary to link, in a cross-country context, agricultural growth to growth of employment in agriculture and elsewhere, wage rates, and agricultural productivity.

In this context, the present study uses cross-country panel data to investigate the relationships between agricultural productivity, employment, wage rates and poverty, using state-of-the-art econometric methods.

Specifically, we extend Gaiha and Imai (2008) by (i) updating the datasets, (ii) adding additional variables such as gender indices,¹ and (iii)

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

estimating poverty by a system of equations where agricultural productivity is treated as an endogenous variable.

The rest of the paper is organized as follows. The next section discusses the theoretical arguments that motivate our models. Then, we outline the data sources and present the econometric models we will use. This is followed by discussions of the results. The final section offers concluding observations.

Theoretical Foundations

While the present study's focus is broad and it does not aim to test a particular model, it is useful to review relevant theoretical foundations related to the four econometric models we will test empirically.

The first model assumes that agricultural productivity is determined by technology, R&D, agricultural employment, inequality in land distribution, openness, and agricultural wages (where agricultural employment and wage are endogenously determined). This is related to Schultz's (1964) seminal work that stressed two propositions: (i) allocation of factors of production is efficient in traditional agriculture; and (ii) technological change, driven by knowledge advancement as well as the effective supply of land, is important for improvement in agricultural productivity. In line with Schultz, Hayami and Ruttan (1971) introduced a "metaproduction" (aggregate homogeneous) function to measure the determinants of agricultural development where reallocation of factors takes place through changes in the returns to factors.

The second model focuses on dynamic changes in farm and non-farm employment where we take into account the effect of farm employment on non-farm employment. The linkages between farm and non-farm activities have been emphasized in the development literature (e.g. Mellor 1976; Mellor & Lele 1972; Imai, Gaiha, & Thapa 2012).

and women in education, health, the economy, and protection under the law. See below for the definition and further discussion.

First, there are production linkages, both backward and forward. Backward linkages relate to the demand of farmers for inputs such as ploughs, engines and tools. Forward linkages are linked to the need for agricultural commodities processing (spinning, canning and milling etc). Second, there are consumption linkages. As agricultural income rises, it feeds into higher demand for non-farm goods produced locally or in neighboring villages and towns.

Finally, there are linkages through the supply of labor and capital. As agricultural productivity rises, either labor is released or wages go up. Also, agricultural surpluses could finance expansion of the non-farm sector. And, the latter in turn could stimulate agricultural production via lower input costs, technological change and the plowing back of profits into farming (Gaiha & Imai 2008). While the linkages between these two sectors are complex, our empirical model focuses only on the dynamic inter-linkages of farm and non-farm employment by assuming out other forms of linkages.

The third model estimates how changes in inequality are influenced by changes in agricultural and non-agricultural value added activities or employment. This model draws upon Kuznets's 1955 argument that aggregate inequality will be influenced by changes in compositions of agricultural workers (whose incomes are relatively more equal and lower on average) and non-agricultural workers (whose incomes are more unequal and higher on average). Inequality will increase as workers move from the agricultural to the non-agricultural sector, but beyond a certain point, inequality will fall as the majority of workers receive the constant non-agricultural/industrial wage (Gallup 2012: 7).

However, the inequality-growth link is more complex than Kuznets portrayed as both are endogenous (e.g. Chen & Turnovsky 2010). Our empirical model treats changes in agricultural and non-agricultural value added and employment as exogenous and focuses only on the causality from these sectoral income and employment changes on overall inequality to avoid complicating the model.

The fourth model estimates the effects of GDP per capita on

poverty where GDP per capita is a function of agricultural income as a straightforward extension of the first model where the effects of conflict on GDP per capita and poverty are taken into account. This is embedded in the large theoretical literature where agricultural growth is fundamental for overall growth, and follows the ideas of Imai, Gaiha and Thapa (2010).

Data and Econometric Models

Data

We have constructed the panel data from various data sources, such as the World Development Indicators (WDI) (World Bank 2014), FAOSTAT (FAO 2014), and LABORSTA (ILO 2014). The data on agricultural R&D (government expenditure) are sourced from FAOSTAT. The gender index is based on data from the 2014 WDIs. We still face a constraint as agricultural wage series and R&D data are available only for a limited number of developing countries. Descriptive statistics of the variables are provided in the appendix.

Model 1: relationships between agricultural productivity, employment, technology, openness of the economy, and 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:

$$\begin{aligned} \log Y_{a,it} = & \alpha + \beta_1 \log Am_{it} + \beta_2 \log Irr_{it} + \beta_3 \log Fert_{it} + \beta_4 \log L_{it} + \beta_5 \log AgriR\&D_{it} \\ & + \beta_6 \log GINI(Land)_i + \beta_7 Open_i + \beta_8 Gender_{it} + \gamma_t + \pi_i + \varepsilon_{it} \end{aligned} \quad (1)$$

where $\log Y_{a,it}$ is a log of value added per hectare of arable land (in constant 2005 US dollars, taken from World Bank 2014), i denotes country, and t denotes year. This $\log Y_{a,}$ measures a country's agricultural productivity. The explanatory variables include technology (comprised of a log of agricultural machinery/tractors per hectare of arable land ($\log Am_{it}$)),² a log of share of irrigated land in total arable land ($\log Irr_{it}$), and a log of fertilizer consumption per hectare of arable land ($\log Fert_{it}$). A log of total employment in the agricultural sector per hectare of arable land is referred to by $\log L_{it}$ (based on World Bank 2014), and $\log AgriR\&A_{it}$ is the logarithm of agricultural R&D expenditure per hectare (in constant 2005 US dollars, taken from FAO 2014).³ The logarithm $\log GINI(Land)_i$ is of the Gini coefficient of land distribution to capture 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 laborers in agricultural production or activities. This raises total agricultural productivity and production.

