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ICT and agricultural productivity: evidence from cross-country data

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Abstract

This article carries out agricultural production function estimations, based on data for the period 1995–2000 on 81 countries, to present empirical evidence on the relationship between the adoption of information and communication technology (ICT) and agricultural productivity. It is found that new ICT has a significantly positive impact on agricultural productivity. The evidence suggests that the adoption of modern industrial inputs in agricultural production relies on the information and communication infrastructure. However, the empirical evidence from this study also suggests that new ICT could be a factor for the divergence between countries in terms of overall agricultural productivity. Not only do we find that the ICT adoption levels of the richer countries are much higher than those of the poorer countries, but also that returns from ICT in agricultural production of the richer countries are about two times higher than those of the poorer countries. A plausible explanation for the poorer countries' relatively low productivity elasticity of ICT is the lack of important complementary factors, such as a substantial base of human capital.

JEL classification: Q10, O10

Keywords: Agricultural productivity; ICT adoption; Digital divide

1. Introduction

By estimating the inter-country agricultural production function, this article sets out to explore the relationship between information and communication technology (ICT) deepening and agricultural productivity, using cross-country data for 1995–2000. The most significant breakthrough in ICT came during the second half of the 1990s, with the wave of popularity in personal computers, the use of the Internet, and the adoption of mobile phones. As ICT diffusion grew in leaps and bounds across many countries, the application of ICT to agricultural development began to attract the attention of both researchers and policy analysts.

Why might ICT have an impact on agricultural development? Primarily, market transactions are critically dependent on information, but in many rural areas market-related information tends to be seriously lacking due to the distance from the market. Consequently, in these areas development is hampered, as they cannot be effectively integrated into the market. By providing a powerful tool of information transfer, ICT could substantially improve the efficiency of transactions between rural areas and core markets. Therefore, ICT may have high returns in rural areas by offering such areas opportunities to overcome the negative effects of distance from core markets (Forestier et al., 2002; Grimes, 2000).

Various case studies have suggested that ICT could play an important role in agricultural development. For example, in 1994 a microwave-radio telephone system was installed in the remote region of Tumaco, Columbia, along with community access points. Within three years, residents of the region were reporting that the service provided by the system had resulted in better trade and market opportunities. A number of other studies have also indicated that rural telephony helps farmers to receive better prices for their crops and leads to significantly increased earnings (Forestier et al., 2002). In Bangladesh, the Grameen Bank, a village-based micro-finance organization, leased mobile phones to member villagers. A survey showed that the telephone services had a perceptible influence on production, marketing, and other important economic decisions confronting rural households. The introduction of the mobile phones lowered transaction costs, especially those for communications on the poor. The mobile phones helped raise farm output prices and lower farm input prices through the mechanism of information diffusion. Furthermore, the mobile phones seemed to have perceptible and positive effects on the empowerment and social status of phone-leasing women and their households (Bayes, 2001).

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While many observations indicate that ICT could enrich poorer people and improve their quality of life, these opportunities might not be fully grasped by people in rural areas in poorer countries, whereas those in richer countries, with easier access to ICT, have benefited greatly. Dewan and Kraemer (2000) find that there exist significant differences between developed and developing countries with regard to returns from IT capital investment. As found in Forestier et al. (2002), telecommunications rollout has historically had a positive and significant impact on increasing inequality. Forestier et al. (2002) further suggest that new ICT, particularly the Internet, may have an even stronger impact on income divergence than telephony, due to the following features. First, the Internet is more expensive than telephone access. Second, the Internet requires a higher level of education and skill to operate than a telephone, and lower levels of education and skills are clearly concentrated among the poorest. Third, the dominant languages of the Internet are generally not those used by the poor. Finally, the Internet requires access to electricity, skilled personnel, and a critical mass of users to make it sustainable, and these are particularly lacking in the rural areas of the poorer countries.

