LIUC

The European Journal of Comparative Economics
Vol. 19, no. 1, pp. 103-141
ISSN 1824-2979

Separating innovation short-run and long-run technical efficiencies: Evidence from the Economic Community of West African States (ECOWAS)

Dorgyles C.M. Kouakou*

Abstract

A stream of literature has been developed on the measurement of the efficient production of innovation, that is, innovation technical efficiency. However, the efficiency measured is quite fuzzy as no distinction is made between innovation short-run and long-run efficiencies. Also, African economies have been heavily neglected, despite the need to explore ways to improve the poor levels of innovation they usually exhibit. In this paper, we measure innovation technical efficiency by separating short-run and long-run efficiencies. Overall technical efficiency, that is, efficiency both in the short and long run is also assessed. The empirical evidence makes use of data from countries from the Economic Community of West African States, one of the most important economic areas in Africa. To obtain efficiency scores, we carry out a stochastic frontier analysis. Results show that research and development, market sophistication and human capital significantly influence innovation output. No country is found to be efficient following one of the types of efficiency. The long-run and average short-run efficiencies over the study period are not similar, which shows the need to separate the types of efficiency. Domestic credit to private sector and governance are highlighted as determinants of innovation efficiency. Some policies are suggested based on these findings.

JEL classification: E23, O11, O30, O55

Keywords: Innovation technical efficiency, Short-run efficiency, Long-run efficiency, Determinant factors, West Africa

1. Introduction

The quest for economic performance is of interest in nations and for-profit organizations. Innovation is one of the important sources of this performance (Steil *et al.*, 2002). Indeed, for instance, it is known to be a source of economic growth (Akcigit and Kerr, 2018), productivity and competitiveness (Carayannis and Grigoroudis, 2016). In view of its importance, factors amenable to increase innovation production have been investigated extensively in many papers. In such a context, many studies have been carried out on the determinants of innovation (see for instance, Gebreeyesus and Mohnen, 2013; Paunov, 2016; Rooks *et al.*, 2012), and especially on those of R&D (see

* CREM, UMR CNRS 6211, Université de Rennes 1, France, and LAMPE, Université Alassane Ouattara, Côte d'Ivoire. E-mail: kouakoudcm@hotmail.com

Acknowledgements: The author acknowledges two anonymous referees for helpful suggestions. He is also grateful to (late) Bédia F. Aka, Eric Avenel, Farid Gasmi, Sophie Larribeau, Stéphane Lemarié, Nadine Massard, Edward Maunder, Pierre Mohnen, and Aké G.M. N'gbo, for helpful comments on earlier versions of this study, and to Subal C. Kumbhakar and Hung-pin Lai for sharing with him the Stata code used for the econometric estimations. All remaining errors are his own.

Conflict of interest: The author declares no conflicts of interest.

http://dx.doi.org/10.25428/1824-2979/010
First published online: 01/09/2022

for instance, Balsmeier, 2017; Maskus *et al.*, 2019) which is generally shown to be an important innovation input (Mairesse and Mohnen, 2002).

A relatively recent stream of literature has been developed concerning the analysis of innovation technical efficiency (henceforth, ITE), that is, the efficient production of innovation. Technical efficiency, indeed, refers to productive efficiency (Farrell, 1957). It is of particular interest as it measures a decision-making unit's ability to achieve the maximum output given a certain level of inputs. In other words, technical efficiency assesses a decision-making unit's ability to produce better. We are interested in ITE in this paper.

In the current literature, to the best of our knowledge, papers do not measure innovation short-run and long-run technical efficiencies. This is interesting to do as short-run and long-run efficiencies capture different kinds of efficiency and are not associated with the same policy implications (Kumbhakar and Heshmati, 1995). In fact, innovation short-run technical efficiency assesses a decision-making unit's ability to achieve the maximum level of innovation in the short run given its inputs, while innovation long-run technical efficiency refers to this ability in the long run. Also, ceteris paribus, short-run efficiency should be more affected by short-run policies while long-run efficiency should be more targeted through long-run policies. The short-run part of efficiency can be adjusted over time for each individual, while the long-run part varies across individuals but is constant over time (Kumbhakar and Lien, 2017). Measuring short-run and long-run technical efficiencies permits to properly measure the overall technical efficiency which is technical efficiency both in the short and long run (Colombi *et al.*, 2014; Kumbhakar *et al.*, 2014, 2015).

Furthermore, the current literature on the measurement of ITE has neglected developing countries from Africa, presumably due to lack of data. Indeed, to the best of our knowledge, Kao's (2017) study is a rare example of a research that considers an African country, that is, South Africa which is an emerging country. A study of ITE in African countries is of particular interest in view of the fact that a significant part of these countries is usually found to be part of the countries that exhibit the lowest levels of innovation in the world[1]. Technical inefficiency could be an explanation for this fact

[1] See the innovation indexes published yearly by the World Intellectual Property Organization (WIPO), INSEAD and Cornell University.

as it leads to achieve a level of innovation that is lower than what is possible to be achieved given the inputs.

In this paper, we therefore measure innovation short-run technical efficiency, innovation long-run technical efficiency, and innovation overall technical efficiency, using data from Africa. In particular, we exploit data from the Economic Community of West African States (ECOWAS). We also investigate the potential determinants of innovation efficiency. This is operationalized through the panel data stochastic frontier analysis framework proposed recently by Lai and Kumbhakar (2018), in which the variances of short-run and long-run inefficiencies are modeled as functions of the determinants, and possible endogeneity issue in the estimation of the frontier is handled.

Our study follows the macroeconomic literature on ITE, where the investigation of African developing countries is a real omission. Among other factors, it is important to fill this gap since for the purposes of designing policies to improve the use and allocation of resources, it is necessary to evaluate ITE levels at the country level (Wang and Huang, 2007). Carrying out such a study in the ECOWAS area would permit to identify both the best innovation practitioners (for benchmarking) and the lagging ones, and then to investigate ways to improve ITE (Guan and Chen, 2012).

The remainder of the paper is organized as follows. Section 2 highlights ITE as a development issue in West Africa. Section 3 is a literature review on the analysis of ITE at the macroeconomic level. Section 4 presents the econometric modeling. The data, variables and descriptive statistics are presented in section 5. The empirical results are presented and discussed in section 6. Section 7 concludes.

2. The efficient production of innovation in West Africa: A development issue

West Africa is one of the most important economic areas in Africa. Indeed, it includes Nigeria, one of Africa's leading economic powers, and Côte d'Ivoire, one of the countries exhibiting the highest economic growth rates in Africa in recent years[2]. West African countries are grouped within the ECOWAS which includes 15 countries, namely: Benin, Burkina Faso, Cabo Verde, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone and Togo.

[2] See the World Development Indicators database of the World Bank.

The real gross domestic product per capita (GDPPC) averaged 1,285 United States Dollars (USD) in 2019 in West Africa[3]. There are significant differences in terms of GDPPC between countries like Niger (524 USD), Togo (631 USD), Guinea-Bissau (650 USD), Liberia (650 USD) or Sierra Leone (650 USD), and other countries like Cabo Verde (3,482 USD), Nigeria (2,503 USD), Côte d'Ivoire (2,328 USD) and Ghana (2,054 USD)[4]. Beyond these differences, the figures presented show the need for West African countries to increase their levels of wealth per capita. Indeed, compared to more advanced countries, their levels of GDPPC seem quite low. For instance, in 2019, the GDPPC of France was 38,912 USD. That of the United States of America (USA) was 60,687 USD.

More generally, at the level of human development, the average human development index (HDI) in West Africa in 2018 was equal to 0.49[5]. This implies a low level of human development, the value of the HDI being lower than 0.5. In 2019, we observed an improvement as the HDI was equal to 0.51. This suggests a kind of medium level of human development. We also note that in recent years, especially since 2009, the rate of monetary poverty[6] in West African countries has very often been between 10% and 69%[7], which is not negligible. From these figures, it appears a need to analyze the factors that can improve the level of development in West Africa and reduce monetary poverty.

In the economic literature, innovation is acknowledged as a factor promoting economic growth and development (see for instance, Akcigit and Kerr, 2018; Schumpeter, 1912), among other factors, through an increase in competitiveness, productivity and social welfare (see for instance, Amable et *al.*, 2016; Carayannis and Grigoroudis, 2016; Gambardella et *al.*, 2016). A good redistribution of the fruits of the economic growth can then help to reduce the rate of monetary poverty. The production of innovation in West Africa therefore constitutes a development issue, all the more so

[3] Data on GDPPC come from the World Development Indicators database of the World Bank.

[4] The values in parentheses are GDPPC in 2019.

[5] The HDI is published by the United Nations Development Programme (UNDP).

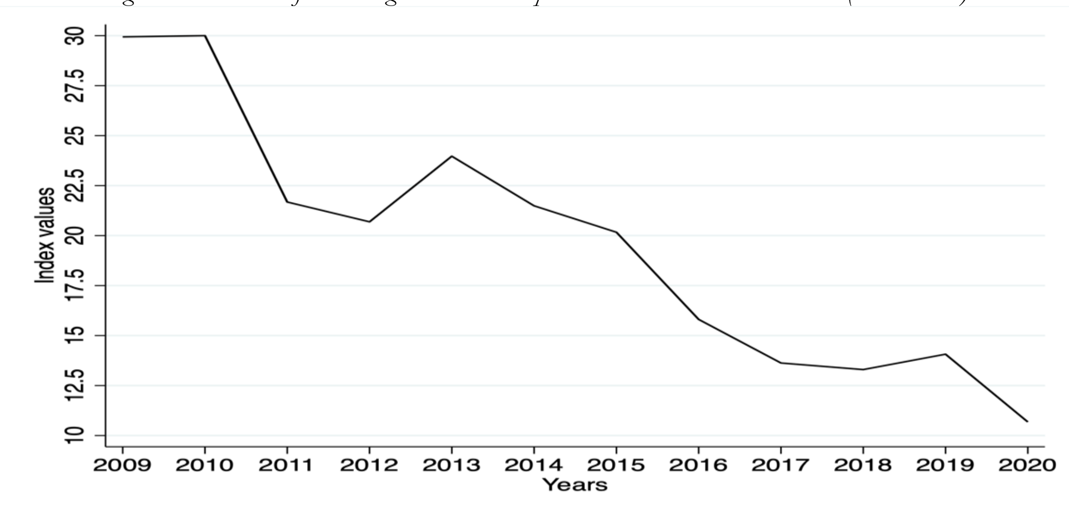
[6] The rate of monetary poverty refers to the percentage of the population of a country living on less than 1.90 USD a day.

[7] See the World Development Indicators database of the World Bank.

since the average innovation output index in this area has been decreasing since 2009[8] (see Figure 1).