$Open_i$ refers to the openness of an economy to the rest of the world or to the degree of integration with global markets. We have used trade share (the share of sum of exports and imports in GDP), a Frankel-Romer measure and a Sachs-Warner measure. The Frankel-Romer index is the

² $\log Am_{it}$ captures the total value of powered agricultural machinery and tractors (in use) as an aggregate category and as such these are labor saving in nature. We realise the importance of distinguishing the type of implements, e.g. by the requirement for labor use, but FAOSTAT does not allow us to do so for the sample countries.

³ Gaiha and Imai (2008) used Thirtle, Lin and Piesse's (2003) data, but we use FAOSTAT2014 because the latter covers more countries.

aggregated fitted values of trade share, derived from a bilateral trade equation with geographical variables (e.g. area, population) (Frankel & Romer 1999). By contrast, the Sachs and Warner measure is a binary variable based on a series of trade related indicators: tariffs, quotas, black market premium, social organization and the existence of export marketing boards (Sachs & 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, and protection under law.⁴ The time effect constant for all countries for a particular year is designated γ_t , π_i is an unobservable individual (country) effect, and ε_{it} is an error term for independent and identically distributed random variables (i.i.d.). The coverage of countries and the period varies considerably according to the specifications (see Table 1).

Equations 2 and 3 specify the determinants of agricultural employment and wage rates, respectively. First, let us look at Equation 2.

$$\log L_{it} = \chi + \delta_1 \log Ya_{it} + \delta_2 \log Wage_{it} + \delta_3 \log NonCereal_{it} + \delta_4 Gender_{it} + v_i + \mu_i + \omega_{it} \quad (2)$$

where $\log L_{it}$ (log of agricultural employment per hectare) is estimated by log of agricultural value added ($\log Ya_{it}$), and log of monthly agricultural wage ($\log Wage_{it}$). Monthly agricultural wages have been taken from ILO (2014). We use both nominal agricultural wage rates—derived as “average agricultural monthly wage rate in local currency adjusted only by exchange rates” (Table 2a)—and real agricultural wage rates—“average agricultural monthly wage rates in local currency adjusted by

⁴ It is noted that employment and wage data disaggregated by gender and aggregated at country levels are unavailable for most of the sample countries. A gender index has thus been used to address the gender issue of employment and wages.

both the annual average Consumer Price Index and exchange rates” (Table 2b). The logarithm $\log NonCereal_{it}$ is the share of total arable land used for crops other than cereal crops. 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, v_i is a time effect, μ_i is an individual (country) effect, and ω_{it} is an error term.

The log of agricultural wages is then estimated by Equation 3:

$$\begin{aligned} \log Wage_{it} &= \phi + \varphi_1 \log Ya_{it} + \varphi_2 \log FoodPrice_{it} + \varphi_3 \log Schooling Years(primary) \\ &+ \varphi_4 \log Population Growth_{it} + \varphi_5 \log Inflation + \zeta_t + \pi_i + \epsilon_{it} \end{aligned} \quad (3)$$

where $\log Wage_{it}$ refers to either the log of the nominal agricultural wage rate (the results of which are presented in Table 3a) or the log of the real agricultural wage rate (Table 3b). Our proxy for agricultural productivity, $\log Ya_{it}$, has been inserted to examine how agricultural productivity has translated into wage rates. The logarithm $\log FoodPrice_{it}$ is the log of the consumer food price index, which will negatively affect real wage rates, or negatively or positively affect nominal wage rates depending on the general-equilibrium effect of food prices on wage rates, which could be positive or negative. $\log Schooling Years(primary)$ is the log of average years of schooling years at the level of primary education. The expected sign is positive as the quality of the labor force tends to be improved by education. The log of population growth, $\log Population Growth_{it}$, captures the increase in labor supply of younger generations. The inflationary pressure of the economy (e.g. excessive money supply) or the degree of uncertainty in the economy is captured with $\log Inflation$, the log of the rate of inflation. Inflation is supposed to reduce real wage rates, 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 rates by adding $\log L$ and $\log LN$ as explanatory variables, as in Equation 3'.

$$\begin{aligned} \log Wage_{it} &= \phi + \phi_1 \log Ya_{it} + \phi_2 \log FoodPrice_{it} + \phi_3 \log SchoolingYeas(primry) \\ &+ \phi_4 \log PopulationGrowth_{it} + \phi_5 \log Inflation + \phi_6 \log L + \phi_7 \log LN + \zeta_t + \pi_i + \epsilon_{it} \end{aligned} \quad (3')$$

In order to examine the dynamic relationship between agricultural wage rates and agricultural productivity and how the relationship between the two variables has changed over time, it is necessary to examine the change in agricultural wage rates and the change in the agricultural productivity. As a variant of Equation 3, we will therefore estimate Equation 3''.

$$\begin{aligned} D \log Wage_{it} &= \phi' + \phi'_1 D \log Ya_{it} + \phi'_2 D \log FoodPrice_{it} + \phi'_3 D \log SchoolingYeas(primry) \\ &+ \phi'_4 D \log PopulationGrowth_{it} + \phi'_5 D \log Inflation + \zeta'_t + \pi'_i + \epsilon'_{it} \end{aligned} \quad (3'')$$

As an extension, $D \log Ya$ has been replaced by the first difference of log Agricultural Value Added per Worker to examine the relationship between the growth rate of labor productivity and that of the 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.⁵ Second, we estimate real agricultural wages using the fixed or random effects specifications of Equation 3. Using the predicted

⁵ The issue of endogeneity will be addressed later.

values, we use instrumental variable (IV) specifications for Equations 1 and 2 simultaneously.

