Economic complexity and human development: comparing standard and slack-based data envelopment analysis models

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Abstract

Several studies have argued economic complexity is an alternative way to understand well-being. There is a growing literature using standard data envelopment analysis (DEA), but we did not find studies comparing them with more advanced models, such as slack-based measure (SBM), or considering economic sophistication as an input in human development. To fill the gap, this article aims to compare standard models with SBM DEA models as tools for measuring countries' efficiency in converting economic complexity into human development. We developed the Composite Index of Human Development and Economic Complexity (CIHD-EC) and used it to analyse 50 countries with data from 2013, finding that the standard models overestimated countries' efficiency, especially that of developed and prosperous countries. In contrast, the SBM model provides a better ranking. Lastly, the CIHD-EC shows that Singapore is the only economy in the world that is efficient at transforming economic complexity into human development.

Keywords

Economics, economic growth, human development, development models, development indicators, measurement, econometric models

JEL classification

O14, O15, O3

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I. Introduction

Economic growth cannot provide a full understanding of human development and well-being. Sen (2001) developed the human capabilities approach, prompting the creation in a number of studies of new indicators for understanding human development (Despotis, 2005a and 2005b; Zhou and Zhou, 2010; Morais and Camanho, 2011; Toffalis, 2014; Mariano and Rebelatto, 2014). For example, the transformation of wealth into human development was dubbed social efficiency (a structural literature review can be found in Mariano, Sobreiro and do Nascimento Rebelatto, 2015) in an approach that aims to show how countries can use their wealth to improve several aspects of quality of life, such as education, health, sanitation and employment. However, the social efficiency approach has many gaps (Mariano, Sobreiro and do Nascimento Rebelatto, 2015). For example, different models have to be compared to measure social efficiency, and there is a need to understand which variables apart from economic growth can explain human development (Mariano, Sobreiro and do Nascimento Rebelatto, 2015).

A new theoretical approach argues that economic sophistication influences several dimensions of human capabilities, since technological goods depend on available knowledge for their production (Hidalgo and Hausmann, 2009; Hausmann and others, 2014; Hartmann, 2014; Guevara and others, 2016; Hartmann and others, 2017; Hidalgo and others, 2007). Thus, on the one hand, economic complexity requires more human capabilities, and on the other, it affects living conditions such as education levels, health systems, infrastructure (ports, roads and airports), the labour market and wages (Hartmann, 2014; Hartmann and others, 2017). Economies are capable of generating useful knowledge through a network of people producing a variety of high-technology products, which can be translated into human development (Hausmann and others, 2014; Hartmann and others, 2017).

The literature demonstrates that economic complexity can improve the production structure, creating better conditions and more opportunities for people to develop their capacities and increase the social progress of a nation. A sophisticated country creates new sectors and generates better-quality jobs, and the country becomes more resilient to economic crises. Thus, the literature has shown the importance of economic complexity to economic development and well-being (Hartmann, 2014; Hartmann and others, 2017; Antonelli, 2016; Ferrarini and Scaramozzino, 2016; Guevera and others, 2016).

Despite the growing literature, these studies have not analysed how efficient any country is at transforming economic complexity into human development. A simple way to do this is to create an indicator using the data envelopment analysis (DEA) technique. DEA can help to address this difficult question because it allows economic complexity and human development to be measured in a single indicator. DEA uses methods from linear mathematical programming to measure how efficient decision-making units (e.g., in our case countries) are at translating inputs (e.g., economic complexity) into the highest possible levels of output (e.g., human development). DEA methods can be used to reveal the maximum number of social outputs that can be produced per unit of economic complexity by comparator countries or regions. Thus, DEA is ideally suited to measuring how efficient nations are at converting their economic structure into human capabilities. This permits better identification of inefficiencies and bottlenecks in countries as well as facilitating learning from more efficient regions that achieve higher levels of human development with an equally or less developed production structure. This indicator is relevant because it reveals best practices around the world, information that is crucial for policymakers. With it, authorities can compare regions and evaluate public and industrial policies.

A contribution of this paper is to compare standard DEA models, such as constant returns to scale (CRS) and variable returns to scale (VRS) models, with slack-based measure (SBM) models. Studies comparing DEA models in this field might show the importance of using models suited to the human development index approach, but we found none in the literature. To answer the questions raised, this study aims to compare standard and SBM DEA models, measuring how efficient countries are at converting economic complexity into human development by looking at 50 countries around the world with 2013 data available from a database developed by the World Bank (2018a). This information is used in a new indicator we have developed, the Composite Index of Human Development and Economic Complexity (CIHD-EC), to show how economic complexity is transformed into human development.

The remainder of this article is structured as follows. Section II reviews the literature on economic growth, human development and economic complexity. Section III introduces DEA models and presents our methodology. Section IV gives the results, discusses our models and findings, presents the Composite Index of Human Development and Economic Complexity (CIHD-EC) and provides some maps for illustration purposes. Lastly, section V provides concluding remarks.

II. Literature review

1. Human development and economic growth

Inclusive growth is a global concern. According to the International Monetary Fund (IMF, 2017), both large and small countries with developed or advanced economies have struggled to provide employment for the entire labour force. Furthermore, countries need to equalize opportunities of access to markets and resources. This new concept of economic growth is aligned with the human development perspective presented by the United Nations Development Programme (UNDP, 2016). Economic growth is commonly regarded as the only way to achieve economic development and increase human capabilities. However, the United Nations has shown that the relationship between economic growth and human development is complex, meaning that suitable methods are required to understand this process (UNDP, 2000).

To better understand the relationship, Sen (1998) analysed the correlation between income and life expectancy in a number of countries. The author found that some countries with relatively low incomes achieved relatively high life expectancy. Furthermore, some low-income countries had similar life expectancy to high-income nations. This complex phenomenon shows that economic growth does not guarantee human development (Sachs, 2004; Schumpeter, 1982), so that an alternative or new interpretation of this process is required. Other studies have argued that economic sophistication can improve the ability of a nation to deal with social problems and promote better human development (López, Thomas and Wang, 2008; Hartmann, 2014; Guevara and others, 2016; Hartmann and others, 2017). Accordingly, a number of them have focused on analysing how economic sophistication affects human development through economic complexity. The next section discusses how economic complexity can improve human development.

2. Economic complexity: innovation and structural change

Many economic sectors have been created since the Industrial Revolution, changing the goods produced and the social actors involved in the economic development process (Saviotti and Pyka, 2013). This is important because, according to Prebisch (1962) and Furtado (1959), the limitations of the production structure were responsible for countries' problems with income distribution and employment. Structural factors such as the aggregate value of agriculture, industry and services, the size of the urban population, educational levels and demographic patterns in the form of fertility and mortality rates are associated with economic development and play an essential role in explaining inequality between countries (IMF, 2017). A new approach, called economic complexity, revisited this issue, analysing the importance of economic sophistication and the export basket to economic growth and social matters (Hidalgo and others, 2007; Agosín, 2009; Hidalgo and Hausmann, 2009; Hausmann and others, 2014; Hartmann and others, 2017).

The economic complexity argument is that countries with high per capita incomes are characterized by the diversification of their export agenda and ability to export technology-intensive products (Tacchella and others, 2013; Ferrarini and Scaramozzino, 2016; Tacchella and others, 2013; Gala, 2017; Gala, Camargo and Freitas, 2017). Thus, economic complexity is defined by the types of products a country develops, with the production of technological products perhaps involving the combination of multiple kinds of available knowledge. In a complex economy, individuals work in a variety of jobs (finance, marketing, technology, human resources, operations, law) and need to interact and combine their knowledge to make sophisticated and valuable products. In contrast, when a nation lacks human capital, it is not possible to create new sectors or technological products, increase wealth and improve living conditions (Hausmann and others, 2014).

Economic complexity generates wealth because competitive advantage increases exports of high-technology products. According to Tacchella and others (2013), countries with a more exceptional ability to produce sophisticated goods are likely to have higher incomes than less productive countries. This is because countries that rely on commodity exports face macroeconomic volatility due to unpredictable commodity prices and real exchange-rate volatility, which discourages investment in tradable goods and services (Agosín, 2009; Ferrarini and Scaramozzino, 2016; Nkurunziza, Tsowou and Cazzaniga, 2017).

The sophistication of an economy can be measured by the Economic Complexity Index (ECI), which is calculated with data from the United Nations (Hidalgo and Hausmann, 2009). However, the ECI has been criticized for its theoretical and mathematical formulation, which makes it difficult to ascertain the real importance of economic sophistication in a country (Tacchella and others, 2013). Another issue arises because the ECI presents positive and negative values, making its use in econometric and DEA models problematic.

An alternative way of understanding economic complexity is to use the elements that influence economic sophistication. Two main elements affect economic complexity: (i) the diversification of exports, i.e., the ability to export high-technology products, and (ii) research and development (R&D) expenditure. R&D is vital because diversification and the exporting of high-technology products require innovation. Companies carry out R&D to generate better-quality goods, create new procedures and make production more efficient. It is research that provides the knowledge necessary for the creation of innovations (Saviotti and Pyka, 2004). In addition, new sectors and product improvements compensate for the decreasing capacity of established sectors and provide new jobs for skilled workers (Saviotti and Pyka, 2013).

According to Saviotti and Pyka (2004), R&D is the most common but not the only example of the research and innovation activities that take place in companies. R&D is considered a non-standard input that determines a significant percentage of the efficiency and competitiveness of enterprises. In developed economies, it occurs primarily in the agricultural machinery and equipment industry, which is generally the core of the capital goods sector, serving as the first step towards the creation of new sectors (Moralles and Rebelatto, 2016).

