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The Impact of Domestic and Foreign R&D on Agricultural Productivity in sub-Saharan Africa

Morakinyo O. Adetutu

Global Sustainable Development, University of Warwick, CV4 7AL, UK
morakinyo.adetutu@warwick.ac.uk

Victor Ajayi

Judge Business School, University of Cambridge, Trumpington Street, UK
va301@cam.ac.uk

We use a stochastic frontier analysis (SFA) model to investigate the impact of domestic and foreign R&D on agricultural productivity for a sample of 30 sub-Sahara African (SSA) countries during the period 1981-2011. The results reveal that total factor productivity is strongly influenced by both domestic and foreign R&D spending in the agricultural sector, albeit the former plays a more important role. The decomposition of TFP and its components show an annual average rate of productivity growth of 4.8%, driven mainly by technical change with an average annual improvement of 3.2%. Efficiency change had a negative impact on productivity and generally exhibited a net reduction in TFP growth at an average annual growth rate of -0.8%. Our sub-regional analyses indicate the West African region recorded the highest performance productivity growth during the period under consideration. Overall, our findings highlight the crucial role of knowledge stocks in driving agricultural productivity in the SSA region.

JEL codes: O30, O47, Q16

Keywords: Agricultural productivity, R&D, technological spillover, sub-Saharan Africa, Stochastic frontier analysis

1. Introduction

Investments in R&D are generally seen as crucial to achieving productivity growth through new knowledge and innovation (Alston et al, 1999; Hall and Scobie, 2006; Alene, 2010; Rahman and Salim, 2013). This notion is also well established within the Sub-Saharan African (SSA) context (see Masters et al., 1998; Maredia et al., 2000; Beintema and Stads, 2011) where agriculture significantly contributes to household income and country GDP. Meanwhile, there is also a long-standing consensus that growth in the use of conventional inputs do not account for much of the productivity growth in agricultural output (Schultz,1956; Fan *et al.* 2004; Timmer, 2005). Hence, there is a need for clearer understanding of mechanisms linking R&D investments and agricultural productivity. In this study, we evaluate the impact of domestic and foreign R&D on agricultural productivity by investigating the role of knowledge shocks as a mechanism of effect. Although, a relatively sparse body of literature suggests that total factor productivity (TFP) in the agricultural sectors of developing countries is shaped by both domestic and foreign R&D investments (Johnson and Evenson, 1999; Gutierrez, 2003; Luh et al., 2008), the available body of evidence does not provide compelling evidence on the relative contributions of both R&D investment sources across the agricultural sector in the SSA region.

For instance, while Luh et al. (2008) focus on eight East Asian economies, Gutierrez (2003) and Johnson and Evenson (1999) used only six SSA countries (Kenya, Malawi, South Africa, Tanzania, Zambia and Zimbabwe) in their data samples. In addition, the above studies also tend to adopt a two-stage approach in which TFP is treated as exogenous and estimated using the traditional growth-accounting procedure in the first stage. In the second stage, it is then regressed on measures of domestic and foreign R&D. This approach has been criticized for its logical inconsistency and a potential to result in substantial regressor problems since the first stage treats

TFP as exogenous, while the second stage treats it as a function of a range of endogenous determinants such as R&D investments (Koop et al., 1999; Liao et al., 2009). Moreover, the methodology and estimation methods in these studies are largely dominated by non-parametric productivity techniques (e.g. data envelopment analysis (DEA)) [1] that do not allow for measurement error and random shocks such as bad luck. In this paper, study the extent to which domestic and foreign R&D contributes to agricultural productivity across the SSA region. The reasons are two-fold.

First, rather than the parametric productivity analysis previously employed by extant studies, we use a stochastic frontier analysis (SFA). The SFA confers the relative advantage of analyzing the efficiency and productivity of economic units while also permitting the incorporation of random measurement error and random shocks such as bad luck. At the same time, the SFA approach employs a single-step evaluation of the relationship between R&D and agricultural productivity, which overcomes the methodological inconsistency observed in the two-step estimation described above. Further, within the SFA framework, we are able to decompose TFP growth into its components: returns to scale (RTS), technological progress (TP) and technical efficiency change (TEC).

Second, an evaluation of the relative contributions of domestic and foreign R&D to agricultural productivity in the SSA region could shed new light on the hitherto unclear mechanism through which knowledge and innovation shape agricultural productivity in the SSA. At first blush, one could argue that the SSA region is likely to benefit more from foreign knowledge spillovers. For instance, Pardey and Alston (2010) showed that the research-intensity gap between developed

[1] For an extensive review of this non-parametric approach, see Hatami-Marbini et al. (2011)

and developing countries is growing at the rate of more than tenfold. Given the non-excludability nature of knowledge, it is plausible for knowledge spillovers to occur across national boundaries, thereby enabling countries to access foreign knowledge stocks from other countries in addition to its own knowledge stock.[2] However, there is a counter argument that the SSA region is better off focusing on domestic innovation efforts since it suffers from a relative dearth of systems and institutions required to facilitate the transfer of foreign technology (Johnson and Evenson, 2000; O'Gorman, 2015). Consequently, we believe that a comprehensive scorecard on the contributions of R&D investments to agricultural productivity could prove to be a valuable tool for guiding innovation policy in the SSA region (Spielman et al., 2009). With adequate information on these productivity effects, it may well be possible to differentiate and benchmark countries in a way that policy interventions can be better targeted (Balzat and Hanusch, 2004; Grupp and Mogee, 2004; OECD, 2005; Spielman et al., 2009). This is made all the more important by the reality that agriculture is front and center in the region's economy[3].

The remainder of the paper proceeds as follows. Section 2 presents a review of the extant literature. Section 3 contains the basic analytical model which offers a framework to the R&D and productivity nexus, as well as the methodological approach adopted in this paper. Section 4 details the data description and source and section 5 provides the empirical result and discussion. Section 6 presents the concluding remarks and policy recommendation.

2. Literature review

[2] There is a large literature on the contributions of foreign R&D to domestic productivity growth at different levels of aggregation and across different industry contexts (see Coe and Helpman, 1995; Coe et al, 1997; Keller, 2002; Wang and Tsai, 2003; Eaton and Henry et al., 2009; Le, 2013; Ulku and Pamukcu, 2015; Glass et al., 2016).

[3] Majority of the SSA region's population live in often deprived areas such as rural settlements where the main source of economic livelihood depends directly or indirectly on agriculture (Diao et al., 2010).

A plethora of studies have explored the performance and changes in agricultural productivity across sub-Saharan Africa in the context of country-level and cross-country analyses, different methodological approaches, variable choices and samples. One strand of these studies provides evidence of poor aggregate performance of African agricultural productivity in the 1960s and 1970s (see Nkamleu, 2004). The other strand (e.g. Block, 1994; Lusigi and Thirtle, 1997; Fulginiti et al., 2004, Nin-Pratt and Yu, 2008; Alene 2010) reveals a significant recovery and positive gain in African productivity since the mid-1980s. In addition, empirical evidence also identifies technical progress (technological change) as the main source of the agricultural total factor productivity in the sub-Sahara Africa (Alene, 2010; Yu and Nin-Pratt 2011). Consistent with these studies is that fact they all acknowledge the significant impacts of agricultural research and development (R&D) on agricultural productivity in the region.

The wider literature generally suggests that R&D investments in agricultural research create new knowledge and innovation that drive improvement in agricultural productivity (Griliches, 1979; Alston et al, 1999; Hall and Scobie, 2006; Binenbaum et al., 2008; Alene, 2010; Rahman and Salim, 2013). Most of these studies also demonstrate that public and private research show increasing rate of return. However, Binenbaum et al., (2008) found evidence of a decline in the rate of return on public R&D investment in Australian agriculture. Nevertheless, the common consensus that emerges from the existing empirical studies is that R&D investments substantially fuel improvement in agricultural productivity.