Model 2: agricultural and non-agricultural employment growth

We estimate an alternative model for agricultural employment growth and non-agricultural employment growth. While Gaiha and Imai (2008) used the Arellano-Bond GMM estimator (Arellano & Bond 1991) to estimate the dynamic panel model, the present study applies Blundell and Bond's (1998) System GMM (SGMM) estimator⁶ 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 its own lags, both lagged 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, growth in non-agricultural employment is estimated by its own lags and agricultural employment growth (treated as endogenous), and it is instrumented by its own lagged values in the SGMM model:

$$\begin{aligned}
 & DlogL_{it} \\
 &= \beta_1 DlogL_{it-1} + \beta_2 DlogL_{it-2} + \beta_3 DlogYa_{it-1} + \beta_4 DlogYa_{it-2} + \beta_5 DlogWage_{it-1} \\
 &+ \beta_6 DlogNonCereal_{it-1} + \varepsilon_{it}
 \end{aligned}
 \tag{4}$$

⁶ 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.

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

where LN_{it} denotes non-agricultural employment (defined as the total number of people employed in sectors other than agriculture). Growth rate of non-agricultural employment, $DlogLN_{it}$, is estimated by its own lags and growth rates of agricultural employment ($Dlog_{it-1}$ and $Dlog_{it-2}$) 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: the effect of agricultural value added per capita growth and non-agricultural per capita growth on the change in inequality

To see the overall relationship between agricultural and non-agricultural growth on inequality changes, in one of our recent papers we applied various models (e.g. static and dynamic panel models) (Imai & Gaiha 2014). As an extension of this study, in Equation 6 we estimate the first difference in inequality ($DInequality_{it}$), by $\widehat{logAgriVApc_{it}}$, the predicted value of the first difference in agricultural value added per capita, and $\widehat{logNonAgriVApc_{it}}$, the predicted value of the first difference in non-agricultural value added per capita.

A main difference between Imai and Gaiha (2014) and the present study is that here we use the predicted values for changes in agricultural and non-agricultural value added.

$$\begin{aligned} DInequality_{it} &= \vartheta'_0 + \vartheta'_1 DInequality_{it-1} + \vartheta'_2 Dlog \widehat{AgriVApc_{it}} + \vartheta'_3 Dlog \widehat{NonAgriVApc_{it}} \\ &+ \vartheta'_4 Dlog \widehat{L_{it}} + \vartheta'_5 Dlog \widehat{LN_{it}} + \sigma'_t + \mu'_i + \varepsilon'_{it} \end{aligned} \quad (6)$$

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—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 estimator based on Blundell and Bond's SGMM estimator has been applied to incorporate the effect of the lagged inequality changes on the current inequality change:

$$\begin{aligned}
 DInequality_{it} &= \vartheta''_0 + \vartheta''_2 Dlog \widehat{Agri VA pc}_{it} + \vartheta''_3 Dlog \widehat{NonAgri VA pc}_{it} + \vartheta''_4 Dlog \widehat{L}_{it-1} \\
 &+ \vartheta''_5 Dlog \widehat{LN}_{it-1} + \sigma''_t + \mu''_i + \varepsilon''_{it}
 \end{aligned}
 \tag{6'}$$

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: agricultural productivity and poverty

As an extension of Model 1, we apply 3SLS (three stage least squares) to the following system of 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, $\log GDP_{pc,it}$ (log of GDP per capita) and $Poverty_{it}$ (either poverty gap or poverty headcount ratio based on the international poverty lines, US\$1.25 or US\$2.00):

$$\begin{aligned}
 \log Y_{a,it-1} &= \gamma_0 + \gamma_1 \log Am_{it-1} + \gamma_2 \log Irr_{it-1} + \gamma_3 \log Fert_{it-1} + \gamma_4 TradeOpen_{it-1} + \vartheta_t \\
 &+ Region + \varepsilon_{it-1}
 \end{aligned}
 \tag{1'}$$

$$\begin{aligned}
& \log GDPpc_{it} \\
&= \beta_0 + \beta_1 \text{Conflict Intensity}_{it} + \beta_2 \log Ya_{it-1} + \beta_3 \text{TotNonofg}_{it} + \beta_4 \text{Inequality}_{it-1} + \tau_t \\
&+ \text{Region} + \omega_{it}
\end{aligned} \tag{7}$$

$$\begin{aligned}
& \text{Poverty}_{it} \\
&= \alpha_0 + \alpha_1 \text{Conflict Intensity}_{it} + \alpha_2 \text{TotNonofg}_{it} + \alpha_3 \log GDPpc_{it} + \kappa_t + \text{Region} + e_{it}
\end{aligned} \tag{8}$$

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 data availability of explanatory variables for Equation 1. Here we take the first period lag in estimating Equation 1' considering the fact that agricultural productivity, $\log Y_{a,it}$, is endogenous to $\log GDPpc_{it}$, log of GDP per capita. Lagged value of $\log Y_{a,it}$ is estimated by lagged value of $\log Am_{it}$ (log of agricultural machinery/tractors per hectare of arable land), lag of log share of irrigated land in total arable land ($\log Irr_{it-1}$), and lag of log fertiliser consumption per hectare of arable land ($\log Fert_{it-1}$) as well as lagged value of trade openness (Trade Open_{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 Southeast 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). The error term is ϵ_{it} , supposed to be independent and identically distributed (i.i.d.).

The $\log GDPpc_{it}$ in Equation 7 is estimated by *ConflictIntensity_{it}*, capturing the intensity of conflict obtained from CSCW and Uppsala Conflict Data Program (UCDP 2014). This covers armed conflicts, both internal and external, from 1946 to the present. To take account of the endogeneity of agricultural productivity, the lagged value of $\log Ya_{it}$ (estimated simultaneously by Equation 1') is used to capture the effect of agricultural productivity on 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). Lagged value of inequality has been inserted to capture the effect of inequality on growth. 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, the poverty gap or headcount ratio is estimated in Equation 8 by $ConflictIntensity_{it}$, $TotNonofg_{it}$ (uncertainty in export price), and $\log GDPpc_{it}$, 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.

