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Economic complexity and technical efficiency in developing countries: an empirical analysis

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Economic complexity and technical efficiency in developing countries: an empirical analysis

Abstract

The aim of this study is to analyze the role of technical efficiency on the process of economic complexity in developing countries. For this, we have mobilized two complementary techniques. The first technique allowed us to calculate efficiency scores for a panel of 81 advanced and developing countries over a period between 1990 and 2018. The inclusion of high-income countries in the sample is used to ensure the true efficiency frontier, which would be underestimated in their absence. The results obtained by the Data Envelopment Analysis (DEA) method highlight that developing countries produced only 16% of the quantity of outputs they could have produced from their resources, compared to 51% for high-income countries. Moreover, the use of a dynamic panel data analysis on developing countries shows a non-significant impact of technical efficiency on economic complexity in, all else being equal, with disparate effects across regions.

Keywords: Technical efficiency, Economic complexity index, Data Envelopment Analysis (DEA), Generalized Method of Moments (GMM), Developing countries.

JEL Classification : D61, F10, C60, C50, O01

Complexité économique et efficience technique dans les pays en développement : une analyse empirique

Résumé :

L'objectif de cette étude est d’analyser le rôle de l'efficience technique sur le processus de complexité économique dans les pays en développement. Pour cela, nous avons mobilisé deux techniques complémentaires, à savoir la méthode d'enveloppement des données (DEA) et la technique des données de panel dynamique, par l’estimateur GMM, pour un panel de 81 pays avancés et en développement sur une période comprise entre 1990 et 2018. L'inclusion des pays à haut revenu dans l'échantillon sert à garantir la véritable frontière d'efficience, qui serait sous-estimée en leur absence. Les résultats obtenus mettent en évidence que les pays en développement, n’ont produit que 16 % de la quantité d’outputs qu’elles auraient pu produire à partir de leurs ressources, contre 51% pour les pays à revenu élevé. De surcroit, les pays en développement montrent un impact non significatif de l'efficience technique sur la complexité économique avec des effets disparates selon les régions.

Mots-clés : Efficience technique, indice de complexité économique, analyse d'enveloppement des données (DEA), méthode des moments généralisés (GMM), pays en développement.

Introduction

Recent changes in the global economy have shown the importance for developing countries to identify the factors that influence their productive structures. A large literature recognizes that economic development is intrinsically linked to changes in the structure of production and technological improvements (Lewis, 1954; Kaldor, 1966; Kuznets, 1973, Herrendorf et al. 2014). In this process, factors of production shift to higher productivity activities through a gradual accumulation of a more complex set of knowledge and capabilities needed to drive structural transformation and technological diffusion (Hausmann et al. 2013; McMillan et al. 2014).

However, new studies have revived the debate on the factors behind this development process. They emphasize the importance of available knowledge as well as the nature of the goods produced by the country rather than the quantity (Hausmann et al. 2013; Pahl and Timmer, 2019). In their seminal paper entitled "The Building Blocks of Economic Complexity," Hausmann and Hidalgo (2009) explain that differences between countries in terms of productivity and thus economic development could be explained by differences in economic complexity. According to these authors, each country has different productive characteristics that allow them to produce a diversified and more sophisticated set of goods.

In this sense, economic complexity reveals the learning efforts and knowledge accumulation embodied in the goods an economy produces, i.e., its productive knowledge and know-how (Hausmann and Klinger 2007; Hausmann and Hidalgo 2009). It can be seen as a "black box" that includes all the tangible and intangible factors that contribute to the identification of the structures of economies (Hausmann et al. 2013). As countries specialize in different activities, technical efficiency and knowledge accumulation increase, suggesting that the way an economy uses its resources plays a major role in the development process (Hidalgo and Hausmann, 2009). The economic imperative of structural change and economic complexity is also increasingly important in the context of developing countries (Mc Millan et al. 2014). Until very recently, developing countries have been largely absent from empirical analyses in this literature (hausmann et al. 2013).

The notion of efficiency can be defined as the ability of an economy, as a whole, to achieve a given result with a minimum of resources (Farrell, 1957). According to this approach, it is not only about the availability of resources but the efficiency an economy manages the endowments it has (Hidalgo, 2015). Technical efficiency determines the complexity of the products that a country can export; that is, the level of efficiency enhances the productivity of the factors that allow countries to produce more sophisticated goods. Economies with low

technical efficiency are unable to make high complex products, and will have scant benefits from accumulating any individual additional capabilities (Hausmann and Hidalgo 2009).
Taking into account the elements mentioned above, in this paper we will try to highlight the relationship between economic development and the complexity of exports with technical efficiency as a determining factor. This study is organized as follows: Section 1 presents a brief literature review. Section 2 introduces the Data Envelopment Analysis (DEA) methodology and empirical estmation.Then, the interpretation of the results are discussed in section 3. Section 4 concludes.

1. Literature review

The purpose of this section is twofold. First, to explain the concept of economic complexity. Then, to introduce the theoretical foundations of technical efficiency.

