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Assessing Regional Entrepreneurship: A Bootstrapping Approach in Data Envelopment Analysis

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Abstract: The aim of the present paper is to demonstrate the viability of using data envelopment analysis (DEA) in a regional context to evaluate entrepreneurial activities. DEA was used to assess regional entrepreneurship in Greece using individual measures of entrepreneurship as inputs and employment rates as outputs. In addition to point estimates, a bootstrap algorithm was used to produce bias-corrected metrics. In the light of the results of the study, the Greek regions perform differently in terms of converting entrepreneurial activity into job creation. Moreover, there is some evidence that unemployment may be a driver of entrepreneurship and thus negatively affects DEA-based inefficiency. The derived indicators can serve as diagnostic tools and can also be used for the design of various interventions at the regional level.

Keywords: regional entrepreneurship; data envelopment analysis (DEA); bootstrapping; Greece



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1. Introduction

Entrepreneurship, observed either in the formation of new businesses or the expansion of existing ones, contributes significantly to the creation of economic value in today's marketplaces, which are becoming more and more competitive [1]. Regions must match their objectives with the forces promoting economic growth and entrepreneurship in a world dominated by technology and innovation. Growth in the supply of entrepreneurs within an economic system is what is meant by entrepreneurship development. Interventions to support this process include a number of initiatives aimed at expanding the population of potential entrepreneurs.

The concept of entrepreneurship has a long history in economic theory and has been a central economic issue. Schumpeter's [2] assertion that entrepreneurship is the principal engine of economic development has had a significant impact on the history of entrepreneurship. Entrepreneurship, according to Reynolds et al. [3], is any attempt to start a new business, including self-employment (i.e., individual-level activity), the establishment of a new business organization, or the growth of an existing business (i.e., firm-level activity). This can be performed by a single person, a group of people, or an established business organization. Readers interested in learning further definitions of entrepreneurship are referred to Gartner [4] and Lundstrom and Stevenson [5].

Due to the tight relationship between entrepreneurship and small-business management, Schaper [6] distinguishes three main categories of entrepreneurs: the conventional archetype entrepreneur, corporate entrepreneurs or intrapreneurs in major businesses, and new entrepreneurs. Ecopreneurship, also known as green entrepreneurship, is closely tied to several market segments that the sustainable business framework offers. Self-employment and new incorporations are included in studies of entrepreneurship, and they concentrate on the rate of new company entry, which is typically quantified as new incorporations [7].

The Global Entrepreneurship Monitor (GEM) [8,9] provides entrepreneurial indicators at the national level (i.e., the total entrepreneurial activity (TEA) index), but there are

also initiatives for deriving individual indicators (i.e., the TEA index [10]) and composite indicators at the regional level (i.e., the regional entrepreneurship index (REI) [1]. The TEA index measures individual- and firm-level activity by counting the number of new firms and the number of people who launch new ventures [8]. The REI is calculated as the average of the three following indicators' relative rankings (equally weighted): (i) the growth in the number of new firm births; (ii) the proportion of young firms that are growing; and (iii) the number of new firm births per 1000 individuals in the labor force [1].

This paper aims to demonstrate the viability of using data envelopment analysis (DEA) [11] in a regional context to evaluate entrepreneurial activities. DEA was employed to appraise the performance of Greek regions based on the outcomes of the entrepreneurial activity measured by the number of firms per 1000 people in the labor force and the number of new firms in manufacturing per 1000 people in the labor force. The two metrics of entrepreneurial activity utilized in the current paper are on the input side of DEA, whereas the output side uses the employment rate. The information required to calculate the input and output side metrics is available from the Hellenic Statistical Authority (ELSTAT). DEA was used to generate an efficiency frontier that would serve as a benchmark to compare the relative performance of Greek regions in the assessment of regional entrepreneurship. Performance indicators with a range of 0 to 1 are provided through the use of DEA. In particular, the current study details the use of a DEA bootstrapped approach to assess entrepreneurship at the regional level in order to provide useful insights for stakeholders and policymakers to successfully increase entrepreneurial activity. As such, this paper aims to respond to the next central question: How differently do regions perform in terms of converting entrepreneurial activity into job creation? There are no published regional entrepreneurship indicators, despite the fact that Greece has access to the TEA and FEA (firm entrepreneurship activity, an indicator of entrepreneurial activity that reflects innovation and growth among established firms [12]) indexes at the national level since 2004 as part of the GEM [13,14].

