Innovation Systems and Technical Efficiency in Developing-Country Agriculture

Dawit Kelemework Mekonnen
Graduate Student
Department of Ag & Applied Economics
University of Georgia
305 Conner Hall
Athens, Georgia 30602, USA
Email: dawitk@uga.edu

David J. Spielman
Senior Research Fellow
International Food Policy Research Institute
2033 K St NW
Washington, DC 20006, USA
Email: d.spielman@cgiar.org

Esendugue Greg Fonsah
Associate Professor
Department of Ag & Applied Economics
University of Georgia
15 RDC RD, P.O. Box 1209
Tifton, Georgia, 31793, USA
Email: gfonsah@uga.edu

Selected Paper Prepared for Presentation at the Southern Agricultural Economics Association Annual Meeting, Birmingham, AL, February 4-7, 2012

Abstract

The paper uses a stochastic frontier analysis of production functions to estimate the level of technical efficiency in agriculture for a panel of 29 developing countries in Africa and Asia between 1994 and 2000. In addition, the paper examines how different components of an agricultural innovation system interact to determine the estimated technical inefficiencies. Results show that the mean level of technical efficiency among the sampled countries was about 86 percent, with some modest increases during the period in question. These results suggest that there is room for significant increases of production through reallocations of existing resources. Despite significant variation among countries, these results also indicate quite a number of least developed countries have high mean efficiency scores, implying a need to focus on investment that pushes the production frontier outward in these countries. Several measures of agricultural R&D achievement and intensity, along with educational enrollment, are found to enhance agricultural efficiency. On the other hand, countries with higher levels of official development assistance, foreign direct investment, and a greater share of land under irrigation are found to be performing poorly in their agricultural efficiency score.

Keywords: agricultural innovation systems, technical efficiency, developing country agriculture

1. Introduction

Developing-country agriculture is frequently characterized by low productivity, small-scale subsistence farming, acute susceptibility to weather shocks, and low levels of market integration and value addition (World Bank 2008). However, there is significant variation across developing countries. This suggests a need for a better understanding of the factors that influence productivity and variations in productivity among developing countries.

While many studies have estimated the transformation of agricultural inputs into outputs through a standard production function approach, few have ventured into opening the "black box" of this approach, or understanding the factors that influence total factor productivity (TFP) in agriculture, whether in terms of efficiency changes that measure a country's progress in "catching up" to the production frontier in agriculture, or technical changes that measure a country's progress in "pushing out" the production frontier in agriculture.

This paper addresses this issue by grounding a production function analysis within a comprehensive innovations systems approach to agricultural production. The innovation systems approach examines sets of heterogeneous actors who interact in the generation, exchange, and use of agriculture-related knowledge in processes of social or economic relevance, as well as the institutional factors that condition their actions and interactions (Spielman and Birner 2008). In effect, the approach moves our inquiry away from a more linear, input-output model of innovation through research, development, and dissemination, to model of innovation that mirrors a web of related individuals and organizations that learn, change and innovate through iterative and complex processes.

Using variables that characterize a given country's agricultural innovation system, we utilize a stochastic frontier production function analysis to estimate the production possibility frontier under a given innovation system and a given level of input use to determine where each country stands in relation to this frontier. Conditional on this distance, we estimate the technical efficiency of agriculture for each country.

This paper is organized as follows. Section 2 briefly reviews the literature on cross-country analysis of variations in agricultural productivity and the recent contributions of the innovation systems approach to this literature. Section 3 discusses the empirical model and the data used in the econometric estimation while section 4 focuses on results and discussion. Section 5 concludes the paper.

2. Agricultural Innovations System Framework

The literature on *how* total factor productivity changes over time in agriculture is largely tied to the study of investment in agricultural research and development (R&D). Griliches (1963, 1964) provides some of the earliest empirical guidance on the contributions of R&D to the estimation of an agricultural production function. Seminal work by Hayami and Ruttan (1971) enhance the theoretical structure of this relationship with their induced innovation model in which sustained agricultural growth results from technological changes that are induced by agents' responses to changes in relative factor endowments and prices. Evenson and Kislev (1973) and Evenson (1974) provided further empirical evidence that the transfer and dissemination of technology and knowledge across geographic and national boundaries is an essential determinant of agricultural productivity growth, and is accelerated by a given country's imitative capacity but impeded by agro-ecological differences between regions and countries.

This work gave rise to an extensive literature in the field of economics on the rates of returns to agricultural research, including research produced during Asia's Green Revolution that was associated with the introduction of semi-dwarf rice and wheat varieties, as well as many other productivity-enhancing interventions that followed in subsequent decades. In essence, these studies evaluate how investments in agricultural R&D change the ratios in which agricultural inputs are transformed into outputs, how the net benefits of the investment are distributed between consumers and producers, and how the returns on alternative investment opportunities compare. Subsequent studies extended the conceptual, methodological, and empirical frontiers of these seminal works.