The structural change caused by innovation does more than anything else to create new sectors and sustain economic development (Saviotti, Pyka and Jun, 2016). It requires technical and social changes, as well as the development of new skills useful to companies and society (Kruss and others, 2015). An economy focused on the export of technological products and R&D tends to grow and develop socially.

One example are the urban centres present in complex economies. They tend to have better infrastructure and require more capabilities from the agents operating there. Hartmann (2014) argues that the region where people live influences their abilities. The jobs generated in urban centres are generally technologically intensive, requiring more substantial technical training than jobs elsewhere and a network of knowledge shared by a number of individuals. This demonstrates the influence of economic complexity on human development.

3. Linking economic complexity and human development

According to Hausmann and others (2014), knowledge plays a crucial role in complex economies, leading to better living conditions. For example, Hartmann and others (2017) find a strong correlation between economic complexity, income equality, education and GDP growth. In other words, complex countries have higher GDP growth, greater human capital and better income distribution, providing local citizens with better labour market opportunities and adequate access to health and education systems.

For Ferrarini and Scaramozzino (2016), economic complexity requires a better education because it influences the development of new skills and human capital formation. A growing and modernizing economy requires public policies to provide the conditions for greater innovation, competitiveness and economic diversification. Mustafa, Rizov and Kernohan (2017) point out that advanced Asian economies such as Japan, the Republic of Korea and Taiwan have presented rapid human development, bringing them to levels similar to those of the advanced industrialized countries. As a result, these countries have achieved exceptionally high rates of economic growth over the past 30 to 40 years. For example, Japan has the highest life expectancy among the countries analysed, and South Korea presents increasing labour productivity, linked to the great improvement in accumulated human capital. In contrast, China still presents significant shortfalls in human capital, indicating that the Chinese government could stimulate economic growth by investing in education (Lee, 2016).

Hartmann and others (2017) compared income inequality and economic complexity between Latin America and some Asian countries (China, Malaysia, the Republic of Korea and Singapore). Although Latin American economies showed social improvements due to rising commodity prices during the 2000s, the region did not diversify economically, and this was reflected by the lack of better job opportunities. On the other hand, Asian countries invested in human capital and technological innovation, which changed the region's export basket, increased its competitiveness and put it in a stronger position to face economic crises (Lee, 2017).

Structural change is essential because new technological sectors raise average wages and the demand for skilled labour, which requires higher educational levels (Antonelli, 2016). Vocational education increases per capita incomes and consumer purchasing power, as well as improving the quality of goods produced by skilled workers. This virtuous cycle plays a fundamental role in transforming societies with an abundance of low-skilled workers (Saviotti, Pyka and Jun, 2016).

Ferrarini and Scaramozzino (2016) showed that increasing complexity had increased the accumulation of human capital by promoting the acquisition of skills and learning. There was a positive coefficient between education and per capita output. The labour force participation coefficient was negative owing to the low rate of substitution between the factors of production and the employed labour force in weaker economies. Furthermore, Asian countries showed sustained growth, while France, Germany, Italy, Spain, the United Kingdom and the United States showed slow growth.

4. Structural change and public policies

Studies have discussed how structural change and public policies influence countries' development. In Japan, agricultural mechanization freed the labour force to enter the industrial sector, raising wages and generating urbanization. This process lasted more than 15 years and occurred because productivity grew in all economic sectors. In non-agricultural activities, productivity increased because of the adoption, imitation and assimilation of the technical knowledge flows of the advanced nations, which depended on the level of human capital (Esteban-Pretel and Sawada, 2014).

This structural change occurred because the Japanese government subsidized prices and investments with a view to mechanizing agriculture. To promote industrial development, the government lowered the interest rate and raised the level of loans and investments for the sector. These investments financed public enterprises involved with infrastructure. Low interest rates allowed the development of strategic sectors such as maritime transport, electric power, shipbuilding, automobile and machinery manufacturing, iron and steel, coal mining and petroleum refining (Esteban-Pretel and Sawada, 2014).

Another example is South Korea, where development policy is based on exports. According to Lee (2016), trade liberalization allowed intermediate goods to be imported more cheaply and provided access to advanced technologies, contributing to the rapid growth of industrial productivity. An industrialization-oriented export policy encouraged exporters, generating comparative advantages for Korean companies in international trade. Labour-intensive industries gave way to capital-intensive ones in the fields of electronics, machinery, automobiles, ships, and information and communications technology. As a result of this strategy, Korean per capita income rose to the level of developed countries, providing better living conditions for the country's citizens.

China has been growing at an average of 9.5% per year, although the Chinese economy still lags behind those of other Asian countries (Lee, 2016). For example, China's GDP per capita in 2011 (US$ 8,850 at purchasing power parity) was comparable to that of Korea in 1988 (US$ 9,137 at purchasing power parity) and Japan in 1968 (US$ 9,527 at purchasing power parity). Furthermore, China's relative productivity (44%) in 2010 was lower than Korea's in 1980. Lee (2016) states that the Chinese economy is more than 20 years behind Korea and more than 40 years behind Japan. For China to move from a low-income to a high-income economy, it needs to develop more technologically sophisticated industries (Lee, 2017), and its technological progress depends on policies to promote technological innovation, increase R&D investment and upgrade the industrial sector.

Singapore is a high-income economy and provides an excellent environment for business, with friendly regulatory conditions for local entrepreneurs, so that the country ranks among the world's most competitive economies. Singapore industrialized quickly during the 1960s (World Bank, 2018b), and the manufacturing sector drives its economic growth. For example, Singapore grew by 3.2% in 2018, with growth concentrated in value added manufacturing products such as electronics and precision engineering, information and communications industries, and finance and insurance (IMF, 2017). Furthermore, the Singaporean government has applied strong public education and human capital policies (Gopinathan, 2007), so that, according to the World Bank Human Capital Index (2018), it is the best country in the world for human capital development: the average Singaporean child will be 88% as productive when they grow up as if they enjoyed a full education and perfect health.

In contrast, Latin America adopted a much-criticized development model in which the productive modern sector competes with the primary production sector. The availability of land for cultivation absorbs rural workers and migrants, displacing skilled labour from other sectors of the economy. The region is susceptible to so-called Dutch disease, because when commodity prices increase, production and employment growth centre on the commodity export basket it specializes in (Barbier and Bugas, 2014). For example, data from the World Bank (2018a) show that 55.3% of total exports are commodities. Moreover, only 20.8% of the workforce is allocated to the industry sector. From a social perspective, 41.2% of the Latin American population is poor, and there are a number of problems with transport systems, infrastructure and the international competitiveness of the region's products.

Brazil is the biggest country in Latin America, and the Brazilian government still needs to improve its industrial development strategy. One successful example is the adoption of biotechnology for soy production, which has reduced labour intensity in agriculture and expanded employment in industry (Bustos, Caprettini and Ponticelli, 2016). Another example is the mechanization of sugar cane cultivation, which has virtually eliminated migratory flows in the poorest regions and has generated employment opportunities for skilled labour in the country (Moraes, Oliveira and Diaz-Chavez, 2015). On the other hand, there are examples of the adoption of technology being detrimental to local industry, such as the development of a technology that increased the area planted with maize, leading to an increase in the agricultural workforce and a contraction in industrial employment (Bustos, Caprettini and Ponticelli, 2016).

Technological specialization in specific sectors, such as agriculture in Brazil, is due to the adaptation of appropriate technologies to the inputs available in the local economy. Antonelli (2016) argues that technologically backward countries adapt the technological resources of the advanced countries, which reduces technological congruence and total factor productivity. Industrial policies in developing countries should favour structural changes that reinforce the supply of the region's main factors of production, together with a training policy that supports the creation of skills and capabilities for the region's human capital, generating social and economic development.

III. Methodology

1. The database

To evaluate the transformation of economic complexity into human development in 2013, we collected data on 50 countries available from the World Bank database.[2] This database covers four main dimensions of human development: education, health, sanitation and employment. We also selected two variables to represent economic complexity, namely exports of high-technology products and R&D expenditure.

The inputs used in this study are exports of high-technology products as a proportion of GDP (EHTP/GDP) and R&D expenditures (R&D-E) as a proxy for economic complexity. According to the literature, a country must export products with high value added to benefit from comparative advantage and international competitiveness, while R&D is essential because it allows new sectors and products to emerge (Chen, Chen and He, 2014; Waelbroeck, 2003; Caminati, 2006; Amsden and Tschang, 2003). Our outputs are: (i) life expectancy at birth (LEB); (ii) mean years of schooling (MYS); (iii) the sanitation rate (SR) and (iv) the employment rate (ER). Table 1 summarizes the selected variables.