Studies focusing on identifying the sources of agricultural productivity growth for sub-Saharan Africa over the past decades reveal that R&D expenditure is one of the principal sources of productivity growth. The returns on agricultural research investments in SSA have also been shown to be reasonably high (see Masters et al., 1998; Maredia et al., 2000). Beintema and Stads

(2011) showed that investment in agricultural R&D remains crucial to increasing agricultural productivity and reducing poverty in Africa, while also addressing other challenges such as rapid population growth, poor nutrition, and adaptation to climate change.

Following the seminal work of Coe and Helpman (1995), there have been growing interests in assessing the influence of foreign R&D spill over on productivity growth[4]. For instance, Sachs and Warner, (1995); Coe et al., (1997); Keller, (2000) and Liao et al (2009) confirmed the impact of foreign R&D spillovers on productivity using industry level analysis. They identified that both domestic and foreign capital stock have significant effects on total factor productivity. Their findings suggest that foreign R&D spillovers through trade imports are major determinants of TFP growth. Studies which focus on agricultural sector found the presence of robust international spillovers when analysing the effects of foreign R&D spillovers and domestic R&D on agricultural productivity growth (see Johnson and Evenson, 1999; Schimmelpfenning and Thirtle, 1999, Gutierrez and Gutierrez, 2003; Luh, et al., 2008; Le, 2012).

Using Data Envelopment Approach (DEA) to first compute Malmquist TFP, Gutierrez and Gutierrez, (2003) show that total factor productivity is strongly influenced by domestic as well as foreign public research and development (R&D) for a sample of 47 countries. Similarly, Luh et al., (2008) compute Malmquist TFP using DEA and regressed the TFP on other variables including both the domestic R&D and international spillovers for 8 East Asian economies. Johnson and Evenson (1999) show that both international and inter-industrial spillovers add to agricultural total factor productivity and distinguishes between the direct and indirect effects of spillovers as well as public and private, domestic and foreign sources. Le (2012) also reveals that import and tertiary

[4] It is assumed that accumulated spending on R&D by a country and its trade partners helps to explains productivity.

student flows can effectively transmit technological knowledge from industrialized countries to African countries.

Considering the studies above, a prominent theme in the productivity literature has been the relative roles that technology and efficiency may play in explaining productivity growth across countries. Whilst past studies (e.g, Alene, 2010; Beintema and Stads, 2011; Mohan, 2014) have examined the impact of domestic R&D on agricultural productivity, this paper offers three contributions to the literature. First, we incorporate foreign R&D in our model in order to examine if it is an important channel for the spillover of international knowledge stock. Second, this study is closely related to Le (2012) which used panel cointegration estimation techniques to investigate the impact of technological knowledge from industrialized countries on agricultural productivity in Africa. However, this paper differs from Le (2012) as we employ a stochastic frontier analysis technique which enables us to uncover the contribution of efficiency (an equally important source of TFP growth), in addition to accounting for the impact of technology on TFP. Third, by unbundling the different components of TFP growth across regions and sampled countries, we provide a more comprehensive analysis of agricultural productivity.

3. Methodology

The empirical approach used in this study to analyse the impact of domestic and foreign R&D on agricultural productivity in sub-Sahara African countries is the parametric stochastic frontier analysis (SFA) (Aigner et al., 1977; Meeusen and van den Broeck, 1977). Unlike the non-parametric techniques such as the data envelopment analysis (DEA), SFA models allow for measurement error and other random effects such as luck[5] (see Kumbhakar and Lovell 2000; Matousek and Taci, 2004 for extensive reviews and discussions on non-parametric and parametric approaches to estimating efficiency and productivity). To motivate the empirical framework of the approach used in the study, we briefly describe a model that can be used to characterize the relationship between domestic R&D, foreign R&D and productivity growth. The model is similar to the formulations proposed by Kneller and Stevens (2006) and Liao et al (2012).

For simplicity, the starting point for our analysis is a functional relationship between output and three input factors which characterises the agricultural production processes. Let *i* index country and let *t* index time, and let Y_{it} denote the time-*t* agricultural value added produced by country *i* in period *t*. Similarly, let K_{it} denote the time-*t* capital stock of country-i, and K_{it} and N_{it} denote its cultivated area and labor force, respectively. In what follows, when convenient, we will suppress the country and time subscripts. The production function can be expressed as shown in equation (1):

$$Y_{it} = f\left(K_{it}, L_{it}, N_{it;}\, \mathrm{A}_{it}\right) \qquad [1]$$

where A_{it}, is a coefficient that denotes the level of technology i.e. total factor productivity in country *i*.

Drawing from the vast literature on R&D and productivity growth (e.g. Grossman and Helpman, 1991; Coe and Helpman, 1995; Coe et al., 1997; van Pottelsberghe and Lichtenberg, 2001), it is

[5] In the application of frontier modelling techniques to agricultural and manufacturing in developing countries, stochastic frontier analysis is adjudged to be more appropriate than DEA where the data are considerably influenced by measurement error (see Liao et all, 2007)

assumed that technology is factor-neutral but is a function of domestically generated knowledge, D_{it} and knowledge generated by a producer that lie on the technical frontier P_{it}. Then

$$\mathrm{A}_{it} = g(D_{it}, P_{it}) \quad [2]$$

Therefore equation (1) becomes,

$$Y_{it} = g(D_{it}, P_{it})(K_{it}, L_{it}, N_{it}) \quad [3]$$

The literature on innovation and national systems of innovation (see Schumpeter 1934; Freeman 1987) has advocated the vital role of investment in research and development. In variant with the neoclassical exogenous growth model, Romer (1990) extended Grossman and Helpman (1991) and Aghion and Howitt (1992) with the endogenous growth theory showing that advances in technical knowledge are generated by investing resources in R&D. Therefore, innovation feeds on the level of domestic knowledge which is assumed to be a function of the cumulative investment in R&D i.e. the stock of domestic R&D[6].

$$D_{it} = DRD_{it}^{\theta}, \; 0 < \theta < 1 \quad [4]$$

[6] For notational convenience, the stock of domestic R&D is expressed as DRD in the paper. The stock of domestic R&D is measured by accumulating R&D expenditures devoted to agricultural research extracted from Agricultural Science and Technology Indicators (ASTI) database for the period 1981–2011. It only considers expenditures on R&D as there is no available data on the actual adopted technology. According to ASTI, they only consider actual spending data which are processed in accordance with the standard procedures and definitions developed by the Organisation for Economic Co-operation and Development (OECD) and the United Nations Educational, Science, and Cultural Organization (UNESCO), as described in the Frascati Manual, the Oslo Manual, and the Canberra Manual. The perpetual inventory method is used to produce R&D stocks from this expenditure flow data. Details of how R&D stock is constructed is provided under in section 4; data description and sources.

where DRD_{it} is the stock domestic R&D in country i at time t and θ measures the return to domestic R&D.