One important vein of this literature relates to the collection and analysis of data. Pardey and Roseboom (1989) and Pardey, Roseboom, and Anderson (1991) provide an early treatment of this topic by designing and collecting indicators on public investments in agricultural R&D. Evenson (2003) contributes with an effort to measure innovative performance with indicators that capture country stocks of "innovation capital" and "imitation capital." Other studies attempt to compile and analyze hard-to-get innovation-related indicators such as agricultural research organization performance (Peterson and Perrault 1998); biotechnology research capacity in developing country National Agricultural Research Systems - NARS (Byerlee and Fischer 2000, 2002); private investment in agricultural research in Asia (Pray and Fuglie 2001); and changes in agricultural TFP (Coelli and Rao 2003).

The main difference between these approaches and the innovation systems approach is the degree to which R&D-related indicators are perceived as the key drivers of changes in productivity. Arguably, a narrow reliance on R&D indicators omits the contributions of other factors to changes in productivity.

To give more structure to this idea of "other factors," we consider an agricultural innovation system as a theoretical construct that contributes to productivity growth through four main components: knowledge and education, business and enterprise, bridging institutions, and the enabling environment, based broadly on a construct developed by Arnold and Bell (2001) and extended to the realm of agriculture and agricultural development by Spielman and Birner (2008).

In this construct, the key domains of an innovation system are described as follows. The knowledge and education domain captures the contribution of agricultural research and education to technological change, and is essentially the component most frequently measured and examined in the economics literature cited above. The business and enterprise domain captures the set of value chain actors and activities that leverage outputs from research and education for commercial purposes, and is typically far less measured in the economics literature on agricultural development. Bridging institutions represent the domain in which individuals and organizations facilitate the transfer of knowledge and information between the knowledge and business domains, and tend to capture the role of non- or quasi-market actors—for example, public extension services, farmers organizations, or multi-stakeholder projects—in the innovation process. Circumscribing these domains are the enabling or frame conditions that foster or impede innovation, including: public policies on innovation and agriculture; informal institutions that establish the rules, norms, and cultural attributes of a society; and the behaviors, practices, and attitudes that condition the ways in which individuals and organizations within each domain act and interact. See Spielman and Birner (2008) for a more complete description of this construct of an agricultural innovation system.

To date, the literature on innovation systems in agriculture has avoided the use of formal models like the one explored in this paper. Rather, the innovation systems literature focuses on descriptive and context-specific analyses of how technological and institutional changes occur around a given market or commodity, and how diverse actors influenced this process of change (see, e.g., World Bank 2006). However, the growing popularity of this approach among scientists and policymakers alike necessitates more rigorous testing of questions such as whether the approach—with its nuanced recognition of the complexity within developing-country agriculture—translates into a better understanding of the drivers behind productivity growth. If so, then a better understanding can assist public policymakers, private entrepreneurs, and civil society interests in allocating resources to agricultural development more effectively.

3. A stochastic frontier production function

We introduce here a standard stochastic frontier production function based on the specification set forth by Battese and Coelli (1995) in which

$$y_{it} = x_{kit}\,\beta + V_{it} - U_{it} \tag{1}$$

where y_{it} is the value of net agricultural production for country *i* at time *t*, x_{kit} is an *1 x k* vector of the values of inputs of production for country *i* at time *t*; β is an *1 x k* vector of parameters to be estimated; V_{it} is iid $N(0,\sigma_v^2)$ random errors, independently distributed of the U_{it}; U_{it} is a non-negative random variable associated with the technical inefficiency of production which is assumed to be independently distributed, such that U_{it} is obtained by truncation of the normal distribution with mean $z_{it}\rho$ and variance σ^2; and z_{it} is an *1 x m* vector of inefficiency explaining variables with the corresponding unknown *m x 1* vector of coefficients.

A likelihood ratio test is used to identify the proper specification of the production technology (rather than using an a priori assumption of a translog or a Cobb-Douglas production function) by estimating both after including time trend variable (t), its square, its interaction with the production inputs and i-1 country dummy variables where i indexes countries as shown in (2) and (3) below.

$$\ln y_{it} = \alpha_{it} + \sum_k \beta_k \ln x_{kit} + 0.5 \sum_k \sum_j \beta_{kj} \ln x_{kit} \ln x_{jit} + \sum_k \xi_k \ln x_{kit} t + \tau_t t + \tau_{tt} t^2 + \sum_i^{i-1} \gamma_i D_i + V_{it} - U_{it} \qquad (2)$$

$$\ln y_{it} = \theta_{it} + \sum_k \eta_k \ln x_{kit} + \lambda_t t + \lambda_{tt} t^2 + \sum_i^{i-1} \delta_i D_i + V_{it} - U_{it} \qquad (3)$$

With a time variable included to capture linear change in technical efficiency over time (Battese and Coelli 1995), the U_{it} in the above equations is specified as

$$U_{it} = \theta + z_{it}\,\rho + t + \varepsilon_{it} \qquad (4)$$

where z_{it} refers to the inefficiency effects coming from the different domains of the agricultural innovation systems.