Table 1
Variables used in the data envelopment analysis model

Variable	Source	Type	Literature
EHTP/GDP	World Bank	Input	Chen, Chen and He (2014); Waelbroeck (2003); Caminati (2006); Amsden and Tschang (2003); Hartmann (2014); Hartmann and others (2017)
R&D-E	World Bank	Input	Chen, Chen and He (2014); Waelbroeck (2003); Caminati (2006); Amsden and Tschang (2003); Hartmann (2014); Hartmann and others (2017)
LEB	World Bank	Output	Despotis (2005a); Reig-Martínez (2013)
MYS	World Bank	Output	Despotis (2005b); Mariano and Rebelatto (2014)
ER	World Bank	Output	Morais and Camanho (2011); Reig-Martínez (2013)
SR	World Bank	Output	Mariano and Rebelatto (2014); Reig-Martínez (2013)

Source: Prepared by the authors, on the basis of Amsden, A. H. and F. T. Tschang (2003), "A new approach to assessing the technological complexity of different categories of R&D (with examples from Singapore)", *Research Policy*, vol. 32, No. 4; Chen, X., G. Chen and Y. He (2014), "Trade on high-tech complex products", *Information Technology Journal*, vol. 13, No. 15; Caminati, M. (2006), "Knowledge growth, complexity and the returns to R&D", *Journal of Evolutionary Economics*, vol. 16, No. 3; Despotis, D. K. (2005a), "A reassessment of the human development index via data envelopment analysis", *Journal of the Operational Research Society*, vol. 56, No. 8; Despotis, D. K. (2005b), "Measuring human development via data envelopment analysis: the case of Asia and the Pacific", *Omega*, vol. 33, No. 5; Hartmann, D. (2014), *Economic Complexity and Human Development: How Economic Diversification and Social Networks Affect Human Agency and Welfare*, London, Routledge, Taylor & Francis Group; Hartmann, D. and others (2017), "Linking economic complexity, institutions, and income inequality", *World Development*, vol. 93; Mariano, E. B. and D. A. D. N. Rebelatto (2014), "Transformation of wealth produced into quality of life: analysis of the social efficiency of nation-states with the DEA's triple index approach", *Journal of the Operational Research Society*, vol. 65, No. 11; Morais, P. and A. S. Camanho (2011), "Evaluation of performance of European cities with the aim to promote quality of life improvements", *Omega*, 39, No. 4; Reig-Martínez, E. (2013), "Social and economic wellbeing in Europe and the Mediterranean Basin: Building an enlarged human development indicator", *Social Indicators Research*, vol. 111, No. 2; Waelbroeck, P. (2003), "Innovations, production complexity and the optimality of R&D", *Economics Letters*, vol. 79, No. 2.

Note: EHTP/GDP: exports of high-technology products as a proportion of GDP; R&D-E: research and development expenditure; LEB: life expectancy at birth; MYS: mean years of schooling; ER: employment rate; SR: sanitation rate.

[2] The countries analysed are listed in table 3.

Since our analysis measures the efficiency of economic complexity in bringing about human development, we only analyse economic complexity inputs. We do not analyse public expenditure, even though it is relevant, since it would yield a different kind of efficiency ranking. Future studies can use DEA models to compare the efficiency of social expenditure in different regions.

Following collection of the data, the variables were analysed using a correlation matrix and linear regression. Econometric validation was carried out, then the standard DEA models (CRS and VRS), the slack-based measure (SBM) model and the inverted frontier were estimated. The models are output-oriented, on the basis that each country will seek to maximize outputs (human development) without reducing inputs (economic complexity).

2. Econometric validation

DEA is a non-parametric technique requiring econometric validation to prove causality (Charnes, Cooper and Rhodes, 1978; Cook and Zhu, 2014; Mariano, Sobreiro and do Nascimento Rebelatto, 2015). For this reason, we validate our data with eight econometric panel fixed-effect models (from 2010 to 2013). Although several studies have used DEA to measure human development without presenting a statistical validation (Murias, Martínez and De Miguel, 2006; Somarriba and Pena, 2009; Martín and Mendoza, 2013; Mariano, Sobreiro and do Nascimento Rebelatto, 2015), our study uses econometric models to show the correlation between at least one input and one output. This is in line with previous DEA approaches, with Mariano and Rebelatto (2014), for example, using a correlation matrix to validate inputs and outputs. Our validation shows that most of the variables are statistically significant, proving the impact of economic complexity on human development, which validates the DEA procedure. The estimates are presented in annex A1.

The matrix of correlation between inputs and outputs shows that all social variables except mean years of schooling and the employment rate have a statistically significant correlation. All variables present the expected sign. R&D expenditure shows the highest correlation with life expectancy (16.71%), followed by the sanitation rate (12.12%). This means that more R&D expenditure increases life expectancy, access to basic sanitation, education and employment. Exports of high-technology products (EHTP/GDP) show positive and statistically significant correlation with all social variables. Life expectancy (23.94%) is the social variable presenting the highest correlation, followed by the employment rate (22.11%), the sanitation rate (15.87%) and mean years of schooling (12.41%). In other words, a country that exports technological products increases human development through education, basic sanitation, employment and life expectancy.

Regarding mean years of schooling, econometric model 5 shows that R&D-E is statistically significant at the 5% level and has the expected (positive) sign. It should be noted that spending on R&D (0.0114%) explains more years of study than GDP (0.0084%). This result shows that investment in innovation has a 0.0114% impact on mean years of schooling.

For life expectancy, econometric model 1 shows that R&D-E is statistically significant at the 1% level. It also explains more of the variation in life expectancy (0.0113%) than the economically active population (0.0041%). Furthermore, the EHTP/GDP variable shows a sign expected only in model 6.

Regarding the sanitation rate, model 3 proves that R&D-E has positive and statistically significant impacts on sanitation (0.0047%). Regarding the employment rate, both R&D-E and EHTP/GDP show a positive impact. In addition, EHTP/GDP impacts the employment rate by 0.010% in model 3.

In summary, the econometric analysis shows that the inputs selected for this study are correlated with the social variables (outputs) and that this correlation is statistically significant, confirming the theoretical assumptions previously discussed (Hidalgo and Hausmann, 2009; Hartmann, 2014; Hausmann and others, 2014; Hartmann and others, 2017; Antonelli, 2016).

3. Data envelopment analysis

Data envelopment analysis (DEA) is based on linear programming developed by Charnes, Cooper and Rhodes (1978).

The method presents different kinds of models and assumptions such as (i) returns to scale, (ii) orientation and (iii) input and output combinations. According to Mariano and Rebelatto (2014), the type of returns to scale distinguishes the two principal DEA models: constant returns to scale (CRS) and variable returns to scale (VRS). Table 1 shows the formulations of the CRS and VRS models in their two possible orientations. Table 2 shows the mathematical formulation of the VRS model in its two orientations.

Table 2
Main data envelopment analysis radial models in the form of multipliers

Model	Input-oriented	Output-oriented
Constant returns to scale (CRS)	$MAX\sum_{i=1}^{m} u_i \cdot y_{i0}$ Subject to: $\sum_{j=1}^{n} v_j \cdot x_{j0} = 1$ $\sum_{i=1}^{m} u_i \cdot y_{ik} - \sum_{j=1}^{n} v_j \cdot x_{jk} \leq 0 \quad \text{for } k = 1, 2, ..., h$	$MIN\sum_{i=1}^{n} v_j \cdot x_{j0}$ Subject to: $\sum_{j=1}^{m} u_i \cdot y_{i0} = 1$ $\sum_{i=1}^{m} u_i \cdot y_{ik} - \sum_{j=1}^{n} v_j \cdot x_{jk} \leq 0 \quad \text{for } k = 1, 2, ..., h$
Variable returns to scale (VRS)	$MAX\sum_{i=1}^{m} u_i \cdot y_{i0} + w$ Subject to: $\sum_{j=1}^{n} v_j \cdot x_{j0} = 1$ $\sum_{i=1}^{m} u_i \cdot y_{ik} - \sum_{j=1}^{n} v_j \cdot x_{jk} + w \leq 0 \quad \text{for } k = 1, 2, ..., h$	$MIN\sum_{i=1}^{n} v_i \cdot x_{j0} - w$ Subject to: $\sum_{j=1}^{m} u_i \cdot y_{i0} = 1$ $\sum_{i=1}^{m} u_i \cdot y_{ik} - \sum_{j=1}^{n} v_j \cdot x_{jk} + w \leq 0 \quad \text{for } k = 1, 2, ..., h$

Source: E. B. Mariano and D. A. D. N. Rebelatto, "Transformation of wealth produced into quality of life: analysis of the social efficiency of nation-states with the DEA's triple index approach", *Journal of the Operational Research Society*, vol. 65, No. 11, 2014.

Note: x_{jk} represents the amount of input j of decision-making unit (DMU) k; y_{ik} represents the amount of output i of DMU k; x_{j0} represents the amount of input j of the DMU under analysis; y_{i0} represents the amount of output i of the DMU under analysis; v_i represents the weight of input j for the DMU under analysis; u_i represents the weight of output i for the DMU under analysis; θ means the efficiency of the DMU under analysis; λ_k is the contribution of DMU k to the goal of the DMU under analysis; m is the quantity of outputs analysed; n is the quantity of inputs analysed; and w represents the scale factor (without sign restriction).

The hypothesis of the CRS model assumes that outputs vary proportionally to inputs in all regions of the frontier (Charnes, Cooper and Rhodes, 1978). However, this model does not consider the scale gains of a system, which is a limitation (Mariano, Sobreiro and do Nascimento Rebelatto, 2015). The VRS model, on the other hand, assumes that outputs do not necessarily vary proportionally to inputs, with the frontier having three regions: increasing, where outputs grow by more than inputs; constant, where there is proportionality; and decreasing, where outputs grow by less than inputs (Banker, Charnes and Cooper, 1984).

Tone (2001) developed a non-radial model called the slack-based measure (SBM) model. This additive model is invariant as regards the units of measurement used for inputs and outputs (Cooper, Seiford and Tone, 2006) and attains the same efficiency value regardless of the units of measurement adopted for each variable when dealing with gap variables, i.e., with excess inputs and scarce outputs. The SBM model projects the observations to the point farthest from the efficiency frontier in order to minimize the objective function with regard to the maximum clearance amounts (Choi, Zhang and Zhou, 2012). However, the SBM model has been little used in the literature on human development and social efficiency.