Additionally, it is also widely accepted that a country's productivity as well as its economic growth performance depends on the level of technology transfers from innovation leaders and the efficiency with which they are absorbed and diffused (Blomstrom et al, 1994; Eaton & Kortum, 1999; Kneller & Stevens, 2006). Hence, if a country's domestically generated knowledge is a function of the stock of R&D, then we can assume that frontier technology is, in turn, a function of the R&D stock in the foreign country, which can be spread via various channels, notably international trade etc. Knowledge spillovers across production units occur because producers that lie behind the technical frontier attempt to imitate the technologies adopted by producers that lie on the technical frontier, as the marginal costs of knowledge incurred are almost negligible, and therefore they benefit from these positive externalities (Liao et al, 2012).

$$P_{it} = h(FRD_{it}) \qquad [5]$$

where FRD_{it} is foreign R&D stock in country i at time t[7]. Intuitively, two insights emerge from the theoretical formulation. First, an economy's productivity depends on stock of knowledge resulting from the sum of previous investment in R&D. Secondly, a country's productivity is equally a function of R&D stock of its trade partner. So far, we have presumed knowledge spillovers are fully internalized by recipient producer, and there is no inefficiency in knowledge flow. Admittedly, having access to technology transfer from foreign countries is not necessarily

[7] The expression is valid to the extent that we our model is based on the assumption that the trade partners are countries which are technologically advanced that African countries. In effect, the R&D in those countries are more advanced than those of our sampled countries rather than being on par or below. Hence a foreign producer is assumed to lie on the technical frontier. The relationship will no longer hold if the domestic R&D is greater than the foreign R&D. In this case, a domestic producer will occupy the frontier position.

equivalent to productivity growth. However, it is crucial to understand whether the technology transfer can be utilized efficiently in a domestic country. Hence, the actual output (Y) can be given as

$$Y_{it} = g(D_{it}, P_{it})(K_{it}, L_{it}, N_{it})\psi_{it} \quad [6]$$

Where ψ_{it} ($0 < \psi \leq 1$) denotes technical efficiency, reflecting the difference in the outcome from the application of technical knowledge. If $\psi = 1$, a country uses efficiently all of the inputs in the production process and it is 100% efficient; otherwise, impediments to absorption will cause the country to produce within the industry frontier. The frontier approach enables us to capture efficiency change, technological change and scale change as components of productivity change.

3.1 Decomposition of TFP

We employ stochastic frontier analysis for the productivity decomposition which assumes an existence of an unobservable production possibility frontier with production-unit one sided deviation from the frontier. Consider the following generalization of empirical framework of stochastic production frontier;

$$Y_{it} = f(X_{it}, t\colon \beta)\exp(v_{it} - u_{it}) \quad [7]$$

where Y_{it} denotes the agricultural value added by country *i* in year *t*, X_{it} is the set of inputs and β is a vector of parameters to be estimated. As is often done in the literature, we include a linear time trend variable *t*, representing technological progress (TP) arising from other exogenous sources.

The error term u_{it} is non-negative random variables which are assumed to be independently distributed and associated with technical inefficiency of production which restrain producer from achieving the maximum output from their given inputs and technology. The error term v_{it}, represents all random disturbances that are not within the control of the producer such as weather, civil unrest and are assumed to be independent and identically distributed with mean zero and variance. According to Jondrow et al. (1982), the technical efficiency level of production of unit *i* at time *t* is the obtained viz;

$$TE_{it} = \exp(-E[u_{it}|v_{it} - u_{it}]) \qquad [8]$$

According to Kumbhakar, and Lovell (2000), in the primal approach, total factor productivity changes can be split into three components when price information is not available. The rate of technical change is given by the partial differentiation of the deterministic component, $f(x_{it}, t, \beta)$.,

$$TC = \frac{\partial lnf(.)}{\partial t} \qquad [9]$$

The rate of change in efficiency is given by;

$$EC = -\frac{\partial u}{\partial t} \qquad [10]$$

TFP growth can be expressed as output growth unexplained by the input growth i.e. subtracting the weighted growth of factor inputs from the growth rate of output.

$$T\dot{F}P = \dot{y} - \sum_j S_j \dot{x}_j \qquad [11]$$

where a dot over a variable indicates its rate of change, S_j is the expenditure or observed expenditure on input x_j. Total differentiation of equation [7] with respect to time and using the expression of $T\dot{F}P$ in (11), and after some algebraic manipulations, we get:

$$T\dot{F}P = \frac{\partial lnf(.)}{\partial t} + (\mathcal{E} - 1)\sum_j \xi_j \dot{x}_j \sum_j (\xi_j - S_j)\dot{x}_j - \frac{\partial u}{\partial t} \qquad [12]$$

where $\mathcal{E} = \sum_j \mathcal{E}_j$ are the elasticities of output with respect to each of the inputs, $\xi_j = \mathcal{E}_j / \mathcal{E}$.

However, since price information is not available, the allocative component cannot be calculated empirically regardless of whether or not allocative inefficiency exists. In this case it is implicitly assumed that $S_j = \xi_j \ \forall_j$, and the decomposition in equation (12) simplifies to

$$T\dot{F}P = \frac{\partial lnf(.)}{\partial t} + (\mathcal{E} - 1) \sum_j \xi_j \dot{x}_j - \frac{\partial u}{\partial t} \qquad [13]$$

Thus, equation (13) represents a decomposition of the conventional measure of total factor productivity change into three components: technological progress, technical efficiency change, and scale change. The first term, $\frac{\partial lnf(.)}{\partial t}$, corresponds to technical change, where $\frac{\partial lnf(.)}{\partial t} > 0$, represents an upward shift of the production frontier (technical progress). The second term captures the scale change $(\mathcal{E} - 1) \sum_j \xi_j \dot{x}_j$. Finally, the last term represents efficiency change, $-\frac{\partial u}{\partial t}$, where $-\frac{\partial u}{\partial t} > 0$ represents a reduction of inefficiency. This decomposition of TFP growth offers policy implication for differentiating between innovation or adoption of new technology by "best practise" producer from the diffusion of technology. In the event that a high rate of technological progress and a low rate of change of technical efficiency are contemporaneous, this could indicate the failures in achieving technological mastery or diffusion (Kalirajan et al., 1996).

3.2 Model specification

We model our production function, Eq. (7), with more flexible translog function. The translog functional form is a preferred functional form for frontier analysis given that it provides a good first-order approximation and it does not impose constant elasticity of substitution (see Kumbhakar and Wang 2005). Given that the suitability of Cobb-Douglas has been questioned following the work of Duffy and Papageorgious, (2000), the Battese and Coelli (1992) time-varying production frontier is adopted in this study. Notwithstanding the discussions above on functional forms, we avoid arbitrariness in our modelling exercise by estimating both Cobb-Douglas and Translog specifications in our study. We then selected the preferred specification based on likelihood ratio (LR) tests. The Translog production frontier can be expressed as follows:

$$\begin{aligned} \ln Y_{it} = \quad & \beta_0 + \sum_{j=1}^{5} \beta_j \ln X_{jit} \ + \ \beta_t T \ + \ \frac{1}{2} \sum_{j}^{5} \sum_{k=1}^{5} \beta_{jk} \ln X_{jit} \ln X_{kit} \ + \ \frac{1}{2} \beta_{tt} T^2 \\ & + \sum_{j}^{5} \beta_{jt} \ln X_{jit} T + \ \alpha_H HC_{it} + \ \alpha_I INST_{it} + \alpha_r D_r + \ v_{it} - u_{it} \qquad [14] \end{aligned}$$

where Y_{it} is the agricultural value added of country *i* in time *t*, X_{jit} is the *j*th factor inputs including R&D variables by the country *i* in time *t* to produce *Y*. The five inputs included in the production process are capital, land, labour, domestic R&D and foreign R&D, *T* is time trend, HC_{it} is human capital, $INST_{it}$ is institution and output and factor inputs remain as previously defined. Eq. (14) also contains regional dummies (D_r) which captures unobserved characteristics such as weather.

The distribution of the technical inefficiency effect, u, is taken to be non-negative truncation of the normal distribution, following Battese and Coelli (1992), as expressed below;

$$u_{it} = \ u_i . \exp\{-\eta(t - T)\}$$

$$u_i \sim N^+(0, \sigma_v^2)$$

$$v_{it} \sim N(0, \sigma_v^2) \qquad [15]$$

The parameter η represents the rate of change in technical efficiency, and the non-negative random variable u_i is the technical inefficiency effect for the i-th production unit. A negative value of η implies that there is no improvement in the level of technical efficiency in the production unit overtime. A value of $\eta = 0$ means no time effect.