In this paper, the variables that represent the different components of the agricultural innovation system serve as the inefficiency effects or z_{it} variables in equation 4, representing the environment under which agricultural production takes place in the countries under consideration. Our empirical strategy is to use the innovation system variables to directly influence the stochastic component of the production frontier by estimating either equation (2) or (3) with equation (4) simultaneously. Maximum likelihood estimation of the stochastic frontier model is conducted using panel data for 29 developing countries between 1994 and 2000. Our general hypothesis in this study is that the different components of the agricultural innovation system will significantly affect the technical efficiency of agricultural production.

3.2. Data

Data for this study cover 29 developing countries in Africa and Asia between 1994 and 2000. The dependent variable, output, is defined as the value of net agricultural production in 1999-2001 international dollars. International commodity prices from FAOSTAT (2010) are used to avoid the use of nominal exchange rates and facilitate more accurate cross-country comparisons. These international prices are derived using a Geary-Khamis formula for the agricultural sector. The method assigns a single price to each commodity regardless of the country where it was produced (FAOSTAT 2010).[1]

Inputs to agricultural production, measured as follows, are obtained from FAOSTAT (2010). Fertilizer is measured in terms of the quantity (in metric tons) of plant nutrient consumed in agriculture by a country in a given year. Land is measured in terms of arable land under permanent crops in thousand hectares in a given year. Tractors denote the number of tractors in use in a country in a given year. Data on agricultural labor per hectare of arable land was obtained from WRI (2010) and we have computed total agricultural labor by multiplying agricultural worker per hectare by the amount of arable

[1] In the FAOSTAT (2010) data, the amount of seed and feed are subtracted from the production data to avoid double counting once they are accounted for in the production data.

land that was obtained from FAOSTAT (2010).

Stocks of live animals were obtained from FAOSTAT (2010) in heads for all animals except bees which are measured in numbers of beehives. The different stocks of live animals were converted to livestock units using conversion factors that not only make aggregation possible but also usable for international comparisons since the weights are different for different regions of the world as suggested by Chilonda and Otte (2006).

Average annual precipitation data for each country was obtained from Mitchell et al. (2003).

The variables that were used to explain the character and performance of a given country's agricultural innovation systems are as follows. The knowledge and education component was measured by: agricultural R&D intensity using public agricultural R&D expenditure as a share of agricultural GDP (IFPRI 2010); agricultural R&D capacity using the number of public agricultural researchers per million agricultural laborers (IFPRI 2010); and agricultural R&D productivity using scientific journal articles (World Bank 2009) and more widely-defined innovative capacity in the labor force using a combined measure of elementary, secondary and tertiary education enrollment (UNDP various years). We expect all the variables in the knowledge and education domain to be efficiency enhancing as they facilitate the generation, distribution and acquisition of better ways of production.

One of the limitations of this study is that most of the innovation system variables don't particularly pertain to agricultural production due to unavailability of sector-specific data for all the countries in the period considered. Education and number of journal articles from the knowledge and education domain, and almost all of the variables in the other domains are not specific to agriculture. Hence, a cautious interpretation of the coefficients that recognizes the proxy nature of the variables to their agriculture specific counterparts is called for because the proxies may not perform well to the extent that there is a systematic difference in these variables between agriculture and the general economy.

The business and enterprise indicators were assumed to affect agricultural productivity and efficiency by their influence on the nature and performance of business and business innovation in the agricultural sector as well as through the quality of institutions and infrastructure that enables business and business innovation in agriculture. Variables in this domain include the number of telephone lines and mobile phone subscribers per 1000 people, total roads network in kilometers as a share of arable land and land under permanent crops, and net inflows of foreign direct investment as a share of GDP. Data for these three variables were obtained from WB (2009). The impact of net inflows of foreign direct investment on efficiency may be positive due to the transfer of knowledge and technologies or it could be negative if the investments involve sectoral bias in terms of diverting priority and resource allocation from agriculture to other sectors. We also expect improvements in telephone and road networks to be agricultural efficiency enhancing to the extent that such improvements in urban areas are not at the expense or neglect of rural areas.