DEA has been used for a number of research problems and fields, such as the energy sector (Schuschny, 2007), innovation management (Aguilar-Barceló and Higuera-Cota, 2019), total factor productivity in ports (Guerrero and Rivera, 2009), production efficiency and technical change (Sotelsek and Abarca, 2010) and agrarian reform (Sobreiro Filho and others, 2016). There is also a growing literature in which DEA is used to create social indicators and measure human development (Despotis, 2005a and 2005b; Mariano, Sobreiro and do Nascimento Rebelatto, 2015).

For example, DEA can be used to measure social efficiency and thereby analyse the capacity of a country to transform wealth into human development (Mariano Sobreiro and do Nascimento Rebelatto, 2015). The pioneer in calculating countries' social efficiency was Despotis (2005a), using GDP per capita as the input and education and life expectancy as the outputs in the DEA VRS model. Morais and Camanho (2011) also measured the social efficiency of 284 European cities, using GDP per capita as the input and 29 indicators of quality of life as outputs. Mariano and Rebelatto (2014) developed the application of weight restriction and tie-breaking methods in a global analysis. Reig-Martínez (2013) used a DEA SBM model for 42 countries in Europe, North Africa and the Middle East. However, Mariano and others (2015) pointed out that there were a number of gaps to be filled in this field; e.g., there was no study comparing measured efficiency between standard and SBM models. Nor could we find studies that treated economic complexity as an input generating human development or quality of life. Thus, the main contributions of this paper are: (i) to remedy the lack of studies comparing DEA models, (ii) to remedy the lack of studies measuring efficiency around the world, (iii) to compare economic complexity and human development and (iv) to remedy the lack of studies applying the inverted frontier technique.

4. The inverted frontier technique

When ranked using DEA, many regions are tied in the same position, which is a problem because it does not present decision-makers with useful information. This was solved by developing tie-breaking techniques such as the inverted frontier (IF) method (Angulo-Meza and Lins, 2002). The IF method, originally proposed by Yamada, Matui and Sugiyama (1994) and used by Leta and others (2005) as a tie-breaking function, measures efficiency by changing the allocation of inputs and outputs in the DEA model. This technique yields two interesting results: (i) an indicator of regional weaknesses and (ii) a frontier of worst practices.

We used the IF tie-breaking method to create the Composite Index of Human Development and Economic Complexity (CIHD-EC). Leta and others (2005) recommended the use of a composite index, such as the average between the indicator obtained at the standard frontier ($E_{standard}$) and the number 1 minus the indicator obtained with the IF method ($E_{inverted}$) (expression 1).

$$\text{CIHD} - \text{EC} = \gamma * E_{standard} + (1 - \gamma)*(1 - E_{inverted}), \text{ with } 0 \leq \alpha \leq 1 \quad (1)$$

The use of a composite index for the standard and inverted frontiers means that two situations can be considered for both: when countries are compared by their strongest points and when they are compared by their weakest points. We computed a value of 0.5 for γ to aggregate the standard and inverted frontier results (expression 1), i.e., we used the average of the two boundaries. This value was chosen because it is the most commonly used in the literature, being generally considered a neutral value. However, other values of γ could be even more appropriate for this problem. It would be consistent with the capability approach if the inverted frontier (which highlights the worse performance) had a higher weight than the standard frontier (which highlights the factors on which the region performs best). The reason for this is that the capability approach places great emphasis on setting minimum standards, so it is more important for the region not to perform very poorly on some variable or variables than for it to perform excellently only on a restricted number of variables. Ascertaining the most appropriate γ value, however, is beyond the scope of this paper and also requires further in-depth theoretical discussion.

IV. Results and discussion

We use standard models and slack-based measure (SBM) models to compare differences in countries' efficiency at converting economic complexity into human development. This section presents a discussion of the discrepancies found between our DEA models, such as the number of efficient countries and the descriptive statistics (average, standard deviation and the coefficient of variation) for the world, developed and developing economies and high- and low-income nations.

Our findings show that the standard CRS model has a smaller number of efficient DMUs (six countries). The SBM CRS model shows the same number of efficient units (six countries). The averages of the CRS model (0.3594) and the SBM CRS model (0.3374) are close, as are their standard deviations, at 0.3537 for the CRS model and 0.3435 for the SBM CRS model. As expected, we also found similar coefficients of variation for the CRS (0.9842) and the SBM CRS (1.0181) models. This means that we did not find significant divergences between the standard and SBM CRS models when it came to the transformation of economic complexity into human development.

Table 3 summarizes the efficiency of each model, scale efficiency and the returns to scale for the countries.

Table 3
Estimates of the efficiency of standard and slack-based measure models

Country	Standard models						Slack-based models					
	CRS	VRS	IF VRS	CIHD-EC	Scale efficiency	Return	SBM CRS	SBM VRS	IF SBM VRS	CIHD-EC	Scale efficiency	Return
Argentina	0.0841	0.9580	0.9094	0.5243	0.0878	Decreasing	0.0773	0.8977	0.7696	0.5641	0.0861	Decreasing
Armenia	1.0000	1.0000	0.9314	0.5343	1.0000	Constant	1.0000	1.0000	0.7975	0.6013	1.0000	Constant
Australia	0.1440	1.0000	0.8410	0.5795	0.1440	Decreasing	0.1384	1.0000	0.6783	0.6609	0.1384	Decreasing
Austria	0.3807	1.0000	0.8565	0.5718	0.3807	Decreasing	0.3572	0.9997	0.7250	0.6374	0.3573	Decreasing
Belarus	0.3520	0.9461	0.9686	0.4888	0.3721	Decreasing	0.3407	0.9066	0.8093	0.5487	0.3758	Decreasing
Belgium	0.3301	1.0000	0.8889	0.5556	0.3301	Decreasing	0.3086	0.9999	0.7895	0.6052	0.3086	Decreasing
Bosnia and Herzegovina	1.0000	1.0000	1.0000	0.5000	1.0000	Constant	1.0000	1.0000	1.0000	0.5000	1.0000	Constant
Brazil	0.0173	0.9540	0.9212	0.5164	0.0181	Decreasing	0.0124	0.8346	0.7848	0.5249	0.0149	Decreasing
Bulgaria	0.9926	0.9926	0.9618	0.5154	1.0000	Constant	0.9272	0.9272	0.8632	0.5320	1.0000	Constant
Canada	0.0903	1.0000	0.8437	0.5782	0.0903	Decreasing	0.0867	1.0000	0.6793	0.6604	0.0867	Decreasing
Chile	0.1955	0.9900	0.8567	0.5667	0.1975	Decreasing	0.1783	0.9113	0.7403	0.5855	0.1957	Decreasing
China	0.0024	0.9787	1.0000	0.4894	0.0025	Decreasing	0.0017	0.8939	1.0000	0.4470	0.0019	Decreasing
Colombia	0.0728	0.9116	0.9282	0.4917	0.0799	Decreasing	0.0547	0.7776	0.8213	0.4782	0.0703	Decreasing
Costa Rica	0.7256	0.9887	0.8755	0.5566	0.7339	Decreasing	0.6284	0.8854	0.7763	0.5546	0.7097	Decreasing
Croatia	0.8567	1.0000	0.9451	0.5275	0.8567	Decreasing	0.7757	1.0000	0.8561	0.5720	0.7757	Decreasing
Czech Republic	0.3104	0.9910	0.8895	0.5508	0.3132	Decreasing	0.3006	0.9553	0.7389	0.6082	0.3147	Decreasing
Denmark	0.5778	1.0000	0.8639	0.5681	0.5778	Decreasing	0.5687	1.0000	0.7096	0.6452	0.5687	Decreasing
Egypt	0.0530	0.9470	1.0000	0.4735	0.0560	Decreasing	0.0411	0.7372	1.0000	0.3686	0.0558	Decreasing
El Salvador	0.9536	0.9536	0.9463	0.5037	1.0000	Constant	0.8243	0.8243	0.8758	0.4743	1.0000	Constant
Ethiopia	0.1432	1.0000	1.0000	0.5000	0.1432	Decreasing	0.0427	0.9999	1.0000	0.5000	0.0427	Decreasing
Finland	0.6127	0.9972	0.8654	0.5659	0.6144	Decreasing	0.5624	0.9547	0.7583	0.5982	0.5891	Decreasing
France	0.0555	0.9946	0.8753	0.5597	0.0558	Decreasing	0.0511	0.9203	0.7826	0.5689	0.0555	Decreasing

Table 3 (concluded)

