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FINANCING INNOVATIVE PROJECTS IN THE TOP 30 COUNTRIES AND UZBEKISTAN WITH STARTUP DEVELOPMENT INDICATORS WITH DEA MODELS

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ABSTRACT
Recently, the efficiency of implementation of the startups has been investigated from various aspects. One of them is the measurement of efficiency of startup ecosystem per individual countries by means of Data Envelopment Analysis (DEA). In other words, this paper explores the efficiency of startup ecosystem score in the selected countries, Top 30 countries, with a particular reference to Uzbekistan. The efficiency in the selected countries and Uzbekistan differs depending on the applied input- or output-oriented DEA model.
KEYWORDS: *DEA models, CRS, VRS, Global startup ecosystem index, funding, Top 30 countries, efficiency, selective countries, Uzbekistan*

INTRODUCTION

The analysis of innovation and startup implementation efficiency has constantly been an ongoing topic. By applying various accounting and mathematical and statistical models, it has been investigated from various points of view.

The main research issue in this paper is the analysis of factors affecting the efficiency of the score of global startup ecosystem index in Top 30 countries, primarily in Uzbekistan, applying the appropriate methodology, which is to serve as the basis for improving the future indicator of startups by taking appropriate actions. This improvement can be made by the change of input or output values or both, input and output values. The possibilities on the input side are certainly wider.

In terms of methodology, this research is based on the parallel comparative application of the DEA models with the input and output orientation. To a certain extent, comparative analysis, ratio analysis, and statistical analysis have been used.

1. DEA models

DEA was first developed by Farrel in 1957, which later been modified by Charnes-Cooper-and Rhodes (CCR) in 1978. It is a non-parametric method that utilizes linear programming to measure the level of efficiency of comparable decision-making units (DMU) by employing multiple inputs and outputs (Klimberg. et al., 2008). This technique of measuring efficiency was first introduced by Farrel in 1957 based on the basic theory of production on single input and single output such as "output per work hour" in a form of ratio (Cooper. et al., 2006).

$$\text{Efficiency} = \frac{\text{Output}}{\text{Input}}$$

However, this measurement does not entirely represent efficiency as commonly multiple inputs are used to produce single or more outputs, which lead to the modification of original equation to include measurement of multiple inputs and multiple outputs. This concept was further extended into basic CCR DEA model developed by CCR in 1978 by altering the original equation to (Sherman, Zhu, 2006):

$$\text{Efficiency} = \frac{\text{Weighted sum of output}}{\text{Weighted sum of input}}$$

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In DEA, methods to measure efficiency of DMUs are referred to a group of firms under study such as banks, hospital etc. DEA is a most accurate technique to measure efficiency given limited number of DMUs (Ahmad, Luo, 2010).

In the theoretical analysis of the DEA models, we shall briefly present CCR and BCC models with input and output orientation as these models were applied in the examination of trade efficiency for the selected countries and Uzbekistan.

1.1. CCR Model

The CCR model, named by its developers Charnes, Cooper and Rhodes, is based on fixed or constant returns-toscale. This actually means that the proportional increase of all the inputs results in the same proportional increase of all the outputs. Accordingly, the mathematical equation to find the maximum efficiency of DMUs using weighted input-output efficiency measure can be expressed as (Charnes et al., 1978):

$$max \frac{\sum_{j=1}^{J} v_{mj} y_{mj}}{\sum_{i=1}^{I} u_{mi} x_{mi}}$$

Such that

$$0 \leq \frac{\sum_{j=1}^{J} v_{mj} y_{nj}}{\sum_{i=1}^{I} u_{mi} x_{ni}} \leq 1; \qquad n = 1,2, \dots \dots, N$$

$$v_{mj}, u_{mi} \geq 0; \quad i = 1,2, \dots, I; \quad J = 1,2, \dots, J$$

Where:
N: Total number of DMUs
J: Weighted sum of outputs
I: Weighted sum of inputs
M: The base DMU (calculating *m*th DMU)
N: DMUs
I: Inputs
J: Outputs
vmj: Weights for output
umi: Weights for input.