To proxy bridging institutions, we used a press freedom index that captures the contribution of a vibrant media to the adaptation and use of agricultural knowledge and information related to production and marketing, and to the removal of bottlenecks and impediments to efficient market and value chain operations. The press freedom index was obtained from WRI (2010) in a scale of 0 to100 where lower scores of the index refer to higher quality of press freedom. Hence, we expect a positive relationship between this variable and the level of inefficiency in equation (4).

To capture the enabling environments, we introduce a series of indicators that measure the underlying quality of governance and related institutions that directly or indirectly influence the performance of the agricultural sector. Specifically, we use the severity of corruption (WB, 2009) and official development assistance (ODA) per capita measured in US dollars (WB, 2009). The direction of relationship between ODA and the level of inefficiency could be argued to be positive or negative depending on whether development assistance is reinforcing public sector commitment in agriculture or crowding it out and/or creating a sense of complacence by aid receiving countries.

Though loosely related with the enabling environment domain, the size of land under irrigation as a share of arable land (WB, 2009) and rural population density (WB, 2009) were included as factors explaining technical efficiency. Rural population density is included to see if it creates high pressure on the farming system to be efficient to withstand the problems related with high population density or whether its effect in depressing efficiency through perhaps making agricultural labor redundant will be strong. So, the direction of relation of this variable with inefficiency will be determined by the results of the econometric model. Land under irrigation is included to see if countries with better irrigation infrastructure are more technically efficient than those that predominantly rely on rainfed agriculture.

4. Results and Discussion

Both the translog and the Cobb-Douglas production functions were estimated and the likelihood ratio test rejected the hypothesis that the Cobb-Douglas production function is a better fit of the data at one percent significance level with a χ^2 (22) = 228.5. The resulting translog specification of the production function showed strong evidence that fertilizer affects the level of output at higher level of use and its productivity increases when accompanied by enough agricultural labor, good precipitation and where there is no shortage of tractor or livestock to work with (Table 1). Expansion of land under agricultural cultivation is still a viable means of increasing production whenever possible as shown from high responsiveness of output to arable land. Despite high number of rural population in most of the countries, agricultural output is positively affected by increases in labor and tractors and the two inputs are found to be complementary. The estimated coefficients of the production function are presented in Table 1 along with their standard errors and p-values.

Table 1: Maximum Likelihood Estimates of the Translog Production Function

Dependent Variable: logarithm of agricultural production			
Production Inputs and their interaction	Estimate	Standard Error	p-value
(Intercept)	-9.117	6.025	0.130
Fertilizer	-2.292	0.441	0.000 ***
Land	2.263	0.734	0.002 **
Livestock	0.808	0.651	0.215
Tractor	0.815	0.370	0.027 *
Agricultural labor	1.640	0.503	0.001 **
Precipitation	1.311	0.935	0.161
Fertilizer-land	-0.245	0.043	0.000 ***
Fertilizer-livestock	0.093	0.024	0.000 ***
Fertilizer-tractor	0.051	0.032	0.108
Fertilizer-labor	0.137	0.020	0.000 ***
Fertilizer square	0.025	0.012	0.039 *
Fertilizer-precipitation	0.163	0.053	0.001 **
Land-livestock	-0.198	0.048	0.000 ***
Land-tractor	-0.095	0.027	0.000***
Land-labor	-0.289	0.043	0.000 ***
Land square	0.869	0.130	0.000***
Land-precipitation	0.033	0.066	0.622
Livestock-tractor	0.024	0.026	0.355
Livestock-labor	-0.042	0.037	0.247
Livestock square	0.054	0.050	0.279
Livestock-precipitation	-0.113	0.076	0.138
Tractor-labor	0.023	0.027	0.395
Tractor square	-0.037	0.025	0.144
Tractor-precipitation	-0.108	0.031	0.000 ***
Labor square	0.084	0.058	0.149
Labor-precipitation	-0.134	0.055	0.015 *
Precipitation square	0.092	0.105	0.380
Sigma Square	0.082	0.022	0.000 ***
gamma	0.955	0.015	0.000 ***

*,**, *** denote significant at one, five and ten percent levels, respectively.