Econometric Results

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

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

Table 1 reports the results for Equation 1 where $\log Ya$, agricultural value added per hectare, is estimated. We have reported nine cases 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). The selection of an FE or RE model is guided by Hausman specification test results, which are reported in the last row. Coefficient estimates of year dummies are not included to save space.⁷

Table 1.

Elasticity Estimates of Agricultural Value Added per Hectare (Model 1, Single Equation 1)

Column No.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RE	FE	FE	RE	RE	FE	RE	FE	RE
Exp. Variables		with time effects			with time effects		with time effects		with time effects
logAm	0.215*** (0.0263)	0.067 (0.0423)	-0.024 (0.731)	0.0960*** (0.0353)	0.115*** (0.0246)	0.0657* (0.039)	0.134*** (0.0244)	0.0657* (0.0398)	0.123*** (0.0250)
logTrade	0.149** (0.0651)	-0.133*** (0.0414)	-2.823 (1.784)	0.363*** (0.0410)	0.131*** (0.0357)				
logAg R&D		-0.02 (0.0421)		0.108*** (0.0349)	0.0458* (0.0253)	0.192*** (0.0421)	0.0837*** (0.0277)	0.192*** (0.0421)	0.0800*** (0.0294)
logIrr	0.032 (0.109)		0.241 (0.552)	0.149** (0.0714)	0.164*** (0.0469)	0.001 (0.120)	0.075 (0.0591)	0.001 (0.120)	0.125** (0.0530)
logFert	0.602*** (0.167)		-0.237 (0.366)	0.213*** (0.0771)	0.120** (0.0538)	0.455*** (0.107)	0.055 (0.0718)	0.455*** (0.107)	0.076 (0.0685)
logLandGini	-4.017*** (0.951)								
Gender			-0.385 (0.368)						
Sachs and Warner (SW)							-0.266 (0.350)		
Frankel									-0.005 (0.00937)
Year Dummies	No	ü	No	No	ü	No	ü	No	ü
		1982-2006			1982-2008		1982-2006		1982-2006
Constant	22.71 (3.888)	10.50 (0.208)	24.05 (9.577)	6.77 (0.35)	7.826 (0.264)	6.908 (0.428)	8.774 (0.378)	6.908 (0.428)	8.570 (0.295)

⁷ For all of the cases, we do not find evidence of cross-sectional dependence, heteroscedascity, and first-order autocorrelation, which would justify our use of fixed or random effects estimations.

Observations	152	64	12	327	327	276	276	276	276
Number of code1	7	6	5	21	21	18	18	18	18
Hausman Test:	Chi ² (4)=	Chi ² (28)=	Chi ² (5)=37.30**	Chi ² (5)=	Chi ² (32)=	Chi ² (4)=	Chi ² (29)=	Chi ² (3)=	Chi ² (29)=
Test:	5.86	1257.66**		9.21	27.56	9.23*	4.46	10.00**	2.46
Ho: difference in			Prob>Chi ²						
coefficients not	Prob>Chi ²	Prob>Chi ²	=0.0000	Prob>Chi ²	Prob>Chi ²	Prob>Chi ²	Prob>Chi ²	Prob>Chi ²	Prob>Chi ²
systematic	=0.2099	=0.000	Favors FE	=0.1012	=0.6910	=0.0556	=1.0000	=0.0404	=1.0000
	Favors RE	Favors FE	model	Favors RE	Favors RE	Favors FE	Favors RE	Favors FE	Favors RE
	model	model		model	model	model	model	model	model

Note. Dependent variable: log Ya = Agricultural value added per hectare; Fixed Effects (FE) or Random Effects (RE) Model. Standard errors in parentheses. The Sachs & Warner Indicator and the Frankel-Romer indicator have been dropped since there is no time variance.

*** p < .01. ** p < .05. * p < .1.

First, coefficients of the variables on technology, the log of agricultural machinery/tractors per hectare of arable land ($\log Am_{it}$), are mostly positive and significant (seven out of nine cases). That is, more intensive use of labor-saving technology (i.e. agricultural machinery) tends to be associated with improved agricultural land productivity (proxied by agricultural value added per hectare). The share of irrigated land in total arable land ($\log Irr_{it}$) is also positive (significant in columns 4, 5 and 9), suggesting that irrigation is associated with higher agricultural productivity. Fertilizer 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 imports and exports in GDP is positive and significant in column 1, but it is negative and significant in column 2 once year dummies are included. Consistent with earlier research (e.g. Imai, Gaiha, & Thapa 2010), both the Sachs and Warner index and the Frankel index are statistically insignificant. Government agriculture-related R&D expenditure is positive and significant in most cases, underscoring the importance of governmental sector-specific R&D spending 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. The Hausman test favors the fixed-effects model (column 3). However, in the random effects analysis, the gender index is found to be positive and significant in explaining agricultural productivity.⁸ 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. Despite the limitations of using the gender index as one of the explanatory variables,⁹ the results are consistent with the important role of women in promoting agricultural productivity in developing countries.

Table 2 shows the results of elasticity estimates for agricultural employment per hectare ($\log L$) based on Equation 2—with nominal agricultural wage rates (columns 1-3') and with real agricultural wage rates (columns 4-5). In column 1, contrary to Gaiha and Imai (2008), the coefficient estimate for $\log Y_a$ —our proxy for agricultural productivity—is negative and significant. This may reflect the fact that agricultural productivity improvements may sometimes involve the introduction of labor-saving technologies or agricultural machinery. Average nominal monthly wage has the same (negative) sign as in Gaiha and Imai, but it is statistically significant in the present study (column 1). The share of land devoted to non-cereal crops is statistically insignificant. Gender index is statistically insignificant (column 3').

⁸ The result will be supplied on request.

⁹ We do not adjust for the endogeneity of the gender index due to the limited availability of possible instruments. Because of its limited country coverage, the gender index cannot be instrumented. This is unlike, for example, the use of European's settler mortality or population density in 1500 in the empirical literature to estimate the relationship between institutions and growth (Imai et al. 2010).