Since the above equation is in the fractional function, it is difficult to compute, thus, CCR (1978) transform the equation into linear programming equation by setting the denominator of the ratio to one or unity to form a linear programming equation Model 2 or equally known as output-maximization CCR model (Chen, 2008):

$$max \sum_{j=1}^{J} v_{mj} y_{mj}$$

Such that

$$\sum_{i=1}^{I} u_{mi} x_{mi} = 1$$

$$\sum_{j=1}^{J} v_{mj} y_{mj} - \sum_{i=1}^{I} u_{mi} x_{mi} \leq 0; \quad n = 1,2, \dots \dots, N$$

$$v_{mj}, u_{mi} \geq 0; \quad i = 1,2, \dots, I; \quad J = 1,2, \dots, J$$

When DEA is employed to measure banks efficiency for a set of DMUs, the linear programming algorithm will calculate the efficiency of each DMU given the identical inputs and outputs variables to find the maximum ratio of weighted sum of output to the weighted sum of input (most efficient DMU) and to be used as benchmark against other DMUs, causing the best-practice DMUs to lie on the efficient frontier line. It means the best-practice units are relatively efficient and identified by DEA efficiency score as 100% (efficiency = 1) (Charnes et al., 1994).

Charnes et al. (1979) imposed non-negativity restrictions to ensure inputs and outputs have positive weight values, so as the efficiency score assigned will be between 1 and 0, and no efficiency index greater than one. The less productive units or inefficiency are identified with efficiency score of <100% (efficiency <1). The relative units to this frontier represent the degree of inefficiency. Graphically, the Figure 1 below illustrates the production frontier of the CCR Model, where it calculates most efficient DMUs on diagonal line across the area where frontier and other DMUs lies (production possibility sets) (Charnes et al.,1979).

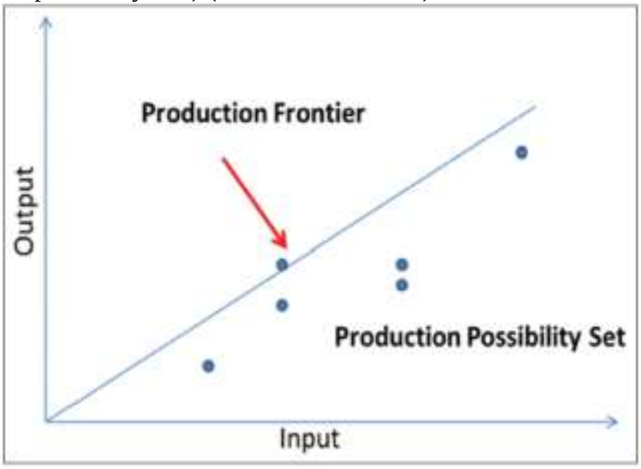

Figure 1. Production frontier of the Charnes-Cooper-and Rhodes model (Cooper et al., 2006)

1.2. BCC Model

The concept of the CCR model was modified by the introduction of the BCC model. The model is named after its developers Banker, Charnes and Cooper who replaced constant returns-to-scale (CRS) by variable returns-toscale (VRS). The DMU operates under VRS if the input increase does not result in proportional changes of the output. The BCC model is formulated as (Banker et al., 1984):

$$Max_{u_j v_i} E_k = \frac{\sum_{j=1}^{q} uY_{kj} - u_0}{\sum_{i=1}^{p} \upsilon X_{ki}}$$

$$\frac{\sum_{j=1}^{q} u_j Y_{kj} - u_0}{\sum_{i=1}^{p} \upsilon X_{ki}}$$

Is<1

Where,
Ek: Efficiency of *k*th DMU
Q: Output
P: Inputs
uj: Weights of output (virtual value)
V: Weights of input (virtual value)
uo: Scalar free in sign (positive or negative or 0).