4. Data description and sources

This study is based on a panel dataset, constructed for 30 African countries[8] over the period beginning from 1981 and extending through 2011, totaling 705 observations as reported in Table 1. The dataset is an unbalanced panel as we eliminated years for which data are unavailable. The selection of the countries in our sample is determined primarily by data availability, especially by data on our main variable of interest, public agricultural R&D expenditure which is extracted from the Agricultural Science and Technology Indicators (ASTI) database[9]. We only consider public agricultural R&D expenditure as there are no documented data on private agricultural R&D investment in Africa. An important feature of our dataset is that the countries in our study share symmetries in that they are largely agrarian with similar patterns of agricultural production practice. Weather conditions across the sample countries are reasonably comparable, especially within their respective regional blocks, with less weather variability. Hence, we include regional dummy variables to capture the regional heterogeneities in addition to the institutional variable that controls for country-specific institutional differences.

[8] Benin, Botswana, Burkina Faso, Burundi, Congo Republic, Côte d'Ivoire, Ethiopia, Gabon, Gambia, Ghana, Kenya, Lesotho, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Tanzania, Togo, Ugandan, Zambia, Zimbabwe.

[9] This is necessary to avoid the unlikely assumption of random data omission across all sub-Saharan African countries as such omission mighty be indicative of lack of R&D investment spending in these countries.

Agricultural output is expressed as the net agricultural production value added in millions of 2004-2006 "international dollars". Specifically, international commodity prices are used in aggregating agricultural production to facilitate cross-country comparative analysis of productivity. The net production value added had been compiled by multiplying gross production in physical terms by output prices at farm gate less the intermediate uses within the agricultural sector (seed and feed). For the analysis of the agricultural production, a range of conventional agricultural inputs (land, labour, fertilizer, machinery and livestock) are commonly used in the literature due to unavailable capital stock variable. In this study, we employ the newly constructed and consistent net capital stock variable [10] by the FAO and specify a three-factor inputs following Echevarria (1998) and Guitierrez & Guitierrez (2003).

Net capital stock is available in millions local currency units before deflating to base year 2005 country –specific implicit gross domestic deflator primarily taking from the *UN National Accounts Main Aggregate* database. Net capital stock now in constant (real) local currency units, were then converted to base year 2005 international dollars using purchasing power parity conversion from the *IMF World Economic Outlook*[11]. Land is an indicator for agricultural area cultivated, which is measured as the sum of arable land and the area used for permanent crops and pastures. This gives us a broadly-based measure of total land used in agriculture than alternative arable land measures. Labour is a major input in agricultural production in Africa, with more than

[10] The net capital stock consists of several agricultural sectors' components of production assets such as machinery & equipment, livestock, orchards, land improvement. The data is measured by the System of National Account concept of Gross Capital Formation (GCFC) and depreciated using perpetual inventory method. We are grateful to the FAO Statistician, Marie Vander Donckt, for making the data available.

[11] See Pardey, Roseboom and Craig (1992) on the analytical support for using this "deflate-first-then-convert" approach.

half of Sub-Saharan African countries' total labour force are employed in agriculture (Barrios et al, 2008). It is measured in thousands of total numbers of economically active population engaged in agricultural production at the end of the year. The primary source of the output and inputs data is the website of the Food and Agricultural Organization of the United Nation, and especially the statistics provided by *FAOSTAT* database.

Table 1: Descriptive statistics

705 Observations	Variable	Mean	SD	Min	Max
Agricultural production ($2005PPP)	*Y*	3062998	4940015	64875.29	3.32e+07
Capital Stock ($2005PPP)	*K*	7786.033	21462.81	1.118	301050.70
Land (hectare)	*L*	22786.93	22975.79	89.00	98125
Labour ('000 people)	*N*	4138845	5253082	44000	3.42e+07
Domestic R&D ($2005PPP)	*DRD*	339.800	549.890	13.480	2715.343
Foreign R&D[12]	*FRD*	9.41e+07	4.18e+08	44300.44	3.75e+09
Human Capital (%)	*HC*	28.989	20.601	2.490	95.7
Institutions (index)	*INST*	4.275	1.832	1	7

[12] Constructed as OECD domestic R&D stock weighted by imports share and measured in million $2005PPP.

Annual data series on public resources devoted to agricultural research were extracted from Agricultural Science and Technology Indicators (ASTI) database. In the same manner with net capital stock, domestic R&D expenditures data are available in millions local currency units before deflating to base year 2005 country –specific implicit gross domestic deflator primarily taking from the *UN National Accounts Main Aggregate* database. Thereafter, domestic R&D expenditures in constant (real) local currency units were then converted to base year 2005 international dollars using purchasing power parity. To obtain domestic R&D capital stock, we convert the domestic R&D expenditure in million 2005 international dollars into stock using perpetual inventory method[13].

On the assumption that international technology spillover is based on trade as a major channel of knowledge diffusion, we consider 15 developed OECD countries (OECD15)[14] as the source of international knowledge stock owing to the fact that global research and development activities tend to be concentrated in these countries[15]. Following international R&D spillover studies (see Keller, 1998; Lichtenberg and de la Potterie, 1998, Henry et al; 2009), we build on a weighting framework used in the literature in computing foreign R&D stock to reflect not only the direction of R&D spillovers but also their intensity. The weighting scheme expressed the stock of foreign R&D spillover through import by African country i from foreign country j (OECD15) as a bilateral-imports-share weighted sum of the OECD15. Therefore, for any year t;

[13]We assume a depreciation rate of 10% for the perpetual inventory method (see Gutierrez & Gutierrez, 2003).
[14] These 15 OECD countries are Australia, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Spain, Sweden, United Kingdom and United States.
[15] Approximately 60% of World total R&D expenditure originated from the US, Japan, Germany, France and United Kingdom (see UNESCO, 2009).

$$FRD_{it} = \sum_{j\in\{OECD15\}} \frac{M_{ijt}}{Y_{jt}} DRD_{jt}\,, \qquad \text{for } j \neq i$$

[16]

where FRD_{it} is stock of foreign R&D spillover, DRD_{jt} is level of domestic agricultural R&D capital stock in country j for $j \in \{OECD15\}$, M_{ij} is import of goods and services of country i from country j; M_i represents total imports of sub-Sahara African country i from OECD country j and Y_{jt} is the GDP of the OECD country. To construct a series of domestic R&D stock for each of the *OECD15* countries, we employ data expenditure on agricultural R&D extracted from various sources such as OECD Science and Technology Statistics, Alston et al. (1999) and Pardy et al, (2016). To ensure international comparisons, the domestic R&D capital stock for the OECD countries was constructed in a manner analogous to the domestic R&D stock for African countries and are measured in million 2005 international dollars. GDP is measured in million 2005 international dollars and obtained from Penn World Table 7.1. Data on bilateral trade is taken from the IMF's *Direction of Trade Statistics*[16].

[16] According to IMF Direction of Trade Statistics, there are inconsistencies between exports to a partner and the partner's recorded imports from a particular country, i.e. the exports from Country A to B do not always equal the imports of Country B from A. This is due to the different ways countries report their trade, i.e. differences in classification concepts and detail, time of recording, valuation, and coverage, as well as processing errors. To capture the actual import of African countries from the OECD countries and to avoid estimation bias due to measurement error, we use export valued free on board (f.o.b) from OECD countries to African countries as proxy for import by our sampled countries from their trade partners. This helps to address the inconsistencies as the study considers technology transfer from exporting country to importing countries and not the other way round.

One critical aspect required for an understanding of the production performance of African economies pertains to institutional quality. We use the index of the level of political rights as an indicator for country institutional factors which account for political interference of government on trade and agricultural policies. Data on the ranking of political rights within a country is obtained from Freedom House Database which ranks countries on integers range from 1 (most freedom) to 7 (least freedom). Many of our sampled countries are ranked very low on these institutional quality indicators, except Benin, Botswana, Ghana, South Africa, Senegal and Mauritius which are considered more relatively free and democratic. Democratic institution is required to facilitate polices that promote international trade and investments.