The innovation output index measures a country's level of production of innovation. It is published yearly by the World Intellectual Property Organization (WIPO), INSEAD and Cornell University since 2007, and ranges from 0 to 100. The greater the index, the better the level of innovation output. Figure 1 shows the evolution of the average innovation output index in the ECOWAS area over the recent years. The index fell from 29.94 in 2009 to 10.68 in 2020, which represents a decrease of 19.26 in less than 15 years. It can be seen that the index is stagnating at levels lower than what is achievable, i.e., 30, the value of the 2010 index. These figures show that the level of production of innovation in the ECOWAS area is becoming weaker. Therefore, there is an urgent need to study innovation in this area, in order to make policy recommendations to increase the level of innovation.

Figure 1. Evolution of the average innovation output index in the ECOWAS area (2009-2020)



Source: Author's calculation, using data from the WIPO, INSEAD and Cornell University.

In this context, some studies have investigated the determinants of innovation in countries from the ECOWAS area (see for instance, Fu *et al.*, 2018; Kouakou, 2020; Robson *et al.*, 2009). However, the issue of whether the decision-making units in ECOWAS countries are efficient in producing innovation or not has been completely ignored. This gap is important to fill as inefficiency could also explain the observed

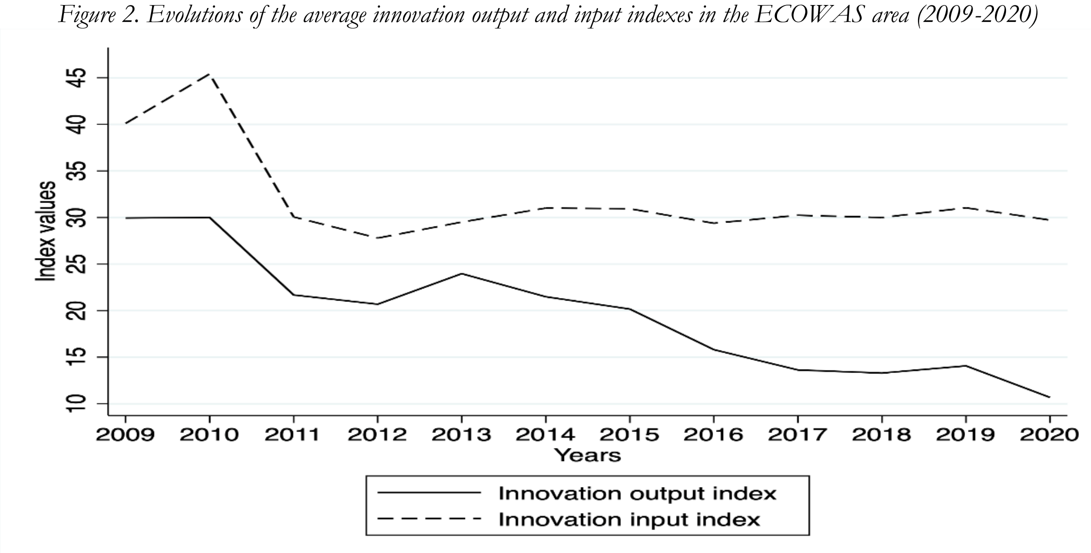
[8] Data on this index are available since 2009 for West Africa.

reduction of the production of innovation in the ECOWAS area in recent years. Stylized facts seem to give intuitions that inefficiency might be an issue in the ECOWAS area (see Figure 2).

Figure 2 shows the evolution of both the average innovation output and input indexes of the ECOWAS area. It can be seen that the input index curve is located above that of the output index. This suggests that the countries could be being producing less innovations than what could be expected in view of their endowments in innovation inputs. It also emerges from Figure 2 that over the 2013-2014 and 2016-2017 periods, the innovation production has fallen while innovation inputs have increased. In other words, over these periods, in ECOWAS countries, the production units have increased the factors allowing innovation production, but this did not lead to more innovations; innovation production has rather decreased.

A plausible explanation for this phenomenon is that the ITE levels of ECOWAS countries have decreased. Therefore, it seems important to measure these ITE levels. Efficiency is really important as it permits to produce more innovations, thereby helping to improve growth, development, and to alleviate poverty through a better redistribution of the fruits of growth. This paper which is a primer on the measurement of ITE in West Africa at the country level contributes to raise the debate of the ITE in Africa, beyond the commonly considered approach that consists in investigating the determinants of innovation.

Figure 2. Evolutions of the average innovation output and input indexes in the ECOWAS area (2009-2020)



Source: Author's calculation, using data from the WIPO, INSEAD and Cornell University.

3. Literature on the measurement of innovation technical efficiency at the macroeconomic level

In the extant literature, studies on ITE have been carried out at both microeconomic (see for instance, Fu, 2012; Wang *et al.*, 2016) and macroeconomic levels (see for instance, Fu and Yang, 2009; Guan *et al.*, 2016; Kao, 2017), as well as at the mesoeconomic level[9] (see for instance, Bai, 2013; Franco *et al.*, 2016; Lee *et al.*, 2019; Li, 2009). We are interested here in studies carried out at the macroeconomic level. Note that the measurement of ITE is usually done using frontier models, whatever the level considered (microeconomic, macroeconomic or mesoeconomic). These models have important microeconomic foundations.

Kao (2017) provides empirical evidence on ITE using a set of 35 countries (developing, emerging and developed) from Europe, Africa, Oceania, America and Asia. Note that for Africa, only South Africa, an emerging country, is considered. Kao (2017) adopts a two-stage innovation production process, as in Lee *et al.* (2019), and estimates a DEA model[10]. Stage 1 is about the production of innovation while stage 2 refers to the commercialization of innovation output. In stage 1, two measures of innovation output are considered, that is, patents and scientific publications. The inputs are gross domestic spending on R&D, full-time equivalent researchers and accumulated knowledge stocks. In stage 2, Kao (2017) considers two measures of the commercialization of innovation output, that is, export in high-tech industries and added value of industries. Non-R&D labor, business enterprise researchers, patents and accumulated knowledge stocks are the inputs.

Results show that only three countries, namely, Switzerland, Poland and Turkey, are efficient in both stages. Greece, Ireland and Romania are efficient in stage 1. In stage 2, the efficient countries are Italy, Mexico, Norway, Argentina and Singapore. The only African country considered, South Africa, appears to be inefficient in both stages, with an ITE score equal to 0.435 in stage 1 and 0.776 in stage 2[11]. Thus, it exhibits more than 50% of inefficiency concerning the production of innovation.

[9] Mesoeconomics typically studies regions, sectors, industries, provinces, and municipalities.

[10] DEA: Data Envelopment Analysis.

[11] Efficiency scores lie in the unit interval. A country is efficient if its score is equal to 1; otherwise, it is inefficient.

A study of ITE in a single-stage innovation framework is carried out by Guan *et al.* (2016). Only the production phase is considered. The analysis is done in a multi-output framework with patents and the number of publications in scientific journals as proxies for the outputs. The inputs are the same as those considered by Kao (2017) in stage 1. By estimating a DEA-Malmquist model, Guan *et al.* (2016) highlight the inefficiency of a set of 32 developing, developed and emerging countries. Results also show that scientific collaboration network structure correlates with efficiency.

Fu and Yang (2009) analyze ITE in 21 countries from the Organisation for Economic Co-operation and Development (OECD). As in Furman *et al.* (2002), issued patents are used as proxy for innovation output. The inputs are gross domestic spending on R&D, R&D personnel, education spending (proxy for human capital) and shares of value added from high-tech industries. By estimating a stochastic frontier model, the authors shed light on the inefficiency of all the countries considered. Fu and Yang (2009) highlight GDP per capita, the share of R&D expenditure financed by private sector, R&D performed by higher education institutions, the degree of protection of intellectual property rights, the degree of availability of venture capital, and exports, as determinants of ITE.

Guan and Chen (2012) consider a sample of 22 OECD countries, with largely countries considered by Fu and Yang (2009), and a different study period. They also consider a two-stage innovation process as in Kao (2017) and Lee *et al.* (2019). The inputs and outputs used are similar to those considered by Kao (2017). Guan and Chen (2012) do not find, in both stages, all the countries to be inefficient, after estimating a DEA model. They investigate the determinants of ITE and confirm most of the determinants highlighted by Fu and Yang (2009). In addition to these ones, Guan and Chen (2012) find legal environment, university-industry and inter-company technological collaborations, as determinants of ITE.

Note that Fu and Yang (2009) do not consider any developing country member of OECD[12]. As a result, their analysis only provides a partial glance at ITE in the OECD area. Kontolaimou *et al.* (2016) extend their analysis by taking into account seven more countries, including a developing country, namely, Turkey. By estimating a Bootstrap-

[12] Non-European OECD member countries were not considered.

DEA model[13], Kontolaimou *et al.* (2016) show that the countries are all inefficient. Turkey's ITE is equal to 0.847, which means a relatively low level of inefficiency. In their frontier model, two outputs are considered, that is, a composite index of intellectual assets (patents, designs, and trademarks), and medium-tech and high-tech exports. The inputs are human capital, R&D spending and entrepreneurial capital related to new technologies.

Wang and Huang (2007) consider a panel of 30 countries (developed, emerging and developing) not all from OECD, with most of the countries considered by Kontolaimou *et al.* (2016). They study R&D efficiency through a DEA model and find that less than one-half of these countries are efficient. Patents and academic publications are used as measures of R&D output. The inputs considered are R&D capital stocks, full-time equivalent researchers, and full-time equivalent technicians and supporting personnel. Wang and Huang (2007) find English proficiency and the gross enrollment rate of tertiary education to influence significantly and positively countries' efficiency.

Note that, unlike macroeconomic studies, firm-level studies of ITE generally focus on firms of specific sizes and specific sectors. For instance, Fu (2012) studies ITE in Great Britain and uses a sample of small and medium-sized enterprises (SMEs) from the manufacturing and business services sectors. Wang *et al.* (2016) analyze ITE in China and use data from new energy enterprises. The focus on firms of specific sizes and specific sectors makes it difficult to generalize the results of these studies to the whole economy. This problem is solved when we consider macroeconomic investigations. Indeed, macroeconomic studies of ITE make it possible to have results which reflect the situation of the whole economy since country-level indicators are used both to estimate the innovation production frontier and for the determinants of ITE. From this point of view, macroeconomic analyses of ITE can be thought to be more relevant as compared to the microeconomic analyses.

The literature review shows, firstly, an impressive lack of studies on African countries, and secondly, the distinction between short-run and long-run efficiencies as a perspective to add knowledge to the extant literature. The present paper contributes to filling these gaps.

[13] See Simar and Wilson (1998).

4. Econometric modeling

4.1. The theoretical model

4.1.1. The econometric framework

In the econometric literature, a stochastic frontier model has been proposed recently almost simultaneously by Kumbhakar *et al.* (2014), Tsionas and Kumbhakar (2014), and Colombi *et al.* (2014), to measure short-run and long-run efficiencies. In this model, the error term is split into four distinct components. The first component captures the individuals' latent heterogeneity as in Greene (2005a, 2005b), and is different from the components related to inefficiency. The second component captures random shocks, and depends on both individuals and time; this is the usual error term. The last two components are short-run inefficiency and long-run inefficiency as in Kumbhakar and Heshmati (1995)[14]. This model is usually referred to as the four-component stochastic frontier model (henceforth, 4CSF model). The 4CSF model is parametric. It can be thought that the production process is better interpreted economically when a parametric approach is adopted (Simar, 1992). For instance, we can calculate elasticities.