Table 2.

Elasticity Estimates of Agricultural Employment per Hectare (Equation 2)

Column No.	(1)	(2)	(3)	(3)'	(4)	(5)
	FE	FE	FE	RE	FE	FE
Exp. Variables						
Log Ya	-0.651*** (0.173)	-0.334 (0.322)	0.0493 (0.351)	0.807 (1.389)	-0.678*** (0.186)	-0.617 (0.367)
Log Wage (nominal agricultural wage rate)	-0.0473* (0.0244)	-0.0389 (0.0284)	-0.0985 (0.509)	2.313 (1.568)	0.00112 (0.0123)	-0.00125 (0.0149)
Log NonCereal	-0.116 (0.490)	-0.485 (0.572)	-0.75 (2.368)	-6.585 (9.220)	-0.144 (0.514)	-1.19 (0.751)
Gender Index *				1.162 (0.907)		
Year Dummies	No	ü 1984 -2008	No	No	No	ü 1984 -2008
Constant	-1.477 (1.710)	-4.849 (3.197)	-6.845 (3.477)	-34.63 (6.954)	-2.301 (1.865)	-3.283 (3.576)
Observations	76	76	8	8	62	62
R-squared	0.293	0.626	0.364		0.249	0.708
Number of countries	17	17	3	3	15	15
Hausman Test: Test:	Chi ² (3)=23.85**	Chi ² (27)=1122.76**	Chi ² (3)=51.84**	Chi ² (3)=9.96*	Chi ² (27)=136.05**	
Ho: difference in coefficients not systematic	Prob>Chi ² =0.0000 Favors FE model	Prob>Chi ² =0.0000 Favors FE model	Prob>Chi ² =0.0040 Favors FE model	Prob>Chi ² =0.018 Favors FE model	Prob>Chi ² =0.0000 Favors FE model	

Note. Dependent Variable: log L = Agricultural employment per hectare; Fixed Effects (FE) or Random Effects (RE) Model, with nominal agricultural wage rates (columns 1-3') and with real agricultural wage rate (columns 4-5). Standard errors in parentheses. Gender Index has been dropped due to multicollinearity.

*** p < .01. ** p < .05. * p < .1.

In columns 4 and 5, 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 the unavailability of CPI data for a few countries, the gender index cannot be added. The results are mostly consistent with those in columns 1-3'. The value for *log Ya* is negative and significant in column 4. Real agricultural wage rate is statistically insignificant in both columns 4 and 5. *Log Non-Cereal* is negative and statistically insignificant.

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 three columns show the results of the level equations and the last three columns 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 column 3 to see the effect of expansion on agricultural wages. In Table 3b we replace the dependent variable with the log monthly real agricultural wage rate while using exactly the same specifications. Furthermore, in Table 3c, in order to investigate the relationship between the growth rate of labor 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 $\log Ya$ with “log Agricultural Value Added per Worker”, our proxy for labor productivity.

Table 3a.

Estimates of log Agricultural Nominal Wage (Model 1, Single for Equation 3), Level and First Difference Equations

Dep. Variable	log nominal agricultural monthly wage					
	Level Equation			Difference Equation		
	(1)	(2)	(3)	(4)	(5)	(6)
		Total Sample 1992-2008			Before 2000 (1992-1999)	After 2000 (2000-2008)
	log Agri Wage	log Agri Wage	log Agri Wage	D.log Agri Wage	D.log Agri Wage	D.log Agri Wage
	RE	FE	FE	RE	RE	RE
Exp. Variables						
logFoodPrice	-0.701*** (0.218)	0.0993 (0.401)	0.0494 (0.0579)			
logYa	-0.661 (0.571)	0.632 (2.769)	0.669 (0.612)			

Log primary ed years	4.623 (3.039)	19.25** (7.712)	- -			
Population growth	-0.45 (0.530)	-0.886 (0.997)	-0.13 (0.186)			
Log inflation	0.732*** (0.204)	0.679*** (0.254)	0.0165 (0.0736)			
Log L (farm employment)			0.0164 (0.279)			
Log LN (nonfarm employment)			-1.873* (1.037)			
D.logFoodPrice				1.551*** (0.552)	-0.229 (0.850)	3.137*** (1.010)
D.logYa				3.892*** (1.500)	-0.859 (3.277)	5.011*** (1.764)
D.log primary edyears				9.019 (5.733)		8.663 (5.826)
D.population growth				0.028 (0.658)	4.039* (2.098)	-0.261 (0.714)
D.log inflation				-0.102 (0.168)	-0.0118 (0.169)	-0.456 (0.502)
Year Dummies	No	ü 1992 -2008	No	ü 1993 -2008	ü 1993 -1999	ü 2001 -2008
Observations	110	110	29	84	34	50
R-squared		0.401	0.1822			
Number of countries	16	16	6	12	9	8
Hausman Test: Test: Ho: difference in coefficients not systematic	Chi ² (5)=8.51 Prob>Chi ² =0.1305 Favors RE model	Chi ² (22)=38.70* Prob>Chi ² =0.0153 Favors FE model	Chi ² (6)=51.66** Prob>C ² =0.0000 Favors FE model	Chi ² (21)=10.86 Prob>Chi ² =0.96 54 Favors RE model	Chi ² (11)=1.86 Prob>Chi ² =0.9989 Favors RE model	Chi ² (12)=1.36 Prob>Chi ² =0.9999 Favors RE model

Note. Dependent Variable: log Wage= log nominal agricultural monthly wage (or First Difference in log Wage); Fixed Effects (FE) or Random Effects (RE) Model. Standard errors in parentheses. Primary education has been dropped in columns 5 and 6 due to multicollinearity.

*** p < .01. ** p < .05. * p < .1.

Table 3b.