Country	Standard models						Slack-based models					
	CRS	VRS	IF VRS	CIHD-EC	Scale efficiency	Return	SBM CRS	SBM VRS	IF SBM VRS	CIHD-EC	Scale efficiency	Return
Georgia	1.0000	1.0000	0.9275	0.5363	1.0000	Constant	1.0000	1.0000	0.7712	0.6144	1.0000	Constant
Germany	0.0392	1.0000	0.8633	0.5684	0.0392	Decreasing	0.0387	0.9963	0.7199	0.6382	0.0388	Decreasing
Greece	0.4347	1.0000	0.9257	0.5372	0.4347	Decreasing	0.3655	1.0000	0.8788	0.5606	0.3655	Decreasing
Hungary	0.3676	0.9800	0.9383	0.5209	0.3751	Decreasing	0.3403	0.8852	0.8218	0.5317	0.3844	Decreasing
Indonesia	0.0148	0.9121	1.0000	0.4561	0.0162	Decreasing	0.0099	0.7364	1.0000	0.3682	0.0134	Decreasing
Ireland	0.7608	1.0000	0.8834	0.5583	0.7608	Decreasing	0.7130	1.0000	0.7676	0.6162	0.7130	Decreasing
Israel	0.4620	1.0000	0.8449	0.5776	0.4620	Decreasing	0.4499	1.0000	0.6967	0.6517	0.4499	Decreasing
Italy	0.0647	0.9970	0.8989	0.5491	0.0649	Decreasing	0.0565	0.9377	0.8474	0.5452	0.0603	Decreasing
Japan	0.0260	1.0000	0.8880	0.5560	0.0260	Decreasing	0.0246	1.0000	0.8149	0.5926	0.0246	Decreasing
Korea (Republic of)	0.0651	1.0000	1.0000	0.5000	0.0651	Decreasing	0.0627	0.9667	1.0000	0.4834	0.0649	Decreasing
Lithuania	1.0000	1.0000	0.9378	0.5311	1.0000	Constant	1.0000	1.0000	0.7753	0.6124	1.0000	Constant
Mexico	0.0307	0.9293	0.9032	0.5131	0.0330	Decreasing	0.0256	0.8267	0.8006	0.5131	0.0310	Decreasing
Netherlands	0.1915	1.0000	0.8508	0.5746	0.1915	Decreasing	0.1814	1.0000	0.7016	0.6492	0.1814	Decreasing
Norway	0.6655	1.0000	0.8418	0.5791	0.6655	Decreasing	0.6225	1.0000	0.6767	0.6617	0.6225	Decreasing
Panama	1.0000	1.0000	0.8906	0.5547	1.0000	Constant	1.0000	1.0000	0.7604	0.6198	1.0000	Constant
Philippines	0.0404	0.8999	0.9903	0.4548	0.0449	Decreasing	0.0320	0.8079	0.8330	0.4875	0.0396	Decreasing
Poland	0.0874	0.9815	0.9113	0.5351	0.0890	Decreasing	0.0839	0.9327	0.7856	0.5736	0.0900	Decreasing
Portugal	0.3053	1.0000	0.8819	0.5591	0.3053	Decreasing	0.2591	1.0000	0.8276	0.5862	0.2591	Decreasing
Romania	0.2385	0.9401	0.9445	0.4978	0.2537	Decreasing	0.2226	0.9096	0.8289	0.5404	0.2447	Decreasing
Russian Federation	0.0224	0.9593	0.9702	0.4946	0.0234	Decreasing	0.0189	0.8591	0.7998	0.5297	0.0220	Decreasing
Singapore	0.6143	1.0000	0.8322	0.5839	0.6143	Decreasing	0.5282	1.0000	0.6660	0.6670	0.5282	Decreasing
Spain	0.0708	1.0000	0.8936	0.5532	0.0708	Decreasing	0.0608	0.9998	0.8508	0.5745	0.0608	Decreasing
Sweden	0.3316	0.9978	0.8469	0.5755	0.3323	Decreasing	0.3207	0.9806	0.7052	0.6377	0.3270	Decreasing
Turkey	0.0553	0.9410	0.9558	0.4926	0.0588	Decreasing	0.0464	0.7890	0.9214	0.4338	0.0588	Decreasing
Ukraine	0.0696	0.9732	0.9655	0.5039	0.0715	Decreasing	0.0656	0.9258	0.7781	0.5739	0.0709	Decreasing
United Kingdom	0.0514	1.0000	0.8587	0.5707	0.0514	Decreasing	0.0507	1.0000	0.7119	0.6441	0.0507	Decreasing
United States	0.0105	1.0000	0.8971	0.5515	0.0105	Decreasing	0.0103	0.9724	0.7461	0.6132	0.0106	Decreasing
Uruguay	1.0000	1.0000	0.8913	0.5544	1.0000	Constant	1.0000	1.0000	0.7467	0.6267	1.0000	Constant

Source: Prepared by the authors on the basis of World Bank, "Human Capital Project", 2018 [online] http://www.worldbank.org/en/publication/human-capital.

Note: CRS: constant returns to scale; VRS: variable returns to scale; IF VRS: inverted frontier variable returns to scale; CIHD-EC: Composite Index of Human Development and Economic Complexity; SBM CRS: slack-based measure constant returns to scale; SBM VRS: slack-based measure variable returns to scale; IF SBM VRS: inverted frontier slack-based measure variable returns to scale.

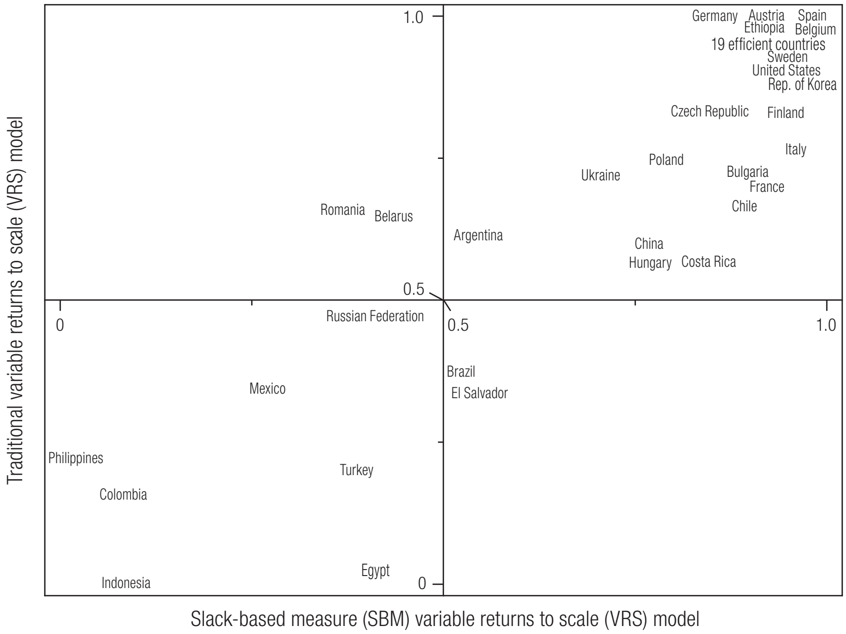
The efficient countries in the CRS and SBM CRS models are Armenia, Bosnia and Herzegovina, Georgia, Lithuania, Panama and Uruguay. With regard to scale efficiency, both the standard and the slack-based measure models presented 42 countries with decreasing returns to scale and eight countries with constant returns to scale. The countries with constant returns to scale are the six efficient countries in the CRS model plus Bulgaria and El Salvador. However, the previous literature has used VRS models.

The standard VRS model shows 26 countries as efficient at converting economic complexity into human development. The SBM VRS model shows only 19 countries as efficient. The change affects the discrepancy between averages. The VRS model average (0.9823) is slightly higher than the SBM VRS model average (0.9390). The standard deviation is lower for the standard VRS model (0.0509) than for the SBM VRS model (0.0770), showing that the latter has greater variability. Furthermore, the coefficient of variation of the VRS model (0.0279) is lower than that for the SBM VRS model (0.0820). Note that the SBM VRS model presents a coefficient of variation four times as high as that of the standard model. This is because the Philippines had the lowest efficiency in the VRS model (0.8322), while Indonesia had the lowest efficiency in the SBM VRS model (0.7364).

The seven countries found to be efficient with the standard VRS model but not with the SBM VRS model are Austria, Belgium, Ethiopia, Germany, the Republic of Korea, Spain and the United States.

Note that all except Ethiopia are developed, high-income countries. This is an important finding for the measurement of human development indicators by DEA. According to our empirical results, the standard models tend to overestimate the efficiency of some DMUs, especially in the case of developed, high-income countries. Figure 1 illustrates the discrepancies between the standard VRS model and SBM VRS model.

Figure 1
Benchmarking the standard and slack-based measure models with variable returns to scale



Source: Prepared by the authors on the basis of World Bank, "Human Capital Project", 2018 [online] http://www.worldbank.org/en/publication/human-capital.

When we use the standard VRS model, our findings are similar to those of Despotis (2005a and 2005b) and Reig-Martínez (2013), because many countries considered efficient at transforming economic complexity into human development are also efficient at converting wealth into human development, such as Austria, Belgium, Germany, the Republic of Korea and Spain. When we use the SBM VRS model, on the other hand, our empirical findings are that these countries cannot be considered efficient, which is not supported by previous studies (Despotis, 2005a and 2005b; Reig-Martínez, 2013).

The number of efficient units is high with the standard VRS model (52%) and SBM VRS model (38%). Models with variable returns to scale present many ties, and these have been solved with the inverted frontier technique. Accordingly, we created the Composite Index of Human Development and Economic Complexity (CIHD-EC). The advantage of this indicator is that it avoids ties by considering the best and worst practices of each country with regard to the transformation of economic complexity into human development. The CIHD-EC also allows policymakers to work out the best industrial policies (R&D expenditure and export of high-technology products) to generate human development.

The CIHD-EC has yielded a significant result: with both the standard VRS model and the SBM model, Singapore is the only efficient country among the 50 nations analysed. This is unexpected, since European and North American countries (i.e., Austria, Belgium, Germany, Spain and the United States) reach the highest-ranking position. However, the finding is supported by previous studies of Singapore's economic development (Gopinathan, 2007; World Bank, 2018a and 2018b).