The 4CSF model is very innovative and fills important gaps in the panel stochastic frontier literature. Firstly, it is the first model taking into account the four components aforementioned, all at the same time, in the econometric modeling of the frontier. This allows to consider different factors impacting production, given the inputs (Kumbhakar *et al.*, 2015). Secondly, both long-run inefficiency and individuals' latent heterogeneity are modeled as two distinct components of the error term. Thus, the 4CSF model extends previous models proposed by Kumbhakar and Hjalmarsson (1993), Greene (2005a, 2005b), Kumbhakar and Wang (2005), Wang and Ho (2010) and Chen *et al.* (2014). Indeed, in these models, the error term is split into three components: individuals' latent heterogeneity, the usual random disturbance and an error term capturing inefficiency (individual-specific and time-varying). Individuals' latent heterogeneity was thereby unfortunately confounded with long-run inefficiency.

[14] In the literature, short-run inefficiency and long-run inefficiency are also referred to as transient and persistent inefficiencies, respectively.

In this paper, we use the 4CSF model in the econometric analysis. The model is specified as follows[15]:

$$Y_{it} = \alpha_0 + f(X_{it};\beta) + \mu_i + \nu_{it} - \eta_i - u_{it} \tag{1}$$

where Y_{it} is the output of individual i at year t ($i = 1, \dots, N$ and $t = 1, \dots, T_i$), X_{it} is the vector of inputs, $f(.)$ is the production function, μ_i is latent heterogeneity, ν_{it} is the usual error term capturing random shocks, η_i is long-run inefficiency ($\eta_i \geq 0$), and u_{it} is short-run inefficiency ($u_{it} \geq 0$). β is the vector of parameters to estimate, and α_0 is a constant.

Recently, Lai and Kumbhakar (2018) extended the 4CSF model to allow the analysis of the determinants of efficiency. This is done by modeling the variances of both long-run and short-run inefficiencies as functions of the determinants. Lai and Kumbhakar (2018) propose an estimation procedure that allows to correct for endogeneity. To be precise, they propose a two-step procedure to estimate the model. In step 1, the individual-effects and long-run inefficiency components are eliminated using the difference or within transformation. This allows to focus on estimating the parameters of the time varying components. The transformed model is estimated by the standard maximum likelihood method as its joint probability function is found to follow a closed skew normal distribution. In step 2, the remaining parameters are estimated using the system nonlinear least squares approach. This approach requires no external instruments. In this paper, we use Lai and Kumbhakar's (2018) version of the 4CSF model and adopt their estimation procedure.

4.1.2. Estimation procedure

To describe the estimation procedure in more detail, let us start with the distributions (half normal) of short-run and long-run inefficiencies[16]. We have:

$$\eta_i \sim N^+\left(0, \sigma_\eta^2(z_i)\right) \text{ and } u_{it} \sim N^+\left(0, \sigma_u^2(w_{it})\right) \tag{2}$$

[15] See Kumbhakar *et al.* (2014).

[16] One can refer to Lai and Kumbhakar (2018) for a more detailed presentation of the estimation procedure.

where z_i and w_{it} are vectors of determinants of long-run and short-run inefficiencies, respectively. In this paper, z_i is the time average of w_{it} for each country. $\sigma_\eta^2(z_i)$ and $\sigma_u^2(w_{it})$ are specified as $\sigma_\eta^2(z_i) = exp(\delta' z_i)$ and $\sigma_u^2(w_{it}) = exp(\gamma' w_{it})$.

For the sake of simplicity, in the following, y and x are natural logarithms of Y and X, respectively. In vector form, the model can be described as follows:

$$y_{i.} = \alpha_0 \ell_T + x_{i.}\beta + (\mu_i - \eta_i)\ell_T + \nu_{i.} - u_{i.} \quad (3)$$

with,

$$\nu_{i.} \sim N(O_T, \sigma_v^2 I_T) \text{ and } u_{i.} \sim N^+(O_T, \Lambda_i) \quad (4)$$

where $y_{i.}$ is a $T \times 1$ vector, and ℓ_T is a $T_i \times 1$ vector of ones. We define $x_{i.}$, $\nu_{i.}$and $u_{i.}$ in a similar way. O_T is a $T \times 1$ vector of zeros, $\Lambda_i = diag\left(\sigma_{u_{i1}}^2, \ldots, \sigma_{u_{iT}}^2\right)$, and I_T denotes a $T \times T$ identity matrix. One can see that the transient components are independent across time as the variances of $\nu_{i.}$ and $u_{i.}$ are diagonal matrices.

As Lai and Kumbhakar (2018) point out, endogeneity in model (1) may arise from a correlation of at least one of the regressors with the individual-effects (μ_i) and/or persistent inefficiency (η_i) components of the error term. In such a case, the maximum likelihood (ML) estimator will be biased. To remove the possible endogeneity issue, μ_i and η_i are eliminated using either the difference or the within transformation.

The difference transformation $(T-1) \times T$ matrix P_D is defined as follows:

$$P_D = \begin{pmatrix} -1 & 1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & 0 & \cdots & 0 & 0 \\ \vdots & & & & \ddots & & \vdots \\ \vdots & & & & & \ddots & \vdots \\ 0 & \cdots & \cdots & \cdots & 0 & -1 & 1 \end{pmatrix} \quad (5)$$

As to the within approach, the $(T-1) \times T$ within transformation matrix P_W is defined as follows:

$$P_W = R \cdot Q \tag{6}$$

with $R = (O_{T-1}, I_{T-1})$ and $Q = I_T - \frac{1}{T}\ell_T\ell'_T$. As suggested by Chen *et al.* (2014), one period observation is dropped. The transformed model is as follows:

$$\tilde{y}_{i.} = \tilde{x}_{i.}\beta + \tilde{v}_{i.} - \tilde{u}_{i.} \tag{7}$$

where $\tilde{x}_{i.} = Px_{i.}$ is a $(T-1) \times k$ matrix. $\tilde{y}_{i.} = Py_{i.}$, $\tilde{v}_{i.} = Pv_{i.}$, and $\tilde{u}_{i.} = Pu_{i.}$ are $(T-1) \times 1$ vectors. P is either P_D or P_W depending on the transformation considered. The vector of the errors is $\tilde{\varepsilon}_{i.} = \tilde{v}_{i.} - \tilde{u}_{i.} = P(v_{i.} - u_{i.}) = P\varepsilon_{i.}$ Lai and Kumbhakar (2018) show that $\tilde{\varepsilon}_{i.}$ has a closed skew normal distribution.

After obtaining the transformed model, the parameters of the time varying components can be estimated by ML in the first step of the estimation procedure. To be precise, one can estimate $\varpi_1 = (\beta, \sigma_v^2, \gamma')'$. We have:

$$\hat{\varpi}_1 = \arg \max_{\varpi_1 \in \Omega_1} \ln L_1(\varpi_1) \tag{8}$$

where $\ln L_1(\varpi_1)$ is the log-likelihood function and is defined as follows:

$$\ln L_1(\varpi_1) = \sum_{i=1}^{N} \ln f(\tilde{\varepsilon}_{i.}; \varpi_1) \tag{9}$$

Ω_1 is the parameter space of ϖ_1[17]. Lai and Kumbhakar (2018) show that the likelihood functions obtained from the difference transformation and the within transformation are equivalent, and therefore that the ML estimates are the same. In our analysis, we elected to use the within transformation.

In step 2, the remaining parameters are estimated using the system nonlinear least squares approach (NLS). Let $\varpi_2 = \left(\alpha_0, \sigma_\mu^2, \delta'\right)'$ denote the vector of the remaining parameters. The model with the residual as the dependent variable is as follows, where β is known:

[17] See Theorem 1 in Lai and Kumbhakar (2018) for a detailed description of $f(\tilde{\varepsilon}_{i.}; \varpi_1)$.

$$r_{it} = y_{it} - x'_{it}\beta = \alpha_0 + \mu_i + v_{it} - \eta_i - u_{it} \tag{10}$$

The expectations of r_{it}, r_{it}^2 and $r_{it}r_{is}$ ($t \neq s$) can be described as follows under the same distribution assumptions as previously[18]:

$$\mathrm{E}r_{\mathrm{it}} = \alpha_0 - \sqrt{\frac{2}{\pi}}\left(\sigma_{\eta_i} + \sigma_{u_{it}}\right) \tag{11}$$

$$\mathrm{E}r_{it}^2 = \sigma_\mu^2 + \sigma_{\eta_i}^2 + \sigma_v^2 + \sigma_{u_{it}}^2 + \left(\alpha_0 - \sqrt{\frac{2}{\pi}}\left(\sigma_{\eta_i} + \sigma_{u_{it}}\right)\right)^2 \tag{12}$$

$$\mathrm{E}r_{it}r_{is} = \sigma_\mu^2 + \sigma_{\eta_i}^2 + \left(\alpha_0 - \sqrt{\frac{2}{\pi}}\left(\sigma_{\eta_i} + \sigma_{u_{it}}\right)\right)\left(\alpha_0 - \sqrt{\frac{2}{\pi}}\left(\sigma_{\eta_i} + \sigma_{u_{is}}\right)\right) \tag{13}$$

As equations (11), (12) and (13) form a nonlinear system, the feasible generalized nonlinear least squares method is used to estimate ϖ_2. We have:

$$\widehat{\varpi}_2 = \arg \min_{\varpi_2 \in \Omega_2} \sum_{i=1}^{N} \sum_{t=2}^{T_i} \zeta_{it}(\varpi_2; \widehat{\varpi}_1)' \Omega^{-1} \zeta_{it}(\varpi_2; \widehat{\varpi}_1) \tag{14}$$

where $\zeta_{it}(\varpi_2; \varpi_1) = (r_{it} - \mathrm{E}r_{it}, r_{it}^2 - \mathrm{E}r_{it}^2, r_{it}r_{is} - \mathrm{E}r_{it}r_{is})'$. $\zeta_{it}(\varpi_2; \varpi_1)$ denotes the vector of residuals. Ω is the variance matrix. Ω_2 is the parameter space of ϖ_2. We get the simple system NLS estimator if Ω is equal to the identity matrix. Note that the jackknife estimate of the standard error may be used to account for the presence of $\widehat{\varpi}_1$[19].

Short-run technical efficiency and long-run technical efficiency are defined as $exp(-u_{it})$ and $exp(-\eta_i)$, respectively. In practice, they are predicted from conditional expectations of $exp(-u_{ij})$ and $exp(-\eta_i)$, respectively, where u_{ij} denotes the jth

[18] See Lai and Kumbhakar (2018) for more details.

[19] See Lai and Kumbhakar (2018) for more details.

component of the vector $u_{i.}$, after estimating all the parameters by ML[20]. Overall technical efficiency (OE) is equal to the product of short-run and long-run technical efficiencies.