Finally, we augment the estimated production technology with a human capital variable, defined as the stock of skills that individuals accumulate through schooling, experience, on-the job training, etc, to make them productive. This important extension allows us to control for quality of labour, a key determinant of capacity to absorb new knowledge (Nelson and Phelps 1966; König et al., 2016; Acemoglu and Restrepo, 2018; Caicedo, 2018). Part of TFP heterogeneity across countries may be explained by the facts that different countries possess different quantities of human capital. One type of that is commonly relatively straightforward to incorporate into the model is education. Nelson and Phelps (1966) propose a hypothesis that the rate of technology diffusion depends upon educational attainment. Education also speeds the process of adopting of new technologies among farmers. Well educated farmers are more receptive to innovative technologies and adopt them quicker than non-educated farmers. Therefore, we use secondary school-enrollment rates as proxy for human capital extracted from WDI.

5. Empirical results

The main results of this study are presented in this section. Before proceeding to any estimation, we attempt to confirm the structure of the production technology in order to avoid placing any a priori and unnecessary restrictions on the characteristic of the technology. We perform a set of specification tests to check for functional form, technical change and the presence of inefficiency. The hypotheses tests were obtained using the generalized likelihood statistic. This is defined by $\lambda = -2[ln(LH_0 - ln(LH_1)]$ with a chi-square distribution χ_p^2 where p is the degree of freedom equal to the difference between the number of parameters estimated under H_0 and H_1. Table 2 presents the test results of the null hypotheses[17]. First, we test for appropriate functional form by comparing Cobb-Douglas functional form with the translog form. The LR test indicates that the null hypothesis of the Cobb-Douglas can be rejected at 1%, implying that the translog function better describes the technology. The finding is consistent with Duffy and Papageorgiou (2000) who argue that the Cobb–Douglas form of the production function estimation is incorrectly specified.

[17] For each hypothesis, a restricted model is nested in the unrestricted model by imposing a set of restriction on the parameter of the unrestricted model.

Table 2: Likelihood ratio tests

Null Hypothesis	LR-Test Statistics	Critical value ($\boldsymbol{\alpha}$ = 0.01)	Decision
Cobb-Douglas specification H_0 : *all the* β*s are equal to zero (df=10)*	187.156	22.525	Reject
No inefficiency effects H_0: $\gamma = \mu = \eta = 0$ *(df=3)*	760.407	10.501	Reject
Hicks neutral technical change $H_0 = \beta_{Kt} = \beta_{Lt} = \beta_{Nt} = 0$ *(df=3)*	37.704	10.501	Reject

Note: The critical values for the tests are obtained from table1 of Kodde and Palm (1986)

Secondly, we test for the hypothesis on the presence of technical inefficiency effects in the production function expressed as $H_0 := \mu = \eta = 0$. Conventional OLS estimation excludes the non-negative random, u, and assumes perfect efficiency in production. The LR test shows that the null hypothesis of no inefficiency is strongly rejected at 1% significance level. Thus, the test result provides evidence for the presence of the one-sided error, suggesting that the stochastic frontier model is an adequate representation of the data and it is preferred to traditional OLS. Third, we test the hypothesis of Hick-neutral technological progress that technology change has no effect on factor augmenting. The null hypothesis that technological change is Hick-neutral is rejected, indicating non-neutral technological progress over time in our model.

Table 3: Production function estimation results[18]

Variable	Coef.	Std. Error	Variable	Coef.	Std. Error
Capital	0.0307*	(0.0165)	DRD $*$ $time$	- 0.0009	(0.0010)
Land	0.5534***	(0.0537)	FRD $*$ time	-0.0023**	(0.0008)
Labour	0.2528***	(0.0652)	Human Capital	-0.0026***	(0.0009)
DRD	0.1146***	(0.0233)	Institution	0.0018	(0.0037)
FRD	0.0226*	(0.0121)	Regional Dummy	Yes	
Capital squared	0.0023	(0.0036)	Constant	0.8602***	(0.0815)
Land squared	-0.0235	(0.0355)	γ	0.9930	(0.0043)
Labour squared	-0.0268	(0.0331)	μ	0.9027*	(0.5164)
DRD squared	0.0302***	(0.0108)	η	-0.0076***	(0.0020)
FRD squared	0.0086**	(0.0039)	Log-Likelihood	543.48	
Capital $*$ Land	0.0052	(0.0158)			
Capital $*$ Labour	0.0293	(0.0200)			
Capital $*$ DRD	-0.0039	(0.0118)			
Capital $*$ FRD	-0.0249***	(0.0057)			
Land $*$ Labour	0.0403	(0.0419)			
Land $*$ DRD	0.0377*	(0.0229)			
Land $*$ FRD	0.0210**	(0.0088)			
Labour $*$ DRD	-0.0458**	(0.0222)			
Labour $*$ FRD	0.0151	(0.0115)			
DRD $*$ FRD	-0.0190*	(0.0111)			
Time	0.0312***	(0.0019)			
Time squared	0.0000***	(0.0001)			
Capital $*$ time	-0.0026***	(0.0006)			
Land $\times$ time	-0.0043***	(0.0012)			
Labour $\times$ time	0.0073***	(0.0013)			

Notes: *, **, * *denote statistically significant at 10%, 5% and 1% respectively*

Based on the specification tests favoring the translog model with time-varying inefficiency effect, we proceed to discuss the empirical results of the production function in Table 3. Since the output

[18] The dependent variable is the log of agricultural output. All input variables are also expressed in logarithmic form. Human capital variable is measured in percentage and institution variable is proxied by the index of the level of political rights which ranges from 1 to 7. Hence, both human capital and institution variables are not logged.

and input variables are in logarithmic form, the estimated coefficients can be directly interpreted as elasticities. The average elasticity of agricultural output with respect to capital (α_K) is 0.03, implying that, other things being equal, a 1% increase in capital stock will, on average, result in a 0.03% increase in output. The average elasticity with respect to land (α_L) is 0.55, meaning that a 1% increase in land will on average result in a 0.55% increase in output while elasticity of output with respect to labour (α_N) is 0.25, which indicate that a 1% increase in labour will likely increase output by 0.25%. We now offer some discussions on the elasticities as follows. First, all the elasticities estimated have expected signs and are statistically significant. Second, on average, our results suggest that agricultural output is most sensitive to a change in agricultural land than a change in labour and capital. Thus, we can conclude that the land input is used more intensively in agricultural production compared with other factor inputs. This finding is consistent with the studies of Sherlund et al (2002), Barrett et al, (2008) and Barrios et al (2008) who argued that output is most responsive to land under cultivation in SSA.

Our next concern relates to the effect of R&D stocks on productivity. As expected, the estimated coefficient on domestic R&D stock is positive and statistically significant at the 5% level, suggesting that the domestic stock of knowledge positively associated with agricultural productivity. Similar results have been reported in past analyses of the productivity of agriculture in African countries; for example, see Alene and Coulibaly (2009), Alene (2010) and Mohar et al (2014)[19]. The coefficient on the foreign R&D transferred through imports (*FRD*) is also positive and significant, which implies that international R&D diffusion through imports helps improve a

[19] Although these studies used a two-stage modelling approach, the application of frontier approach contrasts with the methodology used in the literature where a two-stage modelling strategy is adopted. Hence, we model both the frontier and the determinants in one stage. See Kumbhakar et al. (1991) and Reifschnieder and Stevenson (1991) for detailed discussion on the drawback of a two-stage method.

country's productivity and is congruous with the findings in Gutierrez and Gutierrez (2003) and Liao et al (2009). What is immediately apparent is that the magnitude of the coefficient of domestic R&D stock is substantially larger than that of foreign R&D stock. According to our results, a 1% increase in domestic R&D stock would raise agricultural productivity by 0.12% while the same percentage increase in foreign R&D stock through trade flow will boost productivity by 0.02%, other things being equal. Interestingly, the coefficient on the interaction term between both the domestic and foreign R&D stocks is negative, implying that both knowledge stocks could be substitutes in the agricultural productivity performance across our sample.