1.1. Concept of Economic Complexity

One of the most important issues in economics is the income and growth differences among countries. Explaining these differences among nations is a crucial objective of economics, in particular in the context of developing countries. Hidalgo and Hausmann (2009); Simoes and Hidalgo (2011) and Hausmann et al. (2013) attempted to analyze these differences through international trade data.
According to the authors, there are factors that cannot be imported, such as certain types of physical/human capital, quality of institutions, market regulation, etc. In other words, the productivity of a society must depend on its local and/or non-tradable sources explicitly the productive capabilities. It represents all the inputs of a tacit - or non-tradable - that are integrated into the production process. They are composed of tacit knowledge and ideas that, in combination, determine the frontiers of what an economy can produce. Therefore, the productivity of a country depends on the diversity of its available tacit capabilities and their interactions. In this sense, differences in productive capabilities seem to explain why some economies become rich and some remain poor (Poncet and Waldemar, 2013).
Since it is almost impossible to measure directly the stock of productive knowledge available within an economy, Hidalgo and Hausmann (2009) proposed an indirect measure, called the " Economic Complexity Index ", by applying techniques from the theory of reflections[1] , which

[1] The Method of reflections, used in engineering, is the study of graphs as a representation of a complex symmetrical or asymmetrical relationship. Hidalgo and Hausmann (2009) apply this graphical representation on countries' export data by product. The underlying idea is that endowments in productive capabilities and knowledge are revealed at the level of the products exported by each country.

consists of combining the level of diversification of exports and the average ubiquity of the products that the country exports.

According to this approach, the goods produced are considered as a complex set of tacit know how and technological capabilities that differ from one country to another. To this end, economies that export a wide and diversified range of products are likely to have more productive capabilities (Diversity). Similarly, products that are exported by a small fraction of countries require capabilities and knowledge that only a few countries have in total (Ubiquity). Therefore, the economic complexity index is constructed by taking into account these two factors: the diversity of exports and the ubiquity of exported products (see Appendix A for the calculation of the Economic Complexity Index).

Thus, convergence gap between developing countries and high-income economies could be explained by differences in economic complexity. Indeed, more sophisticated and complex products require capabilities that only some countries possess. These factors are broadly defined to include both tangible factors, such as infrastructure, as well as intangible elements, such as the quality of education, the ability to work in groups and institutions, etc (Khan, 2019).

How technical efficiency can enhances economic complexity? Countries at different levels of development tend to have different economic structures because of their factor endowments (Lectard and Piveteau, 2015). These endowments, in the early stages of development, are generally characterized by relative scarcity of capital, production activities that tend to be labor-intensive of low skills, and that generally leads to a low technical efficiency.

In contrast, high-income countries have a completely different endowment structure. They tend to have a comparative advantage (CA) in capital-intensive activities characterized by a predominance of intangible capabilities (regulatory and legal frameworks, education, know how, etc.). These factor endowments allow for technical efficiency on new technologies as well as diversification of skills and productive capabilities (Ocampo, 2005; Rodrik et al. 2017).

1.2. Theoretical framework of technical efficiency

According to Farrell (1957), the concept of efficiency focuses on the way in which a production unit transforms its inputs into outputs. The role of efficiency relates to the ability of a decision making unit to generate the maximum possible output from a given combination of inputs and production technology. Technical efficiency refers to the physical link between the different baskets of inputs and outputs that it is possible to obtain at the end of the production process (Koopmans, 1951; Debreu, 1951). According to Farrell (1957), it is possible to distinguish between three forms of efficiency : Technical efficiency, Allocative efficiency (or price efficiency) and Economic efficiency.

Technical efficiency identifies whether a firm can increase its output without consuming more resources, or decrease by at least one input while maintaining the same level of output (Amara and Romain, 2000; Latruffe, 2010; Blancard et al. 2013). From this perspective, technical inefficiency corresponds either to production below what is technically possible for a given quantity of inputs, or to the use of quantities of inputs above what is necessary.

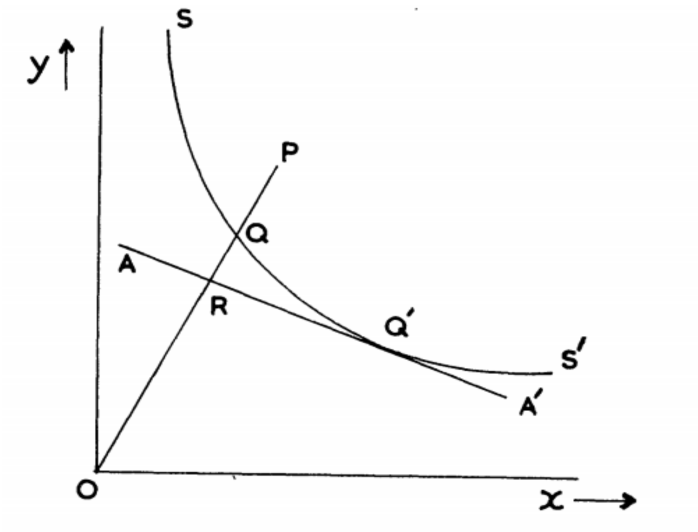
In contrast, allocative efficiency, also known as price efficiency, refers to the firm's ability to operate at its optimal scale. It takes into account the prices of factors of production in the choice of quantities of inputs. This measure provides an idea of how firms allocate their productive resources in relation to the objective of production in order to choose the combination of inputs that minimizes their costs (Piot-Lepetit and Rainelli, 1996). In this sense, allocative inefficiency arises from the use of factors of production that do not minimize costs. According to Albouchi et al (2005) "a production process is said to be allocatively efficient if the marginal rate of substitution between each pair of factors is equal to the proportion of the price of the latter".