The key research questions motivating this study are: To what extent can ICT promote agricultural productivity? Are there significant differences between richer and poorer countries with regard to the effects of ICT on agricultural productivity? Utilizing the inter-country agricultural production function developed by Hayami and Ruttan (1970), Antle (1983) demonstrates that a substantial proportion of the variation in aggregate agricultural output across countries can be attributed to significant inter-country differences in the gross domestic production of transportation and communication industries, as well as to differences in resource endowments, technical inputs, and education, indicating that investments in communication facilities could raise agricultural productivity considerably. Drawing on Antle (1983), this study employs the Hayami and Ruttan model, with a focus on ICT adoption as an infrastructural input, in order to explore the influence of ICT on agricultural productivity.

The main findings of this article can be summarized as follows. A positive and significant relationship exists between ICT adoption and agricultural productivity. However, in contrast to the suggestion of Antle (1983)—that there are no significant differences between developed and developing countries with regard to the returns from the communications infrastructure—this study finds that the productivity elasticity of ICT adoption is much higher in richer countries than in poorer countries. Furthermore, including the education level as an input variable in the agricultural production function considerably reduces the estimated productivity elasticity of ICT adoption, especially in the case of poor countries. This suggests that certain socio-economic characteristics, such as higher levels of education and skills, are prerequisites for the effective driving of agricultural productivity by new ICT. Because better-educated farmers in richer countries can begin to utilize new ICT (especially the Internet) much more effectively, and because they have easier access to skilled personnel to ensure that their ICT is sustainable, new ICT might lead to a widening gap between richer and poorer countries with regard to the general income levels of farmers, although improvements in ICT could increase the income of farmers in poorer countries as well as in richer countries.

The remainder of this article is organized as follows. Section 2 provides a description of the data set and the construction of the endogenous and exogenous variables. The empirical results are presented and discussed in Section 3. Section 4 offers some concluding remarks on the findings of this study.

2. Data and variables

Several cross-country data sets are used in this study, the first of which is based on data from 1995 to 2000 and takes figures from the International Telecommunication Union (ITU) World Telecommunication Indicators (2002) on Internet users per 100 people, the number of personal computers per 100 people, cellular phones per 100 people, and telephone mainlines per 100 people (teledensity). The second data set, also based on data from 1995 to 2000, incorporates figures from the World Bank's World Development Indicators (2002) on total agricultural output, from the Food and Agriculture Organization's statistical databases (FAOSTAT) on agricultural inputs, and from Barro and Lee (2000) on human capital.[1]

The four indicators in the first data set effectively describe the status of ICT adoption within an economy (Quibria et al., 2003). To construct a measure of ICT adoption, or the ICT adoption index, we adopt the equal-weighting approach, in which the simple unweighted average of the four indicators is calculated.[2] As all four indicators are expressed in density, standardization is unnecessary. This equal-weighting approach is the best option when there is no theory or other evidence available to inform the weighting scheme (Eigen-Zucchi, 2001). In order to take account of the digital divide between urban and rural areas, the ICT adoption index is multiplied by the ratio of teledensity outside the largest cities (telephone mainlines per 100 people not living in the largest cities) to teledensity to yield the adjusted ICT adoption index.[3] Table 1 shows the statistics of the unadjusted (general) ICT adoption index and the adjusted (rural) ICT adoption index, averaged over 1995–2000. The countries are classified into four groups in accordance with the World Bank's classification system: high income, upper-middle income, low-middle income, and low income.

Table 1 indicates that there is a significant digital divide between richer and poorer countries, with the unadjusted ICT index of the high-income countries being around 66 times that

[1] The data are available from the authors upon request.

[2] As an alternative to the unweighted average, principal component analysis (PCA) was used to generate an ICT adoption indicator for each economy. However, both methods yielded very similar results ($r = 0.996$). Indeed, PCA assigns almost identical component score coefficients to the four ICT indicators (0.261, 0.264, 0.263, 0.260).

[3] This measure may well underestimate the digital divide between rural and urban areas, since the cost of adopting new ICT, such as the Internet, may be much higher than normal telephone access.