4.2. Empirical specification

In the literature, measures of R&D and human capital are considered as the core variables that should be included in the specification of the innovation frontier (see for instance, Cruz-Cázares *et al.*, 2013; Franco *et al.*, 2016; Fu and Yang, 2009; Guan and Chen, 2012; Guan *et al.*, 2016; Kao, 2017; Kontolaimou *et al.*, 2016). In this context, R&D is like a capital variable and human capital is like a labor variable. The baseline specification is therefore generally a 2-input model. Then, we can include some additional control variables to control for some factors that may induce heterogeneity, and according to what factors we are primarily interested in (Kontolaimou *et al.*, 2016). In this vein, we consider market sophistication in the empirical specification. Market sophistication measures the availability of credit and an environment conducive to investment, access to international markets, domestic market scale and the intensity of local competition. This is a composite and heterogeneous set of essential factors that shape the innovation capacity of production units and countries.

We use a translog production function as specification for $f(.)$ because of its flexibility (Christensen *et al.*, 1973; Kumbhakar and Hjalmarsson, 1995; Kumbhakar *et al.*, 2014). Among other reasons, it is flexible as it gives a second-order differential approximation of any unknown function $f(.)$ (Kumbhakar and Hjalmarsson, 1995). The empirical specification of (1) is as follows:

$$\ln Y_{it} = \alpha_0 + \sum_j \beta_j \ln X_{jit} + \frac{1}{2}\sum_j \sum_k \beta_{jk} \ln X_{jit} \ln X_{kit} + \mu_i + \nu_{it} - \eta_i - u_{it} \quad (15)$$

where Y: innovation output; $X = (X_1, X_2, X_3) = (RD, HC, MS)$: the vector of innovation inputs. RD: research and development (R&D); HC: human capital; and MS: market sophistication. Following Kumbhakar and Hjalmarsson (1995) and Kumbhakar *et al.* (2014), the input variables are normalized by their means respectively before taking

[20] See Lai and Kumbhakar (2018) for more developments on the formulas.

natural logarithm (ln). Hence, in the model, the first-order coefficients (β_j) can be interpreted as elasticities at the means of the data (Kumbhakar and Hjalmarsson, 1995; Kumbhakar *et al.*, 2014).

Note that, as in Lai and Kumbhakar (2018), we include a time trend in the estimation of the frontier model. This allows us to capture technical change that shifted the production function over time (Lai and Kumbhakar, 2018).

5. Data, variables and descriptive statistics

The study of innovation in Africa at the country level is really challenging, the main challenge being related to data availability. Indeed, an important impediment to the study of innovation in Africa at the country level is the lack of data on specific measures of the inputs and output(s). When data are available, in general, there are important missing values or no data over a long period.

In this paper, the data are taken from the 'Global Innovation Index' report, published yearly by the WIPO, INSEAD and Cornell University, since 2007. This annual report provides composite indexes that measure at the country level, and in more than 100 countries, the innovation inputs, the innovation outputs, and the overall innovation level that accounts for both the inputs and outputs. These indexes are 'composite' in the sense that they consist of different sub-measures of a single factor. Therefore, they allow for a quite complete and wide measure of the innovation output and inputs. This characteristic of the data is an important advantage as it could be expected to allow for more realistic results. Such data are of particular importance in the studies of African countries where data for estimating an innovation frontier are really rare due to the issues mentioned previously.

The innovation output index captures the innovation production. It is calculated by considering two important innovation output pillars, which are composite sub-indexes: (1) Knowledge and technology outputs: this index considers knowledge creation (for example, patents and scientific and technical articles), knowledge impact (for example, computer software spending) and knowledge diffusion (for example, intellectual property receipts); (2) Creative outputs: the creative outputs index is computed by considering intangible assets (for example, industrial designs by origin), creative goods and services (for example, creative goods exports), and online creativity (for example, mobile app creation).

At the level of the inputs, the R&D index measures the level and quality of R&D, and is calculated by considering the share of R&D expenditures in the GDP, the number of full-time equivalent researchers, R&D expenditures of the top 3 companies in the country belonging to the 2,500 best R&D investors in the world, and the quality of scientific and research institutions. The human capital index makes it possible to take into account the role of workforce qualification in the innovation production, and is captured through a set of important factors such as tertiary enrollment rate, education expenditures, and school life expectancy. The market sophistication index is a composite indicator encompassing the availability of credit and an environment conducive to investment, access to international markets, domestic market scale and the intensity of local competition. Measures of these factors are used to compute the index.

In this paper, these indexes are used to measure the variables contained in the specification of the innovation frontier. They range from 0 to 100. An increase in a given index reflects a nation-wide improvement in the pillar or factor it measures. In a previous paper, Kontolaimou *et al.* (2016) also used composite indexes in the specification of the innovation production frontier, in particular to measure innovation output and human capital.

The present study exploits data from ECOWAS countries. Data on these countries are available since 2009, the annual report being published since 2007. Thus, the study period is 2009-2020[21]. Recall that the ECOWAS area includes 15 countries (see section 2). However, data are not available (as is often the case) for three countries: Guinea-Bissau, Liberia and Sierra Leone. Ultimately, the database used is composed of an unbalanced panel data of 12 countries for the period 2009-2020. Having recent panel data is an advantage in that it allows to have results that take into account the recent situation of ECOWAS countries.

At the level of the potential determinants of innovation efficiency, we include a number of variables based on the literature, data availability and their relevance in the context of West African countries. These are total population, exports of goods and services as a percentage of GDP, domestic credit to private sector as a percentage of

[21] Unit root tests are irrelevant due to the length of the time period.

GDP, and economic, political and institutional governance. These variables are expected to have positive effects on innovation efficiency.

Total population allows to account for the size effect in the explanation of innovation (Chen and Puttitanun, 2005). Exports are a proxy for a country's degree of openness (Fu and Yang, 2009). The degree of openness is a factor that has proved to be important in explaining innovation, and more specifically innovation efficiency at the macroeconomic level (Fu and Yang, 2009; Guan and Chen, 2012). In fact, countries that export goods and services very often face competitors on international markets, and this is likely to generate significant incentives to innovate. Financial resources provided by financial institutions (monetary authorities, banks, etc.) have also been found to matter in explaining innovation efficiency (Bai, 2013). In fact, the private sector's financial capacity influences its level of financing of innovation activities, and both overinvestment and underinvestment in such activities may impact innovation performance.

Governance, and institutional factors more generally, are usually strongly linked to innovation (Nelson, 2008). In fact, investments in innovation activities are long-term ones. Political instability, high level of corruption or poor-quality regulation can discourage firms from engaging in such investments, thus reducing their propensity to innovate and the country's level of innovation. The issue of the effect of governance on innovation is even more important in developing countries, particularly in African countries, which generally exhibit weak governance performances and poor levels of innovation.

Recently, Franco *et al.* (2016) and Guan and Chen (2012) found evidence of an impact of governance on innovation efficiency by focusing on product market regulation and legal environment, respectively. In this paper, we extend their studies by considering a wide range of governance indicators. To be precise, we consider the Worldwide Governance Indicators, namely, Voice and accountability, Political stability and absence of violence/terrorism, Government effectiveness, Regulatory quality, Rule of law, and Control of corruption. These range from -2.5 (weak governance performance) to 2.5 (strong governance performance). Increases in each indicator mean an improvement in the dimension of governance which is considered. For instance, increases in the 'Voice and accountability' indicator of a given country highlight better levels of voice and accountability in this country, that is, better participation of citizens in selecting their government, better freedom of expression and association, and free media[22].

Besides, note that the various potential determinants of innovation efficiency described above need to be rescaled before being used. Indeed, they have different measurement units, and this induces huge differences in their variability. For instance, there is an extreme difference in the variabilities of total population and exports on the one hand, and domestic credit to private sector and governance on the other hand. To overcome this issue, we rescale the different variables by using the min-max scaling method. This method has the advantage to rescale them to the space [0;1] (unit interval). This is interesting as innovation efficiencies also lie in this interval. To obtain the rescaled version of a given variable m, we apply the following transformation:

$$\frac{m_{it}-min(m)}{max(m)-min(m)} \tag{16}$$

where $min(m)$ and $max(m)$ refer respectively to the minimum and maximum realizations of m for all years and all countries in the database. These are the worst and best performances ever, respectively. Hence, the min-max scaling allows to have the performance of a given country at a given year in terms of m, relatively to the worst and best practices. Therefore, in addition to rescaling the variables to the unit interval, the min-max scaling method normalizes the variables to make them more comparable between countries.

Table 1 summarizes the variables used in this research. Descriptive statistics are presented in Tables 2, 3 and 4.

[22] See Kaufmann *et al.* (2010) for more details on the governance indicators.

Table 1. Definition and source of the variables

Variable	Definition	Source
Output		
Y	Innovation output, measured by the innovation output index.	Annual Report entitled 'Global Innovation Index' (AR-GII) published by the WIPO, Cornell University and INSEAD: 2009-2020.
Inputs		
RD	R&D, measured by the R&D index.	AR-GII (2009-2020).
HC	Human capital, measured by the human capital index.	AR-GII (2009-2020).
MS	Market sophistication, measured by the market sophistication index.	AR-GII (2009-2020).
Time trend		
t	Time trend. Year (1=2009; …; 12=2020).	Lai and Kumbhakar (2018).
Determinants of efficiency		
POP	Total population (rescaled and normalized).	World Development Indicators database of the World Bank (WDI) (2009-2020) and min-max scaling.
EXP	Exports of goods and services (rescaled and normalized).	WDI (2009-2020) and min-max scaling.
CRED	Domestic credit to private sector (rescaled and normalized).	WDI (2009-2020) and min-max scaling.
VA	Voice and accountability (rescaled and normalized).	Worldwide Governance Indicators (WGI) (2009-2020) and min-max scaling.
PS	Political stability and absence of violence/terrorism (rescaled and normalized).	WGI (2009-2020) and min-max scaling.
GE	Government effectiveness (rescaled and normalized).	WGI (2009-2020) and min-max scaling.
RQ	Regulatory quality (rescaled and normalized).	WGI (2009-2020) and min-max scaling.
RL	Rule of law (rescaled and normalized).	WGI (2009-2020) and min-max scaling.
CC	Control of corruption (rescaled and normalized).	WGI (2009-2020) and min-max scaling.

Source: The author.