In both the standard VRS and SBM VRS ranking, the top five countries are Singapore, Norway, Israel, Canada and Australia. The high position for Norway corroborates the findings of Reig-Martínez (2013). According to this author, SBM models showed the Nordic countries to be efficient at converting wealth into human development. In addition, our findings demonstrate that there is no clustering of efficient countries in the CIHD-EC, with the most efficient countries being spread across Europe, North America and Asia. Moreover, according to our empirical results, the inverted frontier technique avoids the discrepancies in efficiency rankings between standard models and the SBM model.

The bottom five countries in the standard VRS model are the Philippines, Indonesia, Egypt, China and Belarus, while the bottom five countries in the SBM VRS model are Indonesia, Egypt, Turkey, China and El Salvador. The standard model places a European country, Belarus, in the bottom five, while the SBM VRS model brings a Eurasian one, Turkey, into the bottom five. Furthermore, while the standard model places the Philippines, an Asian country, in the bottom five, the SBM VRS model includes a Latin American one, El Salvador, in the bottom five.

Table 4 summarizes the differences between the indicators calculated in this study. We analyse these differences for the 50 countries being evaluated by type of economy (developed as against developing) and income level (high-income and upper-middle-income as against low-income and lower-middle-income).

In the analysis by type of economy, we found that the standard VRS model benefited developed countries. While the SBM VRS model yielded only 14 efficient countries, the standard VRS model yielded 19 efficient countries. Among developing economies, in contrast, Ethiopia was the only efficient country with the VRS model. On the other hand, the SBM VRS model did not identify Ethiopia as an efficient nation. The CIHD-EC yields a better fit for developed and developing countries, identifying only Singapore as efficient and avoiding ranking ties.

Concerning income levels, the efficient units identified by the standard VRS model are mainly low-income and lower-middle-income economies (23 countries), while only 3 high-income and upper-middle-income economies are found to be efficient. The SBM VRS model reduces this discrepancy, finding there to be only two efficient high-income and upper-middle-income economies and 17 efficient low-income and lower-middle-income economies.

In summary, we consider that the SBM VRS model is better able to analyse how efficient countries are at transforming economic complexity into human development. It does not identify as efficient some developed countries that are so identified by the standard models. Also, the inverted frontier tie-breaker method was able to demonstrate a better fit among the five most efficient countries. Furthermore, the discrepancy of these models can be applied to the transformation of wealth into human development, bringing new insights to this problem.

Figure 2 shows four maps that illustrate the efficiency of simple indicators in the countries of the world when employing the standard CRS model, the standard VRS model, the SBM CRS model and the SBM VRS model. Figure 3 shows four maps that illustrate the efficiency of composite indicators (using the inverted frontier technique) in the countries of the world when employing the standard CRS model, the CIHD-EC based on the standard VRS model, the SBM CRS model and the CIHD-EC based on the SBM VRS model. More efficient countries are shaded dark green and less efficient countries light green.

Table 4
Comparison of regions using standard and slack-based models

Region	Statistic	Standard models					Slack-based models				
		CRS	VRS	IF VRS	CIHD-EC	Scale efficiency	SBM CRS	SBM VRS	IF SBM VRS	CIHD-EC	Scale efficiency
World	Average	0.3594	0.9823	0.9120	0.5351	0.3623	0.3374	0.9390	0.8038	0.5676	0.3492
	Median	0.2170	1.0000	0.9011	0.5431	0.2256	0.2020	0.9765	0.7852	0.5742	0.2202
	Standard deviation	0.3537	0.0274	0.0509	0.0345	0.3552	0.3435	0.0770	0.0920	0.0721	0.3518
	Coefficient of variation	0.9842	0.0279	0.0558	0.0644	0.9804	1.0181	0.0820	0.1145	0.1269	1.0076
	Maximum value	1.0000	1.0000	1.0000	0.5839	1.0000	1.0000	1.0000	1.0000	0.6670	1.0000
	Minimum value	0.0024	0.8999	0.8322	0.4548	0.0025	0.0017	0.7364	0.6660	0.3682	0.0019
	Efficient countries	6	26	6	1	-	6	19	6	1	-
Developed	Average	0.3710	0.9955	0.8850	0.5552	0.3724	0.3465	0.9797	0.7637	0.6080	0.3537
	Median	0.3301	1.0000	0.8834	0.5583	0.3301	0.3086	1.0000	0.7583	0.6124	0.3147
	Standard deviation	0.2948	0.0121	0.0369	0.0219	0.2951	0.2788	0.0328	0.0653	0.0421	0.2847
	Coefficient of variation	0.7946	0.0121	0.0417	0.0395	0.7924	0.8046	0.0335	0.0855	0.0692	0.8048
	Maximum value	1.0000	1.0000	0.9618	0.5839	1.0000	1.0000	1.0000	0.8788	0.6670	1.0000
	Minimum value	0.0105	0.9401	0.8322	0.4978	0.0105	0.0103	0.8852	0.6660	0.5317	0.0106
	Efficient countries	1	19	0	1	-	1	14	0	1	-
Developing	Average	0.3458	0.9668	0.9438	0.5115	0.3504	0.3267	0.8913	0.8508	0.5203	0.3439
	Median	0.0728	0.9732	0.9463	0.5037	0.0799	0.0627	0.8977	0.8006	0.5249	0.0703
	Standard deviation	0.4119	0.0320	0.0464	0.0314	0.4144	0.4062	0.0861	0.0965	0.0711	0.4170
	Coefficient of variation	1.1912	0.0331	0.0492	0.0614	1.1826	1.2435	0.0965	0.1134	0.1367	1.2128
	Maximum value	1.0000	1.0000	1.0000	0.5667	1.0000	1.0000	1.0000	1.0000	0.6267	1.0000
	Minimum value	0.0024	0.8999	0.8567	0.4548	0.0025	0.0017	0.7364	0.7403	0.3682	0.0019
	Efficient countries	5	7	6	0	-	5	5	6	0	-
High-income and upper-middle-income	Average	0.4093	0.9607	0.9701	0.4953	0.4165	0.3770	0.8789	0.8820	0.4985	0.4028
	Median	0.1064	0.9634	0.9779	0.5018	0.1074	0.0542	0.8751	0.8544	0.4937	0.0633
	Standard deviation	0.4471	0.0372	0.0296	0.0296	0.4532	0.4404	0.1087	0.0965	0.0896	0.4628
	Coefficient of variation	1.0922	0.0387	0.0305	0.0598	1.0883	1.1683	0.1237	0.1094	0.1798	1.1491
	Maximum value	1.0000	1.0000	1.0000	0.5363	1.0000	1.0000	1.0000	1.0000	0.6144	1.0000
	Minimum value	0.0148	0.8999	0.9275	0.4548	0.0162	0.0099	0.7364	0.7712	0.3682	0.0134
	Efficient countries	2	3	3	1	-	2	2	3	1	-
Low-income and lower-middle-income	Average	0.3499	0.9864	0.9010	0.5427	0.3520	0.3298	0.9505	0.7889	0.5808	0.3390
	Median	0.2719	1.0000	0.8910	0.5538	0.2795	0.2409	0.9885	0.7795	0.5859	0.2519
	Standard deviation	0.3322	0.0230	0.0463	0.0298	0.3322	0.3211	0.0631	0.0832	0.0597	0.3254
	Coefficient of variation	0.9493	0.0233	0.0514	0.0549	0.9439	0.9737	0.0664	0.1055	0.1029	0.9601
	Maximum value	1.0000	1.0000	1.0000	0.5839	1.0000	1.0000	1.0000	1.0000	0.6670	1.0000
	Minimum value	0.0024	0.9116	0.8322	0.4888	0.0025	0.0017	0.7776	0.6660	0.4338	0.0019
	Efficient countries	4	23	3	0	-	4	17	3	0	-

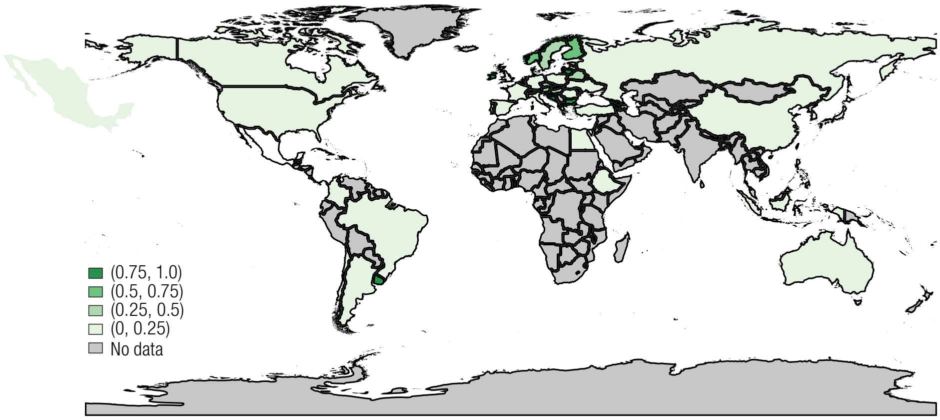
Source: Prepared by the authors on the basis of World Bank, "Human Capital Project", 2018 [online] http://www.worldbank.org/en/publication/human-capital.

Note: CRS: constant returns to scale; VRS: variable returns to scale; IF VRS: inverted frontier variable returns to scale; CIHD-EC: Composite Index of Human Development and Economic Complexity; SBM CRS: slack-based measure constant returns to scale; SBM VRS: slack-based measure variable returns to scale; IF SBM VRS: inverted frontier slack-based measure variable returns to scale.