Log likelihood value: 164.5969

Source: Authors' computation

The level of technical efficiency is predicted simultaneously with the estimated production function and it was found that the mean technical efficiency is about 86 percent. This implies that there is a potential to increase agricultural output in these countries by about 14 percent using the same level of inputs but improved management and resource re-allocation. The mean efficiency score has shown a modest increase from 84.2 percent in 1994 to 87.4 percent in 2000 (Table 2). Countries like Bangladesh, Ethiopia, Malawi, Mozambique, Nigeria, Senegal and Tanzania have gained 15 to 20 percentage points in efficiency scores in the 7 years under consideration. Except Mozambique that started at a very low level of efficiency scores these countries have joined the elite group of countries such as Brazil, China, Colombia, India and South Africa that have efficiency scores in the upper 90s. Despite significant variation among countries, this study revealed that quite a number of least developed countries have relatively high mean efficiency scores implying a need to focus on investment that pushes the production frontier outward in these countries. Table 2 also showed that Southern African countries have low efficiency scores with Zambia being the least efficient country (24 %), Mozambique (52 %), Zimbabwe (76 %) and Botswana (81 %) in 2000. The efficiency of Zimbabwe's agriculture has decreased from 87% in 1994 to 76% in 2000 while that of Zambia has decreased from 27% to 24% within the same period. Pakistan's agriculture, the least efficient from the Asian countries considered here, has lost about 20 percentage points in efficiency scores between 1994 and 2000. Vietnam, with efficiency score of 61%, is the next inefficient country from the Asian countries.

Table 2: Mean Technical Efficiency

mean efficiency (1994 - 2000)				0.865			
	1994	1995	1996	1997	1998	1999	2000
mean efficiency (each year)	0.843	0.862	0.862	0.869	0.864	0.880	0.874
Bangladesh	0.827	0.824	0.846	0.916	0.864	0.962	0.974
Benin	0.960	0.964	0.965	0.933	0.839	0.857	0.928
Botswana	0.829	0.970	0.968	0.965	0.975	0.906	0.817
Brazil	0.990	0.993	0.992	0.993	0.994	0.995	0.995
China	0.996	0.996	0.997	0.998	0.998	0.998	0.998
Colombia	0.990	0.992	0.990	0.991	0.991	0.992	0.994
Ethiopia	0.754	0.827	0.890	0.928	0.868	0.915	0.949
Ghana	0.903	0.952	0.970	0.945	0.920	0.912	0.892
India	0.997	0.997	0.997	0.997	0.997	0.997	0.997
Indonesia	0.911	0.927	0.924	0.965	0.865	0.877	0.868
Kenya	0.933	0.971	0.939	0.951	0.970	0.966	0.954
Malawi	0.778	0.892	0.859	0.847	0.919	0.942	0.970
Malaysia	0.949	0.958	0.969	0.987	0.980	0.962	0.976
Mali	0.940	0.925	0.778	0.914	0.933	0.942	0.815
Mexico	0.974	0.986	0.985	0.987	0.989	0.991	0.991
Mozambique	0.364	0.453	0.511	0.518	0.536	0.560	0.520
Nepal	0.924	0.938	0.913	0.899	0.840	0.945	0.978
Nigeria	0.811	0.819	0.897	0.947	0.944	0.971	0.974
Pakistan	0.645	0.594	0.594	0.591	0.563	0.511	0.429
Philippines	0.957	0.966	0.962	0.976	0.970	0.944	0.967
Senegal	0.744	0.824	0.796	0.756	0.727	0.907	0.932
South Africa	0.992	0.983	0.990	0.990	0.989	0.991	0.991
Sri Lanka	0.952	0.952	0.900	0.845	0.980	0.943	0.966
Tanzania	0.721	0.908	0.862	0.778	0.890	0.965	0.907
Thailand	0.891	0.872	0.927	0.961	0.952	0.950	0.980
Uganda	0.933	0.936	0.923	0.915	0.973	0.985	0.982
Viet Nam	0.626	0.648	0.622	0.667	0.604	0.610	0.610
Zambia	0.276	0.228	0.259	0.242	0.227	0.273	0.241
Zimbabwe	0.874	0.706	0.761	0.789	0.760	0.755	0.765

The inefficiency effects described above were then estimated against the components of the innovation systems approach. The variables from the innovations systems framework are allowed to directly influence the stochastic component of the production function which is achieved by estimating the production function and the inefficiency effects (model 2 and 4) simultaneously using Frontier Version 4.1. Thus, we have avoided the problem that failure to include environmental variables in the first stage causes such as biased estimators of the deterministic part of the production frontier and biased predictors of technical efficiency (Coelli et al, 2005).

Table 3 illustrates that all the variables in the knowledge and education domain of the AIS framework have the expected effects in reducing inefficiency. The inefficiency depressing effects of the number of agricultural researchers per million farmers and number of scientific journal articles published by researchers in the country is statistically significant at 5 and 10 percent significance levels. Agricultural R&D intensity and gross educational enrollment in elementary, secondary and tertiary schools also help in decreasing agricultural inefficiency, even though the results on these two variables are not statistically significant.