The remainder of the paper is organized as follows: Section 2 provides a review on the use of DEA in the entrepreneurship literature. Section 3 describes the DEA method, the selected DEA model, and the bootstrapping algorithm used. In Section 4 the data are presented, and in Section 5 the results are reported and discussed. The final section presents the conclusions.

2. Literature Review

There are thousands of research papers that use DEA in a variety of contexts, including health [15], transportation [16], immigration, and receptivity to refugees [17]. The interested reader is also directed to recent surveys by authors such as Emrouznejad and Yang [18] and Liu et al. [19].

The usage of DEA in the entrepreneurship literature is reviewed in this section. Models directly derived from production theory and models built for the derivation on composite indicators are the two main modeling approaches that are discussed.

In the first research strand, DEA models take into account many variables and produce a consolidated efficiency measure with respect to a frontier made up of entities being evaluated, such as nations, regions, or people that act as entrepreneurs. Sutter and Stough [20] employed DEA to quantify the impact of entrepreneur capital on the performance of U.S. metropolitan areas. Fried and Tauer [21] used the free disposal hull (FDH) and *order-m* FDH [22] to create an index of entrepreneur success at the level of the individual enterprise. Lafuente et al. [23] used the DEA model's input variable of the national-level entrepreneurship indicator to explain the variations in efficiency among the chosen nations. DEA and truncated regression with double bootstrap are the foundation of Du and O'Connor's [24] two-stage modeling approach. In the first stage, they estimated the bias-corrected bootstrapped DEA scores of the sampled countries, and in the second stage, they calculated the effect of entrepreneurship on the estimated DEA scores. Silva et al. [25] investigated, by

means of two-stage DEA, whether and to what extent socioeconomic conditions influence entrepreneurship-based activities in 18 European countries.

The work of Rezaei et al. [26], which used DEA along with other competing methodologies to generate a DEA-based composite indicator addressing three dimensions of entrepreneurship at the business level, including innovativeness, risk taking, and proactiveness, is included in the second research strand.

According to the previous review, there is little literature on the impact of DEA on regional entrepreneurship. The purpose of this research is to evaluate regional entrepreneurship in Greece using DEA in light of this gap in the pertinent literature. Regarding the paper's original content, it adheres to the first research strand, which uses models that are directly derived from production theory. Individual measurements of regional entrepreneurship are employed as inputs, and employment rates are used as outputs to construct the DEA-based performance indicators. Bias-corrected metrics are also produced using a bootstrap approach, in addition to point estimates.

3. Materials and Methods

3.1. Methods

A non-parametric method known as DEA was employed to evaluate the performance of a group of entities known as decision-making units (DMUs) (such as regions) that function under comparable conditions, use the same inputs, and produce the same outputs. Based on production theory, DEA is able to estimate a discrete piecewise frontier without imposing any functional form on the data. The efficient set of DMUs that lie on the frontier in DEA determines its location; inefficient DMUs are located below the frontier [20].

Farrell [27] pioneered the use of DEA to assess efficiency and suggested a single output/input technical efficiency measure. By introducing the CCR model, Charnes et al. [11] extended Farrell's [27] efficiency metric to multiple output/input scenarios and created the term data envelopment analysis. In order to maximize technological efficiency while taking into account the size on which each DMU was functioning, Banker et al. [28] created the BCC model. For more about DEA, the interested reader is referred to classical handbooks [29–32].

This study's application of DEA is based on the standard process: (i) defining DMUs, (ii) specifying and choosing input and output variables, (iii) choosing the DEA model, and (iv) bootstrapping the derived DEA scores. The selection of the DMUs to be analyzed is the first stage in conducting a DEA study. The specification and selection of output and input variables, the choice of DEA model, and bootstrapping are the following steps that are taken in order to examine the sampling characteristics of the DEA estimators and to compute confidence intervals.

3.1.1. Definition of DMUs

The thirteen Greek areas are used to represent the various DMUs being examined in the current study.

3.1.2. Selection of Input and Output Variables

Two requirements of the dataset must be satisfied for the DEA application to be successful. The first is the isotonicity property assumption, which states that efficiency rises as outputs rise and declines as inputs rise [32]. The second is the requirement of the number of inputs and outputs to select and its relationship to the number of DMUs [32]: $n \geq \max\{mxk, 3(m + k)\}$, where n is the number of observations, m is the number of inputs, and k is the number of outputs. Other rules have also been suggested [33–35]. The reader who is interested in learning more about this is directed to Sarkis [36].