Table 2. Descriptive statistics on the output and inputs variables

	Y				***RD***				***HC***				***MS***			
	M	**SD**	**Min**	**Max**	**M**	**SD**	**Min**	**Max**	**M**	**SD**	**Min**	**Max**	**M**	**SD**	**Min**	**Max**
Benin	2.76	0.47	1.87	3.36	0.62	1.21	0	3.05	3.43	0.25	3.03	3.85	3.36	0.32	2.49	3.71
Burkina Faso	2.77	0.48	2.12	3.36	1.10	0.92	0	2.87	3.28	0.25	3.04	3.83	3.49	0.19	3.09	3.76
Cabo Verde	3.02	0.22	2.68	3.29	0.33	0.34	0	0.79	3.45	0.24	3.26	3.84	3.54	0.31	3.13	3.86
Côte d'Ivoire	3.02	0.35	2.41	3.58	0.67	1.11	0	2.97	3.15	0.28	2.90	3.96	3.47	0.21	3.06	3.75
Gambia	3.20	0.15	2.93	3.37	0.72	1.03	0	2.71	3.29	0.38	2.90	3.78	3.52	0.31	2.98	3.86
Ghana	3.08	0.24	2.66	3.36	1.54	1.05	0	3.75	3.50	0.18	3.21	3.84	3.63	0.11	3.46	3.85
Guinea	2.58	0.33	2.25	3.28	0	0	0	0	2.48	0.21	2.22	2.89	3.38	0.12	3.21	3.57
Mali	3.08	0.31	2.40	3.44	1.39	0.96	0	3.10	3.06	0.35	2.72	3.77	3.45	0.20	2.97	3.72
Niger	2.43	0.28	2.04	2.99	0	0	0	0	3.10	0.32	2.66	3.48	3.38	0.26	2.94	3.77
Nigeria	3.06	0.37	2.35	3.62	0.92	0.97	0	2.83	3.03	0.42	2.48	3.94	3.71	0.14	3.44	3.92
Senegal	3.17	0.22	2.74	3.46	1.70	0.94	0	3.13	3.35	0.36	2.93	3.99	3.53	0.23	2.98	3.83
Togo	2.24	0.33	1.94	2.80	0.86	0.22	0.41	1.13	3.09	0.08	2.97	3.23	3.55	0.19	3.31	3.82

Notes: The values are in natural logarithm. Y: Innovation output. RD: $R\&D$. HC: Human capital. MS: Market sophistication. M: Mean. SD: Standard deviation. Min: Minimum. Max: Maximum.

Source: Author's calculation.

Table 3. Descriptive statistics on the determinants of efficiency (1/2)

	POP				*EXP*				*CRED*				*VA*				*PS*			
	M	SD	Min	Max	M	SD	Min	Max	M	SD	Min	Max	M	SD	Min	Max	M	SD	Min	Max
Benin	0.05	0.01	0.04	0.06	0.37	0.09	0.25	0.51	0.14	0.01	0.12	0.16	0.69	0.06	0.57	0.77	0.74	0.10	0.57	0.85
Burkina Faso	0.08	0.01	0.07	0.10	0.37	0.09	0.11	0.43	0.23	0.08	0.12	0.32	0.53	0.05	0.46	0.63	0.47	0.14	0.21	0.73
Cabo Verde	0.00	0.00	0	0.00	0.62	0.18	0.36	0.81	0.86	0.09	0.77	1	0.99	0.01	0.97	1	0.95	0.07	0.83	1
Côte d'Ivoire	0.11	0.01	0.10	0.13	0.43	0.11	0.29	0.60	0.14	0.05	0.09	0.21	0.37	0.13	0.16	0.50	0.36	0.07	0.20	0.45
Gambia	0.01	0.00	0.01	0.01	0.22	0.06	0.13	0.29	0.03	0.01	0.02	0.04	0.10	0.07	0	0.19	0.72	0.03	0.67	0.76
Ghana	0.13	0.01	0.12	0.15	0.54	0.10	0.37	0.71	0.10	0.03	0.06	0.13	0.82	0.02	0.78	0.85	0.73	0.03	0.67	0.77
Guinea	0.06	0.00	0.05	0.06	0.57	0.24	0.29	1	0.04	0.02	0	0.07	0.26	0.04	0.18	0.30	0.47	0.09	0.32	0.59
Mali	0.08	0.01	0.07	0.10	0.35	0.05	0.29	0.46	0.23	0.05	0.14	0.29	0.51	0.11	0.30	0.67	0.23	0.24	0.00	0.69
Niger	0.10	0.01	0.08	0.12	0.11	0.05	0.03	0.18	0.05	0.01	0.04	0.07	0.45	0.06	0.35	0.52	0.31	0.08	0.15	0.43
Nigeria	0.87	0.08	0.75	1	0.21	0.18	0	0.51	0.08	0.04	0.04	0.19	0.37	0.08	0.25	0.47	0.07	0.04	0	0.11
Senegal	0.07	0.01	0.06	0.08	0.29	0.03	0.24	0.35	0.29	0.05	0.18	0.34	0.65	0.10	0.49	0.76	0.67	0.04	0.58	0.73
Togo	0.03	0.00	0.03	0.04	0.52	0.22	0.29	0.85	0.37	0.08	0.29	0.50	0.29	0.06	0.19	0.38	0.54	0.11	0.42	0.66

Notes: POP: Total population (rescaled and normalized). EXP: Exports of goods and services (rescaled and normalized). CRED: Domestic credit to private sector (rescaled and normalized). VA: Voice and accountability (rescaled and normalized). PS: Political stability and absence of violence/terrorism (rescaled and normalized). M: Mean. SD: Standard deviation. Min: Minimum. Max: Maximum.

Source: Author's calculation.

Table 4. Descriptive statistics on the determinants of efficiency (2/2)

	GE				*RQ*				*RL*				*CC*			
	M	**SD**	**Min**	**Max**	**M**	**SD**	**Min**	**Max**	**M**	**SD**	**Min**	**Max**	**M**	**SD**	**Min**	**Max**
Benin	0.51	0.07	0.43	0.67	0.55	0.07	0.40	0.61	0.37	0.03	0.32	0.44	0.33	0.10	0.19	0.56
Burkina Faso	0.45	0.04	0.36	0.48	0.65	0.11	0.52	0.80	0.48	0.06	0.41	0.59	0.44	0.07	0.34	0.53
Cabo Verde	0.92	0.05	0.88	1	0.79	0.10	0.67	0.93	0.96	0.03	0.93	1	0.97	0.03	0.94	1
Côte d'Ivoire	0.32	0.18	0.02	0.53	0.44	0.22	0.11	0.72	0.29	0.14	0.05	0.40	0.28	0.11	0.05	0.38
Gambia	0.40	0.08	0.26	0.51	0.57	0.08	0.46	0.70	0.38	0.04	0.33	0.43	0.28	0.03	0.23	0.32
Ghana	0.75	0.05	0.66	0.82	0.89	0.10	0.70	1	0.71	0.03	0.66	0.76	0.52	0.03	0.49	0.58
Guinea	0.18	0.10	0.05	0.34	0.15	0.09	0	0.24	0.06	0.04	0	0.11	0.13	0.03	0.10	0.16
Mali	0.22	0.07	0.10	0.33	0.45	0.07	0.38	0.56	0.34	0.08	0.22	0.50	0.25	0.03	0.20	0.29
Niger	0.40	0.04	0.33	0.45	0.34	0.06	0.26	0.44	0.39	0.04	0.34	0.49	0.29	0.02	0.26	0.32
Nigeria	0.16	0.05	0.06	0.23	0.21	0.08	0.08	0.33	0.18	0.07	0.10	0.28	0.07	0.04	0	0.11
Senegal	0.61	0.12	0.47	0.85	0.75	0.06	0.64	0.85	0.56	0.06	0.46	0.64	0.50	0.11	0.29	0.60
Togo	0.14	0.13	0	0.40	0.24	0.09	0.11	0.39	0.31	0.07	0.20	0.39	0.21	0.06	0.11	0.27

Notes: GE: Government effectiveness (rescaled and normalized). RQ: Regulatory quality (rescaled and normalized). RL: Rule of law (rescaled and normalized). CC: Control of corruption (rescaled and normalized). M: Mean. SD: Standard deviation. Min: Minimum. Max: Maximum.

Source: Author's calculation.

Table 2 shows that, over the study period, the most significant averages of innovation output are achieved respectively by Gambia, Senegal, Ghana, Mali and Nigeria. These countries can be considered as the top five innovative countries in the ECOWAS area over the study period. The five least innovative countries are Togo, Niger, Guinea, Benin and Burkina Faso, respectively. The maximum level of innovation output is achieved by Nigeria, West Africa's leading economic power. The minimum level is achieved by Togo.

Looking at the level of the inputs, it emerges from Table 2 that the poorest levels of R&D are exhibited by Guinea and Niger. Overall, all the West African countries exhibit drastically low levels of R&D. This appeals for questions about the effect of this level on the achievement of the maximum innovation output in West Africa, in view of the generally acknowledged positive role of R&D in the innovation production process. The countries' performances in terms of human capital and market sophistication are much better than those related to R&D. This is interesting as these factors are also expected to be important for innovation. In fact, they are expected to greatly complement R&D in the innovation production process. On average, over the study period, Ghana exhibits the best level of human capital. The poorest level is achieved by Guinea. Nigeria exhibits the strongest average level of market sophistication, followed respectively by Ghana and Togo. The lowest levels are from Benin, Niger and Guinea.

As to the determinants of efficiency, Table 3 shows that, on average, Nigeria is the most populated country, while Cabo Verde is the least populated one. In terms of openness, Cabo Verde exhibits the highest average level of exports. The maximum level of exports is achieved by Guinea. As to domestic credit to private sector, the country, however, exhibits the minimum level and is among the least-performing countries. The highest average level of domestic credit to private sector and the maximum level are achieved by Cabo Verde.

At the level of governance, Cabo Verde exhibits the best average performance and the maximum performance for almost all the variables. One can expect that such a good performance will result in greater innovation efficiencies for the country. The minimum levels of control of corruption and political stability and absence of violence/terrorism are observed in Nigeria.

As to rule of law and regulatory quality, Guinea exhibits the minimum levels. Table 4 shows that Ghana has achieved the best performance in terms of regulatory quality, when we consider both the average level of regulatory quality and the maximum level over the study period. In terms of government effectiveness, Togo seems to lag behind the other West African countries. The level of voice and accountability in Gambia appears to be the weaker one in the sample.

6. Results and discussion

Table 5 shows the results of the estimation of the innovation production frontier model. It emerges that market sophistication significantly and positively affects the level of innovation output in the ECOWAS area. At the means of the data, 1% increase in the market sophistication index results in 0.29% increase in the innovation output index. Therefore, an improvement in market sophistication in ECOWAS countries should increase the level of production of innovation in these ones. Indeed, market sophistication leads to establish favorable conditions for implementing innovation activities and for achieving significant levels of innovative outcome. This helps in achieving optimal levels of innovation output given the inputs.