Economic efficiency, also called global technical efficiency, corresponds to the product of the two forms of efficiency : technical (maximum possible output) and allocative (minimum costs) (Coelli et al, 1998). To this end, a decision unit is said to be economically efficient if it uses an optimal combination of factors of production at the lowest cost, or in an equivalent manner, that allows the maximum possible output to be obtained, given the inputs and the technology used (Bhat et al, 2001).

To better understand the concept of technical efficiency and its components, Farrell (1957) proposes a graphical illustration in the case of a firm's production function that uses two inputs (x) for a given output (y) (Figure 1). The isoquant SS' represents the set of input combinations that are technically efficient for a given level of output. It is defined as the production frontier[2]. The points above the isoquant represent the inefficient firms. If we consider point P as the quantity of inputs consumed by a firm to produce one unit of output, then its technical inefficiency can be measured by the distance QP, which corresponds to the proportions of inputs that could be reduplicated without a decrease in the quantity of output.

[2] This production frontier is obtained by the Data Envelopment Analysis method.

Figure 1: Measure of technical and allocative efficiency



***Source**: Farrell (1957), p. 254.*

In this sense, for each unit of production i the technical efficiency (TE) can be measured by the following ratio :

$$TE_i = \frac{OQ}{OP} \quad with\ (0 \leq ET_i \leq 1)$$

If the TE ratio is equal to 1, it means that the production unit is technically efficient. However, although a unit is technically efficient, not all points on the isoquant are allocatively efficient. The tangent AA' represents the isocost line whose slope is equal to the ratio of factor prices. At the optimum, it is tangent to the isoquant SS'.

A combination of factors is said to be allocatively efficient if the marginal rate of substitution is equal to the ratio of market determined factor prices. Thus, the slope AA' is a measure of allocative efficiency (AE) which is given by :

$$AE_i = \frac{OR}{OQ} \quad with\ (0 \leq EA_i \leq 1)$$

The point Q' corresponds to the situation where both technical and allocative efficiency are present. In this sense, the distance RQ represents the share of cost reduction. According to Farrell (1957), the economic efficiency or Total Technical Efficiency **(TTE)** at point P is the combination of ET and EA :

$$TTE_i = \frac{OR}{OP} = \frac{OQ}{OP} \times \frac{OR}{OQ} = ET_i \times EA_i$$

The measurement of the total technical (economic) efficiency of a firm or a sector requires the estimation of a production frontier. There are multiple methods for estimating frontiers and efficiency scores, namely the **Data Envelopment Analysis method (DEA).**

2. Methodology and empirical estimation

In this section, we present the methodology of the DEA method on the one hand and the empirical model of the study on the other.

2.1. Measuring technical efficiency in developing countries using the DEA method

The Data Envelopment Analysis (DEA) is a non-parametric approach, based on linear programming, which allows the estimation of an empirical production frontier on a sample of observations. This method was developed by Farrell (1957) based on the "resource utilization or technical coefficient" of Debreu (1951) and popularized by the empirical work of Charnes et al. (1978) and Banker et al. (1984).

The production frontier, obtained by the data envelopment method, is the set of the most efficient decision units (DMUs) - these units can be either firms, regions or countries - that manage to provide the best practices with the least amount of resources (maximize outputs or minimize inputs). This methodology consists of calculating the distance between each decision unit and the efficiency frontier. For each deviation from the envelope, an efficiency score is assigned. In this sense, the DEA method assigns to each decision unit an efficiency score that is equal to 1 when the DMU is on the frontier or less than 1 if it is below.

The interest of the DEA method is to be able to compare all similar decision units by taking into account several characteristics. Based on this, each DMU_i uses a combination of different « m » inputs $X_j = \{x_{ij}\}, (i = 1, \dots, m)$ in order to produce a given quantity of « s »outputs, $Y_j = \{y_{rj}\}, (r = 1, \dots, s)$.For each decision making unit "j" the measure of productive efficiency is given by the following ratio :

$$\theta_j = \frac{(W_1 * Y_1 + W_2 * Y_2 + \dots\dots + W_n * Y_j)}{(W_1 * X_1 + W_2 * X_2 + \dots\dots + W_n * X_j)}$$

Where θ_j formally represents :

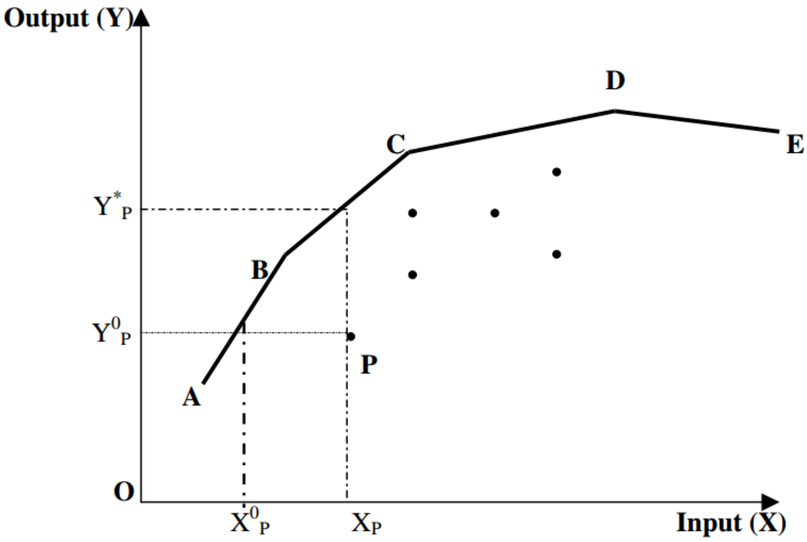
$$\theta_j = \frac{Weighted\ sum\ of\ outputs}{Weighted\ sum\ of\ intputs}$$

The DEA method is considered as a benchmarking technique where each decision unit is compared to its most efficient counterparts on the path to best practice. To better understand the semantics behind the DEA approach, we use the following graphic representation (Figure 2).