3.1.3. Selection of DEA Model

There are two ways to construct a DEA model: input orientation and output orientation. An output orientation analysis provides information on how much proportional

expansion of the output levels of an inefficient region is necessary while maintaining current input levels for it to become DEA-efficient, whereas an input orientation analysis determines the proportional reduction in inputs without changing the output level for an inefficient region to become DEA-efficient.

The DEA-based regional relative performance indicator results from the solution of the following linear programming problem, given a set of j ($j = 1, 2, \dots, n$) regions whose entrepreneurial activity (i.e., inputs) can be measured by a set of i ($i = 1, 2, \dots, m$) single indicators denoted by x and whose output r ($r = 1, \dots, k$) (i.e., employment creation) can be measured by a set of r single indicators denoted by y . The model is the output-oriented ‘BCC envelopment model’, in reference to its authors (Banker, Charnes, and Cooper) [30]:

$$\begin{aligned}
 & \text{Max } \varphi \\
 & \text{s.t.} \\
 & \sum_{j=1}^n \lambda_j x_{ij} \leq x_{ij_0} \\
 & \sum_{j=1}^n \lambda_j y_{rj} \geq \varphi y_{rj_0} \\
 & \sum_{j=1}^n \lambda_j = 1 \\
 & \lambda_j \geq 0, j = 1, 2, \dots, n, i = 1, 2, \dots, m, r = 1, 2, \dots, k
 \end{aligned} \tag{1}$$

where

λ_j = intensity variables estimated by the model.

With reference to the various sizes of the Greek regions examined here, the assumption of variable returns to scale (VRS) reflected by the restriction $\sum_{j=1}^n \lambda_j = 1$ is thought to be the most pertinent assumption. Furthermore, the usage of ratios as inputs and outputs supports this supposition [37].

3.1.4. Bootstrapping

Typical DEA applications presume that any divergence from the estimated frontier is caused by various types of inefficiency without accounting for the uncertainty underlying DEA score estimates (i.e., inefficiency). It is important to keep in mind that the DEA contains uncertainty due to sample variability or uncertainty resulting from the estimation of the frontier. Unawareness of these statistical characteristics and uncertainty can cause DEA score estimations of efficiency to be skewed, which can lead to false results.

In order to examine the sample characteristics of DEA estimators and assess the robustness of DEA point estimates by correcting the bias and creating confidence intervals, the general multi-output and multi-input situation is considered to be an ideal setting for bootstrapping [38–41]. The bootstrapping method relies on replicating the data generation process (DGP) to simulate the sampling distribution (i.e., the process of generating the efficiency scores in our case). The statistical model is composed of assumptions about the DGP. Under the presumption that the distribution of efficiency scores is independently distributed, Simar and Wilson [40] suggested the bootstrap for DEA. In DGP, a sizable number, B , of pseudo-datasets are created using the DEA scores derived from the actual data. The distributions of inefficiency in each pseudo-dataset are identical to those in the original dataset, ensuring that the performance levels shown by the bootstrapping results are consistent with the actual behavior. The DEA scores can be computed using the B pseudo-datasets, and the B efficiency scores can be used to build the empirical distribution for the efficiency measures.

It is important to keep in mind that the typical bootstrap may only be appropriate when the relevant statistics are smooth functions of the input data. Simar and Wilson [40] suggested the usage of a smoothed bootstrap as a resampling method for DEA in order to address the drawback of the inconsistent behavior of naive bootstraps when applied to DEA. It is possible to obtain a consistent estimate with the boundary condition on efficiency scores by employing a smoothing technique that is centered on the kernel density estimator.

The algorithm for the bootstrap of DEA efficiency ratings, according to Simar and Wilson's methodology, is as follows [40]:

- (i) Determine each region's initial DEA efficiency scores, $\hat{\varphi}_j (j = 1, \dots, n)$, by solving Model (1).
- (ii) Generate a random sample with a replacement of size n from the non-parametric kernel density function used to estimate the distribution of the original point efficiency scores, $\hat{\varphi}_1, \dots, \hat{\varphi}_n$.
- (iii) Create a pseudo-dataset for each region of the sample.
- (iv) To create new efficiency scores, $\hat{\varphi}_j^*$, solve the DEA-BCC model for the new set of data.
- (v) Repeat steps (ii) through (iv) $B = 2000$ times.