In the Business and Enterprise Domain, foreign direct investment is shown to exacerbate agricultural inefficiency rather than decreasing it. This could partly be due to the nature and type of foreign investments taking place in these countries. One could argue that if the foreign investments have a sectoral bias in terms of diverting public priorities and resource allocations from agriculture to other sectors such as mining and oil exploration, then FDI can have efficiency-depressing effects on agriculture. However, the effect of road networks on inefficiency is not consistent with our expectation unless growth in road networks in these countries on average is brought about at the expense or neglect of rural areas.

Press freedom from the bridging institutions domain has the expected result of improving agricultural efficiency. Since high values of the press freedom variable indicate severely constrained media, the positive coefficient in Table 3 on this variable shows that free media can play an important role in reducing inefficiency by allowing effective communication among innovation actors.

In the enabling environment domain, corruption is found to be positively related with agricultural efficiency despite our expectation that it increases agricultural inefficiency by diverting resources to rent seeking activities away from productive uses. The result is, however, consistent with the 'grease the wheels hypothesis' which argues that corruption may raise efficiency in a country plagued with a very slow and ineffective bureaucracy (Lio and Hu, 2009). Rural population density has inefficiency decreasing effect and it appears that the effect of high population density in forcing the farming system to be efficient to withstand the resulting land shortages outweighs its effect in depressing efficiency through perhaps making agricultural labor redundant. Despite operating at a higher input higher output part of the production frontier, countries with higher irrigated land as a percentage of crop land appears to operate further away from their production frontier as compared to those that heavily depend on rainfed agriculture. This is consistent with micro-level evidences that farmers without access to irrigation, despite operating at a lower production frontier, operate very close to it possibly because of the pressure paused by lack of resources and trying to use whatever small resources they have efficiently (Makombe et al., 2007). Countries receiving higher aid per capita are bound to be technically less efficient than the other countries and the result is statistically significant at five percent level. This could perhaps be interpreted as evidence that development assistance is crowding out public sector commitment in agriculture or creating a sense of complacence by aid receiving countries. However, this effect should be interpreted cautiously since the aid variable doesn't particularly refer to assistance to the agricultural sector but includes all types of official development assistance.

Table 3: Efficiency effects from the AIS Framework

Dependent Variable: Inefficiency Score	Estimate	Standard error	p-value
Knowledge and Education Domain			
R&D intensity	-0.178	0.123	0.150
Ag researchers per million farmers	-0.005	0.002	0.005 **
Scientific journals	-0.003	0.001	0.021 *
Educational enrollment	-0.007	0.006	0.192
Business and Enterprise Domain			
Telephone networks	0.006	0.004	0.158
FDI	0.074	0.023	0.002 **
Road networks	0.061	0.016	0.000 ***
Bridging Institutions Domain			
Press freedom	0.021	0.008	0.006 **
Health expenditure	0.032	0.101	0.749
Enabling Environment Domain			
Corruption	-0.192	0.115	0.093 .
aid	0.005	0.002	0.005 **
Rural population density	-0.003	0.001	0.002 **
Irrigation	0.415	0.106	0.000 ***
Time trend	-0.044	0.030	0.150

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The likelihood ratio test was also used if indicators representing a domain of the Agricultural Innovation System (AIS) were simultaneously zero by comparing the log likelihood functions of the full translog model and the model in which variables in a given domain are all set to zero. In all the four domains, the test showed that the full translog model is a better fit of the data and the hypotheses that the knowledge and education domain, the business and enterprise domain, the bridging institution domain and the enabling institutions domain do not explain the inefficiency level were all rejected at one percent significance level with $\chi^2(4)$ = 43.34, $\chi^2(3)$ = 20.06, $\chi^2(2)$ = 15.32, and χ^2 (4) = 18.13, respectively.

5. Conclusion

The paper uses a stochastic frontier analysis of production functions to estimate the level of technical efficiency of developing countries' agriculture for about 29 countries in Africa and Asia between 1994 and 2000. The stochastic production function was modeled in such a way that agricultural innovation systems framework and indicators of its different domains (the knowledge and education domain, the business and enterprise domain, the bridging institutions domain and the enabling environment domain) serve as an environment that determines the level of technical inefficiency. The production function and the inefficiency effects were estimated simultaneously. Translog and Cobb-Douglas production function were estimated and likelihood ratio test revealed that the translog technology is a better fit of the data.

The result showed that the mean level of technical efficiency among the sampled countries is about 86 percent and there is room for significant increase of production by reallocation of the existing resources. Despite significant variation among countries, this study revealed that quite a number of least developed countries such as Bangladesh, Benin, Ethiopia, Malawi, Nepal, Senegal, Uganda and Tanzania have relatively high mean efficiency scores implying a need to focus on investment that pushes the production frontier outward in these countries. Some Southern African countries such as Zambia, Zimbabwe, and Mozambique and a couple of Asian countries such as Pakistan and Vietnam have very low efficiency scores and hence calling for a focus on efficiency enhancing investments. Agricultural R&D intensity, number of agricultural researchers per million farmers, gross educational enrollment, number scientific journal articles, press freedom and high rural population density were found to be efficiency enhancing. The overall mean efficiency score in the countries under consideration has shown a modest increase from 84.2 percent in 1994 to 87.4 percent in 2000.