Table 1
ICT adoption statistics index, averaged over 1995–2000

Countries	Unadjusted ICT index (1)		Adjusted (rural area) ICT index (2)		(2)/(1)	N
	Mean	Standard deviation	Mean	Standard deviation		
Worldwide	11.02	12.69	9.97	12.50	0.91	81
High income	30.40	7.52	28.84	8.89	0.95	20
Upper-middle income	10.42	6.01	8.69	6.02	0.83	20
Low-middle income	3.35	2.09	2.56	1.88	0.76	20
Low income	0.46	0.33	0.25	0.24	0.54	21

of the low-income countries. Rural areas in poorer countries suffer more from the digital divide than urban areas, with the adjusted ICT index of the high-income countries being around 115 times that of the low-income countries. For the poorer countries, the digital divide between rural and urban areas is sizable, while for high-income countries the difference in the status of ICT adoption between rural and urban areas seems to be insignificant.

Total agricultural output (Q) is measured by value added in agriculture in 1995 US\$.[4] The agricultural inputs are: labor, measured by thousands of participants in agriculture in the economically active population; livestock, measured by the number of cow equivalent livestock units as calculated by Hayami and Ruttan (1970); machinery, measured by the number of agricultural tractors; fertilizer, measured by the sum of nitrogen, potash, and phosphate content of various fertilizers consumed, measured in thousand metric tons; and land, measured by thousands of hectares of arable and permanent cropland and permanent pastures.

Several alternative measures of the education level, or the stock of human capital, were attempted, such as the literacy ratio, the school enrollment ratio for primary and secondary levels, and average years of schooling. However, as Kawagoe et al. (1985) found out, it is difficult to generate statistically significant and economically meaningful estimates from such general measures of education level. In order to obtain economically meaningful estimates, this study uses the proportion of the population aged 15 and over that have attained tertiary education to represent the education level. This indicator emphasizes higher education, and is chosen because it is consistent with the finding of Kawagoe et al. (1985), that technical education, measured by the number of agricultural graduates above secondary level per 10,000 farm workers, can explain a significant amount of the variation in total agricultural output across countries. Table 2 displays the summary statistics of the key variables (averaged over 1995–2000) for the full sample, the sample of the richer countries (higher-middle and high-income countries), and the sample of the poorer countries (lower-middle and low-income countries), respectively.

It is worth examining the correlation between the status of ICT adoption and some important social-economic characteristics, including the education level (representing the stock of human capital), the ratio of the labor force in the nonagricultural sector to that in the agricultural sector (representing the level of specialization), tractors per worker, and fertilizer per worker. Table 3 reports the corresponding simple correlation coefficients.

We first observe that the correlation between the ICT variable and the level of specialization is 0.74, which reflects the well-known association between transaction efficiency and the division of labor. Furthermore, as Forestier et al. (2002) pointed out, new ICT, such as the Internet, requires great numbers of skilled specialists to ensure its sustainability. We also note that the correlation between the ICT variable and tractors per worker is 0.63, and that between the ICT variable and fertilizer per worker is 0.74. The argument of Stigler (1951)—that the adoption of capital-intensive production methods is a function of specialization relying on transaction conditions—explains these relationships. The correlation between education and the ICT variable is 0.69. This could be explained by the fact that the adoption of new ICT relies heavily upon the stock of human capital, as suggested by Dewan and Kraemer (2000). At the same time, as Antle (1983) has argued, education may be a function of the information and communication structure.

3. Production function estimates

The widely used Cobb–Douglas production function is adopted for this study. The economic theory of production places certain technical constraints on the choice of the functional form, such as quasi-concavity and monotonicity. Furthermore, as multiple inputs are used in agricultural production, the agricultural production function form should display sufficient flexibility to allow continuous adjustment between inputs as relative factor prices change. The simplest production function form consistent with these constraints is the Cobb–Douglas specification, which is also the most common specification used for estimating agricultural production functions in the literature.

