MANAGING ENTREPRENEURIAL CONDITIONS TO SUPPORT EARLY-STAGE ENTREPRENEURIAL ACTIVITY: A DATA ENVELOPMENT ANALYSIS

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ABSTRACT
In this paper, we apply Data Envelopment Analysis with constant and variable returns to scale to study the technical efficiency of 42 countries for 2019 starting from 12 inputs and 3 outputs. The inputs represent the features of entrepreneurial framework conditions, which can be managed by governments to enhance or hinder new business creation, i.e., the outputs of total entrepreneurial activity (TEA) and the ratio of male-female TEA together with (iii) entrepreneurial intentions. The two models show that for the VRS approach, the number of efficient entities is larger than in the case of the CRS approach. The results show that the mean values of the CRS and VRS models reveal that the countries have entrepreneurial activities on the efficient frontier if the use of the input may be reduced by 7.73%, and by 3.17% under CRS and VRS models, respectively, without any decrease in the outputs.

KEYWORDS : *CRS ,DEA, entrepreneurial activity, technical efficiency, VRS.*

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1. INTRODUCTION AND LITERATURE

Entrepreneurship is the act of creating a new business venture and assuming a great amount of risk associated with it. Entrepreneurs bring innovation and also reduce the gap between people with and without internet access. There are four types of entrepreneurships: small business, scalable startup, large company, and social entrepreneurship. A scalable startup is a business that uses or creates technology. This type of business has a big potential to expand. Large company entrepreneurship may consist in spinning off a new division. Social entrepreneurship may have any size and usually are social mission. In the literature, entrepreneurship has been associated with profit-creating activities over the return rate of land, labor, and capital (Gedeon, 2010; Matley, 2005). The creation of new businesses has become important in different fields such as the generation of employment, economic growth, innovation, and well-being (Coduras et al, 2008; Kinnunen et al., 2019).
Kinnunen et al. (2022) studied short- and long-run drivers of early-stage entrepreneurial activity in ten European Union countries using regression analysis and time-series data from the period 2011-2019 with the focus on entrepreneurial motivations and attitudes together with selected entrepreneurial conditions (Androniceanu et al., 2022a; Androniceanu & Georgescu, 2022; Androniceanu et al., 2022b; Androniceanu et al., 2020a). They report that entrepreneurial finance, and government grants and subsidies support early-stage entrepreneurial activity (TEA) finding, further that the female-male ratio of entrepreneurs is positively driving TEA in the short-run; perceived business opportunities and established ownership were further found statistically significant motivational factors for new

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entrepreneurs. The paper by Coduras et al. (2008) studies the relationship between entrepreneurial activity and perceived university support to entrepreneurs using the 2006 Spanish total national GEM Adult Population Survey. The study concludes that skills development and the ability to start a business should be integrated into vocational programs in universities. Habib and Mourad (2022) use the Malmquist index, DEA, and Tobit regression to show that most Gulf companies have a conservative strategy for working capital management and their performance was not affected by the Coronavirus crisis (Androniceanu, 2021; Androniceanu et al., 2021).

Androniceanu et al. (2022a) extend Androniceanu et al. (2022b) and Kinnunen et al. (2022) using fixed and random effects models and data from the period 2011-2019 for sixteen world countries, but they limit the explanatory variables of TEA to motivations and attitudes of potential new entrepreneurs (instead of entrepreneurial conditions) (Ciobanu et al., 2019). They argue that when individuals recognize their business capabilities with perceived opportunities, it supports their entrepreneurial intentions, and they all positively and significantly affect TEA. Also, established business ownership, female-male TEA ratio, and expectations of high job creation were statistically insignificant explanatory variables of TEA (Androniceanu A-M et al., 2022; Grondys et al., 2021; Tamulevičienė & Androniceanu, 2020)

Kinnunen and Georgescu (2020) focused on twelve entrepreneurial conditions and another twelve economic freedoms, which have earlier been found important for economic and social well-being in OECD (cf. Georgescu & Kinnunen, 2019; 2019a; 2021) and EU (cf. Georgescu et al., 2018; 2020), using artificial neural network and multiple correspondence analyses on cross-sectional data from the year 2019. They reported economic freedoms more meaningful in countries with a relatively low level of early-stage entrepreneurship (TEA), while the other entrepreneurial conditions were more important drivers in countries with a relatively high level of TEA; Of the entrepreneurial conditions, R&D transfers, entrepreneurial financing, governmental support and policies, internal market dynamism, and cultural and social norms were found the most important predictors for TEA.