The decision units A, B, C, D and E constitute the frontier of the most efficient producers, which is by definition equal to 1. On the other hand, the units that lie below the frontier are considered the least efficient, in our example it is the production unit P. The quantity of

output produced by P is given by Y*P which is obtained by a level of inputs XP that it has. In this sense, the technical efficiency of P corresponds to Y*P/ XP which is less than 1.
Thus, using the DEA method, it is possible to quantify the possibilities of improving technical efficiency either by adopting an output orientation or an input orientation. The first approach focuses on the possibility of this DMU to increase the quantity of inputs without changing the quantity of output. Conversely, the second approach allows us to understand by how much it is possible to increase the output without changing the quantity of inputs. As a corollary, when introducing types of returns to scale in the construction of the efficiency frontier, a distinction is made between the CCR model of Charnes et al. (1978) with constant returns to scale and the BCC model of Banker et al. (1984) with variable returns to scale.

Figure 2: Measure of technical efficiency using the DEA method



Source : *Kamgna et Dimou (2008), p.17.*

2.2.Stylized facts on technical efficiency in developing countries

To analyze the technical efficiency in developing countries using scores obtained by the DEA method, first, we will look at the choice of inputs and outputs used in our model and the orientation adopted. Then, we will interpret the efficiency scores obtained on a sample of 81 high-income and developing countries. The introduction of high-income countries in the calculation of the efficiency scores is used to ensure the true efficiency frontier that would be underestimated in their absence.
In line with previous studies, as Afzal (2014) and Tasnim and Afzal (2018), the model adopted to measure the technical efficiency of developing countries is based on the DEA

method with the assumption of variable returns to scale, « output oriented[3] ». This choice is motivated by the fact that not all economies operate at the optimal scale, the increase in income level will depend on how its resources are managed (Coelli et al. 1998).

In our study, we selected a panel of 81 developed and developing countries for the period between 1990 and 2018[4]. The inclusion of high-income countries in the sample is used to ensure the true efficiency frontier, which would be understated without them. Our choice of inputs focused on total employment, capital stock, and the human capital index. They are taken from the Penn World tables 9.1 database. The output, on the other hand, is GDP per capita in purchasing power parity, which is obtained from the World Development Indicators database of the World Bank.

By analyzing the efficiency scores by income level, we can see that the average total technical efficiency (TE) index of the countries in our sample was around 0.271 over the entire study period[5] . This score means that with the same level of inputs mobilized, the countries in the sample could have increased their income level by 73%. In other words, the countries in our sample produced on average over the study period only 27% of what they were capable of producing from their resources (capital and labor). Nevertheless, developed countries have the highest efficiency scores, with an average score of around 0.51 compared to 0.15 for developing countries (graphic 1).

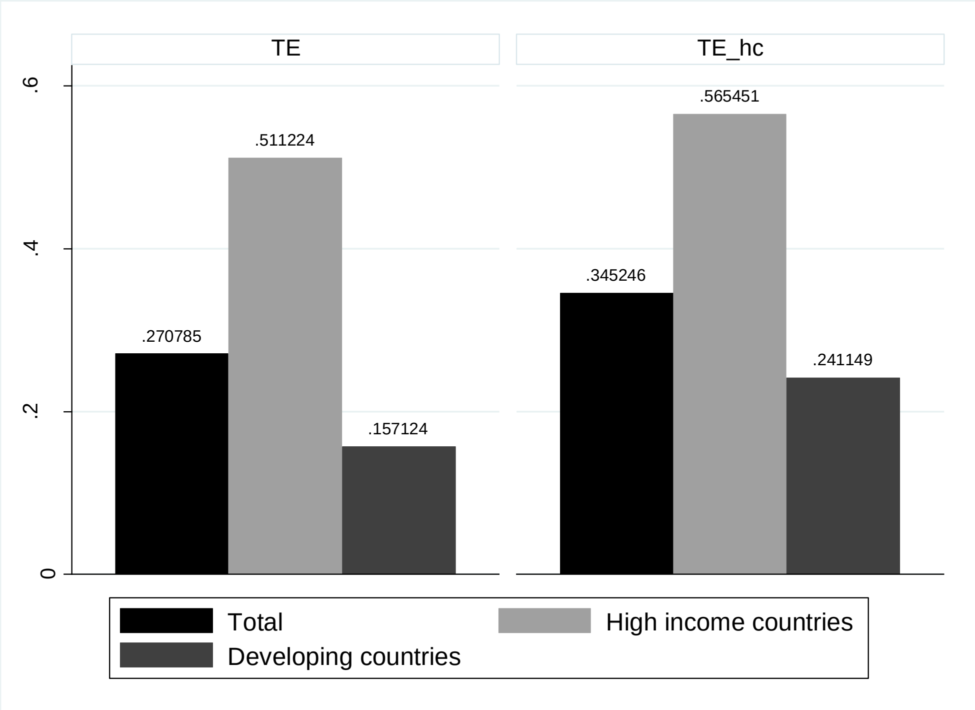
On the other hand, when the human capital index is introduced as an additional input (TE_hc), the results of the efficiency scores show a significant increase. This improvement is, however, disparate, as developing countries still score below the overall sample average with a value of 0.24 compared to 0.56 for high-income countries.