The inter-country agricultural production function for estimation is specified as follows:

$$\log Q_{jt} = \log \beta_{0jt} + \beta_1 \log X_{1jt} + \cdots + \beta_n \log X_{njt} + \varepsilon_{jt}; \quad j = 1, \ldots, m; \quad t = 1, \ldots, T, \tag{1}$$

where Q_{jt} is the total agricultural output of the jth country in year t, X_{ijt} is the ith conventional input (including labor, land, livestock, machinery, and fertilizer) used in the jth country in year t, and ε_{jt} is the random error term. Each country's Hicks-neutral productivity level, measured by β_{0jt}, is specified

[4] Converting the production value in domestic currency to US\$, as a *numéraire* currency, may cause a downward bias for LDC products. An alternative choice would be to use international dollars; however, as Antle (1983) demonstrated, the purchasing power parity adjusted values might well overstate the agricultural production value for LDCs; therefore, exchange rate values are preferable.

Table 2
Key variable summary statistics, averaged over 1995–2000

Variables	All countries (N = 81)		Higher–middle & high–income countries (N = 40)		Lower–middle & low–income countries (N = 41)	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Total output (millions)	12,811	24,296	14,058	18,985	11,596	28,743
Labor (thousands)	13,538	62,770	1,663	3,255	25,123	87,128
Land (thousands Ha)	38,494	86,988	37,252	84,966	39,706	89,956
Livestock (thousands)	17,679	46,502	13,179	25,849	22,070	60,278
Machinery (thousands)	233.8	425.2	360.8	505.4	110.0	283.9
Fertilizer (thousand MT)	1,335.7	4,360.8	1,041.9	1,270.3	1,622.4	6,024.0
Higher education (%)	10.560	9.026	15.196	9.325	6.046	5.981
Adjusted ICT index	9.966	12.497	18.767	12.659	1.380	1.755

as a function of education and the ICT adoption (rural areas) variables, as follows:

$$\log \beta_{0jt} = \log \beta_{00} + \beta_{01} \log(Education_{jt}) + \beta_{02} \log(ICT_{jt}). \tag{2}$$

Panel heteroscedasticity is often an issue in the analysis of panel data. Several acceptable methods are available for detecting panel heteroscedasticity. In this article the Breusch–Pagan test is performed for the full country models. The values of $\chi^2(1)$ in columns (1)–(4) of Table 4 range from 14.23 to 20.64, showing that the heteroscedasticity is statistically significant.

There are three ways of dealing with panel heteroscedasticity: the fixed-effect model, the random-effect model, and the feasible generalized least squares (FGLS) approach. Both the fixed-effect model and the random-effect model assume that the disturbance terms can be separated into a time-invariant country-specific effect and residual terms with white noise. Different from the above two approaches, the FGLS approach assumes that, in the case of panel heteroscedasticity, the error variances vary across countries, but remain constant over time and within each country.

In order to select a suitable estimation method for dealing with the problem of panel heteroscedasticity, we adopt three criteria: the log-likelihood ratio, AIC, and SIC. For the OLS model (the full country sample) the log-likelihood ratio, AIC, and SIC are –550.24, 1,114.48, and 1,141.35, respectively; for the fixed-effect model are –472.60, 1,119.20, and 1,453.08, respectively; for the random-effect model they are –542.29, 1,098.59, and 1,125.45, respectively; for the FGLS model they are –147.76, 229.52, and 326.38, respectively. The FGLS model has the highest log-likelihood ratio, the smallest AIC, and the smallest SIC, indicating that FGLS is the most suitable estimation method for this study.

FGLS is used to estimate a cross-sectional time-series linear model in the presence of panel heteroscedasticity. In the cross-sectional data set the variance for each of the panels will differ, but it is common to have data on countries that have a variation of various attributes. The heteroscedastic model assumes that:

$$\Omega = \begin{bmatrix} \sigma_1^2 I & 0 & 0 & \cdots & 0 & 0 \\ 0 & \sigma_2^2 I & 0 & \cdots & 0 & 0 \\ 0 & 0 & \ddots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \sigma_j^2 I & \cdots & 0 \\ 0 & 0 & 0 & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_m^2 I \end{bmatrix},$$