The main objective of this paper is to study the effects of entrepreneurial conditions (but not motivations and attitudes) on the total early-stage entrepreneurial activity by data envelopment analysis with the most recent cross-sectional data.

The paper is structured as follows. Next, section 2 describes the data and the used methodology. The analysis and results are presented in section 3. Section 4 concludes the paper with contributions, limitations, and suggestions for future research.

2. DATA AND RESEARCH METHODOLOGY

In this study, we have a dataset consisting of 42 world countries for which 15 attributes related to TEA are collected. The heterogeneous sample of countries consists of 17 European (Austria, Croatia, Cyprus, Germany, Greece, Italy, Latvia, Luxemburg, Netherlands, Norway, Poland, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, and United Kingdom), 7 American (Brazil, Chile, Colombia, Guatemala, Panama, United States, and Uruguay), 6 Asian (India, Indonesia, Kazakhstan, Russia, South Korea, and Taiwan), 7 Middle-Eastern (Iran, Israel, Kuwait, Oman, Qatar, Saudi Arabia, and United Arab Emirates), and 5 African (Angola, Burkina Faso, Egypt, Morocco, and Togo) countries. For this dataset, we will apply DEA, a non-parametric technique based on linear programming with the purpose of evaluating the efficiency of units from the same field. The main outputs of economies are Total early-stage Entrepreneurial Activity (TEA), Female/Male TEA and Entrepreneurial intentions. The remaining 12 attributes are inputs. All the data is acquired from the Global Entrepreneurship Monitor (see GEM Data, 2022, https://www.gemconsortium.org/data). The complete definitions of the attributes are reported (see, GEM Definitions, https://www.gemconsortium.org/wiki/1154.

Data Envelopment Analysis (DEA) is a non-parametric comparative statistical technique applied to a set of entities, transforming a set of inputs into a set of outputs. DEA is also a linear programming

technique that allows the relative comparison of the set of entities with respect to their performance (Coelli, 1995, Kourtis et al., 2022). Charnes et al. (1978) introduced this method to measure the efficiency of converting the inputs into outputs, without existing a relationship between the two sets. Farrell (1957) gave a definition of the technical efficiency of a firm as the ability to obtain maximum output from a set of inputs in a framework of an output-oriented model. DEA has three concepts of efficiency: technical efficiency, allocative efficiency, and economic efficiency (Hassan, 2021). According to Hassan, 2021, technical efficiency is defined as the maximum feasible output from a specified set of inputs (output-oriented DEA) or minimum feasible input for a specified set of output (input-oriented DEA). Another concept is the DMU (=Decision Making Unit) which is an entity that converts multiple inputs into multiple outputs (Cooper et al., 2011).
We follow the approach of El-Mahgary and Lahdelma (1995) and we apply two input-oriented models, namely CRS (constant returns to scale) and VRS (variable returns to scale) for a set of 42 world countries and 15 variables (12 inputs and 3 outputs) collected for the year 2019 to determine the relative efficiency of each unit (here country) with respect to the other units in the analysis. DEA divides DMUs into efficient and inefficient ones. The DMUs that get a score of 1 are called efficient with respect to the other DMUs and are located on the efficient frontier; these DMUs become a benchmark for comparison (Kourtis et al., 2022). The efficient DMUs are Pareto optimal. The inefficient DMUs have a score of positive and less than 1.

3. ANALYSIS AND RESULTS

In the CSR model, we obtain that Angola and Togohave an efficiency equal to 1, meaning that they are efficient DMUs. The worst performer is India (0.205783899) (see Table 1).