Once the bootstrap values, $\{\hat{\varphi}_b^*, b = 1, \dots, B\}$, have been obtained, the bootstrap bias for the original estimator, $\hat{\varphi}(x, y)$, is computed as follows:

$$\hat{bias}_B[\hat{\varphi}(x, y)] = B^{-1} \sum_{b=1}^B \hat{\varphi}_b^*(x, y) - \hat{\varphi}(x, y) \quad (2)$$

Bias-corrected efficiency estimates are produced by deducting the bias from DEA efficiency estimations. A bias-corrected estimator of the original estimator $\hat{\varphi}(x, y)$ can therefore be calculated as follows:

$$\hat{\hat{\varphi}}(x, y) = \hat{\varphi}(x, y) - \hat{bias}_B[\hat{\varphi}(x, y)] = 2\hat{\varphi}(x, y) - B^{-1} \sum_{b=1}^B \hat{\varphi}_b^*(x, y) \quad (3)$$

The bias-corrected estimators should only be employed if the ratio, r , as defined in Equation (4), is significantly greater than unity [39]. This assertion also implies that bias correction is required because there is significant bias present and DEA scores lack robustness if $r \leq 1$.

$$r = \frac{1}{3} (\hat{bias}_B[\hat{\varphi}(x, y)])^2 / \hat{\sigma}^2 \quad (4)$$

where $\hat{\sigma}^2$ is the estimated variance in the φ_j provided by the sample variance of the estimations from the bootstrap method.

Using the above procedure, confidence intervals can be constructed based on bootstrap percentiles [38], but the DEA estimators need to be corrected for bias, and this introduces additional noise [40]. In order to create confidence intervals, Simar and Wilson [35] proposed the following procedure, which automatically corrects for bias: use the pseudo-estimations $\{\varphi_b^*, b = 1, \dots, B\}$ to figure out a_a, b_a for a $(1 - a)$ percent confidence interval. With the known the distribution of $\hat{\varphi}^*(x, y) - \hat{\varphi}(x, y)$, it is trivial to find values a_a, b_a with the following probability:

$$\Pr(-b_a \leq \hat{\varphi}^*(x, y) - \hat{\varphi}(x, y) \leq -a_a) = 1 - a \quad (5)$$

The procedure for finding \hat{a}_a, \hat{b}_a involves sorting the values $\hat{\varphi}^*(x, y) - \hat{\varphi}(x, y)$ in increasing order, deleting $100\frac{a}{2}$ percent of the elements at either end of the sorted list, and setting $-\hat{b}_a, -\hat{a}_a$ equal to the endpoints of the array with $\hat{a}_a \leq \hat{b}_a$.

The bootstrap approximation of (5) is then:

$$\Pr(-\hat{b}_a \leq \hat{\varphi}^*(x, y) - \hat{\varphi}(x, y) \leq -\hat{a}_a) \approx 1 - a \quad (6)$$

Therefore, the estimated $(1 - \alpha)$ -percent confidence interval is then:

$$\hat{\varphi}^*(x, y) + \hat{a}_a \leq \hat{\varphi}(x, y) \leq \hat{\varphi}^*(x, y) + \hat{b}_a \quad (7)$$

The interested reader is directed to Simar and Wilson [39] for more information.

4. Dataset

The data from ELSTAT were used to derive the indicators for the input side. The two distinct indicators of regional entrepreneurship employed in the input side of the DEA were: (i) the number of firms in 2015 per 1000 labor force members and (ii) the number of new manufacturing firms per 1000 labor force members. Only the employment rate was on the output side.

The potential of regions to turn entrepreneurship into employment was considered as a means to meet the aim of employment generation when examining regional entrepreneurship activities. This transformation to employment generation placed employment generation (i.e., the employment rate) on the output side and entrepreneurial activities (i.e., single entrepreneurship metrics) on the input side. We used the transformation paradigm to evaluate the relative effectiveness of the regions in turning entrepreneurship into employment. In the Greek scenario, the measures that reflect entrepreneurial activity at the regional level were used as the input-side variables instead of absolute numbers, and as a result the employment rate served as a proxy for the output side.