where j refers to the jth country and $j = 1, \ldots, m$. The FGLS results are given by the estimations of coefficients for the regressors and their variances: $\hat{\beta}_{GLS} = (X'\hat{\Omega}^{-1}X)^{-1}(X'\hat{\Omega}^{-1}y)$ and $\hat{V}(\hat{\beta}_{GLS}) = (X'\hat{\Omega}^{-1}X)^{-1}$, where X denotes the regressor matrix. Ω can be written in terms of the Kronecker product: $\Omega = \Sigma_{m\times m} \otimes \mathrm{I}_{T\times T}$, where m refers to the number of sample countries and T denotes the period length. The estimated variance matrix is derived by substituting the estimator $\hat{\Sigma}$ for Σ, where $\hat{\Sigma} = (\hat{\varepsilon}_i'\hat{\varepsilon}_j)/T$. The residuals for estimating Σ are first obtained from an OLS regression. Through the iterated estimation procedure, residuals are derived from the last estimated model.

Table 3
Correlation coefficients for ICT adoption and selected socio-economic variables

Variables[a]	AICT[b]	EDU[c]	SPECIAL[d]	TRACPW[e]
sEDU	0.689	—	—	—
SPECIAL	0.743	0.607	—	—
TRACPW	0.629	0.478	0.773	—
FERTPW[f]	0.743	0.746	0.820	0.700

[a] All variables are averaged over 1995–2000.
[b] AICT refers to the adjusted ICT adoption index for rural areas.
[c] EDU refers to the proportion of the population aged 15 and over having attained tertiary education.
[d] SPECIAL refers to the level of specialization measured by the ratio of the labor force in the industrial and service sectors to the labor force in agriculture.
[e] TRACPW refers to tractors per agricultural worker.
[f] FERTPW refers to fertilizer per agricultural worker.

Table 4
Agricultural cross-country production function estimates, 1995–2000

	All countries ($N = 81$)				Higher-middle and high-income countries ($N = 40$)				Lower-middle and low-income countries ($N = 41$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	13.59***	13.86***	13.57***	13.839***	11.71***	12.09***	11.79***	11.99***	12.95***	13.67***	13.01***	13.11***
	(244.95)	(155.25)	(260.09)	(144.68)	(116.98)	(85.59)	(74.78)	(69.85)	(114.80)	(98.42)	(115.10)	(121.70)
Labor	0.150***	0.285***	0.173***	0.278***	0.118***	0.312***	0.144***	0.284***	0.400***	0.584***	0.710***	0.754***
	(30.79)	(18.75)	(19.98)	(16.69)	(10.28)	(18.76)	(7.18)	(14.39)	(12.38)	(14.32)	(21.72)	(21.82)
Land	−0.149***	−0.102**	−0.158**	−0.098***	−0.112***	−0.142***	−0.113***	−0.136***	0.221***	0.152***	0.211***	0.233***
	(−13.17)	(−6.38)	(−12.98)	(−6.02)	(−6.33)	(−12.08)	(−6.16)	(−11.07)	(7.45)	(7.63)	(8.66)	(13.77)
Livestock	0.295***	0.287***	0.312***	0.279***	0.075***	0.187**	0.051***	0.139***	−0.019	−0.085	−0.217***	−0.240***
	(15.32)	(13.45)	(15.05)	(13.29)	(3.48)	(9.49)	(2.51)	(6.19)	(−0.40)	(−1.58)	(−7.54)	(−8.19)
Machinery	0.258***	0.189***	0.252***	0.194***	0.241***	0.159***	0.215***	0.163***	0.161***	0.172***	0.083***	0.038***
	(40.99)	(14.21)	(36.60)	(14.01)	(21.56)	(9.77)	(13.85)	(9.33)	(9.40)	(6.78)	(6.10)	(3.09)
Fertilizer	0.289***	0.199***	0.268***	0.206***	0.588***	0.416***	0.592***	0.464***	0.162***	0.078***	0.111***	0.115***
	(23.65)	(12.78)	(19.36)	(12.26)	(31.72)	(16.30)	(27.86)	(15.85)	(6.55)	(3.33)	(6.09)	(5.34)
Education			0.052***	−0.027			0.090*	0.047			0.423***	0.369***
			(3.17)	(−1.08)			(1.79)	(1.22)			(16.41)	(15.29)
ICT index (rural area)		0.207***		0.208***		0.349***		0.288***		0.181***		0.092***
		(11.18)		(10.79)		(23.08)		(12.28)		(9.91)		(6.01)
Wald χ^2 (n)	$\chi2$ (5) = 41,879.05	$\chi2$ (6) = 12,249.74	$\chi2$ (6) = 49,967.82	$\chi2$ (7) = 11,432.06	$\chi2$ (5) = 15,759.56	$\chi2$ (6) = 8,171.18	$\chi2$ (6) = 8,781.38	$\chi2$ (7) = 15,091.04	$\chi2$ (5) = 25,988.24	$\chi2$ (6) = 15,330.79	$\chi2$ (6) = 29,124.70	$\chi2$ (7) = 24,900.79
Breusch–Pagan test χ^2 (1)	14.23**	20.58**	14.29**	20.64**	—	—	—	—	—	—	—	—
Number of observations	343	343	343	343	188	188	188	188	155	155	155	155