Table 5. Estimation of the innovation production frontier model

	Variable	Parameter	Estimate	p-value
Frontier	(Constant)	α_0	3.716***	0.000
	ln*RD*	β_1	0.024	0.235
	ln*HC*	β_2	0.035	0.614
	ln*MS*	β_3	0.291***	0.000
	$\ln^2 RD$	β_{11}	-0.104***	0.001
	ln*RD*ln*HC*	β_{12}	0.024	0.812
	ln*RD*ln*MS*	β_{13}	-0.006	0.970
	$\ln^2 HC$	β_{22}	-0.444*	0.076
	ln*HC*ln*MS*	β_{23}	0.163	0.715
	$\ln^2 MS$	β_{33}	0.378	0.273
	t	β_4	-0.075***	0.000
$\boldsymbol{\sigma_u^2(w_{it}) = exp(\gamma' w_{it})}$	(Constant)	γ_0	-1.888	0.245
	POP	γ_1	-1.217	0.332
	EXP	γ_2	-0.691	0.640
	CRED	γ_3	-0.095	0.967
	VA	γ_4	-3.386*	0.097
	PS	γ_5	0.894	0.550
	GE	γ_6	0.262	0.933
	RQ	γ_7	-5.203***	0.009
	RL	γ_8	-1.735	0.567
	CC	γ_9	7.171**	0.044
$\boldsymbol{\sigma_\eta^2(z_i) = exp(\delta' z_i)}$	(Constant)	δ_0	-0.873***	0.000
	POP	δ_1	-0.646	0.934
	EXP	δ_2	-6.163	0.328
	CRED	δ_3	-0.778***	0.000
	VA	δ_4	-1.685***	0.000
	PS	δ_5	-0.357***	0.000
	GE	δ_6	-0.963***	0.000
	RQ	δ_7	-0.679***	0.000
	RL	δ_8	-1.837***	0.000
	CC	δ_9	-0.254***	0.000
Wald test of overall significance	208.17***			
Observations	118			

Notes: RD: R&D. HC: Human capital. MS: Market sophistication. t: Time trend. POP: Total population (rescaled and normalized). EXP: Exports of goods and services (rescaled and normalized). CRED: Domestic credit to private sector (rescaled and normalized). VA: Voice and accountability (rescaled and normalized). PS: Political stability and absence of violence/terrorism (rescaled and normalized). GE: Government effectiveness (rescaled and normalized). RQ: Regulatory quality (rescaled and normalized). RL: Rule of law (rescaled and normalized). CC: Control of corruption (rescaled and normalized). z_i *is the time average of* w_{it} *for each country.*

$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

Source: Author's calculation.

The relationship between R&D and innovation output seems to be curvilinear as the coefficient of the square of the variable ln*RD* is significant and negative. This suggests that achieving significant levels of production of innovation takes more than simply increasing the level of R&D. Among other factors, it probably takes choosing an optimal level of R&D investment, and investing in R&D projects that are very likely to have a significant impact on innovation. At the 10% level, the same logic applies for human capital as the coefficient of the square of ln*HC* is significant and negative. Improving merely country-level human capital seems not to be sufficient enough.

As to the time trend, recall that it is introduced to capture technical change that shifted the production function over time (Lai and Kumbhakar, 2018). Table 5 shows that it has a significant and negative effect on innovation output. That is, the production of innovation in the ECOWAS area declines over the years. The negative coefficient of time trend is interpreted as technical regress (Lai and Kumbhakar, 2018). To be precise, a value of -0.075 means a technical regress of 7.5% per annum[23].

Tables 6, 7 and 8 show respectively innovation short-run technical efficiency (henceforth, SRE), innovation long-run technical efficiency (henceforth, LRE) and innovation overall technical efficiency (henceforth, OE) scores. The distributions of the different types of technical efficiency are presented in Figure 3.

At the level of the distribution of SRE, Figure 3 shows that the upper level of the spectrum is observed for a level of efficiency that is greater than 90%. For LRE and OE, the upper levels are observed for efficiencies that are about 80% and 70%, respectively.

[23] As Lai and Kumbhakar (2018) point out, negative technical change is common in the efficiency literature.

Table 6. Innovation short-run technical efficiency scores

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	M	SD	Min	Max
Benin	0.847	0.884	0.969	0.845	0.913	0.950	--	0.954	0.847	0.975	0.985	0.995	0.924	0.059	0.845	0.995
Burkina Faso	0.825	0.736	0.967	0.818	0.830	0.715	0.686	0.992	0.993	0.992	0.756	0.988	0.858	0.121	0.686	0.993
Cabo Verde	0.981	--	--	--	0.982	0.991	0.988	--	--	--	--	0.949	0.978	0.017	0.949	0.991
Côte d'Ivoire	--	0.671	0.890	0.960	0.966	0.742	0.692	0.643	0.703	0.982	0.721	0.983	0.814	0.141	0.643	0.983
Gambia	0.884	0.865	--	0.976	0.756	0.850	0.751	--	--	--	--	--	0.847	0.085	0.751	0.976
Ghana	--	0.984	0.960	0.987	0.979	0.968	0.978	0.979	--	0.983	0.956	0.983	0.976	0.011	0.956	0.987
Guinea	--	--	--	--	0.614	0.896	0.916	0.973	0.982	0.744	0.787	0.826	0.842	0.125	0.614	0.982
Mali	0.910	0.905	0.977	0.920	0.831	0.943	0.838	0.865	0.952	0.899	0.826	0.988	0.904	0.055	0.826	0.988
Niger	--	--	0.978	0.936	0.628	0.703	0.975	0.803	0.734	0.691	0.802	0.823	0.807	0.123	0.628	0.978
Nigeria	0.798	0.904	0.833	0.864	0.896	0.828	0.890	0.964	0.984	0.971	0.816	0.982	0.894	0.068	0.798	0.984
Senegal	0.918	0.957	0.981	0.863	0.933	0.917	0.879	0.953	0.945	0.895	0.866	0.976	0.924	0.041	0.863	0.981
Togo	--	--	--	0.744	0.721	0.995	0.994	0.881	0.965	0.743	0.944	0.832	0.869	0.112	0.721	0.995
M	0.880	0.863	0.944	0.891	0.837	0.875	0.871	0.901	0.901	0.887	0.846	0.939				
SD	0.062	0.107	0.054	0.078	0.131	0.106	0.116	0.109	0.112	0.117	0.089	0.073				
Min	0.798	0.671	0.833	0.744	0.614	0.703	0.686	0.643	0.703	0.691	0.721	0.823				
Max	0.981	0.984	0.981	0.987	0.982	0.995	0.994	0.992	0.993	0.992	0.985	0.995				

Notes: (--) no observations for the country at this year. M: Mean. SD: Standard deviation. Min: Minimum. Max: Maximum.

Source: Author's calculation.

Table 7. Innovation long-run technical efficiency scores

Benin	Burkina Faso	Cabo Verde	Côte d'Ivoire	Gambia	Ghana	Guinea	Mali	Niger	Nigeria	Senegal	Togo	M	SD	Min	Max
0.716	0.611	0.993	0.791	0.770	0.955	0.724	0.866	0.482	0.804	0.930	0.415	0.755	0.180	0.415	0.993

Notes: M: Mean. SD: Standard deviation. Min: Minimum. Max: Maximum.

Source: Author's calculation.

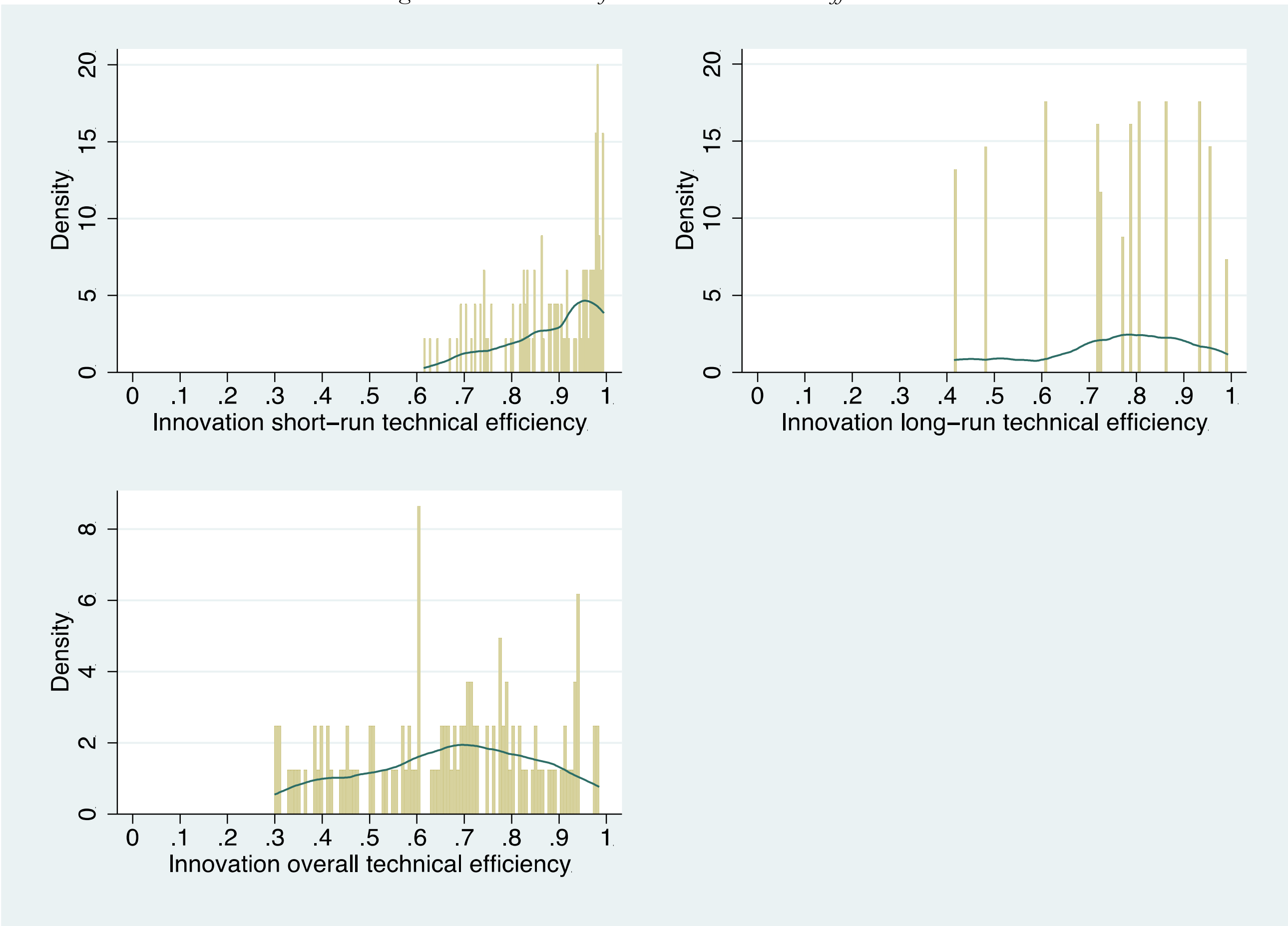
Table 8. Innovation overall technical efficiency scores