Basically, in BCC model, the formula calculates the efficiency of DMUs and most efficient DMUs that lie on the convex line creating efficient frontier after passing through the area of DMUs (production possibility set). The Figure 2 graphically illustrates production frontier of BCC model.

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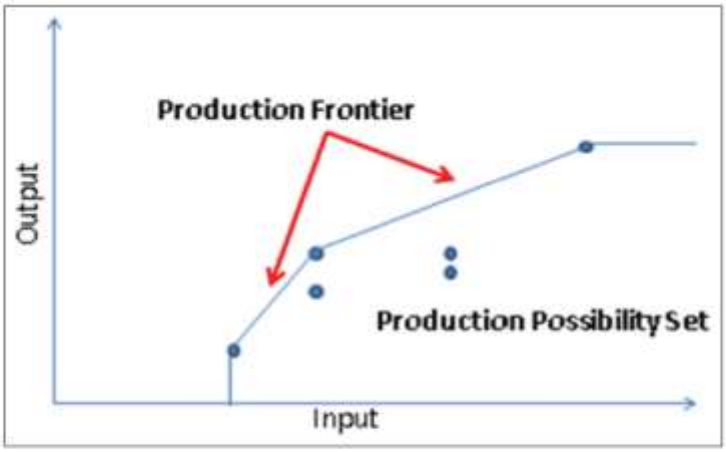

Figure 2. Production frontier of the Banker-Charnes-Cooper model (Cooper et al., 2006)

In the BCC model, technical efficiency (TE) acquired by the CCR model is decomposed into two components –

1) pure technical efficiency (PTE) that ignores the scale size by comparing DMU with the units on a similar scale and measures how DMU uses inputs under exogenous conditions; and

2) scaleefficiency (SE) that shows how scale size affects efficiency, formulated as:

$$SE = TE / PTE.$$

3. Defining Input/Output Data

Table 1 provides a description of the variables considered in DEA model.

Table 1. Description characteristics of the variables considered in the regression model

No.	Variable name	Variable designation	Unit	Variable Description	Source
1	State of the stock market	Mkt	Logical variable	An indicator of the state of the stock market is the state of crisis in the economy: if the economy is at its peak, then the state of the market is bullish and bearish in the opposite situation. This variable is logical, and for crisis years it will take the value 1. The period of attracting investments can take from 6 to 12 months, so for this indicator a 1-year data lag was used.	https://www.imf.org/en/Publications/WEO/Issues/2022/10/11/world-economic-outlook-october-2022
2	Ranking score in the Global Startup Ecosystem Index	RSc	Score	The Global Startup Ecosystem Index (GSEI) is built on the basis of hundreds of thousands of data processed by an algorithm that takes into account several dozen parameters. The index is used annually by hundreds of thousands of startup founders, startup ecosystem developers, corporations and other stakeholders to make critical policy, strategy, relocation and investment decisions.	https://www.startupblink.com/startupecosystemreport
3	Amount of deals	Deal	Units	Number of transactions completed in 2022 in selected countries	https://www.startupblink.com/startupecosystemreport
4	Investments through transactions	Fund	Million $	Number of investments attracted from completed transactions in selected countries in 2022	https://www.startupblink.com/startupecosystemreport
5	Number of pantheons	Pan	Units	The first group is the Pantheon of global startup ecosystems. This group now includes more than 240 organizations around the world and can be seen on the StartupBlink map. The Startup Ecosystem Pantheon is a	https://www.startupblink.com/startupecosystemreport