Note: The t-statistics are in parentheses.
*, **, and *** denote $P < 0.1$, $P < 0.05$, and $P < 0.01$, respectively.

Table 4 presents the estimation of the Cobb–Douglas production function, based on FGLS for panel data. Each coefficient is an estimated elasticity of agricultural output with respect to the corresponding explanatory variable, and the values in parentheses are *t*-statistics. Due to missing data, the numbers of sample observations for all 81 countries, 40 higher-middle and high-income countries, and 41 lower-middle and low-income countries for the years 1995–2000 are 343, 188, and 155, respectively. Generally speaking, the estimated coefficients in column (1) of Table 4 are similar to those of Fuligniti and Perrin (1993).[5] Column (3) of Table 4 shows that in the model that includes the education variable, the coefficients of machinery and fertilizer are comparatively small, and the elasticity of education is positive and statistically significant.

The coefficients of the ICT adoption variable are positive and statistically significant in columns (2) and (4). For all countries, the estimates of the elasticity of ICT are approximately 0.21 and statistically significant, indicating that ICT matters in explaining the differences in agricultural productivity across countries. Our result implies that a smaller amount of labor, livestock, machinery, and fertilizer can produce the same level of agricultural output if these inputs are used within a better information and communication infrastructure. This could be explained by the fact that easier access to ICT helps farmers to realize market opportunities and to enjoy advantages in terms of decision making on market transactions and bargaining power. Moreover, it can be argued that better communication conditions effectively reduce transaction costs and lead to higher levels of specialization. Therefore, our empirical results capture the idea that labor and intermediate goods may be heterogeneous such that a given amount of labor or intermediate goods could make substantially different contributions to output, depending on how specialized they are.

Comparison of columns (1) and (3) to columns (2) and (4) shows that not including the ICT variable in an agricultural production function may result in biased coefficients of labor, machinery, and fertilizer. The coefficients of labor increase from 0.15 in regression (1) and 0.17 in regression (3) in which ICT is left out, to over 0.27 in regressions (2) and (4) in which ICT is included. Similarly, the coefficients of fertilizer decrease from above 0.26 in regressions (1) and (3) to around 0.20 in columns (2) and (4), and the coefficients of machinery decrease from above 0.25 in regressions (1) and (3) to around 0.19 in regressions (2) and (4).

The effect of the ICT variable on the coefficient of labor could be attributed to the fact that in countries with higher ICT adoption, the labor force in the agricultural sector tends to be smaller, and the levels of specialization and division of labor are higher. Therefore, the omission of the ICT variable could lead to an underestimation of the elasticity of labor. The eroded coefficients of machinery and fertilizer variables suggest that part of what they are capturing is higher ICT adoption. As machinery and fertilizer represent modern inputs supplied by the industrial sector, our results indicate that the adoption of modern industrial inputs in agricultural production requires a division of labor between agricultural and industrial sectors, which relies on transaction conditions.