[3] Banker R.D., Charnes A., Cooper W.W. (1984). Some models for estimating technical and scales inefficiencies in Data Envelopment Analysis. Management Science, vol. 30, pp. 1078-1092.

[4] The choice of time horizon and sample size is dictated by data availability.

[5] The list of scores per country is available in the appendix, see table B.

Graphic 1: Evolution of average technical efficiency scores (1990-2018)

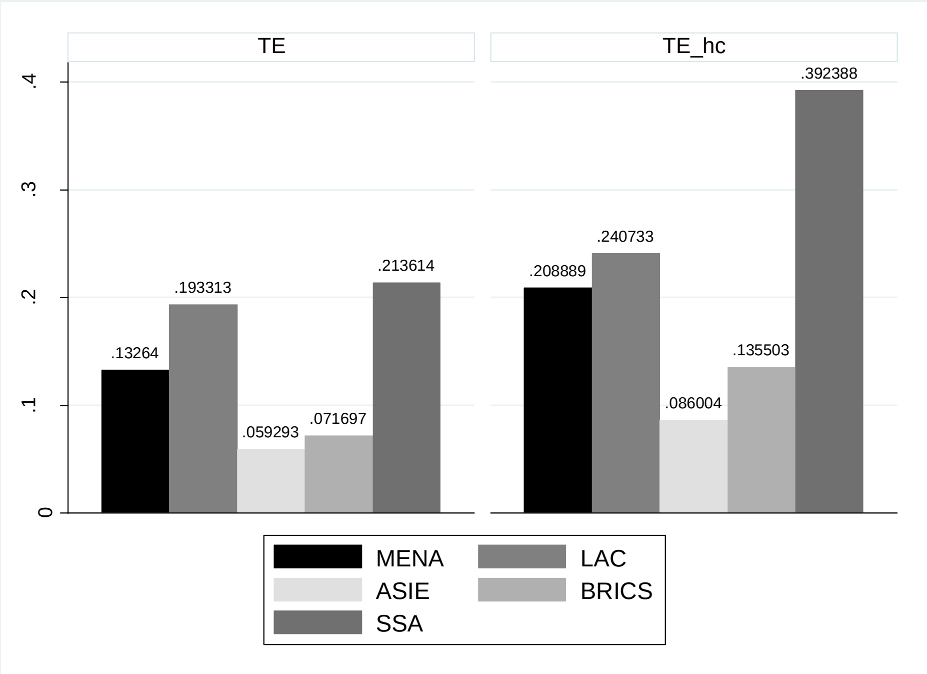


Source: *Authors calculation*.

The distribution of efficiency scores by region shows a non uniform distribution. Indeed, the Latin America (LAC) and Sub-Saharan Africa (SSA) regions show on average the highest efficiency scores among developing countries with values of 0.19 and 0.21 respectively. In contrast, only the Asian and BRICS[6] countries had the weakest performance with average efficiency scores of 0.05 and 0.71 respectively. The use of human capital quality (TE_hc) leads to an increase in efficiency scores for all regions. However, the distribution of scores remained the same (graphic 2).

[6] Brazil, Russia, India, China, South Africa.

Graphic 2: Evolution of average technical efficiency scores of developing countries by region (1990-2018)

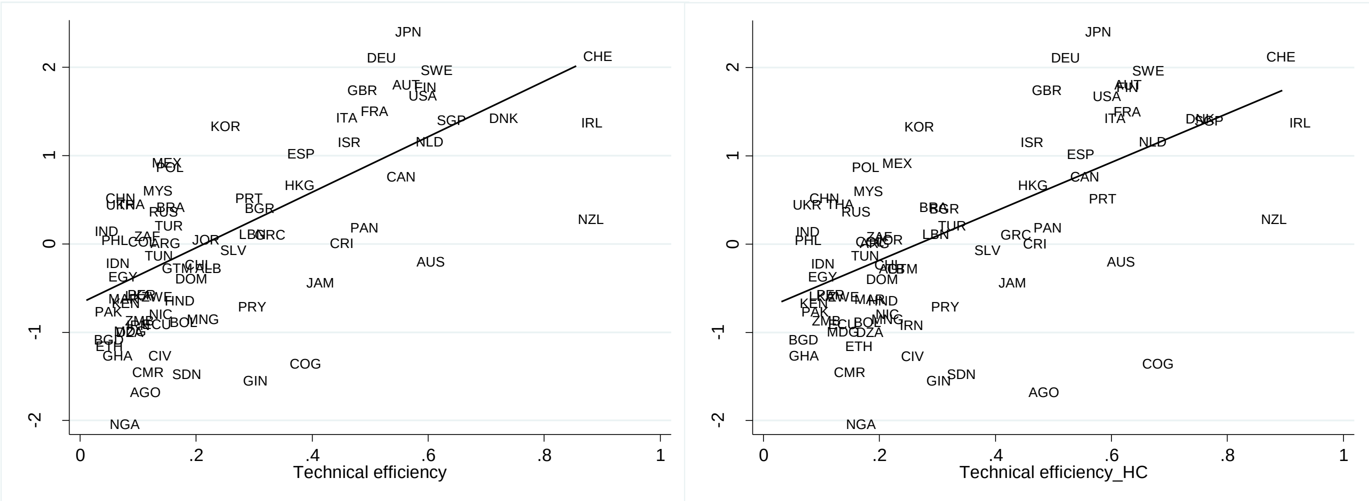


Source: *Authors calculation*.