Estimates of log Agricultural Real Wage (Model 1, Single Equation for (3)), Level and First Difference Equations

Dep. Variable	log real agricultural monthly wage					
	Level Equation			Difference Equation		
	(7)	(8)	(9)	(10)	(11)	(12)
		Total Sample 1992-2008			Before 2000 (1992-1999)	After 2000 (2000-2008)
	log Agri Wage RE	log Agri Wage RE	log Agri Wage FE	D.log Agri Wage RE	D.log Agri Wage RE	D.log Agri Wage RE
Exp. Variables						
logFoodPrice	-1.735*** (0.225)	-2.044*** (0.351)	-0.977*** (0.0862)			
logYa	-0.672 (0.610)	-0.336 (0.364)	1.133 (0.911)			
Log primary ed years	4.524 (3.265)	2.072 (2.241)	- -			
Population growth	-0.425 (0.557)	-0.905** (0.456)	-0.368 (0.277)			
Log inflation	0.818*** (0.210)	1.305*** (0.300)	0.169 (0.110)			
Log L (farm employment)			0.314 (0.416)			
Log LN (nonfarm employment)			-3.424** (1.543)			
D.logFoodPrice				0.876 (0.573)	-1.057 (0.866)	2.991*** (1.039)
D.logYa				3.699** (1.568)	-0.802 (3.339)	5.077*** (1.821)
D.log primary edyears				9.205 (5.956)		8.777 (5.987)
D.population growth				0.0207 (0.683)	3.807* (2.138)	-0.216 (0.734)
D.log inflation				-0.0478 (0.176)	0.0535 (0.172)	-0.472 (0.533)
Year Dummies	No	ü 1992 -2008	No	ü 1993 -2008	ü 1993 -1999	ü 2001 -2008

Observations	108	108	29	83	34	49
R-squared			0.1822			
Number of countries	15	15	6	11	9	7
Hausman Test: Test: Ho: difference in coefficients not systematic	Chi ² (5)=6.43	Chi ² (22)=22.78	Chi ² (6)=244.55**	Chi ² (21)=15.20	Chi ² (11)=2.62	Chi ² (12)=2.97
	Prob>Chi ² =0.2668	Prob>Chi ² =0.4140	Prob>Chi ² =0.0000	Prob>Chi ² =0.8127	Prob>Chi ² =0.9949	Prob>Chi ² =0.9958
	Favors RE model	Favors RE model	Favors FE model	Favors RE model	Favors RE model	Favors RE model

Note. Dependent Variable: log Wage= log nominal agricultural monthly wage (or First Difference in log Wage); Fixed Effects (FE) or Random Effects (RE) Model. Standard errors in parentheses. Primary education has been dropped in columns 5 and 6 due to multicollinearity.
*** p < .01. ** p < .05. * p < .1.

Table 3c.

Estimates of log Agricultural Real Wage (Model1, Single Equation for 3), First Difference Equations

Dep. Variable	log real agricultural monthly wage					
	Difference Equation (First Difference in log Nominal Agricultural Wage)			Difference Equation (First Difference in log Real Agricultural Wage)		
	(13)	(14)	(15)	(16)	(17)	(18)
	Total Sample 1992-2008	Before 2000 (1992-1999)	After 2000 (2000-2008)	Total Sample 1992-2008	Before 2000 (1992-1999)	After 2000 (2000-2008)
	log Agri Wage	D. log Agri Wage	D. log Agri Wage	log Agri Wage	D. log Agri Wage	D. log Agri Wage
	RE	RE	RE	RE	RE	FE
Exp. Variables						
D.logFoodPrice	1.318** (0.550)	-0.256 (0.781)	2.698*** (1.020)	0.649 (0.571)	-1.095 (0.795)	3.835*** (1.010)
D.log Agricultural Value Added per Worker	3.218** (1.610)	-2.057 (3.529)	4.281** (1.951)	2.854* (1.679)	-2.126 (3.594)	5.803*** (1.884)
D.log primary edyears	7.583 (5.869)		7.099 (6.063)	7.907 (6.098)		6.805 (6.164)
D.population growth	0.101 (0.670)	4.369** (2.079)	-0.171 (0.745)	0.0948 (0.696)	4.176** (2.117)	-0.124 (0.722)
D.log inflation	-0.0856 (0.172)	-0.00823 (0.168)	-0.303 (0.527)	-0.0304 (0.179)	0.0576 (0.171)	-0.69 (0.523)
Year Dummies	ü 1993 -2008	ü 1993 -1999	ü 2001 -2008	ü 1993 -2008	ü 1993 -1999	ü 2001 -2008

Observations	84	34	50	83	34	49
R-squared						0.535
Number of countries	12	9	8	11	9	7
Hausman Test: Test: Ho: difference in coefficients not systematic	Chi ² (21)=16.23 Prob>Chi ² =0.7665 Favors RE model	Chi ² (11)=1.81 Prob>Chi ² =0.9991 Favors RE model	Chi ² (11)=11.61 Prob>Chi ² =0.4775 Favors RE model	Chi ² (21)=27.56 Prob>Chi ² =0.1530 Favors RE model	Chi ² (11)=2.47 Prob>Chi ² =0.9960 Favors RE model	Chi ² (12)=85.42 Prob>Chi ² =0.0000 Favors FE model

Note. 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 Labor productivity). Standard errors in parentheses.

*** $p < .01$. ** $p < .05$. * $p < .1$.

As shown in Table 3a (with nominal agricultural wage rates), we have found that food price is negative and significant (column 1). In other words, 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 column 2. Population growth is negative and mostly statistically insignificant. As expected, log inflation—capturing the annual price changes at aggregate levels—is positive and significant in columns 1 and 2, reflecting a positive association between inflation and nominal monthly agricultural wage rate.