For richer countries, as shown in columns (6) and (8) of Table 4, the coefficients of the ICT adoption variable are, respectively, 0.35 and 0.29 and statistically significant. For the poorer countries, the corresponding coefficients of the ICT adoption variable are also significant but considerably lower at 0.181 in column (10) and 0.092 in column (12). The richer countries display about two times the estimated elasticity of the ICT variable than the poorer countries do.

A coefficient-equality test is performed to examine whether the estimated elasticity of the ICT in richer countries is significantly higher than in poorer countries. First, we set a dummy variable, *H*, to differentiate the richer countries from the poorer countries; $H = 1$ if the country is richer, and $H = 0$ if the country is poorer. For simplification, a regression model is specified as Eq. (3):

$$\begin{aligned} \log Q_j = {} & \bar{\beta}_{00} H + \bar{\beta}_{01} H * \log(EDU) + \bar{\beta}_{02} H * \log(ICT_j) \\ & + \bar{\beta}_1 H * \log X_{1j} + \cdots + \bar{\beta}_n H * \log X_{nj} \\ & + \beta_{00} + \beta_{01} \log(EDU) + \beta_{02} \log(ICT_j) \\ & + \beta_1 \log X_{1j} + \cdots + \beta_n \log X_{nj}, \end{aligned} \tag{3}$$

where $\bar{\beta}_i$ refers to the interaction term of the dummy variable and explanatory variable *i*, and other notations of variables are the same as in Eqs. (1) and (2). The null hypothesis is that $\bar{\beta}_{02} = 0$ if the coefficients of the ICT adoption variable in the richer countries are not significantly different from those in the poorer countries. Drawing on the same data set, we perform FGLS to estimate Eq. (3). The empirical result is shown in Table 5.

In Table 5 the observed *P*-value for the Wald χ^2 test is 0.00 for Eq. (3), which indicates that the null hypothesis that $\bar{\beta}_{0j} = \bar{\beta}_i = \beta_{0j} = \beta_i = 0, \forall i = 1, \ldots, n$ and $j = 0,1,2$ can be rejected at the 0.05 probability. The significant and positive coefficient of H*log(ICT) ($\bar{\beta}_{02} = 0.196$), leads to rejection of the null hypothesis that $\bar{\beta}_{02} = 0$. This confirms that the elasticity of the ICT variable in the richer countries is higher than in the poorer countries.

This empirical result may be relevant to the relationship between human capital and ICT adoption. A substantial base of human capital stock may be a prerequisite for ICT to be productive. In comparison with poorer countries, richer countries have well-established education infrastructures. Thus, in the case of richer countries, including the education variable in the equation has a smaller impact on the elasticity of the ICT variable, and ICT is dominant over education in determining the differences in agricultural productivity. By contrast, in the case of poorer countries, the necessary education base for effectively

[5] The estimates of the production elasticity of land range from statistically insignificant to negative in the literature. For example, see Kawagoe et al. (1985) and Fulginiti and Perrin (1993).

Table 5
The coefficient-equality test for elasticities of ICT in the richer and the poorer countries

H	H*log(ICT)	H*log(EDU)	H*log(labor)	H*log(land)	H*log(livestock)
−1.125***	0.196***	−0.322***	−0.471***	−0.369***	0.379***
(−5.55)	(6.99)	(−7.12)	(−11.82)	(−17.65)	(10.27)
H*log(machinery)	H*log(fertilizer)	log(ICT)	log(EDU)	log(labor)	log(land)
0.125***	0.349***	0.092***	0.369***	0.754***	0.233***
(5.84)	(9.62)	(6.01)	(15.29)	(21.82)	(13.77)
log(livestock)	log(machinery)	log(fertilizer)	Intercept		
−0.240***	0.038***	0.115***	13.115***		
(−8.19)	(3.09)	(5.34)	(121.7)		

Notes: Number of observations = 343, Wald $\chi^2(15) = 40{,}076.56^{**}$.
Numbers in brackets are asymptotic t-statistics.
*, **, and *** denote $P < 0.1$, $P < 0.05$, $P < 0.01$, respectively.

utilizing ICT has not yet been well established, and education and ICT are highly complementary in determining the agricultural productivity. In these countries the adoption of ICT relies heavily upon the stock of human capital.