The analysis of the interaction between the technical efficiency and economic complexity scores by country shows a positive association for both scores with and without human capital (graphic 3). This stylized fact confirms our hypothesis that the efficiency with which resources are used acts in the same direction as the economic complexity of countries. Nevertheless, the efficiency scores obtained using the quality of human capital show a strong dispersion. This supports the idea that countries with strong human capital are likely to produce more complex goods from the resources and technology at their disposal.

Indeed, several explanations can be highlighted, including in particular, the capacity to absorb new technologies and their diffusion, the availability of basic and advanced infrastructure, the regulatory system, etc. (El Mokri, 2016; Stojkoski and Kocarev (2017). All these factors can be linked both directly and indirectly to the technical efficiency of the countries in our sample.

Graphic 3: Relation Between technical efficiency and economic complexity (1990-2018)



Source : *Authors calculation.*

3. Empirical strategy and results

3.1. Presentation of the empirical model

To understand the structural characteristics - tangible and intangible - specific to each country that affect the role of efficiency in the development process, our analysis will be completed by a second step to identify the impact of efficiency on economic complexity. In this sense, we have been inspired by the empirical literature on the subject and more particularly by the work of Tasnim and Afzal (2018) and Afzal (2014). Using the generalized method of moments estimation in panel data, our study focuses on a sample panel of 55 developing countries over the period 1990 - 2018.

To this end, our econometric specification is as follows[7], where i for country and t for period:

$$\begin{aligned} \boldsymbol{ECI_{i,t}} = {} & \boldsymbol{\alpha_0 + \beta_1 ECI_{i,t-1} + \beta_2 TE_{i,t} + \beta_3 TE\_HC_{i,t} + \beta_5 FDI_{i,t} + \beta_6 TRADE_{i,t} + \beta_7 POP_{i,t}} \\ & \boldsymbol{+ \beta_8 M\_H\_TECH_{i,t} + \beta_9 INTENS_{i,t} + \beta_{10} HC_{i,t} + \beta_{11} GOUV_{i,t} + \beta_i\,(TE} \\ & \boldsymbol{* REGION) + \mu_t + \delta_i + \varepsilon_{it}} \end{aligned}$$

Where:

$\boldsymbol{ECI_{i,t}}$ **:** Economic complexity index

$\boldsymbol{ECI_{i,t-1}}$ **:** Lagged Economic complexity index

$\boldsymbol{TE_{i,t}}$ **:** Technical effciency scores, authors calculation.

$\boldsymbol{TE\_HC_{i,t}}$ **:** Technical effciency scores with human capital, authors calculation.

$\boldsymbol{FDI_{i,t}}$ **:** Foreign direct investment (% of GDP)

$\boldsymbol{TRADE_{i,t}}$ **:** Trade openness

$\boldsymbol{POP_{i,t}}$ **:** Working age population (% of total population)

[7] For sources of the variables, see Table C in the Appendix.

$\boldsymbol{M\_H\_TECH_{i,t}}$ **:** The share of the value of medium and high technologies in the total manufacturing value added

$\boldsymbol{INTENS_{i,t}}$ **:** The industrial intensity index

$\boldsymbol{HC_{i,t}}$ **:** Human capital index

$\boldsymbol{GOUV_{i,t}}$ **:** Institution quality

Given the dynamic nature of our model, we will use an alternative econometric method based on the generalized method of moments (GMM). To this end, according to Roodman (2006), the use of the OLS or fixed effects estimator could biased, mainly beacause:

- The existence of a possible endogeneity effect of the explanatory variables - due to the omission of one or more factors - which could lead to biased and inconsistent estimates;

- The presence of the lagged dependent variable on the right side of the equation, as well as the potential problem of reverse causality between explanatory variables and explained variable.

In this sense, the empirical literature proposes to types of dynamic panel data estimation method: difference and system. The difference approach was introduced by Arellano and Bond (1991), they propose to use the level lagged variables as instruments to estimate the reference equation in difference. However, according to Blundell and Bond (1998), level lags can be weak instruments, especially in small samples. To correct for this bias, the system GMM estimator combines the first difference equations with the level equations. The instruments in the first difference equation are expressed in level, and then vice versa.

The advantage of the GMM method in the analysis of our model lies both in the treatment of the problem related to the correlation of individual effects and in the possibility of accounting for the potential endogeneity of the explanatory variables. The assumption of no autocorrelation of the residuals is essential to be able to use the lagged variables as instruments for the endogenous variables.

3.2.Empirical Results

The results show that technical efficiency has a non-significant relationship with the complexity of developing countries. This result is associated with a positive correlation between the economic complexity index and its initial level. The latter refers to the existence of a divergence in complexity among all the countries in the sample.

The absence of a significant effect of technical efficiency in developing countries is inherent in the specialization model. Indeed, these economies have specialized in very specific and simple tasks, known as "task-based production". These countries have experienced a shift in comparative advantage towards low skilled labor intensive activities (Lectard, 2017). In this respect, the risk is to remain stuck in simple tasks without accumulating new productive capacities, which could represent a brake on future structural transformation (OECD, ADB and UNDP, 2014).