Although the study's sample size of 13 regions was limited, there are other studies with similar sample sizes in the DEA literature [42]. Evanoff and Israilevich [43] asserted that DEA may be utilized with small sample sizes, despite Simar and Wilson's [44] claim that DEA, a non-parametric estimator, gives slower convergence and needs more data compared to parametric estimators. The 13 sampled regions complied with the general guideline given in Section 3.1.2 on the number of selected input and output variables and their relationship to the number of DMUs with regard to the number of inputs and outputs and their relation to the number of DMUs.

The most widely used entrepreneurship metric in economic research may be the number of new firms. This statistic can easily be normalized to account for regional size and is theoretically clear and manageable to monitor. By dividing the total number of new firm births by the number of labor force members (in thousands) in each region, the current paper controlled for regional size. The quantity of newly formed firms indicated how rapidly or slowly an area's level of indigenous entrepreneurship was changing. If regional economic growth was positively impacted by entrepreneurship, a region's capacity to increase its level of entrepreneurial activity can be viewed as a significant competitive advantage in the emergence and expansion of new businesses.

Another particular indicator of entrepreneurship is the ratio of newly founded manufacturing firms per 1000 labor force members. Although the idea of entrepreneurship has traditionally been associated with small firms, it should be highlighted that traditional entrepreneurs may be found in both manufacturing and large firms (i.e., corporate entrepreneurs or intrapreneurs, where they help to create new business divisions and products and bring about changes to internal operations [6]).

The descriptive data for each of the metrics of regional entrepreneurship activity are shown in Table 1.

Table 1. Descriptive statistics of the individual measures of regional entrepreneurship activity.

Measures of Regional Entrepreneurship Activity	Minimum	Maximum	Mean	Standard Deviation
Number of enterprises ^a per 1000 persons of labor force	204.13	436.51	344.01	62.41
Number of new enterprises ^b in manufacturing per 1000 persons of labor force	0.01	0.21	0.06	0.05
Employment rate	0.69	0.85	0.76	0.04

^a Source: [45]. ^b Source: [46].

An isotonicity test employing the Pearson's correlation coefficient was carried out between the input and output variables with regard to the isotonicity property assumption. The input and output variables passed the isotonicity test because there were positive (and significant) correlations between them.

5. Results and Discussion

For each region, Table 2 displays the DEA-BCC point estimates, $\hat{\phi}_j(x_j, y_j)$, that stem from Model (1); the related bias estimates, $\hat{bias}_B[\hat{\phi}(x, y)]$; the estimated variance, $\hat{\sigma}$, across bootstrap replications; the ratio, r , the bias-corrected DEA point estimates, $\hat{\hat{\phi}}(x, y)$; the calculated 95% confidence lower and upper bounds; the rankings based on the point estimate of the bias-corrected efficiency scores; and the classification of regions into three classes (high-, medium-, and low-level regions).

Table 2. Original DEA and bootstrapping estimates.

	Single DEA				DEA-Bootstrapping Estimates					
Regions	DEA-BCC Point Estimates	Bias	Variance	r	Bias-Corrected Point Estimates	Lower Bound	Upper Bound	Ranking ^a	Classification	
Attica	1.0000	0.0460	0.0012	453.16	0.9540	0.9060	0.9987	5	HLR	
Central Macedonia	0.9331	0.0153	0.0001	5812.17	0.9177	0.8944	0.9319	10	MLR	
Crete	0.9201	0.0148	0.0001	5901.32	0.9053	0.8806	0.9190	11	MLR	
Eastern Macedonia and Thrace	0.9517	0.0134	0.0001	7935.58	0.9382	0.9178	0.9505	7	MLR	
Epirus	0.9772	0.0214	0.0002	2863.59	0.9560	0.9246	0.9763	2		
Ionian Islands	1.0000	0.0462	0.0012	462.13	0.9538	0.9061	0.9991	6	HLR	
Mainland Greece	0.9409	0.0159	0.0001	6640.96	0.9249	0.9025	0.9396	9	MLR	
Northern Aegean	1.0000	0.0251	0.0004	1661.56	0.9749	0.9397	0.9987	1	HLR	
Peloponnesus	0.9445	0.0144	0.0001	4129.23	0.9301	0.9021	0.9435	8	MLR	
Southern Aegean	1.0000	0.0453	0.0009	803.72	0.9547	0.9208	0.9986	3	HLR	
Thessaly	0.9057	0.0149	0.0001	7031.98	0.8908	0.8701	0.9048	12	LLR	
Western Greece	1.0000	0.0453	0.0013	431.87	0.9547	0.9055	0.9989	4	HLR	
Western Macedonia	0.9092	0.0220	0.0002	2697.25	0.8870	0.8561	0.9079	13	LLR	

^a Rankings are based on bias-corrected DEA estimates generated with 2000 bootstrap iterations. HLR: High-level region; MLR: Medium-level region; LLR: Low-level region.