Table 1. CRS efficiencies

Country	Efficiency	Country	Efficiency	Country	Efficiency
Angola	1	Iran	0.46472027	Russian Federation	0.746905676
Austria	0.677088766	Israel	0.556586271	Saudi Arabia	0.719479365
Brazil	0.778378378	Italy	0.30106808	Slovak Republic	0.4937847
Burkina Faso	0.9515486	Kazakhstan	0.958798805	Slovenia	0.602610386
Chile	0.716899576	Kuwait	0.797448166	South Korea	0.533894405
Colombia	0.787846093	Latvia	0.577540107	Spain	0.769327145
Croatia	0.641600552	Luxembourg	0.411646586	Sweden	0.485625486
Cyprus	0.641600552	Morocco	0.720788326	Switzerland	0.795258621
Egypt	0.707755613	Netherlands	0.474343928	Taiwan	0.522636268
Germany	0.726559326	Norway	0.398832685	Togo	1
Greece	0.518375242	Oman	0.901154837	United Arab Emirates	0.472014674
Guatemala	0.942063118	Panama	0.851953089	United Kingdom	0.579075544
India	0.205783899	Poland	0.556418498	United States of America	0.713012478
Indonesia	0.723043156	Qatar	0.536227289	Uruguay	0.767054013

Source: own computations

In Figure 1 one can see the visual representation of the CRS efficiency, taking into accounts the three outputs. On the vertical axis the DMU's efficiency is represented. The three outputs colored in different shades of gray suggest the contribution of each one to each DMU efficiency.

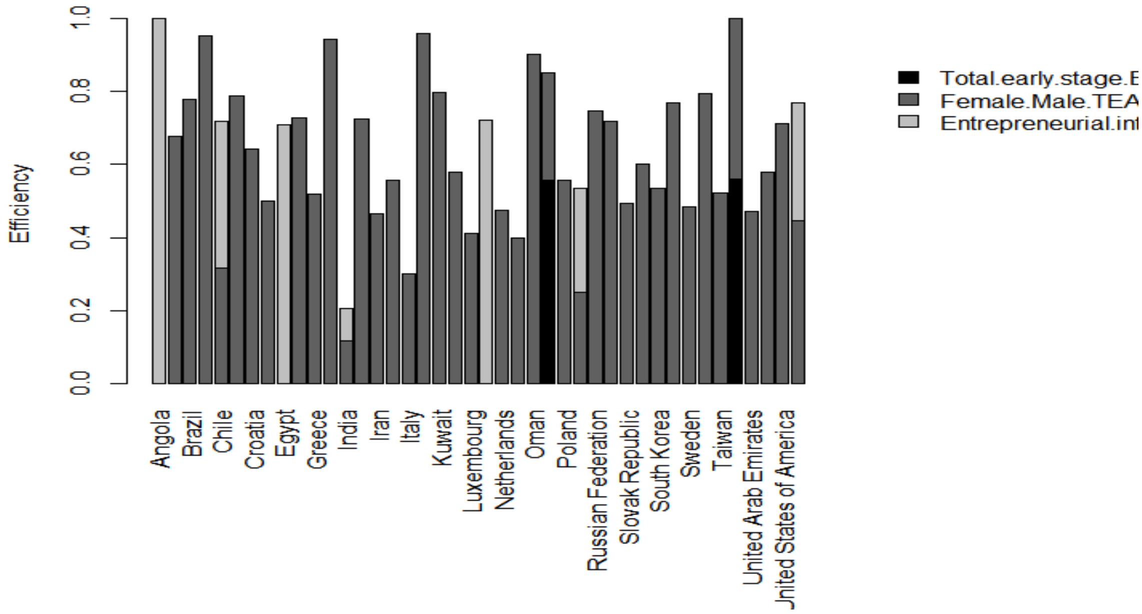

Figure 1. Top CRS efficiencies
Source: own computations

Banker et al. (1984) extended the CRS to VRS, by relaxing the CRS assumptions. VRS model envelops the data more closely and provides more accurate technical efficiency than CRS model.
The difference between VRS and CRS models is that CRS estimates the gross efficiency of a DMU, while VRS measures the pure technical efficiency. CRS assumes that DMUs perform at their optimal scale and that a change in inputs leads to a proportional change in outputs. CRS assumes that DMUs may not perform at their optimal scale, therefore their technical efficiency scores are compared (Hernández and San Sebastián, 2014).