6. References

IFPRI. Agricultural Science and Technology Indicators, International Food Policy Research Institute, 2010. http://www.asti.cgiar.org/

Arnold, E., and M. Bell. 2001. Some New Ideas about Research and Development. Copenhagen: Science and Technology Policy Research/Technopolis.

Balzat, M., and H. Hanusch. 2004. Recent trends in the research on national innovation systems. Journal of Evolutionary Economics 14: 197–210.

Battese, G. E., and T. J. Coelli. A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. Empirical Economics, 20(2):325 – 332, 1995.

Byerlee, D., and K. Fischer, "Accessing modern science: Policy and institutional options for agricultural biotechnology in developing countries" (Agricultural Knowledge and Information Systems Discussion Paper, The World Bank, Washington, DC, 2000).

Byerlee, D., and K. Fischer. 2002. Accessing Modern Science: Policy and Institutional Options for Agricultural Biotechnology in Developing Countries. World Development, 30, 931-948.

Coelli, T. J., and D.S. P. Rao. 2003. "Total Factor Productivity Growth in Agriculture: A Malmquist Index Analysis of 93 Countries, 1980-2000," CEPA Working Papers Series WP022003, School of Economics, University of Queensland, Australia

Coelli, T. J., D.S. P. Rao, C. J. O'Donnell and G. E. Battese. An Introduction to Efficiency and Productivity Analysis. Second Edition. 2005. Springer Science+Business Media, LLC.

Chilonda, P., and J. Otte. Indicators to Monitor Trends in Livestock Production at National, Regional and International Levels. Livestock Research for Rural Development, 18, 2006.

Evenson, R. E. 1974. The Green Revolution in Recent Development Experience. American Journal of Agricultural Economics, 56(2): 387 – 394.

Evenson, R. E. 2003. Modern variety (MV) production: a synthesis. Chap. 21 in Evenson and Gollin (eds.). Crop Variety Improvement and Its Effect on Productivity: The Impact of International Agricultural Research. Wallingford, U.K.: CAB International.
Evenson, R. E. and Y., Kislev, 1973, 'Research and Productivity in Wheat and Maize', Journal of Political Economy, 81, 1309-1329

Griliches, Z. 1964. Research expenditures, education, and the aggregate agricultural production function. American Economic Review 54: 961-74.

Griliches, Z. 1963. Estimates of the aggregate agricultural production function from cross-sectional data. Journal of Farm Economics 45: 419-28.

Hayami, Y. and V. W. Ruttan. 1971. Agricultural Development: An International Perspective. Baltimore: Johns Hopkins University Press.

Lio, M., and J. Hu. Governance and Agricultural Production Efficiency: A Cross Country Aggregate Frontier Analysis. Journal of Agricultural Economics, Vol. 60, No. 1, 2009, 40 - 61.

Makombe, G., D. Kelemework and D. Aredo. A Comparative Analysis of Rainfed and Irrigated Agricultural Production in Ethiopia. Irrigation & Drainage Systems, 21(1):35 – 44, 2007.

Mitchell, T.D., T.R,. Carter, P.D. Jones, M. Hulme, and M.A. New. Comprehensive Set of Climate Scenarios for Europe and the Globe. Manuscript, 2003. http://www.cru.uea.ac.uk/cru/data/.

Mugunieri, G.L., G. A. Obare, and S.W. Omamo. Does the Structure of Agricultural Science and Technology Policy System Matter in Developing Country Agricultural Productivity Growth Trends? Evidence from Kenya and Uganda. International Association of Agricultural Economists Conference, Beijing, China, August 2009.

Pardey, P. G., and J. Roseboom. 1989. ISNAR agricultural research indicator series: A global data base on national agricultural research systems. Cambridge, U. K.: Cambridge University Press.

Pardey, P. G., J, Roseboom, and J. R. Anderson. 1991. Regional Perspectives on national agricultural research policy: International quantitative Perspectives, edited by P. G. Pardey, J. Roseboom, and J. R. Anderson. Cambridge U. K.: Cambridge University Press.

Peterson, W., and P. Perrault. 1998. Agricultural research organizations: The assessment and improvement of performance. Knowledge, Technology and Policy, 11(1&2), 145–166.

Pray, C.E., and K. Fuglie. 2001. Private Investment in Agricultural Research and International Technology Transfer in Asia. Economic Research Service Technical Report 805, USDA, Washington, DC.