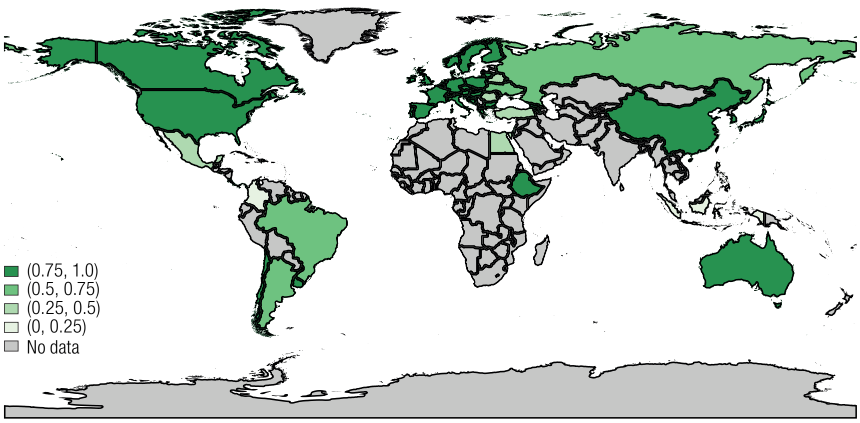
Figure 2

World: efficiency in converting economic complexity into human development as measured by simple indicators

A. Standard CRS model



B. Standard VRS model



C. SBM CRS model

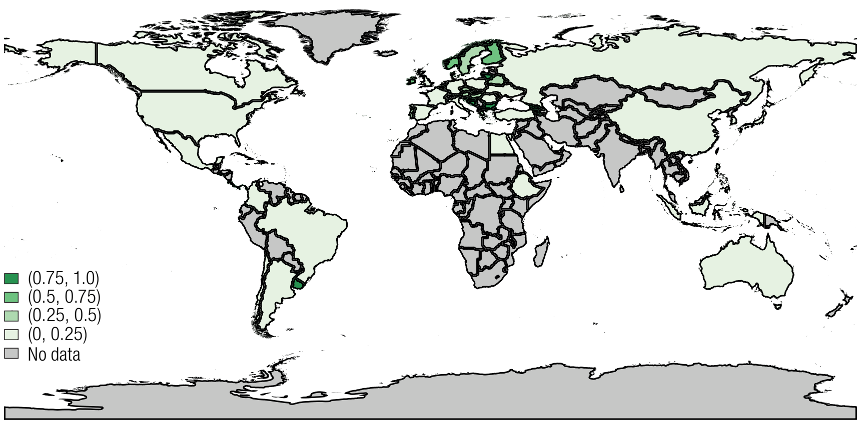
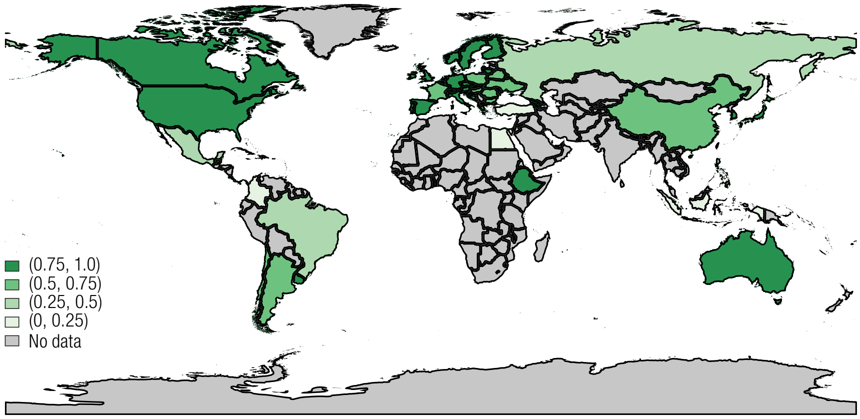


Figure 2 (concluded)

D. SBM VRS model



Source: Prepared by the authors on the basis of World Bank, "Human Capital Project", 2018 [online] http://www.worldbank.org/en/publication/human-capital.

Note: CRS: constant returns to scale; VRS: variable returns to scale; SBM CRS: slack-based measure constant returns to scale; SBM VRS: slack-based measure variable returns to scale.

Figure 3

World: efficiency in converting economic complexity into human development as measured by composite indicators (standard and inverted frontiers)

A. Standard CRS model

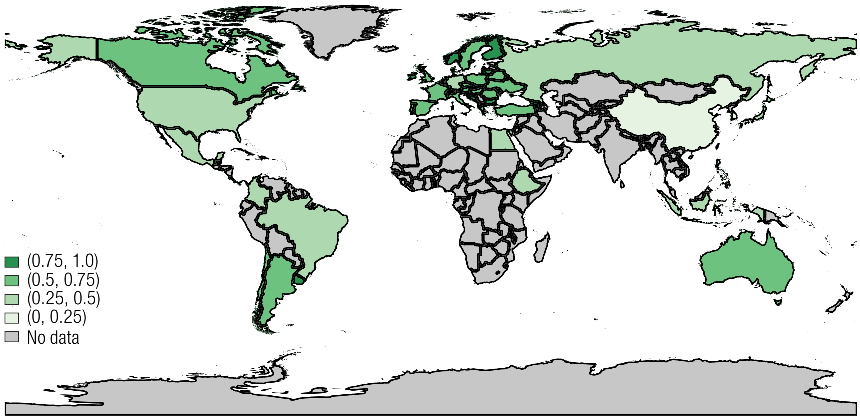
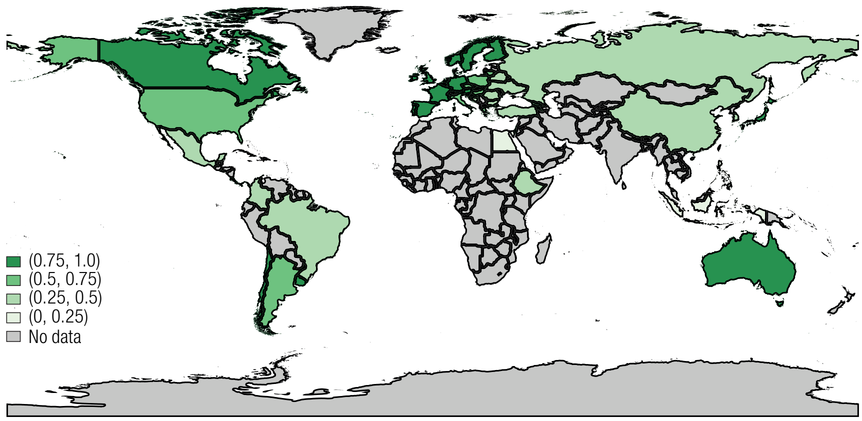
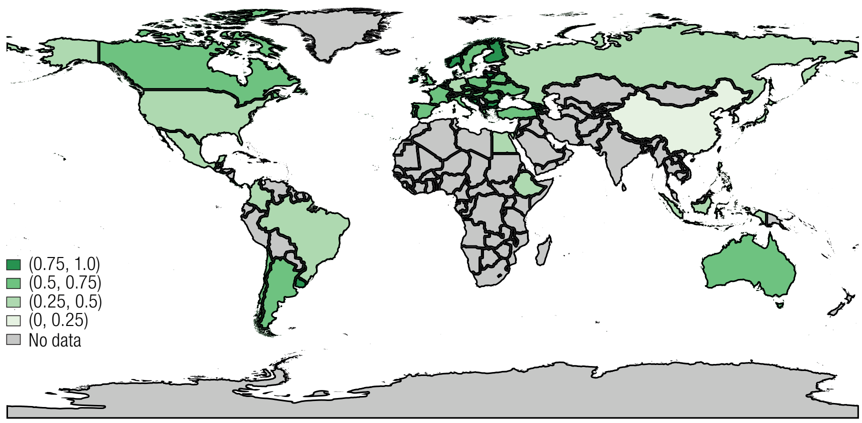


Figure 3 (concluded)

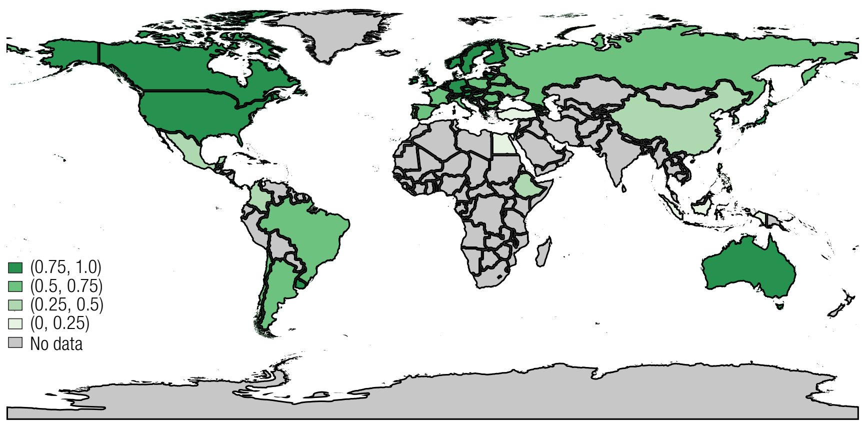
B. CIHD-EC (standard VRS model)



C. SBM CRS model



D. CIHD-EC (SBM VRS) model



Source: Prepared by the authors on the basis of World Bank, "Human Capital Project", 2018 [online] http://www.worldbank.org/en/publication/human-capital.

Note: CRS: constant returns to scale; CIHD-EC: Composite Index of Human Development and Economic Complexity; VRS: variable returns to scale; SBM CRS: slack-based measure constant returns to scale; SBM VRS: slack-based measure variable returns to scale.