The importance of fundamentals is such that despite an accumulation of factor endowments, the relationship between efficiency and the level of complexity remains insignificant. In the face of weak capacities to create and diffuse innovations and knowledge, this situation tends to reduce the place of developing countries within global value chains (Lectard, 2017). In contrast to high-income countries, developing economies struggle to generate significant basic fundamentals for technology adoption and imitation through the accumulation of knowledge and know-how (Hausmann et al. 2013). This tends to reinforce the distance of developing economies from the global technology frontier (Vandenbussche et al. 2006).

Table 1 : Econometric results

Variables	1	2
ECI_{t-1}	0.695***	0.605***
TE	-0.852	-
TE_HC		0.721
TRADE	0.003***	0.004**
FDI	-0.016***	-0.019**
POP	-0.031**	-0.072**
MVHA	0.932**	1.351**
INDINT	-0.262	-0.052
GOUV	-0.0008	0.0007
TE_MENA	3.654**	2.235*
TE_LAC	1.219*	-0.188
TE_ASIE	-3.293**	-2.201*
TE_BRICS	6.945***	4.462**
TE_SSA	0.857	-0.315
Constante	-0.432***	-0.723***
AR(1)	0.000	0.000
AR(2)	0.633	0.478
Hansen test	0.101	0.230

Source : *Authors calculation. Note : Significant coefficient à 10%*,5%**,1%***.*

If we look at the structural factors, we find that the variables TRADE and FDI have positive and negative values respectively. In addition to the disadvantages of international competitiveness, the demographic factor, industrial intensity and the institutional framework represent a major brake on improving the complexity of exports. On the other hand, only the total manufacturing value added acts as an inhibiting effect to a better insertion in the value chains.

The introduction of interaction variables allows us to capture the effect of technical efficiency on complexity by region. Our results show a positive and significant effect of technical efficiency in the MENA and BRICS countries. In contrast, the Asian region shows a negative relationship with economic complexity. In addition, technical efficiency shows a positive effect for the LAC region, however this result becomes negative when considering human capital.

As for the statistical validity of our different results, the Hansen test on the restrictions of over-identification confirms the validity of the instruments, the probabilities associated with this test are higher than 5%. On the other hand, the probabilities associated with the AR(1) and AR(2) tests are respectively lower than 5% and higher than 5%. We therefore accept the presence of an AR(1) effect for the residuals and we accept the absence of an AR(2) effect.

Conclusion

Recent changes in the global economy have shown the importance for developing countries to identify the factors that influence their productive structures. This is especially true since recent literature has highlighted the role of knowledge and economic complexity as drivers of structural transformation. To this end, as countries specialize in different activities, the efficiency with which an economy uses its resources becomes a key element in the development process.

The objective of this work was to study the process of economic complexity of developing countries by exploiting the factor of technical efficiency. In this sense, we have adopted a two-step approach, first, we have calculated the efficiency scores. Then, we carried out an econometric estimation of the relationship between technical efficiency and economic complexity for the case of developing countries.

The results show that technical efficiency has a non-significant relationship with complexity in developing countries. This result is associated with a positive correlation between the economic complexity index and its initial level. The latter refers to the existence of a divergence in complexity among all the countries in the sample. In contrast, the regional distribution of developing countries shows disparate effects. Technical efficiency has a negative effect on economic com-plexity for countries in the Asian region. In contrast, only the BRICS region shows a high positive and significant coefficient on technical efficiency.

These results could be explained by the fact that developing countries have specia-lized in very precise and simple tasks, known as "task-based production", and have thus switched to low-skilled labor-intensive activities. Moreover, this situation has led developing economies to specialize in limited production activities, in other words, to an "impoverishing specialization".

In conclusion, it can be said that the accumulation and diffusion of knowledge is a constraint on the productivity of developing countries and thus on their competitiveness with other global players in world markets. The channels through which technology transfer can occur include the import of intermediate goods, learning through export and foreign direct investment.

Our study can be improved in three way. First, it can be useful the relation between technical efficiency and economic complexity across sectors/industries. Second, economic complexity focuses only on exported goods, but not on tasks produced in the economy, possibly not reflecting accurately the nature of the productive structure. Third, it is possible to explore an exogenous instrument as an alternative to the lags, offering further robustness and validity to our results.

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Appendix

A: calculation of the Economic Complexity Index

The calculation of the economic complexity index is based on exports data where the matrix M_{cp} which takes 1 if the country c produces the good p, and 0 otherwise. This matrix is given by the following formula

$$M_{cp} = \begin{cases} 1 \ \ si\ RCA_{cp} \geq 1 \\ 0\ otherwise \end{cases}$$

RCA_{cp}refers to the revealed comparative advantage of a country over a given product defined by Balassa (1965) as follows:

$$RCA_{cp} = \frac{X_{cp} \big/ \sum_c X_{cp}}{\sum_p X_{cp} \big/ \sum_{c,p} X_{cp}}$$

From the M_{cp}, we can obtain the two main indicators to calculate the economic complexity index:

$$UBIQUITE_k = K_{k,0} = \sum_j M_{jk}$$

$$DIVERSITE_J = K_{J,0} = \sum_k M_{jk}$$

Where j denotes the country, k the product, and M_{jk} is a dummy variable equal to 1 if country j exports product k with revealed comparative advantage and 0 otherwise.

The complexity index is then given as follows:

$$ECI = \frac{\vec{K} - \langle \vec{K} \rangle}{stdev(\vec{K})}$$

For a given country, the economic complexity index is calculated as the eigenvalue of $\vec{\boldsymbol{K}}$ minus the annual average over the **K** products, all divided by the annual standard deviation.