To examine the effect of non-farm employment on the agricultural wage rate where primary education is excluded due to multicollinearity, $\log L$ and $\log LN$ have been inserted in column 3. This is motivated by the idea that the expansion of non-farm employment may result in reduced farm labor supply, which will exert an upward pressure on the agricultural wage. In this case, we find that non-farm employment is negatively and significantly associated with the nominal agricultural

wage rate, while farm employment is not significant. This implies that the expansion of non-farm employment tends to exert upward pressure. The pattern of the results is unchanged if we estimate the real agricultural wage rate (column 9 of Table 3b).

Columns 4–6 of Table 3a report the results of Equation 3'' (wage equation), where the variables are first differenced. Both growth in agricultural land productivity ($D\log Ya$) and 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, a 1% increase in the growth rate of agricultural productivity (value added per hectare of arable land) tends to lead to a 3.9 % increase in agricultural wage rate growth (column 4). A 1% increase in food price inflation tends to increase agricultural wage rate growth by 1.6 %.

These results are mainly driven by figures after 2000. For instance, after 2000, a 1% increase in agricultural productivity growth tends to increase agricultural wage growth by 5.01%, while a 1% increase in growth rate of food price tends to raise agricultural wage growth by 3.14%.¹⁰ These results imply that in more recent years agricultural wage rates have become more sensitive to changes in agricultural productivity or food inflation.

For the results shown 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 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 (columns 7 and 8). 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)

¹⁰ These elasticity estimates appear to be high because they are applied to first differences, not levels.

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 for this is not clear. However, the related factors influencing this relation include: (i) 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 sudden price surges/shocks while the latter is calculated on an accumulated basis (using monthly prices of multiple items); and (iii) change in price levels are not necessarily positively correlated with price levels in general. The first difference equation estimations for real average monthly agricultural wage rate are shown in columns 10–12 of Table 3b.

We examined the relationship between growth rate of nominal or real agricultural wage and growth rate of labor productivity (Table 3c). The pattern of the results is unchanged once land productivity is replaced by labor productivity. It has been found that a 1% increase in labor productivity growth tends to lead to a 3.22% increase in the growth rate in nominal agricultural wage, and a 2.85% increase in the real equivalent (columns 13 and 16). This is mostly explained by the relation of these variables after 2000 (columns 15 and 18). That is, the International Labor Organization's (ILO) (2012) argument for the widening gap between agricultural wage and labor productivity in recent years—based on the data of developed countries—is unlikely to hold for developing countries.

The results suggest that in more recent years there has been a closer link between agricultural wages and labor productivity for developing countries. This is related to the possible reasons for the relatively high growth rate of real wages in 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, and 0.8% to 3.5% for Latin America and the Caribbean) (ILO 2012: 8–9). While it

may be true to argue that the labor income share has been declining in developing countries, as in developed countries, for example due to the negative effect of financialization on labor income share (ILO 2012: 52-53), this should not be used as evidence for the widening gap between wages and productivity. Rather, it may be conjectured that both real wages and labor productivity have risen in recent years (e.g. after 2000) and this must continue to be supported by appropriate governmental policies.

Table 4 shows the results of our estimations of Equations 1 and 2 simultaneously by 2SLS. In the first stage, agricultural employment per hectare ($\log L$) is estimated. 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.¹¹ 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 a 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 (Instrumental Variable) Model for Equations 1 & 2)

	First Stage	Second Stage
Dep. Variables	$\log L$	$\log Ya$
Exp. Variables		
$\log L$	-	0.141*

¹¹ The result of 2SLS should be interpreted with caution as the 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, Hausman, & Kuersteiner 2004).

		(0.0730)
logAm	-5.026*** (0.005)	0.879*** (0.132)
logIrr	-8.081*** (2.176)	1.963** (0.101)
logFert	2.541** (1.034)	-0.903*** (0.191)
logAg R&D	-2.470*** (0.848)	0.163 (0.214)
logTrade	3.903*** (0.744)	-0.517* (0.280)
logYa	4.326*** (1.357)	- -
Log NonCereal	2.353** (1.146)	- -
Predicted logWage	-0.285*** (0.095)	- -
Constant	-35.749 (10.270)	10.75 (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		

Note. Dependent Variable in the First Stage: log L = agricultural employment per hectare.

Dependent Variable in the Second Stage: log Ya = agricultural value added per hectare.

*** p < .01. ** p < .05. * p < .1.

Model 2: agricultural and non-agricultural employment growth

Next, we estimate the agricultural employment growth and non-agricultural employment model using the dynamic panel model (SGMM) for each variable (Table 5). The first column shows the results where $DlogL$ is estimated. First, the lagged dependent variables are

negative and significant, implying an adjustment process whereby higher agricultural employment growth tends to be followed by lower agricultural employment growth, or vice versa. The coefficient estimate for $DlogYa(-1)$ (lagged agricultural land productivity growth) is positive and significant, implying that agricultural productivity growth leads to larger agricultural employment (per hectare) over time.¹²

The results for $DlogLN$ (non-agricultural employment growth) are 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 to say, if agricultural employment growth increases by 1%, non-agricultural employment growth will increase by 0.017%, other things being equal, and after adjusting for the endogeneity of agricultural employment growth. Or more simply, 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 over-identifying restrictions has been carried out for each case. For the Arellano-Bond test, the null for zero autocorrelation is rejected for order 1 (Cases 1 and 2) and for order 2 (Case 2) at the 10% significance level, broadly justifying our use of a dynamic panel model. The Sargan test statistic is statistically insignificant at the 10% level in both Cases 1 and 2, which broadly validates the instruments in SGMM.

¹² 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 a small sample. 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.

Table 5.

Estimates for log agricultural employment and non-agricultural employment growth

Dep. Variable		Case 1 D.logL	Case 2 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 (0.0209)	0.0144 (0.00295)
Observations		44	656
Number of Countries		9	56
Arellano-Bond test for zero autocorrelation in first-differenced errors	Order 1 2	Prob>z 0.0908 0.9005	Prob>z 0.0973 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

Note. 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). Robust standard errors in parentheses.