Furthermore, the positive coefficient estimate for the time trend indicates continued improvement via technological progress over the sample period. The coefficient on the interaction between time and labour is positively significant while the coefficient on the interaction between time and capital negative. In theory, our results imply that technical change has been labour saving and capital using. In other words, technologies cause producers to shift input proportions by increasing the relative use of capital and decreasing the relative use of labour inputs. In terms of our findings, these capital-consuming and labor-saving technologies shift agricultural production function thereby increasing agricultural productivity (see FAO, 2003). These findings also reinforce our earlier hypothesis test that production technology is non-neutral technological change.

Regarding human capital, the coefficient is statistically significant but has a negative sign, suggesting a higher level of human capital leads to lower output. The negative coefficient appears counter-intuitive, but is not overly surprising, especially in the context of SSA agriculture production function. This finding is consistent with Aboagye and Gunjal (2000) and Aboagye (1998). We are of the opinion that this negative coefficient possibly reflects the higher labour turnover associated with SSA agriculture as educational attainment improves. For instance, Bryceson (1996) identifies the increasingly less rural character and increasingly prevalent national industrialization policies across SSA as contributors to the process of "deagrarianization". Another potential critical factor includes the need for rural income diversification, prompted by changing structures of the macroeconomy and economic hardships; which have resulted in "depeasantization" as reflected by the transitory effects from agrarian employment towards other employment in other sectors (see Bryceson, 1996). Hence, increases in educational attainment could conceivably lead to a large shift in labour away from agriculture to other high paying sectors, thereby decreasing agricultural productivity. Although not statistically significant, we establish a positive relationship between agricultural output and institution.

Finally, we estimate returns to scale as the sum of the elasticities of output and our result shows that the production technology exhibits decreasing returns to scale. We check for linear homogeneity by testing the null hypothesis that the sum of the elasticities is not statistically different from one. If we reject the null hypothesis, then we can confirm that the technology has decreasing returns to scale as the sum of the elasticities is below unity. Table 4 reports the results, which show that the hypothesis of constant returns to scale can be rejected, in favour of decreasing return to scale. The implied scale diseconomies suggest that, all else equal, an increase in the sampled agricultural sectors' size or input usage yields a less than proportionate increase in output.

Table 4: Return to scale: sum of elasticity of output vector

Model	**RTS** $[(\alpha_K + \alpha_L + \alpha_N)]$	**Standard error**	**Test: RTS = 1 p-value**
Model 1	0.974	0.0404	0.5204

5.1 Total Factor Productivity and its Decomposition

The changes in the indices in total factor productivity and its components for the sample period are reported in Table 5. The estimates of TEC, TP and SEC are derived by applying the techniques mentioned in Section 3. The TFP growth is not measured as residual growth of total output but obtained as the sum of technical progress (measured by a shift in the production frontier), changes in technical efficiency and scale change.

We identify which TFP component is the major source of productivity growth in the agricultural sectors in Africa. Where the values of either productivity or any of its components are greater than one, the results imply improvement in the total productivity and its components. However, the values less than one represent deterioration in productivity performance which means that the country is not able to produce as much outputs as before, given the same amount of inputs. All the cross-country averages reported here are weighted by the agricultural output. It is evident from the decomposition of average TFP growth that, technical change is the major source of TFP growth with an average growth rate of 3.2% per year. The technical change is characterized by a continuously rising trend throughout the study period. This trend could potentially stem from increasing spending on agricultural R&D investment for innovation generation by sample countries during the study period and technologies induced through imports.

Table 5: Annual productivity growth, technical change, efficiency change and scale change

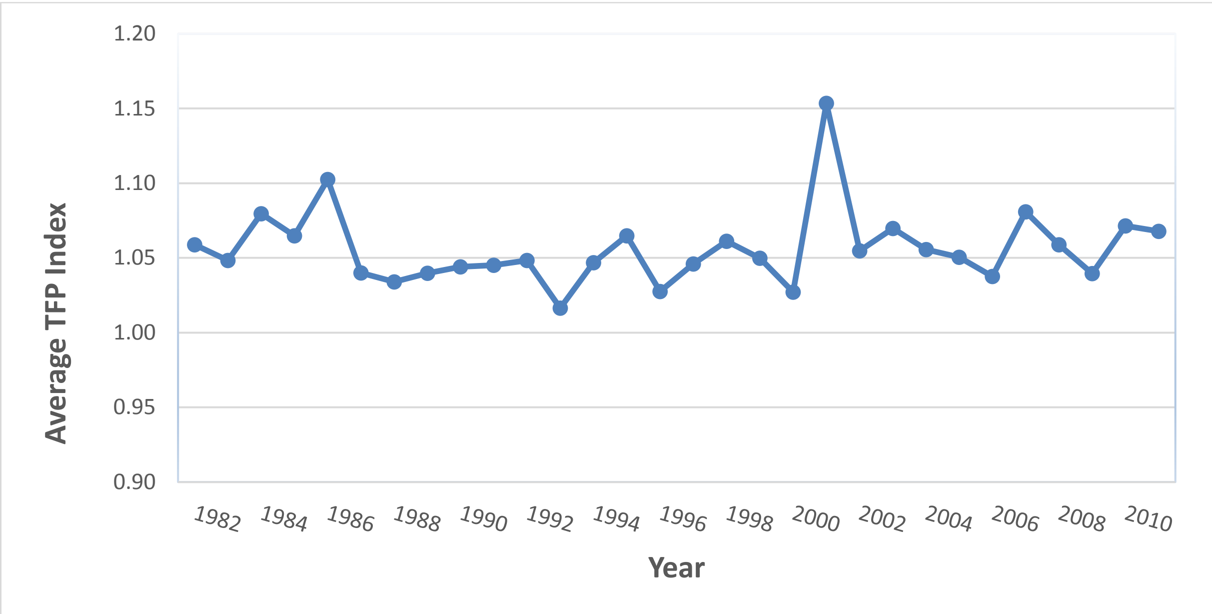
Year[20]	TC	EC	RTS	TPF
1982	1.0283	0.9952	1.0346	1.0589
1983	1.0283	0.9950	1.0246	1.0484
1984	1.0279	0.9953	1.0547	1.0795
1985	1.0279	0.9952	1.0409	1.0650
1986	1.0280	0.9951	1.0773	1.1026
1987	1.0279	0.9951	1.0166	1.0400
1988	1.0282	0.9952	1.0106	1.0340
1989	1.0283	0.9952	1.0161	1.0398
1990	1.0284	0.9953	1.0201	1.0442
1991	1.0289	0.9955	1.0204	1.0451
1992	1.0295	0.9953	1.0231	1.0483
1993	1.0303	0.9945	0.9919	1.0164
1994	1.0299	0.9946	1.0220	1.0468
1995	1.0302	0.9945	1.0393	1.0647
1996	1.0310	0.9940	1.0028	1.0276
1997	1.0313	0.9934	1.0209	1.0459
1998	1.0312	0.9934	1.0359	1.0612
1999	1.0311	0.9934	1.0249	1.0498
2000	1.0310	0.9935	1.0027	1.0271
2001	1.0306	0.9931	1.1268	1.1535
2002	1.0299	0.9929	1.0314	1.0547
2003	1.0302	0.9931	1.0456	1.0697
2004	1.0334	0.9898	1.0321	1.0556
2005	1.0338	0.9895	1.0270	1.0505
2006	1.0346	0.9892	1.0139	1.0377
2007	1.0332	0.9923	1.0544	1.0809
2008	1.0335	0.9923	1.0325	1.0589
2009	1.0340	0.9919	1.0136	1.0395
2010	1.0341	0.9918	1.0446	1.0714
2011	1.0344	0.9916	1.0411	1.0679
Mean	**1.0317**	**0.9917**	**1.0246**	**1.0483**

[20] Please note that 1982 refers to the change between 1981 and 1982, etc. Mean value is expressed in geometric mean

The improvement in scale change with annual average growth rate of 2.5% also made a considerable contribution to TFP growth, except in year 1992 when the scale change was negative. However, efficiency change made a negative impact on productivity and generally drags down the TFP growth due to persistent decline in efficiency throughout the sample period, averaging -0.8% per year. The worsening efficiency change could be an indication of inefficient subsistence agricultural practice in SSA. We find a positive average productivity growth rate of 4.8% per annum over the sample period. The estimated annual productivity growth in our study is slightly higher that the TFP growth rate findings in earlier studies (see Alene, 2010, Avila and Evenson, 2010, Heady et al, 2010; Nin and Yu, 2008). The improved SSA agricultural productivity gains in our study is not surprising as we adopt a different analytical approach as opposed to non-parametric method of these studies. The study by Heady et al, (2010) confirmed that estimates of SSA agriculture productivity based on frontier approach yields a much higher TFP growth than estimates based on DEA. The inclusion of both domestic R&D and foreign R&D as factor inputs in our model also provides some confidence in the robustness of our TFP growth estimates.