V. Concluding remarks

This article contributes to the comparison of differences between standard and slack-based measure models for human development indicators. It also considers economic complexity as a new variable in the measurement of countries' efficiency at generating human development, since economic sophistication is an alternative perspective from which to analyse economic development.

We find that standard models tend to overestimate the number of efficient countries, especially in the case of developed and prosperous nations. In contrast, the slack-based measure model provides a better fit when measuring human development around the world because it yields a lower number of efficient countries and presents a better average and standard deviation than standard models.

The inverted frontier technique also provides a better understanding of the problem under analysis. Using this tie-breaking technique, we found that only Singapore was efficient at converting economic complexity into human development among the 50 countries under analysis. Furthermore, the inverted frontier technique ranks the same five countries as most efficient, which shows more synergy between the standard (IF VRS model) and slack-based model (IF SBM VRS). Using the inverted frontier, we found that North American, European and Asian countries had the world's best practices.

This study has some limitations, such as the lack of indicators for income inequality (Gini index) and the democratic environment. Although these variables are essential in Amartya Sen's approach, we did not find data available for all 50 countries. Also, we were using our econometric models to show correlation between inputs and outputs. Future studies can develop more advanced models and measure the impact of economic complexity on human development around the world. Another shortcoming of this study is that it did not evaluate efficiency over time, something that is vital for ascertaining how nations may have evolved (or not) during the last few decades.

Notwithstanding the limitations outlined above, our work reveals the need to use different data envelopment analysis (DEA) models to measure social indicators. Slack-based models can provide new rankings and identify different efficient countries, which affects how the human development approach is understood.

Lastly, our Composite Index of Human Development and Economic Complexity (CIHD-EC) sheds light on the economic complexity approach and its relationship with human development. These findings are essential for the production of new and improved social indicators and justify the need for complementary social and industrial policies to improve human capabilities. Furthermore, the CIHD-EC can provide policyholders, especially in developing economies, with straightforward aggregated information.

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Annex A1

Using data from 2010 to 2013, we measured a matrix of correlation and linear regressions between the inputs and each of the outputs. We proceeded with Cobb-Douglas functions adapted to the research problem (see expression 2).

$$\log y_{it}^{social\ variable} = \beta_0 + \beta_1 \log GFCF + \beta_2 \log EAP + \beta_3 \log GDP + \beta_4 \log EHTP + \beta_5 \log R\&D + \varepsilon \quad (2)$$

Where $y_{it}^{social\ variable}$ is one of the quality of life variables; β_0 is the intercept; $\beta_1 logGFCF$ is the logarithm of gross fixed capital formation; $\beta_2 logEAP$ is the logarithm of the economically active population; $\beta_3 logGDP$ is the logarithm of gross domestic product; $\beta_4 logEHTP$ is the logarithm of exports of high-technology products; and $\beta_5 logR\&D$ is the logarithm of R&D expenditure. A log-log regression is proposed since it is possible to interpret the parameters as elasticities (Greene, 2011). Table A1.1 presents the estimations of the correlation matrix.

Table A1.1
Matrix of correlation between input and outputs

Variable	MYS	LEB	SR	ER	EHTP/GDP	R&D-E
MYS	1					
LEB	0.3506*	1				
SR	0.4924*	0.5773*	1			
ER	0.0958	0.0342	-0.2224*	1		
EHTP/GDP	0.1241***	0.2394*	0.1587**	0.2211*	1	
R&D-E	0.1085	0.1671**	0.1212***	0.0998	0.1094	1

Source: Prepared by the authors.
Note: MYS: mean years of schooling; LEB: life expectancy at birth; SR: sanitation rate; ER: employment rate; EHTP/GDP: exports of high-technology products as a share of gross domestic product; R&D-E: research and development expenditure.
* significant at 1%; ** significant at 5%; *** significant at 10%.

Eight econometric models were estimated in order to analyse which variables best explained the variability of each social variable analysed. In addition to verifying the statistical significance of the parameters and the adjusted R^2, a comparative analysis of the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) was used to select the best model (Greene, 2011). Table A1.2 summarizes the results arrived at in multiple linear regressions.

Regarding mean years of schooling, econometric model 5 was the one that yielded the highest adjusted R^2 (18.56%) and lowest BIC (-1672.5160), which shows the best fit among the models analysed. Regarding life expectancy, model 1 had the greatest explanatory power, with an adjusted R^2 (48.65) and BIC (-1994.7540) higher than those found in the other models. Regarding the sanitation rate, model 4 was the most robust, since it presented the highest adjusted R^2 (26.35%) and a BIC statistic equal to -1974.3780. All estimates can be found in table A1.2.

Table A1.2
Coefficients, p-values and R² of outputs relative to inputs

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Mean years of schooling								
EAP	0.1390*	0.1351*	0.1410*	0.1543*	0.1339*	0.1755*	0.1405*	0.1450*
GDP	0.0172	0.0089	-	0.0192***	0.0084	-	-	-
GFCF	-0.0065	-	0.0020	-	-	0.0061	0.0019	-
EHTP/GDP	0.0023	0.0023	0.0008	0.0121	-	0.0121	-	0.0001
R&D-E	0.0102***	0.0110**	0.0127**	-	0.0114**	-	0.0128*	0.0130*
Constant	-0.0221	-0.0363	-0.0712	-0.1416	-0.0269	-0.2720	-0.0675	-0.0792
Adjusted R^2	0.1875	0.1858	0.1829	0.1652	0.1856	0.1496	0.1829	0.1825
AIC	-1682.1770	-1683.7590	-1683.0560	-1680.7660	-1685.7090	-1677.0710	-1685.0500	-1684.9510
BIC	-1662.3870	-1667.2670	-1666.5640	-1667.5730	-1672.5160	-1663.8770	-1671.8570	-1671.7570
F test	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Life expectancy at birth								
EAP	0.0041	-0.0042	0.0090	0.0187	-0.0010	0.0572*	0.0145	0.0238
GDP	0.0432*	0.0253*	-	0.0376*	0.0266*	-	-	-
GFCF	-0.0140*	-	0.0073**	-	-	0.0131*	0.0085*	-
EHTP/GDP	-0.0062	-0.0061	-0.0099	0.0055	-	0.0059	-	-0.0124
R&D-E	0.0113*	0.0131*	0.0177*	-	0.0120*	-	0.0161*	0.0190*
Constant	1.7509*	1.7206	1.6278*	1.5948*	1.6963*	1.3476*	1.5812*	1.5982*
Adjusted R^2	0.4865	0.4603	0.3907	0.3627	0.4558	0.1750	0.3783	0.3712
AIC	-2014.5440	-2006.6110	-1982.3210	-1975.3470	-2006.9360	-1923.7130	-1980.2960	-1978.0240
BIC	-1994.7540	-1990.1200	-1965.8290	-1962.1540	-1993.7420	-1910.5200	-1967.1030	-1964.8310
F test	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Sanitation rate								
EAP	0.0527*	0.0532*	0.0548*	0.0564*	0.0561*	0.0674*	0.0587*	0.0749*
GDP	0.0185**	0.0196*	-	0.0213*	0.0208*	-	-	-
GFCF	0.0008	-	0.0100*	-	-	0.0115*	0.0108*	-
EHTP/GDP	-0.0055	-0.0055	-0.0071	-0.0039	-	-0.0030	-	-0.0104
R&D-E	0.0019	0.0018	0.0047***	-	0.0007	-	0.0035	0.0064*
Constant	1.5086*	1.5104*	1.4560*	1.4931*	1.4883*	1.3825*	1.4226	1.4156*
Adjusted R^2	0.2659	0.2658	0.2444	0.2635	0.2611	0.2261	0.2365	0.2000
AIC	-1984.2260	-1986.1950	-1980.4440	-1987.5710	-1986.9310	-1977.6750	-1980.3870	-1971.0460
BIC	-1964.4360	-1969.7030	-1963.9520	-1974.3780	-1973.7380	-1964.4820	-1967.1940	-1957.8530
F test	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Employment rate								
EAP	0.3395*	0.4191*	0.3288*	0.3980*	0.4022*	0.3041*	0.3058*	0.5048*
GDP	-0.0943*	0.0774*	-	0.0660*	0.0703*	-	-	-
GFCF	0.1340*	-	0.0874*	-	-	0.0845*	0.0826*	-
EHTP/GDP	0.0339	0.0323	0.0420***	0.0216	-	0.0338	-	0.0130
R&D-E	0.0048	-0.0121	-0.0091	-	-0.0059	-	-0.0022	0.0058
Constant	-1.7210*	-1.4307*	-1.4524*	-1.3144**	-1.3015**	-1.3086*	-1.2557**	-1.8058*
Adjusted R^2	0.4160	0.2712	0.3884	0.2661	0.2634	0.3849	0.3750	0.2204
AIC	-1428.1990	-1385.8940	-1420.9520	-1386.5080	-1385.7620	-1421.8280	-1418.6180	-1374.4270
BIC	-1408.4090	-1369.4020	-1404.4600	-1373.3150	-1372.5690	-1408.6350	-1405.4250	-1361.2340
F-test	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Observations					200			

Source: Prepared by the authors.

Note: EAP: economically active population; GDP: gross domestic product; GFCF: gross fixed capital formation; EHTP/GDP: exports of high-technology products as a share of gross domestic product; R&D-E: research and development expenditure; AIC: Akaike information criterion; BIC: Bayesian information criterion.
* significant at 1%; ** significant at 5%; *** significant at 10%.