*** p < .01. ** p < .05. * p < .1.

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

We found that both predicted agricultural growth and predicted non-agricultural growth tend to decrease overall income inequality over time (Table 6). The result is robust to the choice of different estimation methods, such as a dynamic panel model or a CCEMG model (Imai & Gaiha 2014).

Table 6.

Effect of Predicted Agricultural/Non-Agricultural Growth on Inequality Change

Explanatory Variables	Case 1 FE	Case 2 SGMM	Case 3 FE	Case 4 FE
D.Log Agricultural Value Added per capita [Predicted]	-3.947** (1.808)	-6.364 (6.008)	0.318 (18.18)	3.091 (17.84)
D.Log Non-Agricultural Value Added per capita [Predicted]	-9.782*** (3.133)	4.813* (2.481)	-16.99 (10.58)	-17.34* (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 (10.02)	-15.12 (9.236)
D.log L (-1) [Lagged First Difference of log Agricultural Employment Per Hectare] [Predicted]			-82.28 (48.02)	-83.14* (50.03)
Constant	0.331 (0.0791)	6.559 (2.098)	44.97 (0.565)	45.36 (1.169)
Observations	932	100	118	118
Number of countries	49	19	21	21
R-squared	0.014		0.047	

Note. 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). Robust standard errors in parentheses.

*** p < .01. ** p < .05. * p < .1.

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 first differences of agricultural employment per hectare and non-agricultural employment. Our analysis confirms 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: agricultural productivity and poverty

Table 7 presents the results on the determinants of the long-term relationship between agricultural productivity and poverty based on 3SLS. Four different definitions of poverty have been tried according to whether poverty is defined as poverty gap or poverty headcount ratio, based on a US\$1.25 or a US\$2.00 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 the case where a poverty gap definition of poverty based on a US\$2.00 threshold is estimated (Case 1), a 1% increase in agricultural productivity raises GDP per capita by 0.45%, which reduces poverty by 0.51% over time, other things being equal. In other words, a 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, a 1% increase in agricultural productivity tends to reduce the poverty gap based on a US\$1.25 threshold by 0.23% (0.45×-0.51). In Case 3, a 1% increase in agricultural productivity will lead to a 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 in 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		
Variables	(1) poverty	(2) loggdppc	(3) L_logYa	(4) poverty	(5) loggdppc	(6) L_logYa	(7) Poverty	(8) loggdppc	(9) L_logYa	(10) poverty	(11) loggdppc	(12) L_logYa
conflict_int	-0.053 (0.0863)	0.0611 (0.0476)		-0.387*** (0.0907)	0.0624 (0.0476)		0.176*** (0.0680)	0.0248 (0.0389)		0.223** (0.0949)	0.0203 (0.0388)	
L.logYa		0.449*** (0.0848)			0.453*** (0.0848)			0.440*** (0.0799)			0.415*** (0.0786)	
tot_non_ofg	0.0057 (0.00479)	0.00645** (0.00274)		0.0051 (0.00503)	0.00617** (0.00274)		-9E-04 (0.00393)	0.00402* (0.00237)		0.0118** (0.00549)	0.0036 (0.00236)	
L.inequality_D		0.0121 (0.00751)			0.0098 (0.00750)			0.0141** (0.00653)			0.0130** (0.00634)	
Loggdppc	-0.512** (0.224)			-0.512** (0.235)			-0.559*** (0.207)			-0.093 (0.285)		
L.logAm			-0.0857*** (0.0247)			-0.0857*** (0.0247)			-0.0891*** (0.0194)			-0.0872*** (0.0193)
L.logIrr			-0.273*** (0.0400)			-0.272*** (0.0400)			-0.299*** (0.0402)			-0.301*** (0.0402)
L.logFert			0.280*** (0.0361)			0.280*** (0.0362)			0.269*** (0.0341)			0.268*** (0.0341)
L.logTrade			0.736*** (0.0575)			0.737*** (0.0575)			0.707*** (0.0550)			0.706*** (0.0549)
Regional Dummies	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$
Year Dummies	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$	$\bar{u}$
	1980	1980	1980	1980	1980	1980	1980	1980	1980	1980	1980	1980
	-2009	-2009	-2009	-2009	-2009	-2009	-2009	-2009	-2009	-2009	-2009	-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

Note. Standard errors in parentheses.

*** $p < .01$. ** $p < .05$. * $p < .1$.

Conclusions

This paper has re-examined the relationships between agricultural productivity, employment, wage rates and poverty, based on an econometric analysis of cross-country panel data. We have updated the datasets, added additional variables such as gender indices, and estimated poverty by system equations where agricultural productivity is treated as an endogenous variable.

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, and reduction in gender inequality. In policy terms, it is important for governments to allocate a 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 distribution, and to reduce gender inequality by installing institutions and programs to enforce laws and policies that promote equal access for men and women to education, health, economic/employment opportunities and the protection of property rights.

Another important finding is that while agricultural wage rates are negatively associated with agricultural productivity and food price in terms of levels, growth in agricultural wage rates are positively correlated with growth in agricultural productivity and with growth of food price, particularly after 2000. That is to say, agricultural wages have become more sensitive to, or more responsive to, change in food prices and agricultural land or labor productivity in recent years. Contrary to the ILO's (2012) claim that the gap has widened recently, our results suggest a narrowing of the gap between wage and labor productivity. Moreover, agricultural employment per hectare tends to increase agricultural productivity after taking account of the endogeneity of the former. Also, growth in agricultural employment per hectare tends to increase growth in non-agricultural employment over time with an adjustment for the

endogeneity of the former.

Finally, both agricultural growth and non-agricultural growth tend to lead to a reduction in overall income inequality. Increases in agricultural productivity will reduce poverty significantly through overall economic growth. Overall, a number of econometric results in the present study corroborate the view 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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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