The DEA-BCC point estimates $\hat{\phi}(x, y)$ show that 5 of the 13 regions are presumably efficient. The DEA-BCC point estimates for the remaining eight regions range from 0.9057 to 0.9772, with an average of 0.9353.

The calculated biases are positive, as expected, as shown in Table 2. In reality, the computed 95% confidence intervals for the data whose initial DEA-BCC estimates were unity have lower bounds of 0.8561 to 0.9048 and upper bounds of 0.9397 to 0.9991. The ratio, r , for all regions exceeds unity because the estimated variances were frequently fairly small in comparison to the estimated biases. Accordingly, the bias-corrected efficiency estimates ought to be chosen above the original DEA-BCC estimates.

The DEA has a solid framework for classifying regions as efficient or inefficient. The DEA-BCC model results show that regions can be divided into two categories: efficient, or those with scores equal to 1, and inefficient, or those with scores below 1. To classify the regions, DEA-bootstrap was superior to single DEA since it could fully classify both the efficient DEA-BCC regions and the inefficient regions. Regions with scores higher than 0.95 can be classified as “high efficiency level regions” when using the bias-corrected results. “Medium efficiency level regions” are classified as those with a score between 0.90 and 0.94, and “low efficiency level regions” are classified as those with a score below 0.94. The proposed framework appears to have stronger discriminating power than the findings of earlier studies [26], as the above categorization employs higher cut-off points—0.9 instead of 0.5 [26] for low-level regions and 0.95 instead of 0.8 [26] for high-level regions. Among high-level regions, according to the bootstrapping method, the most efficient region is the Northern Aegean, followed by Epirus, Southern Aegean, Western Greece, and Attica. Thessaly and Western Macedonia are low-level regions, whereas the rest are medium-level regions.

An effort was made to identify the drivers of regional performance using the double bootstrap proposed by Simar and Wilson [47]. The current paper includes two explanatory variables to assess their influence on the bias-corrected efficiency (dependent variable), namely the long-term unemployment rate and the gross fixed capital formation as a percentage of GDP. Unemployment and investment (i.e., expenditures in fixed capital)

are both seen as determinants of entrepreneurship, in line with Silva et al. [25]. Although there is evidence that unemployment may negatively affect regional inefficiency, the results of the double bootstrap were not statistically significant. The results are available upon request from the author.

6. Conclusions

This paper demonstrates the viability of using DEA in a regional context to evaluate entrepreneurial activities. This approach is based on the framework for productive efficiency and makes use of specific indicators of regional entrepreneurship activity.

The two individual measures of regional entrepreneurship activity used on the input side of the DEA were the number of firms in 2015 per 1000 people in the labor force and the number of new firms in manufacturing per 1000 people in the labor force (expressing the classic entrepreneurs and corporate entrepreneurs or intrapreneurs in manufacturing). The employment rate was utilized on the output side. Relative performance indicators with a range of 0 to 1 were offered by the chosen DEA model. The ratio of the weighted sum of the individual entrepreneurship indicators to the employment rate determined a region's relative efficiency score. Additionally, the derived performance indicators were bootstrapped to yield the appropriate bias estimates, estimated variances across bootstrap replications for each observation, the bias-corrected efficiency estimate, and the estimated 95% confidence bounds.

The following conclusions were drawn from the application of the DEA-bootstrapping model to all 13 Greek regions: The regions perform differently in terms of converting entrepreneurial activity into job creation, and they were classified into three classes (high-, medium-, and low-level regions). There is some evidence that unemployment may negatively affect regional inefficiency, but the results were not statistically significant.

The generated performance indicators can be used to develop various interventions at the regional level as well as to identify areas where improvements can be made (i.e., labor market interventions for the promotion of self-employment). Policies to promote regional entrepreneurship must contain guidelines for creating an environment that encourages entrepreneurs to create jobs, particularly in low- and medium-level regions.

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