Figure 1 shows the time series annual average total factor productivity change across our data sample. As illustrated in the figure, the average productivity increased during the early 1980s, until around 1986 when it declined sharply; remaining fairly stable in the 1990s with annual growth rates in the region of 4%. Between 2000 and 2002, there was a sharp increase and decline in average productivity, after which the productivity growth rates largely remained within the 5-8% ballpark.

Fig. 1: Annual average total factor productivity change



We disentangle the estimate of the total factor productivity and its decomposition by region in order to understand the heterogeneity of these regions in terms of the productivity indices. Table 6 reports the estimate of the total factor productivity and its decomposition by region from 1981-2011. For brevity, we discuss the productivity growth rate for the regions as the result clearly shows that there are obvious differences between country's performances. All the regions experienced positive productivity growth. The West Africa region is atop the production technology frontier with an average productivity growth rate of 6.1%, slightly higher than that the sample average TFP. This suggests that the region exhibit the best practice production technologies. It is interesting to note that the East Africa recorded the highest technological progress over the sample period, with an average yearly TFP growth rate of 3.6%. Tellingly, the finding lends credence to the deployment of technological innovation into agricultural sector in past few years in countries in this region such as Rwanda, Kenya. The country-level productivity decomposition results in Table A2 of the appendix reinforces our findings as Rwanda recorded the highest growth in technical progress, with an average annual growth of 5.2%. This finding also seems consistent with past studies that confirm Rwanda as one of the hubs for science and technology in Africa (see Webersik and Wilson, 2009).

Table 6: Average total factor productivity and its decomposition by region

Region	TC	EC	SC	TFP
Central Africa	1.0241	0.9975	1.0107	1.0324
East Africa	1.0361	0.9851	1.0142	1.0351
Southern Africa	1.0274	0.9966	1.0226	1.0418
West Africa	1.0326	0.9944	1.0331	1.0608
Mean	**1.0317**	**0.9917**	**1.0246**	**1.0483**

5.2 Robustness checks

Since our panel data is unbalanced; we used the Fisher-type tests to examine the stationarity of dataset which reject the presence of unit roots in the majority of the data. It is therefore assumed that this is not a problem despite the relative statistical significance of our estimated parameters in our model. We also check the robustness of our results by investigating whether the results do not change when R&D variables are treated as technology shifter as opposed to input as adopted in our study. Consistent with treating domestic and foreign R&D as technology shifters, we introduced non-logged R&D into the model. However, the model failed to converge. We also estimated an alternative model in which labour is adjusted for human capital. The result is presented in Table A1 in the appendix. While most of the model parameters are qualitatively similar to those in our baseline model, this alternative specification violates the monotonicity condition, given that output is found to be decreasing in labour.

Finally, we lagged the R&D variables by one period in order to take into consideration the time lag from R&D to adoption[21]. Again, the main results were not fundamentally affected, with an annual TFP figure averaging 4.7%, which is quite similar to the annual average TFP figure of the original model, 4.8%. The regression results and the TFP decomposition results are reported in Tables A3 and A4 in the appendix.

6 Conclusion and policy recommendations

This study examines agricultural productivity of 30 sub-Saharan Africa countries from 1981-2011 using a stochastic frontier analysis (SFA). Specifically, we evaluate the impact of domestic and foreign R&D on agricultural productivity in the SSA region. The results suggest that domestic stock of knowledge is positively associated with productivity growth of SSA agriculture. This effect is statistically significant at the 1% level. This result is qualitatively similar to the findings in Alene and Coulibaly (2009), Alene (2010) and Mohar et al (2014). Furthermore, in line with Gutierrez and Gutierrez (2003), foreign R&D transferred through import channels was also found to have a positive impact on productivity, albeit this effect is only significant at the 10%- level.

The average rate of productivity growth for the sample period was estimated at 4.8% per year. The decomposition of TFP growth shows that technical change is the source of TFP growth with an average growth rate of 3.2% per year. The technical change is characterized by a continuously rising trend throughout the study period. However, technical efficiency change made a negative impact on productivity and generally drags down TFP growth due to persistence decline

[21] We are very grateful to the anonymous reviewer for suggesting a time lag on the R&D variables.

in efficiency throughout the sample period, averaging -0.8% per annum. The worsening efficiency change could be an indication of inefficient subsistence agriculture and low technological innovation utilisation in SSA agriculture. Thus, a plausible way for enhancing farmers' production efficiency is to augment land use through increased application of capital stock and research expenditures for output expansion.

Overall, our results highlight that total factor productivity is strongly influenced by both domestic and foreign public research and development (R&D) spending in the agricultural sector, although the impact of domestic R&D is statistically and qualitatively stronger. Based on the estimated impacts of the R&D variables, it appears that the productivity returns on the domestic knowledge stocks exceeded those on their foreign counterparts across sampled SSA countries during the study period. One possible interpretation from the relatively larger impact from domestic R&D stock is that innovation and knowledge exhibit decreasing returns to scale (Bitzer and Kerekes, 2008). Additionally, it is plausible that the local conditions (e.g. weather conditions, level of development) and other institutional bottlenecks may inhibit the full absorption of foreign innovation efforts (see Aitken et al., 1999; Johnson and Evenson, 2000; O'Gorman, 2015). This potentially raises the question of whether it might be more beneficial to focus on domestically-driven innovation efforts, complemented by foreign R&D spillovers (D'Agostino and Santangelo, 2012). In this context, an appreciable increase in public R&D spending through extra budgetary allocation to R&D investment will have a far-reaching impact at improving the performance of SSA agriculture. Although, SSA agricultural R&D is still largely publicly funded while the private sector is slowly investing in crop R&D, especially in the area of agricultural biotechnology.

Hence, we suggest that there is a need to complement the existing government R&D expenditure with increasing private R&D investments to boost agricultural productivity. Given that innovation generated from R&D investment is non-rivalrous and often has positive externalities, private companies tend to invest less. Specifically, policies such as targeted subsidies or tax break that foster greater private sector investments in new innovations that improve productivity performance should form the core of national agricultural research strategies.