Table 2. VRS efficiencies

Country	Efficiency	Country	Efficiency	Country	Efficiency
Angola	1	Iran	1	Russian Federation	1
Austria	0.93916771	Israel	0.886426214	Saudi Arabia	0.807214666
Brazil	1	Italy	1	Slovak Republic	1
Burkina Faso	1	Kazakhstan	0.960180831	Slovenia	0.887901067
Chile	0.983377458	Kuwait	1	South Korea	0.841376603
Colombia	0.940916709	Latvia	1	Spain	0.947490418
Croatia	1	Luxembourg	0.94310319	Sweden	0.938221962
Cyprus	0.946582135	Morocco	1	Switzerland	0.993555402
Egypt	0.956917517	Netherlands	0.786464822	Taiwan	0.750180996
Germany	0.873547893	Norway	0.901375865	Togo	1
Greece	0.919429387	Oman	1	United Arab Emirates	0.767236272
Guatemala	1	Panama	1	United Kingdom	0.82353341
India	0.722832494	Poland	0.990128338	United States of America	0.827902734

Indonesia	0.755847904	Qatar	0.792696666	Uruguay	1

Source: own computations

In the VRS model, one obtains that Angola, Brazil, Burkina Faso, Croatia, Guatemala, Iran, Italy, Kuwait, Latvia, Morocco, Oman, Panama, Russia, Slovak Republic, Togo, and Uruguay are the efficient DMUs. The worst performers are India (0.722832494), Taiwan (0.750180996) and Indonesia (0.755847904) (see Table 2).

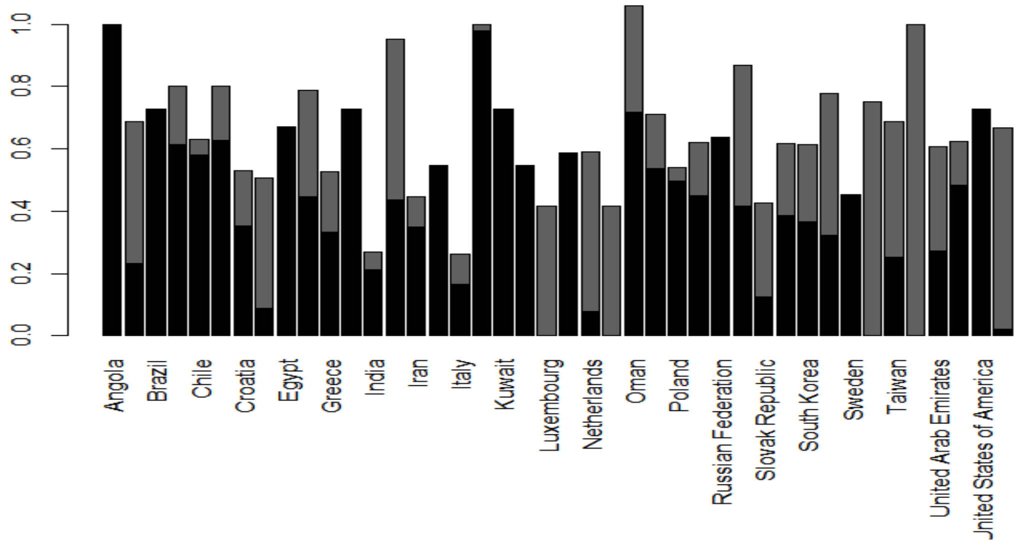

Figure 2. Top VRS efficiencies

Source: own computations

If we compute the scale efficiency (SE) as the ratio CRS/VRS in an input-oriented DEA, we obtain Table 3 and Figure 3. The scale efficiency means the point at which a DMU reaches an optimal scale to maximize its productivity (Hassan, 2021). TE_{CRS} is technical efficiency at constant returns to scale; TE_{VRS} is technical efficiency at variable returns to scale; SE is scale efficiency; SV is standard deviation; and CV is coefficient of variation.