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	M	SD	Min	Max
Benin	0.606	0.633	0.694	0.605	0.653	0.680	--	0.683	0.606	0.698	0.706	0.712	0.662	0.042	0.605	0.712
Burkina Faso	0.504	0.450	0.591	0.500	0.508	0.437	0.419	0.606	0.607	0.607	0.462	0.604	0.525	0.074	0.419	0.607
Cabo Verde	0.974	--	--	--	0.976	0.985	0.981	--	--	--	--	0.943	0.972	0.017	0.943	0.985
Côte d'Ivoire	--	0.530	0.703	0.759	0.764	0.587	0.547	0.508	0.556	0.776	0.570	0.777	0.643	0.111	0.508	0.777
Gambia	0.681	0.666	--	0.752	0.582	0.654	0.578	--	--	--	--	--	0.652	0.065	0.578	0.752
Ghana	--	0.940	0.917	0.942	0.934	0.925	0.933	0.934	--	0.938	0.913	0.939	0.932	0.010	0.913	0.942
Guinea	--	--	--	--	0.445	0.648	0.662	0.704	0.710	0.538	0.570	0.598	0.609	0.091	0.445	0.710
Mali	0.788	0.783	0.846	0.797	0.720	0.816	0.725	0.749	0.824	0.778	0.715	0.856	0.783	0.048	0.715	0.856
Niger	--	--	0.471	0.451	0.302	0.339	0.470	0.387	0.354	0.333	0.387	0.396	0.389	0.059	0.302	0.471
Nigeria	0.642	0.727	0.670	0.695	0.720	0.666	0.715	0.775	0.791	0.781	0.656	0.790	0.719	0.055	0.642	0.791
Senegal	0.853	0.890	0.912	0.802	0.867	0.852	0.817	0.887	0.879	0.832	0.805	0.908	0.859	0.038	0.802	0.912
Togo	--	--	--	0.309	0.299	0.413	0.412	0.365	0.400	0.308	0.391	0.345	0.360	0.047	0.299	0.413
M	0.721	0.702	0.725	0.661	0.647	0.667	0.660	0.660	0.636	0.659	0.617	0.715				
SD	0.160	0.168	0.157	0.193	0.227	0.204	0.196	0.194	0.183	0.211	0.175	0.208				
Min	0.504	0.450	0.471	0.309	0.299	0.339	0.412	0.365	0.354	0.308	0.387	0.345				
Max	0.974	0.940	0.917	0.942	0.976	0.985	0.981	0.934	0.879	0.938	0.913	0.943				

Notes: (--) no observations for the country at this year. M: Mean. SD: Standard deviation. Min: Minimum. Max: Maximum.

Source: Author's calculation.

Figure 3. Distributions of the innovation technical efficiencies



Note: Kernel densities reported.
Source: The author.

Table 6 shows that ECOWAS countries are all inefficient in the short run. However, SRE scores are greater than 0.5 for all the countries. As a result, although ECOWAS countries are found to be inefficient in the short run, their inefficiency levels are lower than 50%. In the context of African countries, this result contrasts with that of Kao (2017), who found an inefficiency level greater than 50% for South Africa. This difference with Kao's (2017) result can be explained by the fact that the author does not distinguish between SRE and LRE. The ITE scores obtained by Kao (2017) seem thereby to be underestimated and the type of ITE measured is somehow fuzzy. It appears that the distinction between SRE and LRE is needed to properly measure ITE, and then to better design and manage innovation policies. Note that the means of SRE scores are all greater than 0.8 for all the countries. Therefore, overall, ECOWAS countries exhibit on average short-run technical inefficiencies lower than 20%. Cabo Verde, Ghana and Benin are respectively the three most efficient countries in the short run (on average). The three least efficient ones in the short run are respectively Niger, Côte d'Ivoire and Guinea.

In the long run, Table 7 shows that there is no country which is efficient. Cabo Verde, Ghana and Senegal have LRE scores greater than 0.9, and are actually the three most efficient countries, respectively. These countries therefore exhibit less than 10% of long-run inefficiency. This performance seems noteworthy although the countries still remain inefficient. Togo exhibits the worst long-run performance, with an efficiency score equal to 0.415. In fact, the three least efficient countries in the long run are Togo, Niger and Burkina Faso, respectively. The average long-run innovation inefficiency level in the ECOWAS area is lower than 30%.

Besides, Table 8 shows that there is no ECOWAS country which is efficient both in the short and long run. It appears that Cabo Verde exhibits the best average level of OE. In fact, it is the best innovation practitioner in the ECOWAS area regarding both short- and long-run efficiencies. The two other countries in the 'top 3' are Ghana and Senegal. The three lowest OE scores are obtained by Togo, Niger and Burkina Faso, respectively. More specifically, Togo and Niger have an average OE score which is lower than 0.5. This result is quite worrying as it implies inefficiency levels greater than 50%.

A deeper analysis of the OE scores reveals a significant heterogeneity of ECOWAS countries in terms of average scores. This heterogeneity is mainly due to the observed differences in LRE scores. The differences in SRE scores are actually not so huge. This reveals somehow the proper heterogeneity of ECOWAS countries. Indeed, in the ECOWAS area, we have Nigeria (502.94)[24], West Africa's leading economic power, and countries such as Ghana (62.47) and Côte d'Ivoire (59.86), not far from each other in terms of GDP. We also have Senegal (22.56), Mali (16.03), Burkina Faso (15.00), and Benin (14.18) on the one hand, and Niger (12.21) and Guinea (12.08) on the other hand, two groups in which the countries are more or less comparable, and the other countries namely, Togo (5.10), Sierra Leone (5.08), Liberia (3.21), Cabo Verde (1.92), Gambia (1.68), and Guinea-Bissau (1.25), which are the lagging ones in terms of GDP.

As to the determinants of innovation efficiency, recall that the variances of inefficiencies (σ_u^2 and σ_η^2) are modeled as functions of the determinants. As such, increases in the variances increase inefficiency, that is, decrease efficiency (Lai and Kumbhakar, 2018).

Table 5 shows that domestic credit to private sector is negatively associated with long-run inefficiency, that is, positively associated with LRE. This means that an increase in domestic credit to private sector will increase LRE. No significant effect is found for SRE. This result is in line with previous studies which found the support of financial institutions to be an important driver of innovation efficiency (Bai, 2013). In fact, a certain level of financing is required to achieve relevant innovation performances. Increases in domestic credit to private sector increase the private sector's financial capacity, and thereby induce more investment in activities and factors amenable to improve (reduce) the level of efficiency (inefficiency), ceteris paribus.

Very interestingly, it emerges that governance is important in explaining innovation efficiency. This is in line with previous studies by Franco *et al.* (2016) and Guan and Chen (2012). More specifically, Table 5 shows that an increase in the level of voice and accountability will increase both SRE and LRE. Similarly, an increase in the level of political stability and absence of violence/terrorism will increase LRE. No

[24] In this paragraph, the values in parentheses are real GDP in billions of USD in 2019. See the World Development Indicators database of the World Bank.

significant relationship is found for SRE. Results also show that the economic and institutional dimensions of governance matter in explaining innovation efficiency in the ECOWAS area.

Indeed, an increase in the level of government effectiveness will increase LRE. Government effectiveness seems not to impact SRE. Regulatory quality rather positively influences both SRE and LRE. The implementation of policies and regulations that contribute to the promotion and development of the private sector, the quality of public services, and more generally, the quality of policy formulation and implementation, among others, play a significant role in explaining innovation efficiency. As to institutional governance, it emerges that an increase in the level of the 'rule of law' dimension of governance will increase LRE. Results show no significant effect for SRE. This implies that, for instance, countries with better property rights protection should exhibit greater levels of LRE, ceteris paribus. Results also show that an increase in the level of control of corruption will decrease SRE, but it will increase LRE. An explanation for this result is that the level of control of corruption is positively associated with innovation efficiency (LRE), but that it is not sufficient enough to impact positively innovation efficiency in the short run.

These results show the importance of governance in shaping decision-making units' ability to achieve significant innovation performances. In fact, it can be thought that a country's level of governance, depending on whether it is poor or good, provides decision-making units with different incentives to effectively commit to innovation activities, and this may lead to inefficiency, for instance, in the case of an underinvestment in R&D.

The analysis of the determinants of innovation efficiency allows us to provide lessons from the best-performing countries to the least-performing countries. Indeed, the three most efficient countries in the short run are respectively Cabo Verde, Ghana and Benin, whereas the three least efficient ones are Niger, Côte d'Ivoire and Guinea, respectively (see Table 6). Recall that voice and accountability and regulatory quality have been identified as drivers of SRE. We can observe that, on the one hand, Cabo Verde, Ghana and Benin exhibit the three best performances in terms of voice and accountability (see Table 3). Cabo Verde and Ghana are the two best-performing countries in terms of regulatory quality, while Benin is among the six best-performing ones (see Table 4). On the other hand, Niger, Côte d'Ivoire and Guinea are among the countries which exhibit the worst performances in terms of voice and accountability and regulatory quality (see Tables 3 and 4). This suggests that the least-performing countries should improve their levels of voice and accountability and regulatory quality to achieve greater levels of SRE.

In the long run, recall that the most efficient countries are Cabo Verde, Ghana and Senegal, whereas Togo, Niger and Burkina Faso are respectively the three least efficient countries. Results highlighted domestic credit to private sector and governance as determinants of LRE. One can see that Cabo Verde and Senegal are among the top 3 countries in terms of domestic credit to private sector, while Niger is among the least-performing countries (see Table 3). At the level of governance, Cabo Verde, Ghana and Senegal exhibit the three best performances for most of the governance indicators, unlike Togo, Niger and Burkina Faso (see Tables 3 and 4). All this highlights that increases in the levels of domestic credit to private sector and governance constitute a way for least-performing countries to improve their levels of innovation efficiency in the long run.

As to the overall efficiency, recall that it results from SRE and LRE. As such, increases in the levels of SRE and LRE should improve countries' OE.

7. Summary and conclusions

This paper contributes to filling an important gap in the literature by distinguishing between short-run efficiency (SRE) and long-run efficiency (LRE) in the analysis of innovation technical efficiency (ITE), and by investigating the determinants of ITE through the modeling of the variances of short- and long-run inefficiencies as functions of the determinants. This distinction appears crucial as these types of ITE do not reflect similar kinds of efficiency. Innovation overall technical efficiency (OE) is also measured. The empirical analysis exploited data from the ECOWAS area, which is interesting in view of the lack of studies of ITE for African countries and the development issue associated with ITE in West Africa.

The paper highlights market sophistication as positively influencing innovation output. R&D and human capital appear to have a curvilinear relationship with innovation output. Negative technical change is highlighted. It also appears that domestic credit to private sector and governance are associated significantly with ITE.

At the level of efficiency scores, results show that ECOWAS countries are all inefficient considering the three types of ITE. Ultimately, it emerges that LRE scores and the average SRE scores over the study period are not similar. This shows the need to distinguish between short- and long-run efficiencies when studying innovation efficiency. It also appears that for 2 out of 12 countries, that is, 17%, the LRE level is greater than the average SRE level, which is quite weak.