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				category coined by StartupBlink, which includes companies such as SpaceX , Microsoft , and Netflix; These companies are no longer a startup or a unicorn, but still have a significant impact on their startup ecosystem and their brand. Organizations such as Y Combinator , StartupChile and the Estonian e-commerce program residencies are also considered part of the Pantheon Group , as their innovative initiatives influence the growth and legacy of their ecosystems. These organizations are divided into three levels (gold, silver, bronze) depending on their influence.	
6	Number of unicorns	unic	Units	Unicorns are startups that are valued at more than $1 billion. Unicorns are critical success stories that not only increase the flow of capital into the ecosystem, but also contribute to the growth of the ecosystem through a powerful narrative that attracts more entrepreneurs and investors to the place.	https://tipalti,com/go-ipo/unicorn-hunting-2022/
7	Investment in innovation	GERD	Billion $	Gross domestic R&D expenditure is defined as the total expenditure (current and capital) on R&D undertaken by all resident companies, research institutes, university and government laboratories, etc. in a country. It includes R&D financed from abroad, but excludes domestic financing of R&D carried out outside the domestic economy. This indicator is measured in constant US dollars .	https://www,rdworldonline,com/2022-global-funding-forecast-rd-variants-cover-more-than-the-pandemic/

From this table, In the research the output data is Ranking score in the Global Startup Ecosystem Index and Investments through transactions. Also, The indicators like GERD, number of unicorns, number of panteons, amount of deals, market state are input ones.

4. RESULTS

Empirical data for the study was downloaded from the platform https://www.startupblink.com, the data includes all transactions that took place in the venture industry in the Top 30 countries of this index and Uzbekistan in 2022. The assessment of countries and the received investments based on transactions were identified as the result/output in this model, all other indicators as input data. As part of the study, 4 basic efficiency models were considered: CCR-input, CCR-output, VRS-input, VRS-output. Assessment was done in R studio program by the author. The results for the models can be seen in Table 2.

Table 2. Country Performance Assessment Results

2022	CCR-I	CCR-O	VRS-I	VRS-O
United States	0.6467239	0.6467239	1.0000000	1.0000000
United Kingdom	0.8405094	0.8405094	1.0000000	1.0000000
Israel	1.0000000	1.0000000	1.0000000	1.0000000
Canada	0.6316357	0.6316357	1.0000000	1.0000000
Sweden	0.7795565	0.7795565	1.0000000	1.0000000
Singapore	1.0000000	1.0000000	1.0000000	1.0000000
Germany	0.4376471	0.4376471	0.7035396	0.7035396
France	0.4667799	0.4667799	0.8822460	0.8822460
Australia	0.4767338	0.4767338	0.7196917	0.7196917

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The Netherlands	0.6186345	0.6186345	0.8862366	0.8862366
Switzerland	0.6269801	0.6269801	0.8808032	0.8808032
China	1.0000000	1.0000000	1.0000000	1.0000000
Finland	1.0000000	1.0000000	1.0000000	1.0000000
Spain	0.8070580	0.8070580	1.0000000	1.0000000
Ireland	1.0000000	1.0000000	1.0000000	1.0000000
Japan	0.9522143	0.9522143	0.9750879	0.9750879
Denmark	1.0000000	1.0000000	1.0000000	1.0000000
South Korea	0.3875879	0.3875879	0.8360456	0.8360456
India	0.6296348	0.6296348	0.8310895	0.8310895
Belgium	0.8683721	0.8683721	0.9133248	0.9133248
Norway	1.0000000	1.0000000	1.0000000	1.0000000
Taiwan	1.0000000	1.0000000	1.0000000	1.0000000
Austria	0.9816718	0.9816718	1.0000000	1.0000000
Portugal	1.0000000	1.0000000	1.0000000	1.0000000
Brazil	0.2955440	0.2955440	0.3114827	0.3114827
UAE	0.6961954	0.6961954	0.7534709	0.7534709
Russia	1.0000000	1.0000000	1.0000000	1.0000000
Italy	1.0000000	1.0000000	1.0000000	1.0000000
Uzbekistan	0.2396240	0.2396240	1.0000000	1.0000000

Analyzing the table, It is clear that according to the CCR model, 11 countries are efficient in using resources to obtain these results. These countries are: Russia, Italy, Portugal, Taiwan, Denmark, Ireland, Finland, China, Singapore and Israel. Also, the conclusions from the table can be clearly seen in Figure 3