Table 3. SE efficiencies

Country	Efficiency	Country	Efficiency	Country	Efficiency
Angola	1	Iran	1	Russian Federation	0.8690613
Austria	0.720945534	Israel	1	Saudi Arabia	1
Brazil	0.778378378	Italy	0.8083389	Slovak Republic	0.7218315
Burkina Faso	1	Kazakhstan	0.9916135	Slovenia	0.9046411
Chile	1	Kuwait	1	South Korea	0.9869591
Colombia	1	Latvia	0.9674117	Spain	0.9530559
Croatia	0.76934764	Luxembourg	0.9305971	Sweden	0.9296512
Cyprus	0.87439195	Morocco	0.8011377	Switzerland	1
Egypt	0.91389072	Netherlands	0.9981363	Taiwan	0.9999332
Germany	0.97802638	Norway	0.9992716	Togo	1
Greece	0.91900758	Oman	0.9983714	United Arab Emirates	0.9686659
Guatemala	1	Panama	1	United Kingdom	0.9947103
India	0.98120896	Poland	0.919262	United States of America	1
Indonesia	0.95870129	Qatar	0.9853163	Uruguay	0.9675317

Source: own computations

In Table 4, one can see that the technical efficiency score ranges from 0.7218 to 1 and from 0.8483 to 1 with a mean value of 0.9227 and 0.9683 under CRS and VRS models, respectively. The mean value reveals that the countries have entrepreneurial activities on the efficient frontier if the use of the input may be reduced by 7.73%, and by 3.17% under CRS and VRS models, respectively, without any decrease in the outputs.

Table 4. Descriptive statistics of efficiency scores in entrepreneurial activity

Efficiency	Mean	SD	CV	Min	Max
TE_{CRS}	0.9227	0.0817	11.28	0.7218	1
TE_{VRS}	0.9683	0.0484	19.99	0.8483	1
SE	0.9529	0.9861	13.68	0.7218	1

Source: own computations

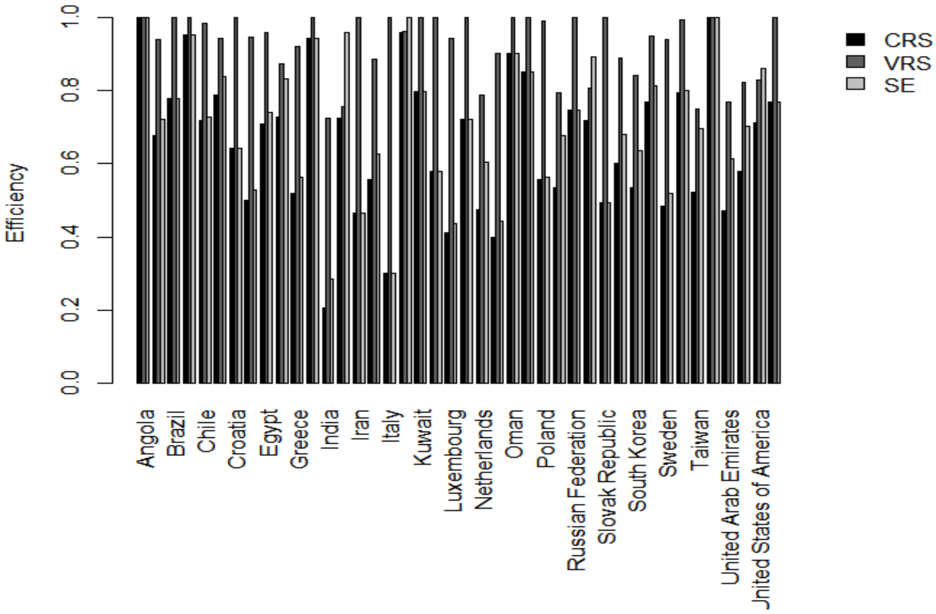

Figure 3. VRS vs. CRS vs. SE efficiency
Source: own computations

3. CONCLUSIONS

In this paper, we compared and measured the technical efficiencies of 42 world countries for year 2019 using 12 inputs and 3 outputs under constant and variable returns to scale models. The mean values of the CRS and VRS models reveal that the countries have entrepreneurial activities on the efficient frontier if the use of the input may be reduced by 7.73%, and by 3.17% under CRS and VRS models, respectively, without any decrease in the outputs. A recognized limitation of DEA is that input usages and output levels may be reduced or increased in terms of fixed proportions. This research could be extended by estimating the Malmquist index introduced by Caves et al. (1982) using DEA.

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