Spielman, J. D., and R. Birner. How Innovative is Your Agriculture? Using Innovation Indicators and Benchmarks to Strengthen National Agricultural Innovation Systems. The World Bank, Agriculture and Rural Development Discussion Paper 41, 2008.

UNDP. Human Development Report, United Nations Development Program, Various Years. http://hdr.undp.org/en/reports/.

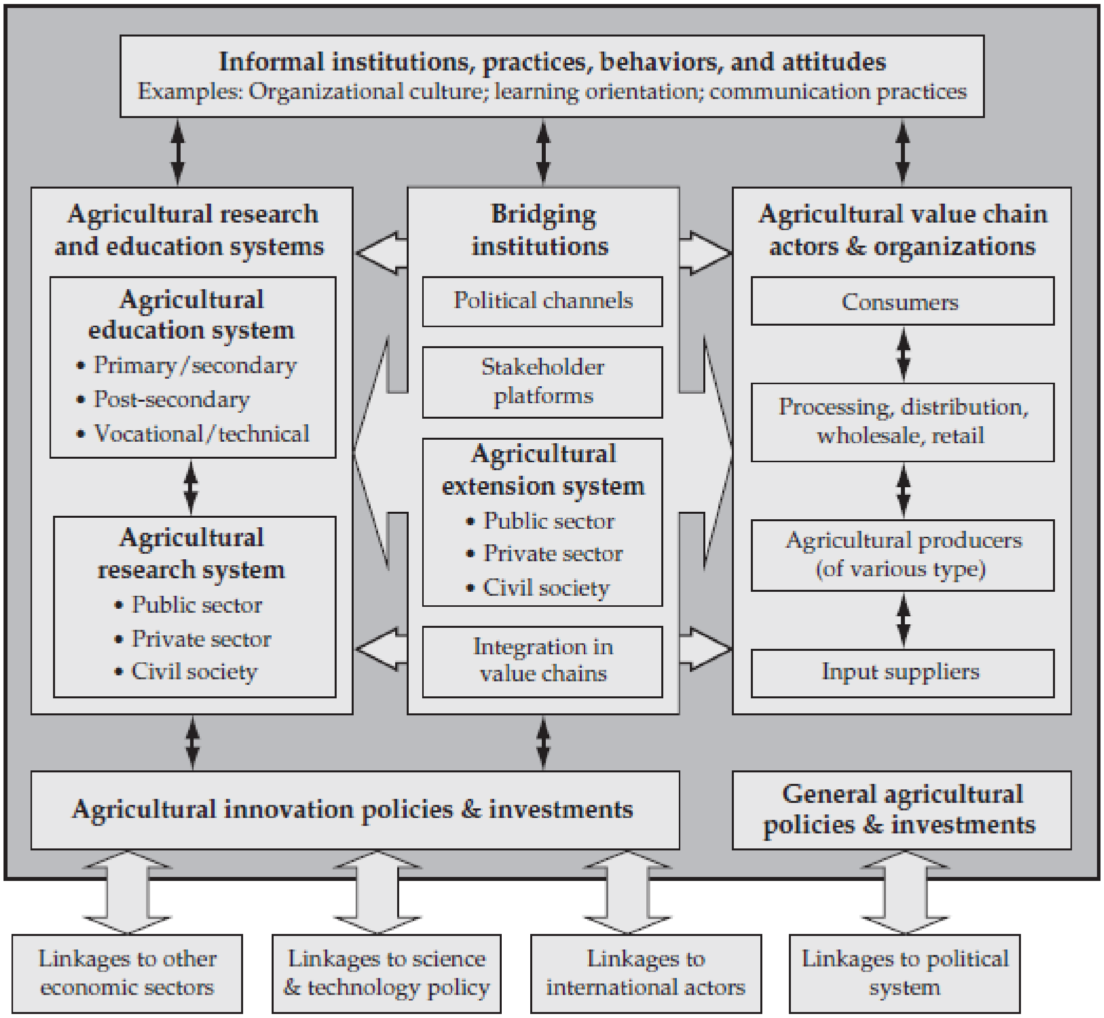
FAOSTAT. United Nations Food and Agriculture Organization Statistical Database, 2010. http://faostat.fao.org/site/291/default.aspx.

World Bank. World Development Indicators, the World Bank, 2009.

World Bank. 2006. Enhancing Agricultural Innovation: How to Go Beyond the Strengthening of Research Systems. Washington, D.C.: World Bank.

WRI. World Resources Institute, 2010. http://earthtrends.wri.org/.

Figure 1: A Conceptual Diagram of National a Agricultural Innovations System



Source: Spielman and Birner, 2008.