Columns (5)–(12) of Table 4 provide us with an indication that the introduction of new ICT widens the gap in agricultural productivity between richer and poorer countries. Although new ICT could improve the agricultural productivity of poorer countries as well as richer countries, both the levels of ICT adoption and the elasticity of ICT are substantially higher in richer countries than in poorer countries. This could be attributed to the fact that richer countries have already made complementary investment in various types of infrastructure, including cheaper electricity and better transportation, human capital, and information-oriented business processes, which can be leveraged by new ICT for higher payoffs.

4. Conclusion

The empirical analysis in this study suggests that new ICT can play a significant role in improving agricultural productivity. With panel data from 81 countries over the period from 1995 to 2000 and utilizing feasible general least squares for estimating the inter-country agricultural production function, this study extends the research of Antle (1983) on the relationship between agricultural productivity and communication infrastructure, and provides evidence of positive returns from ICT. Our results support the hypothesis that farmers benefit from ICT by effectively gaining information on the market and thereby improving their bargaining power. The evidence also suggests that the adoption of modern industrial inputs in agricultural production relies upon the information and communication infrastructure. The empirical evidence further indicates that the labor and intermediate goods used in agricultural production could be quite heterogeneous in terms of their specialization usage. Higher levels of ICT adoption, which imply better transaction conditions, could lead to more specialized labor and intermediate goods, and generate higher levels of agricultural productivity.

The empirical evidence from this study also suggests that new ICT could explain the divergence between countries in terms of overall agricultural productivity. We find that the ICT adoption levels of richer countries are much higher than those of poorer countries, and also that returns to ICT in agricultural production in richer countries are about two times higher than in poorer countries. A plausible explanation for the poorer countries' relatively low productivity elasticity of ICT is the lack of important complementary factors, such as better electricity and transportation infrastructure, productive human capital (stemming from higher levels of education), and business models that have been transformed to deal with the information age.

Some policy implications can be drawn from this study. The exploitation of the potential of ICT in the agricultural sector in poorer countries requires appropriate environmental conditions, such as basic infrastructure, business practices, and appropriate government policies. Such policies should include the promotion of computer usage, training, and content development aimed specifically at rural areas, the promotion of general education and education aimed specifically at nurturing computer professionals, enactment of lower taxes and tariffs on computer imports, and telecommunications liberalization as a means of lowering costs (Dewan and Kraemer, 2000; Forestier, et al., 2002). For poorer countries, investments in both complementary infrastructure and higher education are at least as important as investment in new ICT. Nevertheless, the developments in ICT aimed at providing low-cost access to the Internet for farmers in rural areas that lack appropriate infrastructure may be a vital step toward equalizing all opportunities.

The Jhai PC, designed by the Jhai Foundation as a means of meeting the demands of villagers in a remote region of Laos, provides an example of the above. This machine has no moving parts, and few parts are delicate. It uses a 486-type processor instead of a Pentium processor or above, flash-memory chips are installed instead of a hard disk, and a liquid-crystal display is used instead of an energy-guzzling glass cathode-ray tube. Because of its simplicity, a Jhai type of PC can be powered by a car battery charged with bicycle cranks. Wireless Internet cards connect each Jhai PC to a solar-powered hilltop relay station, which then passes the signals on to a computer within the town which is connected to the Internet. Such access to the Internet therefore reduces the need for expensive infrastructure and is cheap to operate for farmers in poorer countries (The Economist, 2002).

We believe that the specific contributions of this article are worth noting. To our knowledge, this is the first comparative analysis explicitly incorporating new ICT as a production factor, along with the traditional inputs of capital and labor, into an inter-country agricultural production function. Our findings add to the existing evidence—that ICT not only improves productivity, but also generates divergence especially from the wave of globalization—expanding the scope of this evidence to include the agricultural sector. This study is also expected to shed some light on the analysis of other issues, such as the influence of infrastructural factors, and education and national policy on the contribution of new ICT to agricultural productivity.

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