Note that the aim pursued here by the economic policy is mainly to increase LRE. In fact, LRE seems more desirable than SRE since it allows countries to benefit from the long-lasting positive effects of ITE. OE which consists in ITE both in the short and long run, appears to be somehow a 'perfect' ITE, too complicated to achieve. In such a context, the fact that the LRE level is greater than the average SRE level for only 17% of ECOWAS countries, is not good news. Efforts must be made to increase the level of innovation efficiency, in particular the level of LRE.

In this vein, the results obtained in this paper suggest that policies intended to improve ITE in the ECOWAS area could take at least two directions. Firstly, the level of domestic credit to private sector should be increased. Secondly, efforts must be made to improve the level of governance. The policies to be implemented should aim to improve all three dimensions of governance (economic, political and institutional).

Besides, one should note that this paper presents a number of limitations. Among others, the study sample includes 12 out of 15 ECOWAS countries due to lack of data. We hope that data on the three excluded countries (Guinea-Bissau, Liberia and Sierra Leone) will be available in the future, and over a longer study period, so that the knowledge on ITE in West Africa can be further improved. Another limitation of the present research is that the effect of ITE on development is not analyzed. One should also remind that our analysis of the determinants of ITE was done using data from ECOWAS member states. As such, any attempt to generalize the results to other economic areas should be made with caution because the economic and institutional settings in these areas are probably different from those of the ECOWAS area, which may imply different results.

Based on the present research, a number of avenues for future research can be identified. Among others, future papers could consider extending our study sample to all the countries in Africa, and the differences in ITE scores and the determinants across the continent's regions could be investigated. The ITE scores should also be used to engage further analysis[25]. In particular, the effects of ITE on development could be investigated using data from African countries. The differences in the effects between different regions could be assessed. Beyond development, the effects of ITE on the level of employment could also be investigated. Such a study would add knowledge to the stream of literature seeking to know whether innovation destroyed or created jobs in specific regions, countries and industries, by focusing on efficiency.

[25] Asongu *et al.* (2020) and Asongu and Odhiambo (2019) are some examples of the type of analysis that can be conducted.

References

Akcigit U., Kerr W. (2018), 'Growth through heterogeneous innovations', *Journal of Political Economy*, 126(4), 1374-1443.

Amable B., Ledezma I., Robin S. (2016), 'Product market regulation, innovation, and productivity', *Research Policy*, 45(10), 2087-2104.

Asongu S., Nting R., Nnanna J. (2020), 'Market power and cost efficiency in the African banking industry', *Journal of Economic Studies*, 47(6), 1247-1264.

Asongu S. A., Odhiambo N. M. (2019), 'Size, efficiency, market power, and economies of scale in the African banking sector', *Financial Innovation*, 5(4), 1-22.

Bai J. (2013), 'On regional innovation efficiency: Evidence from panel data of China's different provinces', *Regional Studies*, 47(5), 773-788.

Balsmeier B. (2017), 'Unions, collective relations laws and R&D investment in emerging and developing countries', *Research Policy*, 46(1), 292-304.

Carayannis E. G., Grigoroudis E. (2016), 'Using multiobjective mathematical programming to link national competitiveness, productivity, and innovation', *Annals of Operations Research*, 247(2), 635-655.

Chen Y., Puttitanun T. (2005), 'Intellectual property rights and innovation in developing countries', *Journal of Development Economics*, 78(2), 474-493.

Chen Y.-Y., Schmidt P., Wang H.-J. (2014), 'Consistent estimation of the fixed effects stochastic frontier model', *Journal of Econometrics*, 181(2), 65-76.

Christensen L. R., Jorgenson D. W., Lau L. J. (1973), 'Transcendental logarithmic production frontiers', *Review of Economics and Statistics*, 55(1), 28-45.

Colombi R., Kumbhakar S. C., Martini G., Vittadini G. (2014), 'Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency', *Journal of Productivity Analysis*, 42(2), 123-136.

Cruz-Cázares C., Bayona-Sáez C., García-Marco T. (2013), 'You can't manage right what you can't measure well: Technological innovation efficiency', *Research Policy*, 42(6-7), 1239-1250.

Farrell M. J. (1957), 'The measurement of productive efficiency', *Journal of the Royal Statistical Society. Series A (General)*, 120(3), 253-290.

Franco C., Pieri F., Venturini F. (2016), 'Product market regulation and innovation efficiency', *Journal of Productivity Analysis*, 45(3), 299-315.

Fu X. (2012), 'How does openness affect the importance of incentives for innovation?', *Research Policy*, 41(3), 512-523.

Fu X., Mohnen P., Zanello G. (2018), 'Innovation and productivity in formal and informal firms in Ghana', *Technological Forecasting and Social Change*, 131, 315-325.

Fu X., Yang Q. G. (2009), 'Exploring the cross-country gap in patenting: A stochastic frontier approach', *Research Policy*, 38(7), 1203-1213.

Furman J. L., Porter M. E., Stern S. (2002), 'The determinants of national innovative capacity', *Research Policy*, 31(6), 899-933.

Gambardella A., Raasch C., von Hippel E. (2016), 'The user innovation paradigm: Impacts on markets and welfare', *Management Science*, 63(5), 1271-1656.

Gebreeyesus M., Mohnen P. (2013), 'Innovation performance and embeddedness in networks: Evidence from the Ethiopian footwear cluster', *World Development*, 41, 302-316.

Greene W. (2005a), 'Fixed and random effects in stochastic frontier models', *Journal of Productivity Analysis*, 23(1), 7-32.

Greene W. (2005b), 'Reconsidering heterogeneity in panel data estimators of the stochastic frontier model', *Journal of Econometrics*, 126(2), 269-303.

Guan J., Chen K. (2012), 'Modeling the relative efficiency of national innovation systems', *Research Policy*, 41(1), 102-115.

Guan J., Zuo K., Chen K., Yam R. C. M. (2016), 'Does country-level R&D efficiency benefit from the collaboration network structure?', *Research Policy*, 45(4), 770-784.

Jondrow J., Lovell C. A. K., Materov I. S., Schmidt P. (1982), 'On the estimation of technical inefficiency in the stochastic frontier production function model', *Journal of Econometrics*, 19(2-3), 233-238.

Kao C. (2017), 'Efficiency measurement and frontier projection identification for general two-stage systems in data envelopment analysis', *European Journal of Operational Research*, 261(2), 679-689.

Kaufmann D., Kraay A., Mastruzzi M. (2010), 'The worldwide governance indicators: Methodology and analytical issues', Policy Research Working Paper, no. WPS 5430, The World Bank.

Kontolaimou A., Giotopoulos I., Tsakanikas A. (2016), 'A typology of European countries based on innovation efficiency and technology gaps: The role of early-stage entrepreneurship', *Economic Modelling*, 52, 477-484.

Kouakou D. C. M. (2020), *Trois Essais en Economie de l'Innovation*, Ph.D. thesis in Economics, Université de Rennes 1, Rennes, France.

Kumbhakar S. C., Heshmati A. (1995), 'Efficiency measurement in Swedish dairy farms: An application of rotating panel data, 1976-88', *American Journal of Agricultural Economics*, 77(3), 660-674.

Kumbhakar S. C., Hjalmarsson L. (1993), 'Technical efficiency and technical progress in Swedish dairy farms', in Fried H. O., Lovell C. A. K., Schmidt S. S. (eds.), *The Measurement of Productive Efficiency: Techniques and Applications*, Oxford, Oxford University Press.

Kumbhakar S. C., Hjalmarsson L. (1995), 'Labour-use efficiency in Swedish social insurance offices', *Journal of Applied Econometrics*, 10(1), 33-47.

Kumbhakar S. C., Lien G. (2017), 'Yardstick regulation of electricity distribution – Disentangling short-run and long-run inefficiencies', *Energy Journal*, 38(5), 17-37.

Kumbhakar S. C., Lien G., Hardaker J. B. (2014), 'Technical efficiency in competing panel data models: a study of Norwegian grain farming', *Journal of Productivity Analysis*, 41(2), 321-337.

Kumbhakar S. C., Wang H.-J. (2005), 'Estimation of growth convergence using a stochastic production frontier approach', *Economics Letters*, 88(3), 300-305.

Kumbhakar S. C., Wang H.-J., Horncastle A. P. (2015), *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata*, Cambridge, Cambridge University Press.

Lai H.-P., Kumbhakar S. C. (2018), 'Endogeneity in panel data stochastic frontier model with determinants of persistent and transient inefficiency', *Economics Letters*, 162, 5-9.

Lee J., Kim C., Choi G. (2019), 'Exploring data envelopment analysis for measuring collaborated innovation efficiency of small and medium-sized enterprises in Korea', *European Journal of Operational Research*, 278(2), 533-545.

Li X. (2009), 'China's regional innovation capacity in transition: An empirical approach', *Research Policy*, 38(2), 338-357.

Mairesse J., Mohnen P. (2002), 'Accounting for innovation and measuring innovativeness: An illustrative framework and an application', *American Economic Review*, 92(2), 226-230.

Maskus K. E., Milani S., Neumann R. (2019), 'The impact of patent protection and financial development on industrial R&D' *Research Policy*, 48(1), 355-370.

Nelson, R. R. (2008), 'What enables rapid economic progress: What are the needed institutions?', *Research Policy*, 37(1), 1-11.

Paunov C. (2016), 'Corruption's asymmetric impacts on firm innovation', *Journal of Development Economics*, 118, 216-231.

Robson P. J. A., Haugh H. M., Obeng B. A. (2009), 'Entrepreneurship and innovation in Ghana: enterprising Africa', *Small Business Economics*, 32, 331-350.

Rooks G., Szirmai A., Sserwanga A. (2012), 'Network structure and innovative performance of African entrepreneurs: The case of Uganda', *Journal of African Economies*, 21(4), 609-636.

Schumpeter J. A. (1912), *The Theory of Economic Development*, Cambridge, Harvard University Press.

Simar L. (1992), 'Estimating efficiencies from frontier models with panel data: A comparison of parametric, non-parametric and semi-parametric methods with bootstrapping', *Journal of Productivity Analysis*, 3(1), 171-203.

Simar L., Wilson P. W. (1998), 'Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models', *Management Science*, 44(1), 49-61.

Steil B., Victor D. G., Nelson R. R. (2002), *Technological Innovation and Economic Performance*, Princeton, Princeton University Press.

Tsionas E. G., Kumbhakar S. C. (2014), 'Firm heterogeneity, persistent and transient technical inefficiency: A generalized true random-effects model', *Journal of Applied Econometrics*, 29(1), 110-132.

Wang E. C., Huang W. (2007), 'Relative efficiency of R&D activities: A cross-country study accounting for environmental factors in the DEA approach', *Research Policy*, 36(2), 260-273.

Wang H.-J., Ho C.-W. (2010), 'Estimating fixed-effect panel stochastic frontier models by model transformation', *Journal of Econometrics*, 157(2), 286-296.

Wang Q., Hang Y., Sun L., Zhao Z. (2016), 'Two-stage innovation efficiency of new energy enterprises in China: A non-radial DEA approach', *Technological Forecasting and Social Change*, 112, 254-261.