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Appendix

Table A1: Estimation results- Effective Labour[22]

Variable	Coef.	Std. Error	Variable	Coef.	Std. Error
Capital	0.0356**	(0.0170)	DRD $*$ $time$	- 0.0013	(0.0012)
Land	0.7289***	(0.0488)	FRD $*$ time	0.0014*	(0.0008)
Labour	-0.0217	(0.0553)	Institution	-0.0010	(0.0038)
DRD	0.1348***	(0.0235)	Regional Dummy	Yes	
FRD	0.0182	(0.0125)	Constant	1.4370***	(0.2556)
Capital squared	0.0026	(0.0040)	γ	0.9953***	(0.0011)
Land squared	0.0078	(0.0309)	μ	1.3599**	(2.7433)
Labour squared	0.0329	(0.0233)	η	-0.0055***	(0.0023)
DRDsquared	0.0356***	(0.0118)	Log-Likelihood	527.148	
FRD squared	0.0200***	(0.0038)			
Capital $*$ Land	0.0090	(0.0156)			
Capital $*$ Labour	0.0233	(0.0209)			
Capital $*$ DRD	-0.0064	(0.0126)			
Capital $*$ FRD	-0.0278***	(0.0055)			
Land $*$ Labour	-0.0032	(0.0335)			
Land $*$ DRD	0.0535**	(0.0235)			
Land $*$ FRD	0.0225**	(0.0955)			
Labour $*$ DRD	-0.0732***	(0.0250)			
Labour $*$ FRD	0.0182	(0.0113)			
DRD $*$ FRD	-0.2040	(0.0107)			
Time	0.0317***	(0.0023)			
Time squared	-0.0001*	(0.0001)			
Capital $*$ time	-0.0030***	(0.0006)			
Land $\times$ time	-0.0026*	(0.0016)			
Labour $\times$ time	0.0060***	(0.0018)			

Notes: *, **, * *denote statistically significant at 10%, 5% and 1% respectively*

[22]The estimation is based on human capital adjusted labour. However, the result is inconsistent with economic theory due to the violation of monotonicity condition as labour is non-decreasing in output. The dependent variable is the log of agricultural output. All input variables are also expressed in logarithmic form. Institution variable is not logged because the variable is proxied by the index of the level of political rights which ranges from 1 to 7.

Table A2: Average productivity growth and its components, by country.

Country	TC	EC	RTS	TFP
Benin	1.0360	0.9998	1.0470	1.0844
Botswana	1.0128	0.9849	1.0326	1.0300
Burkina Faso	1.0389	0.9933	1.0352	1.0683
Burundi	1.0401	0.9856	0.9867	1.0116
Congo	1.0256	0.9955	1.0207	1.0421
Cote d'Ivoire	1.0289	0.9983	1.0055	1.0329
Ethiopia	1.0422	0.9819	1.0295	1.0534
Gabon	1.0225	0.9996	1.0007	1.0228
Gambia	1.0350	0.9900	1.0129	1.0378
Ghana	1.0315	0.9985	1.0474	1.0787
Kenya	1.0352	0.9824	1.0272	1.0447
Lesotho	1.0220	0.9872	0.9986	1.0075
Madagascar	1.0330	0.9797	1.0221	1.0344
Malawi	1.0349	0.9979	1.0305	1.0643
Mali	1.0268	0.9912	1.0326	1.0510
Mauritania	1.0210	0.9843	1.0673	1.0726
Mauritius	1.0295	0.9964	0.9539	0.9785
Mozambique	1.0355	0.9889	1.0420	1.0669
Namibia	1.0141	0.9852	1.0447	1.0437
Niger	1.0325	0.9888	1.0455	1.0675
Nigeria	1.0292	0.9997	1.0516	1.0820
Rwanda	1.0515	0.9870	1.0178	1.0562
Senegal	1.0348	0.9929	1.0064	1.0340
Sierra Leone	1.0422	0.9917	1.0607	1.0962
South Africa	1.0213	0.9960	0.9993	1.0165
Tanzania	1.0375	0.9812	1.0567	1.0757
Togo	1.0338	0.9942	1.0180	1.0463
Uganda	1.0381	0.9856	1.0541	1.0785
Zambia	1.0443	0.9918	1.0244	1.0610
Zimbabwe	1.0296	0.9931	1.0231	1.0461
Total	**1.0317**	**0.9917**	**1.0246**	**1.0483**

Table A3: Estimation results with R&D lagged variables

Variable	Coef.	Std. Error	Variable	Coef.	Std. Error
Capital	0.0332**	(0.0165)	$\mathrm{DRD}_{t-1} * time$	-0.0011	(0.0011)
Land	0.6958***	(0.1179)	$\mathrm{FRD}_{t-1} *$ time	0.0021***	(0.0007)
Labour	0.2388***	(0.0667)	Institution	-0.0010	(0.0038)
DRD_{t-1}	0. 0933***	(0.0236)	Regional Dummy	Yes	
FRD_{t-1}	0. 0165	(0.0120)	Constant	0.8912***	(0.1353)
Capital squared	0.0006	(0.0038)	γ	0.9921***	(0.0046)
Land squared	0. 0628	(0.0442)	μ	1.0673**	(0.4201)
Labour squared	- 0.0568	(0.0351)	η	0.0066***	(0.0013)
DRD_{t-1} squared	0.0174	(0.0115)	Log-Likelihood	532.053	
FRD_{t-1} squared	0.0079**	(0.0038)			
Capital $*$ Land	-0.0196	(0.0164)			
Capital $*$ Labour	0.0217	(0.0206)			
Capital $* \mathrm{DRD}_{t-1}$	0.0115	(0.0122)			
Capital $* \mathrm{FRD}_{t-1}$	-0.0253***	(0.0059)			
Land $*$ Labour	0.0401	(0.0467)			
Land $* \mathrm{DRD}_{t-1}$	0.0351	(0.0234)			
Land $* \mathrm{FRD}_{t-1}$	0.0144	(0.0089)			
Labour $* \mathrm{DRD}_{t-1}$	-0.0225	(0.0224)			
Labour $* \mathrm{FRD}_{t-1}$	0.0050	(0.0113)			
$\mathrm{DRD}_{t-1} * \mathrm{FRD}_{t-1}$	-0.0098	(0.0111)			
Time	0.0312***	(0.0019)			
Time squared	5.94e-05	(7.80e-05)			
Capital $*$ time	-0.0017***	(0.0006)			
Land $\times$ time	-0.0043***	(0.0026)			
Labour $\times$ time	0.0069***	(0.0015)			

Notes: *, **, *** *denote statistically significant at 10%, 5% and 1% respectively*

Table A4: Annual productivity growth and it components with R&D lagged variables

Year*	ETC	EEC	ERTS	EGMI
1983	1.0281	0.9946	1.0283	1.0515
1984	1.0277	0.9948	1.0850	1.1099
1985	1.0275	0.9947	1.0561	1.0797
1986	1.0275	0.9947	1.0781	1.1022
1987	1.0275	0.9947	1.0136	1.0360
1988	1.0280	0.9947	1.0097	1.0326
1989	1.0283	0.9947	1.0215	1.0449
1990	1.0284	0.9947	1.0206	1.0441
1991	1.0288	0.9949	1.0266	1.0508
1992	1.0294	0.9949	1.0118	1.0362
1993	1.0299	0.9949	1.0204	1.0456
1994	1.0307	0.9942	1.0244	1.0498
1995	1.0307	0.9942	1.0541	1.0804
1996	1.0308	0.9942	1.0125	1.0376
1997	1.0316	0.9940	1.0120	1.0376
1998	1.0320	0.9935	1.0317	1.0577
1999	1.0319	0.9935	1.0261	1.0519
2000	1.0320	0.9935	1.0159	1.0416
2001	1.0318	0.9933	1.0604	1.0869
2002	1.0314	0.9931	1.0164	1.0411
2003	1.0315	0.9932	1.0467	1.0724
2004	1.0324	0.9932	1.0032	1.0285
2005	1.0344	0.9906	1.0244	1.0498
2006	1.0350	0.9905	1.0164	1.0420
2007	1.0342	0.9926	1.0279	1.0552
2008	1.0345	0.9927	1.0238	1.0514
2009	1.0353	0.9924	1.0037	1.0312
2010	1.0356	0.9923	1.0348	1.0634
2011	1.0358	0.9921	1.0383	1.0671
Mean	**1.0317**	**0.9924**	**1.0222**	**1.0466**

*Please note that 1983 refers to the change between 1982 and 1983, etc. Because of the one period R&D lagged variables, the change between 1981 and 1982 is missing. Mean value is expressed in geometric mean