B: Value of efficiency scores by country

Countries	1990	2000	2018
Albania	0.122	0.154	0.338
Algeria	0.056	0.044	0.052
Angola	0.113	0.063	0.053
Argentina	0.111	0.101	0.114
Bangladesh	0.015	0.010	0.012
Bolivia	0.112	0.123	0.196
Brazil	0.124	0.108	0.120
Bulgaria	0.333	0.206	0.309
Cameroon	0.091	0.067	0.091
China	0.011	0.022	0.080
Colombia	0.072	0.060	0.083
Congo, Rep,	0.255	1.000	0.197
Costa Rica	0.346	0.348	0.596
Cote d'Ivoire	0.100	0.100	0.100
Dominican Republic	0.152	0.137	0.199
Ecuador	0.135	0.084	0.091
Egypt	0.085	0.034	0.031
El Salvador	0.187	0.208	0.318
Ethiopia	0.017	0.013	0.013
Gabon	1.000	1.000	1.000
Ghana	0.026	0.024	0.032
Guatemala	0.154	0.126	0.142
Guinea	0.048	0.060	1.000
Honduras	0.128	0.113	0.183
India	0.009	0.010	0.022
Indonesia	0.027	0.026	0.045
Iran	0.065	0.059	0.076
Jamaica	0.343	0.405	0.379
Jordan	0.193	0.191	0.151
Kenya	0.052	0.036	0.045
Lebanon	0.211	0.325	0.209
Madagascar	0.051	0.041	0.050
Malaysia	0.088	0.086	0.128
Mexico	0.121	0.113	0.113
Mongolia	0.153	0.140	0.324
Morocco	0.045	0.032	0.036
Mozambique	0.125	1.000	0.061
Nicaragua	0.074	0.083	0.189
Nigeria	0.055	0.051	0.026
Pakistan	0.019	0.011	0.013
Panama	0.323	0.386	0.540
Paraguay	0.275	0.213	0.374
Peru	0.091	0.049	0.089
Philippines	0.027	0.020	0.033

Russia	**0.149**	**0.079**	**0.126**
Senegal	**0.085**	**0.068**	**0.109**
South Africa	**0.098**	**0.073**	**0.082**
Sri Lanka	**0.054**	**0.072**	**0.066**
Sudan	**1.000**	**0.116**	**0.037**
Thailand	**0.041**	**0.042**	**0.067**
Tunisia	**0.116**	**0.078**	**0.100**
Turkey	**0.105**	**0.101**	**0.162**
Ukraine	**0.062**	**0.022**	**0.033**
Zambia	**0.081**	**0.051**	**0.067**
Zimbabwe	**0.114**	**0.093**	**0.128**
Australia	**0.558**	**0.543**	**0.613**
Austria	**0.543**	**0.514**	**0.536**
Canada	**0.524**	**0.482**	**0.559**
Denmark	**0.739**	**0.684**	**0.718**
Finland	**0.552**	**0.504**	**0.738**
France	**0.505**	**0.469**	**0.470**
Germany	**0.504**	**0.465**	**0.512**
Greece	**0.307**	**0.285**	**0.252**
Hong Kong	**0.428**	**0.282**	**0.414**
Ireland	**0.886**	**0.976**	**1.000**
Israel	**0.516**	**0.345**	**0.496**
Italy	**0.480**	**0.445**	**0.383**
Japan	**0.592**	**0.516**	**0.530**
Korea, South	**0.132**	**0.189**	**0.300**
The Netherlands	**0.555**	**0.569**	**0.589**
New Zealand	**0.832**	**0.760**	**0.992**
Norway	**1.000**	**1.000**	**1.000**
Poland	**0.094**	**0.104**	**0.173**
Portugal	**0.272**	**0.263**	**0.255**
Singapore	**0.834**	**0.588**	**0.627**
Spain	**0.350**	**0.348**	**0.353**
Sweden	**0.596**	**0.550**	**0.628**
Switzerland	**1.000**	**0.830**	**0.849**
United Kingdom	**0.446**	**0.437**	**0.470**
United States of America	**0.560**	**0.548**	**0.583**
Chile	**0.179**	**0.148**	**0.165**

Source : *Authors calculation.*

C: List of variables and data source

<table>
<tr><th>Variables</th><th>Source</th></tr>
<tr><td>GDP per capita</td><td>World Bank-World Development Indicators</td></tr>
<tr><td>Total employment</td><td>Penn World Tables 9.1.</td></tr>
<tr><td>Capital stock</td><td>Penn World Tables 9.1.</td></tr>
<tr><td>Economic complexity index</td><td rowspan="5">World Bank-World Development Indicators</td></tr>
<tr><td>Technical efficiency score</td></tr>
<tr><td>Foreign direct investment</td></tr>
<tr><td>Trade openness (Exports +Imports/GDP)</td></tr>
<tr><td>Working age population (% of total population)</td></tr>
<tr><td>Human capital index</td><td>Penn World Tables 9.1.</td></tr>
<tr><td>The share of the value of medium and high technologies in the total manufacturing value added</td><td rowspan="2">United Nations Industrial Development Organization (UNIDO).</td></tr>
<tr><td>The industrial intensity index</td></tr>
<tr><td>Institution quality</td><td>Polity IV project- Center for Systemic Peace</td></tr>
</table>