CCR-I\O VRS-I\O

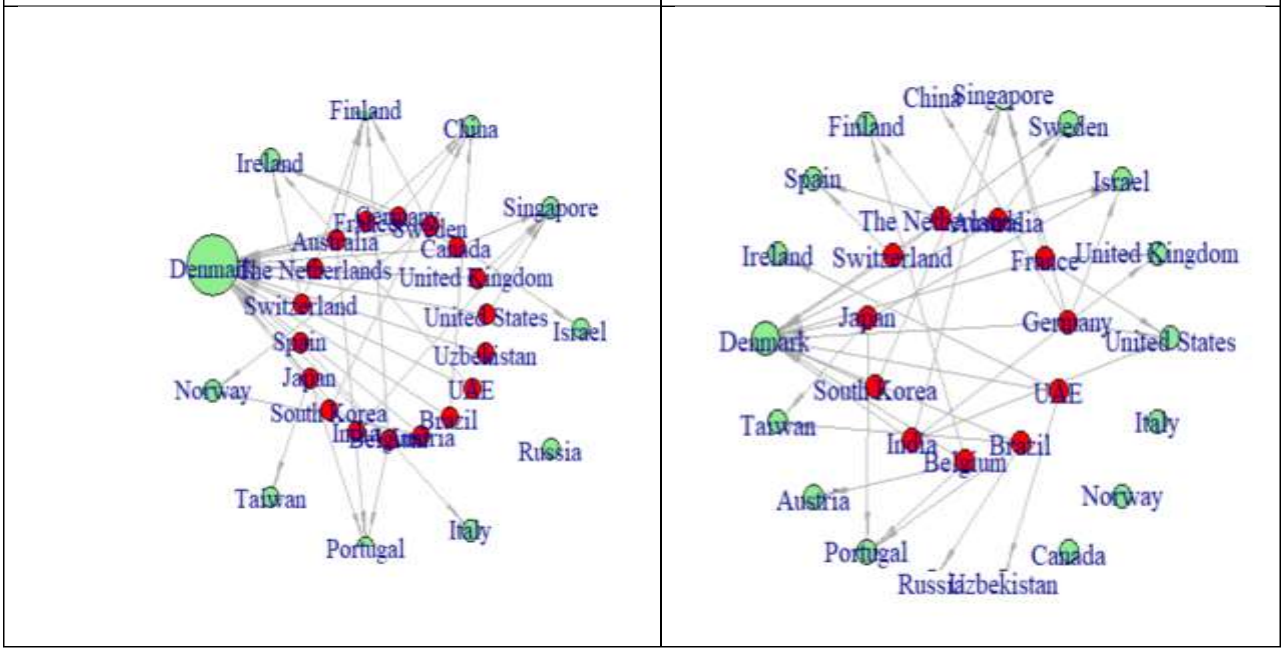

Fig.3 Country Performance Indicators

In this study, the DEA model was used to examine the innovation performance of 30 top startup countries. Currently, the efficiency of innovative IT companies needs to be improved, and low purely technical efficiency is the main reason limiting the growth of comprehensive innovation efficiency in a number of countries.

Based on this, the following proposals are put forward to improve the innovative efficiency of innovative companies: (1) In general, the scale of investment in R&D in a number of countries can be moderately expanded, and at this time special attention should be paid to pure technical efficiency. As a new form of business, industrial companies must constantly reform the system and promote R&D investment management, support the incubation of new innovative products, optimize the innovation cost-benefit structure, and reduce resource redundancy. (2) Further strengthening the development of start-ups, improving support policies, especially government subsidy policies, reasonable control over the amount of subsidies, and greater use of market-oriented subsidies to support the improvement of innovation efficiency. Colleges and universities should further strengthen the training of information technology talents to reserve professional applied talents for the development of this field.

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